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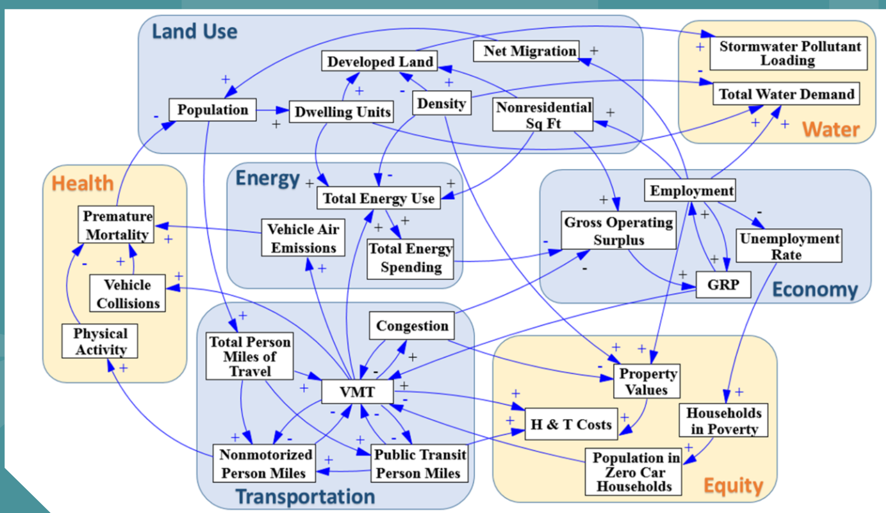
A System Dynamics Model for Integrated Decision Making: The Durham-Orange Light Rail Project



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Acronyms and Abbreviations

Abbreviation	Description
ACS	American Community Survey (from U.S. Census Bureau)
AEO	Annual Energy Outlook
BAU	Business-As-Usual
BEA	U.S. Bureau of Economic Analysis
CAMPO	Capital Area Metropolitan Planning Organization (Raleigh, NC)
CATS	Charlotte Area Transit System
CLD	Causal Loop Diagram
CPP	Clean Power Plan
CV2	CommunityViz 2.0
DATA	Durham Area Transit Authority (now called GoDurham)
DCHC MPO	Durham-Chapel Hill-Carrboro Metropolitan Planning Organization
DEIS	Draft Environmental Impact Statement
D-O LRP	Durham-Orange Light Rail Project
EIA	Environmental Impact Analysis
EIS	Environmental Impact Statement
EMC	Event Mean Concentration
FAR	Floor Area Ratio
FTA	Federal Transit Administration
FY	Fiscal Year
GHG	Greenhouse Gas
GIS	Geographic Information System
GOS	Gross Operating Surplus
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model
GRP	Gross Regional Product
HEAT	Health Economic Assessment Tools
HHI	Herfindahl-Hirschman Index
HIA	Health Impact Assessment
HUD	U.S. Dept. of Housing and Urban Development
IEA	International Energy Agency
LEHD	Longitudinal Employer-Household Dynamics (from U.S. Census Bureau)
LINC	Log Into North Carolina
LODES	LEHD Origin-Destination Employment Statistics (from U.S. Census Bureau)
LRP	Light Rail Project
LRT	Light Rail Transit
MF	Multifamily
MOVES	Motor Vehicle Emission Simulator
MPG	Miles Per Gallon
MPO	Metropolitan Planning Organization
MTP	Metropolitan Transportation Plan

MW	Megawatt
N	Nitrogen
NAICS	North American Industrial Classification System
NC DENR	North Carolina Department of Environment and Natural Resources
NC DHHS	North Carolina Department of Health and Human Services
NC DOR	North Carolina Department of Revenue
NC DOT	North Carolina Department of Transportation
NC DST	North Carolina Department of State Treasurer
NC ESC	North Carolina Employment Security Commission
NEPA	National Environmental Policy Act
NERL	National Exposure Research Laboratory
NHGIS	National Historical Geographic Information System
NOAA	National Oceanic and Atmospheric Administration
NMT	Nonmotorized Travel
NTD	National Transit Database
O&M	Operations and Maintenance
ORD	Office of Research and Development
P	Phosphorus
PTT	Public Transit Trip
QA	Quality Assurance
SD	System Dynamics
SE	Socioeconomic
SF	Single-family
SHC	Sustainable and Healthy Communities Research Program
SIA	Sustainability Impact Assessment
SLD	Smart Location Database
SMP	Sustainable Mobility Project
TAZ	Traffic Analysis Zone
TCRP	Transit Cooperative Research Program
TIGER	Topologically Integrated Geographic Encoding and Referencing
TJCOG	Triangle J Council of Governments
TRM	Triangle Regional Model
TTA	Triangle Transit Authority (later changed to Triangle Transit, then GoTriangle)
UNC	University of North Carolina
US BLS	U.S. Bureau of Labor Statistics
USD	United States Dollar
US DOE	U.S. Department of Energy
US DOT	U.S. Department of Transportation
US EIA	U.S. Energy Information Administration
US EPA	U.S. Environmental Protection Agency
USGS	U.S. Geological Survey
VMT	Vehicle Miles Traveled
WHO	World Health Organization

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Executive Summary

Project Background

EPA's Sustainable and Healthy Communities Research Program (SHC) is conducting transdisciplinary research to inform and empower decision-makers. EPA tools and approaches are being developed to enable communities to effectively weigh and integrate human health, socioeconomic, environmental, and ecological factors into their decisions to promote community sustainability. To help achieve this goal, EPA researchers have developed systems approaches to account for the linkages among resources, assets, and outcomes managed by a community. System dynamics (SD) is a member of the family of systems approaches and provides a framework for dynamic modeling that can assist with assessing and understanding complex issues across multiple dimensions. To test the utility of such tools when applied to a real-world situation, the EPA has developed a prototype SD model for community sustainability using the proposed Durham-Orange Light Rail Project (D-O LRP) as a case study.

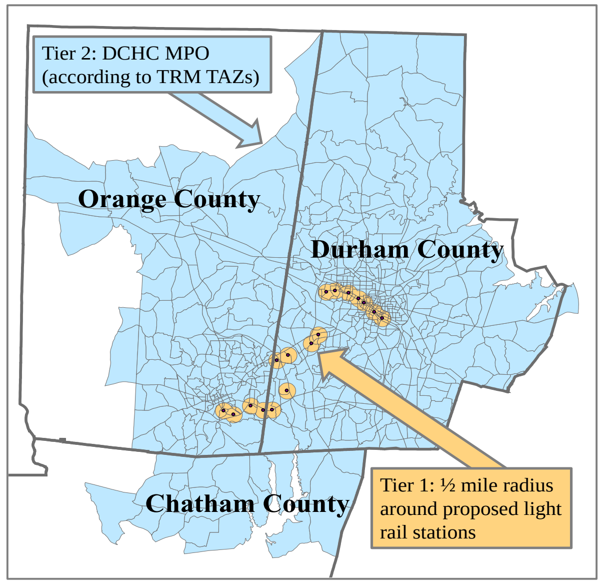
The EPA D-O LRP SD modeling team chose the proposed D-O LRP to demonstrate that an integrated modeling approach could represent the multitude of related cross-sectoral decisions that would be made and the cascading impacts that could result from a light rail transit system connecting Durham and Chapel Hill, NC. In keeping with the SHC vision described above, the proposal for the light rail is a starting point solution for the more intractable problems of population growth, unsustainable land use, environmental degradation, and the persistence of economic, social, and health inequities. To achieve the maximum potential benefits from the light rail across all of the dimensions of sustainability while reducing its potential negative consequences, concurrent policies must be weighed in combination with the light rail to assess the tradeoffs associated with these decisions. Therefore, the D-O LRP SD modeling team developed many concurrent policy scenarios in addition to the light rail that can aid stakeholders in finding leverage points within the system where interventions can have the largest impact.

In the first phase of this modeling effort, a conceptual model for the D-O LRP was designed with a high degree of input from stakeholders, including representatives from the regional transit authority, county health department, stormwater management department, and city and regional land use and transportation planning departments, among others. This conceptual model served as a framework for the operational SD model, which was built to evaluate a number of policy scenarios, many of which were also suggested by stakeholders. The operational model was subjected to rigorous quality assurance tests, including the sensitivity of the model to assumptions and inputs, and the evaluation of outcomes – social, economic, and environmental – resulting from actions that emanate from or impinge on the D-O LRP.

Model Structure

The D-O LRP SD Model was calibrated using historical data and local projections, when available, for its two geographic boundaries: Tier 2 - the area defined as being within the boundaries of the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO); and Tier 1 - the combined area of ½-mile-radius zones surrounding each of the proposed light rail stations (½-mile radius was chosen because it is common practice among urban planners to regard a half mile as the greatest distance that most people are willing to walk to a public transit station).

Figure ES-1. Map of the D-O LRP SD Model Geographic Tiers



Model variable outputs are reported for each Tier annually between 2000 and 2040. The model is designed to explore dynamic interactions among sectors of the urban system, including land use, transportation, energy, economics, equity, water, and health. These sectors are visualized in Figure ES-2, with plus (+) signs indicating a positive association between variables (an increase in A produces an increase in B, and a decrease in B produces a decrease in B), and minus (-) signs indicating a negative association between variables (an increase in A produces a decrease in B, and vice versa). Model scenarios run in a few seconds, and users can edit inputs or equations for any variable in the model.

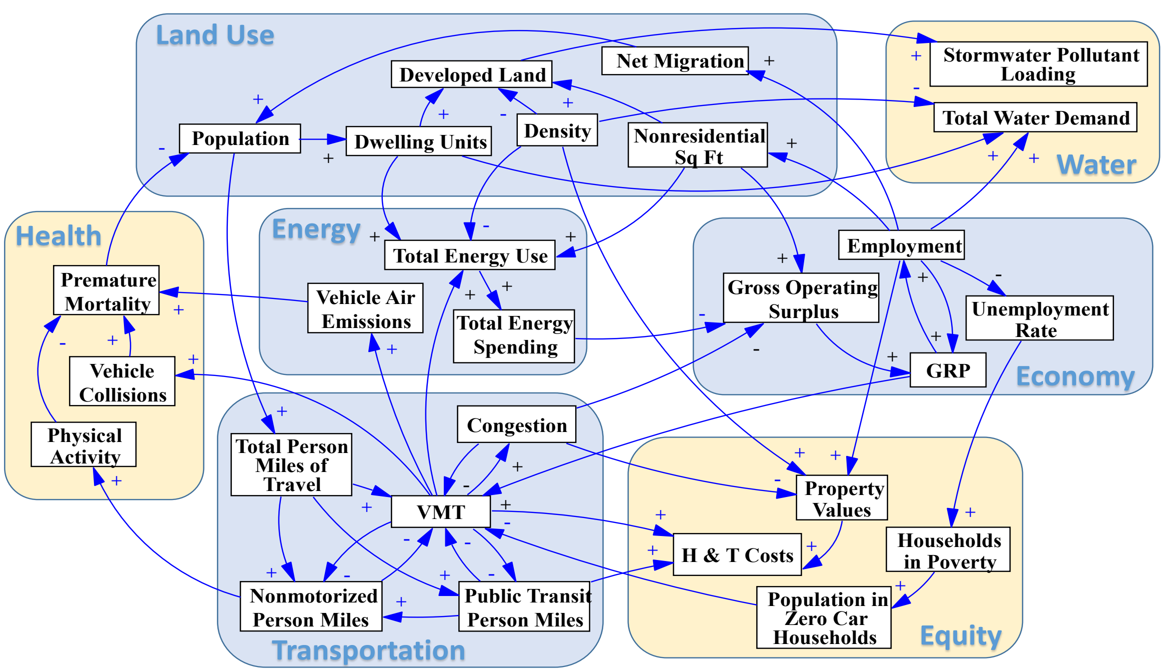


Figure ES-2. Causal Loop Diagram (CLD) for the D-O LRP SD Model

Model Scenarios

Three main scenarios were run in the D-O LRP SD Model to reflect the most likely transportation and land use plans.

1. **Business-As-Usual (BAU) scenario**
The BAU scenario represents expected results if current demographic, land use, and transportation trends continue and serves as a baseline to contrast with the other scenarios described below.

2. **Light Rail scenario**
The Light Rail scenario represents the implementation of the 17-mile light rail transit (LRT) line by 2026 between Durham and Chapel Hill and also deviates from the BAU scenario as follows:

- Assumes LRT motivates more people to use public transit than an equal number of bus service miles;
- Assumes a 10% increase in demand for developed nonresidential (excluding industrial) floor space in Tier 1, gradually phased in during the six-year period of light rail construction; and
- Assumes a higher share of Tier 1 employees will choose to move to Tier 1 rather than commute from elsewhere in Tier 2.

3. **Light Rail + Redevelopment scenario**
The Light Rail + Redevelopment scenario represents the implementation of the LRT line with additional changes to zoning to encourage land redevelopment and increased density around the station areas.

- Assumes 20% of developed land is redeveloped to almost three times its existing density by 2040, starting in 2020 in anticipation of the rail

Testable Interventions

The results of 17 additional policy, demographic, and market scenarios, were also analyzed to demonstrate the breadth of policies and other factors that can be tested with the model. Some of the main policy, demographic, and market levers that can be modified by users include:

- Policy Interventions
  - Density and redevelopment
  - Fare free transit
  - Parking price changes
  - Sidewalk building
  - Clean Power Plan
  - Stormwater management
- Demographic and Market Shifts
  - More multifamily households
  - Higher gas prices
  - Change in wages
- Technology Changes
  - Building energy efficiency
  - Vehicle fuel efficiency
  - Solar capacity

Main Findings

Findings from Model Construction

The model uses defensible explanatory mechanisms to approximate historical trends. We used documented causal relationships between variables to drive behavior in the model. After calibration, these mechanisms were adequate to reproduce historical trends, and they form the basis of future projections. While each variable in the model can potentially influence most other variables, Table ES-1 represents a select set of variables whose values are of high interest to decision makers (labeled "Indicators") and the set of additional variables (labeled "Drivers") that influence them most strongly in the model.

Table ES-1. A Selection of Model Indicators and their Drivers

Indicator	Model Drivers
Economic	
GRP	Earnings, nonresidential sq ft, gross operating surplus per sq ft, energy spending, congestion
Employment	Labor force, GRP, retail consumption
Productivity loss due to congestion	VMT, congestion, per capita earnings
Nonresidential property values	Employment growth, retail density, building size
Residential Property values	Land availability, income growth, commute time, population growth, lot size, retail density
Social	
Poverty rate	Unemployment rate
Transit-dependent population	Population in poverty
Affordability index	Renter costs, vehicle costs, transit costs
Net premature mortalities avoided	VMT, NO_x and $PM_{2.5}$ emissions per VMT, accidents per VMT, person miles of nonmotorized travel
Person miles of public transit travel	GRP, population, fare price, revenue miles, price of gasoline, MPG, traffic congestion, travel by other modes
Person miles of nonmotorized travel	GRP, population, nonmotorized travel facilities, jobs-housing balance, price of gasoline, MPG, traffic congestion, travel by other modes
Environmental	
Energy use	Building stock, building energy intensity, VMT, MPG
CO_2 emissions	Energy use, emissions intensity of electricity generation, solar capacity
Stormwater N and P loading	Developed land, impervious surface, stormwater mitigation (e.g. rain gardens)
VMT	GRP, population, population in zero-car households, price of gasoline, MPG, traffic congestion, travel by other modes
$PM_{2.5}$ and NO_x emissions	VMT, emissions per VMT

The model has facilitated interactions among diverse stakeholders to address complex, interconnected community issues. The CLD was developed based on the input of a diverse group of stakeholders, including local land use and transportation planners, sustainability experts, and public health leaders. This stakeholder group also provided feedback on preliminary model capabilities and results, which drove revisions and additions to the model.

Selected Scenario Results

Economic

Job growth in Tier 1 due to the light rail is accompanied by greater traffic congestion despite decreases in per capita vehicle miles traveled (VMT). When the light rail opens in 2026, there is a shift towards more transit use, decreasing VMT per capita by residents of Tier 1, as shown in Figure ES-3A. However, the D-O LRP SD Model assumes the light rail will increase demand for nonresidential floor space in the station areas, which leads to more employment growth between 2020 and 2040 than the BAU scenario (53% vs. 35%, Figure ES-4). This economic growth spurs population growth by encouraging immigration to the area and leads to increases in total VMT and congestion in Tier 1. Congestion sharply declines in 2026 due to the introduction of the light rail line (Figure ES-3B); however this decline is offset within four years by the increased traffic due to economic and population growth.

(A) (B)

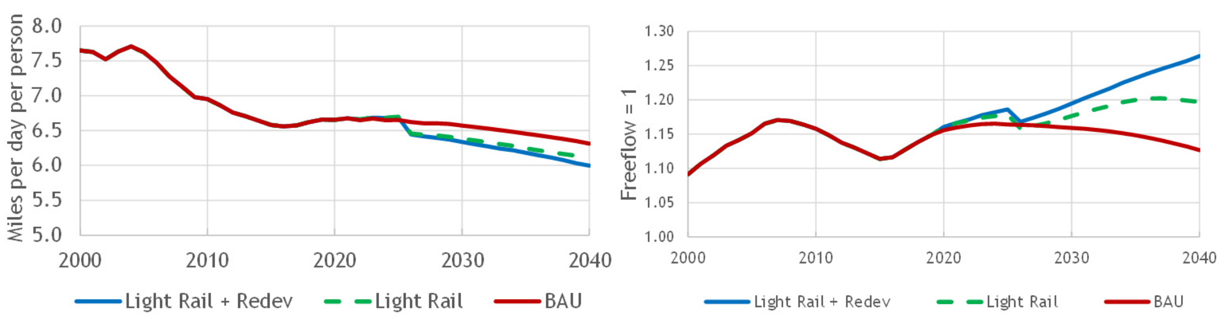


Figure ES- 3. Light Rail Scenarios Compared to BAU for: (A) VMT by Tier 1 Residents per Day per Capita, and (B) Tier 1 Congestion

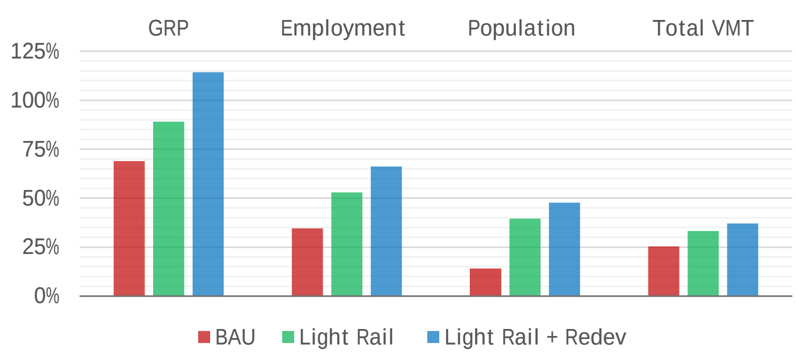


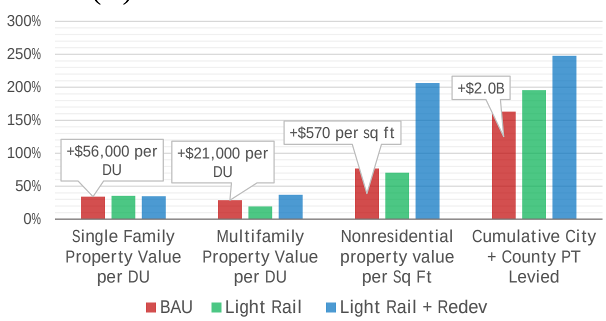
Figure ES- 4. Change in Tier 1 Overall Growth Indicators Between 2020 and 2040

More of the potential economic benefits of light rail are realized in the Light Rail + Redevelopment scenario, due to compact redevelopment in Tier 1. Denser development allows demand for nonresidential square feet to be met, causing gross regional product (GRP) to grow by 114% between 2020 and 2040, compared to only 89% under Light Rail alone (Figure ES-4).

Social

Compact redevelopment increases nonresidential property values far more than residential property values in Tier 1, providing a win-win for tax revenues and housing affordability. In real terms, residential property values in the Light Rail + Redevelopment scenario are no more than 7% higher than BAU in 2040, while nonresidential property values increase by 136% more than under the Light Rail scenario in Tier 1 between 2020 and 2040 (Figure ES-5A). The rise in multifamily property values, coupled with an increase in vehicle costs, drives decline in the affordability index of 4.8% by 2040 in the Light Rail + Redevelopment scenario relative to BAU (Figure ES-5B). However, the rise in nonresidential property values leads to $660M more in cumulative real property taxes (PT) levied between 2020 and 2040 than under the Light Rail scenario in Tier 1 alone (Figure ES-5A).

(A)



(B)

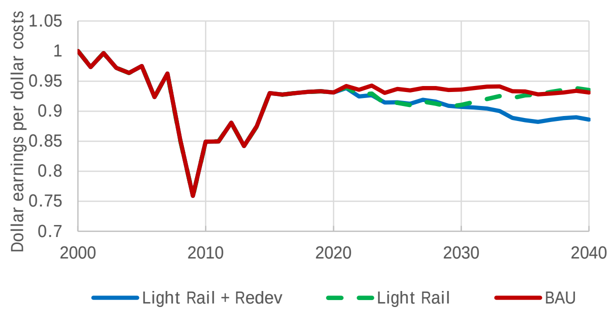
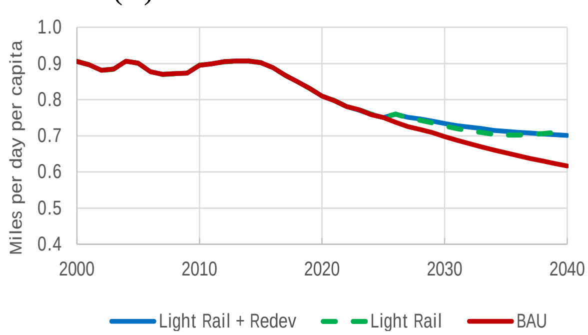


Figure ES- 5. Tier 1 (A) Change in Single Family, Multifamily, and Nonresidential Property Values between 2020 and 2040 in Tier 1, (B) Affordability Index: Main Policy Scenarios Compared to BAU

Residents' health improves due to more walking and cycling under the light rail scenarios. Within the context of an overall declining trend in nonmotorized travel per capita, the light rail encourages more walking and cycling relative to BAU (Figure ES-6A). Consequently, premature mortalities avoided due to an active lifestyle increase, resulting in 46 (Light Rail) and 54 (Light Rail + Redevelopment) cumulative additional avoided premature mortalities (Figure ES-6B). This net health improvement reflects that the benefits of increased physical activity outweigh the negligible impacts of increased $PM_{2.5}$ and NO_x vehicle emissions and the slight increase in vehicle crash fatalities.

(A)



(B)

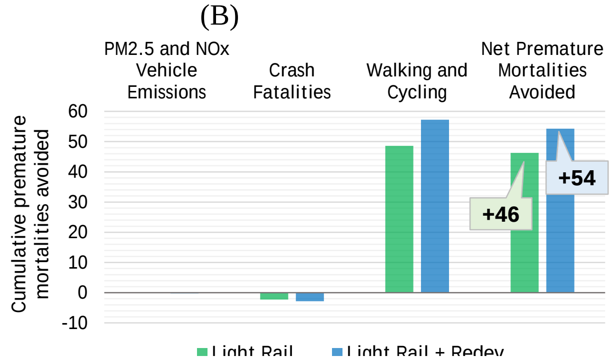


Figure ES- 6. Health Effects in Tier 1: (A) Nonmotorized Travel by Residents per Day per Capita and (B) Cumulative Premature Mortalities Avoided by Cause and Net Cumulative Premature Mortalities Avoided between 2020 and 2040 for the Light Rail Scenarios: Departure from BAU

Environmental

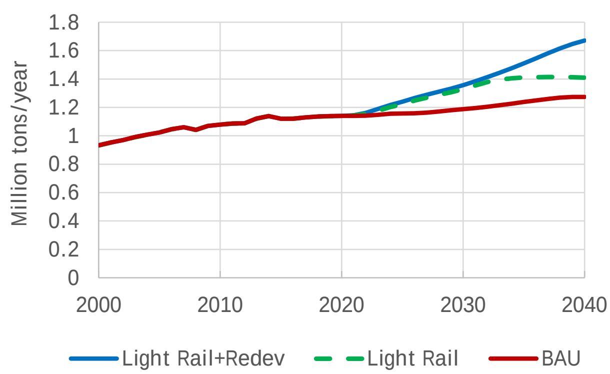
Intensity indicators demonstrate improvements in resource use efficiency under the Light Rail + Redevelopment scenario in Tier 1 despite economic growth. In 2040, impervious surfaces per capita in Tier 1 are 19% lower in the Light Rail + Redevelopment scenario than in BAU (Table ES-2). Daily water demand per capita in Tier 1 is also improved in the Light Rail + Redevelopment scenario, at 1.8% lower than BAU. On the other hand, CO_2 emissions per dollar of GRP increase in the Light Rail + Redevelopment scenario by 3% relative to the BAU. This is due to redevelopment increasing nonresidential use, which is more energy intensive than residential use.

Table ES-2. Selected environmental intensity measures across the BAU, Light Rail, and Light Rail + Redevelopment scenarios

Tier 1	BAU	Light Rail		Light Rail + Redev	
	2040 Value	2040 Value	% diff from BAU	2040 Value	% diff from BAU
Intensity Measures					
Impervious surface (acres) per capita	0.08	0.068	-12%	0.062	-19%
CO2 Emissions per GRP (tons/million USD 2010)	94	93	-1%	97	3%
Daily water demand (Mgal/year) per capita	0.050	0.048	-4.1%	0.049	-1.8%

Determining the cumulative environmental impacts of scenarios requires viewing model results as a time series. Although Light Rail and Light Rail + Redevelopment would appear to have the same impact on CO_2 emissions by 2030 (Fig ES-7A), they diverge afterward, leading Light Rail + Redevelopment to have the highest cumulative CO_2 emissions by 2040. The situation is opposite for stormwater N load (Fig ES-7B): although the two light rail scenarios have similar stormwater N load in 2040, Light Rail sustains this load for a longer time, so its cumulative stormwater N load is higher than Light Rail + Redevelopment by 2040.

(A) CO_2 Emissions



(B) Stormwater N Load

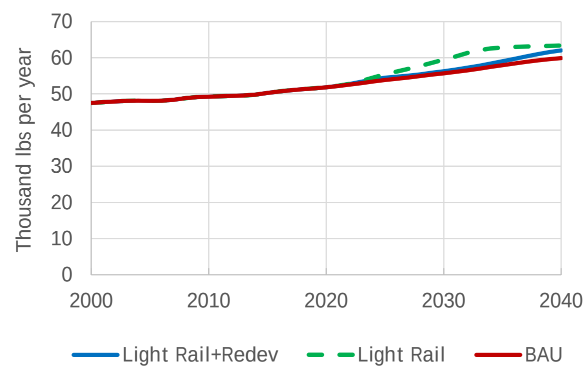


Figure ES- 7. Environmental impacts in Tier 1: Light Rail, Light Rail + Redevelopment Scenarios Compared to BAU

Compact redevelopment increases energy use and CO_2 emissions intensity in Tier 1, due to unlocking growth potential and increasing nonresidential uses. CO_2 emissions reductions strategies and stormwater management policies such as the Durham GHG Plan, the Clean Power Plan, and the Jordan/Falls Lake Rules can help offset the environmental impacts of growth described above. If applied to our model, emissions goals set by the Clean Power Plan would drop Tier 1 emissions by 16% from their projected 2030 level (Figure ES-8A). A stormwater N mitigation plan that would treat 30% of the stormwater N load from development after 2015 and 15% of the load from development existing before 2015 could cause stormwater N load to level off in Tier 1 (light blue line in Figure ES-8B).

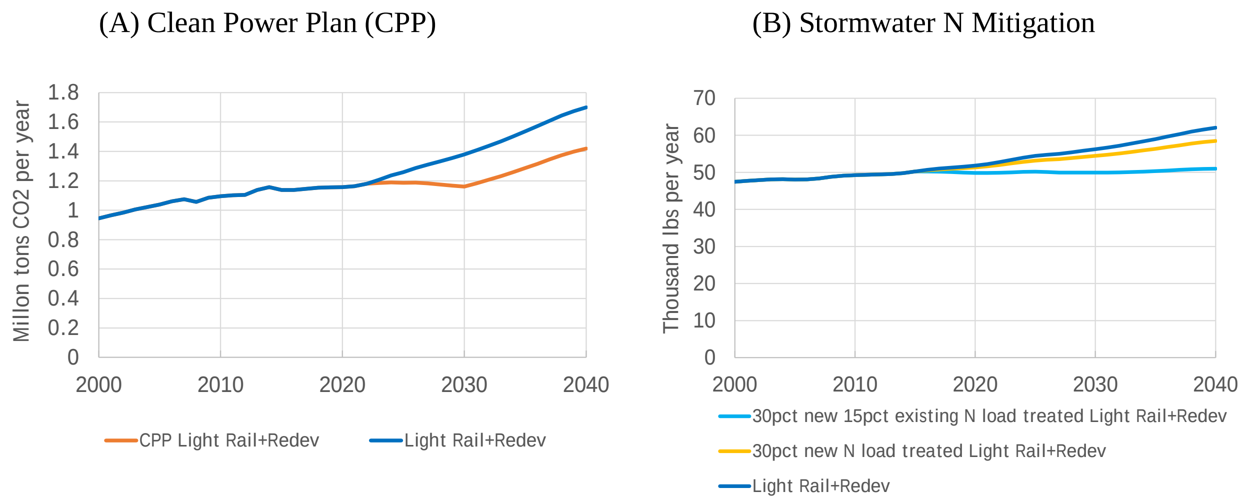


Figure ES- 8. Mitigating the Environmental Effects of Light Rail + Redevelopment in Tier 1

Regional impacts of the light rail are quantified by the D-O LRP SD Model, but those impacts are less pronounced than in the station areas. In terms of population, energy use, and water demand, Tier 2 is between seven and eleven times the scale of Tier 1. Therefore, the cascading impacts of the light rail are diluted in Tier 2. For example, projected annual energy use in 2040 is 10% higher in the Light Rail scenario compared to BAU in Tier 1, but only 3.9% higher than BAU in Tier 2. Similarly, nonmotorized travel by residents per capita is 15% higher in the Light Rail scenario than BAU in 2040 in Tier 1, but only 1% higher in Tier 2.

Limitations of the Model

The D-O LRP SD Model illustrates trends and relative magnitude, not predictions. System dynamics models are intended to explore the complexity and interactions within a system, rather than produce an exact answer to a given question. Although our model explores policies and scenarios related to the role of light rail transit in sustainable regional development, our model does not provide specific directions to urban planners. Rather, it shows potential future trends, relative magnitudes of impact, and interactions among different sectors of the urban system.

The model is not designed to work under extreme conditions or past the year 2040. Model results have been extensively tested for inputs within reasonable value ranges, and model parameters have been set to work within these boundaries. Extreme values, changes to historical inputs, or extrapolation of results past the model timespan could produce unrealistic outputs.

The model is not spatially explicit. All inputs and indicators are aggregated to the level of the two modeled tiers.

Intended Community Value

The system dynamics modeling approach can add value to three types of community processes:

1) **Regulatory process –** applying a multisector SD model like the D-O LRP model could allow the Indirect and Cumulative Impacts section of an Environmental Impact Statement (EIS) to have more quantitative projections. Currently the Indirect and Cumulative Impacts of the D-O LRP EIS are described as general increases or decreases. Applying a SD model would allow the regulatory process to consider the relative size of increases or decreases, so that tradeoffs could be weighed.

2) **Urban planners and planning process –** interactions between transportation, health and sustainability planners could be facilitated through a model that integrates their various sectors. In urban planning, actions in one department may compete with or counteract the interests of another department or agency. Developing and using a stakeholder-invested model could help departments to coordinate their efforts, or at least visualize how the actions of one department influence the interests of other departments.

3) **Public discussion –** an SD model can help explore issues that citizens raise at public meetings. A large-scale public project such as light rail transit requires an education and outreach effort to maintain public support. An SD model like the D-O LRP model can help citizens visualize the various ways in which a project like light rail transit can affect regional development.

Next Steps

- **Model Version 2.0.** An updated version of the model is currently under development. It will include, an updated calibration of employment for the BAU scenario in Tier 1, updated estimates of the elasticities of person miles (by each mode of transportation) to GRP per capita, and additional model enhancements pending our interactions with stakeholders.

- **User Interface**. A more user-friendly interface will be developed to allow stakeholders to test assumptions and policy interventions, access relevant background information, and view indicators for side-by-side comparison.

- **Transferable Tools.** Ultimately, the experiences gleaned from this and other ORD and regional efforts to employ systems approaches will be consolidated into tools and guidance for communities and regions to apply these methods to a wide range of sustainability issues.

1 Introduction

1.1 Project Overview

As our understanding of the nature of sustainability issues evolves, so must the tools and approaches we use to address them. It is now widely recognized that systems previously treated discretely—air, water, land, transportation, energy, health and well-being, quality of place, the economy, and social equity—are inextricably intertwined. By acknowledging that human society exists within highly complex and interdependent systems, each potentially valued subjectively, scientists can provide approaches that transcend the deficiencies of traditional reductionist approaches, such as failure to account for linkages, cross-system impacts, and unanticipated consequences. The United States Environmental Protection Agency (US EPA) Sustainable and Healthy Communities Research Program (SHC) has committed to developing systems approaches that enable communities to act on an enhanced understanding of these interconnections and to comprehensively account for the full costs and benefits of community decisions in the social, economic, and environmental dimensions. This report documents the development and testing of a system dynamics (SD) model as a decision support tool for community sustainability with the proposed Durham-Orange Light Rail Project (D-O LRP) in Durham and Orange Counties, North Carolina, as a case-study.

The proposed D-O LRP, a 17-mile light rail transit system that would connect the city of Durham, NC and the town of Chapel Hill, NC, provides a concrete example for understanding how a SD model could be used to explore the interactions among decision sectors within a community and presents an opportunity for identifying points in the system where coordinated actions could yield a greater net value and possibly offset unintended consequences. The primary goals of the D-O LRP are to enhance mobility, capture untapped markets for transit use, and support desired development patterns in the region (Triangle Transit 2012a). If these goals are achieved, this project could have many positive impacts along the rail corridor. There are concerns, however, that the project could have negative impacts in some areas, such as displacement of low- to moderate-income households by increasing property values and intensification of urban stormwater runoff through higher-density development. It is therefore crucial for decision-makers to be able to identify how the project might interact with other sectors, such as land use change, housing, and water resource management, to maximize benefits and avoid or limit negative consequences.

To illustrate the interconnections in the complex system that would be perturbed by the D-O LRP, the D-O LRP SD modeling team has developed a prototype SD model that can help address the concerns listed above. In Phase I of this project, the modeling team developed a conceptual model for the system potentially affected directly and indirectly by the D-O LRP. This effort was made possible by many collaborations with local stakeholders, described in detail in Chapter 2 of this report. In Phase II of the project, the modeling team built a computer model using relationships derived from literature and calibrated it to historical data and projections (local, to the extent possible) for each of the seven high-priority decision sectors identified by stakeholders: land, transportation, energy, economy, equity, water, and health. Chapter 3 of this report includes an overview of the primary data sources used in the model, a description of the overall model structure, focusing on inter-sector relationships and feedbacks, and by-sector descriptions of intra-sector relationships and feedbacks, data sources and processing, and calibration steps.[1] In Phase III of the project, the modeling team constructed model scenarios based on stakeholder input, described in detail in Chapter 4. These scenarios were designed to not only test the D-O LRP as a policy against a "business as usual" (BAU) case, but also test additional decisions across sectors that could potentially maximize the benefits of the light rail or minimize undesired consequences. The results of these scenarios are given in Chapter 5, and the results of extensive QA model testing are shown in Chapter 6. Ultimately, the goal of this modeling effort is to demonstrate that a SD model constructed for a representative issue of community sustainability (such as the D-O LRP) will contribute to a more generalizable modeling approach that can help community decision-makers and stakeholders explore alternative policy scenarios for a wide variety of sustainability problems, as well as test the assumptions on which those scenarios are based.

1.2 Project Background

This section describes how this project fits within the US EPA SHC program and how systems approaches are necessary for understanding complex, large-scale problems. It then introduces SD models and discusses why such models are appropriate for complex problems. Finally, it provides background information on the D-O LRP, the project to be examined by this model.

The Sustainable and Healthy Communities (SHC) Research Program

American communities face complex challenges as they try to strengthen their economies, meet changing demand for housing and transportation, and protect the environment and public health. Following the strategic realignment of the US EPA Office of Research and Development (ORD) research programs in 2010, the agency has placed a stronger focus on transdisciplinary research to support the growing interest of communities in sustainable practices (Anastas 2012). Providing the scientific foundation to address the complex and multi-dimensional problems communities face is at the heart of SHC's mission. As stated in the US EPA's 2012 report, "Sustainable and Healthy Communities Strategic Action Plan 2012-2016," the overall vision of SHC is:

> "to inform and empower decision-makers in communities, as well as in federal, state and tribal community-driven programs, to effectively and equitably weigh and integrate human health, socio-economic, environmental, and ecological factors into their decisions in a way that fosters community sustainability." (US EPA 2012)

At the Federal level, the recognition that these issues are interconnected has resulted in the formation of the Federal Partnership for Sustainable Communities, which includes the US EPA, the U.S. Department of Transportation (US DOT), and the Department of Housing and Urban Development (HUD). However, Federal agencies and policies represent only a fraction of the interests that must be engaged to solve community problems. Thus, SHC has committed to developing the information, tools, and approaches needed to promote the collaboration required for communities to evaluate problems, proactively assess decision alternatives, implement more effective solutions, and track results (US EPA 2012). While much progress has been made in the development, use, and integration of science-based

[1] For a detailed more detailed description of the structure of each sector, including calibrated variables, exogenous inputs, and equations from literature, see Appendix B.

assessment tools and approaches to solve complex environmental challenges, there remains a need for additional assessment tools to gain a greater understanding of the inter-connected relationships that exist among social, economic, and environmental dimensions when addressing these challenges.

Criteria for Selecting a Modeling Approach

The goal of this SHC research project was to develop and evaluate the use of a tool that captured the dynamics among community decisions and the trends underlying the challenges that communities face in such a way that individual decisions could be evaluated in context and multiple decisions could be aligned to greater net benefit. In reviewing the range of candidate model types, we identified several key capabilities that the model needed to have:

1. The model must represent social, economic and environmental processes.

2. The model must account for actions that lead to multiple consequences, as well as outcomes that are fed by multiple actions.

3. Social and economic processes must have a more complex structure than simple "feed-forward" – that is, social and environmental consequences must have feedbacks to the system, allowing them to be drivers as well as consequences.

4. The model must allow for nonlinear responses, i.e. tipping points that cause a shift in the magnitude of a relationship.

5. Feedback mechanisms (with an emphasis on mechanisms that can be modified by policies or actions) are included in at least the transportation, economy, and land use sectors.

6. The model must incorporate and reflect stakeholder concerns while simplifying them sufficiently enough to be integrated into a complex model depicting many community processes.

As indicated by the criteria listed above, an integrated assessment of sustainable systems cannot be accomplished by simply linking together a collection of domain-specific models. Assessing the higher-level interactions among interdependent systems requires tools that specialize in capturing the emergent behaviors and dynamic relationships that characterize complex, adaptive systems (Fiksel 2006). One such tool is system dynamics.

System Dynamics (SD) Models

System dynamics (SD) is a member of the family of systems approaches and provides a framework for dynamic modeling that can assist with assessing and understanding complex issues across multiple dimensions. SD models can be critical tools for investigating the interdependence, nonlinear responses, feedback loops, and dynamic behaviors of complex systems. The process of constructing a SD model lends itself well to stakeholder engagement because it promotes the understanding and conceptualization of a problem, allowing those who participate in the process to view the behavior of the system and understand how the feedbacks and mechanisms within the model reflect and give rise to its behavior.[2] SD is a policy-oriented modeling technique that provides a framework for the design of policies and

[2] See Chapter 2 for a more detailed description of the process that was followed in building our SD model with the help of local stakeholders.

management of systems to achieve improved system behavior. However, SD models do not provide an explicit answer to a problem and are not meant to replace decision-makers or to inhibit their role in making decisions; rather, they are developed to help and support people in achieving better decisions (Abbas and Bell 1994).

SD modeling offers a whole-system approach to transportation and land use planning, illustrating how decisions regarding such large-scale projects will have cascading direct and indirect impacts across many sectors, including human health and the natural environment. Because SD models meet the criteria listed above, we decided that they offered the best modeling style for developing a tool that meets the research goals of SHC. To ensure that such a tool would have utility when applied to real-life problems, we elected to develop our SD model based on a light rail transit system proposed for our own community, Durham, NC, thus achieving two objectives: (1) providing immediate, practical decision support to real community issues related to sustainability, and (2) providing a test case that motivates the development of the model, demonstrates the "proof-of-concept" for this modeling approach, and provides "lessons learned" for transferring the approach to other communities and/or problem types.

The Durham-Orange Light Rail Project (D-O LRP)

The Triangle Region of central North Carolina (which connects the cities of Raleigh, Durham, and Chapel Hill) has been a hot spot for population growth and development over the past few decades due to a boom in employment and educational opportunities. While this rapid expansion has boosted economic prosperity for the region, it has also put significant stress on infrastructure and the natural environment. In a region that has become known for high average vehicle miles traveled (VMT) for work commuters, the vast majority of people are solely reliant on automobiles for transportation, overtaxing the existing roadway infrastructure. Projected levels of population growth and land conversion will not only exacerbate this problem, but will also lead to increased consumption of materials, energy, and water, and increased levels of air and water pollution. To address these issues, and to promote health and prosperity, a light rail transit system has been proposed to connect the town of Chapel Hill (located in Orange County, NC) and city of Durham (located in Durham County, NC) along a heavily-used corridor. The proposed light rail station locations are pictured in Figure 1-1.

Planning for fixed-guideway transit in the Triangle Region began over 20 years ago, and a number of transit studies have been conducted to advance major transit investments in the area.[3] Evaluation of fixed-guideway alternatives such as bus rapid transit (BRT) and light rail transit (LRT) in the Durham-Orange corridor began with the 1998-2001 US Highway 15-501 Major Investment Study, which included extensive public involvement and resulted in the establishment of an adopted transit corridor between Chapel Hill and Durham that continues to be protected and preserved for transit use by the local governments (Triangle Transit 2012b). In 2011 and 2012, respectively, Durham and Orange County residents voted in favor of a half-cent sales tax dedicated to transit, and in 2012, Triangle Transit (now referred to as GoTriangle), the local project sponsor for the D-O LRP, completed an alternatives analysis for the Durham-Orange corridor as the first step in the Federal Transit Administration (FTA) Project Planning and Development process. The alternatives analysis concluded by identifying a locally preferred alternative, LRT, as the only technology that satisfied the criteria of enhancing mobility, expanding transit options between Durham and Chapel Hill, serving populations with a high propensity for transit use, and fostering compact development and economic growth (Triangle Transit 2012a). Soon after, the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO)

[3] A collection of the transit studies done over the past twenty years can be found at http://ourtransitfuture.com/library/.

Transportation Advisory Committee unanimously adopted the LRT alternative as the locally preferred alternative for further study through Preliminary Engineering and the National Environmental Policy Act (NEPA) review process.

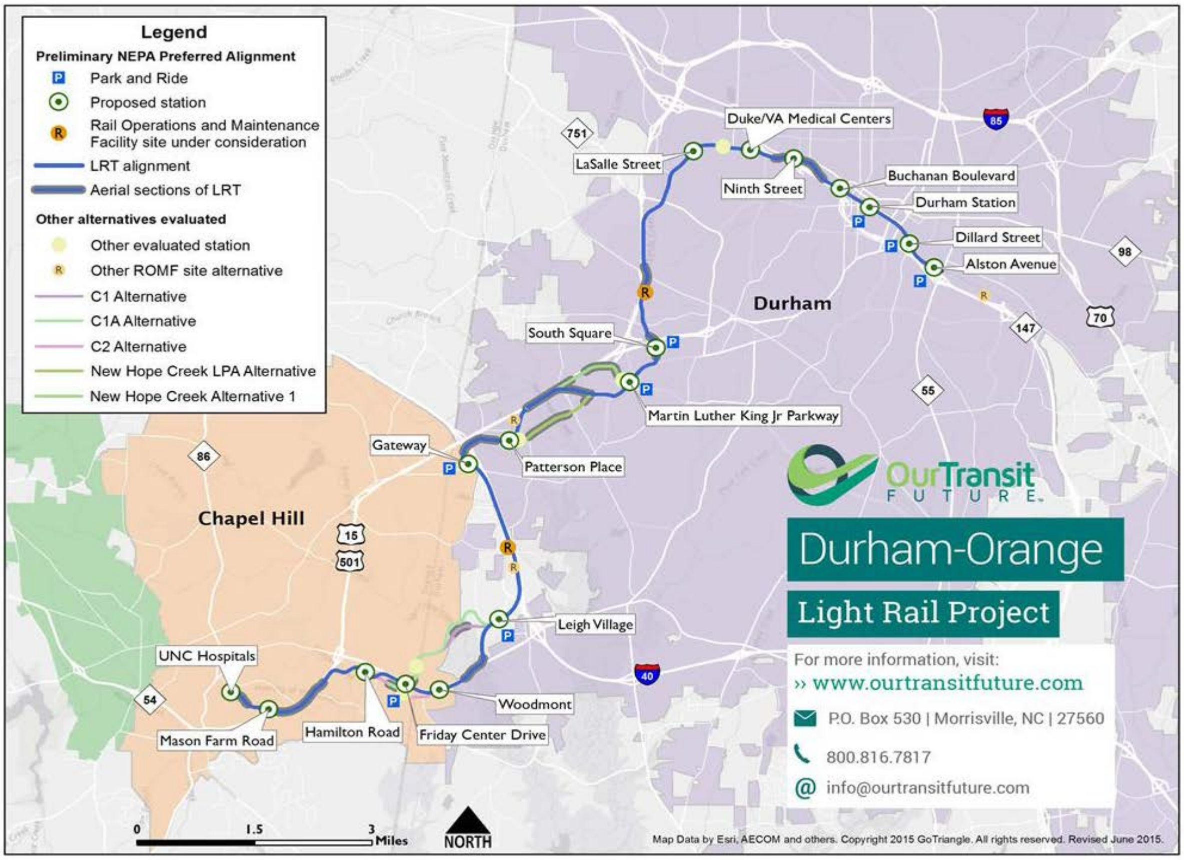


Figure 1- 1. Map of the Proposed Durham-Orange Light Rail Project Station Locations

As part of the approval process for receiving federal grant money under the FTA New Starts program (US DOT 2013), which includes an extensive environmental review process, GoTriangle released a Draft Environmental Impact Statement (DEIS) on August 28, 2015, pursuant to NEPA (FTA 2015a). The primary purpose of the DEIS is "to assist decision-makers and the public in assessing potential impacts associated with the implementation of the proposed D-O LRP" (GoTriangle 2015). The DEIS is circulated for review during a 45-day public comment period to interested parties, including members of the public, community groups, the business community, elected officials, and public agencies. This public comment period of the NEPA process provides a significant opportunity for the community to question and engage with the underlying information and assumptions of the project and to express concerns about direct and indirect impacts. Through the development of the D-O LRP SD Model, the project team sought to provide useful input into this process.

1.3 Potential Uses for the D-O LRP SD Model

The D-O LRP SD Model has multiple potential uses in the D-O LRP planning and assessment process; the model supports the current assessment process by augmenting the ability of NEPA's environmental review process, also called an environmental impact assessment (EIA), to address cumulative and indirect impacts. In the more general sense, we believe that models such as the D-O LRP SD model can support the evolution of the EIA to better address a wider suite of sustainability-oriented considerations, enhance the integration of information and actions in the planning process, and better educate and engage communities about the broader implications of projects and policies. In this section, we consider the larger debate about integrated assessments, integrated planning, and community participation in decision-making as reflected in the literature and also present, in text boxes, specific examples of how those issues play out in the local context of the D-O LRP.

Integrated Assessments for Environmental Review

Since its incorporation into environmental decision making by NEPA in 1969, EIA has been adopted by 100 countries worldwide. Intended to be both anticipatory and participatory, EIA is a systematic process that considers whether a project will have adverse environmental impacts, whether it should proceed, and—if so—what mitigatory measures should be adopted. An Environmental Impact Statement (EIS) is a full-disclosure document that forms part of the EIA process in the U.S.; a Draft EIS is made available for public comment, followed by a Final EIS, and, finally, a Record of Decision. In this section, we will refer to the EIA as the general process, in order to encompass its uses beyond the U.S., reflect the ongoing debates about its uses and suitability in the scientific and policy literature, and maintain a parallelism with alternate forms of Integrated Assessments, such as Health Impact Assessments (HIA) and Sustainability Impact Assessments (SIA).

Increasingly, EIA is being positioned in a broader context of sustainability, raising questions about its effectiveness and suitability for that purpose (e.g. Jay et al. (2007), as well as the extent to which it reflects evolving community values and engagement in the assessment process itself (Weston 2004). Although NEPA calls for the use of "all practical means and measures…to create and maintain conditions under which man and nature can co-exist in harmony and fulfill the social, economic and other requirements of present and future generations of Americans" (FTA 1969), Section 101(a)), the EIA process has, for the most part, been narrowly focused on and based on technical, "objective" tools and approaches. The push to address sustainability concerns, which harks back to the original NEPA language, has largely taken the form of elucidating indirect and cumulative impacts, including social and economic impacts, within the EIA (or the product of the EIA – the EIS). However, because social and economic impacts reflect a wider array of endpoints, many of which are difficult to measure objectively or with certainty, the treatment of indirect and cumulative impacts tends to be less quantitative than the treatment of the direct effects of a project.

NEPA legislation directs federal agencies to examine indirect and cumulative effects but does not prescribe a specific methodology. The Federal Transportation Agency's Planning Assistance and Standards (Title 23 CFR Part 450) indicate that indirect and cumulative effects should be sufficiently detailed such that consequences of different alternatives can be readily identified, based on current data and reasonable assumptions, and based on reliable and defensible analytic methods (FTA 1969). Indirect effects are those that occur either later in time or outside of the immediate geography of the project, and may include changes in the pattern of land use, changes in population, and related effects on air, water, and other natural systems. Cumulative impacts can result from individually minor but collectively significant actions taking place over time (D-O LRP DEIS, Chapter 4.17) (GoTriangle 2015). When impacts are understood to encompass social and economic considerations in addition to environmental ones, the challenges of assessing indirect and cumulative impacts increase many-fold (Gibson 2006).

In recent years, numerous authors have critiqued the ability of the EIA process to address the broader implications of environmental projects on sustainability, a challenge made even more difficult when the subject of the assessment is a policy or set of actions rather than a concrete and well-defined construction project (Jay et al. 2007, Weston 2004). The same authors also critique the EIA process as prioritizing procedure over substance and as being inherently adversarial in nature. In recent years, HIAs have been increasingly employed to assess and communicate a broader set of outcomes, including many social and economic outcomes that contribute to community well-being and environmental justice, but that may be difficult to quantify or predict using conventional indicators (Dannenberg et al. 2008). The strengths of HIAs – especially their ability to assess programs or policies, (as opposed to discrete projects) and their ability to consider community values as well as objectively-determined impacts - contrast with the more technical, project-specific orientation of EIAs, leading some authors to speculate whether HIAs might take the place of EIAs in the NEPA process (Cole et al. 2004).

MORE QUANTITATIVE TREATMENT OF INDIRECT AND CUMULATIVE IMPACTS WOULD SUPPORT BETTER ESTIMATES OF NET BENEFITS AND UNDESIRED CONSEQUENCES

The D-O LRP DEIS, Chapter 4.17, addresses the potential indirect impacts of transportation on Land Use, Economic Development, Visual and Aesthetic, Historic Resources, Natural Resources, Water Resources, Hazardous and Regulated Materials Acquisitions, and Relocations and Displacements. The cumulative impacts considered include Parking, Pedestrian and Bicycle Conditions, Land Use (Community Character), Economic Development, Visual and Aesthetic, Habitat, and Water Quality. Whereas the bulk of the DEIS addresses the expected direct impacts of the rail, this section of the document views transportation as a potential catalyst for induced growth and e))conomic development in the area within ½ mile of the rail and through the year 2040. The DEIS does not use In the absence of tools to evaluate feedbacks and estimate the magnitude of deviations from projections due to such catalysis, so it does not include any quantitative predictions of catalyzed growth or its consequences are included, nor does it characterize uncertainties. Rather, it concludes that the quantity, type, location, and pace of growth are deemed to be consistent with local land use plans based on narrative treatments and best judgment. Moreover, such descriptive treatments of all indirect and cumulative impacts do not permit summing them with more quantitatively estimated impacts, as would be desired determinations of net cost/benefits or the evaluation of ancillary policies that might mitigate undesired or enhance desired indirect or cumulative impacts. (GoTriangle 2015)

Essentially, EIAs struggle to extend their data-driven, techno-rational approaches to the assessment of indirect and cumulative impacts and to the broader suite of outcomes that contribute to emergent properties such as sustainability. HIAs, in contrast, embrace a more value-driven and contextual assessment of programs and policies, but struggle to bring quantitative approaches and rigor to the assessment. Though each has its strengths, both fall short of an ideal process that would bring scientific rigor to a decision that ultimately reflects societal values, that is both responsive enough to engage community participation and robust enough to withstand legal challenges. What we present here can help address the shortcomings of either EIAs or HIAs in the near term, but perhaps more importantly, can combine the strengths of each to move toward the ideal process described above. In essence, a systems dynamics model is a semi-quantitative, testable narrative. The story it tells is built on both community perspectives and well-documented scientific information, creating a whole that is informed by stakeholder values and wherein the magnitude and sensitivity of individual quantities and relationships can be tested and evaluated with respect to the overall behavior of the system.

Integrated, Multi-Sector Approaches to Planning

Urban planning and environmental management communities have long acknowledged a range of interactions among the economic, transportation, and land use sectors, as well as other sectors. To inform planning efforts, managers have invested significant resources in understanding and modeling these interactions. There is a rich literature documenting the impacts of one sector on another and supporting the utility of models for translating the dynamics of one sector into the inputs or drivers for another. Wegener (2004) reviewed twenty models for the interactions of transport and land-use change, noting the challenges of integrating processes that occur at very different time scales (e.g., network construction vs goods movement). That study reviewed the models for comprehensiveness, structure, theoretical foundations, dynamics, data requirements, calibration and validation, operationality, and applicability. Based on this overview, Wegener identified challenges in linking the models to environmental impacts and to social processes. In the years since this review, the challenges of linking land use and transportation to environmental impacts (air emissions) have been addressed by numerous air emission exposure models, as reviewed by Jerrett et al (2005). In most cases, regardless of the approach taken to estimate emissions, such models do not dynamically represent interactions between land use and transportation, but rather take various configurations of those two sectors as exogenous inputs.

For the most part, the models reviewed by Wegener (2004) and Jerrett et al (2005) tend to be feed-forward, linearly designed with drivers as contributory modules culminating in the ultimate outputs, usually that sector of primary interest to the author. When feedbacks or bi-directionality of mechanisms are represented, it is often as an iterative refinement of feed-forward methods. Few integrated models capture the dynamic and multi-directional flow of information and impacts among the multiple concurrent processes that determine the shape and the impact of urban systems.

Rickwood et al. (2007) made the case that population, land use, transport, water, and energy use all need to be examined in an integrated fashion, not only to optimize or evaluate individual sectors, but rather to improve the sustainability of urban systems as a whole. They propose integrating a number of topical models within a framework (UrbanSim) to evaluate policies and trends as they affect urban sustainability. Duran-Encalada and Paucar-Caceres (2009) also take a modeling approach to evaluate urban sustainability, but rather than integrating separate models, they developed a system dynamics model for Puebla, Mexico which they link to a range of policy impact techniques, such as Environmental Impact Analysis, Community Impact Analysis, and Financial Evaluation, thus placing the assessment of individual projects or policies in the broader context of urban sustainability. Fiksel et al. (2014) outlined a systems approach that treats sustainability as a function of the net creation of value among social, economic and environmental dimensions. They demonstrated that SD modeling was useful in elucidating which processes within and among those dimensions interacted to yield net value.

So far, models have been examined for their ability to bring together information from different sectoral domains to inform decisions, which could be achieved without contact among practitioners in each of the sectors. However each knowledge domain also has its corresponding institutions and agencies; for complex decisions, it may not be obvious which agencies have bearing on the issue, especially for agencies primarily associated with indirect or cumulative impacts. Construction of an integrated systems dynamics model has, as its first step, the development of a conceptual model, which can serve the double purpose of linking issues together conceptually, but also mapping the relationships of individual agencies and characterizing the interactions among them, thus allowing them to be brought into the process early and in a way that focuses their participation on the high-value linkages and synergies.

Education and Enhancing Community Engagement

As models have become more complex frameworks for the assemblage and integration of disparate information, their use has shifted somewhat away from direct application to calculate answers and toward constructing narratives. Pfaffenbichler (2011) captures this shift through four identified uses for models in the planning process:

1. Models as eye-openers: can put new environmental issues on the political agenda

2. Models as arguments in dissent: used to challenge assessment by way of counter-expertise or visualization of alternatives

3. Models as vehicles in creating consensus: used to help create a consensus view of a problem among different stakeholders

4. Models for management: used to assist stakeholders in concrete policy decisions

These narratives, in turn, have come to be viewed as potent tools for engaging stakeholders in the planning process (Foth et al. 2008).

EXPLICIT TREATMENT OF FEEDBACKS AND SYNERGIES AMONG SECTORS CAN ENHANCE INTEGRATED PLANNING

Although the planning for the D-O LRP reflects a high degree of communication and coordination among the regional business, utility and planning institutions, the ability of this process to account for feedbacks and synergies is limited by the tools available. An example of this lack of feedbacks and synergies can be seen in the model used to calculate the transportation demand for the light rail as part of the region's 2040 Metropolitan Transportation Plan (MTP), the Triangle Regional Model (TRM). The TRM used as inputs information derived from a number of other sectors, notably demographics, economy and land use. Based on community plans and data from local planning departments, the Office of State Budget and Management, the U.S. Census Bureau, and independent forecasters, estimates of "base year" (2010) and "plan year" (2040) population and jobs were developed for the area covered by the TRM. Using a software tool called CommunityViz, "plan year" people and jobs were allocated to locations deemed suitable for residential and nonresidential development (CAMPO and DCHC MPO 2013). The suitability of locations for development reflected best professional judgment by local urban and transportation planners as part of the Imagine 2040 effort and was consistent, in corresponding scenarios, with existing comprehensive plans and watershed policies (TJCOG 2013). The allocations of people and jobs were coupled with differing assumptions about transportation investments to produce a limited number of scenarios for the TRM, which yielded travel demand by mode for each scenario.

The feed-forward nature of the process was not able to capture or capitalize on the potential for dynamics in economy, land use, urban form and transportation to generate alternative representations of population or employment as inputs. As a result, the TRM was run for a finite number of static scenarios, and lacked a capability to test assumptions about how model internal processes might affect those inputs. Moreover, processes that accounted for indirect and cumulative impacts of the Light Rail Project (e.g. impacts on health, environmental quality) would also be expected to respond to dynamic feedbacks within and among population, land use, economy, etc. Failing to include them in the model meant that they could only be accounted for in the DEIS as non-quantitative descriptions of likely impacts.

Stave (2002, 2010) has suggested that systems dynamics models, especially when developed in a participatory setting, can enhance the role of stakeholders in environmental decision making. In most cases of environmental decision making, stakeholders have divergent views on root causes of the problem, goals for possible solutions, and which aspects of the problem to prioritize. Stave (2002) notes that when public input is elicited for decision making, it often takes the form of decision-makers distributing technical information, gathering public views, and then retreating behind closed doors to make critical trade-offs among stakeholder interests. Uses of system dynamics models as a tool for engaging with stakeholders creates a structure that allows decision makers and stakeholders together to learn about the system, recognize the structural origins of the problem, and identify key policy levers for the solutions. Moreover, stakeholder participation in the model construction can be documented by the model process, especially if iterative versions of the model are retained, this creating a record of stakeholder contributions to an evolving understanding of the problem and refinements of the policy solutions.

Stave (2010) compared the quality of the decision-making process and the decisions that emerged from four cases with differing degrees of public participation in the building of system dynamics models. She found that greater participation in the model-building process generated more trust in the model, greater buy-in to the consensus solutions and greater understanding of feedback interactions among system components. Moreover, the decision process itself was enhanced and streamlined, because the stakeholders did not continually re-visit model assumptions and scenarios, once they had been incorporated into the model.

WORKING FROM A COMMON MODEL COULD ENABLE AGENCIES TO ENGAGE COMMUNITY AND CONVEY HOLISTIC VIEW OF THE PROJECT

A delegate at a recent meeting of the Durham Inter-Neighborhood Council (INC) recently remarked "When we voted on the tax increase to support the construction of the Light Rail in 2012, we were told that it would reduce congestion, reduce air pollution, increase jobs and increase mobility for the transit-dependent population. Since then, we've come to realize that the rail itself isn't required to achieve those goals, which we still support. Rather, the city is being transformed by a massive shift in planning, with high-rise, dense, mixed-use required to justify the Light Rail overtaking our residential neighborhoods."

In the years since the idea of the LRT was introduced, it has become apparent that social, environmental, and economic aspirations that had been attached to the rail will likely only be partly delivered by the rail itself. Rather, the LRT will be a nucleating central event for the timing and location of a greater density of urban development, and that that urban development, while disruptive, is actually required for and the source of a necessary precondition for the greater proportion of the desired benefits. This realization is causing a bit of dismay has caused concern among stakeholders that the environmental impact statement and the meetings held by the transit agency (Triangle Transit, since renamed GoTriangle) to inform and consult with public have focused rather narrowly on the impacts of the rail, neglecting with the attendant redevelopment, which is being planned and communicated by the City/County Planning Departments.

Planning activities related to redevelopment include the designation of high-density, mixed-use Compact Neighborhoods in the 1/2-mile vicinity of the proposed rail station locations. Complementary to Compact Neighborhood designs are efforts to modify the non-motorized travel infrastructure in the form of the Station Area Strategic Infrastructure Initiative (SASI), (Durham City-County Planning Department 2014), and adoption of a Complete Streets approach (by the city, county and state) to street design. For the most part, the public supports the goals of greater walkability/bike ability, and greater traffic safety, while grappling with expected negative impacts, including the disruption to current residential and sometimes historic neighborhoods, rising land prices and costs of housing, and the realization that likely increases in congestion and environmental impacts in some areas congestion and environmental impacts are likely to increase. While the interconnectedness of these issues was, to a large extent, acknowledged by the agencies involved, it is only now starting to be appreciated by the public, which is decrying the lack of tools to evaluate and mechanisms to influence the process.

2 Model Development and Stakeholder Process

2.1 Overview

Constructing a SD model is an iterative process where the modeler or model group, here referred to as the D-O LRP SD modeling team, follows a step-by-step process, which can progress through multiple cycles in which each step is refined in subsequent iterations (Abbas and Bell 1994). According to John D. Sterman, author of *Business Dynamics* (2000), “there is no cookbook recipe for successful system dynamics modeling, no procedure you can follow to guarantee a useful model.” Even so, best modeling practices recommend a disciplined process that involves the following phases:

1. **Problem Definition**: Articulating the problem to be addressed;

2. **Conceptual Model Development:** Formulating a dynamic hypothesis or theory about the causes of the problem and designing a conceptual model that represents that problem and its linkages in a system;

3. **Quantitative Model Construction:** Translating the causal relationships in the conceptual model into tested, research-based mathematical equations, calibrating model variables to historical data and projections, and extensive model testing;

4. **Scenario Design and Evaluation:** Testing policies and interventions that help people visualize the systemic effects of actions.

This chapter describes how the D-O LRP SD modeling team proceeded through each of the four phases listed above. At each phase of the SD modeling process, we consulted with local and regional stakeholders, both individually and jointly at three large stakeholder meetings, who were either directly involved with the D-O LRP or had concerns about the impacts that it would have on the region.[4] These stakeholders had a critical and evolving role in developing the D-O LRP SD Model, and their contributions to each step in model development are also discussed in this chapter.

2.2 Problem Definition

As described in Chapter 1, the D-O LRP SD modeling team focused on the development of the D-O LRP in Durham and Orange counties, both as a proposed solution to existing problems and as a perturbation to the system that could itself give rise to harmful impacts that might need to be addressed with further policies. To identify the high-priority decision sectors within the three pillars of sustainability (social, economic, and environmental) that would be impacted by the

[4] More information on stakeholder meetings, including a list of attendees, meeting agendas, and workshop handouts, can be found in Appendix E.

light rail and subsequent development, we convened an initial meeting of stakeholders involved with the D-O LRP on February 24, 2014. Stakeholders in attendance included:

- City and regional planners from Durham City/County Planning and Triangle J Council of Governments (TJCOG);
- Representatives from GoTriangle and URS Corp. (now AECOM), who were directly involved with the DEIS; and
- Representatives from the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO).

Stakeholders at the first meeting gave several presentations on the sustainability challenges the community expects to face over the next 25 years if existing patterns of urban sprawl continue, including increased pressure on local watersheds that would interfere with meeting nutrient reduction goals, increased automobile dependency and energy use making residents less healthy and more vulnerable to energy price spikes, and government budgets being stretched thin with increasing demand to build roads and other infrastructure to new developments. In addition, stakeholders presented concerns associated with the proposed D-O LRP, including a lack of public funds available to build the infrastructure necessary to make the light rail safely and easily accessible and the risk of gentrification and lack of affordable housing in the light rail station areas due to increased property values.

2.3 Conceptual Model Development

With our stakeholders' concerns in mind, our modeling team sought to construct a conceptual model that would represent both the direct transportation problems that the D-O LRP is intended to relieve (namely, reducing automobile dependency and enhancing mobility in the areas located near the proposed light rail stations), and the long-term issue of how the light rail might help or hinder the community's efforts to achieve its sustainability goals over the next 25 years.

Overview of Causal Loop Diagrams (CLDs)

Defining and describing the structure of a system with conceptual models helps organize information and highlight connections and possible unintended consequences within the system. A conceptual model is best formed with the input of relevant stakeholders and is usually communicated with causal loop diagrams (CLDs). A CLD is a map of the system analyzed – a way to explore and represent the interconnections between the key indicators in the analyzed sector or system (Probst and Bassi 2014). Involving stakeholders in this process ensures that the CLD includes variables and relationships that are high priorities for people living within the system and creates opportunities for group learning in which different stakeholders may discover aspects of the system that they had not previously understood. This then contributes to the next step in the SD model development process, building a simulation model. When simulation models are built, the causal relationships in CLDs are translated into tested, research-based mathematical equations, which can provide an internally consistent tool for comparing the effects of alternative policy options. With the focus of attention on leverage points within the system that can be influenced by decision-makers, rather than on external causes, SD helps people see connections between their actions and systemic effects, and guides participants to answer the question: *where can we intervene in the system?* (Stave 2002).

In a CLD, different variables in a system are connected through simple, "all-else-equal" causal relationships that indicate only the direction of causality and whether the relationship is positive (i.e., both variables move in the same direction) or negative (i.e., the variables move in opposite direction). In Figure 2-1, the relationship between *population* and *vehicles on the road* is positive – as *population* increases, *vehicles on the road* also increases, and vice-versa. On the other hand, the relationship between *functioning roads* and *road congestion* is negative – as *functioning roads* increase, *road congestion* decreases (all else equal), and if *functioning roads* were to decrease, *road congestion* would increase.

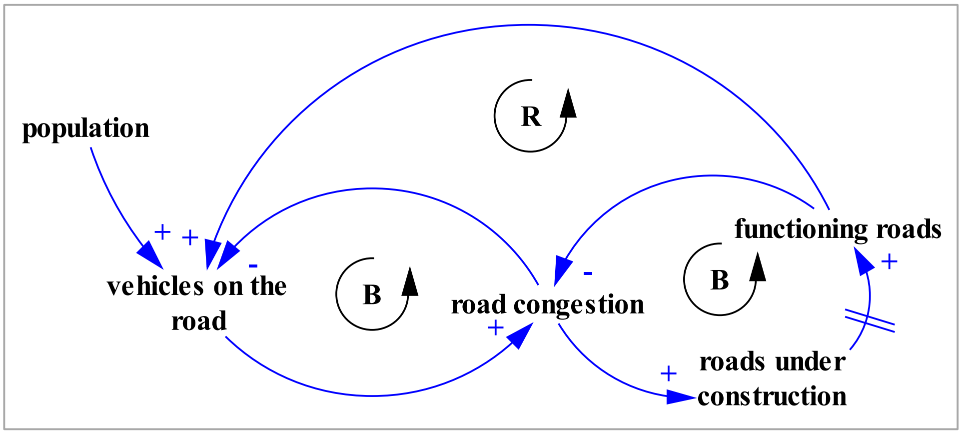


Figure 2-1. Example CLD showing reinforcing (R) and balancing (B) feedback loops

Most relationships in CLDs are assumed to occur within a single specified period of time, though delayed responses can be represented in CLDs as well (e.g., the relationship between *roads under construction* and *functioning roads* is marked with "//" to indicate that it may take some time before roads under construction are ready for use). As the diagram develops – preferably through an interactive process involving modelers and stakeholders – these simple, unidirectional relationships give rise to feedback loops. These loops are either reinforcing (R) or balancing (B) feedback loops. Reinforcing loops amplify what is happening in the system, while balancing loops tend towards maintaining equilibrium, balancing the forces in a system. When systems contain both balancing and reinforcing loops, dynamic changes may move the system to a new equilibrium (Shepherd 2014).

Initial CLD for the D-O LRP SD Model

Immediately after our first stakeholder meeting, the D-O LRP SD modeling team began drafting a CLD using a software program called Vensim® (http://vensim.com/). The CLD construction process allowed us to explore and represent the interconnections between the key social, environmental, and economic components that stakeholders identified as being potentially positively or negatively affected by the D-O LRP. To ensure that the CLD included variables and relationships that were high priorities for stakeholders and to make sure they were being accurately represented, we met with several D-O LRP stakeholders and local experts from the University of North Carolina at Chapel Hill, Duke University, and North Carolina Central

University, on an individual basis throughout the CLD construction process. After several rounds of editing and refining, we invited our stakeholders back for a second meeting, held on June 4, 2014, and presented our initial CLD, shown in Figure 2-2.[5] In addition, we presented more detailed, "zoomed-in" CLDs of the seven key decision sectors (not shown) that were planned to guide model development: land use, transportation, energy, economy, equity, water, and health. For each of the key decisions sectors, we asked for feedback from stakeholders on potential policies and interventions that the SD model could be built to test. At this second stakeholder meeting, we heard from stakeholders that, although they did not expect the D-O LRP on its own to mitigate the environmental, social, and economic issues facing the community, believed that it could be a catalyst for change and for exploring how concurrent policies and interventions could help maximize the benefits of the D-O LRP and minimize its potential consequences.

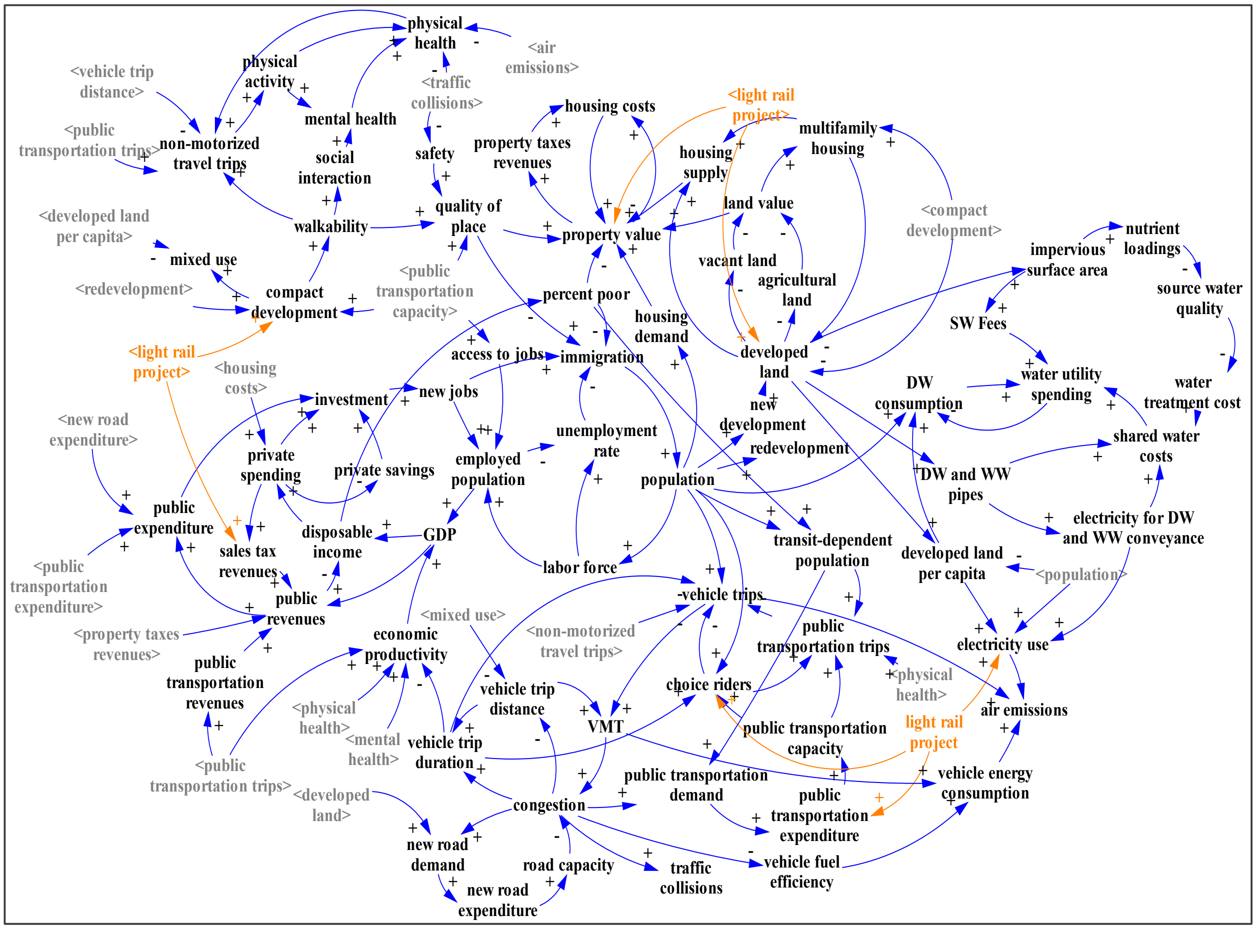


Figure 2-2. Initial CLD for the D-O LRP SD Model, Presented at 2nd Stakeholder Meeting

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[5] This initial CLD does not represent the final version for the D-O LRP SD Model, which is shown at the end of this chapter in Figure 2-7.

2.4 Quantitative Model Construction

With the lessons from the first two stakeholder meetings in mind, the D-O LRP SD modeling team began the task of translating the causal relationships in the CLDs we had built into tested, research-based mathematical equations. After hearing from our stakeholders the desire to see the simulated effects that the D-O LRP would have on both the immediate light rail station areas and the region as a whole, we decided that our model should have outputs for both of these geographic areas. Thus, the D-O LRP SD modeling team delineated two model geographies, called "Tiers," shown in Figure 2-3.

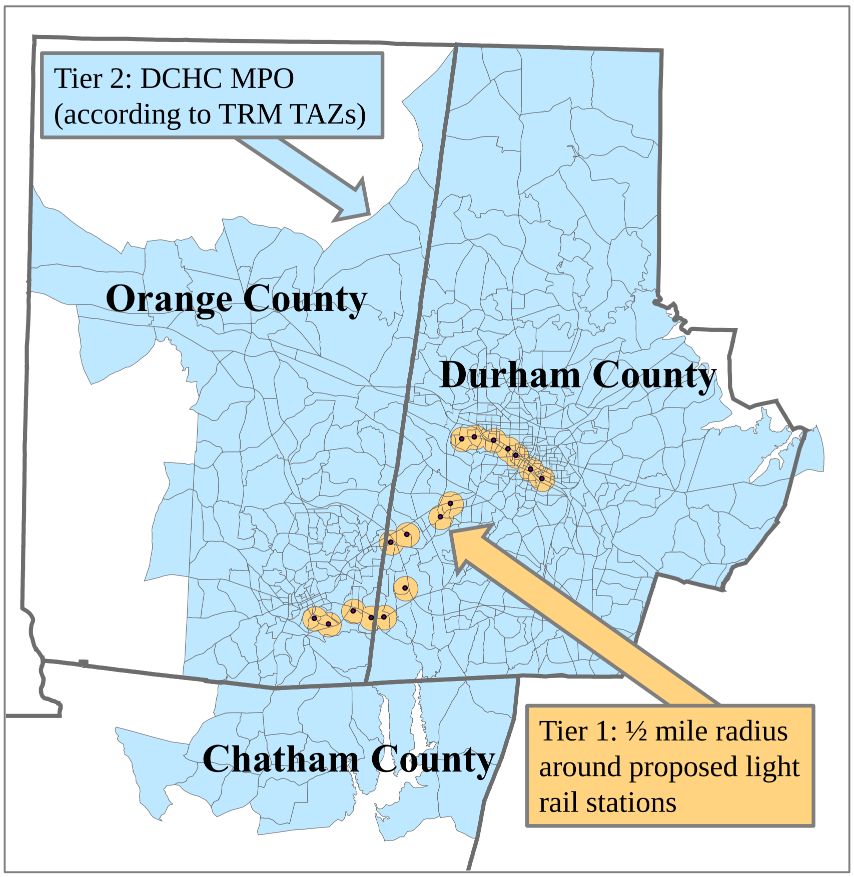

Figure 2-3. Map of the D-O LRP SD Model Geographic Tiers

Tier 1 consists of the combined half-mile-radius zones around each of the proposed light rail stations (shown in yellow circles), since the areas in the immediate vicinity of the proposed light rail stations are where the light rail will likely have its most pronounced direct impacts. Half-mile radii were chosen to define Tier 1 because it is common practice among urban planners to regard a half mile as the greatest distance that most people are willing to walk to a public transit station. The boundary of Tier 2, which encompasses Tier 1, is defined to be equal to the boundary of the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO). We expect that the indirect effects of the D-O LRP and subsequent development on population growth, land use and zoning changes, and resource consumption, among others, are likely to be felt throughout this region, which surrounds the light rail corridor. We defined Tier 2 to include the suburban and rural areas of Orange and Durham Counties, as well as the northern portion of Chatham County, which includes Jordan Lake, a significant regional water supply.

The D-O LRP SD modeling team then began an extensive collection of local data and projections, aggregated for each Tier, to serve both as exogenous inputs to the model (e.g., birth rate and death rate) and as targets for calibration purposes, used to ensure that endogenous formulations of model variables (e.g., population) were able to reproduce historical or projected trends.[6] Where local data and projections were not available, we used state or national data instead. In addition, we used equations and elasticities from the academic literature to inform the mathematical connections between variables represented in the CLDs[7]. These data sources played key roles in the process of building and testing the D-O LRP SD Model.

Like all steps in the SD modeling process, construction of the quantitative model was an iterative process, depicted in Figure 2-4 below, that began with the building of the four main "core" sectors: land use, transportation, energy, and economy. These sectors formed the engine of the model and were built individually at first for Tier 2 and then fully integrated and calibrated so that values for the main indicator variables closely matched historical data and projections, when available, for our "business as usual" (BAU) scenario, which is meant to represent a continuation of current trends without any policy interventions.

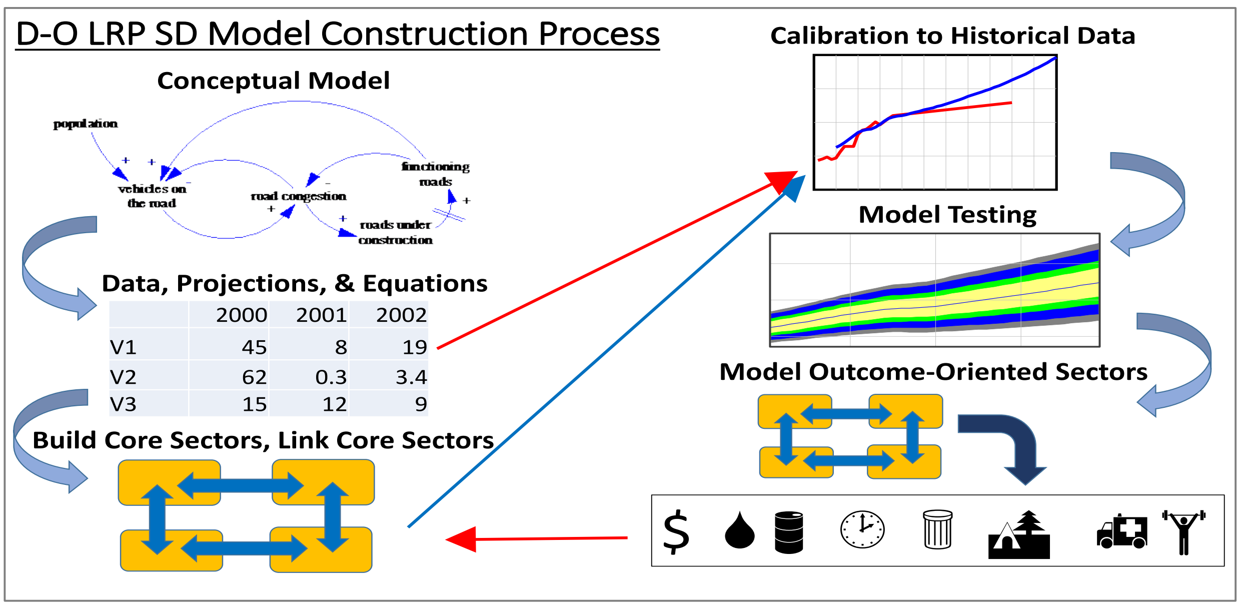

Figure 2-4. Depiction of the Iterative Model Construction Process

After we connected and calibrated these core sectors for Tier 2, we then duplicated all variables for Tier 1. When necessary, and where data sources permitted, we adjusted the model structure and parameter values for Tier 1 so that mechanisms more closely represented reality and outputs

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[6] The primary data sources for the D-O LRP SD Model are described in detail in Section 3A of this documentation.

[7] The data sources used to inform equations and elasticities in the model are described in detail in Appendix B.

could more closely match data and projections for the proposed light rail station areas. We also created connections between the two tiers so that any changes that occurred in Tier 1 were accounted for in Tier 2.

Once the connections between the tiers were in place and indicator variables from both tiers were calibrated to historical data and projections, we added the three outcome-oriented sectors (water, health, and equity), including feedbacks from these sectors to the core sectors. At each stage of the quantitative model construction process and with each new addition, key model variables were monitored and recalibrations were made when necessary to ensure that the BAU scenario represented, as best as possible, the social, environmental, and economic outcomes of extended historical trends and community plans (excluding those that include the light rail project). Model structure and sensitivity tests, described in detail in Chapter 6 of this report, were performed throughout the quantitative model construction to ensure the model functioned properly under varying conditions.

2.5 Scenario Design and Evaluation

For the third stakeholder meeting, held on May 13, 2015, we invited additional representatives from community organizations that, would likely be interested in how the secondary and cumulative impacts of the proposed light rail would impact their own areas of concern, although they were not themselves directly involved with transportation and land use planning. Additional stakeholders who attended included representatives from the Durham County Department of Public Health, Durham Neighborhood Improvement Services, the Durham Coalition for Affordable Housing, and Durham Economic and Workforce Development. Their input and perspectives helped shape the final D-O LRP SD Model modifications and scenarios. Their influence on the model is shown in Figure 2-5, where the names of stakeholder agencies are overlaid on the Final CLD for the D-O LRP SD Model, which is displayed in full in Figure 2-7.

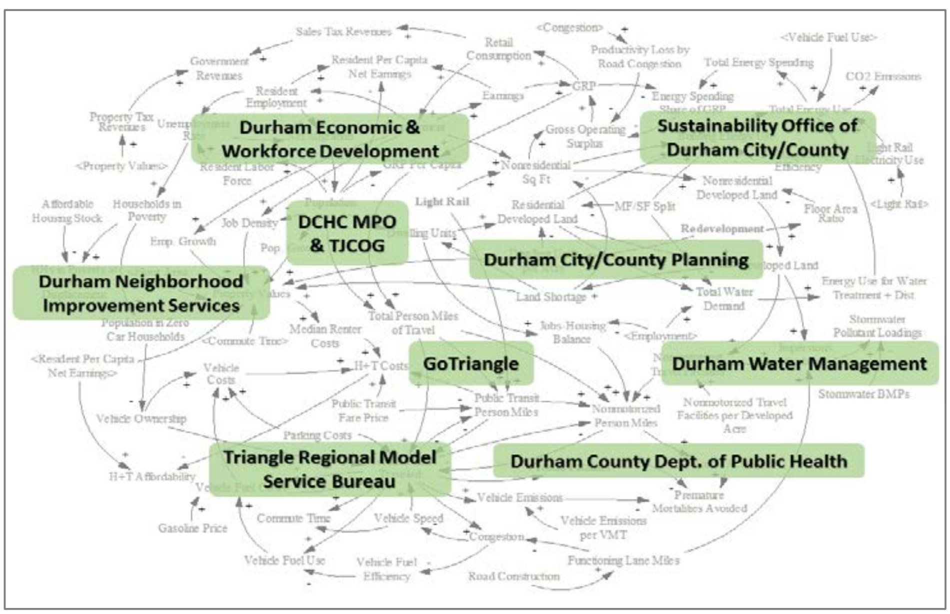

Figure 2-5. Stakeholder Agencies Overlaid on Final CLD for the D-O LRP SD Model

At the third stakeholder meeting, we administered a survey to assess stakeholders' priorities in terms of scenarios for the D-O LRP SD model to run and output indicators that the model should include. Feedback from the survey, summarized in Figure 2-6, helped shape the final three main scenarios and additional scenarios that were chosen for the D-O LRP SD model, described in detail in Chapter 4 of this report. For the three main model scenarios, stakeholders suggested that we include the redevelopment of already developed land to higher densities in the proposed light rail station areas instead of only increasing the density of new development. Participants listed other high priority policies interventions to add, including parking costs and green infrastructure. We were able to add parking costs as an adjustable policy lever. In addition, stakeholders listed as their top priorities output indicators related to affordability and mortality health impacts, all of which were added to the model. Unfortunately, quantifying the displacement of poor households and creating a quality of place index, both of which stakeholders had interest in, proved to be too challenging and time consuming to add in this version of the model.

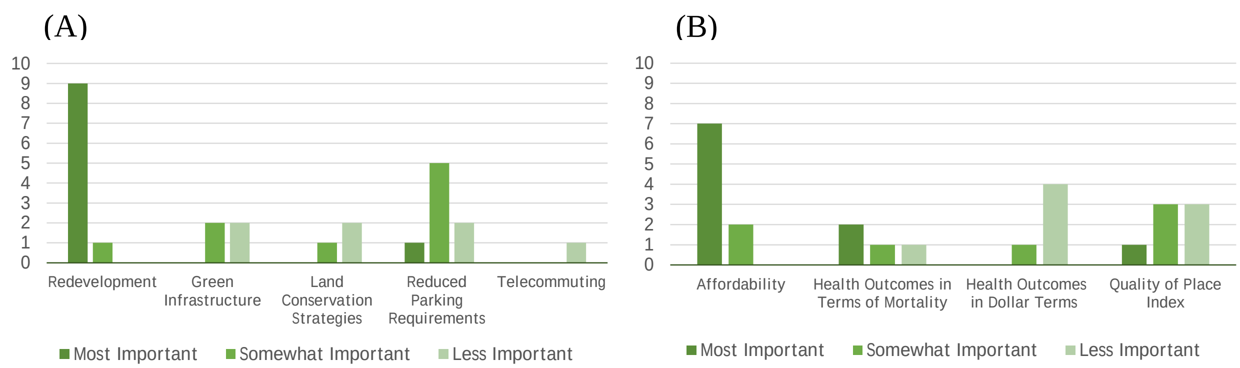

Figure 2-6. Results of Third Stakeholder Meeting Feedback Survey on the Top Priorities for the D-O LRP SD Model: (A) Alternative Policies or Interventions to Test and (B) Output Indicators to Add

Final CLD for the D-O LRP SD Model, Version 1.0

The D-O LRP SD Model, version 1.0, was finalized shortly after the third stakeholder meeting in July of 2015. A final CLD showing the main causal connections in the model is presented in Figure 2-7, with model variables in black and potential policy interventions in red. As described above, stakeholder involvement from many individuals and agencies in the region helped shape the D-O LRP SD Model. Their willingness to not only attend our meetings, but be active participants in our discussions helped demonstrate the potential for a SD model like the D-O LRP SD Model to foster collaborative decision-making between local and regional organizations in support of a more economically, socially, and environmentally sustainable future.

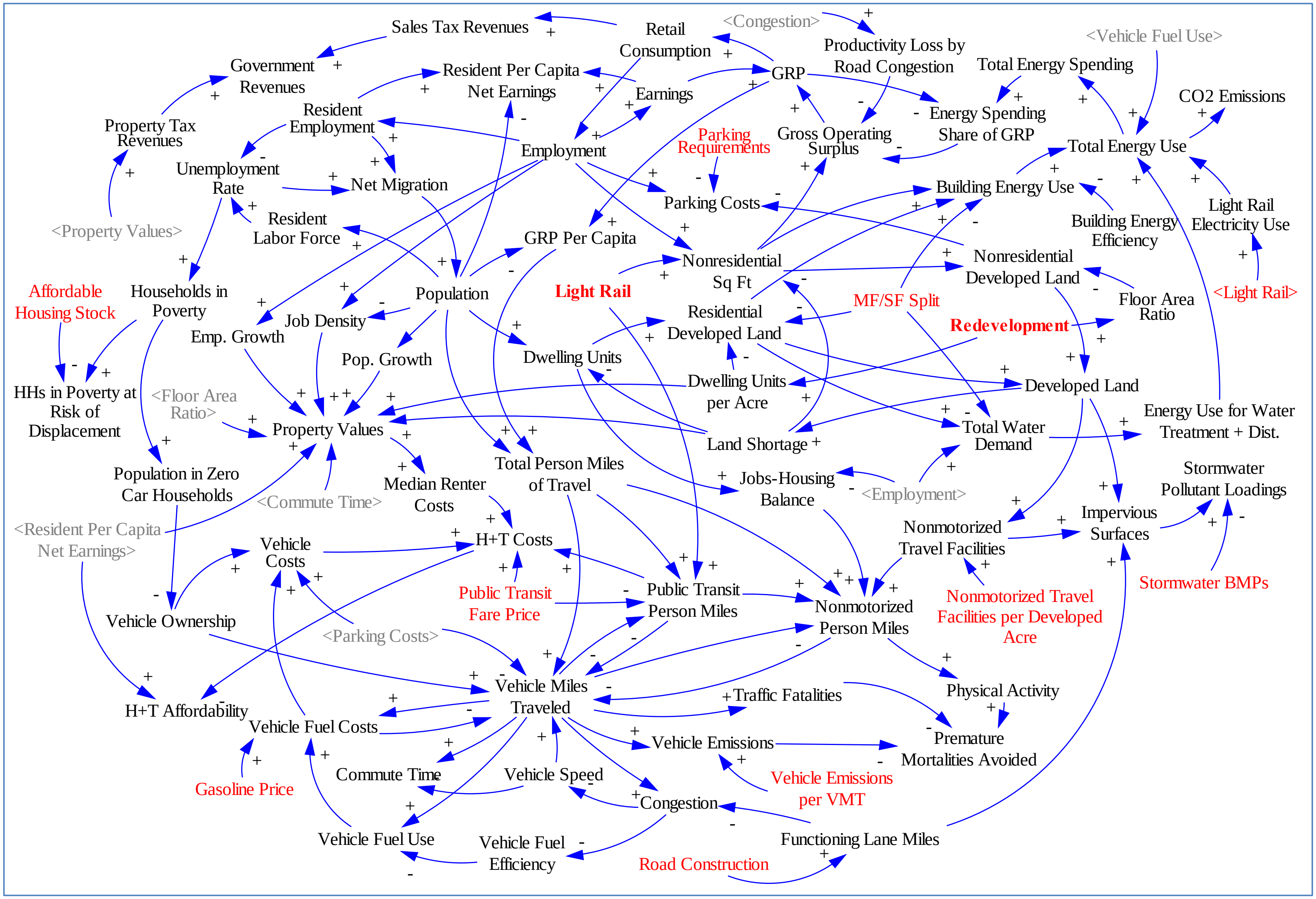

Figure 2-7. Final CLD for the D-O LRP SD Model

3 Model Structure

This chapter discusses the structure of the D-O LRP SD model. The information presented in this chapter is meant to provide a general understanding of the model's structure and function; more detailed documentation of model inputs, data sources, data processing, and calibration can be found in Appendices B and C, and Chapter 6 – Quality Assurance. In the first section, we review primary local data sources that were used in the model. In the second section, we provide an overview of the model's structure, including the organization of the model into seven sectors and a brief description of some of the model's major inter-sector third section, we provide additional information on each of the seven sectors, including the major relationships in each sector, the data sources and processing steps used to develop each sector, and any calibration done to ensure that key variables in each sector produced values consistent with historical data and future projections from highly-regarded forecast models.

3.1 Overview of Data Processing and Primary Data Sources

This section presents an overview of the data processing method, called "clipping," used in ArcGIS by the D-O LRP SD modeling team to scale the data we collected at various geographic levels to our model Tiers (Tier 2 = DCHC MPO; Tier 1 = combined ½ mile radii of proposed light rail stations), and gives an overview of the primary data sources used in the D-O LRP SD Model. More detailed descriptions of the data processing and analysis done for particular data sources can be found in Section 3.3, Chapter 6, and in Appendix B.

Data Clipping Method

An abundance of local data sources were available for the study region thanks to the variety of university modeling groups, local planning agencies, and other city organizations in the area devoted to the collection and organization of local data. While a few local data sources provided outputs in GIS shapefiles that perfectly conformed to the boundaries of our Tiers, the vast majority of the data sources had to be "clipped" in ArcGIS for either one or both Tiers.

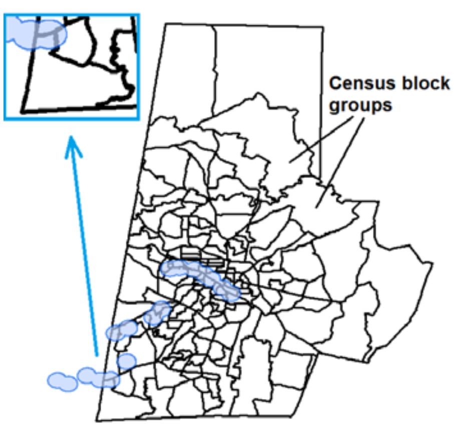

Figure 3-1. Example of Methodology for Clipping in ArcGIS (Blue Circles Indicate Tier 1)

When clipping was necessary, the values for each geographic zone in the source data (e.g., traffic analysis zone, census tract, or census block group) were multiplied by an area multiplier to scale down the results to the portion of the geography contained within the Tier. For example, Figure 3-1 shows the block groups in Durham County overlaid by our Tier 1 area in blue. We calculated the acres of each block group that fell within the blue Tier 1 overlay and divided this by the total acres in the block group to obtain the area multiplier for that block group. We note that this scaling process made the necessary assumption that the scaled values were evenly distributed across the geographic zone. Non-countable variables, such as median renter costs, could not be multiplied by an area multiplier directly. Instead, relevant weighting variables, such as renter-occupied units in each geographic zone, were multiplied by the area multiplier, and the resulting values were used to weight the median value for each geographic zone.

Primary Data Sources

2040 Metropolitan Transportation Plan and Associated Modeling Efforts

Every five years, the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO; www.dchcmpo.org), the organization responsible for transportation planning for the western part of the Research Triangle in North Carolina, is tasked with developing a Metropolitan Transportation Plan (MTP), which is a "guiding document for future investments in roads, transit services, bicycle and pedestrian facilities and related transportation activities and services to match the growth expected in the Research Triangle Region" (CAMPO and DCHC MPO 2013). The 2040 MTP is a synthesis of many individual studies, presenting results from the local transportation and land use modeling efforts, and a detailed financial analysis of the costs associated with those transportation projects chosen for the plan. The results of these modeling efforts make up a large part of the data used in the D-O LRP SD Model and are described in further detail here.

The Triangle Regional Model Version 5

The Triangle Regional Model (TRM) is a travel demand forecasting tool that was developed for understanding how future growth in the Triangle region of North Carolina will impact transportation facilities and services.[8] The TRM can help identify the location and scale of future transportation problems, and the proposed solutions to those problems can be tested using the TRM, making it a valuable tool for local planners. The TRM is an aggregate trip-based model that uses four steps: trip generation (number of trips made and for what purpose), trip distribution (where the trips go), mode choice (what transportation mode is used to make the trip), and trip assignment (what route and facilities are used to make the trip) (TRM Service Bureau and TRM Team 2012). In the primary model step, trip generation, trips are calculated based on population and employment data for each of the model's traffic analysis zones, or TAZs.[9]

For the 2040 MTP, version 5 of the TRM (TRM v5) was used to test the transportation impacts of several different hypothetical 2040 transportation network and land use scenario alternatives. Performance evaluation measures were computed for each alternative based on the TRM v5 output, including vehicle miles of travel, vehicle hours traveled, degree of traffic congestion, number of trips

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[8] The TRM is developed and maintained by the TRM Service Bureau, housed at the Institute for Transportation Research and Education (ITRE) at North Carolina State University on behalf of the Durham-Chapel Hill-Carrboro MPO, Capital Area MPO, North Carolina DOT, and GoTriangle, formerly Triangle Transit.

[9] TAZs are defined as the geographic areas that a given travel demand model represents as a single node in the transportation system, which trips can either begin or end at; there are 774 TAZs in Tier 2 and 178 TAZs are either partly or entirely contained in Tier 1.

taken by travel mode, and public transit ridership, for use by its client agencies (TRM Service Bureau 2008). Based on these performance evaluation measures, a "preferred option" transportation network was chosen for the 2040 MTP that incorporated a road network, a bus transit network, and light rail and commuter rail transit investments (CAMPO and DCHC MPO 2013).

For the D-O LRP SD Model, we used transportation data from both the raw output of the TRM v5, or "TRM v5 result shapefiles," which provided information on traffic volume, distribution, and speed for 2010, 2017, and 2040 at the level of individual road links, and inputs to the TRM that were provided in the socioeconomic (SE) data shapefiles, including parking prices and the availability of nonmotorized travel facilities (DCHC MPO 2013). The 2040 MTP document itself provided TRM v5 performance evaluation measures for the DCHC MPO transportation system under the preferred growth land use scenario. Measures were reported for the base year (2010) and for two projections: (1) the transportation system in 2040 based on the MTP, and (2) the 2040 "Existing + Committed" scenario, essentially a "no-build" scenario, which included only those transportation projects that will be operational by 2017. These performance evaluation measures provided information for Tier 2 on trips by mode and the average distance of a person trip (CAMPO and DCHC MPO 2013).

Imagine 2040

As part of the process for developing the 2040 MTP and for use in the TRM v5, a base year (2010) inventory of population and employment and forecasts of regional population and job growth by 2040 were compiled based on community plans and data from local planning departments, the Office of State Budget and Management, the US Census Bureau, and independent forecasts from Woods & Poole Economics, Inc. (CAMPO and DCHC MPO 2013). With these forecasts, the DCHC MPO, with the help of Triangle J Council of Governments (TJCOG), launched an initiative called Imagine 2040 that used a land use allocation software program called CommunityViz to distribute the forecasted population into single-family and multifamily housing units and to distribute forecasted employment by category into each of the TAZs under several different land-use scenarios: trend development, community plans, and all-in-transit (TJCOG 2013).[10] A hybrid of the tested land use scenarios called the "preferred growth" scenario was chosen for the 2040 MTP, and the results of the CommunityViz modeling were then used in the TRM v5 to forecast 2040 travel behavior.

The "preferred growth" land use scenario concentrated development in the region's activity centers, including along the proposed light rail line between Durham and Chapel Hill. For the D-O LRP SD Model, we made use of GIS shapefiles with socioeconomic (SE) data by TAZ for several interim years (2010, 2017, 2020, 2030, 2035 and 2040), referred to hereafter as the "TRM v5 SE data."

CommunityViz 2.0

As noted above, the land use modeling for the 2040 MTP used CommunityViz to forecast future growth of population and employment to the year 2040. Unfortunately, this modeling work did not produce an inventory scenario for the 2010 base year due to funding constraints. In the second round of CommunityViz modeling for the 2045 MTP (CommunityViz 2.0 or "CV2"), however, the modelers included a 2013 inventory scenario of all parcels in the study area. This inventory scenario categorized

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[10] CommunityViz is an extension of ESRI's ArcGIS desktop software that facilitates the visualization and comparison of alternative development scenarios. More information on CommunityViz and its capabilities for regional planning is available on their website: placeways.com/communityviz

parcels by one of 30 “place types” that best describe the current development on the site today and by one of eight possible “development status” options. Together, the place type and development status designations form a kind of current land use map (TJCOG 2014e). From this parcel data, we were able to estimate baseline stocks of acres of land by development status (e.g., vacant, agricultural, protected open space, and developed) and by use (e.g., single-family, multifamily, retail, office, service, and industrial) for 2013. Note that these files were originally posted online with the parcel data pre-populated with place type and development status designations that were used for the 2040 MTP for the purpose of allowing local planning offices to review and edit the place type and development status for 2013 (TJCOG 2014e). At the time that we downloaded the shapefiles, 29% of parcels in our study area had still not been reviewed, and therefore may have reflected the forecasted 2040 use and status rather than that for 2013.

Community Property Tax Databases

The Durham, Orange, and Chatham County Offices of Tax Administration are responsible for listing, appraising, and assessing all real property in the counties. They therefore maintain detailed property maps and records at the parcel level. Because the databases included fine-grained parcel-level data, the process of generating values for the model’s Tiers was straightforward, with no need for area multipliers. We obtained data on developed commercial square feet and property values, categorized by use, from these parcel-level databases. Databases from the most recent year, 2014, were available for all three counties, in varying levels of detail. For Durham County, sufficient data were available to establish a time series for purposes of calibrating the model, with data from the years 2000-2008, 2010, and 2014.

U.S. Census Bureau

Most historical demographic data used to calibrate the D-O LRP SD model came from the U.S. Census Bureau, including the Decennial Census (2000 and 2010) and the American Community Survey (ACS). When possible, we downloaded the Census data through the ESRI Community Analyst online software program (https://communityanalyst.arcgis.com/esriCA/login/), which allowed us to upload the boundaries of our Tiers as GIS shapefiles and clip the Census data for the exact area we needed. Community Analyst produces more accurate Census information for our Tiers than our own clipping methodology described above since the program’s clipping method (ESRI 2015) weights the data within clipped sections of block groups by Census block-level population or employment, as opposed to our own method which weights data by population, employment, or dwelling units at the Census block group or Census tract level.[11] However, because Community Analyst only reported Census data for most of their variables from the 2010 Decennial Census and later, we used several other internet applications to download historical Census data, including SimplyMap (Geographic Research Inc. 2015a), and the National Historical Geographic Information System (NHGIS) Data Center (Minnesota Population Center 2015, Abbas and Bell 1994).

For historical Census data that were not available from one of these three sources, we downloaded Census data directly from the American Fact Finder website (http://factfinder.census.gov/), joined the data to TIGER/Line shapefiles for the appropriate geographic zone (block group or census tract), and

[11] Census blocks are the smallest geographic level of Census data, then block groups, then tracts.

clipped the geographic zones in ArcGIS to our two model Tiers.[12] As noted above, model inputs prepared in this fashion made the necessary assumption that the scaled values were evenly distributed across the block group or census tract.

3.2 Overall Model Structure

This section provides an overview of the D-O LRP SD Model structure, including specifics about the model and an overall description of the main inter-sector feedback loops that make up the "engine" of the model.

Model Specifications

Table 3-1 presents a summary of the model's specifications. As noted in Chapter 2, the model's geographic scale includes two "Tiers":

- **Tier 1** is defined as the combined half-mile radius zones around each of the proposed light rail stations. Tier 1 is located entirely within Tier 2.

- **Tier 2** is defined to equal the area of the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO), which includes parts of Orange, Durham, and Chatham Counties.

The model begins calculations in the year 2000 and continues simulating through 2040. Though the model calculates the values of variables every 1/16th of a year (or 0.0625 years), it reports outputs only once per year.

Table 3-1. Summary of the D-O LRP SD Model's Specifications

MODEL SPECIFICATION	D-O LRP SD MODEL VALUE
Model Scale and Boundaries	Two model "Tiers," for which all variables are aggregated: • Tier 2 – the DCHC MPO boundary (includes Tier 1) • Tier 1 – the combined ½ mile radii of proposed light rail stations
Model Time Frame	2000-2040, with outputs every year
Model Time Step	.0625 years

Structural Overview

As mentioned in Chapter 2, the D-O LRP SD Model has four "core" sectors – land use, transportation, energy, and economy – and three output-oriented sectors –equity, water, and health. Figure 3-2 presents a simplified CLD of the model with the core sectors in blue and the output-oriented sectors in yellow. The CLD also shows key indicator variables with arrows representing the main intra- and inter-sectoral connections. Note that for the sake of simplicity, the CLD shows only a small subset of the most important variables and relationships in the model, and that the variable names shown in this diagram may not be representative of the actual model variable names.

[12] TIGER/Line shapefiles do not include demographic data, but they do contain geographic entity codes (GEOIDs) that can be linked to the U.S. Census Bureau's demographic data and are available at: www.census.gov/geo/maps-data/data/tiger-line.html

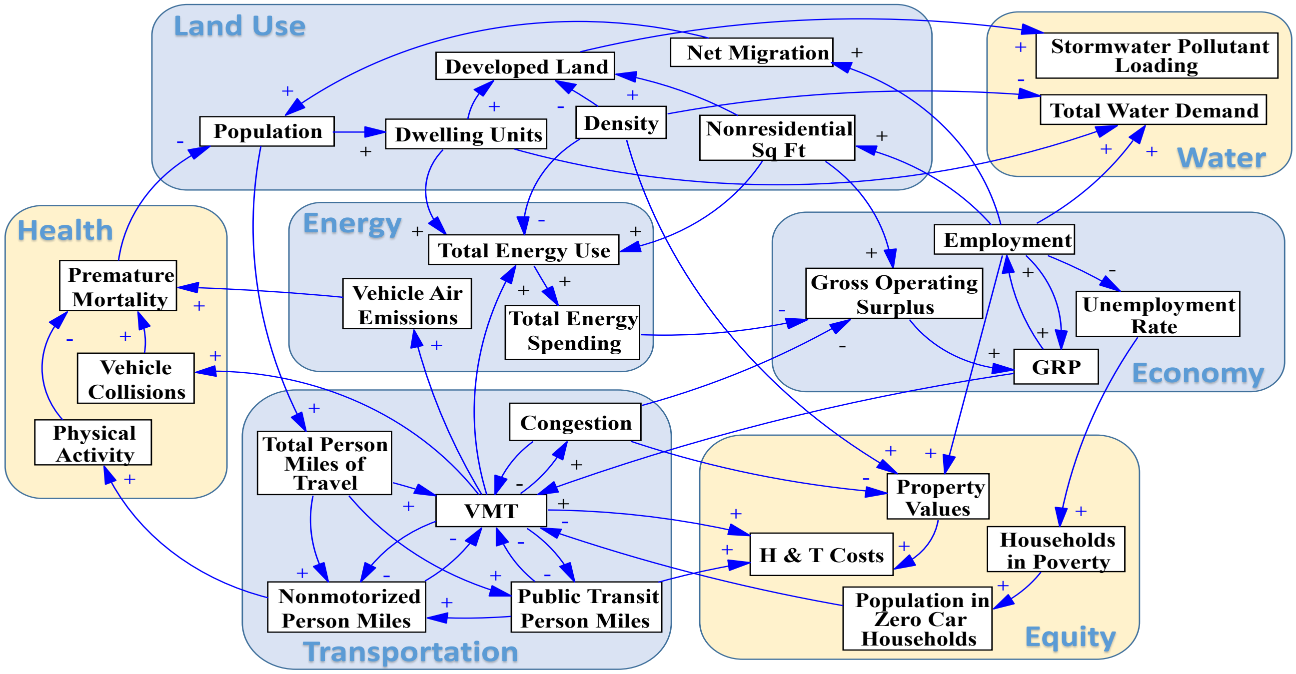

Figure 3-2. Simplified CLD of the D-O LRP SD Model with Core Sectors (Blue) and Output-Oriented Sectors (Yellow)

Inter-Sector Feedback Loops

The core sectors are linked by several strong inter-sector feedback loops, meaning that a change to the value of a model parameter in one of these sectors will have cascading impacts throughout the rest of the model. As a result, these are the places where policies and interventions can have the largest impact in multiple sectors. The outcome-oriented sectors have fewer strong feedbacks to the core sectors, meaning that the variables in these sectors tend to respond to changes in the core sectors, rather than themselves driving change in other sectors. Nevertheless, even the output-oriented sectors have some inter-sectoral feedback loops. The remainder of this section is devoted to explaining the main inter-sectoral feedback loops; intra-sectoral feedback loops will be described in the following section (3.3).

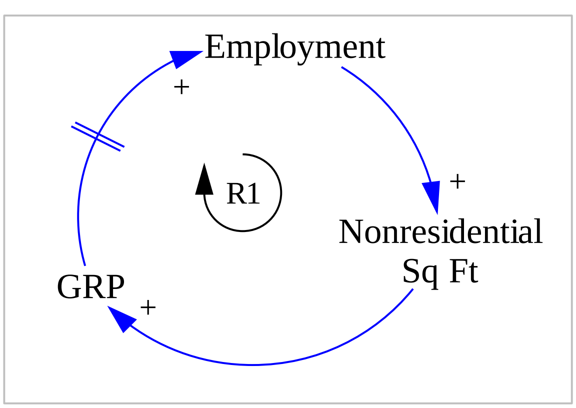

Figure 3-3. Simplified CLD of R1: A Reinforcing Feedback Loop Between the Economy and Land Use Sectors

R1: Economy → Land Use → Economy

The feedback loop shown in Figure 3-3, labeled R1, is a reinforcing loop that links employment growth to a growth in nonresidential square feet, which increases gross regional product (GRP), which (after a two-year delay) contributes to an increase in total employment. Absent other factors affecting these variables, this feedback loop will lead to continued growth in employment, developed commercial area, and GRP.

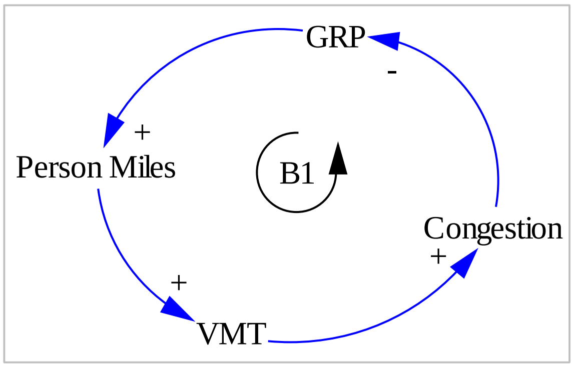

Figure 3-4. Simplified CLD of B1: a Balancing Feedback Loop Between the Economy and Transportation Sectors

B1: Economy → Transportation → Economy

The feedback loop shown in Figure 3-4, labeled B1, is a balancing loop that links economic growth and mobility. With an increase in GRP, transportation by automobile modes (labeled here as “person miles”) increases, hence increasing vehicle miles traveled (VMT), which increases congestion, which decreases economic productivity, thus decreasing GRP and total person miles. Absent other factors affecting these variables, this feedback loop serves as a limit on economic growth.

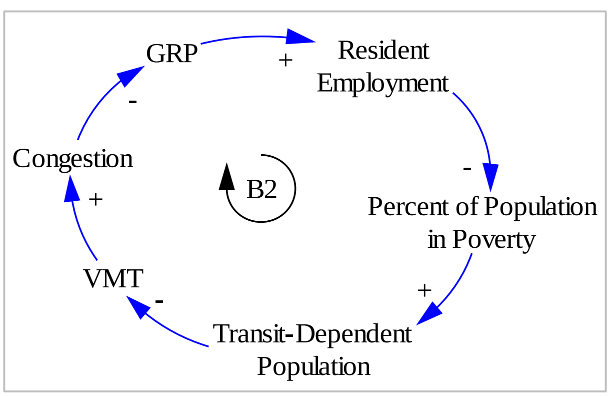

Figure 3-5. Simplified CLD of B2: A Balancing Feedback Loop Between the Economy, Equity, and Transportation Sectors

B2: Economy → Equity → Transportation → Economy

The feedback loop shown in Figure 3-5, labeled B2, is a balancing loop that links economic growth and employment to equity and underserved populations who are more likely to be transit dependent. The model assumes that as GRP increases, resident employment also increases, which lowers the unemployment rate. A drop in the unemployment rate is assumed to reduce the percent of the population living in poverty, which decreases the portion of the population that is transit dependent. Decreasing the number of transit-dependent people (i.e., increasing the number of people who drive cars) increases VMT, which consequently decreases travel by other modes, thus increasing congestion and decreasing GRP. This feedback loop also serves as a limit on economic growth.

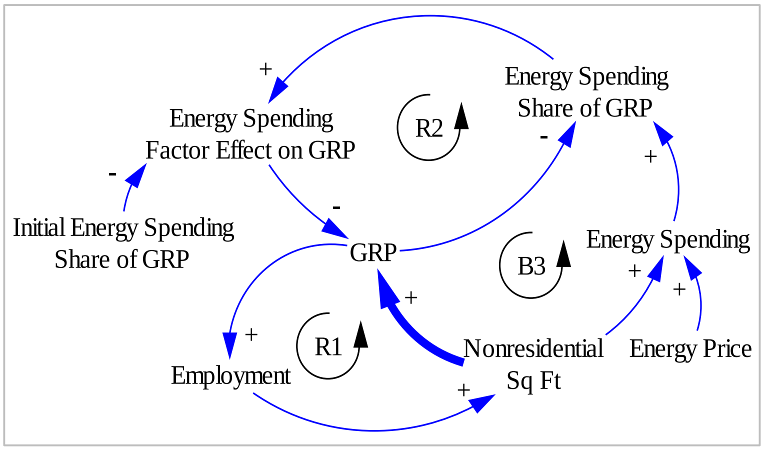

Figure 3-6. Simplified CLD of R1, R2, and B3: Balancing and Reinforcing Feedback Loops Between the Economy, Land Use, and Energy Sectors

R1, R2, and B3: Economy → Land Use → Energy → Economy

The balancing and reinforcing loops shown in Figure 3-6 depict the relationships that exist in the D-O LRP SD Model between the land use, energy, and economy sectors. In the balancing portion (B3), an increase in nonresidential square feet increases spending on energy, which – all else equal – increases the share of GRP that is devoted to energy spending. If GRP is not increasing due to other factors, then an increase in the share of GRP devoted to energy spending reduces the value added through the gross operating surplus (a portion of GRP, not pictured), leading to a reduction in overall GRP. This negative impact on GRP can be reinforced if energy spending does not decrease, since a reduction in GRP further increases the share of GRP that is devoted to energy spending, indicated by the top reinforcing feedback loop (R2) in Figure 3-6. Since energy spending and GRP may both increase (indicated in R1 through the direct effect of nonresidential sq ft on both energy spending and GRP), GRP is negatively impacted only if energy spending grows faster than GRP. Note that R1, the reinforcing feedback loop from Figure 3-3, is also included in Figure 3-6 in order to illustrate how the relationship with the energy sector provides a limit to the reinforcing relationship between the land use and economy sectors.

3.3 Model Sector Descriptions

This section is meant to be an overview of the intra-sector relationships, data sources and processing steps, and calibration steps taken for each of the seven sectors in the D-O LRP SD model. The secondary bullets below give instructions on where to find more detailed information in this report for each of the topics. For each sector, we describe the following:

- The ***Sector Relationships*** section gives an overview of the sector's main relationships – both relationships among variables within the sector and relationships to other sectors in the model. To illustrate the primary feedback loops in each sector, we use sector-specific CLDs. Unless otherwise noted, the relationships described within each sector apply to both Tier 2 and Tier 1.

- Alternative intra-sector relationships and structures that were considered are presented in Section 6.2 of this report.

- The ***Data Sources and Processing*** section briefly describes the primary data sources used in each sector and summarizes the data processing steps that were taken to prepare the values used in the model. Where applicable, we describe how we adjust values taken from external data sources to apply to the geographic areas used in the model – both Tier 1 and Tier 2 – as well as any assumptions that were used in that process.
  - Alternative data sources and equations that were tested but not ultimately chosen for the model are described in Section 6.2 of this report and Appendix D.

- The ***Calibration*** section describes how values for some variables in the model were adjusted in order to produce results that aligned with historical data, projections produced by other models, or both.
  - For a more detailed discussion of the steps taken to calibrate the model to historical data and projections, and a quantitative analysis of how model results fit to data, see Chapter 6 of this report. Appendix B of this report lists all of the model variables that were calibrated and the parameters that were adjusted during calibration.

Land Use

Sector Relationships

The Land Use sector comprises three types of stocks: (1) land disaggregated by use and development status, (2) dwelling units disaggregated into single-family and multifamily, and (3) developed nonresidential square feet disaggregated by category (retail, office, service, and industrial). Broadly speaking, changes in the stocks of dwelling units are driven by changes in population; changes in the stocks of each category of developed nonresidential square feet are driven by changes in category-specific employment; and changes in these two types of stocks together drive changes in the stocks of land use types. These changes are summarized in Table 3-2.

Table 3-2. Summary of Primary Stocks in the Land Use Sector

STOCK TYPE	CATEGORIES OF DISAGGREGATION	VARIABLES DRIVING CHANGES IN THE STOCK	GENERAL EQUATIONS
Land (in acres)	Vacant, Agricultural, Protected Open Space, Right of Way, Retail, Office, Service, Industrial, Single-Family, Multifamily	Dwelling Units and Developed Nonresidential Floor Area (in square feet)	(Nonresidential Square Feet / Floor Area Ratio) + (Dwelling Units / Residential Density) = Total Land Development (capped by Total Amount of Developable Land).
Dwelling Units	Single-Family, Multifamily	Population	Household Population * Average Single-Family and Multifamily Household Sizes = Minimum Dwelling Units.
Developed Nonresidential Square Feet	Retail, Office, Service, Industrial	Employment (disaggregated by category)	Employment * Employee Space Ratios = Demand for Developed Nonresidential Square Feet.

As the figure shows, additional variables mediate these changes. Employee space ratios determine how many square feet of each category are required for each employee in that same category. Average single-family and multifamily household sizes determine how many dwelling units are required by the "household population" (i.e., the population adjusted for the percent of the population who do not live in households, such as students in college dormitories, or those living in institutions). How much land development is required for dwelling units and developed nonresidential floor area is determined by two types of input tables: (1) the floor area ratio input table (square feet of floor area per square foot of land area) determines the total land required for developed nonresidential square feet, and (2) the residential density tables (dwelling unit/acre) determine the total land required for dwelling units. Total land development is capped by the amount of developable land, broken down into stocks of vacant land and agricultural land. These are assumed to be converted to developed use in equal proportion to their supply (i.e., the model holds the ratio of vacant to agricultural land constant). While there is ample available land in Tier 2 for years to come, this cap on land does come into play in Tier 1.

Negative land conversion can also occur if, for instance, population or employment declines, density is increased, or shifts in the share of employment by category leads to a drop in space required for one of the four categories of developed commercial area (e.g., desired industrial land could decline due to a reduction in industrial jobs). Except in extreme testing, this rarely leads to an overall decline in developed land, rather causing declines just in particular categories of developed land, leaving more land to be developed for other categories. This essentially functions as an endogenous redevelopment between uses, responding to demand. See the Economy sector for an explanation of how the model estimates changes in the share of employment by category over time.

In the study area, the total number of dwelling units exceeds the number of households, since there is always some degree of vacancy in housing markets. To capture this in the model, the construction of dwelling units is not only determined by the required units given the number of households, but also by the development of second homes (in the case of single-family units), dwelling unit turnover, and anticipatory development in advance of their use. This leads to an endogenous vacancy rate in the model, which goes on to affect renter costs in the Equity sector.

When the exogenous redevelopment switch is turned on (as in the Light Rail + Redevelopment scenario described in Chapter 4), a portion of the current stocks of each category of developed land are redeveloped to a higher density (by default set to almost 3 times the current). This density was chosen because it is the overall weighted average increase in density (by jobs and housing) across the station areas that was achieved in the Preferred Growth Scenario of the Imagine 2040 Regional Model (Green 2015). This high-density redevelopment has two effects in the model: (1) it boosts the number of dwelling units and/or developed commercial square feet, and (2) this increased supply in turn reduces the demand for regular-density greenfield development, ensuring that land development does not exceed demand.

The land use sector creates many outputs that are then used throughout the model:

1. In the transportation sector, total developed land is used to calculate intersection density and population density, which in turn affect choice of mode of transportation.

2. In the economy sector, total nonresidential square footage impacts gross operating surplus

3. In the energy and water sectors, the quantity and balance of developed land by land use affects energy use and pollutant runoff from impervious surfaces.

4. In the equity sector, nonresidential square footage is used to calculate an endogenous nonresidential density, and retail square footage is used to calculated retail density, both of which

affect property values.

The primary feedback loops involving the land use sector are shown in the CLD presented in Figure 3-7. The reinforcing loop shown in green (R1) illustrates that employment (by category) increases developed nonresidential square feet, which leads to increases in GRP, which then eventually increases employment, completing the loop. Another reinforcing loop is shown in purple (R2): In Tier 1, where there are more jobs than households, increasing dwelling units increases the jobs-housing balance (a higher value is more balanced), which increases walking, eventually feeding back into population and increasing dwelling units, as a result of improved health. Therefore, the loop that runs through the jobs-housing balance is reinforcing in Tier 1, as increases in dwelling units increases walking (though it should be noted that this loop has only a very small impact on population). In Tier 2, jobs and dwelling units are close to balanced at the start of the simulation, so any large shift in either direction would reduce the jobs-housing balance, which would decrease walking, and eventually decreasing (in a very small way) population and dwelling units, making the loop potentially balancing in Tier 2. The larger purple loop running through intersection density (B1) shows that as population and dwelling units increase, developed land also increases, affecting pedestrian accessible (excluding highways and major arterial roads) intersection density in two ways. First, intersection density is calculated as pedestrian-accessible intersections divided by developed land, so increasing developed land (all else equal) decreases intersection density. Second, intersections are assumed to grow along with land development, after a delay, due to both the construction of new intersections, and the addition of pedestrian infrastructure to existing intersections. This causes a minimum increase in intersections as developed land increases. Nonetheless, the net effect of increased land development on intersection density is generally negative in the model (and in cases where land development stops or even declines, intersection density increases). A decrease in intersection density, which is an indicator of walkability, goes on to decrease walking and physical health in the model, which finally feeds back into population and dwelling units by increasing the death rate (albeit very little), making this a balancing loop.

Differences between the Tier 2 and Tier 1 Land Use Sector

The only structural difference between Tier 2 and Tier 1 relevant to the Land Use sector is in what forces drive migration into the area. In Tier 2, the developed portion of residential land drives net migration following an inverted U-shaped curve; a lot of vacant residential land leads to relatively little immigration; as more residential land gets developed (acting as a proxy for popularity of the region), immigration increases; once the percent of land that is developed crosses a specified threshold, immigration slows, reacting to scarcity (Vina-Arias 2013). We decided this relationship would not apply to a small area such as Tier 1. Instead, net migration in Tier 1 is linked to the employment gap (the gap between desired employment and total labor force, which includes the resident labor force and commuters) and the unemployment rate. When the employment gap is positive (desired employment exceeds total labor force), these desired new workers are added to the total labor force after a one year delay and it is assumed that 5% of the new workers filling these jobs are new immigrants to Tier 1, while the remaining 95% commute. After the introduction of the light rail, it is assumed that the percentage of desired new workers who will choose to move to Tier 1 rather than commute will increase from 5% to 10%. Finally, the unemployment rate provides a balancing effect in Tier 1 – if it rises too high, immigration will slow, which reduces the size of the labor force; conversely, if it is very low, immigration will increase. In both tiers, the relationships governing net migration are examples of how nonlinearities are introduced in a system dynamics model: via the U-shaped table function in Tier 2 and via the limits and feedbacks from employment, labor force, and unemployment in Tier 1.

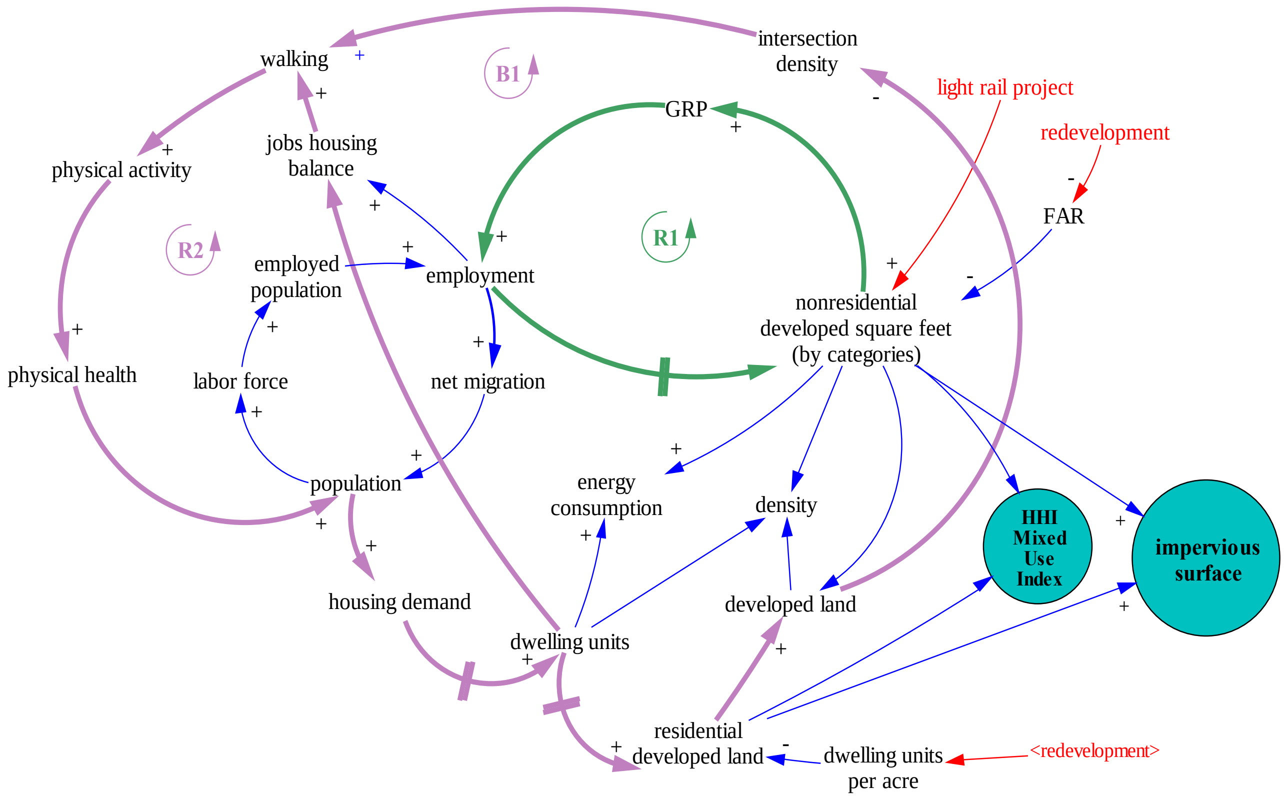

Figure 3-7. CLD for the Land Use Sector

Data Sources and Processing

Historical Demographic Data

Most historical demographic data came from the U.S. Census Bureau, including the Decennial Census (U.S. Census Bureau 2000), and the American Community Survey (U.S. Census Bureau American Community Survey 2014). Methods used to download and scale data to the model's Tiers are described in Chapter 2.

Projected Demographic Data

Most long-term projections for demographic data came from GIS shapefiles with socioeconomic data from modeling done for the "Preferred Growth Scenario" in the 2040 MTP (GoTriangle 2015). Methods used to scale these data to the model's Tiers are described in Section 3-1.

Land Use Data

We obtained parcel-level data on acres of land by use and development status from shapefiles posted on the TJCOG website, labeled *CV2 Parcel Geodatabase for Place Type & Development Status Editing* (TJCOG 2014b). Note that these files were posted for the purpose of allowing local planning offices to review and update the land use and development status since the 2010 version. At the time of use, 29% of parcels in our study area had still not been reviewed, and therefore may have reflected the forecasted 2040 use and status rather than that for 2013.

To arrive at estimates for developed land in 2013, we clipped the parcel data to the Tiers. Because the parcel-level data were already fine-grained, we did not need to apply area multipliers in the scaling process. For each Tier, we then totaled acres of land for each development status, using land use tables from TJCOG used for the 2010 Community Viz modeling effort. These tables contained floor-area ratios (FAR), residential density, percent residential, percent single-family/multifamily, and percent retail/office/service/industrial for each place type in each jurisdiction in the study area. To estimate acres of land by category, we first calculated an average of each value (by place type) from the land use tables, weighted by the proportion of each Tier occupied by each jurisdiction. Within the "developed" development status, we then applied these values to the total acres of each place type to obtain developed acres by use and place type, and then summed these to get final estimates of developed acres of single-family, multifamily, retail, office, service, and industrial use. Finally, we applied an adjustment to the estimates of developed land provided by this source, subtracting out the acreage of parks and open space, which we define as non-developed land for purposes of the D-O LRP SD model.

Nonresidential Square Footage

Property tax databases from the three counties provided parcel-level data on developed nonresidential square feet, organized by land use category (Durham County Tax Administration 2000-2014, Orange County Tax Administration 2014, FTA 1969). Methods used to scale these data to the model's Tiers are described in Section 3-1. Heated building square feet was summed by land use code (residential, commercial, etc). For Durham, the detailed land use codes from the source data were translated into the categories used in the model (single-family and multifamily for housing units, and service, office, retail, and industrial for developed commercial area), using NAICS codes. As noted in Chapter 2, Orange and Chatham County did not have data for years prior to 2014, so we calculated 2000 values for developed nonresidential square feet by category by first calculating per-capita parameters of developed nonresidential building area (based on 2014 data) and then multiplying those parameters by each county's population within each Tier in 2000. Since Orange and Chatham County did not have detailed land use codes, we developed an allocation weighting scheme by dividing total jobs in each category and year (office, service, retail and industrial), obtained from Woods and Poole Economics, Inc by employee-space ratios calculated from the Durham county database. For example, the allocation weight for the service sector in the year 2000 was equal to:

= [service jobs in 2000]/[service employee space ratio in Durham]

The share of total developed nonresidential square footage allocated to each category was determined by dividing each category's allocation weight by the sum of allocation weights across all four categories.

Calibration

While full coverage of the calibration done for this sector can be found in Appendix B: Detailed Documentation by Sector, two primary decisions made during model construction are discussed here.

First, population, total employment, and employment by job category were all considered as potential drivers for nonresidential square footage. When we estimated nonresidential square feet as a function of population alone, the results fit historical data on square feet well, but we rejected this formulation because it would not allow the model to forecast different trends for different categories of nonresidential developed land. Comparing the trends in total employment and employment by category to data on developed nonresidential square feet produced very similar R^2 values, so we chose employment by category so that the model could estimate separate trends by category (though the retail category of developed land in Tier 2 is still driven by population based on the assumption, also made by the Durham City-County Planning Department (2012), that demand for retail space is driven more by consumer demand than by employment).

Second, early in the model construction process, the land development sector aggregated demand for categories of developed land into one function that drove overall land development, which was then allocated to different uses based on fixed zoning percentages. However, this created mismatches between demand and supply and led to dramatic drops in retail density as retail uses were undersupplied relative to demand, which then adversely affected property values. We then restructured the Land Use sector to treat demand for different types of land and land conversion for each use separately and to allow negative land conversion (i.e., conversion of developed to undeveloped land) to take place. This resulted in slightly more variation in the distribution of developed land by category over time, along with more developed land overall, particularly in Tier 1. We then needed to recalibrate gross operating surplus per square foot (which regulates the strength of the relationship between nonresidential sq ft and gross operating surplus and eventually employment), reducing the value of that parameter so that the model's estimate of land development dropped back to historical levels.

Transportation

Sector Relationships

The heart of the transportation model sector is the calculation of mode shares, or the percentage of person miles that are traveled by each transportation mode: automobile driver, automobile passenger, public transit, and nonmotorized. The model first establishes baseline projections of the number of person miles traveled per day by each mode (driven by population and real GRP per capita). These baseline values are adjusted by a series of elasticities (with respect to both exogenous and endogenous variables) and then normalized so that the total person miles of travel per day match the baseline projections. This normalization is done to keep overall person miles of travel per day within expectations and guarantee that an increase or decrease in the use of any one mode will also affect usage rates of the other modes. Variables that drive deviations from the baseline estimates of modal person miles are listed in Table 3-10. The table also notes whether each variable is an exogenous policy variable or calculated endogenously in the model. For endogenous variables, the table notes in which model sector the calculation takes place.

Table 3-3. Variables that Affect Modal Person Miles

VARIABLE AFFECTING MODAL PERSON MILES	SUMMARY OF PRIMARY EFFECT	ENDOGENOUS OR EXOGENOUS	MODEL SECTOR WHERE ESTIMATED (IF ENDOGENOUS)
Average automobile speeds	Lower speeds lead to reduced automobile driver and passenger travel and greater travel by public transit and nonmotorized modes.	Endogenous	Transportation
Fuel costs	Higher costs lead to reduced automobile driver travel and greater travel by all other modes.	Partly endogenous (total fuel costs are affected by the impact of traffic congestion on fuel efficiency)	Transportation
Parking costs	Higher costs lead to reduced automobile driver travel and greater travel by all other modes.	Endogenous	Land Use, Economy, and Transportation

VARIABLE AFFECTING MODAL PERSON MILES	SUMMARY OF PRIMARY EFFECT	ENDOGENOUS OR EXOGENOUS	MODEL SECTOR WHERE ESTIMATED (IF ENDOGENOUS)
Population density	Higher densities lead to increased nonmotorized and public transit travel and reduced automobile travel.	Endogenous	Land Use
Jobs-housing balance	Greater jobs-housing balance leads to more nonmotorized travel	Endogenous	Land Use
Density of intersections that are not purely automobile oriented	Higher densities lead to increased nonmotorized and public transit travel and reduced automobile travel.	Endogenous	Transportation and Land Use
Public transit fare prices	Higher fares lead to reduced public transit travel.	Exogenous	N/A
Proportion of people who are not in zero-car households	Higher proportions lead to increased automobile driver travel.	Endogenous	Equity
Public transit revenue miles per day	More revenue miles lead to increased public transit travel.	Exogenous	N/A

In scenarios where the light rail line is built, the size of its effect on public transit travel is determined by an equation that is driven by traffic volumes, population, and employment rates. The model assumes that the majority of new public transit users resulting from the light rail line will be people who would have otherwise traveled by automobile. In other words, most of any increase in public transit travel caused by the light rail line is offset in the model by decreases in travel by automobile drivers and passengers, but not by decreases in nonmotorized travel.

As noted above, the adjusted modal person miles are normalized so that total person miles in the model match baseline projections. However, there are additional adjustments that are applied after the normalization process is completed. First, traffic congestion is taken to have an additional dampening effect on person miles of automobile driver travel. This adjustment is applied after the normalization because we assume that this decrease in automobile driver travel does not necessarily translate into an increase in use of any of the other modes. Second, for each public transit trip that occurs in the study area, a certain additional amount of nonmotorized travel is taken to occur as a result of people walking to and from transit stops. Similarly, this increase in nonmotorized travel does not translate to an equivalent reduction in travel by any other mode.

The key feedback loops in this sector are illustrated in the CLD presented in Figure 3-8. The most significant feedback loop within the sector is the way in which increasing automobile person miles of travel increases vehicle miles traveled (VMT), which increases traffic congestion, which both reduces vehicle speeds and increases fuel consumption and spending. These two effects both reduce automobile person miles of travel, forming a balancing loop (labeled B1 and B2 in Figure 3-8). Most other significant feedback loops relating to the transportation sector are inter-sectoral. For example, traffic congestion decreases GRP (by first decreasing Gross Operating Surplus, not shown in the diagram), which has a negative effect on person miles of automobile driver travel, and hence VMT, creating another (less significant) balancing loop with traffic congestion (labeled B3 in Figure 3-8).

Some other factors that change the distribution of travel by mode include the construction of roads and nonmotorized travel facilities (e.g., sidewalks, paths, and bike lanes), the light rail line, and changes to the bus transit system. These variables are mostly exogenous policy inputs in the model (the exception is that construction of nonmotorized travel facilities is taken to be reactive to land development), with increases or improvements in facilities or services related to a particular mode of transportation taken to drive an increase in the use of that mode, usually at the expense of the other modes. However, the effect of facility and service increases and improvements on person miles is not modeled in the same way for every travel mode. When the construction of new roadway lane miles increases automobile travel, it is because capacity has been increased relative to demand, which reduces traffic congestion. However, like in most U.S. communities, public transit vehicles in the DCHC MPO rarely reach capacity. Even though the proposed light rail line would likely attract more riders than most bus routes and would consequently be more likely than bus routes to encounter capacity issues in the future, this model does not disaggregate public transit use by type of transit vehicle, given how common it is for riders to transfer between buses and trains. Therefore, this model does not consider the possibility of public transit use being limited by how many people can fit on a transit vehicle. Instead, expanding or improving the public transit system is taken to increase transit use by increasing the number of destinations that can be reached via public transit, expanding the times during which those destinations can be reached, and reducing wait times at transit stops, all of which are factors that make public transit more desirable regardless of whether or not vehicle capacities are adequate to meet demand. In contrast, roadway systems already provide access to most potential destinations in urban areas and rarely ever have limits on when they can be used, making congestion relief the predominant benefit to automobile users of expanding or improving those systems.

Impacts of the transportation sector on other model sectors, some of which are shown in Figure 3-8, include:

- In the health sector, increases in the per capita use of nonmotorized modes of transportation drive increases in physical health outcomes;

- In the energy sector, reductions in VMT reduce vehicle energy use and air emissions (including greenhouse gas emissions);

- In the water sector; building new transportation facilities contributes to increases in impervious surface area;

- In the equity sector, vehicle ownership/maintenance costs (which are a function of vehicle ownership, itself affected by resident net earnings per capita), fuel costs, parking costs, and public transit fares all contribute to overall household spending on transportation.

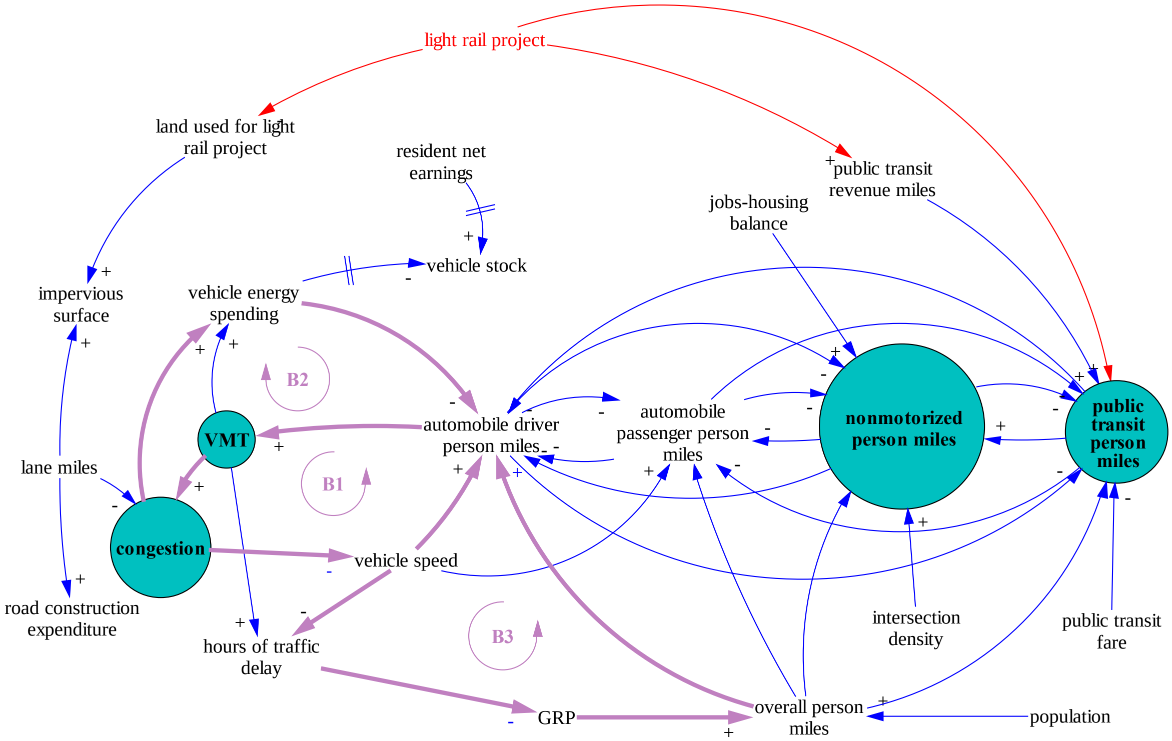

Figure 3-8. CLD for the Transportation Sector

Data Sources and Processing

VMT, Traffic Congestion, and Roadway Lane Miles

The TRM v5 provides data for 2010, 2017, and 2040 at the level of individual road links, which we clipped to the study area of the D-O LRP SD Model (DCHC MPO 2013). We multiplied the TRM's reported traffic volumes on each road link by those links' respective lengths to determine VMT in peak periods, in off-peak periods, and during the entire day. The TRM also reports average vehicle speeds during peak periods and off-peak periods (which we assume represent freeflow conditions). To arrive at a measure of traffic congestion, we divided freeflow speed by peak-period speed, weighted according to the peak-period VMT on each relevant road link. In addition, we used the TRM's data on the number of lanes on each road link to estimate lane miles in each Tier.

Public Transit Use and Operations

The National Transit Database (www.ntdprogram.gov) provides data on entire transit systems on a yearly basis for 1995-2013 (FTA 2015b). For the D-O LRP SD Model, we obtained transit-related data on ridership, person miles of travel, revenue miles, VMT, consumption of diesel and gasoline, agency operating expenses, and agency fare revenues from the NTD entries for Chapel Hill Transit, GoDurham (formerly the Durham Area Transit Authority), and GoTriangle (formerly Triangle Transit). Because only part of GoTriangle's service area is within the DCHC MPO, we adjusted the numbers reported for that agency based on data received from Transit Service Planner Jennifer Green regarding how many of their boardings and revenue miles they attribute to Durham and Orange Counties, as opposed to Wake County (Green 2014).

The Bus and Rail Investment Plan in Orange County (Triangle Transit et al. 2012) and the Durham County Bus and Rail Investment Plan (DCHC MPO et al. 2011) provide information on the expected costs of building and operating the future light rail line. These documents also estimate expected increases in the number of vehicle revenue hours of non-light-rail public transit in the study area. We converted these revenue-hour figures to revenue miles using the NTD's reported ratio of revenue miles per revenue hour in the year 2013 for the transit agencies in question.

We used the Our Transit Future website (http://ourtransitfuture.com) to ascertain the expected length of the future light rail line, as well as the timeframe for its construction and opening. The website also included the light rail line's expected schedule of operations at the time of its opening, which we used to estimate the light rail line's expected vehicle revenue miles per day and per year (Triangle Transit 2015b).

Projections of Person Miles by Mode

As noted above, a key element of the transportation sector of the D-O LRP SD Model is the projection of person miles by mode (automobile drivers, automobile passengers, nonmotorized travel, and public transit). With the exception of base-year (2010) values for Tier 2 person miles of public transit travel (for which we instead used NTD data for 1995-2013), we used the following methodology to generate projections of modal person miles to which to calibrate the model:

(A) Obtain estimates of the number of person trips by mode (drive-alone, carpool, nonmotorized, and public transit) and of the overall average distance per person trip from the DCHC MPO 2040 MTP for 2010 and 2040 (CAMPO and DCHC MPO 2013).
(B) Estimate an average carpool size, using 2008-2012 ACS data from the U.S. Census Bureau (which reports the number of workers by census block group who commute in a carpool with 2, 3, 4, 5-6, or 7+ total people), as reported by ESRI Community Analyst (2014).
(C) Use the average carpool size to convert the MTP's numbers of drive-alone and carpool person trips to driver and passenger person trips.
(D) Use average trip distances by mode from the Household Travel Survey Final Report (originally created to generate data for the Triangle Regional Model) (NuStats 2006) to calculate expected ratios between trip distances by each of the four modes.
(E) Multiply total person trips by average person-trip distance to yield total person miles of travel.
(F) From the number of trips by each mode, the total person miles traveled by all four modes combined, and the ratios between the distances of individual trips by any given mode, calculate the average distance of one trip by each of the modes in question, as well as the number of total person miles by each mode per day.
(G) Use ACS data reported by Community Analyst to scale the Tier 2 person-mile-by-mode results to Tier 1. The methodology for this scaling process can be found in Appendix B.

Nonmotorized Travel Facilities and Parking Costs

We obtained estimates of the number of miles of nonmotorized travel facilities in the area and of the parking cost of an average trip from the TRM v5 SE data (DCHC MPO 2013). The data source provided separate average parking cost estimates for work and non-work trips. From these estimates, we generated a single average parking cost estimate for each year in each TAZ, weighted by the numbers of work and non-work trips ending in each TAZ (estimated using trip-generation equations found in the TRM Version 5 documentation (TRM Service Bureau and TRM Team 2012).

Intersections

The Smart Location Database (SLD) supplies 2010 data on location efficiency at the census-block-group level, including information on intersection densities (US EPA 2013d). We multiplied these density estimates by total land area in the census block groups within the Tiers to estimate the total number of intersections, excluding those that are purely automobile-oriented.

Vehicle Stock

We used SimplyMap to obtain summarized data from the U.S. Census Bureau, clipped to specified geographic areas in accordance with a standardized methodology (Geographic Research Inc. 2015a). From this source, we obtained vehicle-stock figures for the years 2000, 2010, 2011, 2012, and 2014. SimplyMap provides the number of households with 1, 2, 3, or 4+ vehicles; for purposes of this model, we assume that all households in the "4+ vehicles" bin have exactly four vehicles.

Transportation Infrastructure Costs

The DCHC MPO 2040 MTP provides expected overall costs of road construction and road maintenance for the period 2010-2040 (CAMPO and DCHC MPO 2013). We divided these estimates by the reported number of lane miles to be built and the number of lane miles existing, respectively, in the TRM v5 "preferred" scenario to yield estimates of construction and maintenance costs per lane mile. Similarly, we estimated costs per mile of nonmotorized travel facilities by dividing the MTP's expected 2010-2040 spending on such facilities by the TRM v5 SE data's projected increase in nonmotorized travel facilities during that period (DCHC MPO 2013).

Calibration

The transportation sector was originally constructed in isolation from the other sectors of the model. At that stage, we calibrated the outputs from this sector to be consistent with results of the Triangle Regional Model (Version 5), in light of the fact that the TRM was the largest source of this sector's important inputs (including inputs from the DCHC MPO 2040 Metropolitan Transportation Plan, which itself relies mostly on the TRM). During this calibration stage, inputs that were to eventually come from other sectors (e.g., GRP, population, developed land area, and jobs-housing balance) were drawn from TRM data, and those elasticities that were not drawn from literature were based on TRM projections. In addition, we set all lookup tables representing future policy decisions (such as transportation facility construction) to be consistent with the TRM's 2017 and 2040 projections. Finally, the initial year of the model was set to 2010, the same initial year used by the TRM. With these measures in place, major outputs of the transportation sector (VMT, congestion, etc.) were successfully brought within a reasonable range of values projected by the TRM.

When we connected the transportation sector to the economy, land use, equity, energy, water, and health sectors, we reset the initial year to 2000 and adjusted initial values of dynamic variables to (1) produce approximately the same 2010 values as were used during the previous calibration stage, and (2) maintain the same trends out to the year 2040 (with key inputs coming from other sectors of the D-O LRP SD Model, rather than from TRM projections). For the most part, we did not need to change equations in the transportation sector as part of this step. In one exception, we changed the calculation of population density and intersection density to use developed land as the denominator, rather than total land area. Although we made further changes to the model after connecting its various sectors, those changes were mainly about making the model more closely match real-world cause-and-effect relationships, rather than about fitting the model to data. For example, we later adopted a new, more authoritative elasticity for the effect of public transit fare prices on public transit person miles and made the percentage of the population that is not in zero-car households an input to both vehicle stock and miles of automobile travel per day.

As additional changes were made, both to the transportation sector and to the rest of the model, we checked for differences in the values of certain variables that we had designated as key variables to ensure that the transportation sector remained well calibrated. For these variables, we ensured that all modeled values were close to reference data and projections (usually within 5% in the most recent year for which there is historical data). In most cases, we were able to keep modeled values for these variables within the preferred range of their reference data and projections by changing initial-year values. When it was not possible to achieve such a match to all of the reference data and projections for a given variable, we prioritized matching the most recent historical data point. We performed calibration checks in a specific order, beginning with variables that are least affected by the rest of the transportation sector and ending with variables that have the least effect on the rest of the transportation sector. The variables used to calibrate the transportation sector, in the order in which they were routinely checked, are listed below:

1. Vehicle stock
2. Functioning nonmotorized travel facilities
3. Intersections excluding those that are purely automobile oriented
4. Parking cost of average trip
5. Person miles of automobile driver travel per day
6. Person miles of automobile passenger travel per day
7. Person miles of public transit travel per day
8. Person miles of exclusively nonmotorized trips per day
9. Through traffic VMT
10. VMT
11. Congestion
12. Vehicle trip distance
13. People in traffic accidents per year

Energy

Sector Relationships

The energy sector has four main components: (1) estimating total energy used by buildings (divided into commercial, industrial, and residential categories) and for water treatment and distribution; (2) estimating total CO_2, $PM_{2.5}$, and NO_x emissions caused by energy used by buildings, transportation (divided into passenger vehicles, buses, and the light rail), and water treatment and distribution; (3) estimating the total cost of energy use by buildings and transportation; and (4) projecting growth in generation of alternative energy sources within the region.

For the first component, the energy used by buildings in both Tier 2 and Tier 1 is driven by economic and land use factors, including the stocks of single-family and multifamily dwelling units, developed commercial building square feet (defined as the sum of developed office, service, and retail square feet), and developed industrial building square feet. Population growth also drives building energy use, both by increasing the stocks of buildings and by increasing water consumption (because energy is required for water treatment and distribution).

For the second component, the energy sector calculates CO_2 emissions from building energy use and from transportation, using miles traveled by LRT, buses, and automobiles, as calculated by the transportation sector. For each category of energy use, the model calculates CO_2 emissions using fuel-specific emissions factors, assuming a fixed mix of fuel types for each category (e.g., the model assumes that 35 percent of commercial energy use is from natural gas, and this value is held constant throughout the modeled time period). The model also estimates emissions of $PM_{2.5}$ and NO_x, by multiplying automobile VMT by pollutant-specific emissions factors. In turn, emissions of these two pollutants affect outcomes in the health sector.

For the third component, regional energy spending is calculated for four categories (residential, commercial, industrial, transportation) based on energy use, fuel type (divided into gasoline, electricity, and natural gas), and fuel price. As noted above, for each category, the model holds the mix of fuel types constant.

For the fourth component, the model simulates the use of alternative energy sources within the region, namely solar and landfill gas. Currently, most energy used in the region – electricity, natural gas, gasoline and diesel – is generated or produced outside the region. Solar electric capacity is small but growing in the region (about 20 MW capacity as of 2014 (North Carolina Sustainable Energy Association 2015)), and North Carolina has a thriving solar industry, ranked fourth in the US for installed solar capacity (GoTriangle 2015). Based on data provided by the North Carolina Sustainable Energy Association, our model estimates conservatively that solar capacity grows in Tier 2 from 2.5 kW in 2000 to level off at 40 MW by 2020. Our model also explores future scenarios with higher solar capacity. Durham County also recently began generating electricity from landfill gas (~3MW capacity), and our model projects that this capacity is sustained until 2028, representing the 20-year purchased power contract for one landfill. Increased production from these two alternative energy sources decreases CO_2 emissions from building electricity use, as the alternative sources are assumed to be carbon-neutral.

Figure 3-9 presents a CLD for the energy sector. As the figure shows, total energy use in the model is affected by (1) changes in the energy intensity of buildings and vehicles, (2) changes in building stock and vehicle miles traveled (VMT), (3) changes in the use of public transportation, and (4) changes in the proportion of building types (e.g., single-family vs multifamily residential) through development. These energy changes, along with any growth in renewable energy, also affect modeled air pollutant emissions.

The key feedback loops in this sector are labeled in Figure 3-9 Energy spending represents either a balancing or reinforcing loop on electricity use (B1/R1). The loop is balancing if energy spending increases relative to GRP, and reinforcing if the energy spending decreases relative to GRP. Public transit ridership, nonmotorized travel trips, and congestion each form balancing feedback loops through vehicle energy spending, opposing either an increase or decrease in VMT (B2, B3, B4). In the B2 loop, an increase in VMT increases vehicle energy consumption and vehicle energy spending, which stimulates public transit ridership, which reduces VMT. Increased vehicle energy spending due to increased VMT also stimulates nonmotorized travel (in the B3 loop), reducing VMT. In the B4 loop, an increase in VMT produces congestion, which reduces VMT.

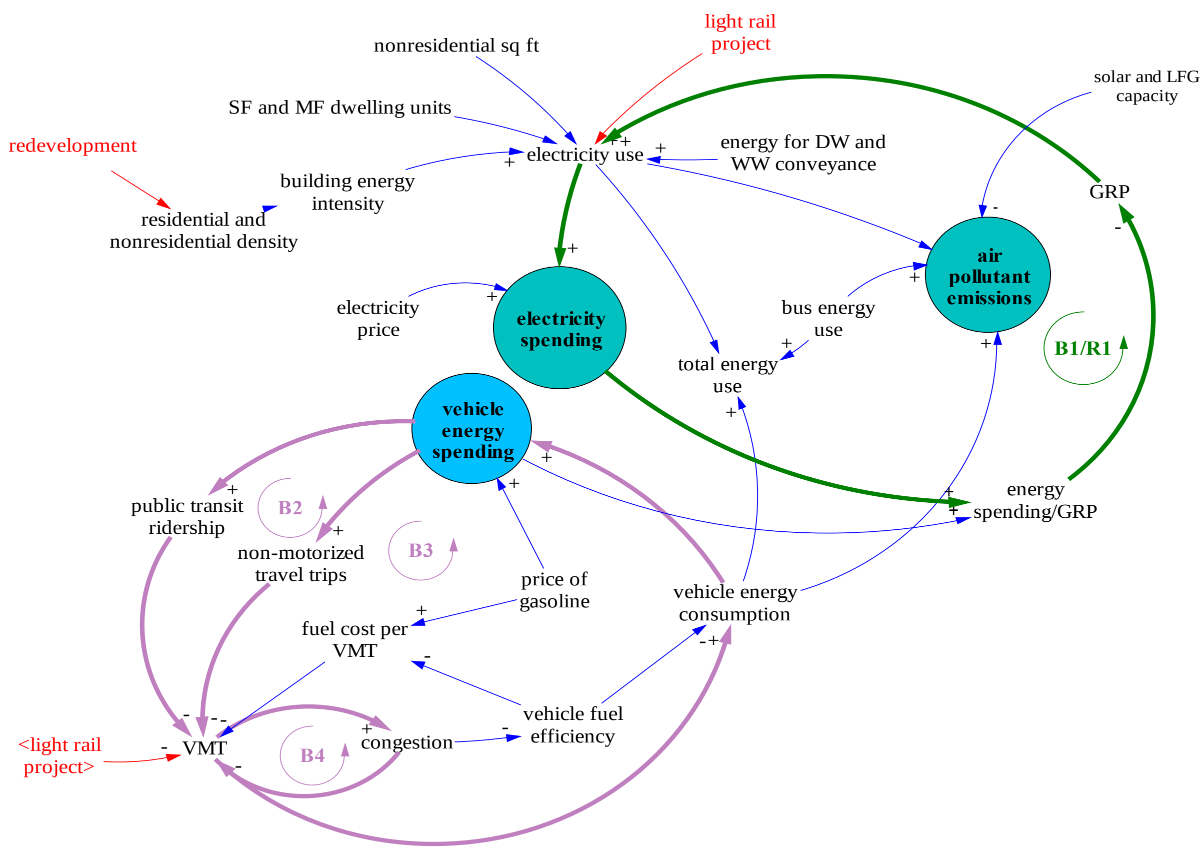

Figure 3-9. CLD for the Energy Sector

Data Sources and Processing

Energy Prices and Energy Intensities

We obtained both historical and projected future data on energy prices, building energy intensities, and passenger vehicle fuel efficiency from the EIA. For projected values, rather than using the specific values forecast by EIA, we converted the projected values from the Annual Energy Outlook 2015 (AEO2015) to annual percent changes through 2040 and applied them to the most recent-year historical data. EIA provided historical energy prices specific to North Carolina (US EIA 2015b) and projected future energy prices for the US South Atlantic region (US EIA 2015a). EIA also projected trends in residential, commercial, and industrial energy intensities (e.g., MMBtu per household or per square foot), which we applied to local historical energy intensity data when possible, or to literature values (for example, Residential Energy Consumption Survey 2009 (US EIA 2009) for national average residential energy intensities). Finally, AEO2015 provided passenger vehicle fuel efficiency trends, in miles per gallon, for the light duty vehicle stock, which assumes a range of vehicle age classes.

$PM_{2.5}$ and NO_x Emissions

We obtained county-level historical $PM_{2.5}$ and NO_x emissions from EPA's National Emissions Inventory (US EPA 2015d). We scaled emissions data from 2002, 2005, 2008, and 2011 from Durham County to Tier 2 based on the 2010 ratio of Durham County VMT to Tier 2 VMT (0.586), assuming that the relationship between VMT and emissions would be consistent across Durham county and the other areas of Tier 2. The ratio of Durham County VMT to Tier 2 VMT was calculated from Durham City-County Sustainability Office data and Triangle Regional Model v5 data (Durham City-County Sustainability Office 2015, DCHC MPO 2013). We recognize that a limitation of these historical data are that they come from two different models (2002 and 2005 emissions data were generated by the MOBILE model but 2008 and 2011 emissions data came from the MOVES model (Driver 2015). Passenger vehicle $PM_{2.5}$ and NO_x emissions rates were estimated from the Argonne National Laboratory GREET model (Cai et al. 2013) which is based on the EPA MOVES model. For purposes of projecting future emissions from vehicles, we estimated overall $PM_{2.5}$ and NO_x emission rates for the passenger vehicle stock by applying emission rates by model year in the GREET model to the age distribution of the US fleet (Jackson 2001c). To estimate emission rates for model years prior to 1990 and after 2020 (the endpoints of the GREET data), we applied a linear extrapolation to the GREET data. We assumed the fleet age distribution provided by EPA data, which includes age classes from 1-17 years, would remain constant through 2040.

Energy consumption and CO_2 emissions

Ms. Tobin Freid, the Sustainability Manager for Durham City-County, provided energy consumption and CO_2 emissions data for Durham County for the years 2006-2013 (Freid 2015). Ms. Freid estimated CO_2 emissions for four categories (residential, commercial, industrial, and transportation) based on energy consumption data provided by local utility companies. For the D-O LRP SD model, we scaled Durham County energy and CO_2 emissions data to Tier 2 for each category as follows: residential data were scaled using the ratio of Durham residential sq ft to Tier 2 residential sq ft (0.703); commercial data were scaled using the ratio of Durham commercial sq ft to Tier 2 commercial sq ft (0.835); industrial data were scaled using the ratio of Durham industrial sq ft to Tier 2 industrial sq ft (0.986); and transportation data were scaled using the ratio of Durham VMT to Tier 2 VMT (0.586 in 2010).

Calibration

When calibrating the variables in the energy sector, we first calibrated total energy use in buildings by adjusting building energy use intensity by category (residential, commercial, industrial) in order to improve the fit between the model's estimated energy use by category and historical data provided by the Durham City-County Sustainability Office for the years 2006-2013. We then adjusted the natural gas fraction of energy use by category in order to improve the fit between the model's estimated CO_2 emissions from natural gas combustion and historical data. Finally, we adjusted average automobile fuel efficiency to calibrate passenger vehicle emissions. We also tested the internal consistency of Durham energy and emissions data, since these were scaled up to generate Tier 2 data.

Calibration allowed modeled total CO_2 emissions and total building energy consumption to match historical data to within 5% on average. Total building energy consumption is the sum of residential, commercial, and industrial energy use; and modeled commercial energy use fit historical data better than modeled residential energy use. Although residential energy use matched the average value of data (5% average deviation), the residential energy data contained "noise" or unexplained variability. Passenger vehicle CO_2 emissions had similar uncertainty in model fit; the model matched the average value of data (10% average deviation) but the vehicle emissions data contained high unexplained variability. These observations about model fit suggest that the D-O LRP SD model projections of aggregate energy variables such as total CO_2 emissions and total building energy consumption may be more accurate than building or vehicle sector-specific projections.

Economy

Sector Relationships

To estimate regional economic activity (i.e. gross regional product or GRP, disaggregated into total earnings and gross operating surplus), the economy sector of the D-O LRP SD Model uses feedback loops within the economy sector and responds to connections from the land use, transportation, and energy sectors. The inter-sector relationships affect gross operating surplus, an indicator that represents the difference between the total monetary value earned by businesses for the production of goods and services in the region and the total earnings of their employees. These relationships are described in the Section 3.2 of this paper, while this section discusses the intra-sector relationships within the economy sector.

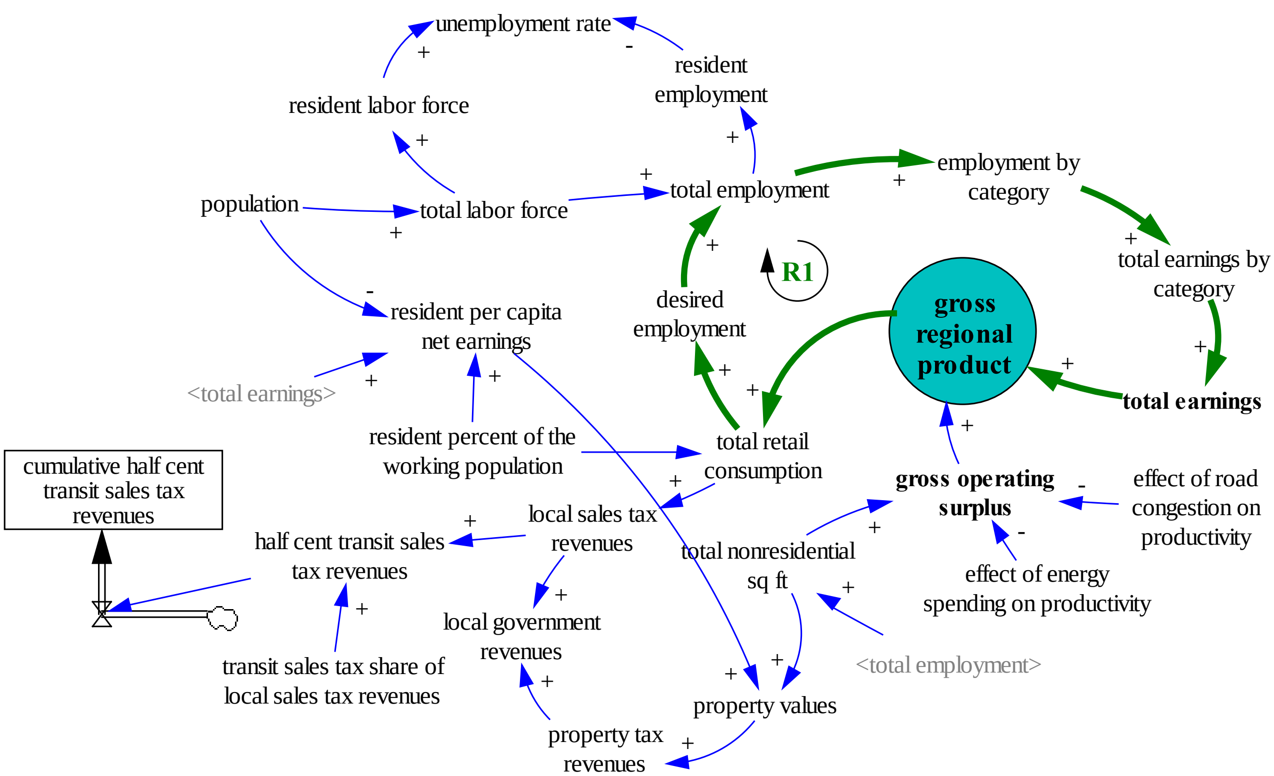

Figure 3-10. CLD of the Tier 2 Economy Sector

The strongest relationship within the economy sector that drives all economic growth in both Tier 2 and Tier 1 is the reinforcing feedback loop between employment and GRP. The CLD pictured in Figure 3-10 shows this loop highlighted in green (R1). Total employment is divided into four categories (industrial, office, retail, and service), each with different earnings per employee. Earnings per employee are multiplied by the number of employees in each category and combined into total earnings, the largest component of GRP. Changes in GRP drive total retail consumption (as does any change in the resident percent of the working population in Tier 2), which is in an indicator of desired employment. The relationship between GRP, total retail consumption, and desired employment is widely accepted in economic theory (Keynes 1936). The standard theory holds that if retail consumption grows (representing demand), the desired production of goods and services also increases along with employment (two key drivers of supply). At the same time, employment only increases as long as there are enough labor force participants to fill the desired employment positions. This constraint is represented by the link between total labor force and total employment in Figure 3-10 (though in the model, this relationship takes the form of a “minimum” function between desired employment and total labor force). Retail consumption also drives the collection of sales tax revenue in the economy sector. Besides local sales tax revenue, the other primary component of local government revenues is property tax revenue, based on property values (described in detail in the Equity sector. This main reinforcing loop (R1) that drives economic growth also affects several variables outside of the economy sector. A summary of these relationships is presented in Figure 3-10.

Table 3-4. Economy Sector Variables Affecting Variables in Other Sectors

ECONOMY SECTOR VARIABLE	DIRECTION OF INFLUENCE	SECTOR AND VARIABLE IT INFLUENCES
Relative GRP per capita	(+)	Transportation: Baseline relative person miles of travel per day per capita (all modes)
Relative total employment	(+)	Land Use: Nonresidential property value per sq ft
Relative resident per capita net earnings	(+)	Equity: Single-family and multifamily property value per dwelling unit
Relative resident per capita net earnings	(+)	Transportation: Income factor affecting desired vehicle ownership per person not in a zero car household
Relative retail per capita net earnings	(+)	Equity: Affordability index
Unemployment rate	(+)	Equity: Percent of population in poverty

Differences Between the Tier 2 and Tier 1 Economic Model

When the Tier 2 economy sector was duplicated for Tier 1, it became apparent that the simple formulation used for total employment was going to be insufficient. Unlike Tier 2, where population and employment grew historically at about the same rate (and were projected to do the same going forward), historical data for Tier 1 show that employment has grown more rapidly than population (U.S. Census Bureau 2015). In addition, whereas 74% of jobs in Tier 2 were held by residents of Tier 2 in 2010 (NC ESC 2014), only about 20% of the jobs in Tier 1 were held by residents of Tier 1 in that year (Geographic Research Inc. 2015a). This result is not surprising, given that the two major employment centers in Durham and Orange County, Duke and UNC Hospitals, are located within Tier 1, and many of the employees that work there commute from outside of Tier 1. Consequently, the "relative resident percent of the working population" variable that was used to influence total retail consumption in Tier 2 did not increase retail consumption in Tier 1enough to match historical trends because much of the retail consumption that takes place in Tier 1 is done by people who reside elsewhere.[13] In addition, a new formulation that allowed a dynamic portion of the desired employment to be filled by commuters, shown in Figure 3-11, allowed employment to grow more rapidly than population in Tier 1. Lastly, the resident employment and unemployment rate calculations were made dynamic for Tier 1, with unemployment rate having an influence on net migration for Tier 1.

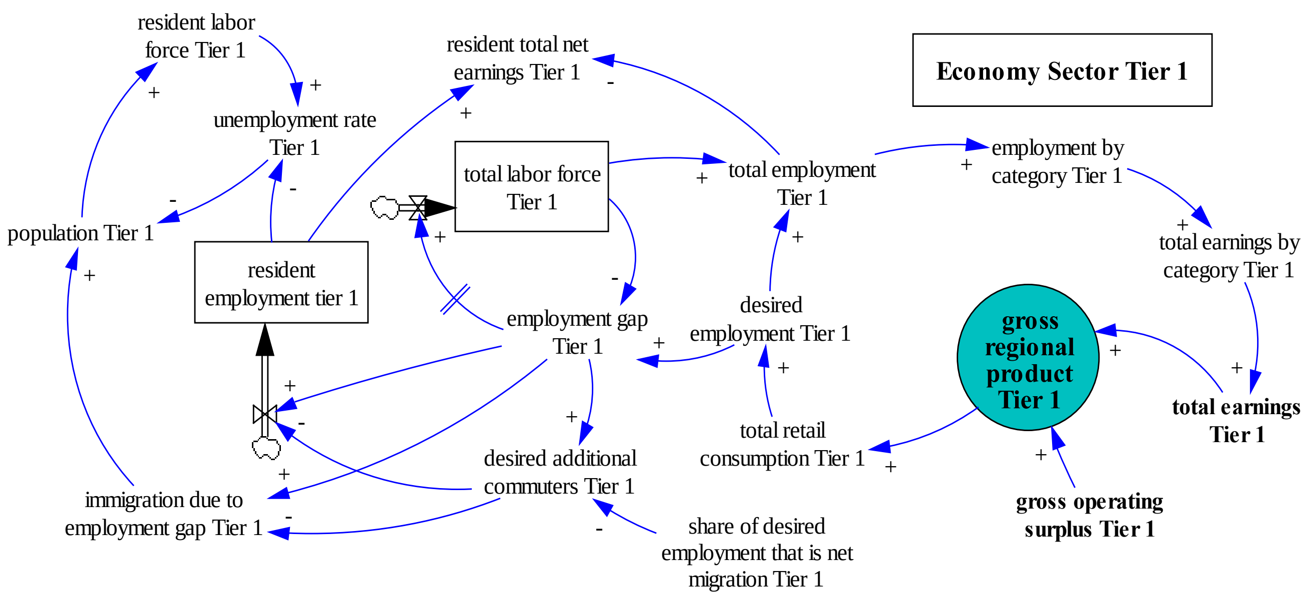

Figure 3-11. CLD of the Tier 1 Economy Sector

Data Sources and Processing

<u>Total Employment and Employment by Job Category</u>

Historical employment data and projections were available from several sources, but we chose to calibrate the model to the employment data (2010) and projections (2011-2040) from the TRM v5 SE data (DCHC MPO 2013). For the preceding model years, 2000-2009, annual employment growth trends from the U.S. Bureau of Economic Analysis (BEA) for Durham and Orange County for Tier 2 (BEA 2014d) and from the U.S. Census Bureau's <u>L</u>ongitudinal Employer-Household Dynamics (LEHD) Program <u>O</u>rigin-<u>D</u>estination <u>E</u>mployment <u>S</u>tatistics (LODES) dataset for Tier 1 (U.S. Census Bureau 2015) were applied to the 2010 value for total employment from the TRM. Although we were able to use total employment data and projections from the TRM v5 SE data files to calibrate total employment in the model for Tier 2 and Tier 1, which also provided delineations of employment into five categories (industrial, office, service, retail, and highway retail), specific job types within a 2-digit NAICS category

[13] A more detailed description of this formulation and why it could not be used for Tier 1 can be found in the "Structure Confirmation Tests" Subsection of Chapter 6, Section 3.

were divided among job categories in the TRM v5 SE data, making it impossible to combine this jobs by category data with Woods & Poole's earnings per employee by job category data and projections to get total earnings. Thus, instead of using the employment by job category numbers from the TRM v5 SE data, we aggregated the 20 job types provided by Woods & Poole[14] (Woods & Poole Economics Inc. Copyright 2014) into four categories, industrial, office, retail, and service, shown in Table 3-5, based off of the 5-tier employment classification scheme used in the Smart Location Database (Ramsey and Bell 2014), and multiplied total employment with the share of employment that fell into each category for the entire study period (2000-2040).

Table 3-5. Job Types by 2-digit NAICS Codes Aggregated into Four Employment Categories Used in the D-O LRP SD Model

JOB TYPE BY CATEGORY	NAICS CODE
Retail Jobs	
Retail Trade	NAICS 44-45
Accommodation and Food Services	NAICS 72
Office Jobs	
Information	NAICS 51
Finance and Insurance	NAICS 52
Real Estate and Rental and Leasing	NAICS 53
Management of Companies and Enterprises	NAICS 55
Industrial Jobs	
Agriculture, Forestry, Fishing, and Hunting	NAICS 11
Mining	NAICS 21
Utilities	NAICS 22
Construction	NAICS 23
Manufacturing	NAICS 31-33
Wholesale Trade	NAICS 42
Transportation and Warehousing	NAICS 48-49
Service Jobs	
Professional, Scientific, and Technical	NAICS 54
Administrative and Support and Waste Management and Remediation Services	NAICS 56
Educational Services	NAICS 61
Health Care and Social Assistance	NAICS 62
Other Services [Except Public Administration]	NAICS 81
Arts, Entertainment, and Recreation	NAICS71
Public Administration	NAICS 92

Total Earnings and Earnings per Employee by Job Category

Since total employment in the model for Tier 2 and Tier 1 was calibrated to historical data and

[14] Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusions drawn from it are solely the responsibility of the US EPA.

projections to match the total employment from the TRM v5 SE data, and the total employment numbers in the TRM v5 SE data were lower than total employment numbers from historical data and projection sources for Durham and Orange County combined (e.g. BEA and Woods & Poole Economics, Inc.), alternative calculations of total earnings were done to calibrate the model. Woods & Poole provided average earnings per employee per year for Durham and Orange County, both historical data and projections, for each of the 2-digit NAICS code classifications. To calculate total earnings, we took the average earnings per employee per year in each of the four employment categories and multiplied them by the number of jobs in each employment category for each year and summed them.

Gross Regional Product (GRP)

Although Woods & Poole provides historical GRP and projections by county, we were unable to use these values because our estimates of total earnings were lower than their estimates. To calculate historical GRP for the three counties in Tier 2 based on our total earnings estimate, we used a variation of an equation from the BEA Regional Economic Accounts Office, GDP-by-metropolitan-area methodology that uses at top-down approach, distributing state-level output to metropolitan areas (Panek et al. 2007):

$$GRP_{ec,county,y} = \left(\frac{GDP_{ec,state,y}}{Earnings_{ec,state,y}} \times Earnings_{ec,county,y} \right)$$

Where: ec = employment category (industrial, office, retail, service), and y = year.

To use this equation, we first obtained GDP and earnings by employment category for North Carolina for 2000-2013 from the BEA(BEA 2014a, c). We then summed the GRP per employment category per county per year to get the total GRP per year for Tier 2 for 2000-2013. We used the same equation to calculate GRP for Tier 1, with Tier 1 earnings replacing county earnings. We projected GRP in Tier 2 from 2014 to 2040 based on our projections of total earnings (calculated from TRM v5 SE data and Woods & Poole data, as described above), holding the earnings percent of GRP constant at its 2013 level of 60%. For Tier 1, we used the same process, though the earnings percent of GRP in 2013 was about 70%, due to the high percentage of service employment in this area.

Total Retail Consumption

Three sources of historical retail consumption data were available to calibrate the Tier 2 economy model, all with data for Orange and Durham County. The first source was “total taxable sales” data for 2000-2014 from NC DOR (NC DOR 2014). The second source was Woods & Poole Economics, Inc. with “total retail sales” estimates between 2000 and 2011, with 2002 and 2007 being actual historical data from the U.S. Department of Commerce (Woods & Poole Economics Inc. Copyright 2014). The third source was “total retail sales” estimates downloaded from SimplyMap for 2011-2014 (data were also downloaded from 2008-2010, but were found to be erroneous), benchmarked from the 2007 Economic Census (Geographic Research Inc. 2015b). Since Woods & Poole’s projections began in 2012, we decided to calibrate the model as closely as possible to the most recent historical data point from 2014 by adjusting the initial value (2000) for retail consumption to a value between the two historical data sources and then used the Woods & Poole total retail sales growth rate to calibrate the model to projections for 2015 to 2040.

Government Revenues (Including D-O LRP Costs and Revenues)

We obtained historical property tax and sales tax data from NC DOR Statistical Abstracts (NC DOR

2013b, 2004-2014, 2013a, 2003-2013, 2013c) and Annual Financial Reports from Durham County, Orange County, the City of Durham, and the Town of Chapel Hill, and assumed that all tax rates were held constant at 2014 values between 2015 and 2040. (City of Durham Department of Finance 2009, 2014, Durham County Finance Department 2009, 2014, The Orange County Financial Services Department 2009, 2014, Town of Chapel Hill Business Management Department 2009, 2014). We obtained information related to the expected costs (including capital costs and operation and maintenance costs) and revenues information for the D-O LRP from the Durham County and Orange County Rail Investment Plans (DCHC MPO et al. 2011, Triangle Transit 2014, Triangle Transit et al. 2012). A summary of the cost and revenue assumptions used in our model for the D-O LRP is presented in Figure 3-12.

Light Rail Capital Cost: $1.345 Billion (split evenly per year of light rail construction 2020-2025)

Light Rail O&M Cost: $14.09 Million/year (beginning in 2025)

½ Cent Sales Tax Revenue: Begins collection in FY 2013 for two months (model year 2013), then all of 2014 = 18% of total local sales tax collected (Durham and Orange County).

$3 and $7 Vehicle Registration Fees: Begins collection in FY 2014 and increases at a 2% growth rate ($10 combined fee in nominal dollars is converted to 2010 dollars for 2014-2040).

Rental Car Tax: Begins collection in FY 2014 and increases at a 4% growth rate.*

Sources: Durham and Orange County Bus and Rail Investment Plans, NC DOR Local Option Sales Tax Reports.

Figure 3-12. D-O LRP Cost and Revenue Assumptions (2010 Dollars)

Calibration

We adjusted several exogenous inputs in the Tier 2 and Tier 1 economy sectors to improve the fit between estimated values for key variables in the business-as-usual (BAU) scenario and historical data and projections. “Gross operating surplus per sq ft” was calibrated so that, with the effects of congestion and energy spending included, gross operating surplus in Tier 1 and Tier 2 would make up 40% and 30% of GRP, respectively. This was required to ensure that the model’s historical estimates of gross operating surplus, which are influenced by several endogenous factors, coherently represent the trends observed in the data and do not under- or over-estimate change over time. We made additional adjustments to ensure that the model’s estimates of total retail consumption for Tier 2 more closely match historical trends. This included slightly adjusting “resident percent of the working population” from the values we originally calculated from historical data and increasing the initial value for “retail consumption.” We slightly modified the value originally calculated from historical data for “employment per dollar of consumption” in both Tiers in order to calibrate total employment. Finally, we added the variable, “effect of unemployment on net migration tier 1” to ensure that the model did not project unemployment levels to fall below zero (this addition is discussed in greater detail in the following section).

Equity

Sector Relationships

The Equity sector is primarily composed of indicators and has relatively few feedbacks to other sectors of the model. Some of the key indicators are shown in blue in Figure 3-13, including property values (disaggregated into single-family, multifamily, and nonresidential), renter costs, transportation costs, population in poverty, zero-car households (a proxy for the transit-dependent population), and affordability indices. The green balancing loop highlights how the number of zero car households, which is affected by the population in poverty, feeds back into the transportation sector of the model, where it reduces VMT and ultimately increases transit ridership. Though the sector does not have many feedbacks to the wider model, the sector does respond to many other sectors in the model. From the economy sector, unemployment rate affects the population in poverty, and resident net earnings, GRP growth rate, and job density affect affordability indices; from the transportation sector, transportation costs affect affordability, and commute time (which is affected by congestion) affects residential property values; and from the land use sector, residential density, nonresidential density, retail density, and available land affect property values. Property values in particular are driven by several other variables in the model. Single-family property value is affected by the population growth rate, vacant land, income, lot size, job density, commute time, and retail density. Multifamily property values are impacted by many of the same factors (minus population growth rate, lot size, and job density), as well as commercial building size and retail density. Nonresidential property values are affected by just three factors: building size, employment growth, and retail density.

There are two affordability indices in the model, both of which are a factor of both transportation and renter costs. The primary affordability index is calculated as the ratio of per-capita earnings (indexed to the initial value) and transportation and renter costs (indexed to the initial value). Therefore, the higher the affordability index, the more affordable it is to live in the Tier for someone who makes average earnings. A second index is calculated as the ratio of a constant housing and transportation cost threshold (set at 45% of the poverty threshold for the average household size in the Tier) and 75% of the actual transportation and renter costs. This index compares forecasted costs to a threshold based on the assumption that wage increases for the average household may not affect households in poverty, and it accounts for the fact that housing and transportation costs will be lower for such households than for average households.

The other two primary output indicators shown in Figure 3-13 are transit-dependent households, which uses the proxy of zero-car households in the model, and the households in poverty at risk of displacement, which is defined as the number of households in poverty not accommodated in subsidized dwelling units. The housing gap is a related indicator, defined as the number of households neither accommodated in subsidized dwelling units nor in organically affordable dwelling units (i.e., the percent of market-rate multifamily units that cost no more than 30% of the monthly income for a household making 60% of the Area Median Income).

Data Sources and Processing

Historical Demographic Data

We obtained most of the data for this sector from the same sources as for the Land Use sector. One exception is SimplyMap, which provided summarized data from the U.S. Census Bureau. We used Census data from SimplyMap (Geographic Research Inc. 2015a) to corroborate other data and, in the cases of median annual renter costs, percent of population in poverty, and zero-car households, for calibration purposes.

Property Value Data

Estimates for property values were derived from the Durham County Tax Administration Real Property Database (Durham County Tax Administration 2000-2014), Orange County Parcel Database (Orange County Tax Administration 2014), and Chatham County Tax Parcel Database (Chatham County Tax Administration Office 2014). To obtain estimates for our Tiers, property values in 2014 from Durham, Orange, and Chatham were summed by category (commercial, single-family, multifamily, and vacant). In Tier 2, we back-cast estimates for previous years by applying the percent change in total residential and commercial real property value for Orange and Durham Counties from the Counties' Financial Reports to the 2014 value. In Tier 1, the percent change in the Durham portion of Tier 1 year to year was applied to the 2014 value for the entire tier. Finally, values were converted to 2010 dollars. More detail on the methods used to download and scale data to the model's Tiers is provided in Chapter 6.

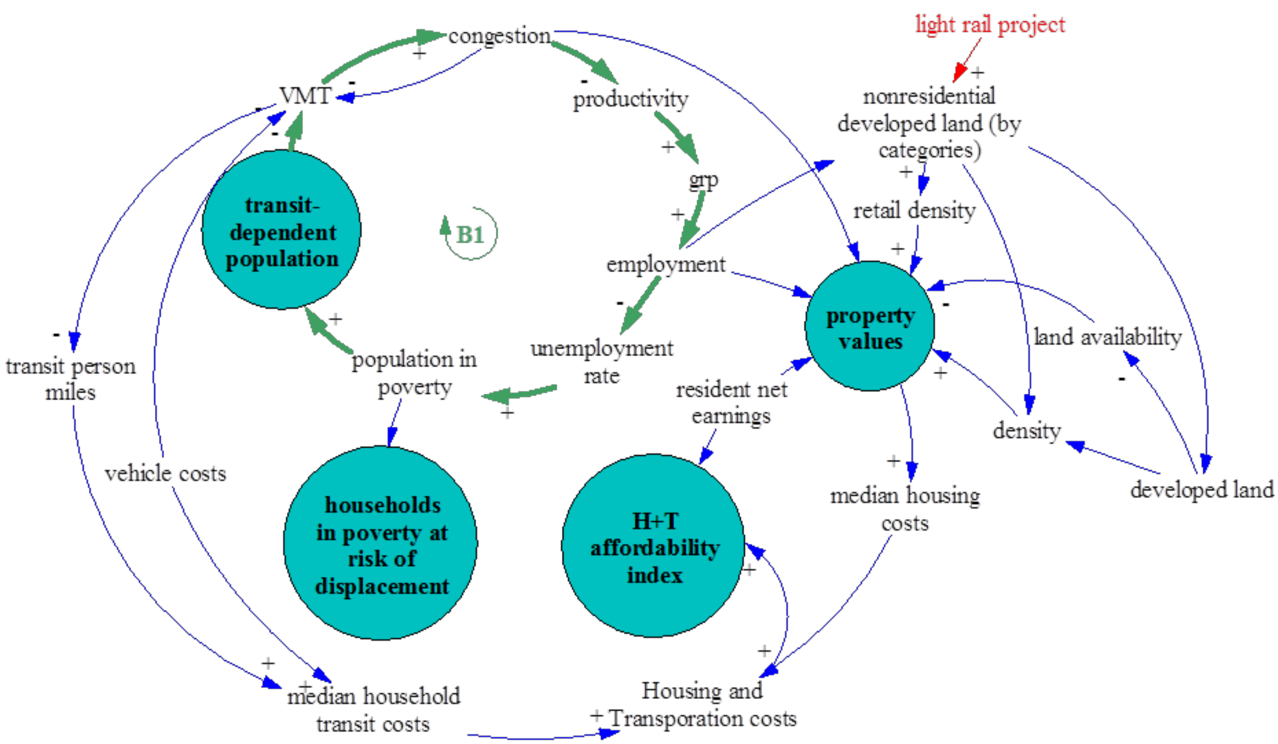

Figure 3-13. **CLD for the Equity Sector**

Calibration

This sector makes heavy use of elasticities and effect tables, both those supported by the literature and those derived from other variables. That fact combined with the challenge of capturing location-specific market dynamics and complex relationships between property values and other variables not yet well documented in the literature, make this one of the more uncertain sectors. Nonetheless, we are confident that the key indicators in this sector move in the right direction in response to an array of endogenous model variables. The most significant calibration that took place in this sector was the calibration of property values. A large amount of literature exists linking various unit-level (e.g., number of bedrooms), local (e.g., accessibility from the home to retail), and regional (e.g., population growth) characteristics to single-family and commercial property values. The literature on factors affecting multifamily property values, on the other hand, is relatively sparse. We therefore borrowed many relationships from the literature on single-family and commercial property values to develop an endogenous model for multifamily property values. Furthermore, the research that does exist typically focuses on a particular city and one point in time, and we did not identify any meta-analyses that summarized the literature. The literature therefore provides a range of elasticities for many characteristics, and we made several judgment calls to determine which characteristics could be modeled with any certainty, what values linking a particular characteristic to property values are reasonable in the local context, and how to account for factors that cannot be captured at the model's scope (e.g., number of bedrooms or quality of nearby schools). In a few cases, elasticities had to be modified from literature values to fit the study area (see Appendix B for details on the modifications made). In addition, a housing crash was exogenously introduced, starting in 2005 to better reproduce this global phenomenon and therefore better fit data on housing costs. Figure 3-14 illustrates the factors affecting property values that we ultimately chose to include in the model for the three categories of properties.

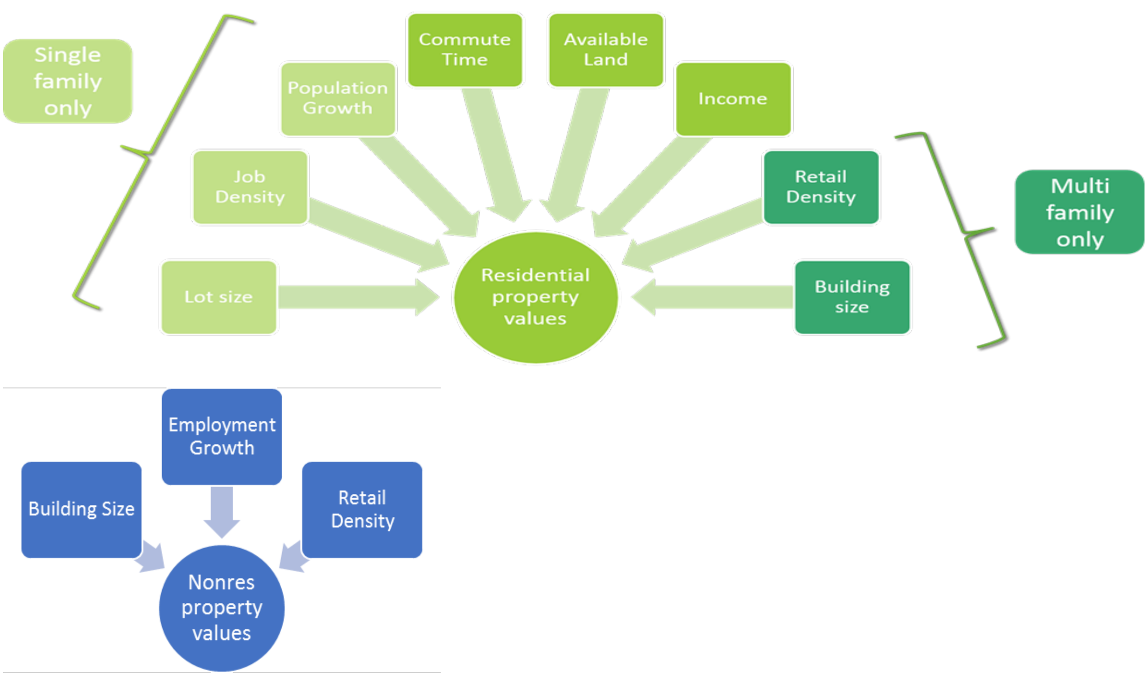

Figure 3-14. Factors Affecting Single-family, Multifamily, and Commercial Property Values in the D-O LRP SD Model

To a smaller degree, a similar calibration process took place for median annual renter costs, though far less literature is available on the topic. Therefore, with one exception, the elasticities governing the relationships with renter costs were borrowed from the literature on property values, derived from available data, or exclusively calibrated. The one elasticity found in the literature is that linking renter costs to renter vacancy, for which we used the median value from a study of 17 U.S. cities (Rosen and Smith 1983). In Tier 1, the elasticity of income to property values used in the property value section was borrowed and applied to renter housing costs as well. (Capozza et al. 2002a). We calibrated the table governing the effect of GRP growth rate on renter housing costs based on the assumption of a balanced S curve shape to the effect. The elasticity of renter costs to multifamily property values was purely calibrated to match historical data on renter housing costs (U.S. Census Bureau 2000, Geographic Research Inc. 2015a (Tier 1), U.S. Census Bureau American Community Survey 2014) (Tier 2)). See Appendix B: Detailed Documentation by Sector, for a variable by variable accounting of the calibration steps taken.

The addition of the variable "effect of unemployment on net migration tier 1," was another significant calibration step that affected unemployment and therefore the percent of the population in poverty. In the absence of this variable, unemployment in the model was driven primarily by economic activity (specifically, total retail consumption). Because the model forecasts economic activity to rise faster than population, it forecasted unemployment to fall below zero. Adding a nonlinear link between unemployment and migration, which boosts migration when the unemployment rate is below 3% and lowers it sharply as the unemployment rate goes above 6%, allowed the model to better represent reality, in that a decrease in unemployment in an area causes more people to move to the area for jobs, which raises the resident population and increases unemployment until it reaches a new equilibrium. This restructuring allowed a more accurate endogenous connection to the percent of the population in poverty in Tier 1.

Water

Sector Relationships

The water model simulates water supply, demand, and stormwater runoff. Within stormwater runoff, the model simulates loadings of nitrogen (N) and phosphorus (P) in stormwater, as well as runoff volume. Water supply is affected by annual rainfall, reservoir volume, and water demand. Average annual rainfall is kept constant, but a random number generator is used to project future annual rainfall, reflecting historic variation around the average. This random projected rainfall is used for calculating water supply, but for ease of trend visualization, stormwater runoff is simulated using a constant average rainfall. Water demand is driven by several outputs from the land and economy sectors, including the number of single-family and multifamily dwelling units and total employment. Water use intensity for nonresidential buildings and for single-family and multifamily dwelling units factor into water demand, with a slight effect of building density on single-family residential water use intensity (gallons/day/dwelling unit).[15] Water demand is an output to the energy sector, where it determines the energy used for water treatment and distribution. Water demand is modeled for both Tier 1 and Tier 2,

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[15] The elasticity of single-family residential water use to residential density (assumed -0.1) is based on a study in Portland, OR (Chang et al. 2010). Therefore a doubling (100% increase) in single-family residential density would cause a 10% decline in single-family residential water use.

while water supply is modeled only for Tier 2, because local reservoirs operate at this regional scale.

Stormwater is modeled for Tier 1 and 2. Using the Simple Empirical Model for stormwater runoff (Shaver et al. 2007), the model calculates runoff volume and N and P loadings as a function of annual rainfall, impervious coefficient (impervious area/total land area, equivalent to percent impervious, an output from the land use sector), land area, and event mean concentrations (EMCs) for each pollutant:[16]

$$Stormwater\ Pollutant\ Loading = Annual\ Rainfall\ Volume \times Runoff\ Coefficient \times EMC$$

$$Annual\ Rainfall\ Volume = Annual\ Precip \times Land\ Area$$

$$Runoff\ Coefficient\ =\ 0.05\ +\ (0.009 \times impervious\ coefficient \times 100)$$

The model estimates EMCs for N and P based on average values from local and national literature and percent impervious cover; EMCs for N are shown in Figure 3-15. Stormwater is modeled separately by land use type, then summed for total N and P load for each Tier.

We estimated EMCs for each land use using the projected impervious coefficient for that land use and literature-based EMCs taken from the Jordan Lake Stormwater Load Accounting Tool User's Manual (NCDENR 2011). In some cases we calculated weighted average EMCs; for example, we estimated the EMC for SF residential stormwater N as a weighted average of the EMC for lawns and roofs:

$$\begin{aligned} EMC\ N\ SF\ Residential \\ &= EMC\ N\ lawns\ or\ open\ space\ \times (1 - SF\ impervious\ coefficient) \\ &+ EMC\ N\ roofs \times SF\ impervious\ coefficient \end{aligned}$$

Modeled EMCs for different land use types in 2015 are shown in Figure 3-15, ordered from largest (agricultural and open space) to smallest (roads and nonresidential). Although agricultural land and open space are assumed to have the same EMCs in Tier 1 and Tier 2, the other EMCs are 6-13% lower in Tier 1 than Tier 2 due to higher impervious coefficients (less open space) in Tier 1.

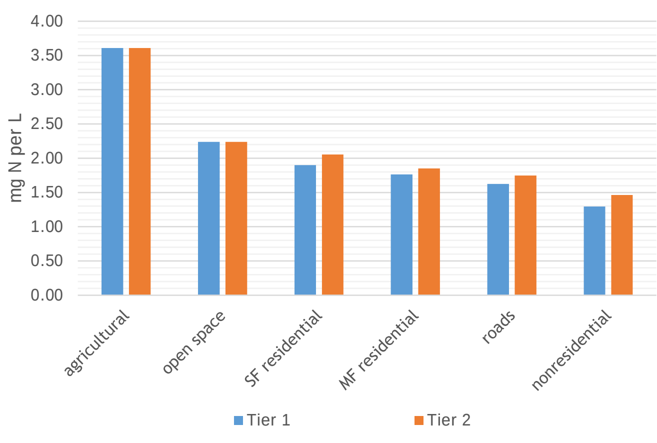

Figure 3-15. Storm Event Mean Concentrations (EMC) of Nitrogen in Both Tiers, Modeled for 2015

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[16] EMCs are converted from mg/L to lb/L when calculating stormwater pollutant loading. In the loading formula, the runoff coefficient is the fraction of rainfall volume that becomes runoff.

As Figure 3-16 shows, several variables from other sectors can affect indicators in the water sector. From the land use sector, population growth and changes in the share of single-family or multifamily residences can affect water demand, as can changes in employment from the economy sector. Changes in impervious cover (resulting from land development in the land use sector) can affect loadings of N and P in stormwater. The model can also run user-specified scenarios that would affect variables in the water sector, including changes in annual rainfall, changes in reservoir capacity, or implementation of low-impact development technologies such as bioretention (rain gardens).

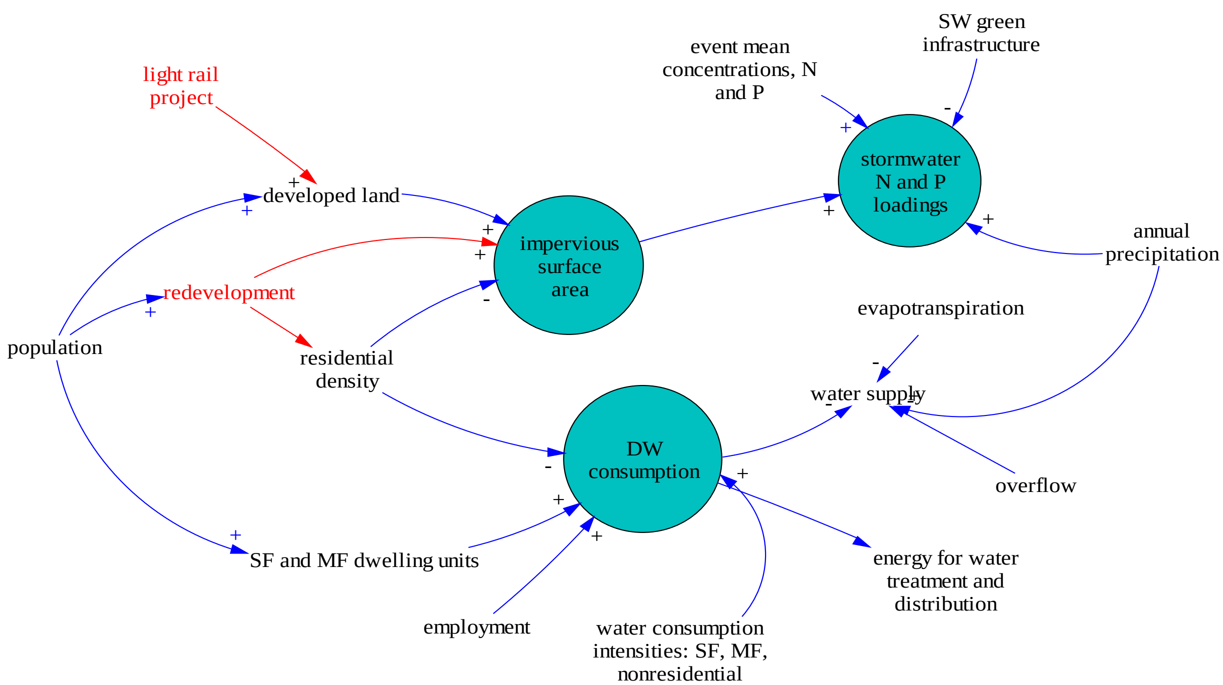

Figure 3-16. CLD for the Water Sector

Data Sources and Processing

Water supply

We obtained historical annual rainfall data for the Northern Piedmont region (covering the years 2000-2013) from the State Climate Office of North Carolina (State Climate Office of North Carolina 2015). Data for the combined volume of Durham County's drinking water reservoirs in 2015 came from the City of Durham Department of Water Management (City of Durham Department of Water Management 2015). To estimate reservoir volume in 2015, we multiplied current days of supply by current daily use rate (Mgal/day).

Water Demand

Data on historical water demand for Durham County came from the North Carolina Department of Environment and Natural Resources (NCDENR) (NC State Data Center 2015). We obtained projected future water demand data from the TJCOG Triangle Regional Water Supply Plan (TJCOG 2012, 2014f), which projects residential water use rate (gallon/day/person), nonresidential use rate (gallon/day/employee), total demand, and demand by sector (residential, nonresidential, and nonrevenue, in Mgal/day). These projections cover the years 2010-2060, but our model uses their projections to 2040. For both historical and projected Durham County water use data, we scaled values for Durham County to Tier 2 based on the ratio of Durham County population to Tier 2 population (0.67).

Impervious Surfaces and Stormwater

The model calculates stormwater runoff using precipitation data (noted above) as well as impervious surface data drawn from the EPAs EnviroAtlas online database (US EPA 2015e). This source provided impervious surface data with a resolution of one square meter for about 86 percent of the study area. Once we estimated total impervious surface area in the portion of Tier 2 covered by EnviroAtlas, we multiplied that estimate by 1.17 to produce an estimate of total impervious surface area for Tier 2 (assuming that the area of overlap is representative of percent impervious surface for all of Tier 2). We corroborated this estimate using impervious surface data shared by the Durham City/County Planning Department, which only addressed impervious surfaces on parcels within the City of Durham (e.g. excluding roads). To estimate runoff loadings of N and P, we obtained event mean concentration (EMC) data from the Jordan Lake Stormwater Load Accounting Tool User's Manual (NCDENR 2011). The EMC values in that source are based on a literature review which included many values from the Piedmont region of North Carolina.

Calibration

We calibrated key output variables from the water sector to historical (before 2015) and projected (after 2015) data for Durham County, scaled to Tier 2 (assuming a constant Durham County/Tier 2 population ratio of 0.67). These variables include total water demand, residential water use, nonresidential water use, and nonrevenue water use. For each of these variables, we were able to achieve a close fit with historical data and projections (R^2 values were greater than 0.94 and average deviations were less than five percent for the combined dataset, which included both historical and projected data).

Residential water use makes up the majority of Tier 2 water use, and we identified data sources for total residential water use, but not separate water use by single-family and multifamily units. Instead, we obtained average single-family and multifamily residential water use rates from national averages in the 2010 Buildings Energy Data Book (US DOE 2011) and applied one calibration factor to all residential water use so that it matched local data.

Health

Sector Relationships

As with the equity and water sectors, the health sector of the D-O LRP SD Model is primarily output-oriented. For any scenario run in the model, the health sector translates changes in variables in the transportation and energy sectors into positive and negative premature mortality and morbidity outcomes. Directly comparing the health effects of the business-as-usual (BAU) scenario to alternative scenarios allows the user to isolate the estimated health benefits and detriments above and beyond those of other actions that would be taken anyway.

The health sector quantifies the net avoided premature mortality that results from scenario changes relative to BAU in: 1) vehicle emissions of $PM_{2.5}$ and NO_x, 2) walking and cycling for transportation, and 3) vehicle crash fatalities. The main outcome variable for the health sector is "net premature mortalities avoided per year from $PM_{2.5}$ and NO_x vehicle emissions, physical activity, and crash fatalities relative to BAU," which is the sum of the positive and negative effects on premature mortality of all three transportation- and energy-related outcomes. The only feedback loop within the health sector is a reinforcing loop (labeled R1 in Figure 3-17) in which changes in mortality risk due to increases or decreases in physical activity affect the overall death rate for the population of the study area.[17]

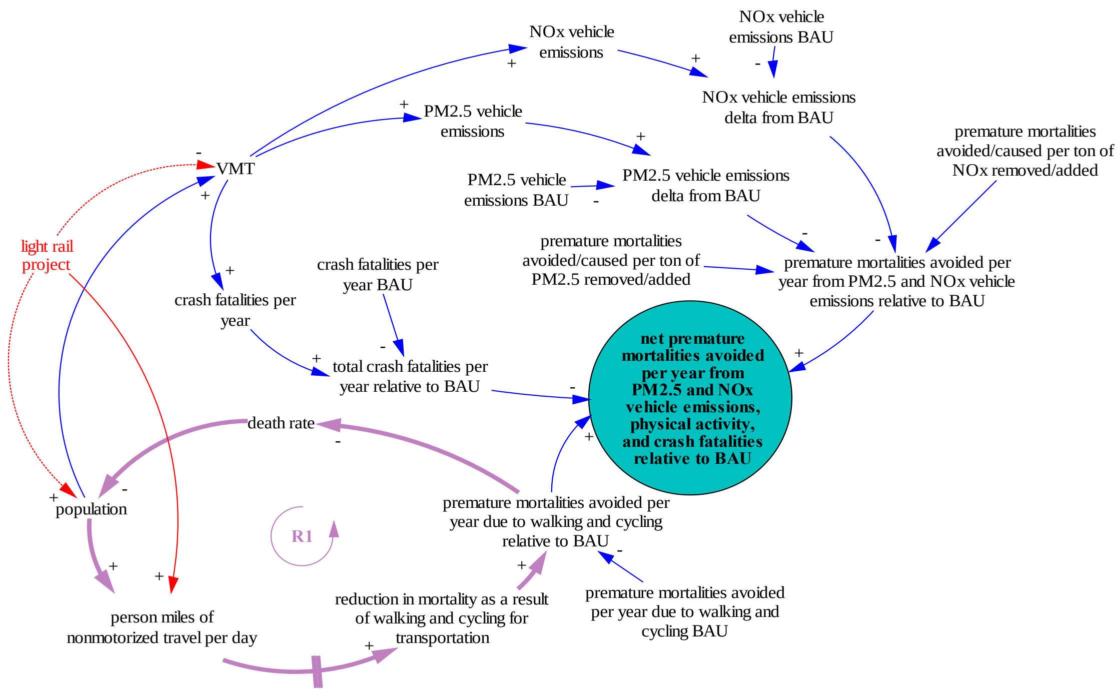

Figure 3-17. CLD for the Health Sector

Data Sources and Processing

<u>Premature Mortality and Morbidity Estimates from Changes in Vehicle Emissions</u>

To estimate the health impacts of changes in vehicle emissions of $PM_{2.5}$ and NO_x on mortality and morbidity (due to changes in vehicle use), we used incidence-per-ton estimates from an EPA nationwide study of the health impacts of removing directly emitted $PM_{2.5}$ and $PM_{2.5}$ precursor emissions, including NO_x, from 17 sectors, including on-road mobile sources (US EPA 2013c). Because the values used for avoided mortality and morbidity per reduced ton of $PM_{2.5}$ or NO_x vehicle emissions were from a nationwide study and were not meant for smaller geographic scales, there is considerable uncertainty about the use of these figures in our model, including translating changes in emissions to changes in ambient pollutant concentrations, and relating changes in ambient pollutant concentrations to changes in health outcomes. Nevertheless, we chose to include the numbers from this study to illustrate the magnitude of the health impacts of air emissions, relative to the magnitude of other health effects in the model (e.g., changes in physical activity and vehicle-crash fatalities).

[17] We decided not to include the premature mortality effects of changes in emissions reductions and crash fatalities (relative to the BAU) on the overall death rate, because testing indicated that the effect of these factors on the death rate was negligible.

Health Benefits of Physical Activity

To estimate the health impacts of model changes in physical activity, or, more specifically, "person miles of nonmotorized travel by residents per day per capita," we used equations from the World Health Organization/Europe Health Economic Assessment Tool (HEAT) (WHO 2014), which is freely available online. The HEAT equations estimate the health effects of active transport over an entire population based on daily average amounts of walking and cycling. Although HEAT is meant to be used for daily average amounts of walking and cycling for all purposes, which the D-O LRP SD Model does not estimate, we instead applied the HEAT equations in the model to the average walking and cycling distances traveled by residents per day solely for transportation purposes (i.e., from trips for which the main mode of transportation was nonmotorized), as well as an assumption of 0.25 miles of walking or cycling per one-way public transit trip. Because the HEAT model assumes a delay between increases in physical activity and measurable benefits to health, we also applied a five-year delay between a change in walking and cycling and the associated avoided premature mortality. We also note that the estimates of premature mortalities avoided due to walking and cycling predicted by the HEAT equations are likely to be conservative estimates of the total health benefits of physical activity, since they do not account for the beneficial effects of physical activity on many aspects of morbidity. This is because current evidence on morbidity, both for walking and cycling, is more limited than that on mortality (WHO 2014).

Premature Mortality and Injury Estimates from Vehicle Crashes

We obtained local data on historical occurrences of traffic accidents, injuries, and fatalities by county from the NC Crash Data Query Web Site (Highway Safety Research Center at UNC Chapel Hill 2015), which we used to calibrate variables related to traffic accidents and fatalities in the D-O LRP SD model. The D-O LRP SD Model estimates values for these variables based on historical numbers of people involved in reportable traffic accidents and the percentages of them who either died or were injured, under the assumption that the relationship between VMT and people in traffic accidents (including people not in vehicles) is constant over time. We investigated the possibility of having the model's estimated number of vehicle-crash fatalities per year be affected by other variables, including nonmotorized travel volumes, vehicle speeds, the frequency of intersections, and traffic-control measures, but we were not able to find data or studies that would allow us to relate these factors to crash and crash-fatality rates at a regional scale.

Calibration

We did not perform any calibration to data or projections for the vehicle-emissions and physical-activity components of the health sector of the model. In the vehicle-crashes component, we adjusted the input variable "people in traffic accidents per VMT" so that the number of people in traffic accidents per year in Tier 2 ("people in traffic accidents per year") would match data from the NC Crash Data Query Web Site for Orange and Durham Counties in the year 2013, the most recent year for which data are available from that authoritative source (data are available for 2001-2013) (Highway Safety Research Center at UNC Chapel Hill 2015). We assume that the number of people in traffic accidents within Tier 2 is the same as the number of people in traffic accidents in the combined area of Orange and Durham Counties, even though Tier 2 (the DCHC MPO) does not conform to county boundaries. Because crash statistics are not available for Tier 1, we assume that the Tier 2 value of "people in traffic accidents per VMT" resulting from this calibration process also applies to Tier 1. We also assume that the percentage of people involved in traffic accidents who are either injured or killed is the same in both Tiers.

4 Scenario Descriptions

This chapter describes the scenarios that were run in the D-O LRP SD Model. We designed these scenarios to explore the effects of the light rail project and a range of policies and other factors that could affect land use, transportation, economic and demographic trends, and energy use. The chapter begins with a description of the three main scenarios – Business As Usual (BAU), Light Rail, and Light Rail + Redevelopment (Light Rail + Redev). It then describes 17 policy, demographic, and market scenarios, grouped into the following categories:

- Land Use Planning Changes
- Transportation Planning Changes
- Market Trends
- Demographic Trends
- Environmental Policy Changes

For the additional scenarios, we list primary variables to review for changes under each scenario. However, these are not listed for the main scenarios, due to the large number of key variables and indicators affected under those scenarios. Most of the indicators on the model dashboard (the summary of policy switches and model indicators in the Vensim model, described in greater detail in Appendix A) would be interesting to review for changes under the two light rail scenarios.

4.1 Main Scenario Descriptions

The three main scenarios serve as the reference points to which the 17 additional decision support scenarios are compared. The BAU scenario represents the without-light rail baseline, the Light Rail scenario represents the implementation of the light rail transit (LRT) line without any additional changes, and the Light Rail + Redevelopment scenario represents the implementation of the LRT line with additional changes to zoning to encourage redevelopment and increased density around the station areas.

Business As Usual (BAU)

Scenario Switch: *Change the "Main policy switch" to 0.*
Scenario(s) for Comparison: Not Applicable (baseline case)

Scenario Summary

The Business As Usual (BAU) scenario is modeled on the assumption that current demographic, land use, and transportation trends continue, with values either remaining constant at current values or extending along historical trends. The scenario is compared to outputs from other projection models for purposes of calibrating the D-O LRP SD Model, and it serves as a baseline against which to compare the effects of the changes described in the other scenarios.

Assumptions and Variable Changes

The BAU scenario makes the following main assumptions:

- Land Use
  - Employee-space ratios remain constant at 2014 values, except for ratios for office and industrial uses, which are extended upward and downward along historical trends, respectively.
  - Floor-area ratios and residential densities remain constant at 2014 values.
  - The division of dwelling units into single-family and multifamily units and their respective household sizes remain constant at values equal to the average values in 2014.
- Transportation
  - Road building between 2010 and 2040 matches the DCHC MPO 2040 Metropolitan Transportation Plan (CAMPO and DCHC MPO 2013), as projected by the Triangle Regional Model (DCHC MPO 2013).
  - The ratio of miles of nonmotorized travel facilities per developed acre that data indicate for 2013 (the only year for which historical data are available for developed acres (TJCOG 2014b); 2013 facility miles are interpolated between 2010 and 2020 figures (DCHC MPO 2013) is a result of the builders of nonmotorized travel facilities attempting to maintain a ratio of miles per developed acre that is assumed to have existed in 2000, with a two-year delay between when additional acres are developed and when the consequent additional miles of nonmotorized travel facilities are completed. In the event of a decline in developed acres, miles of nonmotorized travel facilities hold steady.
  - All changes in public transit non-rail revenue miles per day are in accordance with the Bus and Rail Investment Plans for Orange and Durham Counties (Triangle Transit et al. 2012, DCHC MPO et al. 2011).
  - Most determinants of person miles of travel by mode (automobile driver, automobile passenger, public transit, and nonmotorized) change the distribution of total person miles of travel among these modes, rather than changing the overall number of person miles of travel by all modes.
  - Between 2010 and 2040, the ratio between traffic congestion and the amount of weekday peak-period VMT per lane mile decreases linearly by the amount predicted by the TRM projections created for the DCHC MPO 2040 MTP (DCHC MPO 2013).
  - Barring the effects of changes in the cost of vehicle fuel and the average speed of vehicle traffic, the VMT of through traffic (i.e., vehicle trips that pass through one or both Tiers without stopping) increases by 1.0% per year during 2014-2040, after matching the historical rate of population growth in North Carolina during 2000-2013. The 1.0% assumption for through-traffic VMT growth is based on the growth rate of North Carolina's population in 2013 (NC Office of State Budget and Management 2015).

- The number of people involved in traffic accidents per VMT stays constant at a value that is calibrated to match reported people in traffic accidents per year in 2013, and the percentages of accident-involved people who are injured or killed remain constant at 2013 levels, after matching historical percentages injured or killed during 2001-2013 (Highway Safety Research Center at UNC Chapel Hill 2015).

- Economy
    - Total employment is consistent with projections developed by local planners for the DCHC MPO area (Tier 2) for use in the TRMv5, which allocated the expected employment growth (2010-2040) by TAZ according to the "preferred growth scenario" option generated by local planners using CommunityViz. (DCHC MPO 2013) (TJCOG 2013).
    - Employment and earnings by job category (industrial, office, retail, and service) are consistent with projections (2012-2040) by Woods and Poole Economics, Inc. for Durham and Orange County[18]. (Woods & Poole Economics Inc. Copyright 2014).
    - Total earnings are projected to continue to make up 60% of GRP in Tier 2 (70% for Tier 1) between 2012 and 2040. Therefore, the gross operating surplus constitutes the remaining 40% of GRP in Tier 2 (30% in Tier 1).
    - Retail consumption grows similarly to retail sales growth rate projections from Woods & Poole Economics, Inc. for Durham and Orange County, being influenced by relative growth in GRP and the resident working population (Tier 2 only).
    - Local sales tax rates, property tax rates (both city and county), and the portion of the local sales tax collected that goes toward the D-O LRP transit fund remain at 2014 levels. The percent of nonresidential land that is tax exempt in both Tiers also remains constant at 2014 values.

- Energy
    - Building energy use intensities decline from 2015 to 2040 according to US EIA Annual Energy Outlook 2015 (AEO2015) projections (US EIA 2015a).
    - Passenger vehicle MPG increases from 2015 to 2040 according to US EIA AEO2015 projections (US EIA 2015a).
    - Energy use in buildings continues to be primarily electricity and natural gas.
    - Energy prices (electricity, natural gas, gasoline) rise in real terms from 2015 to 2040 according to US EIA AEO2015 projections (US EIA 2015a).

See Chapter 5: Model Results to view detailed results regarding the calibration process and

[18] Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusions drawn from it are solely the responsibility of the US EPA.

consequences of these baseline model assumptions.

Light Rail

Scenario Switch: *Change the "Main policy switch" to 1.*
Scenario(s) for Comparison: BAU

Scenario Summary

The Light Rail scenario is meant to show what would happen if the planned 17-mile light rail transit (LRT) line between Durham and Chapel Hill were built, but no other policy changes were instituted that deviate from the BAU case. In this scenario, any differences in land use between the BAU and Light Rail scenarios are due entirely to increases in demand that the rail line itself causes, rather than to any changes in zoning (which will be part of the Light Rail + Redevelopment scenario).

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following changes:

- "LRT line mile construction" is set to be equal to "LRT construction schedule," which dictates that construction of the light rail line will take place during 2020-2026, such that "finished LRT line miles" will reach 17 in 2026 (Triangle Transit 2015b) and the value of the variable "LRT open" will change from 0 to 1. The values for "finished LRT line miles" resulting from this change for both Tiers are shown in Table 4-1.

Table 4-1. Values for "Finished LRT Line Miles" in Tier 1 and Tier 2 under the Light Rail Scenario

SCENARIO NAME	FINISHED LRT LINE MILES						
	2015	**2019**	**2020**	**2023**	**2025**	**2026**	**2040**
Tier 1							
Light Rail	0	0	0.41	7.15	11.36	11.55	11.55
BAU	0	0	0	0	0	0	0
Tier 2							
Light Rail	0	0	0.73	10.73	16.80	17	17
BAU	0	0	0	0	0	0	0

- To reflect the expectation that the construction of the LRT line will require the temporary closure of nearby roadways in order to accommodate construction equipment, this scenario changes the values for the stock variable "urban nonhighway lane miles in disruption from LRT construction." During the period 2020-2026, this variable will have the values shown in Table 4-2, based on the assumption that two lane miles of roadway will be disrupted for each LRT line mile currently under construction. These lane miles in disruption represent a temporary reduction in "functioning urban nonhighway lane miles."

Table 4-2. Values for "Urban Nonhighway Lane Miles in Disruption from LRT Construction" in Tier 1 and Tier 2 under the Light Rail Scenario

SCENARIO NAME	URBAN NONHIGHWAY LANE MILES IN DISRUPTION FROM LRT CONSTRUCTION						
	2015	**2019**	**2020**	**2023**	**2025**	**2026**	**2040**
Tier 1							
Light Rail	0	0	1.35	1.73	0.38	0	0
BAU	0	0	0	0	0	0	0
Tier 2							
Light Rail	0	0	1.73	2.13	0.40	0	0
BAU	0	0	0	0	0	0	0

- "LRT construction cost per line mile" is set at $79,112,700 per mile, and once the rail line is near completion, "LRT O and M cost per year" is set to be $14,093,300 per year (both in 2010 USDs) (Triangle Transit et al. 2012, DCHC MPO et al. 2011).

- The value of "land use per LRT line mile" is assumed to be 2.42 acres per line mile, a portion of which is counted towards the study area's impervious surface.

- Once the rail line is open, it will add 2,310 revenue miles per day to the public transit system. We calculated this value on the basis of anticipated service frequencies (Triangle Transit 2015b).

- The light rail trains are assumed to consume 62,800 Btu of electricity per revenue mile. This factor was previously used to estimate energy consumption of the LYNX light rail line in Charlotte, NC (FTA and CATS 2011).

- The effect of the rail line on "person miles of public transit travel" is taken to be determined by a different formula than the effect of other public transit services. Once the LRT is open, the variable "change in person miles of public transit travel per year due to adding fixed guideway transit" is activated, which is driven by "population Tier 1," "total employment Tier 1," "retail plus entertainment employment Tier 1," "jobs earning $3,333 per month in 2010 USDs Tier 1," and Tier 2 "VMT per highway lane mile," all of which indicate greater demand for fixed-guideway public transit (rail or bus routes on exclusive rights-of-way) (Chatman et al. 2014). The entire change in Tier 2 person miles of public transit travel that results from the LRT line is taken to come from Tier 1. In contrast, changes in non-rail public transit revenue miles on the overall transit system affect both Tier 1 and Tier 2 person miles through an elasticity derived from a different source (Sinha and Labi 2007).

- The "share of desired employment that is net migration Tier 1" is allowed to rise from a maximum of 5% to a maximum of 10%.

- The "Effect of LRT on retail/office/service sq ft tier 1" variables are set to 10, indicating that along with the light rail comes a 10% increase in demand for developed commercial (excluding industrial) floor space in the station areas. This increase is gradually phased in during the 6-year period of light rail construction.

Light Rail + Redevelopment

Scenario Switch: *Change the "Main policy switch" to 2.*
Scenario(s) for Comparison: BAU and LRT

Scenario Summary

The Light Rail + Redevelopment scenario aims to show a case similar to the Preferred Growth Scenario of the Imagine 2040 Regional Model. In this scenario, the light rail is constructed, zoning is altered to encourage Transit-Oriented Development, and new demand spurs more and denser growth around the station areas. Local planners believe this to be the most likely land use and transportation scenario, provided the light rail is built.

Assumptions and Variable Changes

This scenario maintains all changes from the Light Rail scenario and adds the following changes:

- The value for "overall target percent of land redeveloped table tier 1" increases gradually from 0 percent in 2020 to 20 percent in 2040. This change begins several years before station construction is completed, in anticipation of increased demand for residential and commercial space.

- The value for "redeveloped density multiplier Tier 1" is changed from 1 (its value in the BAU and Light Rail scenarios) to 2.93, indicating that all redeveloped land gets developed at a density 193 percent higher than previous levels in Tier 1. We used the value of 193 percent to match the weighted-average increase in jobs and housing density realized across the station areas in the Preferred Growth Scenario of the Imagine 2040 Regional Model (Green 2015).[19]

4.2 Additional Scenario Descriptions

Land Use Planning Changes

BAU + Redevelopment Scenario

Scenario Switch: *Change the "Main policy switch" to 4.*
Scenario(s) for Comparison: BAU and Light Rail + Redevelopment

Scenario Summary

This scenario isolates the effects of redevelopment from the introduction of the Light Rail. It conforms to the BAU scenario, plus the changes made for the redevelopment scenario.

[19] The Preferred Growth Scenario of the Imagine 2040 Regional Model projects that the density of all developed land around the light rail station areas (not just the redeveloped land) will increase by 193 percent. Because a change of this magnitude produced unusual development patterns in our model, we did not use it for our primary scenario but instead illustrated it in one of the Land Use Planning scenarios.

Assumptions and Variable Changes

This scenario keeps all assumptions the same as the BAU scenario, with the following exceptions:

- The value for “overall target percent of land redeveloped table tier 1” increases gradually from 0 percent in 2020 to 20 percent in 2040.
- The value for “redeveloped density multiplier Tier 1” is changed from 1 (its value in the BAU and Light Rail scenarios) to 2.93, indicating that all redeveloped land gets developed at density 193 percent higher than previous levels in Tier 1.[20]

The primary variables to review for changes under this scenario include:

- Population Tier 1
- Total nonresidential sq ft Tier 1
- Developed land Tier 1
- SF property value per SF DU Tier 1
- Total impervious surface Tier 1
- Impervious surface per capita tier 1
- Transportation related costs incurred by residents per year per capita Tier 1
- Congestion Tier 1

Bold Redevelopment Scenario

Scenario Switch: *In the Redevelopment Switches box, increase the “overall target percent of land redeveloped table tier 1” value to 0.50 in 2040 and increase the “redeveloped density multiplier tier 1” from 2.93 to 6.*
Scenario(s) for Comparison: Light Rail + Redevelopment

Scenario Summary

In this scenario, the percent of land redeveloped and the density at which is it redeveloped is set high enough to reach an overall increase in density of 193% for all land in Tier 1, developed and redeveloped. This change matches the results of the Preferred Growth Scenario of the Imagine 2040 Regional Model (Green 2015).

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[20] A full listing of the policy, demographic, and market switches meant to be modified by users can be found in the User’s Guide (Appendix A, Table A-1).

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following changes:

- The "overall target percent of land redeveloped table tier 1" value in 2040 is increased from 0.20 to 0.50, indicating that 50% of all land in the Tier will be redeveloped by 2040.
- The "redeveloped density multiplier tier 1" is increased from 2.93 to 6, indicating a 500% increase in the density of land that is redeveloped.

Taken together, these changes lead to an approximately 193% increase in the average density of all developed land in Tier 1.

The primary variables to review for changes under this scenario include:

- Developed land Tier 1
- Total nonresidential sq ft Tier 1
- Nonresidential property value per sq ft Tier 1
- SF property value per SF DU Tier 1
- VMT per capita Tier 1
- Total impervious surface Tier 1
- Impervious surface per capita tier 1
- Transportation related costs incurred by residents per year per capita Tier 1
- Congestion Tier 1

Energy Efficiency

Scenario Switch: *In the Policy Switches box, change "policy switch building energy intensity" from 0 to 1. Also change "policy switch MPG" from 0 to 1.*
Scenario for Comparison: Light Rail + Redevelopment

Scenario Summary

Buildings and vehicles represent the majority of energy use and CO_2 emissions in the model. Redevelopment in Tier 1 presents an opportunity to improve the energy efficiency of buildings. This scenario reduces building energy use intensity by 10% in Tier 1 relative to the Light Rail + Redevelopment scenario. Although redevelopment in the SD model is concentrated in Tier 1, this scenario applies the same building energy efficiency trend to Tier 2 for comparison. This scenario also includes a policy encouraging the use of more fuel-efficient vehicles in both Tiers, increasing average MPG by 10% between 2015 and 2040, compared to the AEO2015 projected trend over that time.

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following changes:

- The variable “building energy intensity policy” decreases linearly from 1.0 in 2015 to 0.9 in 2040 (Table 4-3). “Building energy intensity policy” is a multiplier that the model applies to energy intensity projections.

- The variable “MPG policy” increases linearly from 1.0 in 2015 to 1.1 in 2040 (Table 4-4). “MPG policy” is a multiplier that the model applies to MPG projections, as seen in Table 4-5.

Table 4-3. Values for “Building Energy Intensity Policy” in Tier 1 and Tier 2 under the Light Rail + Redevelopment Scenario

SCENARIO NAME	BUILDING ENERGY INTENSITY POLICY			
	2015	**2020**	**2030**	**2040**
Both Tiers				
Energy Efficiency	1	0.98	0.94	0.9
Light Rail + Redevelopment	1	1	1	1

Table 4-4. Values for “MPG Policy” in Tier 1 and Tier 2 under the Light Rail + Redevelopment Scenario

SCENARIO NAME	MPG POLICY			
	2015	**2020**	**2030**	**2040**
Both Tiers				
Energy Efficiency	1	1.02	1.06	1.1
Light Rail + Redevelopment	1	1	1	1

Table 4-5. Values for “MPG without Congestion” under the Light rail + Redevelopment Scenario

SCENARIO NAME	MPG WITHOUT CONGESTION			
	2015	**2020**	**2030**	**2040**
Both Tiers				
Energy Efficiency	16.5	18.6	25.0	29.7
Light Rail + Redevelopment	16.5	18.2	23.6	27.0

The primary variables to review for changes under this scenario include:

- CO_2 emissions from buildings and transportation

- Gross regional product

- Total energy spending

- VMT
- Congestion
- Nonresidential sq ft

Transportation Planning Changes

No Road Building Scenario

Scenario Switch: *Change the "Main policy switch" to 3.*
Scenario(s) for Comparison: BAU

<u>Scenario Summary</u>

In the DO-LRP SD Model, the number of lane-miles of roadways built each year is determined entirely by exogenous projections, based on the DCHC MPO 2040 Metropolitan Transportation Plan and the Triangle Regional Model. Whether or not the supply of roadway lane-miles keeps pace with the growth of VMT in the study area determines the average severity of traffic congestion, which has implications for people's transportation mode choices, as well as for environmental, economic, and health outcomes. To illustrate the effect of the MPO's projections for road building, this scenario tests what would happen if a choice were made to not build any new lane-miles beyond what is already committed to be built by the year 2017.

<u>Assumptions and Variable Changes</u>

The No Road Building scenario includes the following changes:

- Starting in 2016, the values of the exogenous variables "urban nonhighway lane mile construction," "urban highway lane mile construction," "rural nonhighway lane mile construction," and "rural highway lane mile construction" are set to zero.

- Because the model applies a one-year delay between the start and finish of any given lane-mile under construction, "functioning lane miles" reaches its maximum value in 2017 and remains constant thereafter. This is in contrast to the BAU scenario, where lane miles continue to grow between 2017 and 2040. The differences between the values for "functioning lane miles" in the No Road Building and BAU scenarios is illustrated in Table 4-6.

Table 4-6. Values for "Functioning Lane Miles" in Tier 1 and Tier 2 under the No Road Building and BAU Scenarios

SCENARIO NAME	FUNCTIONING LANE MILES						
	2010	**2017**	**2020**	**2025**	**2030**	**2035**	**2040**
Tier 1							
No Road Building	265	267	267	267	267	267	267
BAU	265	267	269	274	278	282	287
Tier 2							
No Road Building	3,444	3,520	3,520	3,520	3,520	3,520	3,520
BAU	3,444	3,520	3,553	3,609	3,665	3,721	3,777

Main Variables Affected

The primary variables to review for changes under this scenario include:

- Total impervious surface
- Congestion
- VMT
- Public transit unlinked passenger trips per day
- Person miles of nonmotorized travel by residents per day per capita
- Gross regional product
- CO_2 emissions from buildings and transportation
- Cumulative premature mortalities avoided due to walking and cycling relative to BAU

Fare Free Transit Scenario

Scenario Switch: *Change the "fare free transit system in 2026" switch from 0 to 1.*
Scenario(s) for Comparison: BAU

Scenario Summary

One of the three major public transit agencies in the study area, Chapel Hill Transit, has been a fare-free system since 2002, a policy decision which significantly increased its ridership. Therefore, this scenario illustrates what would happen if all public transit in the study area were free to users, as opposed to the assumption in the BAU scenario that the average price per trip remains constant in inflation-adjusted dollars from 2013 forward. If fare-free transit shifts travelers to public transit from other modes, it will produce effects in the areas of health, economics, and the environment. Note that the model does not account for changes in public finances that would result from a loss of fare revenue.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following changes:

- Between 2025 and 2026, the value of the exogenous variable "public transit fare price" decreases to $0.01 (we cannot set its value to $0.00 because that would produce a "divide by zero" error within the model). In all other scenarios, this variable remains at a steady real-dollar value during 2013-2040. This change is illustrated in Table 4-7. The same fare price applies to both Tiers.

- "Money spent by residents on public transit fares per year per capita" and "money spent on public transit fares per year per capita" both become zero in 2020.

Table 4-7. Values for "Public Transit Fare Price" under the Fare Free, BAU, and Light Rail Scenarios

SCENARIO NAME	PUBLIC TRANSIT FARE PRICE	
	2015	**2026-2040**
Both Tiers		
Fare Free Transit	$0.30	$0.01
BAU	$0.30	$0.30
Light Rail	$0.30	$0.30

The primary variables to review for changes under this scenario include:

- Public transit unlinked passenger trips per day
- Person miles of nonmotorized travel by residents per day per capita
- VMT
- Transportation and renter costs per year per household
- CO_2 emissions from buildings and transportation
- Cumulative premature mortalities avoided due to walking and cycling relative to BAU

High Parking Price Scenario

Scenario Switch: *Change the "parking price hike instituted Tier 1" switch from 0 to 1.*
Scenario(s) for Comparison: Light Rail + Redevelopment

__Scenario Summary__

Stakeholders have expressed an interest in seeing what the implications would be of the cost of parking going up in the areas around the future light rail stations (Tier 1). Such a change could affect people's transportation mode choices, with indirect impacts on the economy, the environment, and public health. This scenario therefore tests what would happen if future parking prices in the light rail station areas experienced a sudden, dramatic increase.

__Assumptions and Variable Changes__

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following changes:

- In 2020, the variable "parking cost of average trip Tier 1" increases by $4.00, relative to the Light Rail + Redevelopment scenario. Otherwise, this variable increases in proportion to "jobs per commercial acre Tier 1."
- In 2020, the variable for parking costs in Tier 2 ("parking cost of average trip") increases by an amount equal to $4.00 times "Tier 1 percent of Tier 2 employment," which is meant to approximate how much of overall Tier 2 parking demand is concentrated in Tier 1. As with Tier 1, this effect is on top of whatever changes occur due to forces that are endogenous to the model.

These variable changes are summarized in Table 4-8.

Table 4-8. Values for "Parking Cost of AverageTtrip" in Tier 1 and Tier 2 under the High Parking Price and Light Rail + Redevelopment Scenarios

SCENARIO NAME	PARKING COST OF AVERAGETRIP					
	2015	**2020**	**2025**	**2030**	**2035**	**2040**
Tier 1						
High Parking Price	$1.06	$5.06	$5.01	$5.09	$5.16	$5.26
Light Rail + Redevelopment	$1.06	$1.06	$1.01	$1.09	$1.16	$1.26
Tier 2						
High Parking Price	$0.36	$1.52	$1.50	$1.54	$1.58	$1.64
Light Rail + Redevelopment	$0.36	$0.36	$0.36	$0.36	$0.36	$0.36

The primary variables to review for changes under this scenario include:

- VMT
- Public transit unlinked passenger trips per day
- Person miles of nonmotorized travel by residents per day per capita
- Transportation and renter costs per year per household
- CO_2 emissions from buildings and transportation
- Cumulative premature mortalities avoided due to walking and cycling relative to BAU

Sidewalk Building Scenario

Scenario Switch: *Change the "decision to increase desired nonmotorized travel facilities per developed acre" switch from 0 to 1.*
Scenario(s) for Comparison: BAU

Scenario Summary

In the D-O LRP SD Model, the construction of sidewalks, bike lanes, and other facilities for nonmotorized travel is determined by an assumption that the builders of such facilities attempt, on a delay, to maintain at least a certain ratio of facility miles per developed acre and that that target ratio remains constant. Currently, large portions of the study area do not have many nonmotorized travel facilities. Therefore, this scenario tests what would happen if a policy were instituted to dramatically increase the amount of nonmotorized travel facilities, potentially leading to more travel by nonmotorized modes and less by other modes, which carries implications for people's health, among other outcomes.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following change:

- In 2020, the variable "desired nonmotorized travel facilities per developed acre" is set to twice the value that it has under the BAU scenario.

This variable change is summarized in Table 4-9.

Table 4-9. Values for "Desired Nonmotorized Travel Facilities per Developed Acre" in Tier 1 and Tier 2 under the Sidewalk Building and BAU Scenarios

SCENARIO NAME	DESIRED NONMOTORIZED TRAVEL FACILITIES PER DEVELOPED ACRE	
	2015	**2020-2040**
Tier 1		
Sidewalk Building	0.0385	0.0770
BAU	0.0385	0.0385
Tier 2		
Sidewalk Building	0.00734	0.01470
BAU	0.00734	0.00734

The primary variables to review for changes under this scenario include:

- Person miles of nonmotorized travel by residents per day per capita
- VMT
- Public transit unlinked passenger trips per day
- Cumulative premature mortalities avoided due to walking and cycling relative to BAU
- Total impervious surface
- CO_2 emissions from buildings and transportation

Higher LRT Effect on Public Transit Ridership

Scenario Switch: *Increase the variable "policy test change in public transit person miles due to LRT" from 1 to 1.1. For a larger effect, increase it to 2.*
Scenario for Comparison: Light Rail + Redevelopment

Scenario Summary

We recognize that there is a great deal of uncertainty about projected light rail ridership in this model. Instead of projecting person miles on light rail trains, we project the net effect of the introduction of light rail on person miles of travel on all forms of public transit (including the rail line itself). In the Light Rail + Redevelopment scenario, the light rail increases total public transit use by 16 million person miles per year in 2026 and 45 million person miles per year in 2040 (Table 4-8). This increase in ridership once the light rail is built is calculated using an equation whose inputs include employment, population, and VMT, all of which are positively correlated with greater demand for fixed-guideway transit service. In contrast, changes in vehicle revenue miles of bus and demand-response public transit services affect person miles through an elasticity (i.e., increases in revenue miles lead to increases in public transit person miles and decreases in travel by other modes). The Higher LRT Effect on Public

Transit Ridership scenarios increase the effect of the light rail line on public transit person miles by a constant factor. This represents an increase in light rail ridership without explicitly modeling ridership on the rail line, itself. This change is implemented identically in Tiers 1 and 2, because the effect of the light rail on public transit ridership in Tier 2 is assumed to come entirely from the effect in Tier 1.

Assumptions and Variable Changes

These scenarios are consistent with the Light Rail + Redevelopment scenario, with the following change:

- Beginning with rail operation in 2026, the effect of light rail on public transit person miles per year is increased by 10% or 100% (doubled) compared to its value in the Light Rail + Redevelopment scenario.

The variable change for these two scenarios is summarized in Table 4-10.

Table 4-10. Values for "Change in Person Miles of Public Transit Travel Per Year Due to Adding Fixed Guideway Transit" in Tier 1 and Tier 2 Under the Higher LRT Effect on Public Transit Ridership Scenarios and the Light Rail + Redevelopment Scenario (Million miles per year)

SCENARIO NAME	CHANGE IN PERSON MILES OF PUBLIC TRANSIT TRAVEL PER YEAR DUE TO ADDING FIXED GUIDEWAY TRANSIT				
	2025	**2026**	**2030**	**2035**	**2040**
Both Tiers					
LRT Public Transit Effect +10pct	0	17.9	25.0	35.4	49.3
LRT Public Transit Effect +100pct	0	32.5	45.6	64.6	90.2
Light Rail + Redevelopment	0	16.2	22.8	32.2	44.8

The primary variables to review for changes under this scenario include:

- CO_2 emissions from buildings and transportation
- Gross regional product
- VMT
- Congestion

Market Trends

Higher Gas Prices

Scenario Switch: *Change the "gasoline price scenario" switch from 0 to 1.*
Scenario(s) for Comparison: BAU

Scenario Summary

The D-O LRP SD Model relies on an exogenous projection from AEO2015 to estimate the price of gasoline for the years 2015-2040, with the figures for the years 2000-2014 taken from historical data. During the period where the model uses historical data, gasoline prices were at their highest in 2012, before dropping dramatically over the following three years. In the model, these exogenous price-of-gasoline figures are a major driver of what mode of transportation people use, as well as the environmental, economic, and health implications of each mode choice. In order to explore the significance of the impact of gasoline prices on the model's outputs, we designed this scenario to test what would happen if future gas prices turned out to be substantially higher than what is currently projected, since energy-price trends are often changed by unforeseen events outside the control of local policy-makers.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following change:

- In 2016, the value of the exogenous variable "price of gasoline" is set to be equal to the value it had in 2012 (which is much higher than its values for 2013-2015). It then proceeds to increase at the same year-over-year rate as in the BAU scenario. The price of gasoline is the same in both Tiers, and is summarized in Table 4-11.

Table 4-11. Values for "Price of Gasoline" Under the High Gas Price and BAU Scenarios (USD 2010 per gallon)

SCENARIO NAME	PRICE OF GASOLINE					
	2015	**2020**	**2025**	**2030**	**2035**	**2040**
Both Tiers						
High Gas Price	$2.21	$3.67	$3.95	$4.29	$4.73	$5.23
BAU	$2.21	$2.62	$2.83	$3.06	$3.38	$3.74

The primary variables to review for changes under this scenario include:

- VMT
- Public transit unlinked passenger trips per day
- Person miles of nonmotorized travel by residents per day per capita
- Transportation and renter costs per year per household
- Gross regional product
- CO_2 emissions from buildings and transportation
- Cumulative premature mortalities avoided due to walking and cycling relative to BAU

Retail Wage Increase Scenario

Scenario Switch: *Change the "retail wage increase switch Tier 1" from 0 to 1.*
Scenario(s) for Comparison: Light Rail + Redevelopment

Scenario Summary

The D-O LRP SD Model relies on an exogenous projection from Woods & Poole Economics, Inc. to estimate retail earnings per employee per year. Although the projections from Woods & Poole include an increase in retail earnings per employee per year, they do not increase as much as the earnings per employee in the other job categories (i.e., office, industrial, and service). In the model, retail earnings per employee are one component used to determine the affordability of housing and transportation for lower income residents, which is expected to decrease (i.e., become less affordable) in Tier 1 under the Light Rail + Redevelopment scenario due to the increased property values and increased renter costs around the station areas. This scenario therefore tests what would happen to affordability in Tier 1 if future retail wages were increased above and beyond projections made by Woods & Poole.

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following change:

- Retail earnings per employee Tier 1 remain the same as the Light Rail + Redevelopment scenario until 2016, when a $2.00 increase in the nominal hourly retail wage is added to the original nominal retail wage. For the next three years (2017-2019), an additional $1.00 nominal raise is added to the yearly increase already projected by Woods & Poole. For 2020-2040, the yearly nominal wage increase remains the same as the Woods & Poole projection. These nominal retail hourly wages are then converted to 2010 dollars and multiplied by 2000 hours/year to yield retail earnings per employee per year. This change is summarized in Table 4-12.

Table 4-12. Values for "Nominal Hourly Retail Wage" and "Retail Earnings per Employee" Under the Retail Wage Increase and Light Rail + Redevelopment Scenarios

SCENARIO NAME	NOMINAL HOURLY RETAIL WAGE					
	2015	**2016**	**2017**	**2018**	**2019**	**2040**
Tier 1						
Retail Wage Increase	$15.18	$17.65	$19.15	$20.68	$22.26	$43.42
Light Rail + Redevelopment	$15.18	$15.65	$16.15	$16.68	$17.26	$38.42
	RETAIL EARNINGS PER EMPLOYEE					
Tier 1						
Retail Wage Increase	$27,800	$31,600	$33,400	$35,100	$36,700	$34,700
Light Rail + Redevelopment	$27,800	$28,000	$28,200	$28,300	$28,500	$30,700

The primary variables to review for changes under this scenario include:

- Retail earnings Tier 1
- Resident per capita net retail earnings Tier 1
- Affordability index Tier 1

Higher Rent for Nonresidential Land Scenario

Scenario Switch: *Change the "higher rent switch" from 0 to 1.*
Scenario(s) for Comparison: BAU, Light Rail, and Light Rail + Redevelopment

Scenario Summary

"Gross operating surplus per sq ft" is a variable in the D-O LRP SD Model that represents the monetary profits gained by owning or renting commercial land through the sale of goods and services after all expenses have been subtracted, including payment for employees and payments for owning or renting the space. This variable is an exogenous lookup table with different values for each year, calibrated for the BAU scenario to make up 40% of GRP between 2012 and 2040. For most scenarios, we leave the values of this table unchanged, under the assumption that profits will not change in response to the changes tested in each scenario. In this scenario, however, we test the possibility that nonresidential property values (and thus property tax payments) will increase under the “Light Rail + Redevelopment” scenario, consequently increasing commercial rent at a higher rate than the increase of consumption of goods and services from businesses. This change would cause GOS per square foot to fall below the levels used for the BAU scenario.

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following change:

- “Gross Operating Surplus per Sq Ft” is reduced by $5, relative to the values in the Light Rail + Redevelopment scenario, for each year beginning in 2025. This change is illustrated in Table 4-13.

Table 4-13. Values for “Gross Operating Surplus per sq. ft.” Under the Higher Rent and Light Rail + Redevelopment Scenarios

SCENARIO NAME	GROSS OPERATING SURPLUS PER SQ. FT.				
	2020	**2025**	**2030**	**2035**	**2040**
Tier 2					
Higher Rent	134	134	138	143	151
Light Rail + Redevelopment	134	139	143	148	156

The primary variables to review for changes under this scenario include:

- Gross operating surplus
- GRP
- Total retail consumption
- Total employment
- Total nonresidential sq. ft.

Demographic Trends

More Multifamily Households Scenario

Scenario Switch: *Change the “More Multifamily Households Tier 1” switch from 0 to 1.*
Scenario(s) for Comparison: BAU

Scenario Summary

The D-O LRP SD model uses data from the American Community Survey (U.S. Census Bureau

American Community Survey 2014) to divide total dwelling units between single-family and multifamily from 2000 to 2014. Though the data for these years showed a shift toward more households living in multifamily dwelling units, the BAU scenario keeps the distribution of households between single-family and multifamily constant at levels in the ACS 2008-2012 5-yr estimate for the years 2015-2040. In this scenario, we explore the impacts of extending the linear decline in the percent of dwelling units that are single-family between 2000 and the ACS value (assumed to apply to 2014) out to 2040. Extending this trend results in a 10.6 percent increase in the portion of households that live in multifamily dwelling units by the year 2040.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following change:

- The "percent of people in SFDU table historical Tier 1" was changed from a constant value after 2014 to values reflecting the linear extension of the historical trend from 2000 through 2014. This change is illustrated in Table 4-14.

Table 4-14. Values for "Percent of People in SFDU Table Historical Tier 1" Under the More Multifamily Households and BAU Scenarios

SCENARIO NAME	PERCENT OF PEOPLE IN SFDU TABLE HISTORICAL TIER 1					
	2000	**2010**	**2014**	**2020**	**2030**	**2040**
Tier 1						
More Multifamily Households	0.342	0.309	0.309	0.292	0.264	0.236
BAU	0.342	0.309	0.309	0.309	0.309	0.309

The primary variables to review for changes under this scenario include:

- MF and SF dwelling units Tier 1
- Multifamily and single-family acres Tier 1
- Total residential impervious surface Tier 1
- Energy use residential Tier 1
- Jobs housing balance Tier 1

Fewer Organically Affordable Units Scenario

Scenario Switch: *On the gentrification Tier 1 view, reduce the "percent of MF dwelling units below 77 percent of median renter costs table tier 1" from 0.26 in 2040 to 0.15.*
Scenario(s) for Comparison: BAU

Scenario Summary

In the absence of accurate historical data and projections for the percent of organically affordable multifamily units (i.e., the percent of market-rate multifamily units that cost no more than 30% of the monthly income for a household making 60% of the Area Median Income (AMI)), the D-O LRP model must make assumptions. First, the cost of organically affordable housing was calculated to be approximately 77% of the median renter costs in 2000 and from 2010-2014 in Tier 1. In the BAU scenario, we therefore assume that values for this parameter in the years 2015-2040 remain constant at the pre-2014 level. We recognize that this assumption is likely incorrect for Tier 1, particularly in the face of redevelopment and changes to property values and renter costs expected to result from the light rail. In particular, we expect that, in addition to total renter costs increasing, it is likely that the distribution of renter costs around the median will change. This scenario therefore explores the impacts of reducing the percent of multifamily units that are organically affordable between 2020 and 2040.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following change:

- The value for "percent of MF dwelling units below 77 percent of median renter costs table tier 1" is reduced from 0.26 in 2020 to 0.15 by 2040. This change is illustrated in Table 4-15.

Table 4-15. Values for "Percent of MF Dwelling Units Below 77 Percent of Median Renter Costs Table Tier 1" Under the Fewer Organically Affordable Units and BAU Scenarios

SCENARIO NAME	PERCENT OF MF DWELLING UNITS BELOW 77 PERCENT OF MEDIAN RENTER COSTS TABLE TIER 1					
	2010	**2020**	**2025**	**2030**	**2035**	**2040**
Tier 1						
Fewer Organically Affordable Units	0.26	0.26	0.23	0.21	0.18	0.15
BAU	0.26	0.26	0.26	0.26	0.26	0.26

The primary variables to review for changes under this scenario include:

- Organically affordable dwelling units tier 1
- Housing gap for households in poverty tier 1
- Potential population in poverty displaced tier 1

Environmental Policy Changes

Vehicle Emissions Reduced Scenario

Scenario Switch: *In the Policy Switches box, beside Health, change "vehicle emissions reduced switch" from 0 to 1.*
Scenario for Comparison: BAU

Scenario Summary

The D-O LRP SD model treats vehicle emissions per VMT for both $PM_{2.5}$ and NO_x as exogenous inputs, using data from a study that reports average vehicle emissions by vehicle model year (Cai et al. 2013) for years up to 2020, and applying a linear extrapolation method to extend these average vehicle emissions for 2020-2040. Though Cai et al. assume that emissions from $PM_{2.5}$ and NO_x remain constant at 2010 levels through 2020, recent EPA regulations for stricter fuel economy standards suggest further reductions in $PM_{2.5}$ and NO_x emissions per VMT for vehicles in the future (US EPA 2015g). Although we did not identify any study projecting future vehicle emissions based on these new standards, this scenario explores the possible impacts of reducing vehicle emission rates of $PM_{2.5}$ and NO_x by 10 percent from 2020-2040, relative to the values projected by Cai et al.

Assumptions and Variable Changes

This scenario is consistent with the BAU scenario, with the following change:

- $PM_{2.5}$ and NO_x vehicle emissions per VMT (gram/mile) are decreased by 10 percent relative to the BAU scenario for vehicle model years between 2020 and 2040. Note that this does not translate directly into 10 percent reductions in total vehicle emissions, as the emission factors are weighted by the fraction of vehicles in the U.S. vehicle fleet that are ages 1 to 17 (Jackson 2001a).

Table 4-16. Values for "$PM_{2.5}$ Emissions per VMT" and "NO_x Emissions per VMT" Under the Vehicle Emissions Reduced and BAU Scenarios

SCENARIO NAME	$PM_{2.5}$ EMISSIONS PER VMT				
	2020	**2025**	**2030**	**2035**	**2040**
Tier 2					
Vehicle Emissions Reduced	.0070	.0067	.0063	.0059	.0055
BAU	.0070	.0069	.0067	.0064	.0062
	NO_x EMISSIONS PER VMT				
Tier 2					
Vehicle Emissions Reduced	.1623	.1167	.1075	.1006	.0947
BAU	.1623	.1205	.1151	.1104	.1053

The primary variables to review for changes under this scenario include:

- $PM_{2.5}$ vehicle emissions tons and NO_x vehicle emissions tons
- Premature mortalities avoided from $PM_{2.5}$ and NO_x vehicle emissions relative to BAU

Increased Solar Capacity

Scenario Switch: *In the Policy Switches box, beside Energy and Water, increase "Desired solar capacity" from 40 MW to the appropriate level.*
Scenario for Comparison: Light Rail + Redevelopment

Scenario Summary

Solar electricity generation is one strategy for reducing CO_2 emissions, and solar capacity (MW) in Tier 2 has grown by an annual factor of 3.2 between 2005 and 2014, on average (North Carolina Sustainable Energy Association 2015). In 2005, Tier 2 solar capacity was 2.5 kW, and by 2014 it had reached 22 MW. The D-O LRP SD model assumes electricity generated by solar is carbon neutral, and replaces electricity from the conventional grid. In the BAU, Light Rail, and Light Rail + Redevelopment scenarios, the model assumes that solar capacity increases at historical growth rate, but growth slows as it approaches a desired solar capacity of 40 MW, roughly double the current capacity. "Increased Solar Capacity" scenarios have higher desired solar capacity and explore the timeframe in which solar capacity would reach 10% of regional building electricity demand.

Assumptions and Variable Changes

These scenarios are consistent with the Light Rail + Redevelopment scenario, with the following changes:

- Desired solar capacity is increased from 40 MW to 80, 320, and 640MW. These changes are illustrated in Table 4-17.

Table 4-17. Values for "Desired Future Solar Capacity" Under the increased Solar Capacity and Light Rail + Redevelopment Scenarios

SCENARIO NAME	DESIRED FUTURE SOLAR CAPACITY 2000-2040
Tier 2	
640MW solar LRT+redev	640
320MW solar LRT+redev	320
80MW solar LRT+redev	80
Light Rail + Redevelopment	40

The primary variables to review for changes under this scenario include:

- Solar capacity
- Solar energy production in kWh
- Solar fraction of building electricity use
- CO_2 emissions from buildings and transportation

Clean Power Plan - Decreased Electricity Emissions Factor

Scenario Switch: *In the Policy Switches box, beside Energy and Water, change "Policy switch electricity emissions factor" from 0 to 1.*
Scenario for Comparison: Light Rail + Redevelopment

Scenario Summary

This scenario reflects the Clean Power Plan for reducing carbon pollution from fossil fuel-fired power plants, announced in August 2015 (US EPA 2015a, f). This scenario tests applies Clean Power Plan emissions reduction goals specific to North Carolina (US EPA 2015c). These goals represent technological changes in (1) fossil fuel-fired steam plants and (2) natural gas-fired combined cycle plants.

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following change:

- The variable “ton CO_2 per kWh” decreases linearly from 2022 to 2030, reaching 77% of its 2022 level by 2030. In contrast, the electricity emissions factor stays constant in the Light Rail + Redevelopment scenario. After 2030, the electricity emissions factor is assumed to stay constant in both scenarios, although future policy may reduce the emissions factor further between 2030 and 2040. Changes to the electricity emissions factor are illustrated in Table 4-18.

Table 4-18. Electricity Emissions Factors “Ton CO_2 per kWh” and “Lb CO_2 per MWh” Under the Clean Power Plan and Light Rail + Redevelopment Scenarios

SCENARIO NAME	TON CO_2 PER KWH			
	2022	**2025**	**2030**	**2040**
Both Tiers				
Clean Power Plan	0.000778	0.000711	0.000599	0.000599
Light Rail + Redevelopment	0.000778	0.000778	0.000778	0.000778
	LB CO_2 PER MWH			
Clean Power Plan	1,560	1,420	1,200	1,200
Light Rail + Redevelopment	1,560	1,560	1,560	1,560

The primary variables to review for changes under this scenario include:

- CO_2 emissions from buildings and transportation

Stormwater Management Scenarios

Scenario Switch: *In the Policy Switches box, beside Energy and Water, change “Percent N treated onsite” to 0.3 or 0.4, and/or change “Percent reduction of existing N load” to 0.15*
Scenario for Comparison: Light Rail + Redevelopment

Scenario Summary

Stormwater runoff is a significant and growing problem in the D-O LRP region. Both Jordan Lake and Falls Lake, which receive stormwater runoff from Tier 2, are considered in nonattainment of nutrient-related water quality standards (NCDENR 2014, 2015). Local governments are currently subject to the Jordan Lake and Falls Lake Rules, which require N and P reductions from new and existing development; for simplicity, we focus on N reductions. According to the Falls Lake and Jordan Lake rules, new developments in the Durham County area must plan to reduce their stormwater N load to 2.2 lb/acre/year, through a combination of onsite treatment and mitigation banking (purchased credits for offsite watershed treatment) (NCDENR 2010, 2014, Woolfolk 2015). Durham county has the additional requirement that new developments treat at least 30% of their stormwater N load onsite, with the remainder treated through mitigation banking (Woolfolk 2015). We modeled stormwater management scenarios to explore different targets for reducing stormwater N load. These scenarios simulate growth of stormwater N load as impervious surface increases, as well as treatment of stormwater N load from development after 2015, possibly along with treatment of N load from development before 2015. Reductions of 30% and 40% of the N load from new development are simulated, as well as 30% from new development plus a 15% reduction in N load from existing development. For reference, the 2.2 lb/acre/year target for stormwater N from new development is also simulated.

Assumptions and Variable Changes

This scenario is consistent with the Light Rail + Redevelopment scenario, with the following changes to only Tier 1, described in Table 4-19:

Table 4-19. Percent of Stormwater N Load from Post-2015 Development Treated Onsite, and Percent from pre-2015 Development Treated Onsite Under the Stormwater Management Scenarios

SCENARIO NAME	PERCENT OF STORMWATER N LOAD FROM POST-2015 DEVELOPMENT TREATED ONSITE	
	2020	**2040**
Tier 1		
30pct new N load treated	.3	.3
40pct new N load treated	.4	.4
30pct new 15pct existing N load treated	.3	.3
New N load treated to 2_2 lb_ac_y	-	-
Light Rail + Redevelopment	0	0
	PERCENT FROM PRE-2015 DEVELOPMENT TREATED ONSITE	
Tier 1		
30pct new N load treated	0	0
40pct new N load treated	0	0
30pct new 15pct existing N load treated	.15	.15
New N load treated to 2_2 lb_ac_y	-	-
Light Rail + Redevelopment	0	0

The primary variables to review for changes under this scenario include:

- Total N load after treatment Tier 1
- Total N load after treatment to target Tier 1. Note that this variable is for comparison with, but does not affect, “Total N load after treatment Tier 1”

5 Model Results

5.1 Introduction

This chapter presents the results of the 20 scenarios that we ran in the D-O LRP SD Model, including the three main scenarios (BAU, Light Rail, and Light Rail + Redevelopment) and 17 additional decision support scenarios. These additional scenarios, described in detail in the previous chapter, are listed in Figure 5-1 underneath the main scenario that they were each added onto. This chapter begins by briefly discussing the results of the BAU scenario, including the model fit to historical data and projections (when available) for both Tier 2 and Tier 1. It then provides an overview of the dynamic behaviors that result from the model's inter-sector feedbacks under the Light Rail and Light Rail + Redevelopment scenarios, collectively known as "the light rail scenarios." The last section of this chapter provides an in-depth examination of the three main scenario results by sector, with summaries of the results of the 17 additional scenarios displayed in text boxes. Percent changes in variables under the BAU scenario are typically presented between the most recent year of historical data (in most cases 2014) and 2040, while percent changes under the light rail scenarios are presented from 2020-2040 to isolate the changes that come with the introduction of the light rail line, as both scenarios are identical to the BAU before 2020.

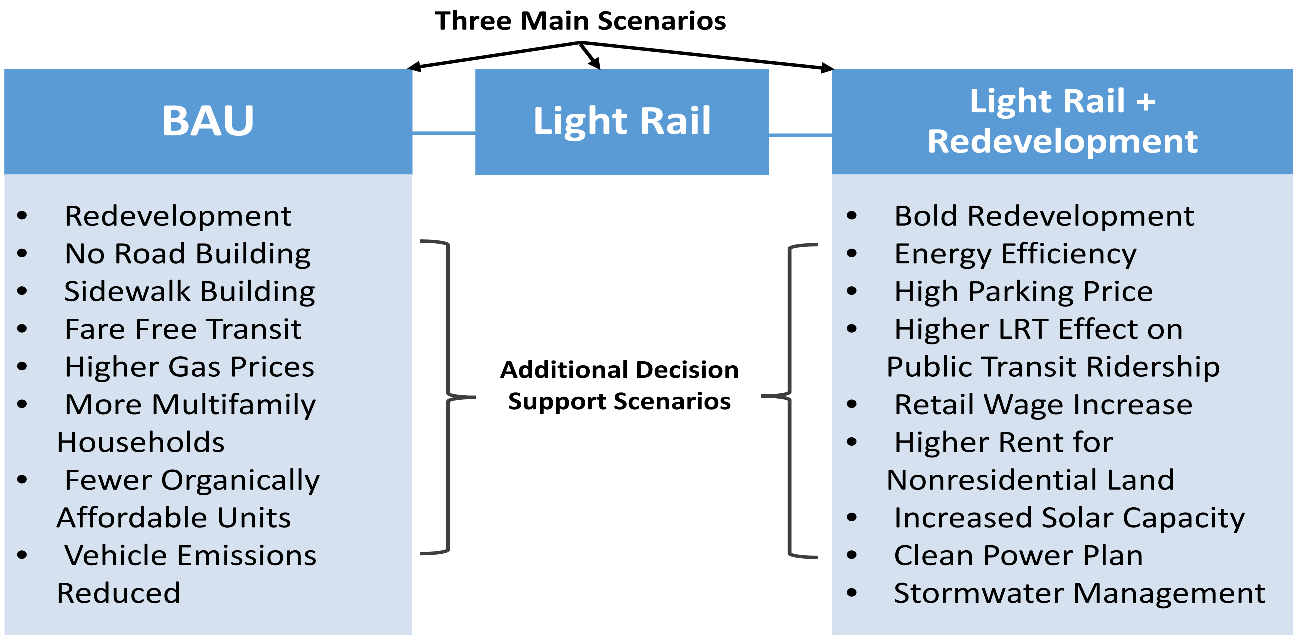

Figure 5-1. Additional Decision Support Scenarios (Bullets) Listed Under the Corresponding Main Scenario With Which They Were Run

5.2 Business as Usual (BAU) Scenario: Model Fit to Data and Projections

The BAU scenario was the basis on which the D-O LRP SD Model was built and for which extensive validation tests were performed (described in more detail in Chapter 6 and Appendix B of this report). For the BAU scenario, we recalibrated the D-O LRP SD Model each time a new connection or adjustment was made in the model. Once all major connections between model sectors were in place, we validated the BAU scenario against historical data and projections. The aim of these validation tests was to ensure that the model generated results consistent with historical data and projections from other sources. Where projections from local data sources were available, the decision to calibrate the model to either match or deviate from those projections (or to match one projection over another when multiple projections were available) was made on a case-by-case basis and was dependent upon the assumptions that went into the modeling that produced those projections. Where projections were not available, we calibrated the BAU scenario so that historical trends were carried into the future. This validation process supported the assertion that the model accurately represents important real-world dynamics in the system that it seeks to represent. The main assumptions that went into the calibrations for the BAU scenario are listed in Chapter 4, and results for key model variables that were calibrated are presented in this chapter. We first present results for Tier 2 (DCHC MPO), followed by results for Tier 1 (combined ½ mile radii around proposed light rail station locations). For each tier, we discuss the behavior of several indicators in the BAU scenario and note the degree to which the model's estimates match historical data and projections from other sources. Graphs in this section present the model's estimates (solid red lines) along with exogenous sources (dashed grey lines and dotted or dashed yellow lines, in the case of multiple sources).

Tier 2

Under the BAU scenario, Tier 2 **population** increases by 53% between 2014 and 2040, reaching 660,000 in 2040 (shown in Figure 5-2). We calibrated this variable to align with population projections for the DCHC MPO used in version 5 of the Triangle Regional Model (TRM v5), and the model's results are within 5% of the TRM v5 Socioeconomic (SE) data projection in the year 2040. The driver for the increase in population in the model, aside from births and deaths, is net migration, which increases by 30% between 2014 and 2040. By 2040, approximately 820 people per year are projected to move to Tier 2.

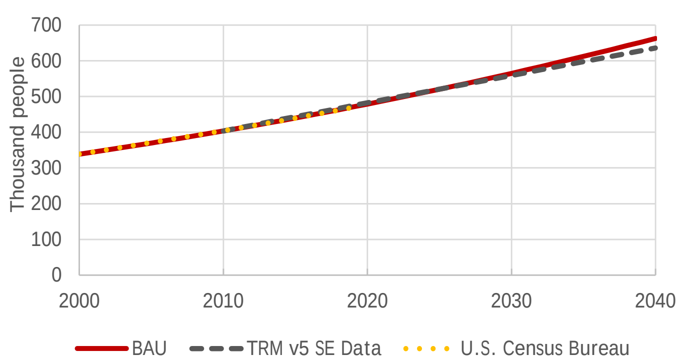

Figure 5-2. Population - Tier 2: BAU and Data, 2000-2040

As a result of the increase in population, total **developed land** in Tier 2 (shown in Figure 5-3) increases by 54%, or 69,000 acres, between 2014 and 2040, with an additional 53 million **nonresidential sq ft** built (shown in Figure 5-4). Figure 5-3 also shows two projections of developed land, both derived from the CommunityViz2 (CV2) Parcel Geodatabase for Place Type & Development Status Editing; the model's estimates of developed land very closely matches the lower of the two projections, with only a 1.9% deviation in 2040. Developed land in the model was not calibrated to these estimates; the fact that they fit is a natural outgrowth of our assumptions and model projections for population, employment, and initial developed land values.

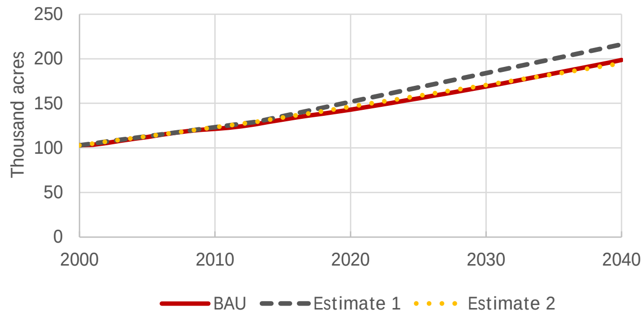

Figure 5-3. Developed Land - Tier 2: BAU and Data, 2000-2040

Figure 5-4 compares the model's estimate for total nonresidential square feet in Tier 2 to historical data derived from the County Office of Tax Administration databases; as the figure shows, the model's estimate deviates from the historical trend by no more than 8.5% during 2000-2014. In the D-O LRP SD Model, the growth in **nonresidential sq ft** is driven by additional employment.

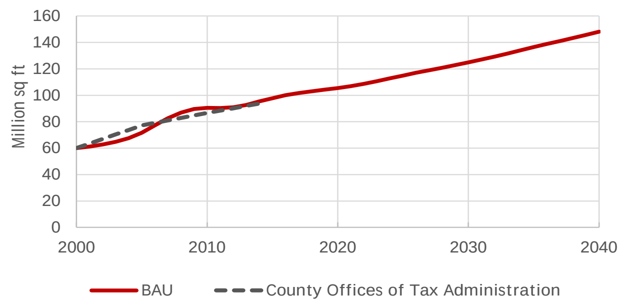

Figure 5-4. Nonresidential Sq. Ft. - Tier 2: BAU and Data, 2000-2040

Total employment in Tier 2 (shown in Figure 5-5) increases by 55% between 2014 and 2040 under the BAU scenario, adding 169,000 jobs during that time. We calibrated total employment to match TRM v5 SE data (2010) and projections (2011-2040), with historical employment growth rates from the U.S. Bureau of Economic Analysis (BEA) from 2000-2010 applied to the 2010 employment value from the TRM to get total employment for 2000-2009.

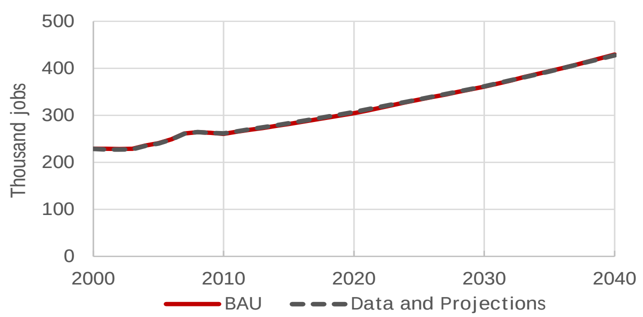

Figure 5-5. Total Employment - Tier 2: BAU and Data, 2000-2040

The change in **total employment** in turn is driven by **total retail consumption** in the model, an indicator of economic growth. Figure 5-6 shows the model's estimates of total retail consumption, together with historical retail consumption data (2000-2014) from the NC Dept. of Revenue (NC DOR) and a projected retail sales growth rate (2015-2040) from Woods & Poole Economics, Inc. We developed the projections shown in Figure 5-6 for comparison with the BAU scenario output by applying an inflation-adjusted retail sales growth rate of 2.5-2.8%/year from Woods & Poole Economics, Inc. to the 2014 retail sales data from the NC DOR. As the figure shows, between 2000 and 2014, the historical retail consumption values were highly volatile from year to year. Though the model, which targets a longer time frame for the analysis, does not replicate the short-term trend in the data, it does capture the overall medium-to–long-term upward historical trend. The model's estimates of **total retail consumption** for the BAU scenario demonstrate a growth rate of 2.6-3.1%, which is slightly higher than the Woods & Poole Economics, Inc. growth rate that we used for the projections (2015-2040). As a result, the model's estimate under the BAU scenario rises more quickly than projections, but the modeled value in 2040 is still only 3% higher than the projected value.

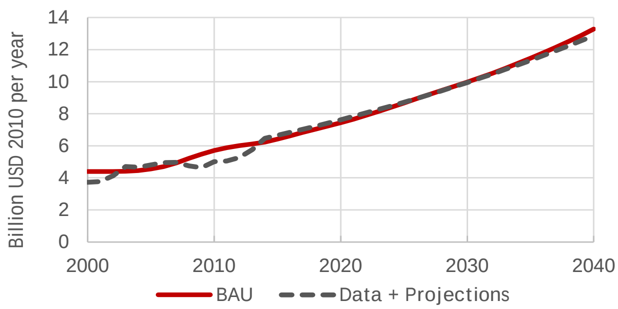

Figure 5-6. Total Retail Consumption - Tier 2: BAU and Data, 2000-2040

Total retail consumption in the model is largely driven by an increase in **Gross Regional Product** (**GRP**), shown in Figure 5-7. We calculated historical values (2000-2013) for this economic indicator in Tier 2 based on a methodology from the BEA. In the model, **GRP** is the sum of two variables: total earnings and gross operating surplus. Historically, total earnings composed between 59-64% of GRP in Tier 2, with a 2013 share of 60%. For the BAU scenario, the model holds the total earnings share of GRP constant at 60% and increases GRP at the same rate as total earnings from 2014 to 2040. The model uses projections of earnings per job (by category) from Woods & Poole and projections of employment from the TRM v5 SE data. **Gross Operating Surplus**, the second component of GRP, was calibrated to make up 40% of GRP, in order to hold the total earnings share of GRP constant at 60%.

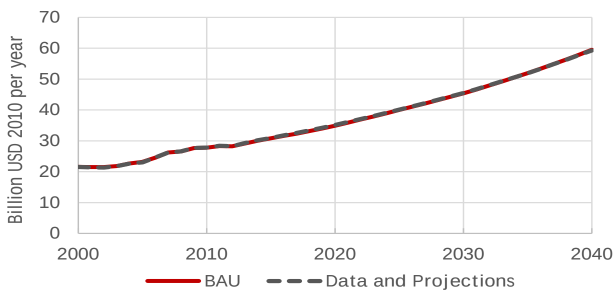

Figure 5-7. Gross Regional Product - Tier 2: BAU and Data, 2000-2040

The increasing population in Tier 2 drives an increase in overall person miles of travel, including nonmotorized travel, public transit travel, automobile driver travel, and automobile passenger travel. At the same time, GRP per capita is projected to grow over time, which increases the growth rate of automobile travel, relative to the growth rates of all other transportation modes. Various other variables in the model, including traffic congestion, gasoline prices, intersection densities, and public transit fare prices, affect the distribution of person miles of travel among the four modes without substantially affecting total person miles of travel by all modes. The model estimates overall automobile vehicle miles traveled (**VMT**) by combining its estimates of automobile driver travel related to trips that either begin or end in the study area (affected by the process described above) with a separate projection of vehicle travel that passes through the area without stopping (based on North Carolina population growth rates). As shown in Figure 5-8, the model estimates that overall VMT increases by 55% during 2014-2040 in the BAU scenario. This forecasted increase is in line with TRM v5 projections, both for the official "preferred" scenario generated for the DCHC MPO 2040 Metropolitan Transportation Plan (2040 MTP, which assumes a light rail line is built in the area, unlike our BAU scenario) and for the "Existing + Committed" scenario (which assumes that no light rail is built but which still differs from the BAU scenario in that it assumes there is no new road building after 2017).

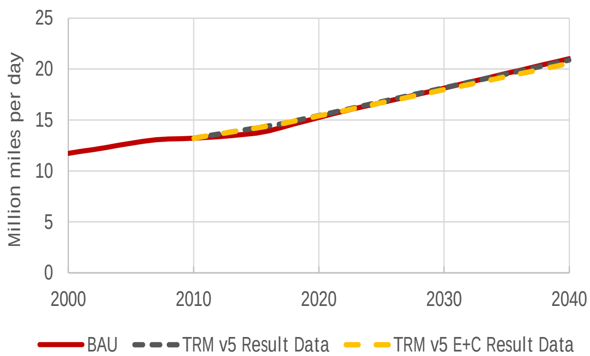

Figure 5-8. Vehicle Miles Traveled (VMT) Tier 2 BAU and Data, 2000-2040

The most significant feedback from increasing VMT is that increasing the ratio of VMT to roadway lane miles (which is driven by an exogenous policy input in the model) increases traffic **congestion**, mitigated by the assumption that during 2010-2040 traffic-management improvements will decrease the amount of congestion that results from any given amount of peak-period VMT per roadway lane mile (in accordance with projected changes in this ratio from the TRM's "preferred" scenario)**.** Congestion in the model is defined as the ratio of travel time in peak traffic to travel time under freeflow conditions, such that a value of "1" indicates a congestion-free state. As shown in Figure 5-9, during 2014-2040, congestion increases from 1.06 to 1.14, with a low point in 2015 and a high point in 2035. The non-linear shape of this projected trend cannot be compared to other projections. The only other available projection of future traffic congestion in the DCHC MPO is from the TRM v5's "preferred" scenario, which only provides figures for 2010 and 2040. However, the D-O LRP SD Model's 2010 and 2040 congestion values in the BAU case are both within 1% of the TRM v5 figures. Changes in VMT are the primary driver of traffic congestion. As such, congestion is partially driven by a balancing loop in the model: When congestion increases, VMT goes down and the use of all other transportation modes goes up.

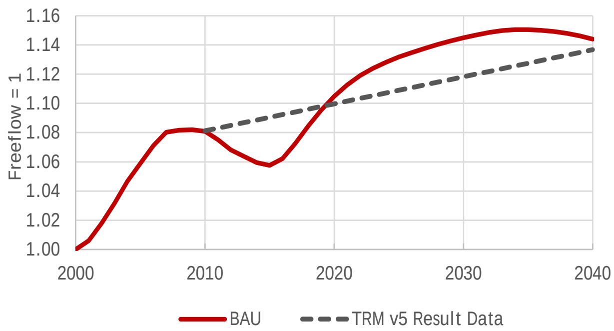

Figure 5-9. Congestion - Tier 2: BAU and Data, 2000-2040

Among the other variables affected by this balancing loop is **person miles of public transit travel per day**, which is shown in Figure 5-10. This variable, which is also affected by population, GRP, and other factors, as described above, increases by 40% between 2014 and 2040. During 2000-2013, this variable fits historical data from the National Transit Database with an R-squared value of 0.81. In future years, it deviates from both of the TRM v5's projections, but, as discussed above, the assumptions in both TRM v5 projections differ from the assumptions in the D-O LRP SD Model's BAU scenario (the light rail is built in TRM v5's "preferred" scenario, and road building does not continue after 2017 in TRM's "Existing + Committed" scenario). As one would expect, the D-O LRP SD Model's BAU scenario projects fewer public transit person miles than TRM v5's "preferred" scenario. Somewhat counterintuitively, the D-O LRP SD Model's BAU scenario projects more future public transit person miles than the TRM v5's "Existing + Committed" scenario, despite the fact that our model's BAU scenario includes a higher road capacity than TRM v5's "Existing + Committed" scenario. This difference is the result of the D-O LRP SD Model using more recent data from the National Transit Database, which indicate an historical trend (2000-2013) of faster growth in public transit use than what the TRM projects forward from 2010. Furthermore, the D-O LRP SD Model accounts for the positive effects on public transit use of increases in public transit bus service that are anticipated by "The Bus and Rail Investment Plan in Orange County" (September 2012) and "The Durham County Bus and Rail Investment Plan (June 2011), plans published after the TRM v5's 2010 base year.

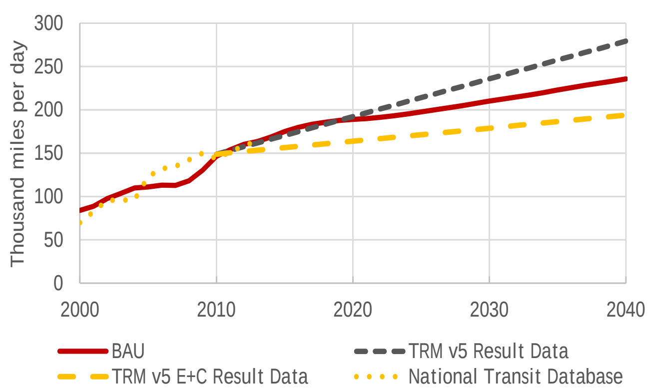

Figure 5-10. Public Transit Person Miles - Tier 2: BAU and Data, 2000-2040

Energy and water use are also projected to increase as a result of increased population, land use, and economic activity. As shown in Figure 5-11, **building energy use** is projected to increase by 33% between 2014 and 2040, reaching 47 million MMBtu/year in 2040. Though building energy use is driven by commercial activity (indicated by nonresidential sq ft) and population growth (indicated by dwelling units), the model projects a lower increase for building energy use than for those other variables (projected to increase by 55% and 53%, respectively, over the same time period) because it assumes that energy intensity will drop by 13-15% during that time (consistent with AEO projections, as described in Chapter 4). Building energy use is calibrated to be within 2 percent of historical data from the Durham City-County Sustainability Office.

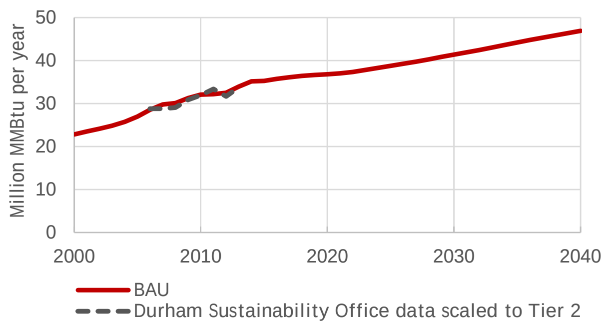

Figure 5-11. Building Energy Use - Tier 2: BAU and Data, 2000-2040

CO_2 emissions are projected to increase by 21% over the same period, reaching 11 million tons/year in 2040, as shown in Figure 5-12). Though CO_2 emissions are driven largely by population, this projected change is smaller than the 53% increase in population over this period due to the combined effects of decreasing building energy intensity (noted above) and increasing passenger vehicle fuel efficiency. Before accounting for the effects of congestion (which tends to reduce fuel efficiency), average fuel efficiency in the study area is projected to increase from 16 MPG to 27 MPG between 2014 and 2040. The D-O LRP's historical estimates of CO_2 emissions are within 4% of historical data from the Durham City-County Sustainability Office. Because our BAU scenario includes projected energy efficiency improvements, our model projects slower growth in CO_2 emissions than the BAU scenario of the Durham GHG Plan (ICLEI 2007). Between 2005 and 2030, the Durham GHG Plan projects a 48% increase, but the D-O LRP model projects a 28% increase. If energy efficiency improvements were excluded from our model (as detailed in Chapter 6), CO_2 emissions would increase by 47% between 2005 and 2030, similar to the Durham GHG Plan projections.

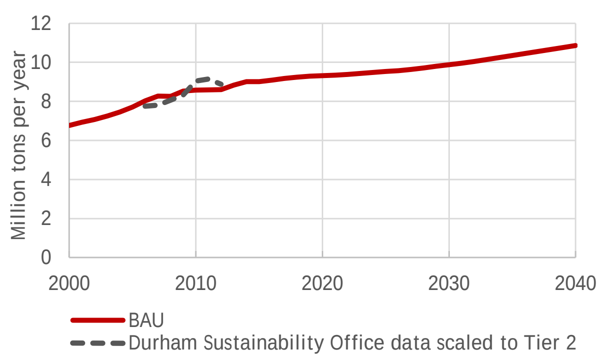

Figure 5-12. CO_2 Emissions - Tier 2: BAU and Data, 2000-2040

Besides increasing energy use, land development causes a 35% increase in **impervious surface** during 2014-2040, reaching 65,000 total impervious acres (33% of developed land) by 2040, as shown in Figure 5-13. The growth of impervious surface causes increased stormwater runoff, which is discussed later in this chapter. Impervious surface is calibrated to within 2% of the one-meter land cover data from EPA EnviroAtlas for 2010 in Tier 2.

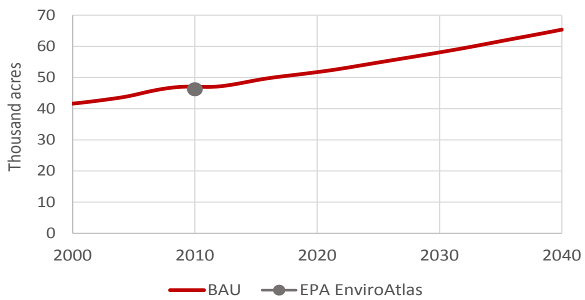

Figure 5-13. Impervious Surface - Tier 2: BAU and Data, 2000-2040

Tier 1

In Tier 1, **population** is projected to increase by 18% during 2014-2040 (compared to 53% in Tier 2), reaching 50,000 in 2040, as shown in Figure 5-14. In Tier 1, we chose to calibrate the model to the historical population trend from the U.S. Census Bureau, rather than the TRM v5 SE data population projection, because the latter source was based off of a "preferred growth" land use scenario with assumptions that differed from our BAU scenario for Tier 1.[21] One cause of the population growth is net migration, which increases by 164% within Tier 1 over this time period. About 310 people per year are projected to move into Tier 1 by 2040.

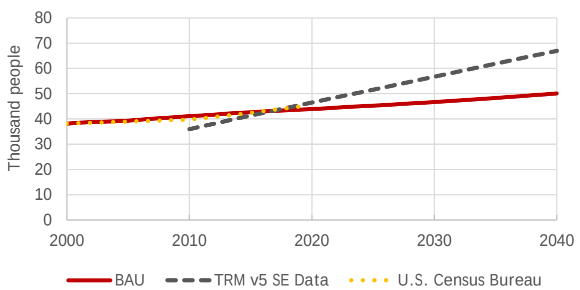

Figure 5-14. Population Tier - 1: BAU and Data, 2000-2040

[21] Specifically, the TRMv5 SE "preferred growth" land use scenario assumed higher density and a higher percentage of multi-family dwelling units in the traffic analysis zones (TAZs) in Tier 1 than the D-O LRT SD model assumes in the BAU scenario. Note that these assumptions are similar to the assumptions that we use in the D-O LRT SD model's Light Rail scenario; as a result, the population projections in that scenario more closely match the TRM population projections. In Tier 2, the TRMv5 SE data population projection was essentially identical to the U.S. Census Bureau data, and therefore no choice had to be made regarding to which to calibrate..

Developed land in Tier 1 is projected to increase by 31% during 2014-2040 (compared to 54% in Tier 2), as shown in Figure 5-15, or about 1,200 acres, with an additional 7.8 million nonresidential building sq ft. The model's projection for developed land closely fits the lower of two estimates derived from the CV2 Parcel Geodatabase for Place Type & Development Status Editing (TJCOG 2014a), with a value within 4% of that source in 2040. The model's projection for total **nonresidential square feet**, shown in Figure 5-16, deviates by no more than 2% in Tier 1 from the estimate derived from the three County Offices of Tax Administration databases (Durham County Tax Administration 2000-2014, Orange County Tax Administration 2014, Chatham County Tax Administration Office 2014).

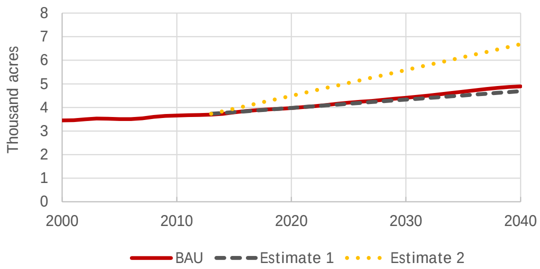

Figure 5-15. Developed Land - Tier 1: BAU and Data, 2000-2040

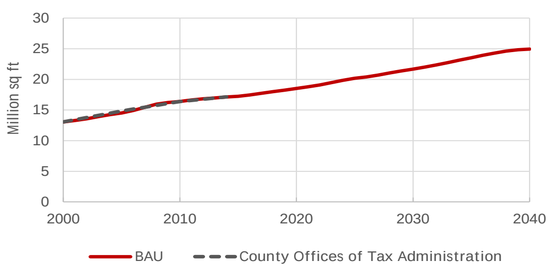

Figure 5-16. Nonresidential sq ft - Tier 1: BAU and Data, 2000-2040

Under the BAU scenario, **total employment** in Tier 1, shown in Figure 5-17, increases by 47% between 2014 and 2040 (compared to 65% in Tier 2). Although we did not use the TRM v5 SE data to calibrate our population projections in Tier 1, we used TRM v5 SE data to calibrate total employment projections, since we did not identify any other employment projections by employment category at the appropriate geographic scale for Tier 1. To calibrate historical employment in Tier 1, we used employment growth rates (2000-2010) from the U.S. Census Longitudinal Employment-Household Dynamics (LEHD).

The combination of increasing employment and nonresidential sq ft in Tier 1 causes a 115% increase in **GRP** between 2010 and 2014 in Tier 1 (shown in Figure 5-18), reaching $14 billion (USD 2010) in 2040. However, with the slow increase in population in Tier 1 under the BAU scenario between 2014 and 2040, the model assumes that the majority of available new jobs are filled by people who reside outside of Tier 1 (though we note that this dynamic changes in the Light Rail scenario). As in Tier 2, the model calculates GRP for Tier 1 as the sum of total earnings and gross operating surplus; the average growth rate for GRP between 2014 and 2040 (which is set to be the same as the growth rate for total earnings) is 2.74% per year. In Tier 1, the total earnings share of GRP is higher than in Tier 2 (70%, as opposed to 60%), since this Tier has a higher percentage of service jobs, which generate less gross operating surplus than industrial, office, and retail jobs.

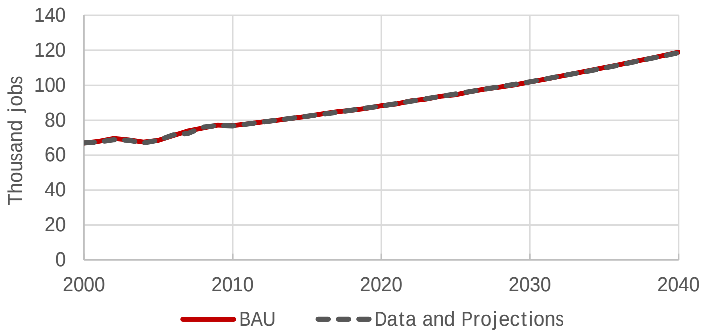

Figure 5-17. Total Employment - Tier 1: BAU and Data, 2000-2040

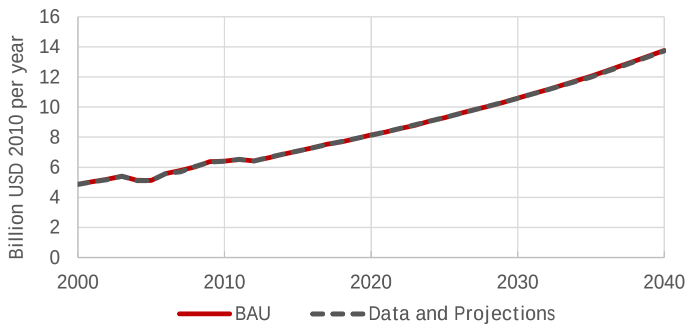

Figure 5-18. Gross Regional Product - Tier 1: BAU and Data, 2000-2040

We calibrated **total retail consumption** in Tier 1 to retail sales data estimates from 2008-2014 downloaded from SimplyMap. As shown in Figure 5-19, this variable increases by 114% between 2014 and 2040 under the BAU scenario, driven by the increase in GRP.

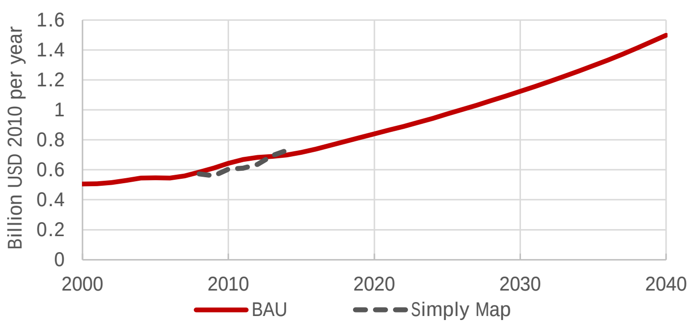

Figure 5-19. Total Retail Consumption - Tier 1: BAU and Data, 2000-2040

In the transportation sector, we used the same variable calculations and calibration sources in Tier 1 as in Tier 2. In some cases, such as VMT and congestion, the source of calibration data is a GIS shapefile that we clipped to each of the two Tiers. In other cases, calibration data for many Tier 1 variables could only be estimated by scaling down Tier 2 data. In some of these cases, such as person miles of travel by individual modes, we were only able to use values from 2010 for calibration purposes, since the scaling process involved deriving ratios from historical Tier-1-scale and Tier-2-scale data for which Tier-1-scale projections were not available. As shown in Figure 5-20, during 2014-2040, **VMT** in Tier 1 increases by 37% (compared to 55% in Tier 2), reaching 1.8 million miles per day in 2040. This represents a greater deviation (-8.0%) from the 2040 MTP's "Preferred" infrastructure case, as projected by the TRM v5, than our estimate of VMT in Tier 2. This deviation is likely caused by the fact that the 2040 MTP's "Preferred" infrastructure case involves the light rail being built (which is expected to lead to an increase in population and VMT), whereas the D-O LRP SD Model's BAU scenario does not.

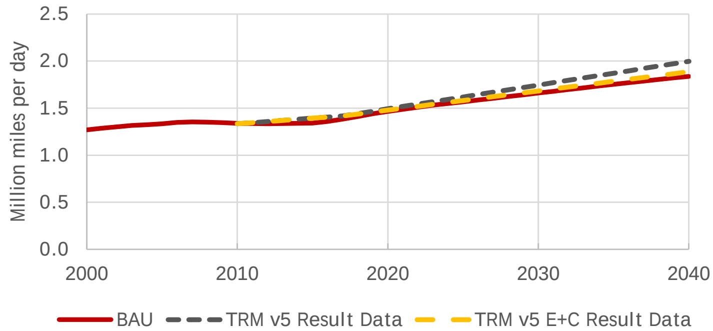

Figure 5-20. VMT - Tier 1: BAU and Data, 2000-2040

The 37% increase in VMT estimated by the D-O LRP SD Model for Tier 1 (which is significantly less than the increase in Tier 2 VMT) leads to an increase in traffic **congestion** of only 0.42% between 2014 and 2040 (compared to an 8.0% increase in Tier 2), as shown in Figure 5-21. In large part, the reason that congestion increases so little relative to the amount that VMT increases is because the D-O LRP SD Model assumes (in both Tiers) that traffic management systems will get better over time, decreasing the amount of congestion that is produced by a given level of peak-period VMT per lane mile. This is in addition to congestion being alleviated by the construction of new roadway lane miles over time. As in Tier 2, Tier 1 congestion in the D-O LRP SD Model can only be compared to other data/projections for the years 2010 and 2040 from the TRM v5's "preferred" scenario, which assumes that a light rail line is built through Tier 1, whereas this model's BAU scenario does not. As mentioned above, we assume that a light rail line would increase the number of people and jobs in Tier 1, meaning that it also increases Tier 1 VMT and traffic congestion. For this reason, 2040 Tier 1 congestion is 6.3% less than the TRM v5 projection used for calibration.

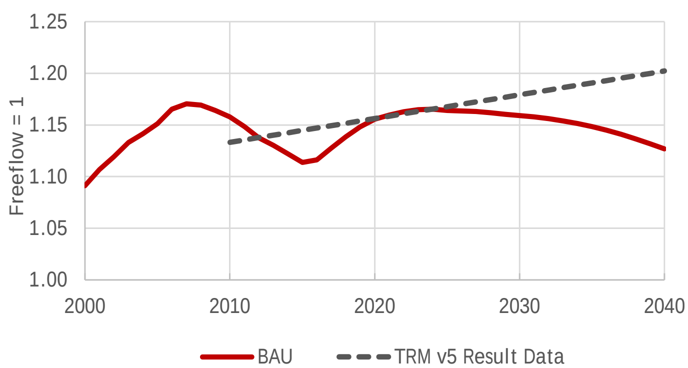

Figure 5-21. Congestion - Tier 1: BAU and Data, 2000-2040

As shown in Figure 5-22, due in part to the small growth in traffic congestion, as well as the projected increase in GRP per capita (among other factors), the model projects that Tier 1 **person miles of public transit travel per day** actually declines by 7.2% during 2014-2040, compared to a 40% increase in Tier 2. Because Tier 1 employment grows faster than population in the BAU scenario, even though overall person miles of travel (encompassing all modes) increase faster than population between 2014 and 2040

(22% growth for total person miles of travel vs. 18% growth for population), the number of person miles by residents increases much more slowly (2.6% growth in the same period). As a result, person miles of travel by residents per capita actually decrease by 13% in Tier 1 over this period (partially because projected increases in densities of jobs and retail reduce the distances that people must travel to get to work or run errands), compared to an increase of 1.9% in Tier 2.

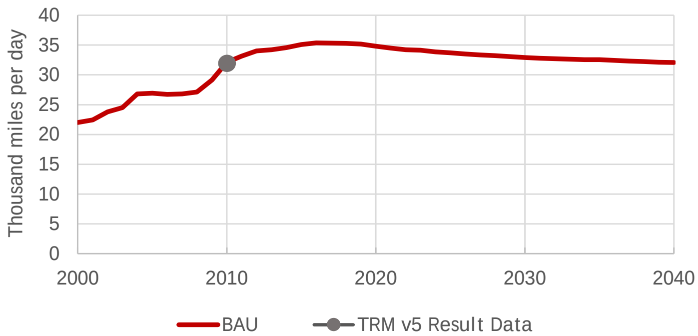

Figure 5-22. Public Transit Person Miles - Tier 1: BAU and Data, 2000-2040

The model's estimates of increased energy and water impacts in Tier 1 reflect the same increases in population, land use, and economic activity as in Tier 2. Due to increased building square footage, **building energy use** is projected to increase 22% between 2014 and 2040, reaching 6.1 million MMBtu/year by 2040. Since there were no historical data for Tier 1 energy use or CO_2 emissions, we used the energy and CO_2 emissions calibration factors from Tier 2 for Tier 1 as well. We assumed technological improvement would cause building energy use intensity to decrease by 13-15% between 2014 and 2040, as in Tier 2. **CO_2 emissions** are projected to increase by 12% during this time, reaching 1.3 million tons/year in 2040. As in Tier 2, the increase in CO_2 emissions follows an increase in VMT and building sq ft. With land development, **impervious surface** in Tier 1 is projected to increase by 27% in the next 25 years (compared to a 35% increase in Tier 2), reaching 3,900 total impervious acres (79% of developed land) by 2040, as shown in Figure 5-23. Growth in impervious surface drives an increase in stormwater runoff, which is discussed in the Scenario Results for the Water sector. As with Tier 2, we calibrated the model's estimates of impervious surface in Tier 1 to one-meter land cover data from EPA EnviroAtlas for 2010; for Tier 1, the model's estimate of impervious surface in 2010 is within 1% of the EnviroAtlas data.

See Table 6-6 and Table 6-7 in Chapter Six on Quality Assurance for a summary of the Tier 1 and Tier 2 indicators discussed in this section, among others. For each indicator, the table notes any external data sources used for calibration purposes – for historical estimates, future projections, or both – and provides the R-squared fit and average percent deviation between the model's estimates and the external data sources.

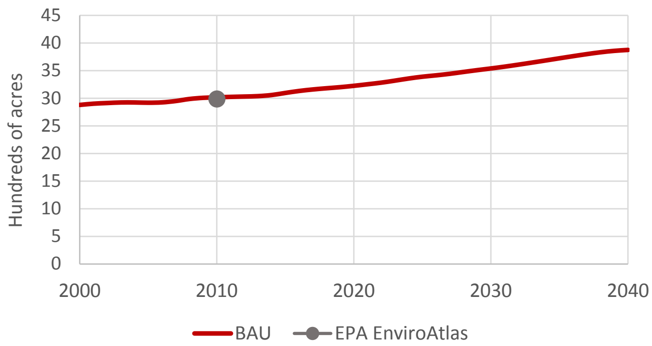

Figure 5-23. Impervious Surface – Tier 1: BAU and Data, 2000-2040

BAU Results Summary

As discussed above, the changes projected to occur in the BAU scenario present several opportunities and challenges to the region. With expected growth in population and economic activity, developed land and the attendant impervious surfaces and runoff are expected to increase significantly over the next 25 years. In addition, in both Tier 1 and Tier 2, public transit use and walking and cycling rates are projected to decline relative to automobile travel, in the absence of any major investment in improving public transit. Though population will continue to grow rapidly in Tier 2, population growth in Tier 1 will not match that expected by the TRM v5 SE Data without greater attractions to the area, such as employment and retail growth. Population growth will also increase energy use and CO_2 emissions, though these increases are mitigated somewhat by increased energy efficiency of buildings and vehicles. The Light Rail and Light Rail + Redevelopment scenarios provide opportunities to explore how two possible approaches for managing growth in the region might affect these outcomes. The remainder of this chapter focuses on those two scenarios, beginning with an overview of inter-sectoral model behaviors, followed by a sector-by-sector discussion of scenario results.

5.3 Light Rail Scenarios: Model Behaviors

The model's fidelity to historical data and projections, as discussed above, suggests that the results of the other two main scenarios in the model – the Light Rail and Light Rail + Redevelopment scenarios – would be indicative of the effects of those alternatives on the modeled system.

As noted in in Chapter 3 (in the "Overview of Model Structure" section), the inter-sector feedback loops that connect the three core sectors (Land Use, Economy, and Transportation) have the largest impacts on the modeled system. Consequently, any scenario that introduces a change to one of the variables in these main inter-sector loops will have cascading impacts on variables throughout the model. This section illustrates this dynamic by presenting an overview of model results for the two main scenarios: (1) the Light Rail scenario and (2) the Light Rail + Redevelopment Scenario.

In the **Light Rail** scenario (as described in Chapter 4), 17 miles of light rail are added to the public transit system over the six-year period between 2020 and 2026. The additional public transit person miles of travel resulting from the light rail are determined by a formula that takes into account population, retail and entertainment jobs, high wage jobs, and overall employment in Tier 1, and VMT per highway lane mile in Tier 2 (Chatman et al. 2014). In addition, demand for commercial square footage in the station areas is assumed to increase by 10% (though this variable can be modified by users in the user interface of the model). In the Light Rail + Redevelopment scenario, on top of these changes, 20% of developed land in Tier 1 is gradually redeveloped to a density almost triple the density in the BAU scenario. The discussion below highlights several of the results of these scenarios by exploring how the changes described above affect the main inter-sector feedback loops described in Chapter 3.

Economy → Land Use → Economy

> **Light Rail scenario:**
>
> - 17 miles of light rail transit added between 2020 and 2026
> - 10% more demand for retail, office, and service sq ft in Tier 1

In this reinforcing feedback loop, employment growth leads to growth in nonresidential square feet, which increases gross regional product (GRP), which eventually increases total employment. In both scenarios, nonresidential sq ft in Tier 1 increases relative to the BAU scenario, though this increase is larger in the Light Rail + Redevelopment scenario. In the Light Rail scenario, total nonresidential sq ft in Tier 1 increases by 16% and 8% relative to the BAU scenario in 2033 and 2040, respectively. Figure 5-24 shows that growth in nonresidential square feet in this scenario levels off around 2033, which is when the maximum allowed expansion of developed land in Tier 1 is reached. In the Light Rail + Redevelopment scenario, the increase in density allows for greater development of nonresidential sq ft per acre of developed land, so the maximum allowed expansion of developed land in Tier 1 is not reached during the model's timeframe. As a result, total nonresidential sq ft in Tier 1 follows a similar path to the Light Rail scenario through 2033, but continues increasing relative to the BAU scenario, reaching a level 34% higher than the BAU value by 2040. As shown in Figure 5-24, in 2040, the Light Rail + Redevelopment scenario projects 34 million nonresidential sq ft, compared to 25 million sq ft in the BAU scenario and 27 million sq ft in the Light Rail scenario. In Tier 2, the increase in nonresidential square feet is limited to the amount added in Tier 1 as a result of development of the Light Rail, peaking at 6.5% higher than BAU in 2040 for both the Light Rail and Light Rail + Redevelopment scenarios (Figure 5-25).[22]

> **Light Rail + Redevelopment scenario:**
>
> - 20% of developed land in Tier 1 redeveloped to densities 193% more dense than originally

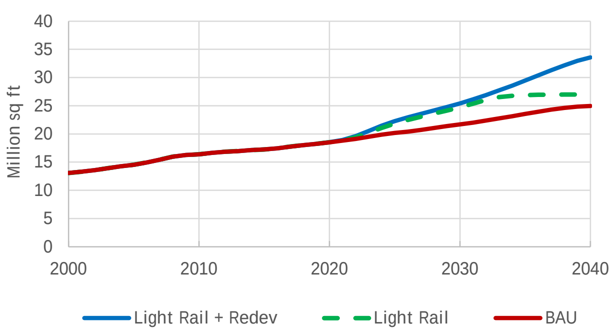

Figure 5-24. Total Nonresidential Sq Ft - Tier 1: Main Policy Scenarios Compared to BAU

[22] Note that the impacts of redevelopment on land use in Tier 1 are not linked to Tier 2. This means that while the Light Rail + Redevelopment scenario results in an increase in nonresidential sq ft even as land development declines in Tier 1, in Tier 2, both land development and square footage remain very similar to the Light Rail scenario. This can be understood as a concentration of square footage – during redevelopment, some businesses decide to move from Tier 2 to Tier 1.

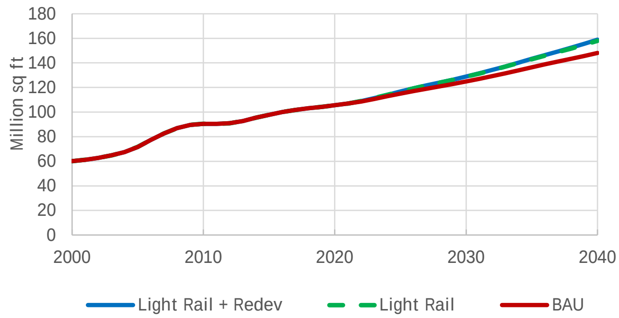

Figure 5-25. Total Nonresidential Sq Ft - Tier 2: Main Policy Scenarios Compared to BAU

As described above, an increase in nonresidential sq ft leads to an increase in employment and GRP, so all three indicators increase under both the Light Rail and the Light Rail + Redevelopment scenarios. As shown in Figure 5-26. Total Employment - Tier 1: Main Policy Scenarios Compared to BAU, in the Light Rail scenario, employment in Tier 1 is about 5.4% higher and 14% higher than BAU in 2030 and 3040, respectively, while in the Light Rail + Redevelopment scenario, employment in Tier 1 is 6.9% higher and 23% higher than BAU in 2030 and 2040, respectively. GRP follows a similar trend. Relative to the Light Rail scenario, the increase in density in the Light Rail + Redevelopment scenario allows for greater economic growth in Tier 1, resulting in 15,000 more jobs created in 2040 (150,000 vs. 135,000). As shown in Figure 5-27 employment is about 6% higher than BAU in Tier 2 in 2040 under both the Light Rail and Light Rail + Redevelopment scenarios (and GRP is about 6.5% higher).

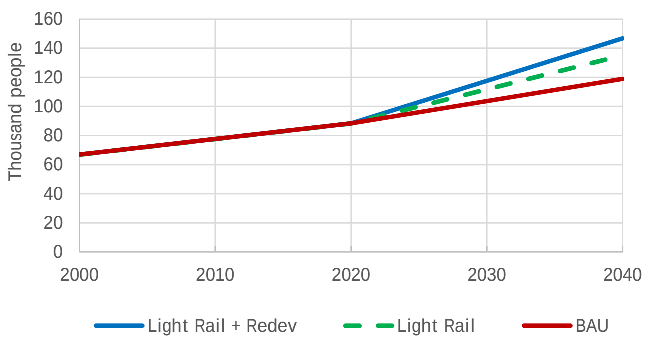

Figure 5-26. Total Employment - Tier 1: Main Policy Scenarios Compared to BAU

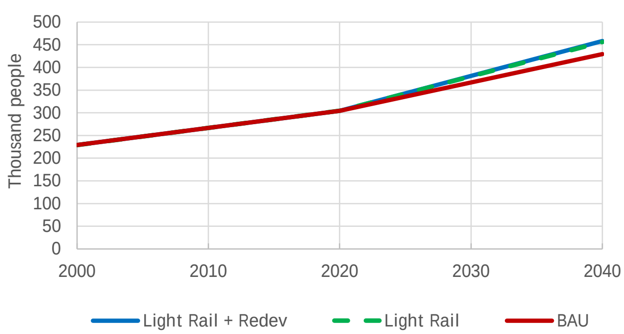

Figure 5-27. Total Employment - Tier 2: Main Policy Scenarios Compared to BAU

Economy → Population → Economy

This pair of balancing and reinforcing loops link employment and population in Tier 1; more employment drives more migration to the area, increasing the population and therefore the labor force. This has two counterbalancing impacts. First, a higher labor force increases the potential employment in the region, so with sufficient demand for employment, an increased labor force increases employment and creates a reinforcing loop. Second, if demand for labor is not sufficient to employ all new additions to the labor force, an increasing labor force increases unemployment, which reduces net migration, creating a balancing loop. In the Light Rail and Light Rail + Redevelopment scenarios, the net result of these two feedback loops is a large increase in population for two reasons: (1) the increase in GRP described above leads to an increase in demand for employment, which directly leads to an increase in net migration to Tier 1; and (2) a decrease in the unemployment rate, with the additional resident population having a higher rate of employment, independently also increases net migration. Consequently, population in Tier 1 is about 7.3% higher and 22% higher than BAU under the Light Rail scenario in 2030 and 2040, respectively, and 8.3% higher and 29% higher in Light Rail + Redevelopment in 2030 and 2040 (Figure 5-28). By 2040, the population of Tier 1 under the Light Rail + Redevelopment scenario reaches 64,910, closely approaching the TRM v5 SE Data projection of 66,980 for that year (see Figure 5-28). In Tier 2, the majority of the change in population comes from the change in Tier 1, leading to increases of 2.8% and 3.7% over BAU by 2040 under the Light Rail and the Light Rail + Redevelopment scenarios, respectively (Figure 5-29). The light rail is the primary attractor for additional population growth, so the model assumes that only 150% of the increase in net migration in Tier 1 is applied to Tier 2 (meaning all of the migration into Tier 1, plus an additional 50% of that migration to areas of Tier 2 outside of Tier 1), despite it covering a much larger area.

In general, percent changes in model variables relative to the BAU scenario are much smaller in Tier 2 than Tier 1. This is due to the fact that the changes implemented in these two scenarios are centered in Tier 1, which only represents a fraction of the overall population, economy, and traffic of Tier 2. Therefore, the effects of the light rail scenarios are proportionally much smaller in the context of Tier 2 than in the context of Tier 1.

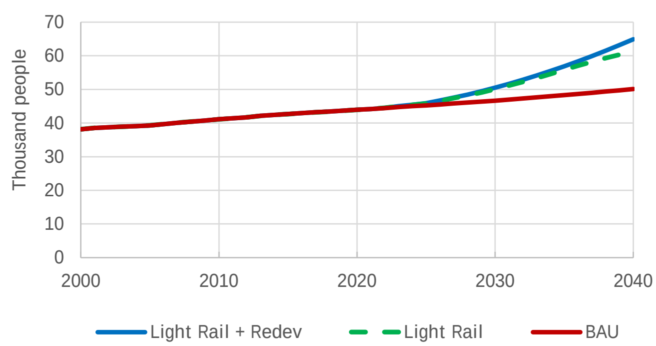

Figure 5-28. Population - Tier 1: Main Policy Scenarios Compared to BAU

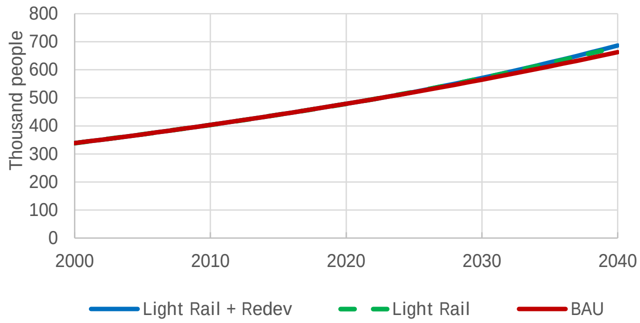

Figure 5-29. Population - Tier 2: Main Policy Scenarios Compared to BAU

Economy → Transportation → Economy

In this balancing feedback loop, an increase in GRP per capita causes an increase in person miles of automobile travel and VMT, which increases congestion, which decreases economic productivity, resulting in a decrease in GRP per capita. Even though the addition of the light rail line increases transit mode share and ridership, which serves to mitigate the effect of a rising GRP on VMT and congestion, the net effect of the shift to more transit use and the feedback loop described above is that increases in GRP cause increases in VMT and congestion in the Light Rail and Light Rail + Redevelopment scenarios. VMT in Tier 1 is about 1.5% higher and 6.3% higher than BAU under the Light Rail scenario in 2030 and 2040, respectively, and 1.7% higher and 9.4% higher in Light Rail + Redevelopment in 2030 and 2040, respectively (Figure 5-30). As discussed above, the policy interventions that distinguish the Light Rail and Light Rail + Redevelopment scenarios from the BAU scenario are centered in Tier 1, which is just one part of Tier 2, causing Tier 2 effects of the light rail scenarios to be less pronounced than the corresponding Tier 1 effects. Therefore, in Tier 2, the increase in VMT relative to BAU is smaller in both light rail scenarios than in Tier 1, reaching 1.6% higher than BAU in 2040 under the Light Rail scenario and 2% higher under the Light Rail + Redevelopment scenario (Figure 5-31).

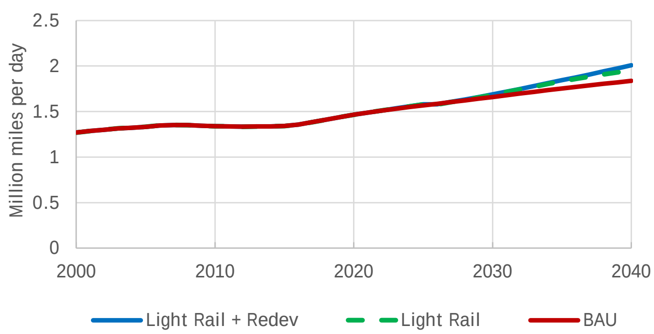

Figure 5-30. VMT – Tier 1: Main Policy Scenarios Compared to BAU

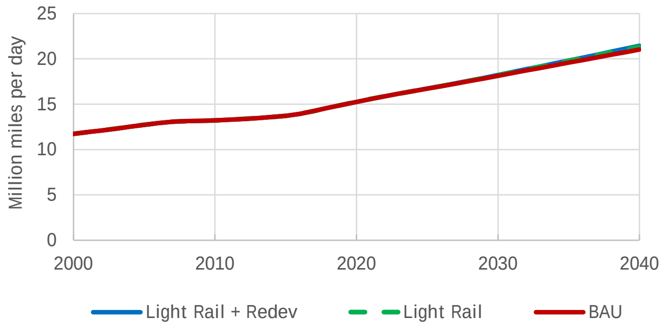

Figure 5-31. VMT, Tier 2: Main Policy Scenarios Compared to BAU

In the Light Rail scenario, Tier 1 congestion increases by 6.2% relative to BAU by 2040 (slightly less than the corresponding increase in VMT), and in the Light Rail + Redevelopment scenario, it increases by 12% relative to BAU (Figure 5-32) (greater than the corresponding increase in VMT). This higher growth in congestion under the Light Rail + Redevelopment scenario is due both to the higher rates of growth in GRP per capita under this scenario and to land being redeveloped with higher Floor Area Ratios (FARs), which also drive traffic congestion in Tier 1, as high FARs are correlated with a greater density of activity, and hence more concentrated traffic. As with VMT, increases in congestion in the light rail scenarios are smaller in Tier 2 than in Tier 1, with only 1.6% and 2% increases over BAU in 2040 in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-33).

As shown in Figure 5-32, Tier 1 congestion sharply declines in 2026 due to the introduction of the light rail line and the consequent increase in public transit usage. But the economic and population growth that also result from the light rail line lead to an increase in traffic that reverses this decline starting the following year. This nonlinear response stems from the two parallel causal chains driving the output's value in opposite directions, where there is a delay in the causal chain with the stronger effect (economic and population growth) but not in the one with the weaker effect (light rail's effect on transit usage). As another product of nonlinearities in the model, congestion starts to decline after 2037 in the Light Rail scenario but not in the Light Rail + Redevelopment scenario. One reason for this is the aforementioned difference in FARs between the scenarios. Another reason is that there is a finite amount of land in Tier 1 that can be developed. Whereas greater-than-BAU economic growth causes this limit to be reached in the Light Rail scenario, the higher development densities under the Light Rail + Redevelopment scenario cause developable Tier 1 land to not be exhausted before 2040. Since limiting developed land also limits nonresidential floor space, and therefore employment, GRP growth in the Light Rail scenario slows down in the latter years of the model run, hence also slowing down VMT growth. Even though Tier 1 FARs and VMT do not decline in the latter years of the model run in the Light Rail scenario, the average FAR stops increasing and VMT increases little enough that the continued construction of roadway lane miles and the improvements we assume will occur in traffic-control measures over time are able to produce a net decline in congestion after 2037 that is not mirrored in the Light Rail + Redevelopment scenario.

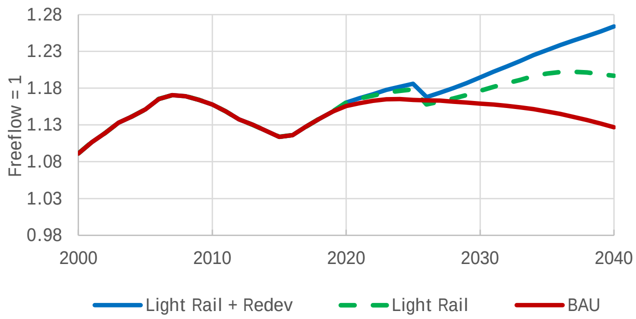

Figure 5-32. Congestion - Tier 1: Main Policy Scenarios Compared to BAU

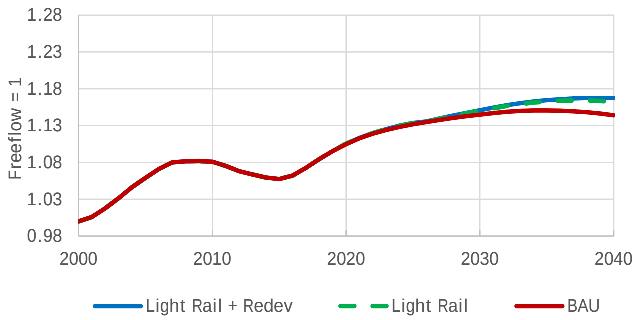

Figure 5-33. Congestion - Tier 2: Main Policy Scenarios Compared to BAU

Economy → Equity → Transportation → Economy

This balancing feedback loop links economic growth and employment to equity and underserved populations, who are more likely to be transit dependent. Economic growth decreases the percent of people who are transit dependent, which increases VMT (at the expense of travel by other modes), which increases congestion and decreases GRP. As employment increases due to the Light Rail scenarios, unemployment declines, leading to a decline in the percent of the population in poverty in both Tiers. In the Light Rail scenario, the percent of the population in poverty in Tier 1 is about 6.4% lower and 7.5% lower than BAU in 2030 and 2040, respectively; in the Light Rail + Redevelopment scenario, these values are and 7.7% lower and 17% lower, respectively (Figure 5-34). The poverty rate rises near the end of the Light Rail simulation ultimately in response to the cap on developable land being reached. This stops expansion of nonresidential sq ft, which slows employment growth, leading to higher unemployment and poverty, demonstrating how systemic limits produce nonlinear results in the model. In Tier 2, the percent of the population in poverty under the light rail scenarios drops more relative to the BAU (21%) than in Tier 1, because the rate starts at a lower level overall (Figure 5-35).

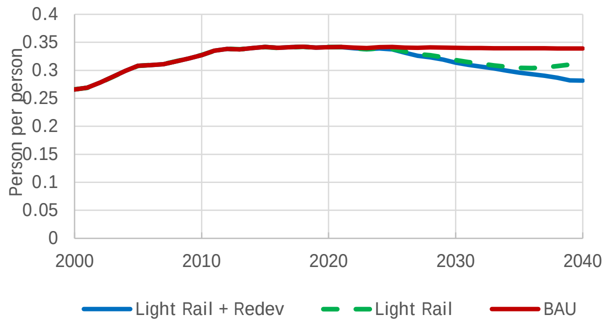

Figure 5-34. Percent of Population in Poverty - Tier 1: Main Policy Scenarios Compared to BAU

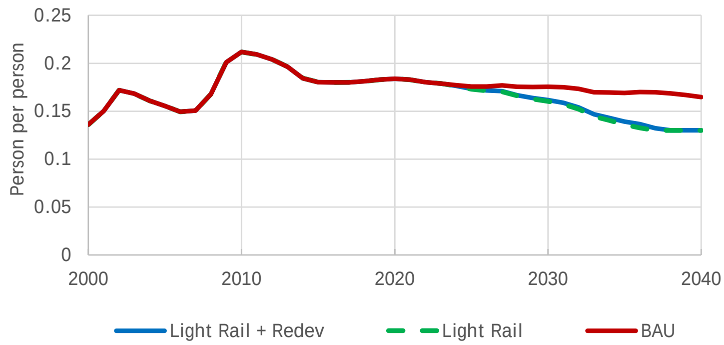

Figure 5-35. Percent of Population in Poverty - Tier 2: Main Policy Scenarios Compared to BAU

The population in poverty in turn affects the number of transit-dependent households. Though the percent of the population in poverty declines in Tier 1 under the Light Rail scenarios, the population grows enough that the total number of households in poverty still increases, leading to a rise in the number of zero-car households (the proxy used in the model for transit-dependent households). However, the percent of households with zero cars declines in both tiers, mirroring the changes in the percent of the population in poverty. As shown in Figure 5-36, the percent of households with zero cars is 6.7% lower and 16%lower in Tier 1 under the Light Rail scenario than BAU in 2030 and 2040, respectively. Under the Light Rail + Redevelopment scenario, it is 7.7% and 22% lower than the BAU in 2030 and 2040 respectively. As described above, this relative drop in transit-dependent households increases VMT and congestion, leading to a drop in GRP, completing the balancing loop. In Tier 2, the decline is much less pronounced. As shown in Figure 5-37, the percent of households with zero cars is 1.5% lower and 4.4% lower in Tier 2 under the Light Rail scenario than BAU in 2030 and 2040, respectively, and the Light Rail + Redevelopment scenario changes this only marginally.

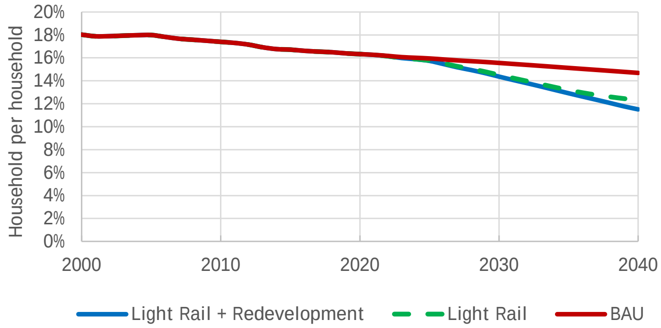

Figure 5-36. Percent of Households with Zero Cars - Tier 1: Main Policy Scenarios Compared to BAU

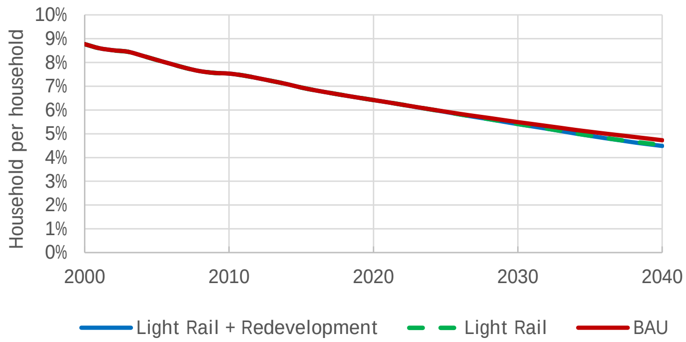

Figure 5-37. Percent of Households with Zero Cars - Tier 2: Main Policy Scenarios Compared to BAU

Economy → Land Use → Energy → Economy

In this feedback loop, as GRP and nonresidential sq ft increase due to the development of the light rail, total energy spending increases. At the same time, residential energy spending increases as population and dwelling units increase. As shown in Figure 5-38, total energy spending in Tier 1 is about 9.4% higher and 10% higher than BAU under the Light Rail scenario in 2030 and 2040, respectively, and 11% higher and 26% higher under Light Rail + Redevelopment in 2030 and 2040, respectively. As described in Chapter 2, if energy spending grows fasters than GRP, gross operating surplus is negatively affected. This is not the case in either Tier in the two light rail scenarios: In Tier 1, GRP grows at an annual rate of 3.2% and 4.0% in Light Rail and Light Rail + Redevelopment, respectively between 2026 and 2040. During this same time period, energy spending grows at the slower rates of 1.8% and 2.7% for the two respective scenarios. In Tier 2, the growth in total energy spending is also surpassed by the growth in GRP, with about 3.1% annual GRP growth between 2026 and 2040 in both light rail scenarios, compared to 2.1% annual growth in total energy spending (Figure 5-39).

Along with energy spending, the light rail scenarios cause an increase in energy consumption and CO_2 emissions in both Tiers. Compared to BAU, Tier 1 energy consumption is 10% higher in the Light Rail scenario in both 2030 and 2040; and 12% and 28% higher in those respective years in the Light Rail + Redevelopment scenario. Tier 1 CO_2 emissions are 12% and 11% higher than BAU under the Light Rail scenario in 2030 and 2040, respectively, and 14% and 31% higher than BAU under the Light Rail + Redevelopment scenario. In Tier 2, the light rail causes a lower percentage increase in energy consumption and CO_2 emissions than in Tier 1. In both light rail scenarios, energy consumption is about 2% higher in 2030 than in the BAU scenario. By 2040, energy consumption is about 4% higher than

BAU in the Light Rail scenario and about 5% higher than BAU in the Light Rail + Redevelopment scenario. CO_2 emissions are about 2% higher than BAU in 2030 and 5% higher in 2040 in both light rail scenarios.

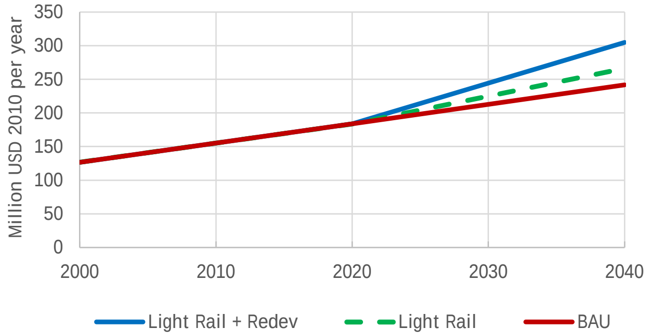

Figure 5-38. Total Energy Spending - Tier 1: Main Policy Scenarios Compared to BAU

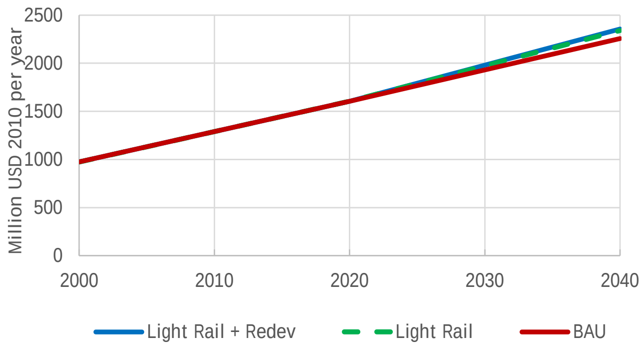

Figure 5-39. Total Energy Spending - Tier 2: Main Policy Scenarios Compared to BAU

Light Rail Scenarios Results Summary

The previous section outlined several opportunities and challenges expected to occur by 2040 in the BAU scenario, and this section highlights several areas in which the light rail and redevelopment might respond to these changes. The largest impacts of the light rail scenarios are seen in Tier 1, since this where the light rail is located and has the largest effect. Under the BAU scenario, population in Tier 1 falls short of the TRM v5 SE Data projection by 25% in 2040. The growth stimulus provided by the Light Rail scenario goes a long way towards matching this projection, leading to a level 8.5% lower in 2040, while the TRM v5 SE Data projection for population in Tier 1 is essentially matched under the Light Rail + Redevelopment scenario (with a 3% difference in 2040). Total employment rises as well, reaching 23% higher than BAU under the Light Rail + Redevelopment scenario by 2040. Along with this boom in population and economic growth however, comes increased land development, impervious surfaces, nitrogen loadings due to stormwater runoff, energy use, and emissions. In 2040, CO_2 emissions per year in Tier 1 are 11% and 31% higher than the BAU scenario in the Light Rail and Light Rail + Redevelopment scenarios, respectively. However, the densification and centralization of development that occurs under the Light Rail + Redevelopment scenario offers an opportunity to mitigate some of these effects. On a per capita basis, impervious surfaces, nitrogen loadings, water demand, energy use, and emissions all decline. Furthermore, walking and bicycling rates in Tier 1 are about 15% higher than BAU in both light rail scenarios, reversing the declining trend shown in the BAU scenario. Nonetheless, congestion in Tier 1 remains 12% higher than BAU in 2040 under the Light Rail + Redevelopment scenario, and 6.2% higher than BAU under the Light Rail scenario.

Section 5.4 presents a sector-by-sector discussion of scenario results. Section 5.5 summarizes these results and includes several tables presenting the change in key indicator variables over time and between scenarios.

5.4 Scenario Results by Sector

This section presents detailed sector-specific results showing the percent change in model outputs between 2020 and 2040 for the three main scenarios and walks through the impacts of the primary feedbacks in each sector. Following each sector are text boxes which present the results of relevant additional decision support scenarios.

Land Use

The Light Rail scenario directly impacts land use in the D-O LRP SD Model through a 10% increase in the demand for retail, service, and office square feet in Tier 1. This small change is compounded in the model due to the reinforcing feedback loop involving developed nonresidential sq ft, GRP, and total employment (see Figure 3-3). In addition, the higher population in the light rail scenarios in Tier 1 causes an increase in demand for residential development, leading to a higher number of single-family and multifamily dwelling units, relative to BAU. As seen in Figure 5-40, both light rail scenarios show a larger percent increase in nonresidential and residential development than BAU over the period from 2020 to 2040. For the Light Rail + Redevelopment scenario, it is worth noting that although the percent growth in nonresidential sq ft is larger than the percent growth in dwelling units over this time, the change relative to the BAU scenario is much larger for dwelling units (dwelling units increase by 300% more than BAU while nonresidential sq ft increase by 130% more than BAU).

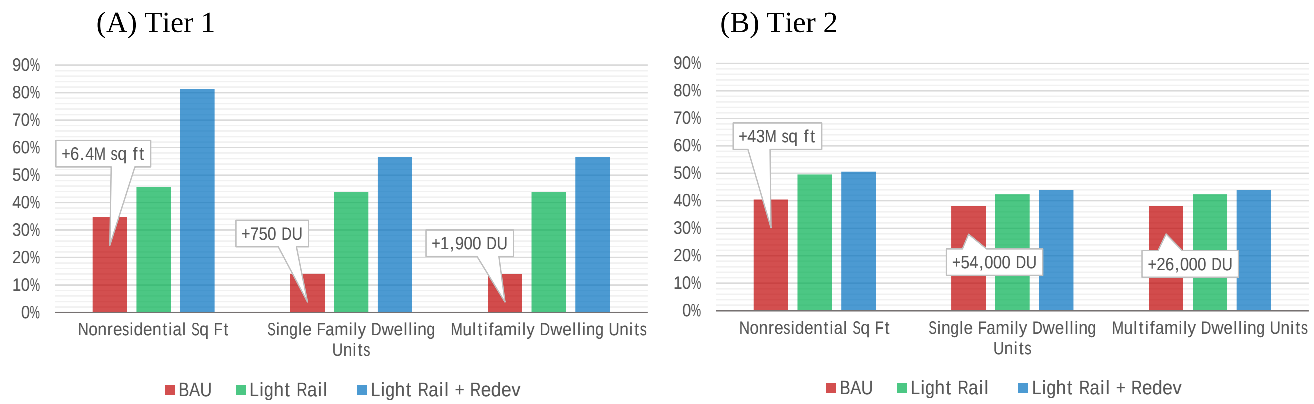

Figure 5-40. Percent Change in Land Use Sector Model Outputs Between 2020 and 2040 for Three Main Scenarios[23]

[23] Note: Data labels are the absolute change in the model output between 2020 and 2040 for the BAU scenario. All dollar values are in constant 2010 dollars. B=Billion, M=Million. Model changes due to the Light Rail and Light Rail + Redevelopment begin in 2020.

There is no internal feedback mechanism in the model that would cause density to increase endogenously. As a result, demand for nonresidential sq ft in the Light Rail scenario leads directly to increased land development. As shown in Figure 5-41 (see the green dashed line), this land development leads the Tier 1 areas to reach the maximum allowable expansion at around 2033. In the Light Rail + Redevelopment scenario, we increase density exogenously, allowing more nonresidential sq ft and dwelling units to be developed on the same amount of land. More nonresidential sq ft leads to growth in employment, which increases migration to Tier 1, resulting in a higher population than the Light Rail Scenario by 2040. Because demand for nonresidential sq ft in the Light Rail + Redevelopment can be satisfied by adding to previously developed lots, the expansion of developed land slows considerably. In the Light Rail scenario, developed land in Tier 1 is 15% and 9.2% higher relative to the BAU case in 2030 and 2040, respectively. In the Light Rail + Redevelopment scenario, developed land in Tier 1 only exceeds the BAU around 2033 (see the blue line in Figure 5-41), reaching 4.9% higher than BAU in 2040. Specifically, developed land is forecasted to reach the maximum allowable expansion of 5,300 acres by 2040 in the Light Rail scenario. In the Light Rail + Redevelopment scenario, on the other hand, developed land only increases by 200 acres over BAU (5,100 acres vs. 4,900 acres), while allowing for more nonresidential sq ft, employment, and economic activity.

(A) Tier 1

(B) Tier 2

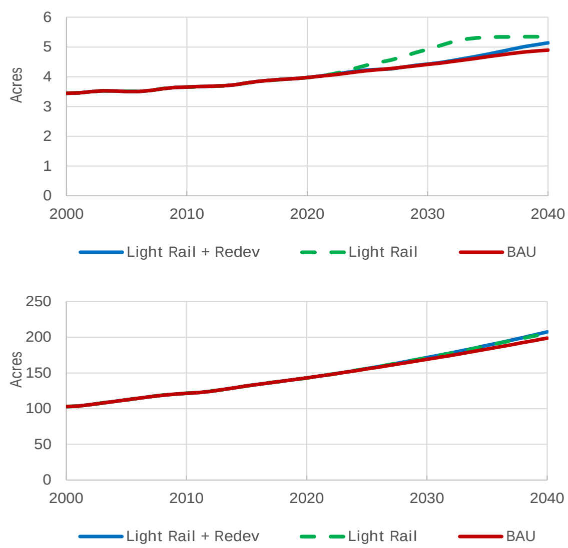

Figure 5-41. Developed Land: Main Policy Scenarios Compared to BAU

At the introduction of the light rail, the impacts to population and nonresidential sq ft in Tier 2 are merely equal to the absolute changes in Tier 1, since Tier 1 is contained within Tier 2. However, over time, the feedbacks from this initial push cause a slightly greater increase in both variables (e.g., the initial population increase from migration leads to increased births and subsequent population growth), as shown in Figure 5-39B. The Light Rail + Redevelopment scenario does not significantly impact either variable in Tier 2, due to the fact that redevelopment in Tier 1 is not connected to Tier 2.[24]

[24] While the full effect of redevelopment in Tier 1 does not show up in Tier 2, it does result in a small increase in total nonresidential sq ft in Tier 2 under the Light Rail + Redevelopment scenario, relative to the Light Rail scenario.

Developed land is split between six categories: four nonresidential categories, which are driven by employment, and two residential categories, which are driven by the split between single-family and multifamily homes and their respective household sizes. Figure 5-42 shows the distribution of developed land by category in both Tiers in the BAU scenario in 2000. In Tier 1, the shares vary in small ways, both over time and between scenarios, largely reflecting a shift towards more nonresidential land as economic activity increases. In the BAU scenario, the portion of land dedicated to residential use drops from 57% in 2000 to 52% in 2040, driven by job growth increasing more quickly than population in this scenario. In the Light Rail scenario, it is assumed that more workers will move to Tier 1 for jobs rather than commuting, and the resulting increased population growth slows the trend of declining residential land, with to the portion of land dedicated to residential use declining only to 53% in 2040. In Tier 2, the shares of land by use remain largely constant over time and between scenarios, with more than 75% of developed land dedicated to single-family residences.

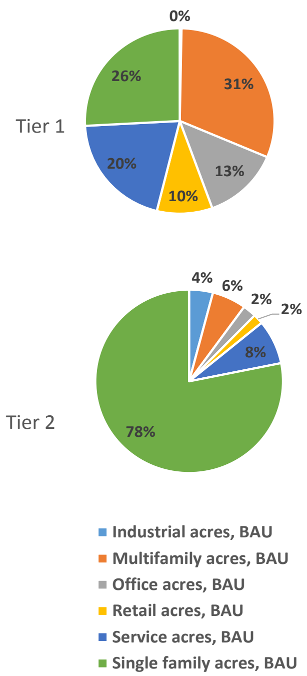

Figure 5-42. Developed Acres by Use in 2000: BAU

Nonresidential sq ft are divided into four categories (industrial, office, retail, and service), with growth in each category driven by growth in employment, the shares of employment in each category, and the employee-space ratios which determine how many square feet are necessary for each employee in a given category. In Tier 2, between 2000 and 2040, the industrial category declines from 20% to 12% of the total, while the retail category declines from 33% to 26% of the total. Service remains at about 25% for the duration, while the office category increases from 22% to 36% of the total by 2040. In Tier 1, larger shifts in the shares of square footage occur, as shown in Figure 5-43. Because the light rail scenarios do not affect employment shares and employee-space ratios, the distribution of nonresidential sq ft by category is not significantly impacted by the main policy scenarios in either Tier.

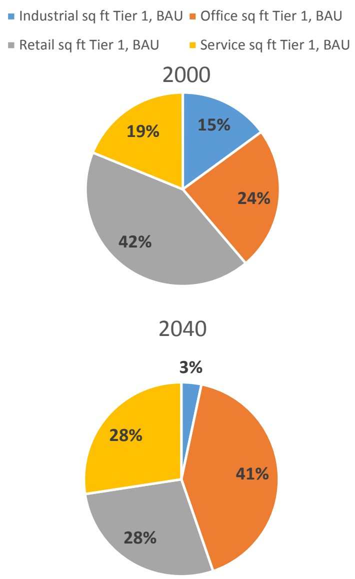

Figure 5-43. Nonresidential Sq. Ft. by Use in 2000 and 2040 - Tier 1: BAU

(A) Tier 1

(B) Tier 2

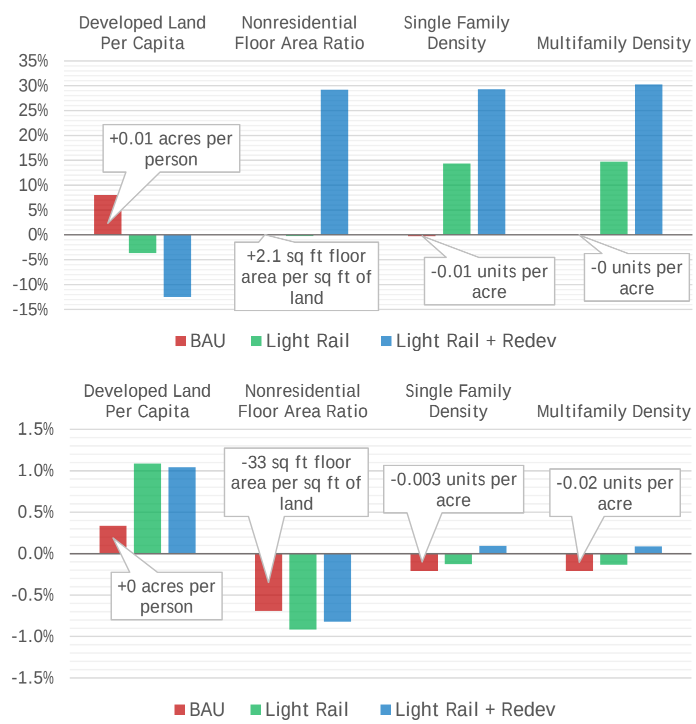

Figure 5-44. Percent Change in Density Measures Between 2020 and 2040 for Three Main Scenarios

The unique impacts of the Light Rail + Redevelopment scenario can most clearly be seen in its impact on several land use intensity measures in the model, shown in Figure 5-44. In Tier 1, there is little change in most of the intensity measures under the BAU scenario between 2020 and 2040, though developed land per capita increases slightly. In the Light Rail scenario, residential density increases by about 14% between 2020 and 2040 due to the increase in population and the fact that the cap on developed land is reached.[25] The overall nonresidential floor area ratio (FAR) does not change, on the other hand, as development of nonresidential space is capped along with the cap on developed land. Because it forces both residential and nonresidential density to increase through the process of redevelopment, the Light Rail + Redevelopment scenario has a more dramatic effect on the land use intensity variables, relative to BAU, with a 30% increase in all three density measures, and a 13% drop in developed land use per capita. On the residential side, this increased density corresponds to an increase from almost 11 dwelling units (du) per acre in 2020 to over 14 du/acre in 2040. The situation in Tier 2 is more complex. In the BAU scenario, single-family residential units grow from 65% of all units in 2000 to 67% in 2040; because single-family units use more land per unit than multifamily, residential density decreases over time. In both light rail scenarios, developed land per capita increases by 1.1%, a larger increase than the BAU scenario. This change is because land in the service category grows slightly relative to other categories in the light rail scenarios, and because this category has a small FAR, this growth leads to higher land use.

(A) Tier 1

(B) Tier 2

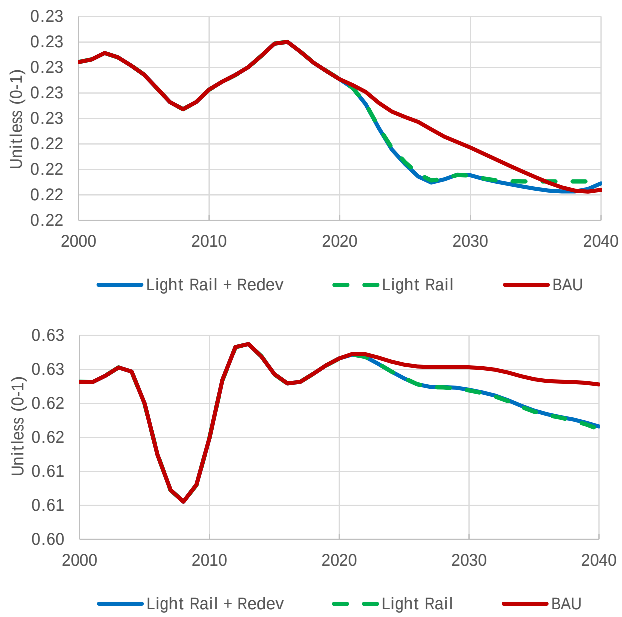

Figure 5-45. HHI of Mixed Use: Main Policy Scenarios Compared to BAU

The impact of the change in shares of land use can be seen more clearly in Figure 5-45, which presents a zoomed-in view of the Herfindahl-Hirschman Index (HHI), a dissimilarity index that has been applied to measuring land use mix (Song and Rodriguez). A value of 1 in this index indicates that all the land is

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[25] During model development, we decided it would be unrealistic for the model to force population growth to stop once the cap on developed land is reached. We instead allowed the model to increase residential density to meet demand, since the current level of residential density in the area is below limits established by zoning (unlike nonresidential density, which generally requires approval prior to redevelopment to a higher density). After the cap on developed land is reached, the model therefore assumes that any increases in dwelling units take place on already developed land, increasing the endogenously calculated density indicator that affects several other variables in the model, including property values, impervious surface coefficients, and residential water usage.

occupied by only one land use; the lower the value, the more equally mixed are the uses. The overall increase in mixed use (indicated by a decline in the HHI) under the BAU scenario is due both to changes in employment shares (which drive demand for nonresidential land) and to the different densities applied to new land development. The industrial and service categories account for the largest percentages of land use historically, and both decline in land use between 2015 and 2040, creating a more equal split. In the Light Rail scenario in Tier 1, the HHI reaches its lowest point in 2026, with a value 1.8% lower than BAU, due to the 10% increase in demand for retail, service, and office uses under this scenario. In Tier 2, the measure declines slightly under both light rail scenarios (for the same reason as in Tier 1), reaching a value 1.1% lower than BAU by 2040.

(A) Tier 1

(B) Tier 2

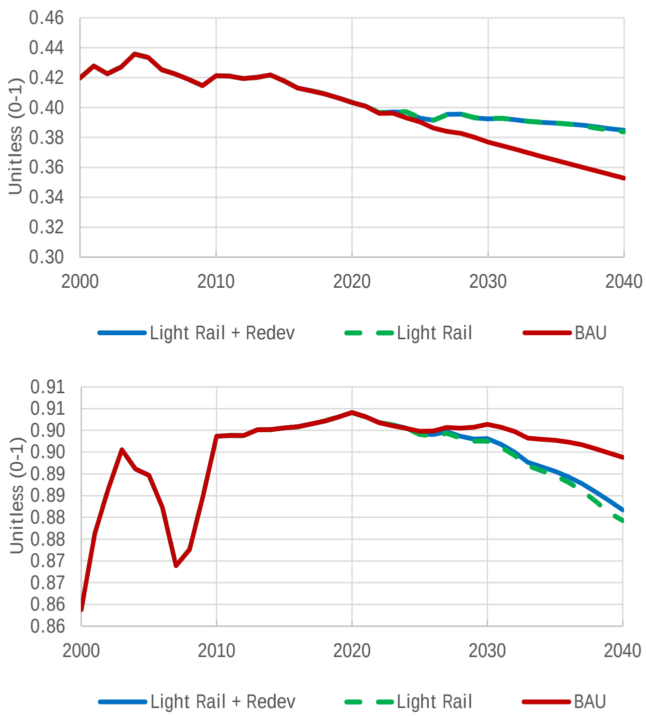


Figure 5-46. Jobs-Housing Balance: Main Policy Scenarios Compared to BAU

The shifts in the ratios of residential and nonresidential land also impact the jobs-housing balance, an indicator of the equality of mix between residential and commercial uses that is often used in the transportation planning literature as an indicator of the propensity for commuting between regions. If an area has many more homes than jobs, it is likely that many people will need to commute long distances to other areas. This balance is used in the model to affect the automobile driver mode share. The measure ranges from 0 for zones with only jobs or housing, not both, to 1 for zones with a nominal balance of jobs and housing (determined by the number of workers per household, e.g., in Tier 2, there are 1.2 workers per household, so 1.2 jobs for every household would lead to a jobs-housing balance of 1). Figure 5-46 shows the job-housing balance for both tiers in the BAU and light rail scenarios. In both Tiers, there are more jobs than workers in households, leading to jobs-housing balance values less than one. The imbalance is stronger in Tier 1, however; as of 2014 (the most current year of data on jobs and housing), Tier 1 had a balance value of 0.42, while Tier 2 had a value of 0.90. In Tier 1, the introduction of the Light Rail brings new residents and accompanying dwelling units in higher proportions than it does jobs, increasing the balance by 8.8% over BAU by 2040. The Light Rail + Redevelopment scenario does not significantly impact the balance. In Tier 2, jobs grow more quickly than population under the Light Rail Scenario, leading to a small drop in the balance of -1.6% relative to BAU in 2040. These changes also impact rates of walking and driving, which contribute to a minor feedback loop connecting to population by affecting health through physical activity and vehicle emissions.

Alternative Policy Scenario: BAU + Redevelopment

This scenario isolates the effects of redevelopment from the introduction of the Light Rail. As described in Chapter 4, it conforms to the BAU scenario plus the density-related changes made for the Light Rail + Redevelopment scenario. In Tier 1, land use density measures increase at roughly the same pace and magnitude as in the Light Rail + Redevelopment scenario, but there is relatively little increase in demand for land (which in other scenarios is primarily driven by the revitalization of Tier 1 from the light rail). In fact, total nonresidential sq ft, total employment, and population all look much more similar to the BAU scenario than the Light Rail + Redevelopment scenario (Figure 5-47). Because this scenario combines BAU-level demand for developed land with increased density in development, it leads to a flattening in the growth of developed land (Figure 5-48), and a steeper drop in developed land per capita (Figure 5-47), since densities increase more than enough to compensate for the lower population growth. Figure 5-47 also shows that housing costs decline relative to the BAU (the increase from 2020 to 2040 is 11% lower than the BAU) as land scarcity declines and the desirability of living in Tier 1 does not increase (due to the absence of the light rail). In this scenario, Tier 2 looks almost identical to the BAU scenario.

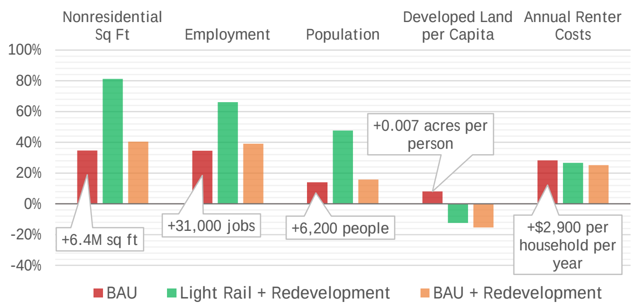


Figure 5-47. Percent Change in Selected Land Use Sector Outputs Between 2020 and 2040 for BAU + Redevelopment – Tier 1

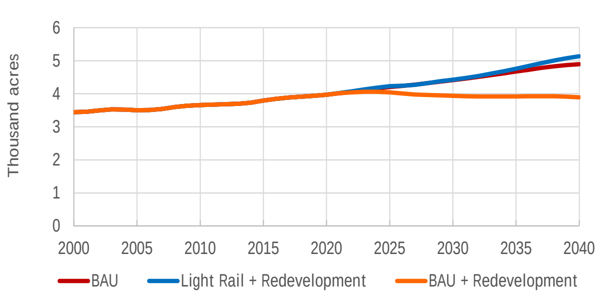


Figure 5-48. Developed Land - Tier 1: BAU + Redevelopment

Alternative Policy Scenario: Bold Redevelopment

In this scenario, which is run on top of Light Rail scenario, the percent of land redeveloped and the density at which is it redeveloped is set high enough to reach an overall increase in density of 193% for all land in Tier 1, developed and redeveloped. As noted in Chapter 4, this change matches the results of the Preferred Growth Scenario of the Imagine 2040 Regional Model. Due to the initial boost to nonresidential sq ft allowed by the high-density redevelopment, nonresidential sq ft, employment, population, and GRP rise above their levels in the Light Rail + Redevelopment scenario beginning in 2020, reaching between 6.3% (population) and 9.1% (nonresidential sq ft) higher by 2040. However this increase in factors that contribute to demand for development is smaller than the increase in density, so the model actually forecasts a decrease in developed land, implying that some land is returned to vacant or park use (Figure 5-49). Developed land per capita drops precipitously, reaching a low of 0.04 acres per person in 2040, compared to 0.079 acres per person under the Light Rail + Redevelopment scenario. The dramatic shifts in density and land use under this scenario impact the three categories of property values in very different ways (Figure 5-50). Single-family property values decline relative to the Light Rail + Redevelopment scenario due to decreasing lot sizes and the increased supply of land. Multifamily property values show relatively little change from the reference scenario, pushed in opposite directions by the increased supply of land on the one hand and increasing building size and retail density on the other. Finally, nonresidential property values increase dramatically, with an increase nearly three times as large (598%) as the increase seen in the Light Rail + Redevelopment scenario (207%) between 2020 and 2040 due to increasing building size, retail density, and employment growth. Affordability worsens relative to the reference scenario, but interestingly, this is not primarily due to any change in housing costs, which increase by only 0.05% over the Light Rail + Redevelopment scenario between 2020 and 2040. By contrast, transportation-related costs per multifamily household increase by 245%, due almost entirely to a spike in parking costs, which are affected by the number of jobs per commercial acre.

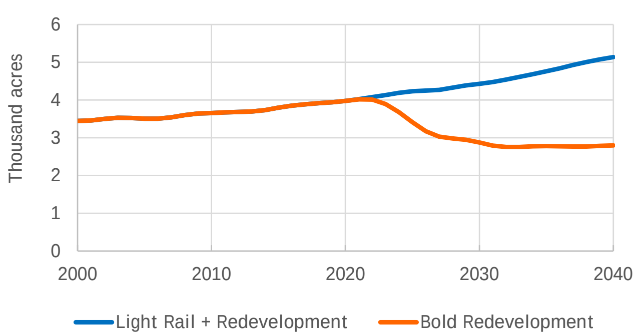


Figure 5-49. Developed Land - Tier 1: Bold Redevelopment

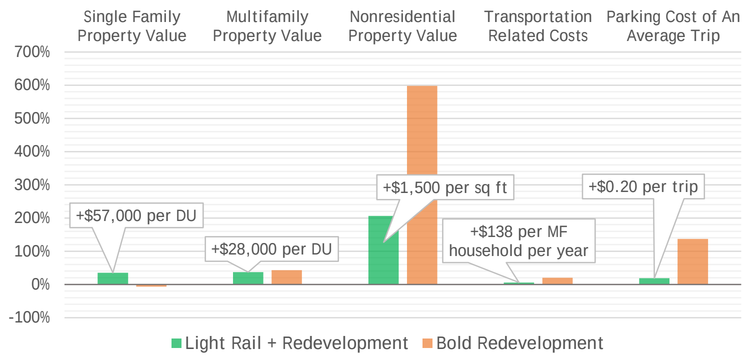


Figure 5-50. Percent Change in Housing & Transportation Costs Between 2020 and 2040 for Bold Redevelopment

Transportation

In the Light Rail scenario, the opening of the light rail line in 2026 produces an increase in the number of public transit person miles that exceeds the next-best realistic alternative transit development (i.e., the introduction of a new bus line without an exclusive right-of-way). The size of this increase in public transit use is a function of population and employment levels in the station areas (Tier 1), as well as VMT per highway lane mile in the broader metropolitan area (Tier 2). The literature suggests that people with high-income jobs (those making at least $40,000 per year in 2010 dollars) and jobs in the retail and entertainment sectors are particularly responsive to light-rail-induced improvements to public transit (Chatman et al. 2014). As shown in Figure 5-51, the increase in public transit ridership is approximately the same in both Tiers, meaning that all public transit ridership caused by the light rail in Tier 2 is attributed to trips that either begin or end in Tier 1. In the first year of light rail service, 2026, there are 11,000 more transit trips per day in the Light Rail scenario than BAU, an increase of 133% for Tier 1 and 22% for Tier 2. By the year 2040, public transit ridership in the Light Rail scenario is 375% higher than BAU in Tier 1 and 48% higher in Tier 2. This continued widening of the transit-ridership gap between the Light Rail and BAU scenarios occurs primarily because Tier 1 population and employment continue to grow in the Light Rail scenario between 2026 and 2040, due in part to the assumed increase in demand for nonresidential development in Tier 1 caused by the light rail (as noted in Chapter 4). In the Light Rail + Redevelopment scenario, the increased density of development leads to increases in population and employment. Therefore, by 2040, Tier 1 and Tier 2 transit ridership are 8.8% and 4.1% higher in the Light Rail + Redevelopment scenario than in the Light Rail scenario, respectively.

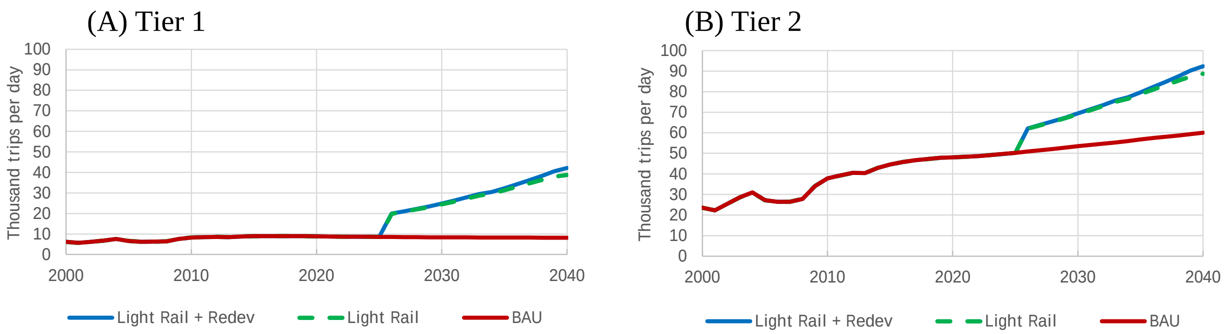


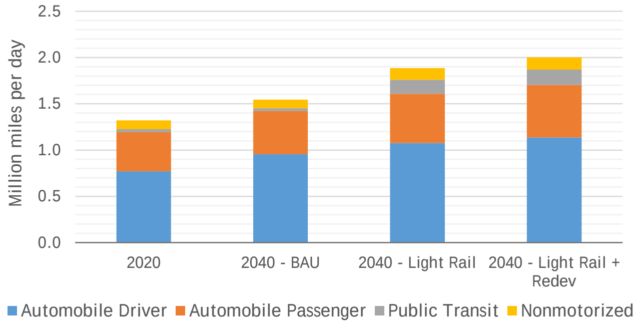
Figure 5-51. Public Transit Ridership Under Three Main Scenarios

Note: Model changes due to the Light Rail and Light Rail + Redevelopment scenarios begin in 2020 and the rail line opens in 2026.

In all three main scenarios, population consistently increases over time, causing overall person miles of travel per day (by all modes) to increase over time, as well. Because Tier 1 population growth significantly exceeds BAU in both light rail scenarios after 2020, the overall number of person miles of trips that either start or end in Tier 1 is also greater than BAU in these scenarios (Figure 5-51). In 2040, overall Tier 1 person miles of travel are 22% and 30% greater than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively. For Tier 2, 2040 overall person miles of travel are only 3.1% and 3.9% greater than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively, since the impact on Tier 2 population in these scenarios is a result of changes that only occur in Tier 1.

As discussed in Chapter 3, overall person miles of travel by all modes are determined primarily by population and GRP, while other factors influencing travel behavior merely shift travel from one mode to another. As shown in Figure 5-52, though the two light rail scenarios increase person miles of travel by all modes, they also increase both absolute public transit use, relative to BAU, as well as the percentage of overall person miles of travel that are on public transit. In 2040, the Tier 1 public transit mode share (by person miles) is 8.1% and 8.3% in the Light Rail and Light Rail + Redevelopment scenarios, respectively, as opposed to only 2.1% in the BAU scenario. In Tier 2, the difference in public transit mode shares is less dramatic (1.8% and 1.9% of overall person miles in the Light Rail and Light Rail + Redevelopment scenarios, respectively, vs. 1.3% in the BAU scenario). The model assumes that the average one-way public transit trip involves 0.25 miles of additional nonmotorized travel, since public transit users generally walk or bicycle some distance to and from transit stations. As a result, the two light rail scenarios also cause the nonmotorized share of person miles to increase in Tier 1 (from 6.0% in the BAU scenario to 6.6% in both light rail scenarios). At the Tier 2 level, the difference between scenarios in the nonmotorized share of person miles is negligible.

(A) Tier 1



(B) Tier 2

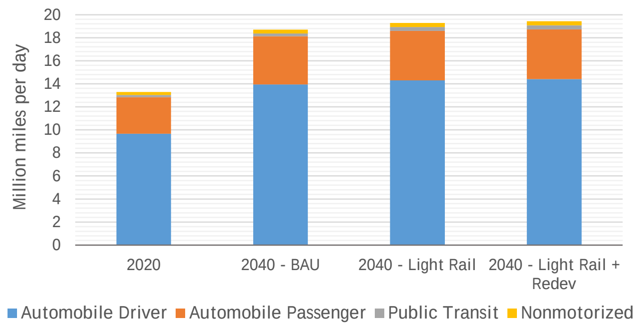


Figure 5-52. Modal Person Miles of Travel Per Day in 2020 and in 2040 Under Three Main Scenarios

Note: Model changes due to the Light Rail and Light Rail + Redevelopment scenarios begin in 2020.

Although the two light rail scenarios increase the public transit and nonmotorized mode shares at the expense of vehicle travel, relative to BAU, the simultaneous increases in population, employment, and GRP under these scenarios lead to a net increase in VMT relative to BAU (Figure 5-53). Between 2020 and 2040, VMT in Tier 1 increases by 33% and 37% in the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to a 25% increase in the BAU scenario. This greater VMT in the two light rail scenarios leads to greater traffic congestion than in the BAU scenario, despite the much greater public transit ridership seen in these two scenarios (Tier 1 2020-2040 increases of 337% in the Light Rail scenario and 376% in the Light Rail + Redevelopment scenario, compared to a decrease of 8% in the BAU scenario; Tier 2 increases of 85% in the Light Rail scenario and 92% in the Light Rail + Redevelopment scenario, compared to an increase of 25% in the BAU scenario). In the BAU scenario, traffic congestion in Tier 1 actually decreases by 2% during 2020-2040, due to assumed improvements in traffic management and the building of new roadway lane miles, but it increases by 3% and 9% in the Light Rail and Light Rail + Redevelopment scenarios, respectively. Similar trends are seen in Tier 2, though the difference between the two light rail scenarios and BAU is much less dramatic. Between 2020 and 2040, Tier 2 VMT increases by 40% in the Light Rail scenario, 41% in the Light Rail + Redevelopment scenario, and 38% in the BAU scenario. In the same period, Tier 2 traffic congestion increases by 5% in the Light Rail scenario, 6% in the Light Rail + Redevelopment scenario, and 4% in the BAU scenario.

(A) Tier 1

(B) Tier 2

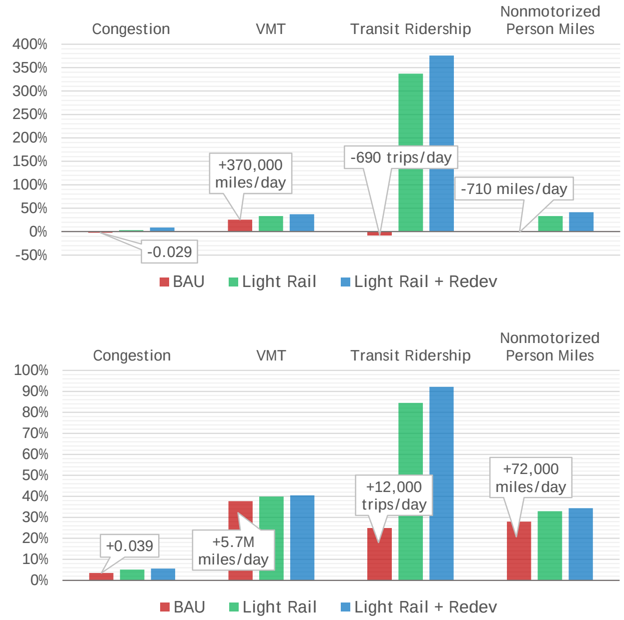


Figure 5-53. Percent Change in Transportation Sector Model Outputs Between 2020 and 2040 for Three Main Scenarios

Note: Data labels are the numeric change in the model output between 2020 and 2040 for the BAU scenario. Congestion (unitless) is measured as the ratio of peak-period travel time to travel time under freeflow conditions. All other outputs are aggregate counts of miles or trips per day. M=Million. Model changes due to the Light Rail and Light Rail + Redevelopment scenarios begin in 2020.

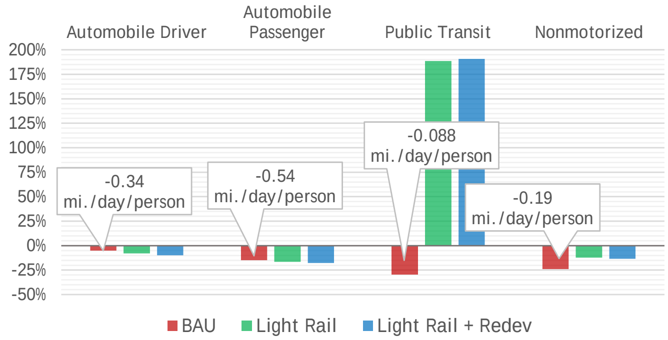
These single-digit-percentage increases in traffic congestion in both Tiers show that, even though traffic congestion is a product of GRP, employment, and population, it is not especially sensitive to changes in these variables.[26] This is due in part to the balancing feedback loop between roadway congestion and VMT: as roadway congestion increases, automobile traffic decreases, mitigating the effects of any factor otherwise increases congestion. Two additional factors that prevent dramatic increases in traffic congestion in the model are as follows: First, all three scenarios share the common assumption that gradual traffic-management improvements will decrease the amount of congestion that results from any given amount of peak-period VMT per roadway lane mile. Second, the three scenarios also all assume that there will be increases in roadway lane miles (of 6.4% in Tier 1 and 6.3% in Tier 2) during 2020-2040. Furthermore, traffic congestion forms another balancing loop by reducing Gross Operating Surplus and GRP, which decreases VMT and reduces the upward pressure on congestion.

[26] By contrast, Tier 1 GRP increases by 69%, 89%, and 114% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively, during 2020-2040; Tier 1 employment increases 35%, 53%, and 66% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively; and Tier 1 population increases 14%, 40%, and 48% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively, during the same time period. At the Tier 2 scale, GRP increases 70%, 82%, and 83% during 2020-2040 in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively; employment increases 41%, 50%, and 51% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively; and population increases 38%, 42%, and 44% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively, during the same period.

As noted in Section 5.2, total employment in Tier 1 grows faster than population in the BAU scenario. As a result, even though overall person miles of travel in Tier 1 increase faster than population between 2020 and 2040 (17% growth for total person miles of travel vs. 14% growth for population), the number of person miles by residents increases much more slowly (2.4% growth in the same period). Consequently, person miles of travel by residents per capita actually decrease in Tier 1 over this period (Figure 5-54). In the two light rail scenarios, the public transit mode reverses this trend, increasing by a dramatic 189% and 191% in the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to a 29% decrease in the BAU scenario. Because public transit in general, and rail transit especially, is most often used for trips that the traveler considers to be too long for the use of nonmotorized modes, the increase in public transit person miles resulting from the opening of the light rail line comes primarily at the expense of automobile travel, rather than at the expense of nonmotorized travel. Furthermore, the additional nonmotorized travel related to public transit use in the two light rail scenarios significantly mitigates the reduction in Tier 1 nonmotorized travel that occurs in the BAU scenario, carrying potential health benefits. Nonmotorized person miles by Tier 1 residents per capita decrease by only 12% and 13% in the Light Rail and Light Rail + Redevelopment scenarios, respectively, during 2020-2040, compared to a 24% decrease in the BAU scenario. As one would expect from the shifts toward public transit and nonmotorized travel modes described above, automobile driver person miles by Tier 1 residents per capita decline by more in the Light Rail and Light Rail + Redevelopment scenarios between 2020 and 2040 (7.9% and 9.9%, respectively) than in the BAU scenario (5.1%). As a result, Tier 1 residents do not spend as much on vehicle fuel in the two light rail scenarios in 2040 as they would in the BAU scenario. Because of increased expenditures on public transit fares, however, the average amount of money spent on transportation by Tier 1 residents per year per capita in 2040 is 1.5% and 2.7% greater than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively.

Whereas person miles traveled by residents per capita decline for all travel modes in the BAU scenario in Tier 1, Tier 2 automobile-driver person miles by residents per capita increase by about 3% between 2020 and 2040 (Figure 5-54). The two light rail scenarios feature similar increases because all three scenarios see increases in GRP per capita, which leads people to favor automobile travel at the expense of other modes. In the BAU scenario, this leads to negative changes in person miles of travel by residents per capita for all other travel modes, including a 10% decrease in public transit person miles of travel by residents per capita. In the Light Rail and Light Rail + Redevelopment scenarios, however, Tier 2 public transit person miles of travel by residents per capita increase by 29% and 34%, respectively, during 2020-2040. In all three scenarios, automobile passenger and nonmotorized person miles by residents per capita decrease during 2020-2040 in both Tiers, though the two light rail scenarios feature slightly smaller reductions in walking and cycling than BAU.

(A) Tier 1



(B) Tier 2

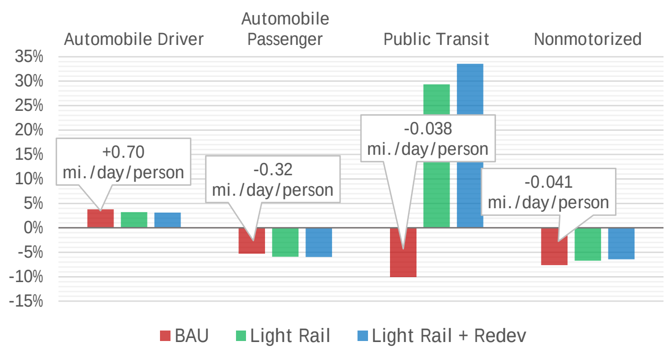


Figure 5-54. Percent Change in Modal Person Miles of Travel by Residents Per Day Per Capita Between 2020 and 2040 for Three Main Scenarios

Note: Data labels are the numeric change in the model output between 2020 and 2040 for the BAU scenario. Model changes due to the Light Rail and Light Rail + Redevelopment scenarios begin in 2020.

Higher Gas Prices

The Higher Gas Prices scenario, which is run on top of the BAU scenario, tests what would happen if future gas prices turned out to be substantially higher than what is currently projected. As noted in chapter 4, the model sets gas prices at 2016 to be equal to 2012 levels and then applies the same annual increase to gas prices as in the BAU scenario. This change produces gas prices that are consistently 40% higher than BAU between 2016 and 2040. In both this scenario and the BAU scenario, gas prices increase by 48% during 2016-2040.

Compared to BAU, the Higher Gas Prices scenario produces a 5.7% reduction in Tier 2 VMT by 2030 and a 6.1% reduction by 2040 (Figure 5-55), due to people driving less in order to save money on vehicle fuel. In Tier 1, the reduction in VMT relative to BAU is 7.2% in 2030 and 8.0% in 2040. Because traveling less by one mode results in people traveling more by other modes, the Higher Gas Prices scenario also results in public transit person miles by Tier 2 residents per capita increasing by 5.8% during 2015-2040, as opposed to an 11% decrease under the BAU case (Figure 5-55). Nonmotorized person miles by Tier 2 residents per capita go down during 2015-2040 in the Higher Gas Prices scenario, but only by 1.8%, vs. 13% with BAU.

(A) (B)

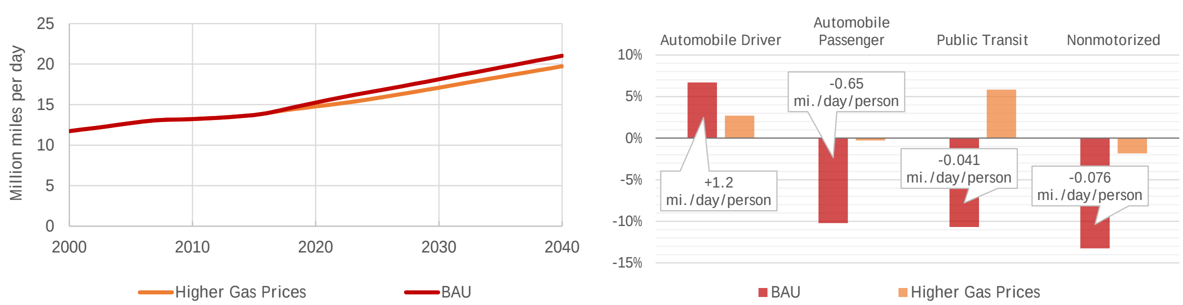


Figure 5-55. (A) VMT – Tier 2 and (B) Percent Change in Modal Person Miles of Travel by Tier 2 Residents Per Day Per Capita between 2015 and 2040 for Higher Gas Prices Scenario vs. BAU

Note: Data labels in the bar chart are the numeric change in the model output between 2015 and 2040 for the BAU scenario. Model changes due to the Higher Gas Prices scenario begin in 2016.

No Road Building

This scenario, which is run on top of the BAU scenario, tests the effects of not investing in new road construction. Whereas the BAU scenario uses an exogenous projection of continuous future road-building activity, no new roadway lane miles are built after 2017 in this scenario. By 2040, there are 257 fewer Tier 2 lane miles than BAU (6.8% less) and 20 fewer Tier 1 lane miles (7.0% less).

Building lane miles under BAU causes Tier 2 congestion to be 3.2% lower than in the No Road Building scenario in 2030 and 5.3% lower in 2040 (Figure 5-56), because there is more road capacity for comparable demand. In Tier 1, BAU congestion is 2.9% less than in the No Road Building scenario in 2030 and 4.8% less in 2040. Meanwhile, the Light Rail scenario's Tier 2 congestion is less than the No Road Building scenario's by 2.7% in 2030 and 3.8% in 2040, and Tier 1 congestion is 1.4% less than in the No Road Building scenario in 2030 and 1.1% greater in 2040. This means 2040 Tier 1 population, GRP, and VMT in the Light Rail scenario increase congestion (by increasing VMT) by more than the congestion reduction caused by (1) people switching modes due to the rail line and (2) the congestion-mitigation effect of lane miles built after 2017. Congestion has a relatively small, negative effect on GRP. The congestion relief of road building that happens in the BAU scenario but not the No Road Building scenario increases 2040 GRP by only 0.44% in Tier 2 and 0.47% in Tier 1.

The increased congestion under the No Road Building scenario relative to BAU does not greatly change travel by individual modes. Automobile driver person miles by Tier 2 residents per capita increase by 5.3% during 2017-2040 in the No Road Building and Light Rail scenarios, vs. 5.9% with BAU (Figure 5-56). Public transit and nonmotorized person miles by residents per capita in the No Road Building scenario see slightly smaller declines during 2017-2040 than BAU (9.0% and 9.5%, respectively, vs. 12% for both modes under BAU). However, nonmotorized travel by residents per capita decreases by less in the No Road Building scenario (9.5%) than in the Light Rail scenario (11%), possibly because the Light Rail scenario affects mode shares in a smaller area and is instituted in a later year.

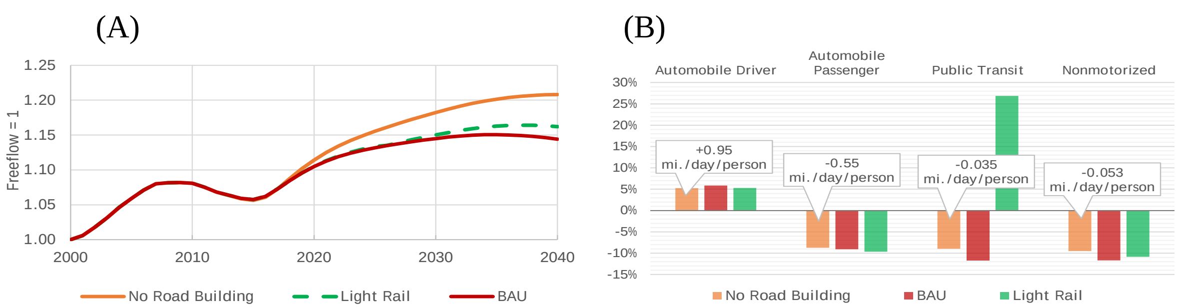


Figure 5-56. (A) Congestion – Tier 2 and (B) Percent Change in Modal Person Miles of Travel by Tier 2 Residents Per Day Per Capita Between 2017 and 2040 for No Road Building Scenario vs. BAU and Light Rail Scenarios

Note: Data labels in the bar chart are the numeric change in model outputs during 2017-2040 for the No Road Building scenario. Model changes due to the No Road Building scenario start after 2017. Model changes due to the Light Rail scenario begin in 2020 and the rail line opens in 2026.

Fare Free Transit

This scenario, which is run on top of the BAU scenario, tests what would happen if public transit agencies stopped charging fares on all transit vehicles in both Tiers, rather than building a light rail line with stations in Tier 1. For this scenario, the model changes fare prices from $0.30 per trip (the value in 2010 USDs where they are held constant after 2013 in the BAU and light rail scenarios) to zero in 2026, the year that rail transit service would otherwise commence in the Light Rail scenario.

The Fare Free Transit scenario has a far more dramatic effect on people's transportation mode choices relative to BAU than does the Light Rail scenario, both because of the price elasticity of demand and because it affects the entire public transit system, not just the fraction that is in Tier 1. In 2030 and 2040 the Fare Free Transit scenario causes Tier 2 ridership to be 274% and 272% greater than BAU, respectively, compared to increases relative to BAU of 29% and 48% in the Light Rail scenario. In 2040, public transit person miles by Tier 2 residents per day per capita in the Fare Free Transit scenario are 0.94 miles per day per person greater than BAU, compared to 0.15 miles per day per person greater in the Light Rail scenario (Figure 5-57). Similarly, the increase in 2040 nonmotorized person miles by Tier 2 residents per day per capita (relative to BAU) is about eight times larger in the Fare Free Transit scenario than in the Light Rail scenario (0.0388 vs. 0.0049 miles per day per person). Finally, both the Fare Free Transit and Light Rail scenarios yield 2020-2040 increases in automobile driver person miles by Tier 2 residents per day per capita, but these increases are 0.62 and 0.11 miles per day per capita less than BAU, respectively.

Because automobile driver miles per capita are lower than BAU in the Fare Free Transit scenario, traffic congestion is lower than BAU as well. The amount of time lost to congestion delay per vehicle mile of travel in the Fare Free Transit scenario is 18% and 15% less than BAU in 2030 and 2040, respectively (Figure 5-57). By contrast, because the Light Rail scenario significantly increases population relative to both the BAU and Fare Free Transit scenarios, it results in congestion delay per vehicle mile of travel that is 3.5% and 12% greater than BAU in 2030 and 2040, respectively.

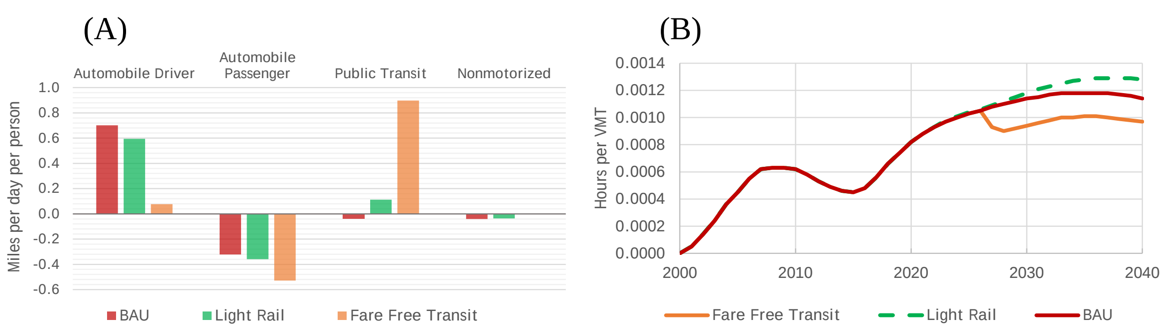


Figure 5-57. (A) Change in Modal Person Miles of Travel by Tier 2 Residents Per Day Per Capita Between 2020 and 2040 for Fare Free Transit Scenario vs. BAU and Light Rail Scenarios and (B) Hours of Congestion Delay Per VMT – Tier 2

Note: In the three scenarios shown here, 2020 modal person miles by Tier 2 residents per day per capita are as follows: Automobile Driver = 18; Automobile Passenger = 6.1; Public Transit = 0.38; Nonmotorized = 0.54. Model changes due to the Fare Free Transit scenario start in 2026.

High Parking Price

This scenario tests the effects of a sudden, steep increase in parking costs. In Tier 1, the scenario assumes an increase of $4.00 per trip (in 2010 USDs) in 2020, in addition to increases caused by endogenous factors in the model, while Tier 2 parking costs are only affected to the extent that Tier 1 is in Tier 2. Otherwise, this scenario's inputs are identical to the Light Rail + Redevelopment scenario. We selected the Light Rail + Redevelopment scenario as a reference because its dense Tier 1 development would produce conditions most likely to result in high demand for parking.

Because higher parking costs discourage driving, the High Parking Price scenario results in a larger 2020-2040 decrease in automobile driver person miles by Tier 1 residents per capita (15%) than the Light Rail + Redevelopment scenario (10%, see Figure 5-58). The model incorporates a tradeoff among transportation modes, so this larger decline in automobile driver miles per capita leads to a smaller decline in automobile passenger miles by Tier 1 residents per capita (11% vs. 18%) and a smaller decline in nonmotorized person miles by Tier 1 residents per capita (6.4% vs. 13%). Because both of these scenarios incorporate the boost to transit ridership that comes from the light rail line and the land use changes associated with it, they also both feature significant increases in public transit person miles by Tier 1 residents per capita, but the increase in the High Parking Price scenario is slightly larger (194% vs. 191%). The reduction in driving, and hence congestion, that results from higher parking prices produces a small increase in GRP (<1% above the Light Rail + Redevelopment scenario in 2040), with corresponding increases in jobs, net migration, and population, in both Tiers.

In the first year of increased parking prices in the High Parking Price scenario (2020), they increase combined transportation and renter costs, relative to the Light Rail + Redevelopment scenario, by 18% and 12% in Tier 1 and Tier 2, respectively (see Figure 5-58 for Tier 1 impacts). During 2020-2040, renter costs increase faster in Tier 1 than Tier 2, so the Tier 1 impact of higher parking costs as a percent of total costs declines over time. As a result, by 2040, the percent difference in combined transport and renter costs relative to the Light Rail + Redevelopment scenario is 13% in both Tiers.

(A) (B)

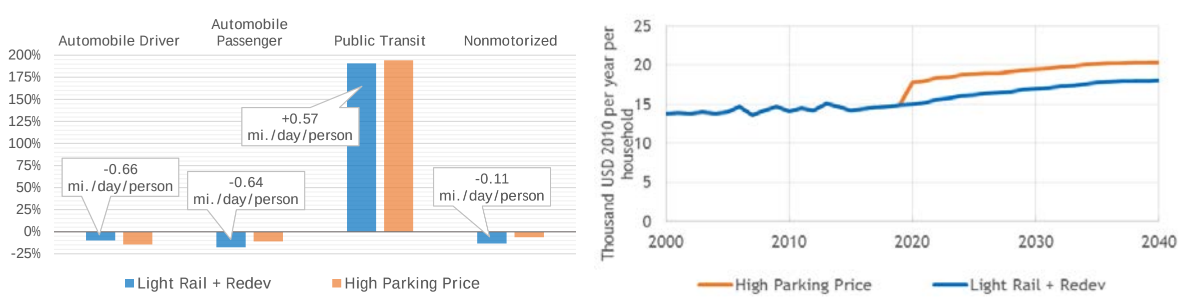


Figure 5-58. (A) Percent Change in Modal Person Miles of Travel by Tier 1 Residents Per Capita Between 2020 and 2040 for High Parking Price Scenario vs. Light Rail + Redevelopment Scenario and (B) Transportation and Renter Costs – Tier 1

Note: Data labels in the bar chart are the numeric change in the model output between 2020 and 2040 for the Light Rail + Redevelopment scenario. Model changes due to the High Parking Price scenario begin in 2020. The line graph is specific to households in multifamily housing.

Sidewalk Building

This scenario tests the effects of doubling the demand for nonmotorized travel facilities (e.g., sidewalks, bike lanes, and paths) per developed acre in 2020. Otherwise, the Sidewalk Building scenario is identical to the BAU scenario. Due to a delay built into the model to account for construction time, the increase in demand for nonmotorized travel facilities does not produce an increase in sidewalks, bike lanes, and paths in the study area until 2022. In both Tiers, by 2026, there are approximately twice as many nonmotorized-travel facility miles in the Sidewalk Building scenario as in the BAU scenario, and they stay within 1% of twice the BAU number of facility miles through 2040 (Figure 5-59).

The primary effect of the Sidewalk Building scenario is an increase in nonmotorized travel, which carries health benefits for residents. When nonmotorized travel facilities are limited, even if a particular origin and destination are close enough together for people to walk or bicycle between them, they may still choose to make the trip by other modes out of concern for their safety, given the risk inherent in traveling by a slow, nonmotorized mode in a transportation corridor that is only designed for fast, motorized travel. Consequently, the doubling of the amount of nonmotorized-travel facility miles in this scenario causes nonmotorized person miles of travel by Tier 2 residents per capita to increase by 26% during 2020-2040, as opposed to decreasing 7.6% under the BAU scenario (Figure 5-59). Since the model assumes that using public transit entails some amount of walking or cycling to and from transit stops, policy actions that increase nonmotorized travel tend to also increase public transit travel, and vice-versa. As a result, in the Sidewalk Building scenario, public transit person miles by Tier 2 residents per capita increase by 10% during 2020-2040, vs. a 10% decrease in the BAU scenario. Finally, as people travel more by walking, cycling, and using public transit, they travel less by automobile. In the Sidewalk Building scenario, automobile driver person miles by Tier 2 residents per capita increase by only 0.98% during 2020-2040, vs. a 3.8% increase in the BAU scenario.

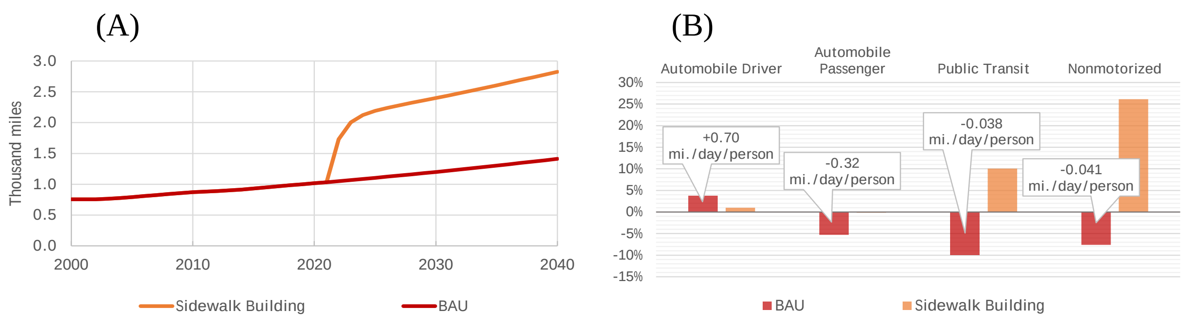


Figure 5-59. (A) Nonmotorized Travel Facilities – Tier 2 and (B) Percent Change in Modal Person Miles of Travel by Tier 2 Residents Per Day Per Capita Between 2020 and 2040 for Sidewalk Building Scenario vs. BAU

Note: Data labels in the bar chart are the numeric change in the model output between 2020 and 2040 for the BAU scenario. Model changes due to the Sidewalk building scenario begin in 2020.

Energy

In Tier 1, energy use is projected to grow by 7% between 2020 and 2040 in the BAU scenario and by 17% and 36% in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-60). In all three scenarios, this increase is driven mainly by increases in passenger vehicle VMT, dwelling units, and nonresidential sq ft. Dwelling units and nonresidential sq ft increase due to population growth and the higher demand for nonresidential sq ft stimulated by the light rail. As noted above, the two light rail scenarios have higher growth in population and GRP per capita, which together lead to increased VMT (higher GRP per capita increases vehicle use because wealthier people are assumed to drive more). These increases are larger than the factors that reduce energy use in the future (improved vehicle fuel efficiency and reduced building energy intensity), leading to the net increase in energy use seen in Figure 5-60A. Despite this increase in total energy use, regional energy intensity (energy use per GRP and energy use per capita) is projected to decrease in both Tiers.

(A) Tier 1 (B) Tier 2

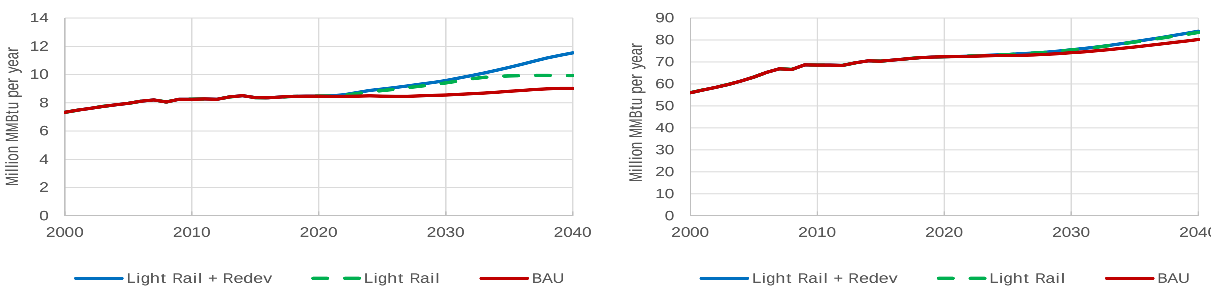


Figure 5-60. Energy Use: Light Rail, Light Rail + Redevelopment Scenarios Compared with BAU

Tier 2 energy use is projected to grow by 11% between 2020 and 2040 in the BAU scenario and by 15% and 16% in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-60). The smaller Tier 2 impact of the Light Rail + Redevelopment scenario is expected, as the model only changes development density in Tier 1 in this scenario. The increase in energy use in Tier 2 is driven by the same factors as in Tier 1 (increases in VMT, population, dwelling units, and nonresidential sq ft, offset by improvements in vehicle fuel efficiency and building energy intensity), though the increases are smaller in proportion to the larger baseline values in Tier 2.

(A) Tier 1 (B) Tier 2

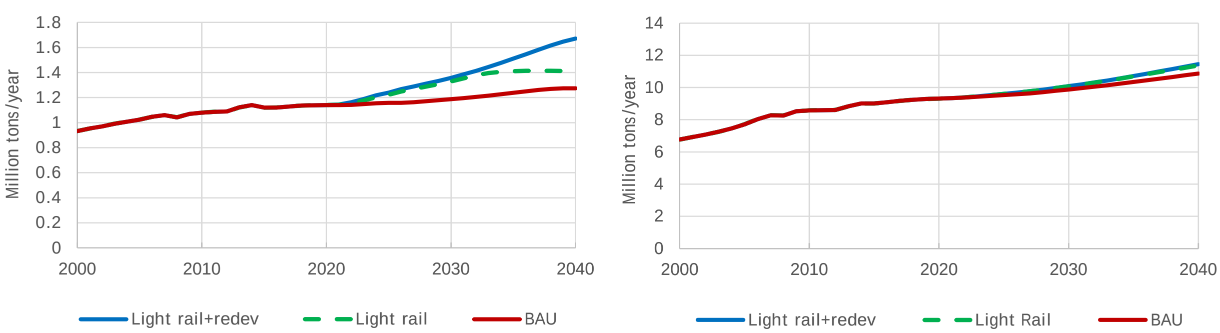


Figure 5-61. CO_2 Emissions: Light Rail, Light Rail + Redevelopment Scenarios Compared with BAU

Between 2020 and 2040, Tier 1 CO_2 emissions increase by 12% in the BAU scenario and by 24% and 47% in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-61). As the figure shows, CO_2 emissions level off around year 2033 in the Light Rail scenario (due to the halt in land development as the Tier 1 cap is reached) but continue to increase in the Light Rail + Redevelopment scenario, reaching 1.7 million tons/year in 2040. Because buildings make up the majority of CO_2 emissions, the scarcity of space for new dwelling units and nonresidential sq ft that occurs in the Light Rail scenario explains why CO_2 emissions plateau and why they continue to increase in the Light Rail + Redevelopment scenario, where this scarcity is less of a factor. In Tier 2, CO_2 emissions increase by 17% between 2020 and 2040 in the BAU scenario and by 22% and 23% in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-61). Because land scarcity is not a factor in any of the scenarios in Tier 2, CO_2 emissions continue to grow through 2040, reaching 11 million tons/year in the Light Rail + Redevelopment scenario.

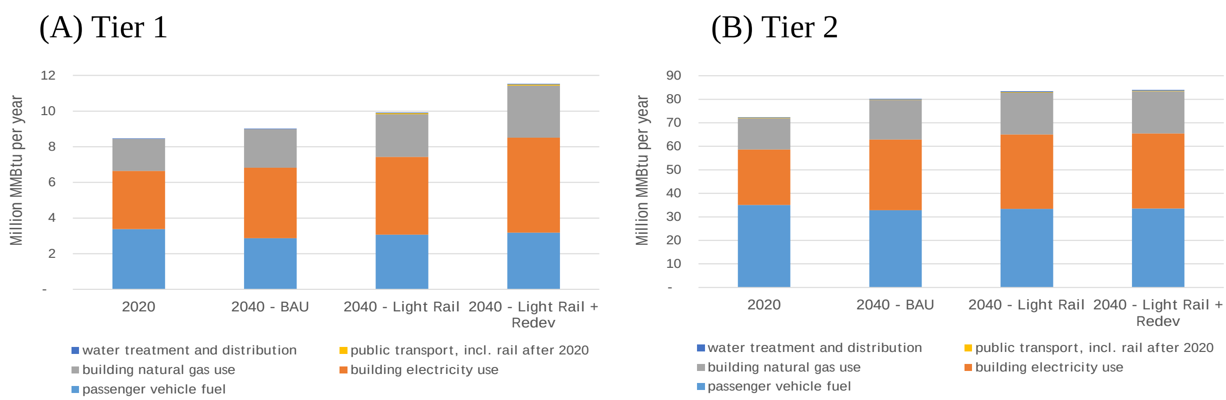


Figure 5-62. Energy Use in 2020 and 2040 Under the Three Main Scenarios

Figure 5-62 shows the distribution of total energy use in 2020 (same for all scenarios) and in 2040 for the BAU and light rail scenarios. As the figure shows, building natural gas, building electricity, and passenger vehicles compose the largest shares of total energy use in all scenarios in both Tiers, with only minor contributions from water treatment and distribution and public transportation (which includes energy use by the light rail after 2020). In Tier 1, passenger vehicles and building electricity are 40% and 39% of 2020 energy use, respectively. Energy consumption by passenger vehicles declines slightly between 2020 and 2040 in all scenarios, due to a projected 50% increase in fuel efficiency (from 18 MPG in 2020 to 27 MPG in 2040). This decline brings vehicle energy use from 3.4 million MMBtu in 2020 to 2.9 million, 3.1 million, and 3.2 million MMBtu in 2040 in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively. Despite decreased building energy use intensity between 2020 and 2040 (by about 7-12%, depending on building type), building electricity use increases between 2020 and 2040, by 21%, 34%, and 63% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively.

Tier 2 consumes about eight times as much energy as Tier 1. As in Tier 1, passenger vehicles and building electricity constitute the largest shares of regional energy use with 48% and 33% of the BAU total in 2020, respectively (Figure 5-62). Despite an increase in VMT between 2020 and 2040, passenger vehicle energy use declines slightly in Tier 2 in the three main scenarios over this period, as it does in Tier 1, due to increased fuel efficiency. Tier 2 passenger vehicles consume 35 million MMBtu in 2020, compared with 33 million, 33 million, and 34 million MMBtu in the 2040 BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively. Building electricity use in Tier 2 grows by 27% between 2020 and 2040 in BAU, and by 34% and 35% in Light Rail and Light Rail + Redevelopment, respectively. The largest difference between the Tiers in terms of energy use is that building energy use increases by about the same amount in both light rail scenarios in Tier 2, whereas the increase in building energy use in Tier 1 is much higher in the Light Rail + Redevelopment scenario than in the Light Rail scenario. As noted above, this difference is due to the fact that the density assumptions in the Light Rail + Redevelopment scenario are felt almost entirely in Tier 1, since land scarcity is modeled as a constraint in Tier 1 but not in Tier 2.

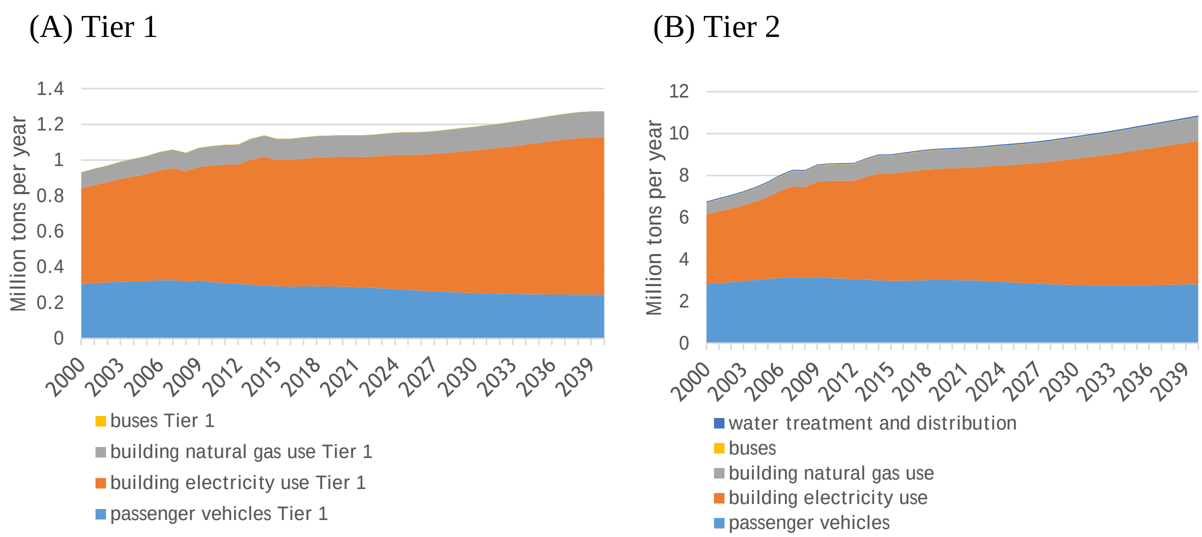


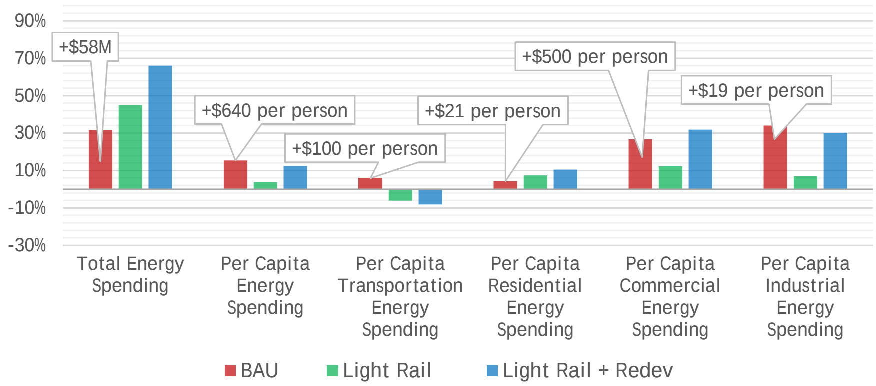
Figure 5-63. CO_2 Emissions Over Time in the BAU Scenario, Color Coded by Source

Note: Colors in this figure match energy budget components in the previous figure.

Figure 5-63 presents the distribution of CO_2 emissions by source over time in the BAU scenario for Tier 1 (Figure 5-63) and Tier 2 (Figure 5-63). In both Tiers, the largest source of CO_2 emissions is building electricity use (colored in orange in Figure 5-61). In Tier 1, building electricity use in the BAU scenario grows from 57% to 69% of total emissions between 2000 and 2040. Building electricity use is a larger share of CO_2 emissions in Tier 1 than in Tier 2, because nonresidential buildings (which tend to have a higher energy intensity than residences) compose a higher percentage of developed land in Tier 1 than in Tier 2 (about 40% vs. about 20%). Due to increases in fuel efficiency, passenger vehicle emissions decline from 33% of total Tier 1 emissions in 2000 to 19% in 2040.

Similar patterns are seen in CO_2 emissions in Tier 2 in the BAU scenario (Figure 5-63), with building electricity use growing from 49% to 63% of total CO_2 emissions between 2000 and 2040. As in Tier 1, CO_2 emissions from passenger vehicles decrease over this same period, from 42% of the total in 2000 to 26% by 2040. Meanwhile, municipal water treatment and distribution accounts for less than 1% and buses account for less than 0.5% of Tier 2 CO_2 emissions. If light rail were added, the electricity used to power the rail line would represent less than 0.5% of Tier 2 CO_2 emissions.

(A) Tier 1



(B) Tier 2

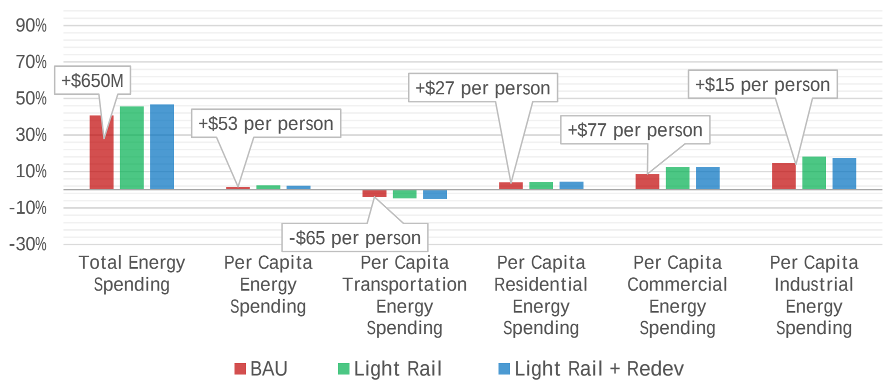
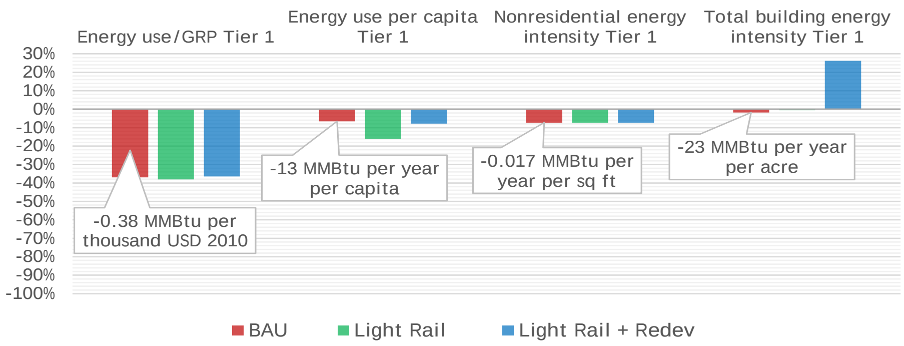


Figure 5-64. Percent Change in Energy Spending Between 2020 and 2040 for Three Main Scenarios

Figure 5-64 summarizes the percent change in several categories of energy spending between 2020 and 2040 in the three main scenarios in Tier 1 (A) and Tier 2 (B). As the figure shows, total energy spending increases over this time period in both Tiers for the three main scenarios. In Tier 1, energy spending increases by 32% ($58M in USD 2010) between 2020 and 2040 in the BAU scenario, and by 45% and 66% in the Light Rail and Light Rail + Redevelopment scenarios, respectively. Overall per capita energy spending in Tier 1 increases in all three scenarios (by 15% in BAU, 4% in Light Rail, and 12% in Light Rail + Redevelopment, respectively), but dividing total energy spending into transportation, residential, commercial, and industrial categories reveals some differences. Transportation energy spending per capita decreases in the two light rail scenarios, where population increases faster than vehicle energy spending, but increases in BAU, where the reverse is true. Per capita energy spending in residential, commercial, and industrial buildings increases in all three scenarios, but the Light Rail scenario has the lowest per capita commercial and industrial energy spending due the land scarcity constraint on development of nonresidential sq ft around 2033.

Tier 2 energy spending follows many of the patterns of Tier 1, although differences between the three main scenarios are proportionately smaller. Tier 2 energy spending increases between 2020 and 2040 by 41% ($650M in USD 2010) in the BAU scenario, and by 46% and 47% in the Light Rail and Light Rail + Redevelopment scenarios, respectively. Overall per capita energy spending increases by 1.6%, 2.3%, and 2.2% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively. Tier 2 transportation energy spending per capita declines in all three scenarios, but by more in the Light Rail and Light Rail + Redevelopment scenarios (-4.7% and -5.0%, respectively) than in the BAU scenario (-3.8%). This decline is due to increases in vehicle fuel efficiency and decreases in VMT per capita, with larger VMT per capita decreases in the light rail scenarios than in the BAU scenario. In all three scenarios, per capita energy spending in residential, commercial, and industrial buildings increases due to increased development and increased electricity and natural gas prices, despite a decrease in building energy intensity (see Figure 5-65 below).

(A) Tier 1



(B) Tier 2

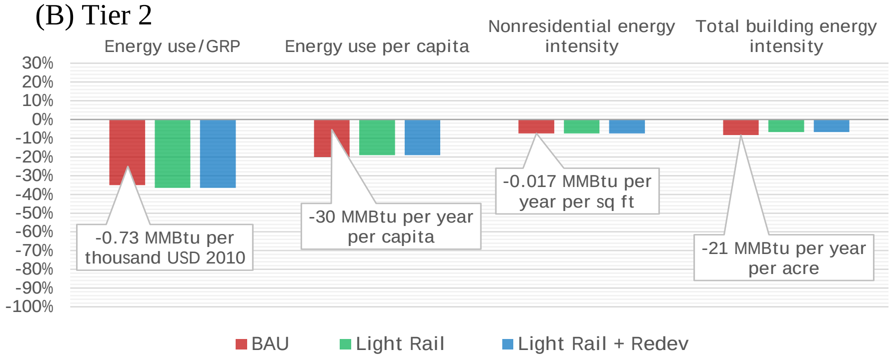


Figure 5-65. Percent Change in Energy Intensity Between 2020 and 2040 for Three Main Scenarios

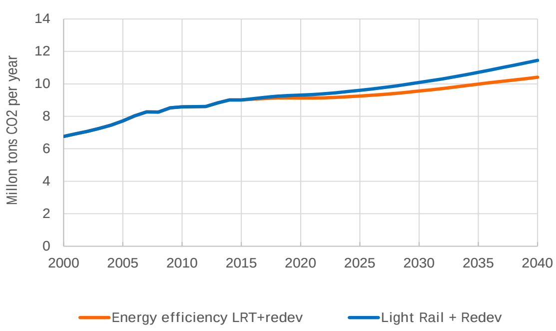
Figure 5-65 presents percent changes in four measures of energy intensity between 2020 and 2040 in both Tiers for the three main scenarios, including overall energy use per GRP, energy use per capita, nonresidential energy intensity (energy use per year per sq ft), and total building energy intensity (energy use per year per developed acre). In almost every measure, energy intensity decreases in both Tiers over this time period for the three main scenarios. This reflects assumptions in the model that technological improvements will improve efficiency of energy use in buildings and vehicles. Energy use per GRP decreases by about a third in both Tiers across all three scenarios, meaning that the economy becomes significantly more energy efficient. Energy use per capita declines in both Tiers in all three scenarios. In Tier 1, energy use per capita sees the largest drop (-16%) in the Light Rail scenario, due to continued population growth and a plateauing of building energy use around 2033 as a result of land scarcity. In Tier 2, energy use per capita declines by about 20% in all three scenarios, since land scarcity is less of a factor in this Tier. In Tier 1, total building energy intensity (MMBtu per year per acre) declines by about 1-2% in the BAU and Light Rail scenarios, but increases by 26% in the Light Rail + Redevelopment scenario. In that scenario, higher density development causes an increase in building energy use without any corresponding increase in developed land, leading to an increase in energy intensity (per developed acre) that dominates over the decline in energy intensity caused by energy efficiency improvements.

Energy Efficiency

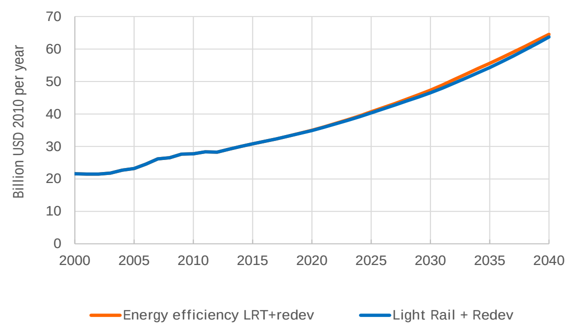
In this scenario, beginning in 2015, energy intensity of residential, commercial, and industrial buildings drops linearly to a value 10% lower than the Light Rail + Redevelopment projection by 2040. At the same time, passenger vehicle MPG is multiplied by a factor that increases linearly to reach a value 10% higher than the Light Rail + Redevelopment projection by 2040. This scenario tests the effects of energy efficiency on overall energy use and CO_2 emissions, as well as on economic effects which themselves indirectly affect energy consumption.

The Energy Efficiency scenario causes CO_2 emissions from buildings and transportation in Tier 2 to drop by 9.1% relative to the Light Rail + Redevelopment scenario by 2040 (Figure 5-66). This decrease in energy spending leads to increased economic growth (see the Energy→Economy→Land Use→Energy loop in Chapter 3), causing GRP to increase by 1.3% by 2040 (Figure 5-66). The same feedback loop that connects energy spending to GRP also has a balancing effect, however, as GRP growth leads to increased development of nonresidential sq ft (Figure 5-66), which causes energy spending to rise again. These feedback effects are small compared to the overall effect on energy use, as the increase in nonresidential sq ft between 2020 and 2040 is only 0.8% higher in the Energy Efficiency scenario (at 51.5%) than in the Light Rail + Redevelopment scenario (at 50.7%).

(A)



(B)



(C)

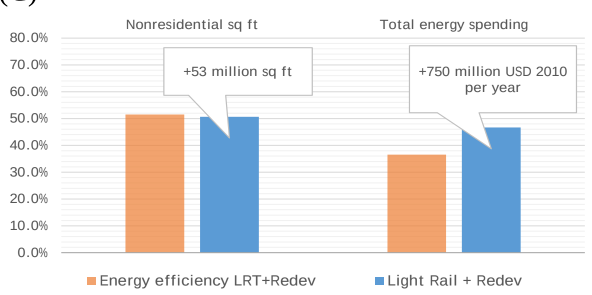


Figure 5-66. (A) Tier 2 CO_2 Emissions, (B) Tier 2 GRP, and (C) Percent Change between 2020 and 2040 (Tier 2): Light Rail + Redevelopment Scenario with Energy Efficiency

Higher LRT Effect on Public Transit Ridership

Estimates of future light rail usage are highly uncertain, but these estimates play an important role in the D-O LRP model and affect energy variables. In two scenarios, beginning with rail operation in 2026, the effect of light rail on public transit person miles per year is increased by 10% or by 100% (doubled) compared to its value in the Light Rail + Redevelopment scenario. Whereas the Light Rail + Redevelopment scenario sees 45 million person miles of public transit use in 2040, the 10% increase in ridership leads to 50 million person miles of public transit use, and the 100% increase leads to 90 million person miles in that same year (Figure 5-67). These increases in public transit usage due to the light rail are assumed to occur entirely in Tier 1.

In these scenarios, the increase in Tier 1 VMT between 2020 and 2040 is smaller than in the Light Rail + Redevelopment scenario, with increases of 36.6% and 32.3% in the 10% ridership increase and 100% ridership increase scenarios, respectively, compared to 37.1% in the reference scenario (Figure 5-67). Slower VMT growth leads to slower growth in congestion, which increases by 8.5% and 5.0% in the two high-ridership scenarios, compared to 8.8% in the reference scenario. Despite the smaller increase in VMT, these scenarios show little difference in total Tier 1 CO_2 emissions, which increase by only 0.3% less in the doubled-ridership scenario than the Light Rail + Redevelopment scenario. Although doubling the LRT ridership effect on public transit substantially reduces VMT, even higher LRT ridership levels would be needed to reduce CO_2 emissions by 1% or more.

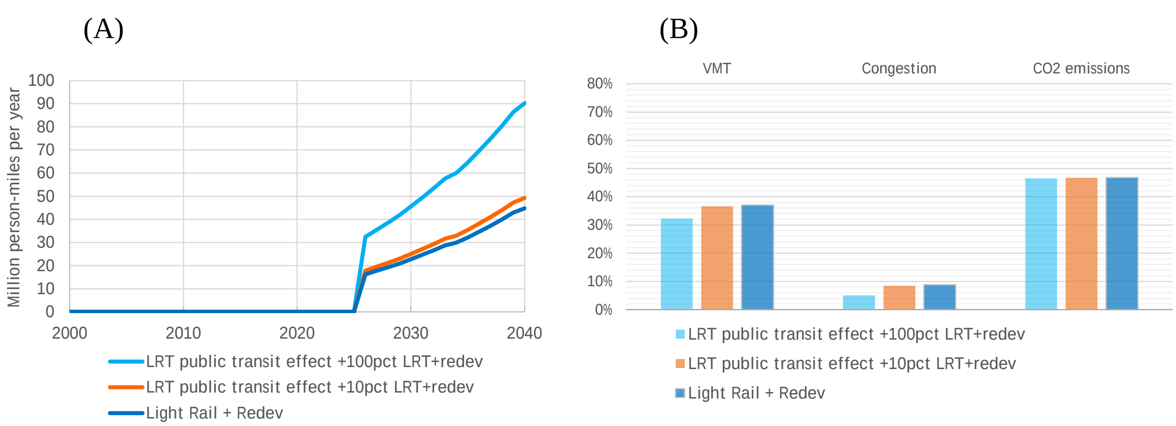


Figure 5-67. (A) Light Rail Effect on Public Transit Usage – Tier 2 and (B) Energy and Transportation Indicators – Tier 1: Light Rail + Redevelopment With Higher Light Rail Effect on Public Transit Ridership

Clean Power Plan

This scenario approximates the Clean Power Plan goal for North Carolina (US EPA 2015c), which includes technology change in (1) fossil fuel-fired steam plants and (2) natural gas combined cycle plants. To represent these changes, this scenario decreases the electricity emissions factor linearly between 2022 and 2030 to reach 77% of its level in the Light Rail + Redevelopment scenario. This percentage change results in a drop from 1,560 lb CO_2 per MWh in 2022 to 1,200 lb CO_2 per MWh in 2030, after which it remains constant. As a result, CO_2 emissions from buildings and transportation drop by 7.7% in Tier 2 between 2022 and 2030, then increase between 2030 and 2040 due to economic and population growth (Figure 5-68A, orange line). Without any further reductions to the electricity emissions factor between 2030 and 2040, CO_2 emissions reach 9.7 million tons per year, slightly above the 2022 emissions rate but still 15% below the Light Rail + Redevelopment emissions rate in 2040.

In Tier 1, the Clean Power Plan would decrease CO_2 emissions by 1.7% between 2022 and 2030 (Figure 5-68B, orange line). This lesser decline relative to Tier 2 is due to the steeper growth in emissions after 2020 in the Light Rail + Redevelopment scenario in Tier 1. As in Tier 1, CO_2 emissions increase between 2030 and 2040 due to economic and population growth, reaching 1.4 million tons per year, a value 16% below the Light Rail + Redevelopment emissions rate.

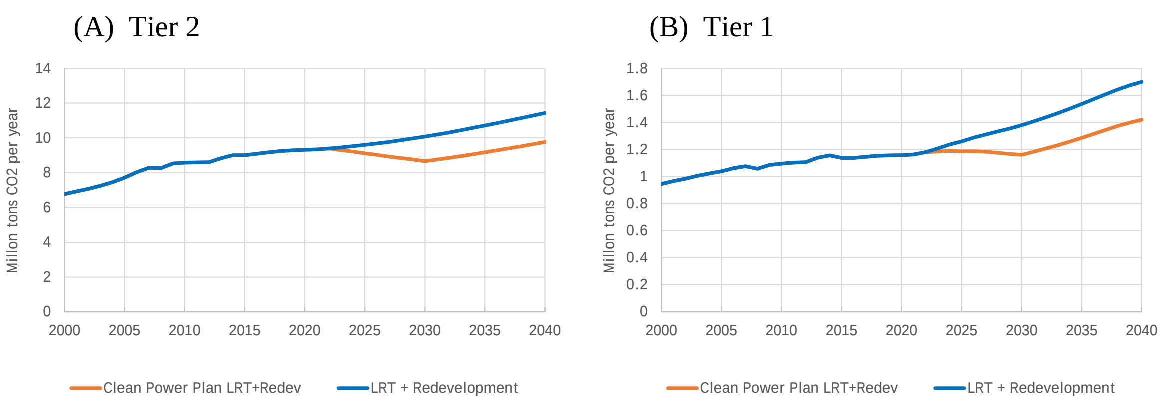
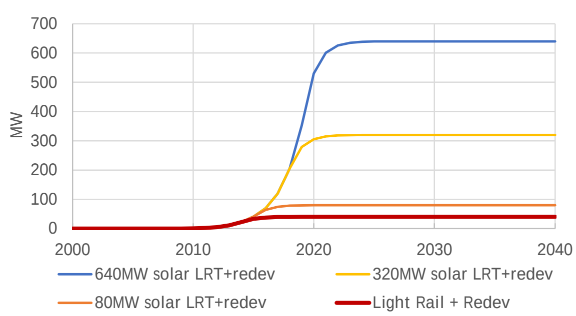


Figure 5-68. CO_2 Emissions: Light Rail + Redevelopment Scenario With and Without Clean Power Plan

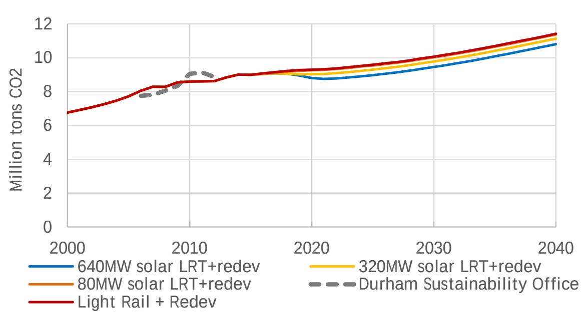
Increased Solar Capacity

In these scenarios, desired solar capacity is increased from 40 MW to 80, 320, and 640 MW, such that solar capacity reaches a level 2, 8, and 16 times as high as in the Light Rail + Redevelopment scenario by 2022, at which point it remains constant. This scenario is meant to examine the effects of rapid growth in solar capacity on CO_2 emissions (continuing current trends where solar capacity has roughly doubled annually between 2010 and 2014). Increasing solar capacity 16-fold (blue line in Figure 5-69A) results in CO_2 emissions from buildings and transportation that are 5.4% lower than the Light Rail + Redevelopment scenario by 2040 (blue line in Figure 5-69B). Assuming a solar capacity factor of 0.15 for North Carolina (Kaplan and Ouzts 2009) and 640 MW desired solar capacity, the 640-MW solar scenario results in solar meeting almost 12% of building electricity demand by 2022, dropping to 9% by 2040 due to growth in building sq ft and overall building electricity use (Figure 5-69C). Because solar represents a fraction of the Tier 2 energy mix (about 0.8% of total building electricity use in 2015) it can begin reducing regional CO_2 emissions more than a few percent if solar capacity grows about tenfold.

(A)



(B)



(C)

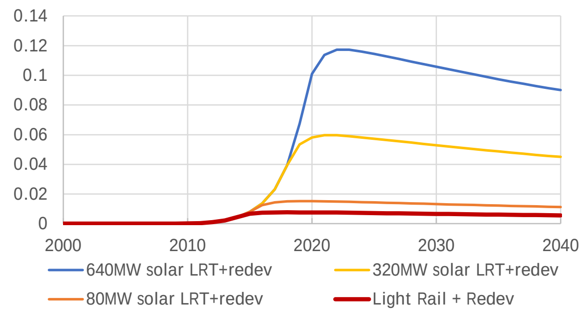


Figure 5-69. (A) Solar Capacity, (B) Annual CO_2 Emissions, and (C) Solar as a Fraction of Building Electricity Use: Light Rail + Redevelopment Scenario Compared With Increased Solar Capacity Scenarios in Tier 2

Economy

The model outputs in the economy sector illustrate the importance of redevelopment in order to fully realize the direct and indirect benefits of the light rail in the station areas and the DCHC MPO region as a whole.[27] The light rail itself attracts economic activity that has cascading impacts throughout the region, but the ability of people to reap the economic benefits of the light rail in Tier 1 is limited by the amount of space in this area. In order for economic growth in Tier 1 to continue, high-density redevelopment must therefore occur in this area. In the Light Rail + Redevelopment scenario, the economic benefits of redevelopment in Tier 1 are not felt in Tier 2 during the time frame of our model because of the current assumption that an increase in density in Tier 1 leads to a decrease in density in the area in Tier 2 that is outside of Tier 1 (a.k.a. “Tier 2 donut”). We ran the “Higher Tier 2 Density” scenario to explore the impacts of changing this assumption.

Figure 5-70. Change in Overall Economic Growth Indicators between 2020 and 2040

[27] Figures in the economy sector results section present model outputs of the main economic indicators in the D-O LRP SD Model between 2020 and 2040, with 2020 being the initial year that model outputs for the three main scenarios begin to diverge. The majority of the figures presented are bar graphs showing either the absolute or percent change (relative to 2020 values) in model outputs between 2020 and 2040 for the three main scenarios.

Figure 5-70A-D shows the absolute and percent change between 2020 and 2040 of four economic growth indicators for Tier 1 and Tier 2. The increase in demand for commercial sq ft (nonresidential sq ft that is retail, office, or service, but not industrial) that occurs in Tier 1 under the Light Rail scenario is the primary driver of economic growth in that Tier between 2020 and 2040. Under the Light Rail + Redevelopment scenario, the additional nonresidential sq ft added to Tier 1 due to high-density redevelopment compounds this economic growth. Because nonresidential sq ft is directly linked to gross operating surplus (GOS), Tier 1 GOS increases by 140% under the Light Rail + Redevelopment scenario (Figure 5-70B) compared to a 90% increase in the Light Rail scenario and an 80% increase in the BAU scenario. This increase in the GOS in Tier 1 leads to an increase in GRP and total retail consumption, which lead to an increase in employment, total earnings, and finally an additional increase in GRP (due to a reinforcing feedback loop within the economy sector). These increases can be seen in Figure 5-70, where all four economic growth variables show larger increases in the Light Rail + Redevelopment scenario than in the Light Rail scenario, which in turn shows larger increases than in the BAU scenario.

Because redevelopment does not occur in Tier 2, the difference between the Light Rail and Light Rail + Redevelopment scenarios in the four overall economic growth indicators in Tier 2 (shown in Figure 5-70) is not as pronounced as in Tier 1. In Tier 2, the difference between the BAU and light rail scenarios in the four indicators is mostly attributable to the Tier 1 changes mentioned above. The slight difference between the Light Rail + Redevelopment scenario and Light Rail scenario in overall economic growth indicators in Tier 2 is due to a mechanism in the model that links the effect of the light rail on demand for nonresidential sq ft in Tier 1 to Tier 2. The model endogenously calculates the ratio of nonresidential sq ft in Tier 1 to nonresidential sq ft in Tier 2 (varying between about 17% and 21%), so an increase in nonresidential development in Tier 1 leads to a higher Tier 1/Tier 2 nonresidential sq ft ratio. As a result, this higher ratio increases the demand for nonresidential sq ft in Tier 2 under the light rail scenarios by the same amount as in Tier 1. The increase is magnified over time due to feedback loops, leading to a slightly higher increase in Tier 2 nonresidential sq ft than in Tier 1. We used this model structure on the rationale that 1) Tier 2 includes the changes in Tier 1, and 2) additional new development is expected to take place in the portion of Tier 2 just outside of Tier 1 in response to the light rail, though to a lesser extent than development in Tier 1.

(A) Tier 1 (B) Tier 2

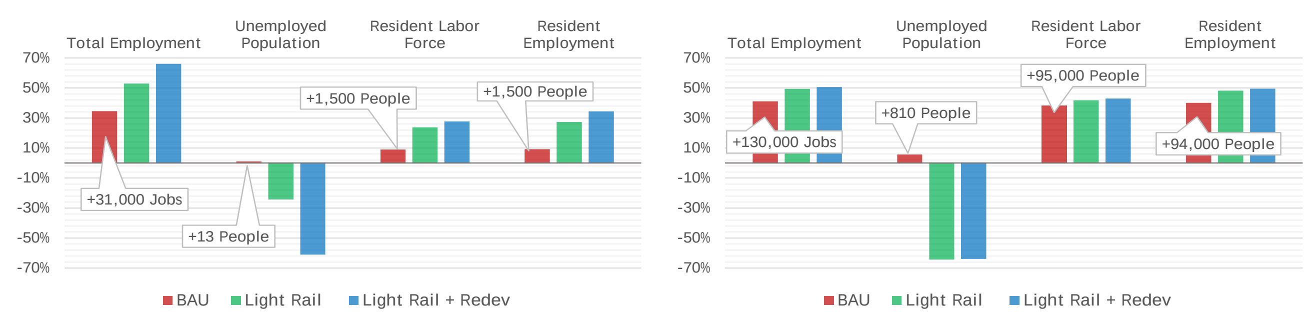


Figure 5-71. Percent Change in Economy Sector Employment Indicators between 2020 and 2040 for Three Main Scenarios

Total employment in Tier 1 (Figure 5-71) increases by nearly twice as much between 2020 and 2040 under the Light Rail + Redevelopment scenario as in the BAU scenario, with an increase in jobs of 66% and 35%, respectively. The increase in the amount and density of nonresidential sq ft added to Tier 1 leads to increased employment creation, immigration, and residential development. In Tier 2, the largest increase in total employment (Figure 5-71) also happens under the Light Rail + Redevelopment scenario, but the increase is due more to economic growth caused by the Light Rail than to redevelopment, since the redevelopment that occurs in Tier 1 in the Light Rail + Redevelopment scenario essentially relocates the nonresidential development that took place in the Tier 2 donut in the Light Rail scenario to Tier 1. In other words, the overall employment growth potential remains the same in Tier 2 for both scenarios but Tier 1 becomes more attractive than the Tier 2 donut in the Light Rail scenario.

For both Tier 1 and Tier 2, the total unemployed population (Figure 5-72) and the unemployment rate (Figure 5-72) are reduced significantly in both the Light Rail and Light Rail + Redevelopment scenarios due to resident employment increasing faster than the resident labor force (Figure 5-72). This is due in part to the way the model calculates resident labor force by using a fixed share of the resident population in the labor force. This share is based on historical data and is held constant between 2020 and 2040 at 52% for Tier 2 and 42% for Tier 1. By assuming that the percent of the population in the labor force remains constant, the model does not allow for the possibility that more people might enter the labor force if additional jobs are created, so it is possible that it overestimates the decline in unemployment associated with a given increase in economic development. The decrease in the unemployment rate in Tier 1 under the light rail scenarios causes an increase in net migration to Tier 1, which causes the population in Tier 1 to grow significantly faster than the BAU under both scenarios (Figure 5-73). It is difficult for the model to predict unemployment in Tier 1, because its small geographic area makes it less certain how many of the new residents to Tier 1 would both live and work there, but the larger size of Tier 2 makes it much more likely that the percent of the residential population in the labor force will remain consistent with historical trends.

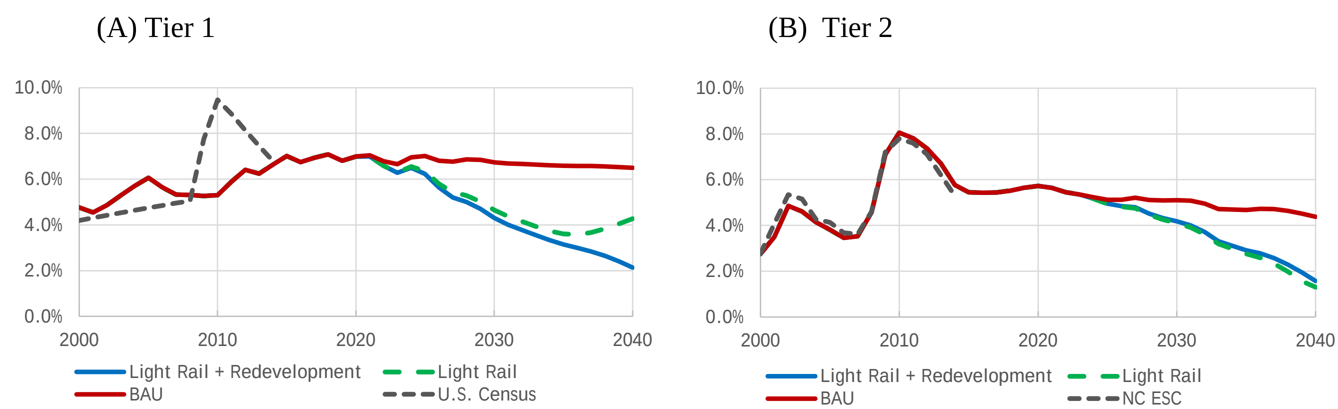


Figure 5-72. Time Series of Unemployment Rate over the Entire Study Period (2000-2040)

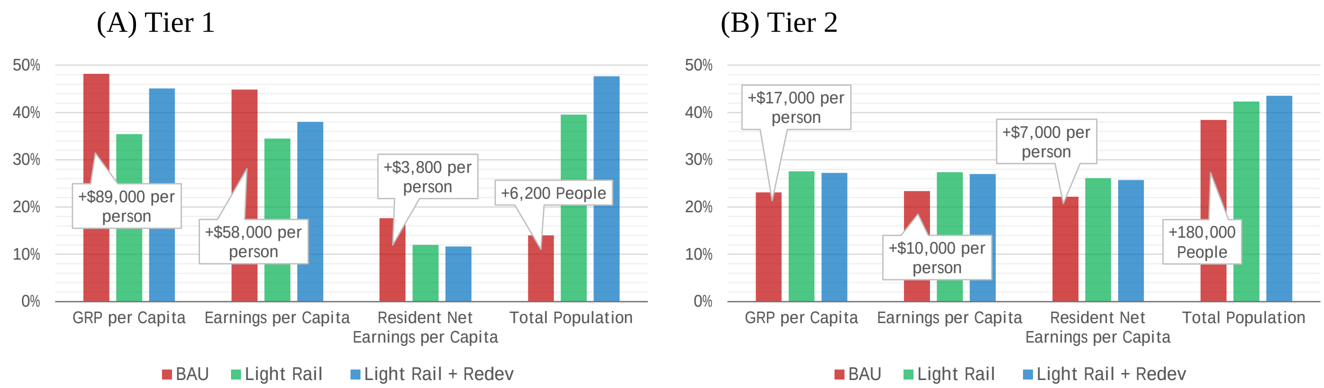


Figure 5-73. Percent Change in Per Capita Economic Growth Indicators between 2020 and 2040 for Three Main Scenarios

Just as the unemployment rate in Tier 1 is harder to predict than in Tier 2, per capita economic growth variables, shown in Figure 5-73, carry a great deal of uncertainty in Tier 1. In Tier 1, GRP per capita, earnings per capita, and resident per capita net earnings are higher in the BAU scenario than in the Light Rail and Light Rail + Redevelopment scenarios because employment grows much faster than population in the BAU scenario.[28] In the Light Rail scenario, the rail makes Tier 1 more attractive for businesses and families, but without redevelopment to higher densities, nonresidential sq ft is capped, so population continues to grow, but businesses do not, leading to lower growth for GRP and earnings per capita between 2020 and 2040. In the Light Rail + Redevelopment scenario, redevelopment allows nonresidential sq ft to increase in Tier 1 relative to the Light Rail and BAU scenarios, but this increase is still slower than the growth in population caused by the light rail, leading to per capita economic growth that is lower than in the BAU scenario. Resident per capita net earnings growth in Tier 1 is also highest in the BAU scenario because this variable only represents the earnings of residents that are also working in Tier 1, and the model assumes that the family members of new workers migrating to Tier 1 would likely work outside of Tier 1, causing their income to be excluded from this variable. Another factor that contributes to the lower per capita growth in earnings in the light rail scenarios is that the model assumes that average earnings per job by category is not affected by economic growth. Therefore, even though Tier 1 becomes more economically attractive and total employment increases under the light rail scenarios, the average earnings per job in each employment category, which are exogenous lookup tables with data and projections from Woods & Poole Economics Inc. (Copyright 2014), remain the same for all three main scenarios.

In Tier 2, the per capita economic growth indicators, shown in Figure 5-73, demonstrate the increased economic potential that the light rail scenarios bring to individuals living in the DCHC MPO region. Relative to the BAU scenario, GRP, earnings, and resident net earnings per capita increase at a higher rate under both light rail scenarios in Tier 2, though the Light Rail scenario increases slightly more than

[28] BAU scenario employment growth in Tier 1 was calibrated to closely match projections to 2040 from the TRM v5 SE data, which was based off of the "preferred growth" land use scenario that included additional employment in the light rail station areas proposed under the 2040 MTP. These projections were the only employment projections available to us by TAZ at the time that version 1.0 of the D-O LRP SD Model was created, but we subsequently received employment growth projections to 2040 by TAZ under a "trend development" scenario, which more closely matches our BAU scenario, and we will be using them to re-calibrate the BAU scenario in the 2.0 version of our model.

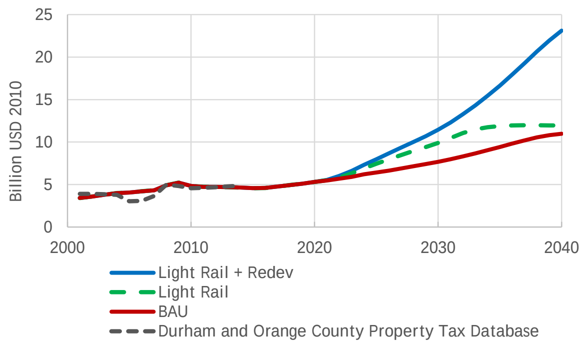
the Light Rail + Redevelopment scenario because redevelopment causes population to increase more than employment in Tier 2.

Property Tax Revenues

Real property (which includes land and buildings) has been rising in value steadily over the past 15 years for both Tiers, as shown in Figure 5-74. The D-O LRP SD Model was calibrated in the BAU scenario to match this historical rise in real property values, which includes both residential (single-family and multifamily) and nonresidential (not tax exempt) properties.[29] In 2022, real property values diverge in the light rail scenarios in anticipation of completion of the light rail and (in the Light Rail + Redevelopment scenario) high-density redevelopment, as shown in Figure 5-74, with significant increases in property values relative to the BAU scenario.

Figure 5-75 shows the absolute change in each category of real property value between 2020 and 2040 for the three main scenarios in Tier 1 and Tier 2. As the figure shows, the largest increase in property values in Tier 1 occurs in nonresidential property value, with a $16 billion increase (2010 dollars) in the Light Rail + Redevelopment scenario. In both Tiers, the greatest increase in each property value category occur in the Light Rail + Redevelopment scenario.

(A) Tier 1



(B) Tier 2

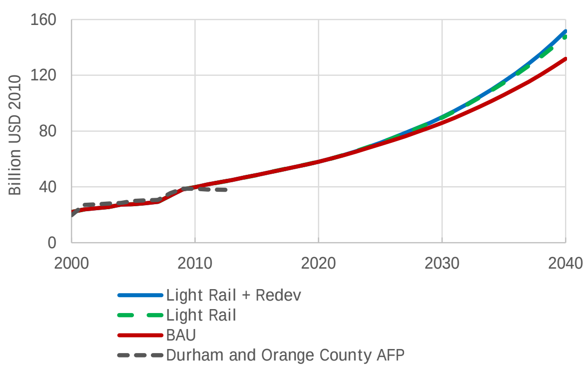
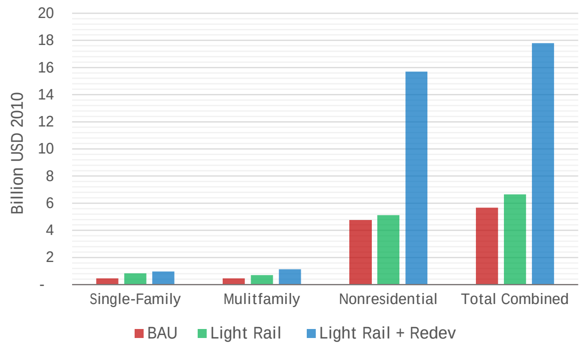


Figure 5-74. Time Series between 2000 and 2040 of Total Real Property Value: Model Scenario Outputs and Historical Data

[29] For a detailed explanation of the factors influencing property values in the model, see the Land Use Sector Overview in Chapter 3.

(A) Tier 1



(B) Tier 2

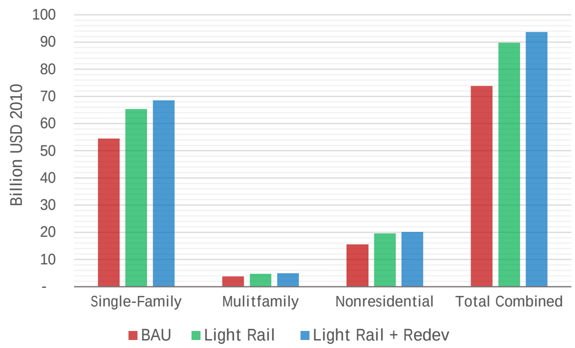


Figure 5-75. Absolute Change in Real Property Value by Type between 2020 and 2040 for Three Main Scenarios

The increase in real property values in both Tiers leads to significant increases in property tax revenues collected between 2020 and 2040 for both city (City of Durham and Town of Chapel Hill only) and county (Durham and Orange County) governments, as shown in Figure 5-76. In Tier 2, this results in a cumulative increase in combined (city and county) property taxes collected between 2020 and 2040 of $1.1 Billion and $1.2 Billion (2010 dollars) for the Light Rail and Light Rail + Redevelopment scenarios, respectively. In Tier 1, these totals are $410 Million and $1.1 Billion (2010 dollars), respectively. Per acre of developed land, an additional $28,000 per year (2010 dollars) in property tax revenues are collected in Tier 1 in 2040 under the Light Rail + Redevelopment scenario, an increase of 225% over 2020 levels (Figure 5-76).

(A) Tier 1 (B) Tier 2

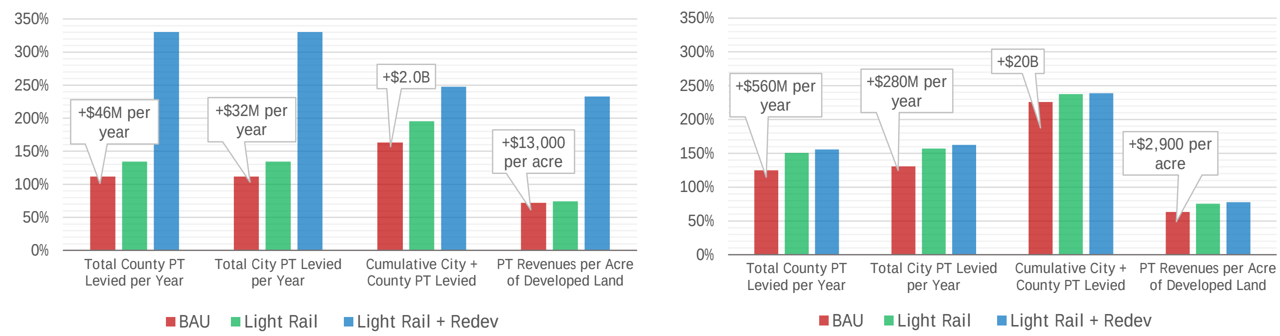


Figure 5-76. Percent Change in Property Tax (PT) Revenues between 2020 and 2040 for Three Main Scenarios

D-O LRP Budget

Figure 5-77 presents the model-estimated changes in D-O LRP revenues between 2020 and 2040, disaggregated by revenue source. Vehicle registration fees (set at $10 per vehicle) are projected to decrease during that period due to inflation rising faster than the vehicle stock. However, increases in public transit fares and transit sales taxes (driven by increases in total retail consumption in both light rail scenarios) lead to a net increase in combined D-O LRP revenues collected per year that is larger in both light rail scenarios (81% and 82%, respectively) than in the BAU scenario (71%) during that same period. Rental car tax revenues aren’t shown in Figure 5-77 because they are the same for all three main scenarios.

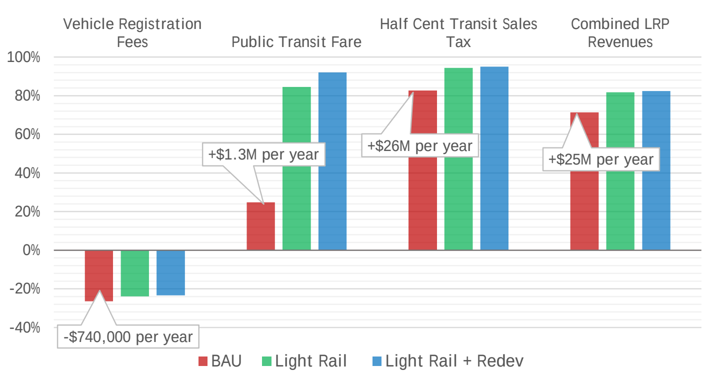


Figure 5-77. Percent Change in D-O LRP Revenue Sources between 2020 AND 2040 for Three Main Scenarios

Figure 5-78 compares D-O LRP SD Model outputs for the three main scenarios with two local projections for the cumulative D-O LRP revenues collected between 2013 and 2040 in nominal or year-of-expenditure dollars (not inflation-adjusted). The “MIN” projection is from the Durham and Orange County bus and rail investment plans and assumes an annual growth rate in the half cent sales tax revenues collected for transit services of 3.0% in Durham County and 3.5% in Orange County (DCHC MPO et al. 2011, Triangle Transit et al. 2012). The “MAX” projection assumes annual growth rates of 4.65% in Durham County and 4.4% in Orange County (CAMPO and DCHC MPO 2013). As the figure shows, all three main scenarios for the D-O LRP SD Model project cumulative D-O LRP revenues that far exceed local projections, with the cumulative divergence exceeding $1.2 Billion by 2040. This difference is because the local projections assume much lower annual growth rates in retail sales than the D-O LRP Model, which is calibrated in the BAU scenario to closely match retail sales projections from Woods & Poole Economics Inc. (Copyright 2014).[30]

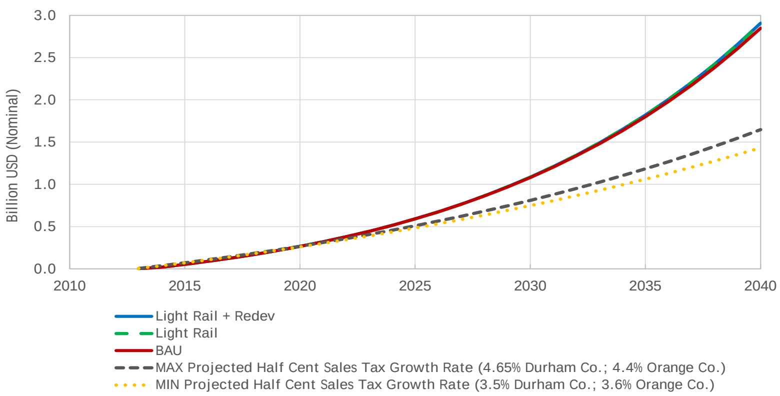
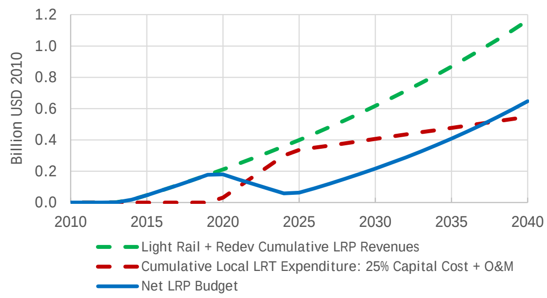


Figure 5-78. Cumulative Nominal D-O LRP Revenues between 2010 and 2040, Three Main Model Scenarios vs. Local Projections

Figure 5-79 presents model estimates for two D-O LRP budget scenarios. The first scenario (shown in Figure 5-79) assumes that 25% of the total capital cost to build the light rail will be paid for by local revenue sources, while the second scenario (shown in Figure 5-79) assumes that 50% of the capital costs will be paid for locally. Both scenarios assume that 100% of the light rail's operations and maintenance (O&M) costs will be paid for locally. The reason for this comparison is to show how the D-O LRP budget would be affected if the State of NC did not cover their expected share of the light rail capital cost (25%). The figures show the net D-O LRP budget (blue solid line) in each scenario, calculated by subtracting the cumulative local expenditure for the light rail (capital + O&M, red dotted line) from the cumulative D-O LRP revenues collected in the Light Rail + Redevelopment scenario (green dotted line). In the second scenario, the budget becomes negative between 2022 and 2033, an indicator that additional revenues or funding sources would be necessary if local funding sources were responsible for 50% of the light rail's capital costs.

[30] Woods & Poole does not guarantee the accuracy of these data. The use of their data and the conclusions drawn from it are solely the responsibility of the US EPA.

D-O LRP Budget with
Capital Cost = 25% Local



(A) D-O LRP Budget with
Capital Cost = 50% Local

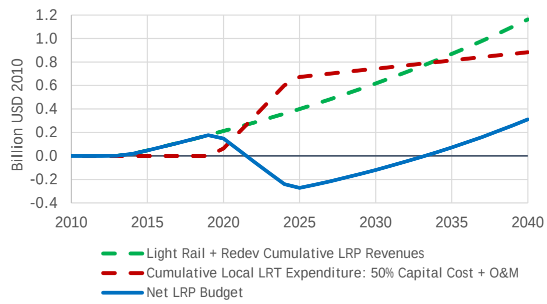


Figure 5-79. D-O LRP Revenues, LRT Costs, and Net Budget between 2010 and 2040.

Higher Tier 2 Density Scenario

In this scenario, which is run on top of the Light Rail + Redevelopment scenario, density in Tier 2 increases starting in 2020 (when redevelopment begins in Tier 1), reaching a level 6.5% higher than the reference scenario by 2040 (Figure 5-80A). This causes an increase in nonresidential sq ft approximately equal to the increase in nonresidential sq ft caused by redevelopment in Tier 1. In this scenario, growth in the Tier 2 economy exceeds the growth caused by the light rail, with all four economic indicators in Figure 5-80B increasing more between 2020 and 2040 than in the reference scenario, though two of these indicators (earnings per capita and resident per capita net earnings) increase at the same rate in this scenario as in the Light Rail scenario.

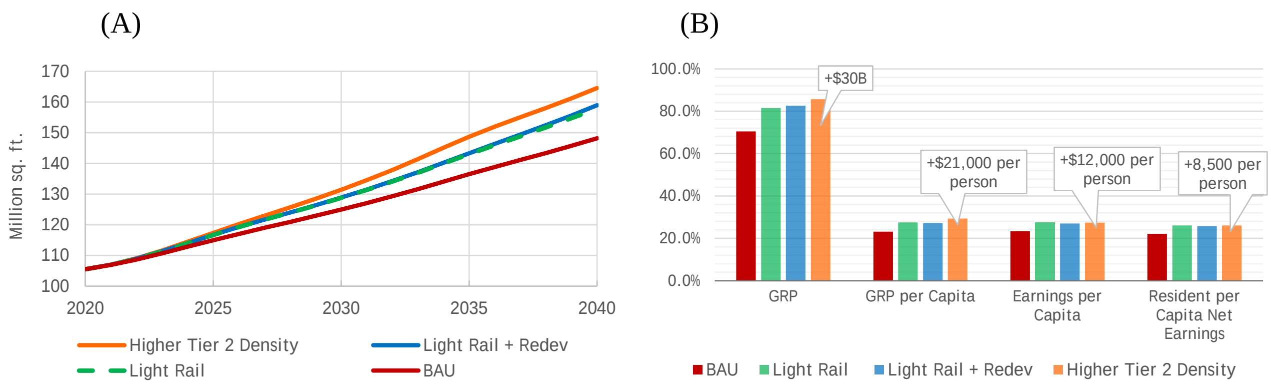


Figure 5-80. (A) Total Nonresidential Sq. Ft. – Tier 2 and (B) Economic Indicators - Tier 2

Higher Rent for Nonresidential Land Scenario

In this scenario, run on top of the Light Rail + Redevelopment scenario, we decrease gross operating surplus (GOS) per sq ft by $5 each year from 2025 to 2040 to simulate the economic consequences of higher property values leading to higher rent that is not being offset by increases in profits. This reduction in GOS per sq ft has profound impacts on the economy, reducing the overall GOS per year to levels below BAU (Figure 5-81), essentially offsetting all of the economic gains from the light rail and redevelopment. Between 2020 and 2040, the Higher Rent scenario GRP per year increases by only 62% compared to 83% in the Light Rail + Redevelopment scenario, and the smaller increase in employment leads to 50,000 fewer jobs in 2040.

(A) (B)

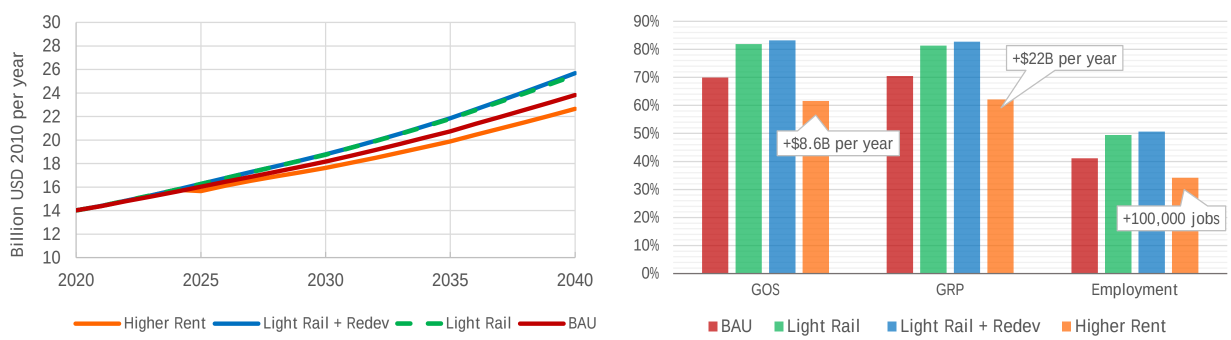


Figure 5-81. (A) Gross Operating Surplus Tier 2 and (B) Change (%) in Economic indicators – Higher Rent Compared to Three Main Scenarios

Equity

Though the two main scenarios do not directly affect the equity sector, the changes they produce lead to large indirect impacts, partially due to the balancing feedback loop that connects the economy, equity, and transportation sectors (see Chapter 3). Through this feedback loop, a decline in the unemployment rate reduces the percent of the population in poverty. A reduction in the overall number of households in poverty reduces the number of zero-car households (a proxy for transit-dependent households), which in turn increases VMT and congestion. Increased congestion affects the economy sector by reducing productivity, grp, and employment, completing the loop by increasing unemployment. Under both light rail scenarios, unemployment rates decline significantly, leading to declines in the percent of the population in poverty in Tier 1 between 2020 and 2040 of 8% in the Light Rail scenario and 18% in the Light Rail + Redevelopment scenario (Figure 5-82). In Tier 2, the percent of the population in poverty declines by 29% between 2020 and 2040 in both light rail scenarios (Figure 5-82). The impact on the percent of households in zero-car households is similar, with a 30% drop in Tier 2 under both light rail scenarios, and a 26% and 27% decline in Tier 1 between 2020 to 2040 under the Light Rail and Light Rail + Redevelopment scenarios, respectively.

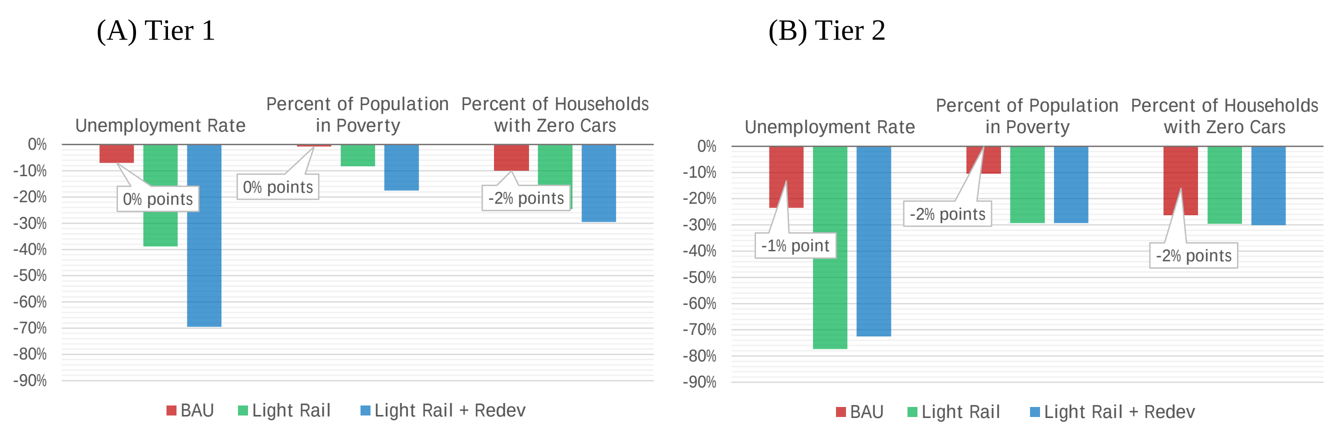


Figure 5-82. Percent Change in Equity Outcomes between 2020 and 2040 for Three Main Scenarios

The majority of the light rail scenario's impacts in the equity sector are in the sector's output indicators, rather than variables which affect other sectors through feedback loops. The primary indicator variables in this sector are property values, the percent of the population in poverty, the transit-dependent population, the households in poverty at risk of displacement, and the housing + transportation (H+T) affordability index, which is calculated in different ways for the average household and for those in poverty.

In Tier 2, all three categories of property values respond similarly to the main scenarios between 2020 and 2040, with a moderate increase in value over BAU in the Light Rail scenario, and a small additional increase with the Light Rail + Redevelopment scenario. Of the three categories, the largest change in Tier 2 is in single-family property values in the Light Rail + Redevelopment scenario, with per dwelling unit values increasing by 95% (Figure 5-82, all values are in 2010 dollars and are inflation adjusted). In the Light Rail + Redevelopment scenario, multifamily property values see a larger increase relative to the BAU scenario, however, with an increase 43% larger than the increase in BAU. This is because the value of multifamily homes is more strongly affected by retail density, which grows faster under the light rail scenarios. Tier 1 has more dramatic changes both between scenarios and between land use categories. Nonresidential unit property values (expressed per sq ft rather than per dwelling unit for residential property values) in Tier 1 see the largest change, with a 207% increase under the Light Rail + Redevelopment scenario (Figure 5-82). This is primarily due to the almost tripling of density for the 20% of land that gets redeveloped, which leads to a large increase in building size, one of the factors linked to nonresidential property values. In the Light Rail scenario, however, nonresidential unit property values actually show a smaller increase than under the BAU scenario, with increases of 71% and 77%, respectively. This smaller growth, which is reflected among multifamily property values as well, is due to the drop in retail density that occurs in Tier 1 once all available land is built out at the allowable density and development of nonresidential sq ft stops (property values are higher than BAU between about 2020 and 2035 but lower from 2035 to 2040). The light rail has very little net impact on single-family unit property values, relative to BAU, with unit property values increasing by slightly less than BAU in the Light Rail + Redevelopment scenario. This is due to the fact that factors that increase single-family property values relative to BAU in these scenarios (e.g., population growth and retail density) are offset by factors that decrease value (e.g., decreasing lot sizes, relatively more vacant land in the Light Rail + Redevelopment scenario).

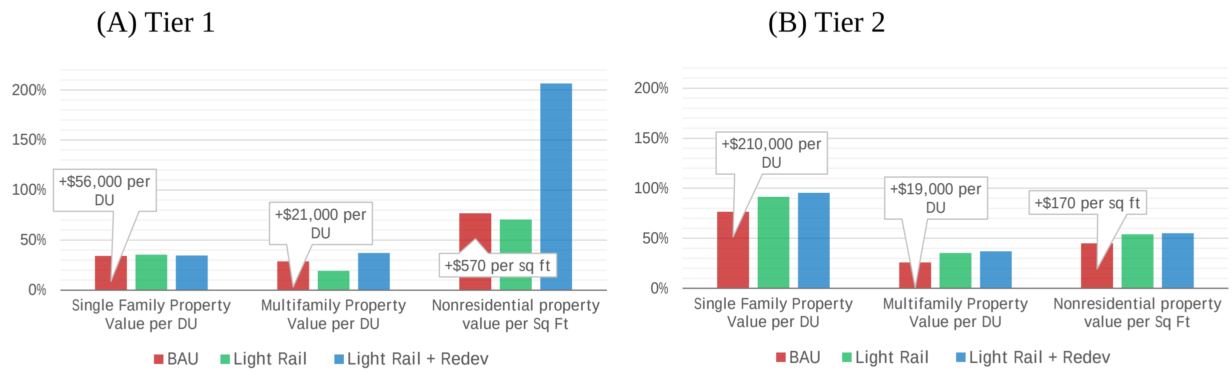


Figure 5-83. Change (%) in Property Values between 2020 and 2040 for Three Main Scenarios

The overall percent change values shown in Figure 5-83 do not tell the whole story of how property values change in each scenario over time. Multifamily property values in Tier 1 in particular follow a nonlinear trend (see Figure 5-83). In the Light Rail scenario, multifamily property values first increase to levels higher than the other two scenarios, and then decline after 2030. As described in Chapter 3, property values in the model are calculated by several different variables, and the changing trajectory of multifamily property values in this scenario is the result of different variables and feedback loops dominating during different periods. At first, the steep decline in available land is the dominant factor, initially pushing multifamily unit property value to levels 1.3% above values in the Light Rail + Redevelopment scenario and 8.1% above the BAU scenario, between 2025 and 2030. Starting around 2030, however, the maximum impact of limited land availability is reached, and other factors become more dominant. Slower growth in relative incomes, commercial building size, and job density all contribute, but the most important factor becomes retail density per capita, which declines starting in 2033, as population continues to increase while nonresidential development is stopped by the land cap. Ultimately, multifamily property values are 7.3% lower in the Light Rail scenario than in the BAU scenario in 2040. Without the effects of the land cap, property values under the Light Rail + Redevelopment scenario follow a steadier increase as land is developed more slowly and retail density per capita grows steadily, reaching values 6.5% higher than the BAU scenario in 2040.

(A) Multifamily (B) Single-Family

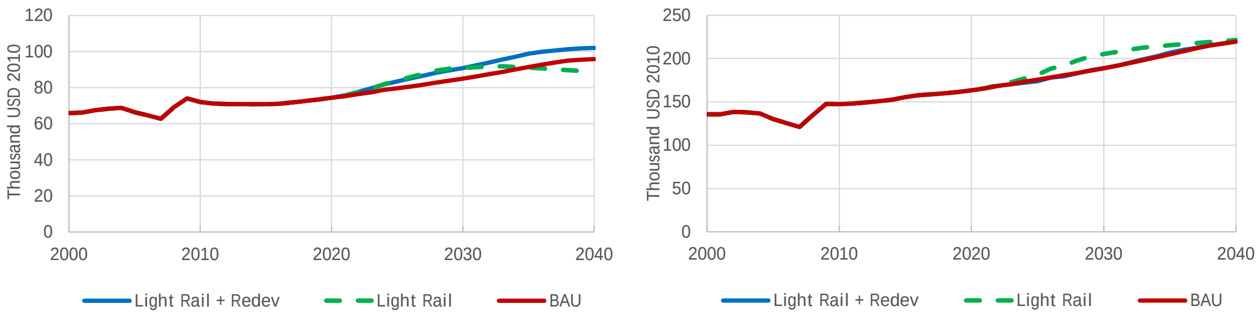


Figure 5-84. Multifamily and Single-Family Unit Property Values – Tier 1

The changes in multifamily property values affect renter costs, which is one of the two affordability measures tracked in the model (Figure 5-84).[31] In Tier 1, annual renter costs grow the most between 2020 and 2040 in the BAU scenario, but because the increase accelerates earlier in the Light Rail + Redevelopment scenario, that scenario actually has the highest cumulative costs per household over that period ($254,000 versus $250,000 in the BAU scenario). The Light Rail scenario shows the lowest increase in renter costs and therefore the lowest increase in overall housing and transportation costs (14%). Though vacancy rates and GRP growth rates also affect estimates of annual renter costs, this discrepancy is driven primarily by the differences in multifamily property values described above, meaning that renter costs in the Light Rail scenario exceed costs in the Light Rail + Redevelopment scenario between 2024 and 2030 but end up below BAU costs by 2040. By 2040, annual renter costs are forecasted to grow by 28%, 18% and 27% under the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively, with the lowest cumulative costs in the Light Rail scenario. Conversely, in Tier 2, the increases in both renter and transportation costs are highest in the Light Rail scenario, though the magnitude of cost increases in all scenarios is much smaller (e.g., 6% increase in renter costs in Tier 2 versus 18% in Tier 1 in the Light Rail scenario). The Light Rail scenario has the highest increase in renter costs in Tier 2 because multifamily property values consistently rise, rather than falling as described above in Tier 1.

In Tier 1, transportation costs in the two light rail scenarios show a larger increase than in the BAU scenario primarily due to the expected increase in money spent on transit fares. Vehicle related costs per capita drop below BAU to a low around 2027, though by 2040 they are higher than in the BAU scenario. The initial per capita drop is due to a drop in VMT per capita with the introduction of the light rail. The eventual increase in vehicle-related costs is due to two primary factors: 1) higher vehicle ownership per capita due to the drop in the transit-dependent population, and 2) increased parking costs (though this is a much smaller share of total vehicle costs). The extra increase in transportation costs under the Light Rail + Redevelopment scenario is largely due to higher parking costs, which is driven by changes in job density. In Tier 2, the increase in transportation costs is almost equal across all three scenarios because vehicle related costs per capita do not change significantly relative to the BAU and the increase in money spent on transit fares is negligible compared to spending for vehicles.

[31] Single-family property values were not considered as a part of affordability.

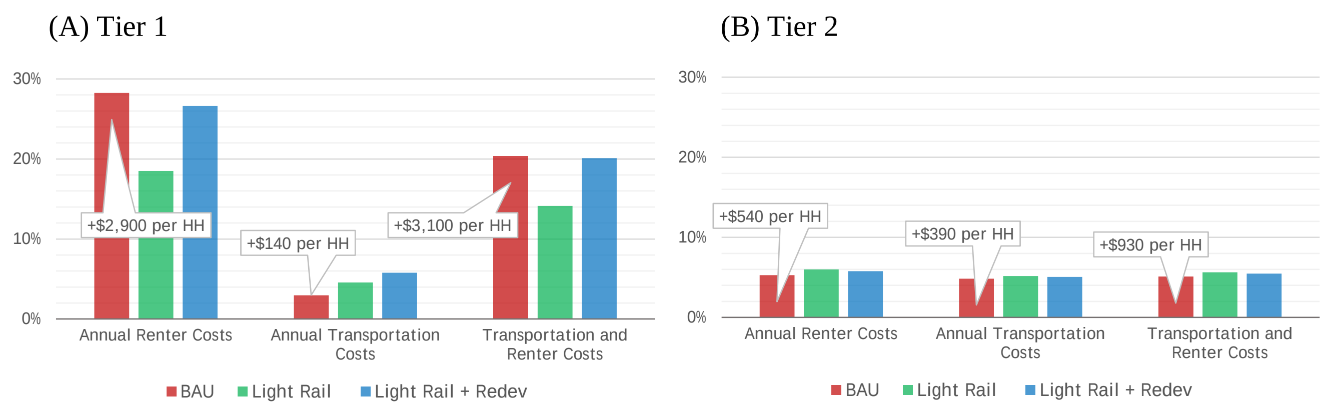


Figure 5-85. Percent Change in Housing and Transportation Costs between 2020 and 2040 for Three Main Scenarios

Transportation and renter costs are used in the calculation of two affordability indices in the model. The primary affordability index (for average households, as described in Chapter 3.3 in the Equity sub-section) shows improvement under every scenario in Tier 2 between 2020 and 2040 (Figure 5-86), but especially under the light rail scenarios (5% increases vs. 2% increases under the BAU), due to increased earnings and relatively flat housing and transportation costs. In Tier 1, this measure changes significantly only in the Light Rail + Redevelopment scenario (where it declines by 5%), due to relatively slow per-capita earnings that do not increase fast enough to keep up with increases in housing and transportation costs (which are equivalent to the increases in the BAU scenario).[32] In contrast, the affordability index for households in poverty worsens under every scenario and Tier. This is to be expected, since the index is essentially the inverse of patterns in overall housing and transportation costs; moderate increases in these costs in Tier 2 lead to moderate drops in affordability (roughly 5% in all scenarios), and larger increases in costs in Tier 1 lead to more pronounced affordability drops, of 15%, 11%, and 15% in the BAU, Light Rail, and Light Rail + Redevelopment scenarios, respectively.

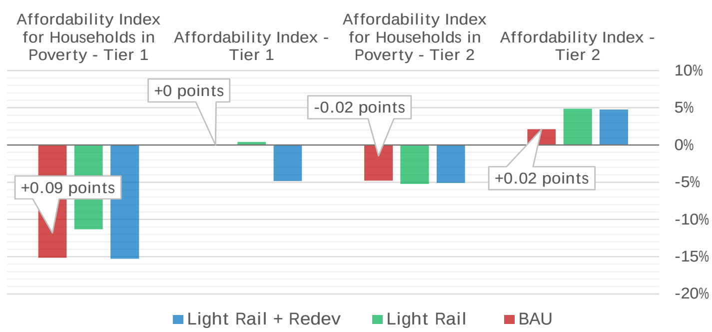


Figure 5-86. Percent Change in Affordability Indices between 2020 and 2040 for Three Main Scenarios

Finally, the model's estimates of the percent of the population in poverty suggest that the risks of

[32] The percent of the population in the labor force in Tier 1 declines given the assumption that when workers move to the area to fill a job opening, they bring with them families and spouses who may still work outside the Tier, resulting in more families living in the area. Thus per capita earnings decline slightly, even though per household earnings do not.

gentrification vary between the two Tiers in the three main scenarios. In Tier 2, the decline in the percent of the population in poverty under the light rail scenarios leads to a corresponding decline in the number of households at risk of displacement (defined as the number of households in poverty not accommodated in subsidized dwelling units). In Tier 1 however, the decline in the percent of the population in poverty is offset by the rise in population, leading to an overall rise in the number of households in poverty, and an increase in the number of households at risk of displacement. Figure 5-86 shows that, at current levels of subsidized dwelling units, the number of households at risk of displacement will surpass the BAU scenario starting in 2024 in the Light Rail scenario and 2031 in the Light Rail + Redevelopment scenario, reaching 4,800 households in risk of displacement in 2040 under the Light Rail scenario, a level 18% higher than the BAU.

(A) Tier 1

(B) Tier 2

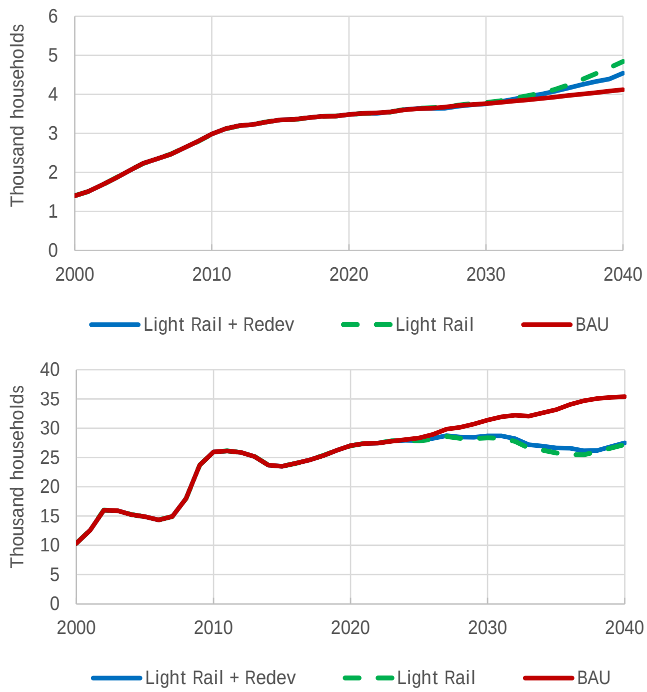


Figure 5-87. Households in Poverty at Risk of Displacement

Alternative Policy Scenario: Fewer Organically Affordable Units Scenario

This scenario, which is run on top of the Light Rail + Redevelopment scenario, is meant to explore the uncertainty around the percent of multifamily units that will be organically affordable (defined as the number of dwelling units that cost no more than 40% of the poverty threshold income) in the future, since it is unlikely that the percent of units that are affordable will remain constant (as the model assumes), particularly in the face of the light rail and redevelopment. In this scenario, the percent of multifamily units that are assumed to be organically affordable in Tier 1 declines gradually from 26% in 2020 (the value derived from data for 2014) to 15% by 2040, with the decline starting in anticipation of the light rail. With this change, the absolute number of dwelling units still grows, but the portion that are affordable declines. This altered assumption directly leads to a rise in the housing gap for households in poverty, which is defined as the number of households neither accommodated in subsidized dwelling units nor in organically affordable dwelling units. The housing gap is initially negative under the Light Rail + Redevelopment scenario, only becoming positive between 2016 and 2025 before becoming negative again as poverty levels fall (Figure 5-88). In contrast, under this scenario, the housing gap continues to rise, reaching a high of about 1,400 households in 2040. On the other hand, in order to prevent the housing gap from exceeding zero in the Light Rail + Redevelopment scenario, the percent of multifamily units that are affordable would need to rise from 26% to 27% by 2020.

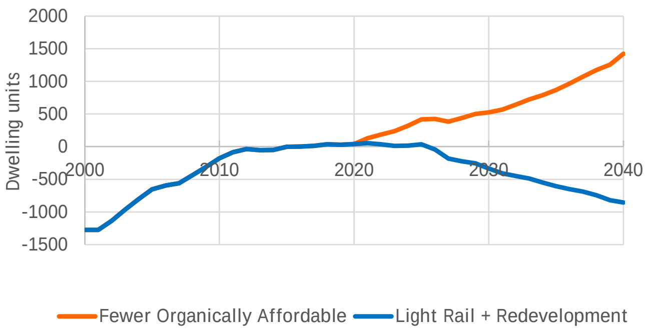


Figure 5-88. Housing Gap for Households in Poverty - Tier 1

Alternative Policy Scenario: More Multifamily Households Scenario

This scenario, which is run on top of the Light Rail + Redevelopment scenario, extends the demographic shift towards more households living in multifamily dwelling units in Tier 1. Extending the linear trend in the percent of single-family households between 2000 and 2010 to 2040 results in a 10.3% increase in the portion of households that live in multifamily dwelling units by the year 2040, relative to the reference scenario. As a result of this shift, multifamily acres grow by 30% between 2020 and 2040 (relative to a 20% increase in the reference scenario), while single-family acres decline by 5% (relative to a 21% increase in the reference scenario) (Figure 5-89). This leads to a drop in total developed land (and correspondingly, residential impervious surface), falling to a level 2.5% below the reference scenario by 2040 (Figure 5-90). Residential energy use also declines over this period, due to a lower assumed energy use intensity for multifamily households, with 31% growth, compared to 38% growth in the reference scenario. The increase in multifamily dwelling units provides more organically affordable units (since the percent that is organically affordable is assumed to remain constant), causing the housing gap to disappear, and leading the potential population in poverty displaced to remain at zero for the entire simulation (Figure 5-91).

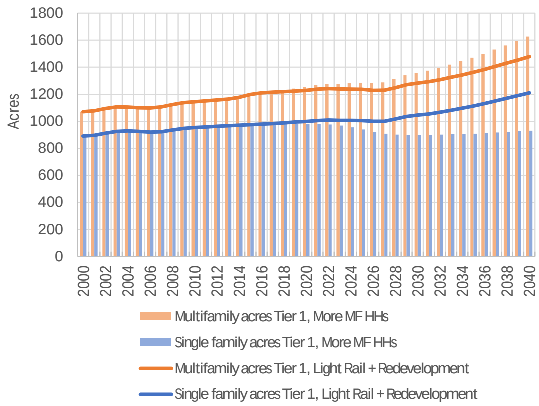


Figure 5-89. Multifamily and Single-Family Acres Under Light Rail + Redevelopment and More Multifamily Households Scenarios - Tier 1

Figure 5-90. Percent Change in Developed Land, Residential Impervious Surface, and Residential Energy Use Between 2020 and 2040 for More Multifamily Households Scenario Compared to Light Rail + Redevelopment – Tier 1

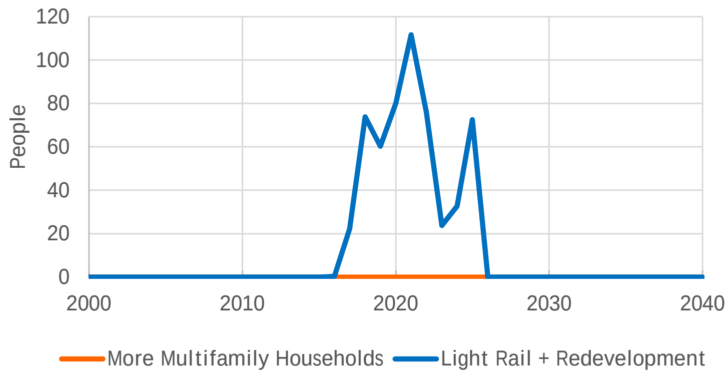


Figure 5-91. Potential Population in Poverty Displaced – Tier 1

Retail Wage Increase Scenario

In this scenario, which is run on top of the Light Rail + Redevelopment scenario, retail earnings per employee in Tier 1 experience an increase in the nominal hourly retail wage of $2.00 in 2016, with additional $1.00/hour increases added over the following three years (2017-2019), on top of the yearly increase already projected by Woods & Poole.

As a result, total retail earnings in Tier 1 (Figure 5-92) increase by 23% more than the Light Rail + Redevelopment scenario by 2040 (note that the percentage difference between this scenario and the reference scenario actually peaks at 30% in 2019 but decreases over time due to inflation). This increase in retail wages lead to an increase in GRP in Tier 1 (Figure 5-92) that starts at 1.0% in 2019 and grows to 8.4% in 2040.

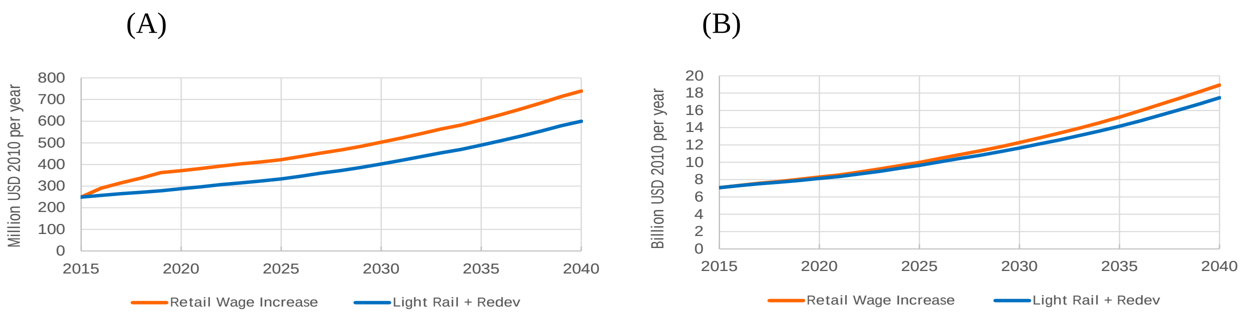


Figure 5-92. (a) Retail Earnings Tier 1 and (b) GRP Tier 1 – Retail Wage Increase Scenario vs. Light Rail + Redevelopment Scenario

The retail wage increase also has an immediate impact on resident per capita net earnings Tier 1 (Figure 5-93) and the affordability index in Tier 1, shown in Figure 5-93. Since the retail wage increase is nominal, its value depreciates over time, thus affordability peaks in 2019 at 1.2 under the Retail Wage Increase scenario, a 28% increase from the affordability index in Tier 1 in 2020 under the Light Rail + Redevelopment scenario.

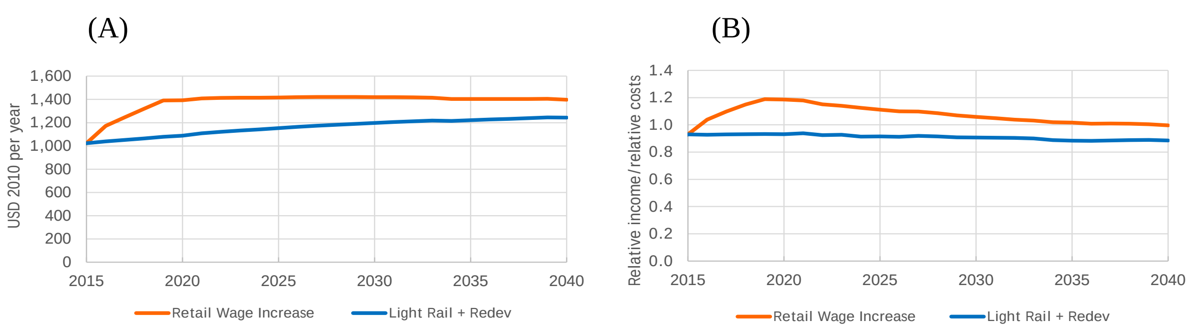


Figure 5-93. (a) Resident Per Capita Net Retail Earnings Tier 1 and (B) Affordability Index Tier 1 – Retail Wage Increase Scenario vs. Light Rail + Redevelopment Scenario

Water

Municipal Water Demand and Supply

Figure 5-94 shows the modeled estimates of water demand in both Tiers for the three main scenarios, for the period 2000-2040. Municipal water demand dropped in both Tiers prior to 2010 due to conservation practices that began during the 2007 drought and continued afterward. In Tier 1, the model projects daily water demand in 2040 that is 1.2 and 1.9 Mgal/day higher than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively (representing increases of 17% and 27% over the 2040 BAU value of 6.9 Mgal/day). Light rail scenarios increase water demand due to increases in dwelling units, employment, and population, which drive the residential, nonresidential, and nonrevenue components of water demand, respectively. In Tier 1, dwelling units increase by 44% and 57% in the light rail scenarios between 2020 and 2040 (compared to 14% in BAU), while employment increases by 53% and 66% (compared to 35% in BAU). Nonrevenue demand, which is tied to changes in population, increases 40% and 48% in the light rail scenarios between 2020 and 2040, compared to 14% in BAU. In the Light Rail scenario, water demand increases more slowly after 2035 due to land scarcity, which reduces residential construction and also slows down Tier 1 GRP growth, including employment growth (which affects nonresidential demand).

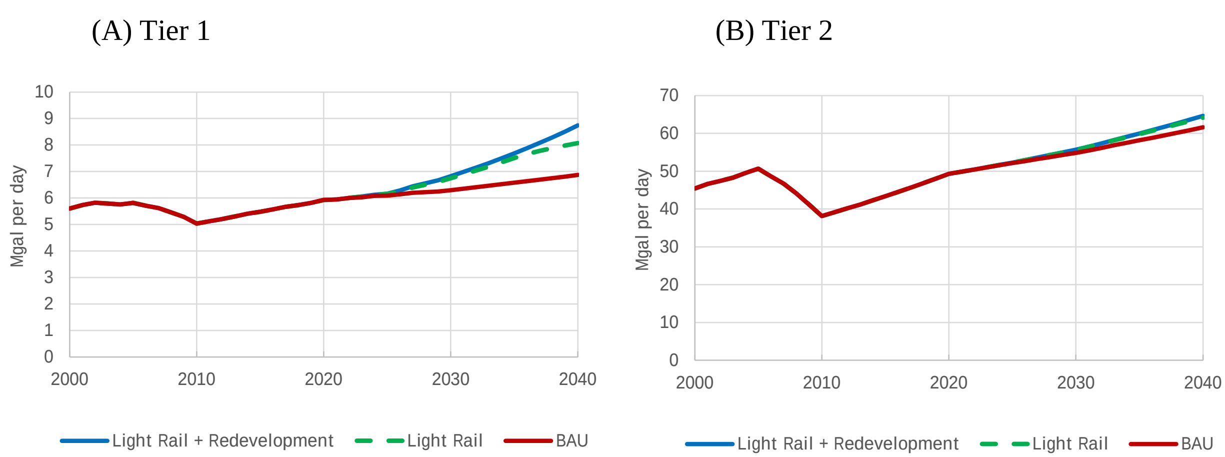


Figure 5-94. Water Demand: Light Rail, Light Rail + Redevelopment Scenarios Compared to BAU

In Tier 2, the changes in the light rail scenarios also increase water demand relative to BAU, but proportionately less than in Tier 1, and with less difference between the two light rail scenarios. In 2040, water demand is 2.5 and 3.1 Mgal/day higher than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively (Figure 5-94), representing increases of 4.1% and 5.0% over the 2040 BAU value of 62 Mgal/day. As in Tier 1, development of the light rail stimulates water demand due to increases in dwelling units, employment, and population. Between 2020 and 2040, dwelling units and population both increase by 42-44% in the light rail scenarios compared to 38% in BAU, while employment increases 50-51% in the light rail scenarios, compared to 41% in BAU.

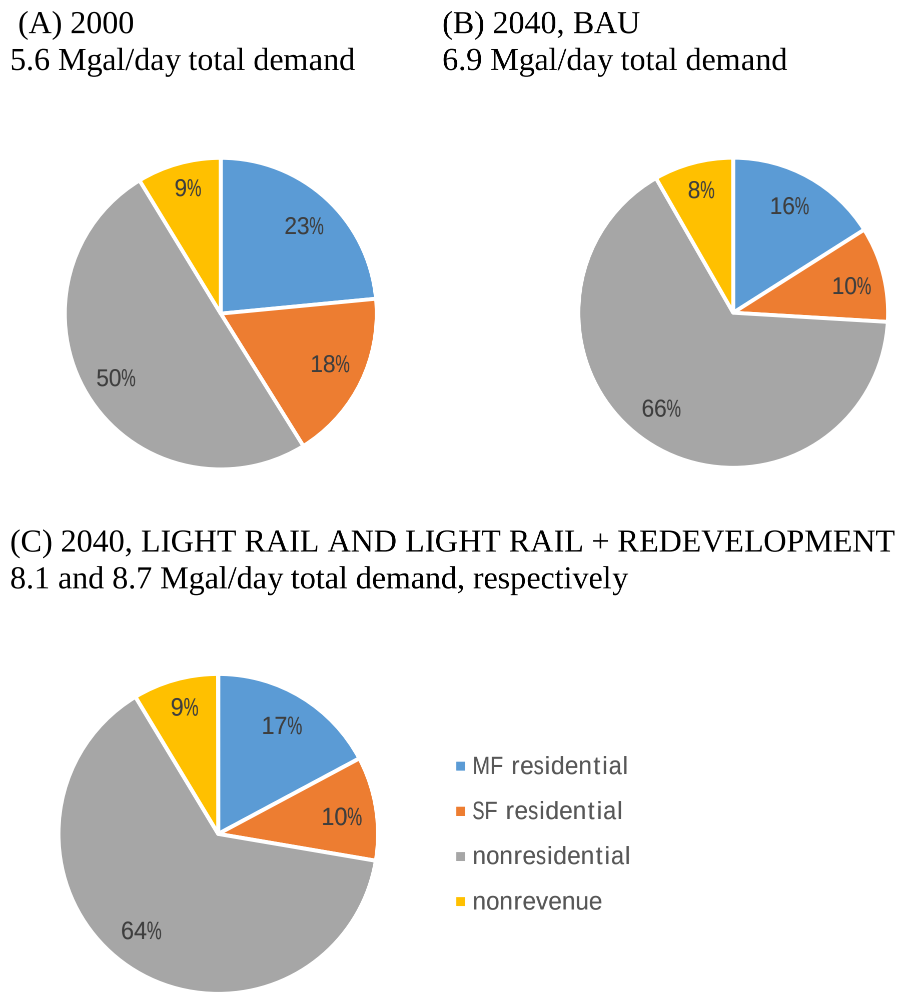


Figure 5-95. Tier 1 Water Demand (MGAL Per Day) in (A) 2000 and (B) 2040, BAU Scenario Compared to Light Rail Scenarios

In the BAU scenario, total Tier 1 water demand grows from 5.6 Mgal/day to 6.9 Mgal/day between 2000 and 2040 (Figure 5-95A-B), representing an increase of 23%. During this time, nonresidential (commercial and industrial) facilities remain the largest portion of water demand, increasing from 50% of total demand in 2000 to 66% in 2040. Though the residential share of water demand decreases during this period, the shift from single-family to multifamily dwelling units in Tier 1 is also reflected in the distribution of water demand, with single-family residential demand decreasing from about 44% of residential demand in 2000 to about 38% in 2040. Nonrevenue demand remains less than 10% of total demand between 2000 and 2040.

The two light rail scenarios change the proportions of water demand only slightly, with slight increases in the multifamily residential and nonrevenue shares of total water demand (Figure 5-95C). These shifts are due to the light rail causing a proportionately larger increase in MF dwelling units than in employment. Relative to the BAU change from 2000-2040, MF dwelling units increase by 26% and 36% more than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively, while total employment increases by 13% and 24% more than BAU.

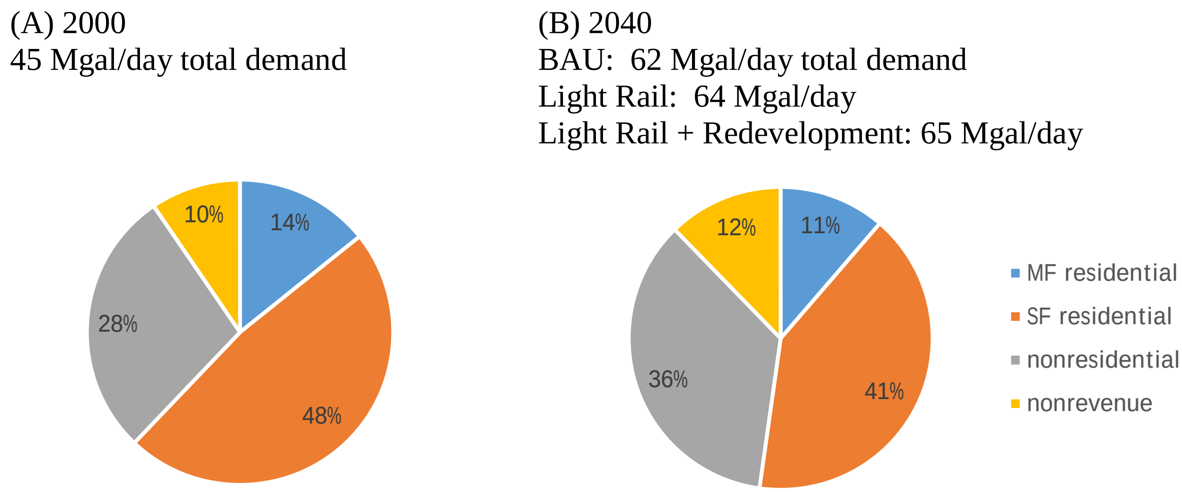


Figure 5-96. Tier 2 Water Demand (MGAL Per Day) in (A) 2000 and (B) 2040, BAU Scenario Compared to Light Rail Scenarios

Tier 2 water demand grows from 45 Mgal/day to 62 Mgal/day between 2000 and 2040 in the BAU scenario, representing an increase of 38%, a larger percent increase than in Tier 1 (Figure 5-96). Unlike Tier 1 water demand, which is mostly nonresidential, the majority of Tier 2 water demand is residential, with most of that demand coming from single-family homes, as opposed to multifamily homes using more water in Tier 1. In 2040, nonresidential demand represents a larger share of total demand in all three scenarios (growing from 28% to 36%, as shown in Figure 5-96), because water use intensity drops more for residential than for nonresidential users over this period, even though dwelling units grow faster than employment in Tier 2 (100% vs. 87% growth between 2000 and 2040). Residential water use per dwelling unit drops by 55% between 2000 and 2040, while nonresidential water use per employee drops by 10%. Despite increasing total water demand relative to BAU, the two light rail scenarios have no effect on the distribution of water demand by use (Figure 5-96B), because the drivers of demand (numbers of dwelling units and employed people) grow at roughly equal rates among the three main scenarios.

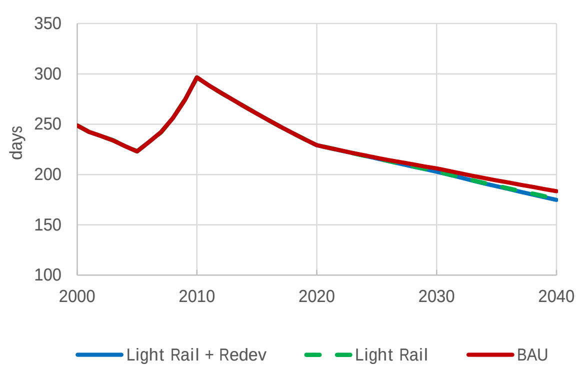


Figure 5-97. Days of Supply in Durham County Water Reservoirs: Three Main Scenarios

In the absence of supply augmentation, water supply in Durham County's combined water reservoirs is projected to drop in the BAU scenario from 250 days of supply in 2000 to 180 days in 2040 (Figure 5-97), due to growing water demand from population and employment growth. Further residential and employment growth in the light rail scenarios reduce days of supply by 7 and 9 days in 2040 relative to BAU in the Light Rail and Light Rail + Redevelopment scenario, respectively.[33]

Stormwater N Load

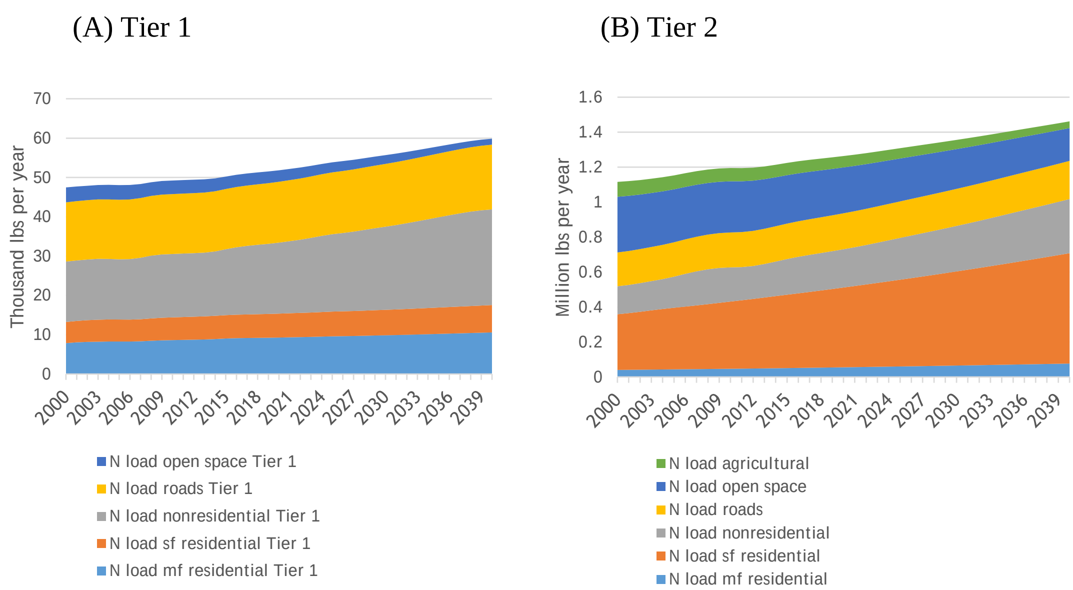


Figure 5-98. Stormwater N Load by Land Use: BAU Scenario

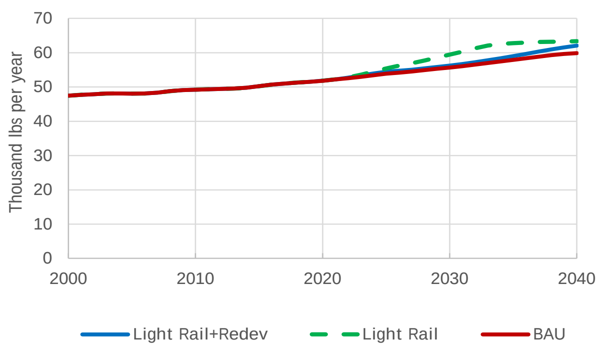
Figure 5-98 presents the model's BAU projections of stormwater load for five different land use types (open space, roads, nonresidential, single-family residential, and multifamily residential). As shown in Figure 5-98A, in Tier 1, nonresidential land (gray area) has the largest stormwater N load, with about 41% of total load by 2040, while roads (yellow) represent 28% of the total, and multifamily residential (light blue) represents 18% of the total. Nonresidential land also shows the largest growth in stormwater load over time, increasing from 32% of total load in 2000 to 41% by 2040. This disproportionate increase in stormwater N from nonresidential land reflects growth in nonresidential land, due to employment growing more quickly than population in this Tier under the BAU scenario. This result is consistent with the decline in the jobs-housing balance in Tier 1 (mentioned in the Land Use section), which also results from nonresidential land use growing faster than residential land use.

As shown in Figure 5-98B, single-family residential land (orange area) has the largest stormwater N load in Tier 2, with about 43% of total load by 2040, while nonresidential land (gray) contributes 21%, and roads (yellow) contribute 15% of the total. Single-family residential land shows a significant increase in N load, growing from 29% of total loads in 2000 (the same as loads from open space) to 43% by 2040, as open space is primarily converted to single-family residential use.

[33] The model's projection of days of supply is a rough estimate, as it assumes constant rainfall (45 inches/year) and constant reservoir supply (7,568 Mgal, based on March 2015 data). Further, the model assumes that Durham County demand remains at 67% of Tier 2 water demand, based on the historical ratio of Durham County to Tier 2 population.

In Tier 1, the Light Rail and Light Rail + Redevelopment scenarios increase stormwater N load relative to BAU by 6% and 4%, respectively, in 2040 (Figure 5-99A). In the Light Rail scenario, stormwater N load increases rapidly starting in about 2022 and levels off by 2035, while in the Light Rail + Redevelopment scenario, it shows gradual, continual growth through 2040. The nonlinear growth pattern in Stormwater N load in Tier 1 largely reflects the growth pattern for impervious surface (Figure 5-100A), which increases by 930 acres and 830 acres in Light Rail and Light Rail + Redevelopment, respectively, between 2020 and 2040 (compared to an increase of 650 acres in the BAU scenario). These changes in impervious surface in turn reflect underlying changes in land development (reproduced in Figure 5-100B), which reflect the effects of the developed land cap in 2033 in the Light Rail scenario, but not in the Light Rail + Redevelopment scenario, which shows more gradual, but steady growth. In Tier 2, stormwater N load is about 2% higher than BAU in Light Rail and Light Rail + Redevelopment in 2040 (Figure 5-99B). As in Tier 1, this reflects growth in impervious surface due to land development. Stormwater P load follows many of the same patterns as stormwater N load, since both are driven by increases in land development and impervious surface. In Tier 1, the Light Rail and Light Rail + Redevelopment scenarios increase stormwater P load by 4.9% and 3.2%, respectively, relative to BAU in 2040 (Figure 5-101A). In Tier 2, stormwater P load is 1-2% higher in the two light rail scenarios compared to BAU in 2040 (Figure 5-101B). Annual stormwater P load is about one-fifth of annual stormwater N load.

(A) Tier 1



(B) Tier 2

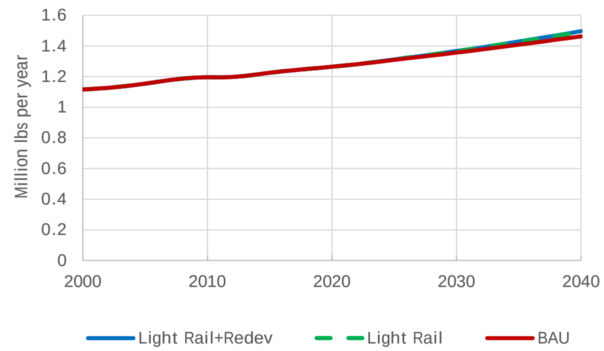
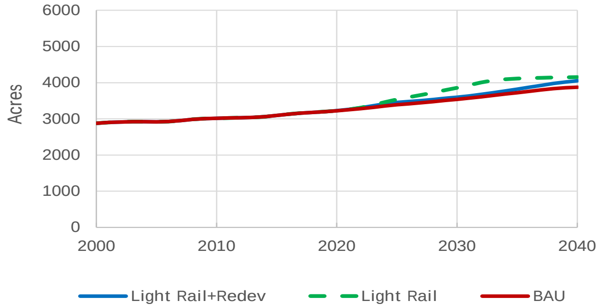


Figure 5-99. Stormwater N Load: Light Rail, Light Rail + Redevelopment Scenarios Compared to BAU

(A)



(B)

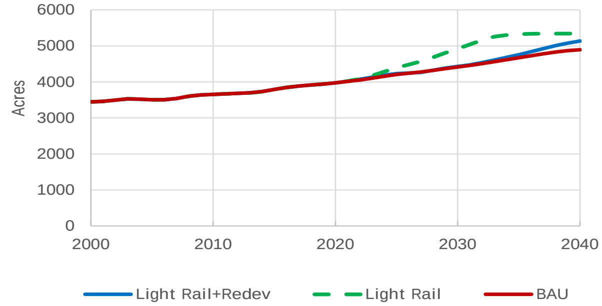


Figure 5-100. (A) Total Impervious Surface - Tier 1 and (B) Total Developed Land – Tier 1: Light Rail, Light Rail + Redevelopment Scenarios Compared to BAU

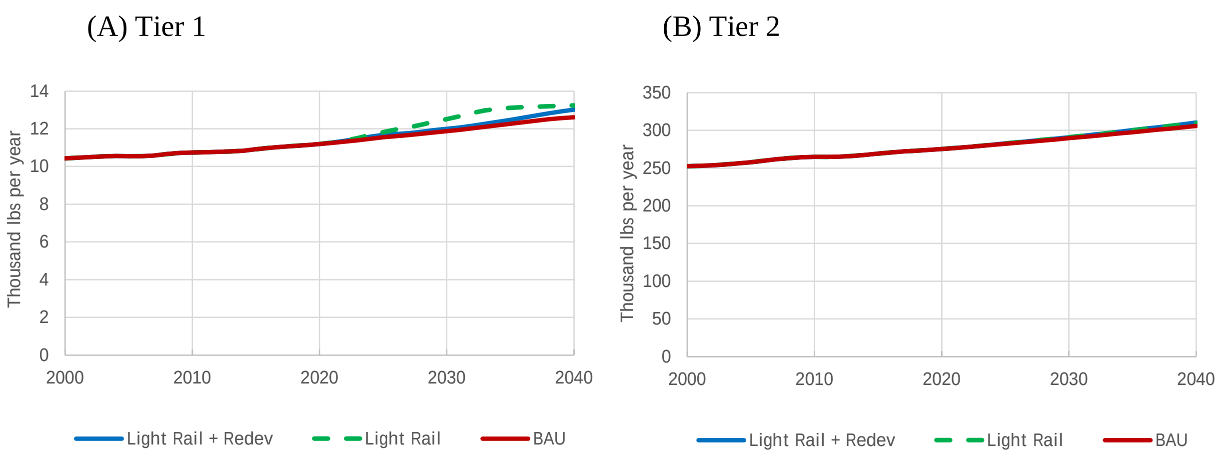


Figure 5-101. Stormwater P Load: Light Rail, Light Rail + Redevelopment Scenarios Compared to BAU

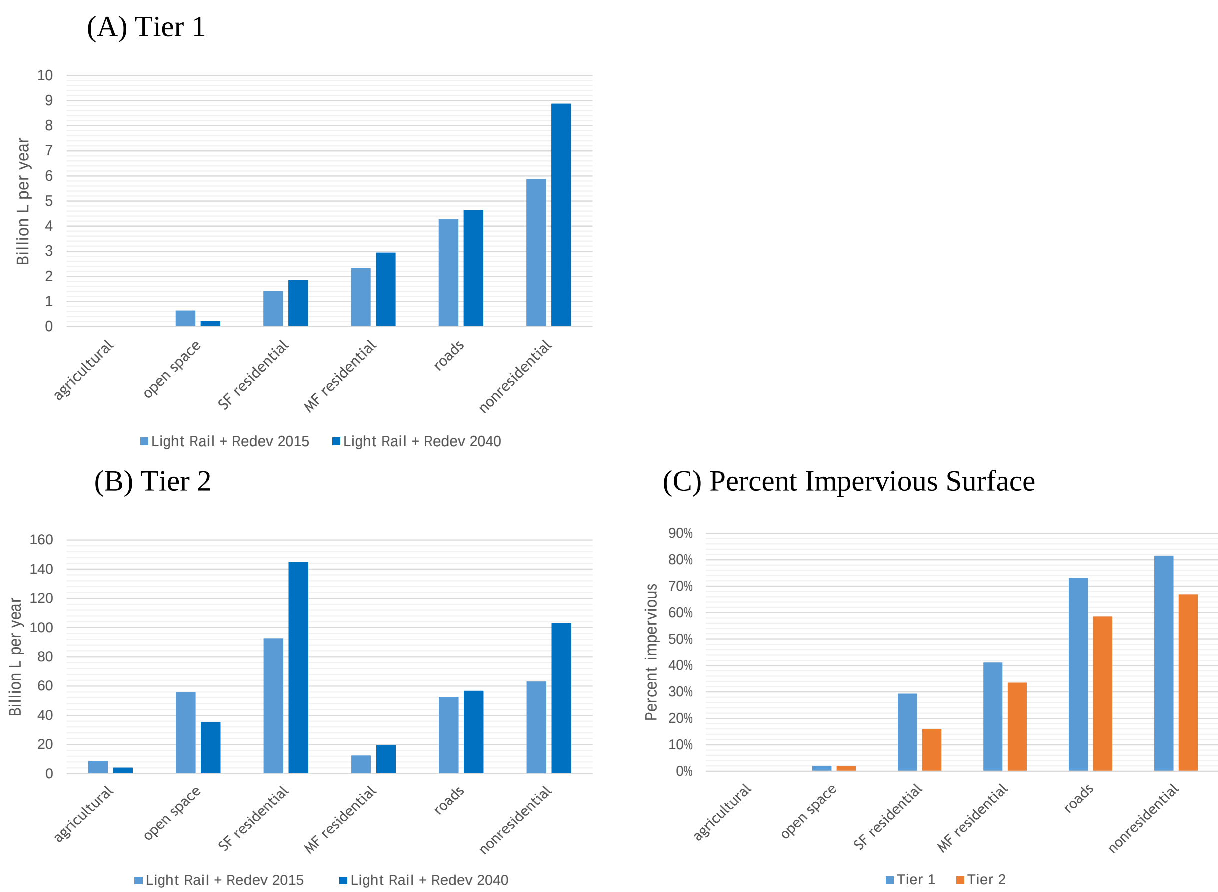


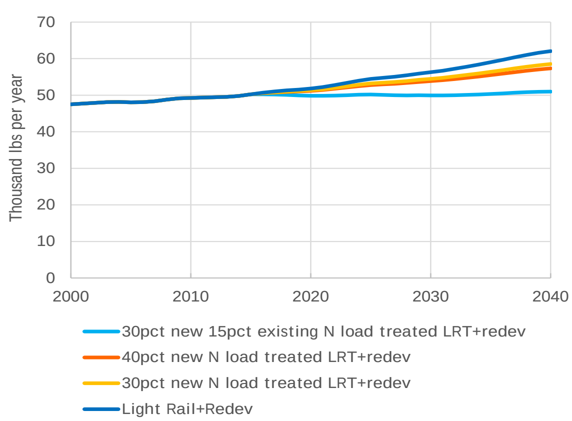
Figure 5-102. Annual Stormwater Runoff Volume and Percent Impervious Surface, Modeled for 2015

In Tier 1, nonresidential land has the highest stormwater runoff, at nearly six billion L/year in 2015, growing to nearly nine billion L/year by 2040 (Figure 5-102A). There is no agricultural land in Tier 1, so it has the lowest (zero) runoff volume at all years. Tier 2 stormwater runoff volume is roughly ten times that of Tier 1, and its largest components are single-family residential, nonresidential, and open space (Figure 5-102B). As open space is converted to developed land, open space runoff volume decreases between 2015 and 2040, while SF residential and nonresidential land have 52 billion and 40 billion L/year more runoff by 2040, respectively. Since rainfall volume is assumed to be constant over the region, differences in stormwater runoff volume by land use are driven by land area and percent impervious cover. Like runoff volume in Tier 1, impervious surface by land use is lowest for agricultural land and highest for nonresidential land, where it reaches over 80% in 2015 (Figure 5-102C). With the exception of agricultural land and open space, all land uses had higher impervious surface in Tier 1 than in Tier 2, so that aggregate impervious surface is 43% of Tier 1 land area and 14% of Tier 2 land area in 2015. As impervious cover changes, the model calculates new EMCs for each land use type (see graph of stormwater N EMCs in Chapter 3) and multiplies them by runoff loading to calculate stormwater N loading. Modeled EMCs change by less than 2% between 2000 and 2040.

Stormwater Management Scenarios

These scenarios, which are run on top of the Light Rail + Redevelopment scenario, simulate compliance with rules designed to protect water quality in Jordan Lake and Falls Lake. Accordingly, they reduce stormwater N loads from developed land to reflect (1) 30% onsite stormwater treatment in new developments, (2) 40% onsite stormwater treatment in new developments, or (3) 30% onsite stormwater treatment in new developments plus 15% onsite stormwater treatment in existing developments. For the purposes of this scenario, new development is defined to be everything developed after 2015. In the Light Rail + Redevelopment scenario, a 30% reduction in stormwater N from new development equals a decrease in N load of 3,500 lb/year by 2040 (yellow line, Figure 5-103A), a 40% reduction causes an additional 1,200 lb/year decrease (orange line), and a 30% reduction in new development stormwater N with a 15% reduction in existing development stormwater N keeps the stormwater N load at roughly 2015 levels (51,000 lbs/year) through 2040 (light blue line). For reference, the orange line in Figure 5-103B shows the projected stormwater N load from a 2.2 lb/acre/year target for new development (Falls Lake and Jordan Lake development rules).

(A)



(B)

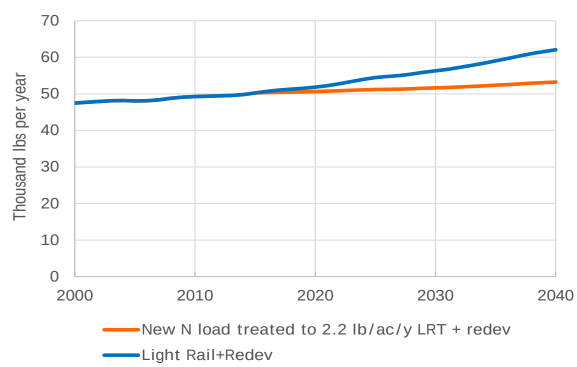


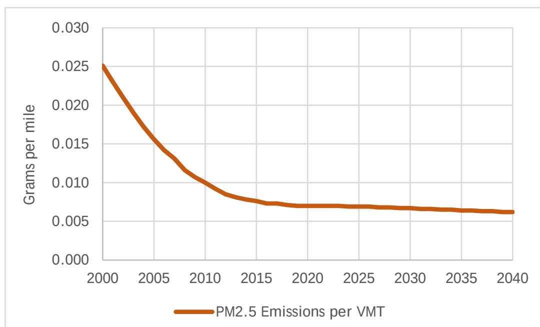
Figure 5-103. Stormwater N Load – Tier 1: (A) Percent Reduction Targets and (B) Reduction to 2.2 lb/acre/year

As a scoping estimate, if the 30% reduction in stormwater N from new development were accomplished with bioretention (rain gardens), it would cost $510,000/year in 2020 and $3.8 million/year in 2040, in USD 2010. A 40% reduction in new development stormwater N would cost $680,000/year in 2020 and $5.1 million/year in 2040. A bioretention strategy that gradually reduces stormwater N from existing development from 0% in 2015 to 15% by 2040 would cost an additional $3.1 million/year in 2020 and $15 million/year in 2040, in USD 2010. These bioretention estimates assume a USD 2010 cost of $1,064/lb N/year removed from new development and $2,038/lb N/year removed from existing development (The Center for Watershed Protection 2013, Cox 2015).

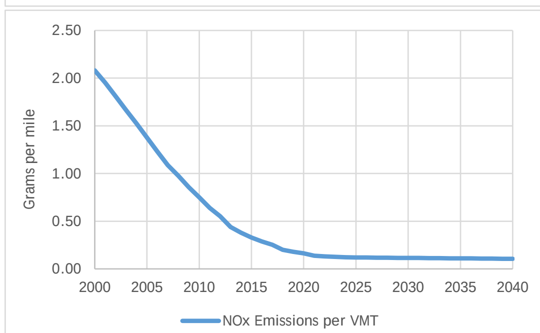
Health

In the D-O LRP SD Model, the contributions to avoided premature mortalities resulting from changes between scenarios in vehicle air emissions, transportation-related physical activity (cycling and walking), and vehicle crash fatalities are estimated individually and summed to yield net premature mortalities avoided (per year and cumulatively) for Tier 1 and Tier 2. Health sector outcomes from the D-O LRP SD Model for the three main scenarios are therefore largely dependent on changes in the transportation and energy sectors. Although the Light Rail and Light Rail + Redevelopment scenarios result in net health benefits for the population in both Tier 1 and Tier 2, projected increases in vehicle fuel efficiency (and therefore reductions in the cost of driving per VMT), which are the same in the two light rail scenarios as in the BAU scenario, have a much larger impact on health outcomes (by shifting travel toward more vehicle use and away from nonmotorized travel) than do the changes in either of the light rail scenarios. For this reason, we present three scenarios that correspond to additional health interventions which create stronger health responses than either the Light Rail or Light Rail + Redevelopment scenario alone (see text boxes), two of which are already discussed in this chapter in the context of the transportation sector (Higher Gas Prices and Sidewalk Building scenarios).

(A) PM2.5 Emissions per VMT



(B) NOx Emissions per VMT



(C) Crash Fatalities per Billion VMT

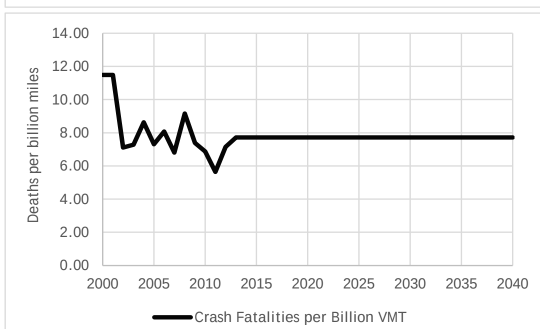


Figure 5-104. Time Series of Three Exogenous Inputs Affecting Health Outcomes – Same for all Three Main Scenarios

The model estimates vehicle air emissions and crash fatalities as a proportional function of VMT, using exogenous parameters, some of which are projected to change in value over time.[34] The values for these parameters are the same for the three main scenarios and are shown in Figure 5-104A-C. Despite steep reductions in historical vehicle emissions of $PM_{2.5}$ and NO_x per VMT between 2000 and 2015, projected $PM_{2.5}$ emissions per VMT (Figure 5-104A) plateau after 2015, causing total $PM_{2.5}$ vehicle emissions to increase slightly in the model between 2020 and 2040 in both Tiers in all three main scenarios, as shown in Figure 5-105. Due to higher VMT in both scenarios, $PM_{2.5}$ vehicle emissions increase more than BAU in the Light Rail and Light Rail + Redevelopment scenarios in both Tiers, with increases of 18% and 22% in Tier 1, and 24% and 25% in Tier 2, respectively (compared to BAU increases of 11% in Tier 1 and 22% in Tier 2). Because NO_x emissions per VMT are projected to decline more than $PM_{2.5}$ emissions during the model timeframe (Figure 5-104B), overall NO_x emissions from vehicles in all three scenarios decline even as VMT increases, although NO_x emissions do not decline as much in the Light Rail and Light Rail + Redevelopment scenarios (decreases of 14% and 11% in Tier 1, and 9% and 8% in Tier 2, respectively, vs. BAU decreases of 19% and 11%), due to VMT increasing more than in the BAU scenario. Since the model assumes that crash fatalities per VMT after 2013 remain constant at 2013 levels (Figure 5-104C), percent increases in crash fatalities in Tier 1 and Tier 2 between 2020 and 2040 are the same as percent increases in VMT, resulting in 33% and 37% increases in crash fatalities per year in Tier 1 for the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to a BAU scenario increase of 25% (Figure 5-105). In Tier 2, annual crash fatalities increase by 40% and 41% between 2020 and 2040 in the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to a BAU scenario increase of 38% (Figure 5-105B).

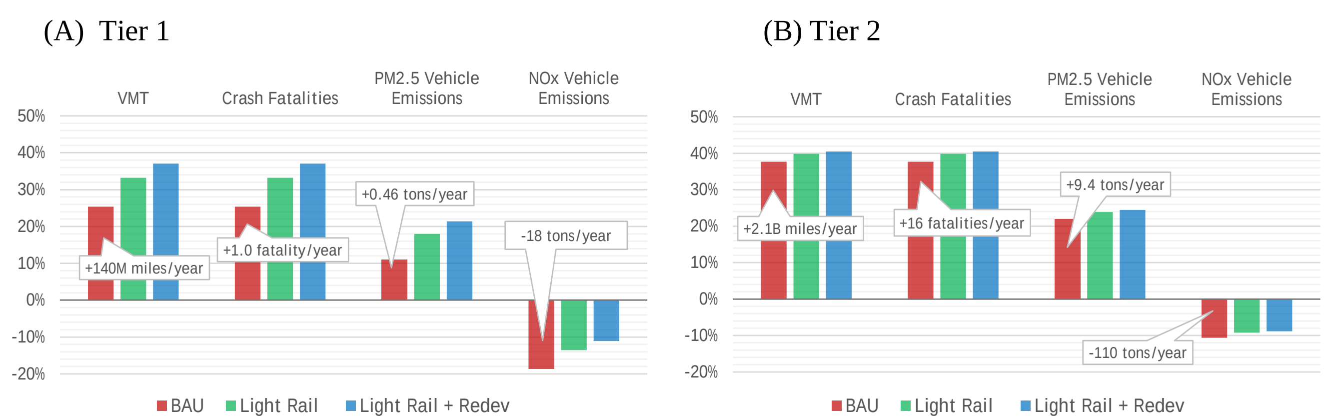


Figure 5-105. Percent Change in VMT and VMT-Related Health Indicators between 2020 and 2040 for Three Main Scenarios

[34] Explanations of the calculations for $PM_{2.5}$ and NO_x Emissions per VMT can be found in the Energy Sector portion of Appendix B, and Crash Fatalities per VMT calculations are explained in the Health Sector portion of Appendix B.

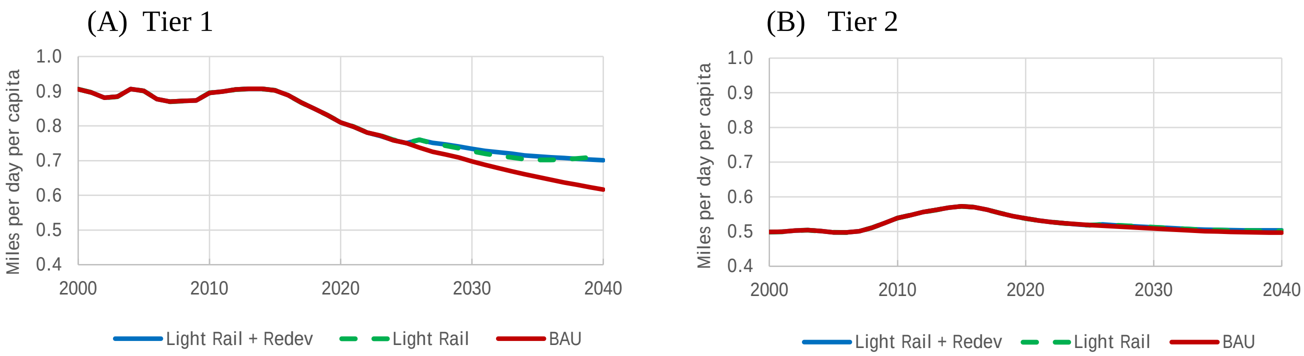


Figure 5-106. Time Series (2000-2040) of Nonmotorized Travel for Transportation by Residents Per Day Per Capita for Three Main Scenarios

Figure 5-106 shows the declining trend in nonmotorized travel (walking and cycling) by residents per day per capita in both Tiers between 2015 and 2040. This decline is due in large part to increases in fuel efficiency that reduce the cost of driving. On average, residents of Tier 1 walk or cycle significantly more per day for transportation purposes than do residents of Tier 2. In Tier 1, nonmotorized travel for transportation declines by about 24% in the BAU scenario between 2020 and 2040, though this decline is somewhat mitigated in the Light Rail and Light Rail + Redevelopment scenarios, where it decreases by only 12% and 13%, respectively (Figure 5-106A). In Tier 2, the two light rail scenarios have little or no effect on nonmotorized travel by residents per day per capita for transportation purposes relative to the BAU scenario, since the effects the light rail line and associated land use changes are concentrated in Tier 1 (Figure 5-106B). In all three main scenarios, nonmotorized travel by residents per capita declines more rapidly in Tier 1 than Tier 2. This is because Tier 1 employment grows faster than Tier 1 population in all three scenarios, which increases GRP, resulting in more people traveling by automobile and fewer traveling by nonmotorized modes. This change indicates that a greater proportion of travel is by nonresidents, and is associated with people having to travel shorter distances to get to work or run errands. Also, this model does not reflect nonmotorized travel at the beginning or end of a trip whose primary mode is automobile travel; nonmotorized travel of this sort is more common in highly developed areas, such as Tier 1.

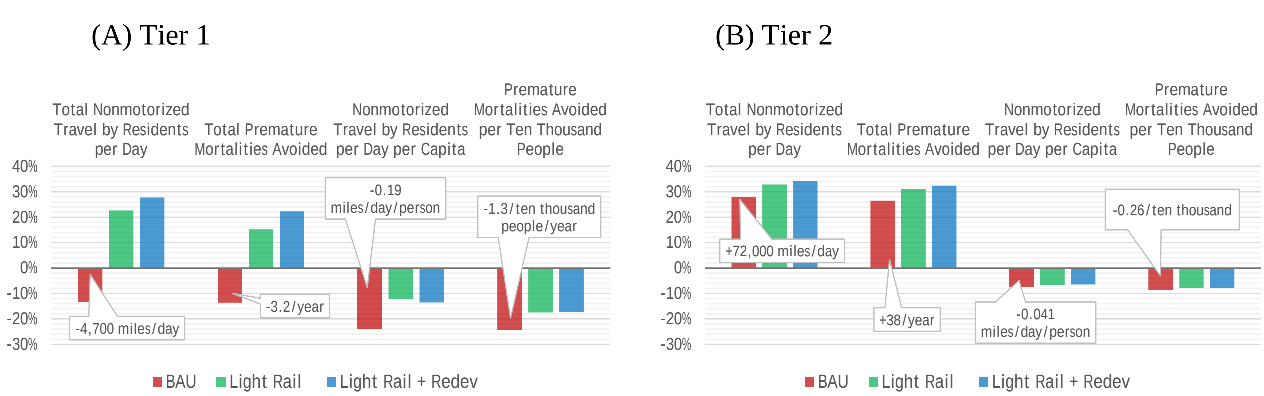


Figure 5-107. Percent Change in Nonmotorized Travel by Residents Per Day and Associated Percent Change in Avoided Premature Mortalities between 2020 and 2040 for Three Main Scenarios: Total and Population-Normalized

Despite the decreases in nonmotorized travel by residents per day per capita in both Tiers for all scenarios, the higher population growth in the light rail scenarios in Tier 1 increases total daily nonmotorized travel by Tier 1 residents by 23% and 28% under the Light Rail and Light Rail + Redevelopment scenarios, respectively, during 2020-2040 (Figure 5-107A), compared to a 13% decrease in the BAU scenario. These 2020-2040 increases in walking and cycling for transportation purposes in Tier 1 increase the total number of premature mortalities avoided by 15% and 22% under the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to a 14% decrease in the BAU scenario (Figure 5-107A). Even though nonmotorized travel by residents per capita declines more quickly in Tier 1 than Tier 2 in all three main scenarios, Tier 1 nonmotorized travel rates are still higher than Tier 2 rates for the entire model run. Therefore, because the two light rail scenarios increase the proportion of people living in Tier 1 (in addition to resulting in more walking by residents per capita than the BAU scenario), the average health of Tier 1 residents is improved in these scenarios. In Tier 2, total nonmotorized travel by residents increases under all three scenarios during 2020-2040, but the increase is larger in the light rail scenarios, at 33% and 34% in the Light Rail and Light Rail + Redevelopment scenarios, respectively, compared to 28% in the BAU scenario (Figure 5-107B). This results in increased avoided premature mortalities of 26% in the BAU scenario, 31% in the Light Rail scenario, and 32% in the Light Rail + Redevelopment scenario. However, the additional avoided premature mortalities in Tier 2 in the two light rail scenarios relative to BAU are all in the portion of Tier 2 that constitutes Tier 1. Regardless, these results suggest that the addition of the light rail line and associated redevelopment policies in Tier 1 could have lasting health benefits for the population living in that Tier.

Figure 5-108 presents a summary of the net health impacts of the Light Rail and Light Rail + Redevelopment scenarios relative to BAU, calculated by summing the effect of all three health outcomes (air emissions, traffic accidents, and nonmotorized travel) on premature mortalities avoided per year. When the health effects of $PM_{2.5}$ and NO_x vehicle emissions, differences in crash fatalities, and nonmotorized travel are combined, the two light rail scenarios increase avoided premature mortalities relative to BAU in both Tiers. By 2040, an additional 5.7 net premature mortalities per year are prevented in Tier 2 in the Light Rail scenario and 7.2 premature mortalities per year are prevented in the Light Rail + Redevelopment scenario, relative to BAU (Figure 5-108B). Interestingly, the combination of larger population growth relative to BAU in Tier 1 under the light rail scenarios and the larger relative increase in nonmotorized travel (compared to BAU) results in more premature mortalities avoided per year in 2040 in Tier 1 than in Tier 2, with 6.3 additional premature mortalities avoided per year under the Light Rail scenario and 7.8 avoided per year in the Light Rail + Redevelopment scenario.[35] Because Tier 2 includes Tier 1, this implies that under the light rail scenarios premature mortality rates in the portion of Tier 2 that is outside Tier 1 are slightly worse than BAU. The net increase in avoided mortality in Tier 1 (and, by extension, Tier 2) relative to BAU occurs despite a slight increase in premature mortalities due to vehicle air emissions and crash fatalities in the two light rail scenarios.

[35] The health benefits of nonmotorized travel are estimated based on the average amount of walking and cycling per day by residents, which is much lower in Tier 2 than Tier 1. Consequently, the two light rail scenarios result in slightly fewer premature mortalities avoided per year in Tier 2 than in Tier 1 in 2040, even though Tier 2 includes Tier 1.

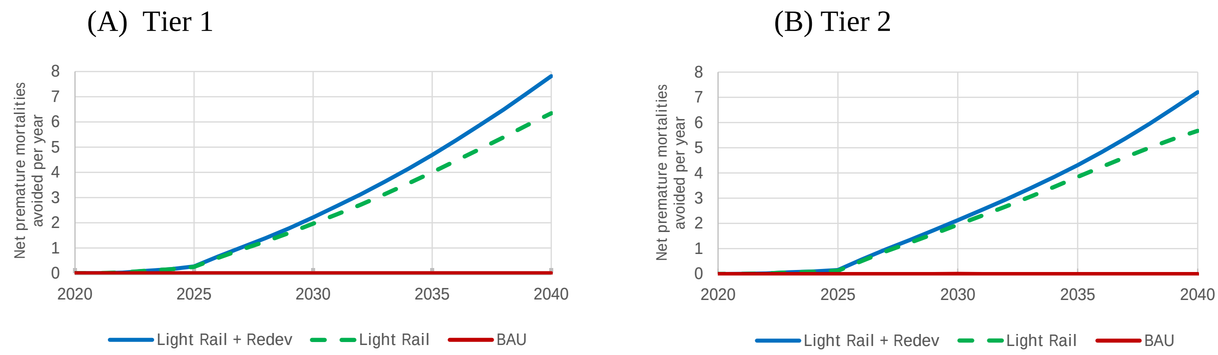


Figure 5-108. Net Premature Mortalities Avoided Per Year from $PM_{2.5}$ and NO_x Vehicle Emissions, Crash Fatalities, and Nonmotorized Travel Combined between 2020 and 2040, Departure from BAU

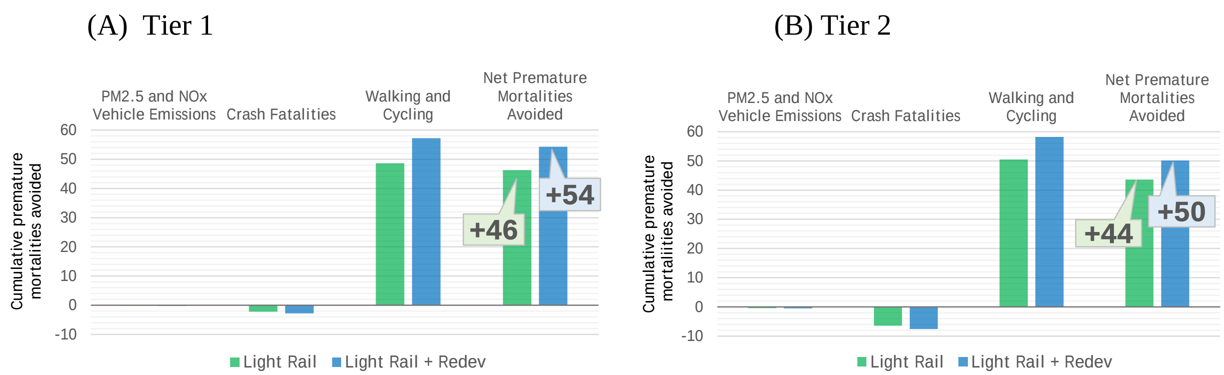


Figure 5-109. Cumulative Premature Mortalities Avoided by Cause and Net Cumulative Premature Mortalities Avoided between 2020 and 2040 for the Light Rail and Light Rail + Redevelopment Scenarios: Departure from BAU

Finally, Figure 5-109 summarizes the health benefits of the light rail scenarios by showing the difference in cumulative premature mortalities avoided for each health outcome and for all three outcomes combined between 2020 and 2040, relative to BAU. In Tier 1, the Light Rail and Light Rail + Redevelopment scenarios result in 46 and 54 additional avoided premature mortalities, respectively (Figure 5-109A). In Tier 2, the cumulative totals are 44 and 50 additional avoided premature mortalities, respectively (Figure 5-109B). The largest difference relative to BAU in avoided premature mortality comes from additional walking and cycling for transportation in the light rail scenarios, which offsets slight reductions in avoided premature mortalities caused by increased crash fatalities. Between 2020 and 2040, in both light rail scenarios, $PM_{2.5}$ and NO_x vehicle emissions increase premature mortalities by fewer than 0.5 cumulative deaths relative to the BAU scenario. The insignificant effect of differences in vehicle emissions, in spite of increased VMT, between scenarios on health outcomes in the model may be credited to the higher emissions standards on new vehicles that are represented in every scenario and which make it less likely for changes in VMT to have significant health impacts in the future, as each mile of vehicle travel is projected to generate less pollution than historical levels.

Vehicle Emissions Reduced

In this scenario, rather than having $PM_{2.5}$ and NO_x vehicle emissions per VMT plateau between 2020 and 2040, both vehicle emission factors are reduced by an additional 10% for all new vehicles built between 2020 and 2040 ($PM_{2.5}$ emissions factors per VMT are shown in Figure 5-110; NO_x emissions per VMT are not shown). This change does not translate into an immediate 10% reduction in vehicle emissions in the model in 2020, but instead causes a gradual reduction over 17 years, as vehicle model year average emission factors (Cai et al. 2013) are weighted each year by the fraction of vehicles in the U.S. vehicle fleet that are aged 1 year through 17 years (Jackson 2001b); we assume that the average vehicle remains in use for 17 years (International Energy Agency 2009). Between 2020 and 2040, the additional reductions in vehicle emissions in this scenario result in a cumulative four premature mortalities being prevented between 2020 and 2040 relative to BAU (Figure 5-110).

(A) Tier 1 (B) Tier 2

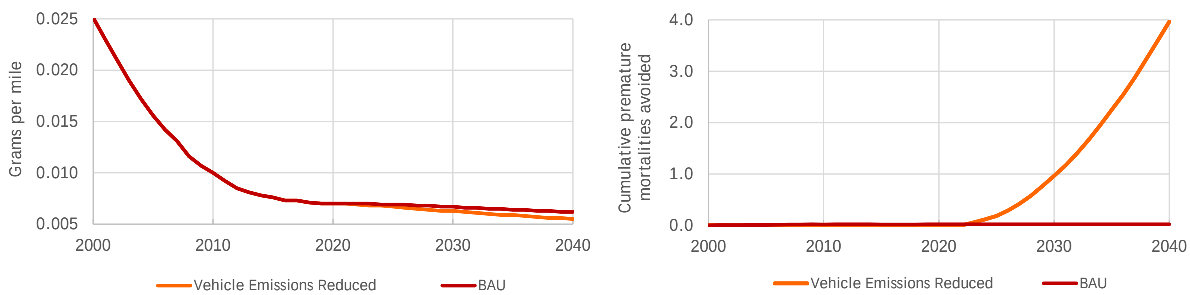


Figure 5-110. (A) $PM_{2.5}$ Vehicle Emissions Per VMT: Vehicle Emissions Reduced Scenario Compared to BAU and (B) Cumulative Premature Mortalities Avoided from $PM_{2.5}$ and NO_x Vehicle Emissions – Tier 2: Vehicle Emissions Reduced Scenario Departure from BAU

Higher Gas Prices

In this scenario (which is also described in the Transportation section), gas prices are set to be consistently 40% higher than BAU between 2016 and 2040. This increase in the cost of automobile fuel makes other transportation modes more attractive to travelers. As a result, Tier 2 nonmotorized travel by residents (walking and cycling) stays near its peak of 0.56-0.57 miles per day per capita between 2015 and 2040, rather than dropping to less than 0.50 miles per day per capita by 2040, as in the BAU scenario (Figure 5-111). Between 2015 and 2040, the health benefits of maintaining the higher rates of walking and cycling for transportation in this scenario lead to a cumulative 280 additional premature mortalities avoided in Tier 2 relative to BAU (Figure 5-111).

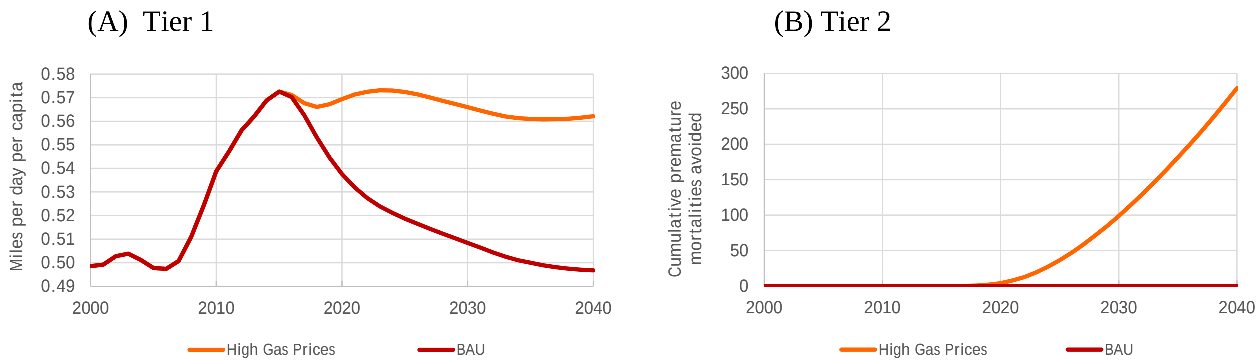


Figure 5-111. (A) Nonmotorized Travel by Residents Per Day Per Capita – Tier 2: Higher Gas Price Scenario Compared to BAU and (B) Cumulative Premature Mortalities Avoided Due to Nonmotorized Travel – Tier 2: Higher Gas Price Scenario Departure from BAU.

Sidewalk Building

In this scenario (which is also described in the Transportation section), demand for nonmotorized travel facilities (e.g., sidewalks and bike lanes) per developed acre, which is normally held constant, is set to double its value in BAU in 2020. Due to sidewalk and bicycle path/lane construction time and a lag in the health effects of walking and cycling, there is a delay of about five years before this change causes any noticeable health effects. As nonmotorized travel facilities are increased, walking and cycling levels increase as well, to a lesser degree (the model includes this relationship on the assumption that increased nonmotorized travel facilities improve the perceived safety of nonmotorized travel). In Tier 2, sidewalk and bicycle path/lane building leads to an increase in nonmotorized travel by residents, up to a plateau of about 0.68 miles per day per capita by 2033 (when the increase in nonmotorized travel facilities has been fully realized and travel mode shares have reach a new equilibrium in response), as opposed to dropping to less than 0.50 nonmotorized person miles by residents per day per capita by 2040, as in the reference scenario (Figure 5-112). Between 2020 and 2040, the health benefits of the increase in daily walking and cycling for transportation by residents lead to a cumulative 560 additional premature mortalities avoided relative to BAU (Figure 5-112).

(A) Tier 1

(B) Tier 2

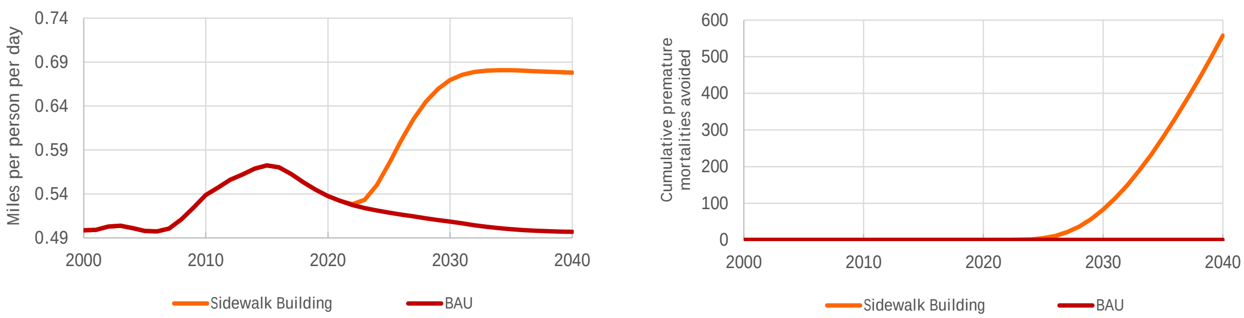


Figure 5-112. (A) Nonmotorized Travel by Residents Per Day Per Capita – Tier 2: Sidewalk Building Scenario Compared to BAU and (B) Cumulative Premature Mortalities Avoided Due to Nonmotorized Travel – Tier 2: Sidewalk Building Scenario Departure from BAU

5.5 Summary of Results

As the discussion throughout this chapter shows, both of the light rail scenarios result in increased population growth, land use and development, economic activity and employment, and VMT and congestion, relative to the BAU scenario in the D-O LRP SD Model. Some of these changes result in improvements to local quality of life (e.g., a reduction in the percent of the population living in poverty), while others have more negative effects (e.g., increased traffic congestion and stormwater runoff from increased impervious surfaces). In this section, we summarize results for some of the model's main social, economic, and environmental indicators. We first summarize model results by isolating the changes in model outputs between 2020 and 2040 for the three main scenarios in Table 5-1 to emphasize the magnitude of the impacts that our SD model estimates for the light rail scenarios. Next, we summarize the overall differences in model outputs in 2040 for the three main scenarios in Table 5-2 to show the end result of the model's many feedbacks. Finally, we summarize and list benefits and tradeoffs of the light rail scenarios, with a third list summarizing the Light Rail Scenario tradeoffs that are mitigated in the Light Rail + Redevelopment Scenario.

In Table 5-1, we summarize the magnitude of the changes to indicators for each light rail scenario between 2020 and 2040, relative to the BAU scenario. For each indicator, the table presents the absolute change in each Tier in each scenario, as well as the relative change (as a percentage of the BAU change) for the Light Rail and Light Rail + Redevelopment scenarios. For example, Tier 1 population increases by 6,160 people in the BAU scenario between 2020 and 2040, while the population change in the Light Rail scenario is 182% higher, at 17,400 people. Of the 12 indicators listed in Table 5-1, all moved in the same direction as BAU in Tier 1 in both of the light rail scenarios, with the exception of public transit use by residents per capita (which increased rather than declining) and impervious surfaces per capita (which declined rather than increasing). For most variables, the relative difference between the BAU and the light rail scenarios was larger in Tier 1 than Tier 2, consistent with the expectation that light rail impacts will be locally concentrated around the station areas.

Table 5-1. Summary of Changes in Key Indicators between 2020 and 2040 for the BAU, Light Rail, and Light Rail + Redevelopment Scenarios

Variable – Tier 1	BAU (Δ 2020-2040)	Light Rail		Light Rail + Redev	
		Δ 2020-2040	% diff from Δ in BAU	Δ 2020-2040	% diff from Δ in BAU
Stocks					
Population	+6,200	+17,000	182%	+21,000	240%
Nonresidential sq ft	+6.5M	+8.4M	32%	+15M	134%
Developed land (acres)	+920	+1,400	47%	+1,200	26%
Employment (jobs in area)	+31,000	+47,000	53%	+58,000	91%
Zero car households	+71	+140	103%	+114	61%
Rates					
GRP (USD 2010/year)	+5.6B	+7.3B	29%	+9.3B	66%
Total retail consumption (USD 2010/year)	+660M	+860M	31%	+1.0B	82%
VMT (miles/day)	+370,000	+490,000	31%	+540,000	46%
Intensity Measures					
Energy spending share of GRP (percentage points)	-0.50	-0.53	5.6%	-0.51	2.0%
Public transit use by residents (person miles/day/capita)	-0.088	+0.57	-743%*	+0.57	-750%*
CO2 emissions per GRP (tons/million USD 2010)	-48	-49	2.2%	-45	-6.6%
Impervious surfaces per capita (acres/thousand people)	+4	-5.7	-245%*	-11	-377%*

Variable – Tier 2	BAU (Δ 2020-2040)	Light Rail		Light Rail + Redev	
		Δ 2020-2040	% diff from Δ in BAU	Δ 2020-2040	% diff from Δ in BAU
Stocks					
Population	+180,000	+201,000	10%	+207,000	13%
Nonresidential sq ft	+43M	+52M	23%	+53M	25%
Developed land (acres)	+56,000	+62,000	13%	+64,000	16%
Employment (jobs in area)	+125,000	+150,000	21%	+154,000	23%
Zero car households	+230	+11	-95%	+17	-92%
Rates					
GRP (USD 2010/year)	+25B	+28B	16%	+29B	17%
Total retail consumption (USD 2010/year)	+5.8B	+6.7B	14%	+6.7B	15%
VMT (miles/day)	+5.8M	+6.1M	5.7%	+6.2M	7.5%
Intensity Measures					
Energy spending share of GRP (percentage points)	-0.81	-0.91	12.7%	-0.91	13.2%
Public transit use by residents (person miles/day/capita)	-0.039	+0.11	-391%*	+0.13	-432%*
CO2 emissions per GRP (tons/million USD 2010)	-84	-87	3.8%	-87	4.0%
Impervious surfaces per capita (acres/thousand people)	-9.3	-8.9	-5%	-9.2	-1%

** Percent difference not visualized due to scale.*

The Light Rail + Redevelopment scenario suggests that it is possible to maintain the economic benefits of expansion while mitigating some harmful effects of increased land development (i.e., it slows the growth of impervious surface). Between 2020 and 2040, the increase in Tier 1 developed land is 47% higher than BAU in the Light Rail scenario but only 26% higher than BAU in the Light Rail + Redevelopment scenario (see Table 5-1). This reduction in land development does not limit economic growth in the Light Rail + Redevelopment scenario, as it still sees a GRP increase in Tier 1 that is 66% higher than BAU (compared to 29% higher in the Light Rail scenario). The increased economic growth does increase the carbon intensity of the economy in Tier 1 under the Light Rail + Redevelopment scenario relative to BAU, but within an overall trend of decreased carbon intensity. Due to increasing energy efficiency in buildings and vehicles, CO_2 emissions per GRP are projected to decline by 48 tons per million USD 2010 between 2020 and 2040 in the Tier 1 BAU scenario (Table 5-1). CO_2 emissions per GRP decline 2.2% more, and 6.6% less, in the Light Rail and Light Rail + Redevelopment scenarios, respectively.

Besides stimulating GRP, the two light rail scenarios project dramatic increases in Tier 1 public transit use by residents per day per capita between 2020 and 2040 (189% in the Light Rail scenario and 191% in the Light Rail + Redevelopment scenario). This is counter to the declining trend in Tier 1 public transit use in the BAU scenario. However, the increase in population and economic activity in both light rail scenarios leads to growth in overall VMT. During 2020-2040, Tier 1 VMT in the Light Rail and Light Rail + Redevelopment scenarios increases by 31% and 46% more than in the BAU case, respectively. In addition to increased CO_2 emissions, greater VMT results in more traffic congestion and more emissions of $PM_{2.5}$ and NO_x. Thus, even though the development of the light rail results in a larger number of people using public transit and nonmotorized travel modes (with corresponding reductions in VMT per person), it does not fully mitigate the negative consequences of population and economic growth in the region.

Finally, below we present a summary of the main benefits, tradeoffs, and mitigating effects of the two light rail scenarios evident in the year 2040. Table 5-2 visually summarizes these effects, showing the values of several indicators in 2040 in the BAU and two light rail scenarios, together with percent differences from the BAU values.

Benefits of the Light Rail Scenarios

- **The light rail attracts more economic growth to the region,** increasing employment in 2040 by 28,000 jobs in Tier 2 and by 16,000 jobs in Tier 1 in the Light Rail scenario relative to the BAU scenario (see Table 5-2).

- **The light rail creates more mixed uses** more quickly in Tier 1, as measured both by the HHI (reaching its maximum divergence at a level 1.8% lower than BAU in 2026) and the jobs-housing balance (peaking at 8.8% higher than BAU in 2040). Redevelopment does not significantly affect mixed uses, however (i.e., no significant difference between Light Rail and Light Rail + Redevelopment scenarios).

- Because it improves the public transit system through the addition of fixed-guideway service on an exclusive right-of-way, **the Light Rail scenario causes 2040 Tier 2 public transit ridership to be 48% greater** than what it would have been in the BAU scenario, even though it only causes Tier 2 population to be 2.8% greater than what it would have been in the BAU scenario. Because it takes the additional step of allowing denser development in light rail station areas (and hence allowing more people and businesses to locate there), **the Light Rail + Redevelopment scenario causes 2040 Tier 2 public transit ridership to be 54% greater** than the BAU scenario, accompanied by an increase in population that is only 3.7% greater than BAU.

- As the Light Rail and Light Rail + Redevelopment scenarios increase public transit use, they have the added benefit of increasing nonmotorized travel. In 2040, the average resident of Tier 1 walks or bicycles 0.095 more miles per day in the Light Rail scenario than in the BAU scenario (a difference of 15%) and 0.084 more miles per day in the Light Rail + Redevelopment scenario (a difference of 14%).

Table 5-2. Summary of Key Indicators in 2040 for the BAU, Light Rail, and Light Rail + Redevelopment Scenarios

Tier 1	BAU	Light Rail		Light Rail + Redev	
	2040 Value	2040 Value	% diff from BAU	2040 Value	% diff from BAU
Stocks					
Population	50,000	61,000	22%	65,000	30%
Employment (jobs in the Tier)	119,000	135,000	14%	147,000	23%
Rates					
GRP (USD 2010/year)	14B	15B	12%	17B	27%
VMT (miles/day)	1.84M	1.95M	6.3%	2.01M	9.4%
Peak period automobile speed (miles/hour)	43	40	-5.9%	38	-11%
Total energy use (MMBtu/year)	9.0M	9.9M	10%	12M	28%
CO2 emissions from buildings and transportation (tons/year)	1.3M	1.4M	11%	1.7M	31%
Stormwater runoff N load (lbs/year)	60,000	63,000	5.8%	62,000	3.6%
SF property value (USD 2010/dwelling unit)	220,000	221,000	0.9%	220,000	0.2%
MF property value (USD 2010/dwelling unit)	96,000	89,000	-7.3%	102,000	6.5%
Nonresidential property value (USD 2010/sq ft)	1,310	1,270	-3.4%	2,280	74%
Net premature mortalities avoided per year*	15	21	42%	23	52%
Indices					
Jobs-housing balance (1 is balanced)	0.35	0.38	8.8%	0.39	9.1%
HHI Index (lower is more mixed uses)	0.22	0.22	0.3%	0.22	0.2%
Cumulative Measures					
Cumulative city and county real property tax levied (USD 2010)	3.3B	3.7B	13%	4.4B	33%
Intensity Measures					
Developed land (acres) per capita	0.10	0.087	-11%	0.079	-19%
Public transit ridership by residents (trips/year) per capita	20	81	308%	81	311%
Nonmotorized travel by residents (person miles/day) per capita	0.62	0.71	15%	0.70	14%
Daily water demand (Mgal/year) per capita	0.050	0.048	-4.1%	0.049	-1.8%
Percent of the population in poverty (percentage points)	34	31	-7.5%	28	-17%

Tier 2	BAU	Light Rail		Light Rail + Redev	
	2040 Value	2040 Value	% diff from BAU	2040 Value	% diff from BAU
Stocks					
Population	660,000	680,000	2.7%	690,000	3.5%
Employment (jobs in the Tier)	430,000	455,000	5.9%	459,000	6.7%
Rates					
GRP (USD 2010/year)	60B	63B	6.3%	64B	7.2%
VMT (miles/day)	21M	21.3M	1.5%	21.4M	2.0%
Peak period automobile speed (miles/hour)	47	46	-1.5%	46	-1.9%
Total energy use (MMBtu/year)	80M	83M	3.9%	84M	4.6%
CO2 emissions from buildings and transportation (tons/year)	10.8M	11.3M	4.5%	11.4M	5.2%
Stormwater runoff N load (lbs/year)	1.46M	1.49M	1.9%	1.49M	2.2%
SF property value (USD 2010/dwelling unit)	480,000	510,000	7.9%	520,000	10.0%
MF property value (USD 2010/dwelling unit)	93,000	100,000	7.1%	101,000	8.4%
Nonresidential property value (USD 2010/sq ft)	543	577	6.3%	583	7.3%
Net premature mortalities avoided per year*	125	130	4.5%	132	5.7%
Indices					
Jobs-housing balance (1 is balanced)	0.89	0.88	-1.7%	0.88	-1.7%
HHI Index (lower is more mixed uses)	0.62	0.62	-1.1%	0.62	-1.1%
Cumulative Measures					
Cumulative LRP revenues (USD 2010)	1.1B	1.2B	2.0%	1.2B	2.1%
Cumulative city and county real property tax levied (USD 2010)	28.9B	29.9B	3.5%	30.0B	3.8%
Intensity Measures					
Developed land (acres) per capita	0.30	0.30	0.6%	0.30	0.4%
Public transit ridership by residents (trips/year) per capita	32	46	44%	48	48%
Nonmotorized travel by residents (person miles/day) per capita	0.50	0.50	1.0%	0.50	1.2%
Daily water demand (Mgal/year) per capita	0.034	0.034	1.1%	0.034	1.1%
Percent of the population in poverty (percentage points)	16	0.13	-21%	0.13	-21%

** The net effect of $PM_{2.5}$ and NO_x vehicle emissions, physical activity, and crash fatalities.*

Tradeoffs Due to the Light Rail Scenarios

- **The economic growth produced by the light rail scenarios increases motor vehicle travel and hence increases traffic congestion**, in spite of the light rail line shifting a portion of travelers from automobiles to public transit. In Tier 1, the average peak-period automobile speed in 2040 is 2.5 mph less than BAU in the Light Rail scenario and 4.7 mph less than BAU in the Light Rail + Redevelopment scenario. In Tier 2, the average peak-period automobile speed in 2040 is 0.72 mph less than BAU in the Light Rail scenario and 0.94 mph less than BAU in the Light Rail + Redevelopment scenario.

- **The light rail scenarios increase energy consumption and CO_2 emissions** relative to BAU, with a larger relative increase in Tier 1 than in Tier 2. In Tier 1, energy consumption and CO_2 emissions in 2040 are about 10% higher in the Light Rail scenario than BAU, and 30% higher in the Light Rail + Redevelopment scenario than BAU. In Tier 2, energy consumption and CO_2 emissions increase by less than 5% over BAU in both light rail scenarios. **Due to the effects of land scarcity on development in the Light Rail scenario, energy consumption and emissions level off around 2033 in Tier 1**, but they continue to increase out to 2040 in the Light Rail + Redevelopment scenario.

- In all three main scenarios, the energy intensity of the economy is projected to decrease. Energy use per real dollar of GRP decreases by about 35% between 2020 and 2040 in the three main scenarios, in both Tiers. However, **whereas area-based building energy intensity in Tier 1** (MMBtu/year/acre) declines by 1-2% in the BAU and Light Rail scenarios between 2020 and 2040, it **increases by 26% in the Light Rail + Redevelopment scenario, due to higher-density development.**

- **Due to the growth in impervious surface, the light rail scenarios increase stormwater runoff N load in Tier 1** by 6% over BAU in 2040 in the Light Rail scenario and 4% over BAU in the Light Rail + Redevelopment scenario. Despite the effect of land scarcity on development starting in 2033, the Light Rail scenario has the highest stormwater N load in Tier 1 by 2040.

- **Due to growth in population and employment, the light rail scenarios increase total municipal water demand relative to BAU**, with a larger relative increase in Tier 1 than in Tier 2. In 2040, projected daily water demand in Tier 1 is 17% and 27% higher than BAU in the Light Rail and Light Rail + Redevelopment scenarios, respectively. In Tier 2, daily water demand in 2040 is forecasted to be 4-5% higher in the light rail scenarios than BAU. Land scarcity after 2033 in Tier 1 causes slower growth in economic and residential development, leading to **slower growth in water demand in the Light Rail scenario compared to the Light Rail + Redevelopment scenario**. Although total water demand increases under the light rail scenarios, **daily water demand per capita is 2-4% lower in 2040** relative to BAU in Tier 1, and nearly unchanged in Tier 2.

- **The Light Rail + Redevelopment scenario causes the largest decrease in the percent of the population in poverty in Tier 1** (17% lower than BAU in 2040) due to a drop in unemployment, which results in a smaller increase in the number of transit-dependent households in Tier 1 than in the Light Rail scenario (1.5% and 2.6% higher than BAU in 2040, respectively), which **reduces transit ridership** relative to what it otherwise would be.

Light Rail Scenario Tradeoffs Mitigated in the Light Rail + Redevelopment Scenario

- **The Light Rail + Redevelopment scenario is assumed to significantly increase the density of land use**, and this change is evident through a 13% drop in developed land per capita between 2020 and 2040 in Tier 1.

- **The Light Rail + Redevelopment scenario offers a benefit of reducing annual stormwater N load**, relative to the Light Rail scenario, in Tier 1, with only a 4% higher annual N load relative to BAU in 2040 compared to 6% higher under the Light Rail scenario.

- Although **the Light Rail + Redevelopment scenario** only marginally increases economic growth in Tier 2 relative to the Light Rail Scenario, it **concentrates employment in Tier 1**, adding 12,000 additional jobs to Tier 1 in 2040 relative to the Light Rail Scenario.

- Increasing property values in Tier 1 under the Light Rail + Redevelopment scenario provide a win-win for tax revenues and affordability; in real terms, residential property values are no more than 7% higher than BAU in 2040 (compared to 7% lower under the Light Rail scenario), while nonresidential property values increase by 136% more than under the Light Rail scenario in Tier 1 between 2020 and 2040. This leads to $660M more in cumulative real property taxes levied between 2020 and 2040 than under the Light Rail scenario in Tier 1 alone.

- Since more people live in Tier 1 in the Light Rail + Redevelopment scenario (compared to the BAU and Light Rail scenarios), more people realize the health benefits of increased walking and cycling for transportation purposes caused by the light rail. This results in approximately 7.8 more premature mortalities avoided per year in 2040 in Tier 1 than in the BAU scenario (compared to 6.3 avoided per year in the Light Rail scenario relative to BAU), despite the small increase in deaths due to vehicle air emissions (0.03 per year) and crash fatalities (0.5 per year) in Tier 1 due to increased VMT.

6 Quality Assurance

This chapter presents a detailed description of the quality assurance (QA) steps taken to calibrate and validate the D-O LRP SD model. At the onset of model development, the modeling group developed a Quality Assurance Project Plan (QAPP) (dated September 16, 2014), which was approved by the National Exposure Research Laboratory (NERL) and Office of Research and Development (ORD) Directors of Quality Assurance. After we developed the conceptual model in Phase I of this research project, we constructed and calibrated the operational model (Phase II) and presented its results for several transportation and land use scenarios to stakeholders. Based on their reactions, we made modifications to the model and identified a number of alternative scenarios that could maximize the benefits of the D-O LRP or minimize its consequences, which we analyzed in Phase III of the project. This chapter presents the results of thorough model testing at both Phases II and III in accordance with the QAPP. Additional exploration of the D-O LRP SD Model's structure and functionality can be conducted in the Vensim file itself. For assistance in navigating the model in Vensim, please refer to the User Guide provided in Appendix A.

6.1 QA Overview

Models can be classified in many different ways and assessed according to different criteria, such as physical versus symbolic; dynamic versus static; deterministic versus stochastic, and others. As it relates to the notion of validity, a crucial distinction must be made between models that are "correlational" (i.e., purely data-driven or "black-box") and models that are "causal-descriptive" (i.e., theory-like or "white-box").

In correlational models, since there is no claim of causality in structure, what matters is the aggregate output behavior of the model; the model is assessed as valid if its output matches the "real" output within a specified range of accuracy, without any questioning of the validity of the individual relationships that exist in the model. This type of "output" validation can often be cast as a classical statistical testing problem. Models that are built primarily for forecasting purposes (such as time-series or regression models) belong to this category.

On the other hand, causal-descriptive models make statements about how real systems actually operate in some aspects. In this case, generating an "accurate" output behavior is not sufficient for model validity; what is crucial is the validity of the internal structure of the model. A causal-descriptive model, in presenting a theory about the real system, must not only reproduce or predict its behavior, but also explain how the behavior is generated, and possibly suggest ways of changing the system's behavior.

System dynamics models, such as the Durham-Orange Light Rail model, fall into the causal-descriptive category of models. Such models are built to assess the effectiveness of alternative policies or design strategies at improving the behavior of a given system. This is only possible, of course, if the model has an internal structure that adequately represents those aspects of the system that are relevant to the problem behavior at hand. In short, it is often said that a system dynamics model must generate the "right output behavior for the right reasons."

This section discusses model parameterization (i.e., calibration), corroboration (i.e., validation and simulation, and sensitivity analysis), and computational reproducibility of the results of the model. The main purpose of these procedures is to ensure that the model is accurate and precise enough to meet the project needs. Because the model is intended to provide information about causal pathways and the magnitudes and directionalities of policy impacts, rather than yielding numerical results that in themselves form the basis for decisions, there are no formal data quality objectives. However, the ability of the model to reproduce historical data and to match projections where applicable is an important indication of its structural validity. We have identified a target of 10% for goodness of fit, which, in most cases, was easily met. The sections that follow describe the testing of the model and interpret the results of those tests with respect to model structure, performance and reliability. Section 6.1, Model Parameterization (Calibration), describes sources of historical data and projections used (including other models); the integration of D-O LRP model sectors; the characterization of uncertainty among inputs to the D-O LRP model; and calibration statistics comparing model output to data. Section 6.2, Model Corroboration (Validation and Simulation), describes tests of model structure (equations, linkages); and sensitivities of model behavior to the value of uncertain parameters. Section 6.3 (Computational Reproducibility) describes how users can obtain the D-O LRP model source code, which includes documentation of the model equations.

6.2 Model Parameterization (Calibration)

This section describes the calibration steps that took place during two stages of model development:

1. Intra-sectoral calibration, which took place separately within each sector; and
2. Inter-sectoral calibration, which took place after the sectors were linked into a single model framework.

In both stages, model outputs were compared against external data sources and projections. Where necessary, we adjusted parameter values in order to improve this fit. We first describe data sources (including other models) used to calibrate the D-O LRP model, and then describe the results of model integration (inter-sector calibration) and the fit of major variables to data in the business-as-usual scenario (intra-sector calibration).

Data Collection and Analysis

In the initial phase of the development of the D-O LRP model, we selected historical data from existing literature for use in populating and calibrating the model. When relevant historical data were not available, the modeling team consulted experts in order to determine baseline assumptions that would allow for further calibration and validity testing. These assumptions include parameter values as well as equations for relationships between model variables that would allow the model to reproduce historical or projected data trends.

Historical Data and Projections

Table 6-1 lists a selection of the main variables of the model, together with data sources that provided historical and (where applicable) projected trends used for calibration purposes. Further detail on the calibration and data processing steps used for these variables can be found in Appendix B.

Table 6-1. Selected Variables and Data Sources for Historical and Projected Data

VARIABLE	DATA SOURCES (HISTORICAL)	DATA SOURCES (PROJECTIONS)
LAND USE SECTOR		
Population	ESRI Community Analyst	TRM v5 SE Data
Developed Land	CV2 Parcel Geodatabase for Place Type & Development Status Editing	Imagine 2040 Results GIS Data
Nonresidential Sq Ft	Durham County Tax Administration Real Property Database; Orange County Parcel Database; Chatham County Tax Parcel Database	None used
Dwelling Units	ESRI Community Analyst	ESRI Community Analyst
TRANSPORTATION SECTOR		
VMT	TRM v5 travel demand result shapefiles	TRM v5 travel demand result shapefiles
Person Miles of Public Transit Travel per Day	FTA. 2015. National Transit Database. Supplemented by information from Jennifer Green at Triangle Transit (now called GoTriangle)	(1) CAMPO and DCHC MPO. 2013. “2040 Metropolitan Transportation Plans.”; (2) TRM v5 travel demand result shapefiles; (3) Greater Triangle Travel Study, Household Travel Survey Final Report (conducted for the TRM); (4) ESRI Community Analyst. 2014.
Traffic Congestion	TRM v5 travel demand result shapefiles	TRM v5 travel demand result shapefiles
ENERGY SECTOR		
Building Energy Use	Durham City-County Sustainability Office	None used
CO_2 Emissions	Durham City-County Sustainability Office	Durham City-County Sustainability Office
Energy prices	US EIA. 2015: (1) “Weekly Retail Gasoline and Diesel Prices.” (2) “North Carolina Price of Natural Gas Delivered to Residential Customers.” (3) “Electricity: Sales (consumption), revenue, prices & customers.”	US EIA. 2015. “Annual Energy Outlook 2015.”
ECONOMY SECTOR		
Total Employment Tier 2	U.S. Bureau of Economic Analysis (BEA) and TRM v5 SE data	TRM v5 SE data
Total Employment Tier 1	LODES (U.S. Census Bureau) and TRM v5 SE data	TRM v5 SE data
Total Retail Consumption Tier 2	North Carolina Dept. of Revenue and Woods & Poole Economics, Inc. Copyright 2014	Woods & Poole Economics, Inc. Copyright 2014
Total Retail Consumption Tier 1	U.S. Census Economic Census data downloaded from SimplyMap	None used
Gross Regional Product (GRP)	Methodology from BEA (Panek et al. 2007)	None used
EQUITY SECTOR		
Property Values	Durham County Tax Administration Real Property Database; Orange County Parcel Database; Chatham County Tax Parcel Database	None used
WATER SECTOR		
Impervious Surface	U.S. Environmental Protection Agency EnviroAtlas	None used
Average Precipitation	State Climate Office of North Carolina	None used
Total Water Demand	NC Department of Environment and Natural Resources	Triangle Regional Water Supply Plan Vol. 1
HEALTH SECTOR		
Crash fatalities per year	Highway Safety Research Center at UNC Chapel Hill. 2015.	None used

Other Existing Simulation Models

A variety of models were used to obtain additional information to be used in the D-O LRP model. These were needed either to fill gaps in historical data or to provide a higher degree of disaggregation for projecting behavior (or outcomes) that otherwise cannot be measured. These include the Triangle Regional Model for transportation planning, the CommunityViz 2.0 model for land use planning, and the Jordan Falls Stormwater Load Accounting Tool for water infrastructure planning, as indicated in the Model Description report:

Table 6-2. Existing Simulation Models Used in the D-O LRP Model

MODEL	SECTOR WHERE USED	INFORMATION USED	REFERENCE
1. Triangle Regional Model (TRM) v5	Land Use, Economy, and Transportation	Projections for population, households, employment, VMT, and many other transportation-related variables	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario and travel demand result shapefiles."
2. CommunityViz 2.0	Land Use	Acres by development status and type in 2013	TJCOG. 2014. "CommunityViz 2 (CV2) Parcel Geodatabase for Place Type & Development Status Editing."
3. IEA/SMP Transportation Model	Transportation	Equation (including an elasticity) describing effect of economic indicators on vehicle ownership	International Energy Agency and World Business Council for Sustainable Development. 2004. "IEA/SMP Transportation Model." Spreadsheet model discussed in: Fulton, Lew, and G. Eads. 2004. "IEA/SMP Model Documentation and Reference Case Projection."
4. "Draft Spreadsheet Tool: Estimated Ridership and Cost of Fixed-Guideway Transit Projects," created as part of TCRP Project H-42	Transportation	Equation for the change in person miles of public transit travel per year due to adding fixed-guideway transit.	"Draft Spreadsheet Tool: Estimated Ridership and Cost of Fixed-Guideway Transit Projects," created as part of TCRP Project H-42: Chatman, Daniel G., Robert Cervero, Emily Moylan, Ian Carlton, Dana Weissman, Joe Zissman, Erick Guerra, Jin Murakami, Paolo Ikezoe, Donald Emerson, Dan Tischler, Daniel Means, Sandra Winkler, Kevin Sheu, and Sun Young Kwon. 2014. "TRCP Report 167: Making Effective Fixed-Guideway Transit Investments: Indicators of Success."
5. Jordan Falls Stormwater Load Accounting Tool	Land Use, Water	Coefficients for impervious surfaces by residential density; event mean concentration N and P.	NCDENR. 2011. "Jordan Lake Stormwater Load Accounting Tool User's Manual."
6. Simple Method for Calculating Stormwater Runoff	Water	Equation for stormwater nitrogen and phosphorous loading.	Shaver et al. 2007. "Fundamentals of urban runoff management: technical and institutional issues."
7. National Energy Modeling System (NEMS)	Energy	The basis for EIA Annual Energy Outlook 2015 projections, which were used for future building and vehicle energy intensity as well as future energy prices.	US EIA. 2009. "The National Energy Modeling System: an overview."
8. Health economic assessment tools (HEAT) for walking and for cycling (from the World Health Organization)	Health	Equation for number of deaths avoided due to walking for transportation, and number of deaths avoided due to cycling for transportation.	WHO. 2014. "Health economic assessment tools (HEAT) for walking and for cycling: Methodology and user guide, 2014 update."

The use of these models, including (1) the data inputs employed by each model, (2) the results each model generated, and (3) the specific equations used to estimate these results, allowed us to include sectors in the D-O LRP model for which data on parameter values and structural relationships would otherwise not have been available.

Other Existing Studies Providing Selected Model Equations

Certain parameters for model setup and calibration were obtained from studies of other areas, primarily due to the lack of data to inform particular relationships for the Durham and Orange County area. These studies generally focus on specific relationships, such as that between employment and person miles of public transit travel. Table 6-3 provides a list of all equations taken from the literature and other models, with their sources. Note that this table only includes sources for equations. For a complete listing of all other inputs (e.g. elasticities and effect tables) taken from the literature, as well as on the actual equations used from the sources below, see Appendices B and C.

Table 6-3. Equations Obtained from Existing Studies and Models

VARIABLE	MODEL PARAMETERS USED TO CALCULATE	SOURCE
LAND USE SECTOR		
Jobs-housing balance	Total employment, workers per household, total dwelling units	Ewing, R., et al. 1996. "Land use impacts on trip generation rates."
Herfindahl-Hirschman Index (HHI)	Industrial, office, retail , service, multifamily, and single family percents of developed land	Song, Y. and D. A. Rodriguez. "The measurement of the level of mixed land uses: A synthetic approach."
TRANSPORTATION SECTOR		
Change in person miles of public transit travel per year due to adding fixed guideway transit	Total employment Tier 1; population Tier 1; retail plus entertainment employment Tier 1; jobs earning $3,333 per month in 2010 USDs Tier 1; VMT per highway lane mile (Tier 2)	“Draft Spreadsheet Tool: Estimated Ridership and Cost of Fixed-Guideway Transit Projects,” created as part of TCRP Project H-42: Chatman, Daniel G., Robert Cervero, Emily Moylan, Ian Carlton, Dana Weissman, Joe Zissman, Erick Guerra, Jin Murakami, Paolo Ikezoe, Donald Emerson, Dan Tischler, Daniel Means, Sandra Winkler, Kevin Sheu, and Sun Young Kwon. 2014. “TRCP Report 167: Making Effective Fixed-Guideway Transit Investments: Indicators of Success.”
Desired vehicle ownership per person not in a zero-car household	Initial vehicle ownership per person not in a zero-car household, relative resident per capita net earnings	International Energy Agency and World Business Council for Sustainable Development. 2004. “IEA/SMP Transportation Model.” Spreadsheet model discussed in: Fulton, Lew, and G. Eads. 2004. “IEA/SMP Model Documentation and Reference Case Projection.”
ECONOMY SECTOR		
Desired employment (both Tiers)	Employment per dollar of consumption, total retail consumption	Keynes. 1936. "General theory of employment, interest and money”; Trends. 2010.
WATER SECTOR		
Nitrogen loading (“Total N load”)	Event mean concentrations of N, average precipitation per year, total land, impervious coefficient	Shaver et al. 2007. "Fundamentals of urban runoff management: technical and institutional issues;" NCDENR. 2011. "Jordan Lake Stormwater Load Accounting Tool User's Manual;" State Climate Office of North Carolina. 2015. "Historical Data."
Phosphorus loading (“Total P load”)	Event mean concentrations of P, average precipitation per year, total land, impervious coefficient	Shaver et al. 2007. "Fundamentals of urban runoff management: technical and institutional issues;" NCDENR. 2011. "Jordan Lake

VARIABLE	MODEL PARAMETERS USED TO CALCULATE	SOURCE
		Stormwater Load Accounting Tool User's Manual;" State Climate Office of North Carolina. 2015. "Historical Data."
HEALTH SECTOR		
Number of premature mortalities avoided due to walking for transportation & number of premature mortalities avoided due to cycling for transportation	Person miles of walking, cycling for transportation by residents per day per capita	WHO. 2014. "Health economic assessment tools (HEAT) for walking and for cycling: Methodology and user guide, 2014 update."

Given that the D-O LRP model uses causal relationships to generate projections for all the variables included in the model, it is important to ensure that the model built with the information received from various data sources represents a coherent system and produces consistent results. To accomplish this goal, we employed an integrated framework in which we evaluated equations and parameters obtained from existing studies by incorporating them into the model in an iterative fashion, and – at each step – comparing model outputs to historical data and projections.

To illustrate this framework, the team performed structural and sensitivity tests on the equity sector to quantify the variability of property value estimates in response to the many factors affecting them. A literature search revealed a wide variety of relationships based on diverse geographies: from small studies based in one neighborhood to papers looking at trends in all major metro areas of the U.S. Most studies that created relationships based on spatially explicit measures could not be used (such as proximity to retail) since our model is not spatially explicit.[36] In addition, relationships that rely on associations with variables not included in our model (e.g., housing age or number of rooms) could not be used. Since there was very little literature available on factors affecting multifamily property values, we borrowed relevant elasticities from the literature on both single-family and nonresidential property values to complete the relationships in this sector.[37] Through this process, we found that some relationships had to be modified to maintain a close fit between model outputs and external data sources. For example, an elasticity between available land and home prices (Capozza et al. 2002b) produced reasonable outputs for Tier 2, but in Tier 1, the use of this parameter value produced results that diverged significantly from historical data. We found that this result was caused by the fact that land availability in Tier 1 approaches zero, which is outside of the range of values where the estimate from the literature applies. Since this represents a somewhat artificial restraint, we replaced this elasticity with an effect table which simulates the same elasticity for moderate values of land availability, but dulls the effect at the extremes. For a complete listing of all changes made during calibration, and the adjustments made to data and equations drawn from the literature, see Appendix B.

[36] The exception is average commute time to work (Kockelman 1997), for which we were able to create a proxy in the model based on person miles of peak period automobile travel by residents per day and peak period vehicle speed.

[37] For example, we used the elasticity between job density and single-family home values and the elasticity between building size and nonresidential property value (Srour et al. 2002) to relate job density and building size, respectively, to multifamily property values.

Systemic Model Creation

The second phase of calibration takes place after various model sectors are linked, and exogenous assumptions (or drivers) of certain sectors are replaced by the outputs (endogenous variables) of others, creating a cross-sectoral causal network. In this section we (1) describe the effects of this model integration, summarizing how the integration process adds functionality and realism to the model; (2) present a model input characterization table assessing the quality of variables used within each sector; and (3) summarize the uncertainty within each sector, based on the input characterization table.

In the model integration stage, the modeling team once again compared model outputs to historical data and projections and adjusted parameter values to improve the model's fit with external data sources. This calibration process is systematic, as there are precise steps to follow and validation tests to perform, as well as systemic, given that various modules have to be linked horizontally (i.e., across sectors). This process allowed the modeling team to identify any incorrect sectoral parameters, as errors in one sector would be propagated to others, and to carry out a more precise and comprehensive calibration. Figure 6-1 illustrates the cross-sectoral linkages in green (both Tier 2 and Tier 1) and purple arrows (Tier 1 only) that were established when the core model sectors (land use, transportation, energy, and economy) were integrated. Intra-sector relationships that already existed are shown in dotted black arrows.

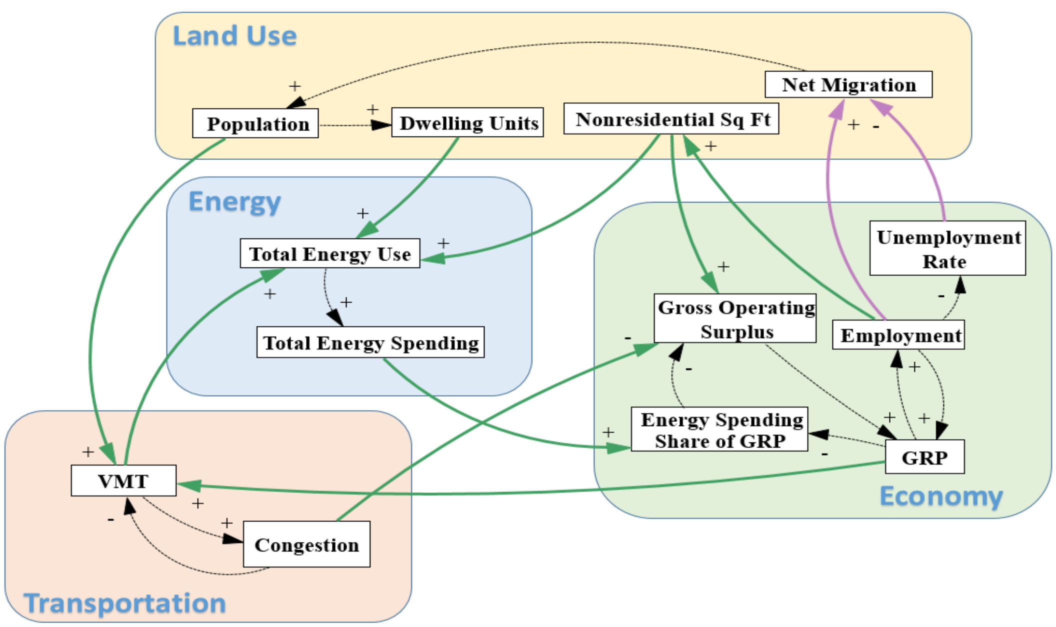


Figure 6-1. Schematic Illustrating Cross-Sectoral Linkages Established After Model Integration

Improvements Resulting From Model Integration

The integration of the seven sectors in the D-O LRP SD Model is one of the key features that sets this model apart from sector-specific models. This section discusses the major changes that occurred in each of the four core sectors as a result of this integration process, including completing feedback loops that allowed changes in one sector to affect outcomes in another sector. For each sector, we describe the differences between the pre-integration and post-integration versions of the model and discuss how those differences add functionality and realism to the model.

Integrating the Land use and Economy Sectors

Integrating the land use sector with the other model sectors involved replacing an exogenous projection for employment (which drives demand for nonresidential sq ft) by the endogenously calculated employment from the economy sector. This step completed a reinforcing feedback loop from employment to nonresidential square feet, to gross operating surplus to GRP, and back to employment (See Figure 6-1). This change also affected the calculation of the jobs-housing balance. Through this integration, outputs from the land use sector, including endogenous population, developed land, housing units, and nonresidential sq ft were linked to most of the other sectors of the model.

As shown in Figure 6-2 (for the service sector), this integration caused very little change to nonresidential sq ft in the short term, but the reinforcing feedback loop with employment lead to rising demand starting in 2014. As the figure shows, non-residential sq ft in the service sector was 34% higher post-integration.

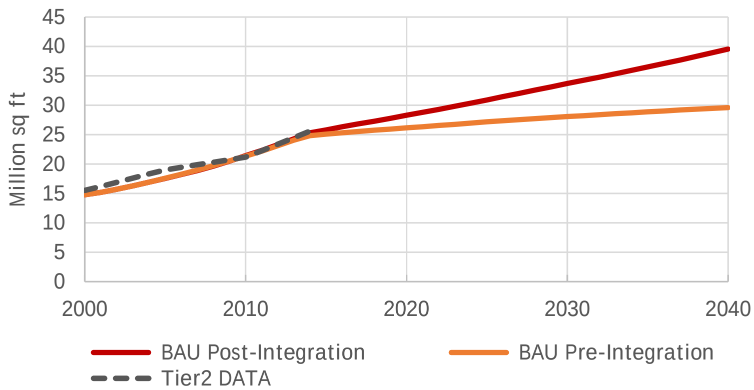


Figure 6-2. Service Square Feet – Tier 2: Before and After Model Integration

Completing this loop makes land use responsive to changes in the economy, allowing alternative scenarios to have effects that ripple through the sectors. To illustrate this, the test shown in Figure 6-3 below shows the percent change in total nonresidential sq ft caused by a 20% increase to the demand for nonresidential sq ft in Tier 2. While the 20% increase in demand leads to a boost in total nonresidential sq ft of about 2.3% over the model time period before integrating the Land Use and Economy sectors, the same change leads to an increase of about 2.8% post integration.[38] The feedback loop means that the increased nonresidential sq ft increase economic activity and employment, which in turn increases demand for nonresidential sq ft over what it would have otherwise been.

[38] The percent increase in total nonresidential sq ft is much lower than the percent increase in demand due to two factors: 1) the 20% boost does not apply to industrial sq ft, and 2) this test was conducted using the models as they existed immediately pre and post-integration, before the land development sector was restructured to allow development to better reflect demand, as described in Structure Confirmation Tests subsection of Section 6.3.

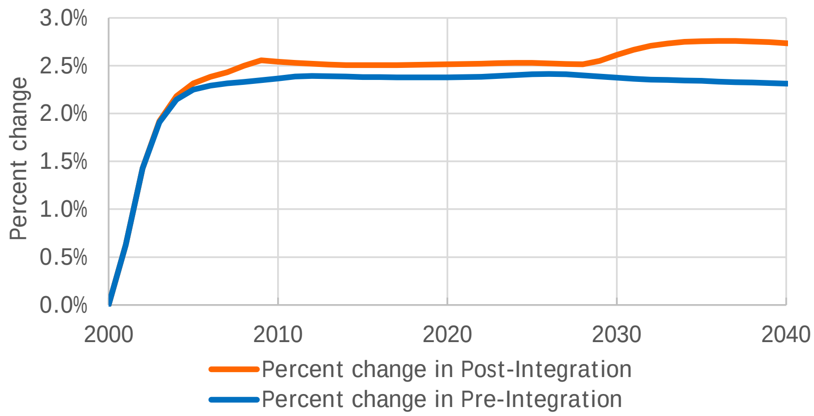


Figure 6-3. Percent Change in Total Nonresidential Sq. Ft. – Tier 2: 20% Increase in Demand Scenario Over BAU, Pre- and Post-Integration

Integrating the Transportation Sector with Economy, Land, and Energy Sectors

When we integrated the transportation sector, we replaced exogenous population and GRP projections with endogenous estimates of these variables. Before model integration, we assumed in the transportation-sector model that population would exactly match the Triangle Regional Model's projections. Pre- and post-integration outputs for these variables, as well as several other variables in the transportation sector, are presented in Figure 6-4. So as to avoid calibrating to data and projections that might be based on inconsistent assumptions, other exogenous projections in the transportation-sector model before integration (e.g., for employment, dwelling units, nonmotorized travel facilities, and parking prices) were, as often as possible, derived from the TRM. Because population in the integrated model is driven by feedback loops for births, deaths, and migration, its growth follows a slightly exponential trajectory, while the TRM projections reflect more linear growth (Figure 6-4A). Meanwhile, the pre-integration exogenous projection of inflation-adjusted GRP per capita (which was based on the BEA's estimates of the average annual rate of change for the Durham-Chapel Hill, NC Metropolitan Statistical Area) showed higher growth than the post-integration endogenous results, though the overall trend was otherwise fairly similar (Figure 6-4B). The model integration process also created a balancing feedback loop wherein traffic congestion reduces GRP, which discourages automobile travel, which reduces congestion (see Section 3.2). However, the effect of traffic congestion on GRP is small compared to total GRP, so the impact of this feedback loop is minor.

Baseline travel volumes increase when population goes up, but baseline automobile travel decreases when GRP goes down. As such, the effects on VMT of the greater population and lesser GRP that resulted from model integration mitigate one another, hence reducing the net effect on VMT. In part for this reason, Tier 2 VMT in 2040 in the integrated D-O LRP SD Model is 1.4% less than in the pre-integration transportation-sector model (Figure 6-4C). Tier 2 VMT in the present, integrated model is also 8.8% greater than in the pre-integration model in the year 2000, but that is largely due recalibrations that we performed after updating the assumed lookup table for gasoline prices in the model, rather than being attributable to the model-integration step. Tier 2 public transit person miles in 2040 are 25.5% less in the present, integrated model than in the pre-integration transportation-sector model (Figure 6-4D), largely thanks to changes that we made to the model after integration. If not for these post-integration model changes, we would expect the present, integrated model to produce higher public transit person mile values than the pre-integration transportation-sector model.

Other variables affecting the transportation sector that became dynamic as a result of the model-integration process include employment, dwelling units, and earnings by residents, whose pre-integration lookup tables were all derived from the TRM. We use dwelling units and employment to calculate the jobs-housing balance, which helps to drive levels of nonmotorized travel. The present, integrated model's Tier 2 jobs-housing balance only differs from the pre-integration model by an average of 0.8% in any given year and is 2.3% greater than in the pre-integration model in 2040 (Figure 6-4E). We also use employment per commercial acre to represent demand for parking, and hence drive parking prices, replacing an unrealistic lookup table for parking prices that we calculated from TRM data and projections. By 2040, Tier 2 parking prices in the integrated model are 28.7% greater than in the unintegrated transportation-sector model (Figure 6-4F). Meanwhile, the endogenous variable of resident per capita net earnings replaces an exogenous lookup table for the purpose of driving demand for automobiles, and hence the actual stock of vehicles. The endogenous earnings variable increases more quickly than the exogenous one. By 2040, Tier 2 vehicle stock in the integrated model is 29.2% greater than in the unintegrated transportation-sector model (Figure 6-4G). Finally, we added a mechanism whereby nonmotorized-travel-facility-building is driven by developed land, rather than a lookup table of TRM-derived figures, assuming that demand for sidewalks and bike lanes mostly exists around developed land, because that is where there are destinations to walk or bicycle to. As a result of this change, Tier 2 miles of nonmotorized travel facilities (which affect travel by nonmotorized modes) now increase more quickly and in 2040 are 15.3% greater than in the pre-integration model (Figure 6-4H).

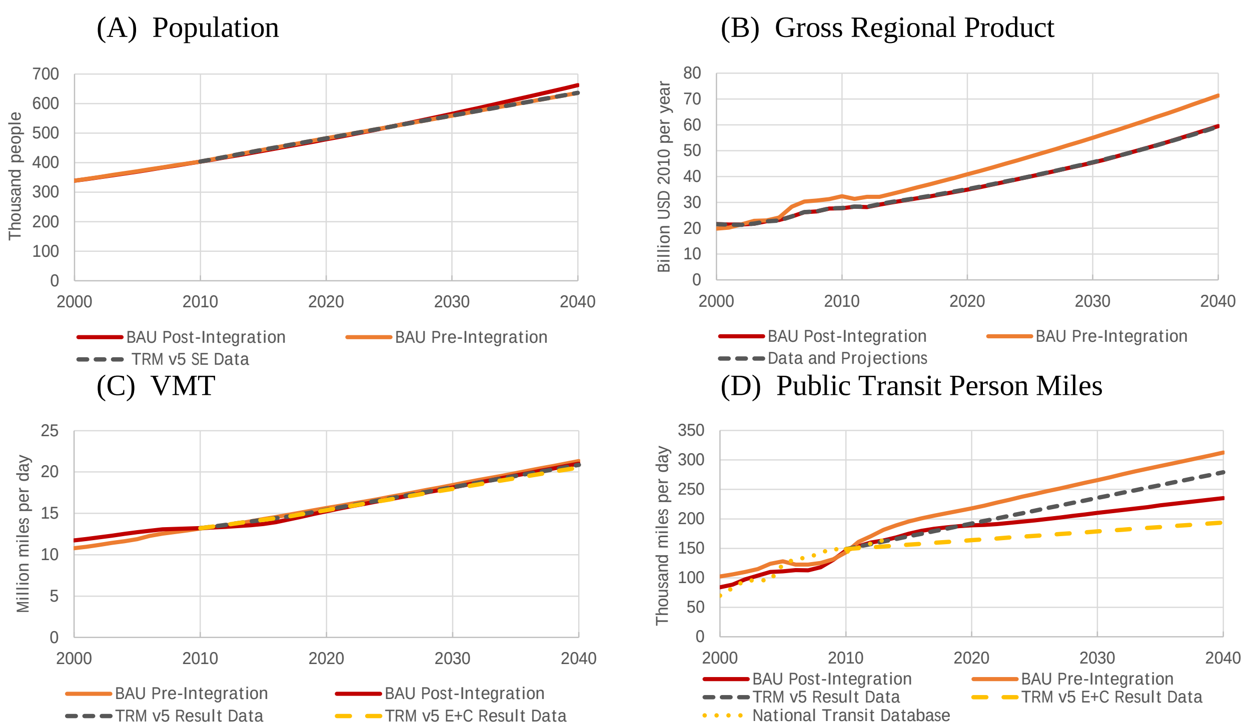


Figure 6-4. Transportation Sector in Tier 2, Before and After Sectoral Integration

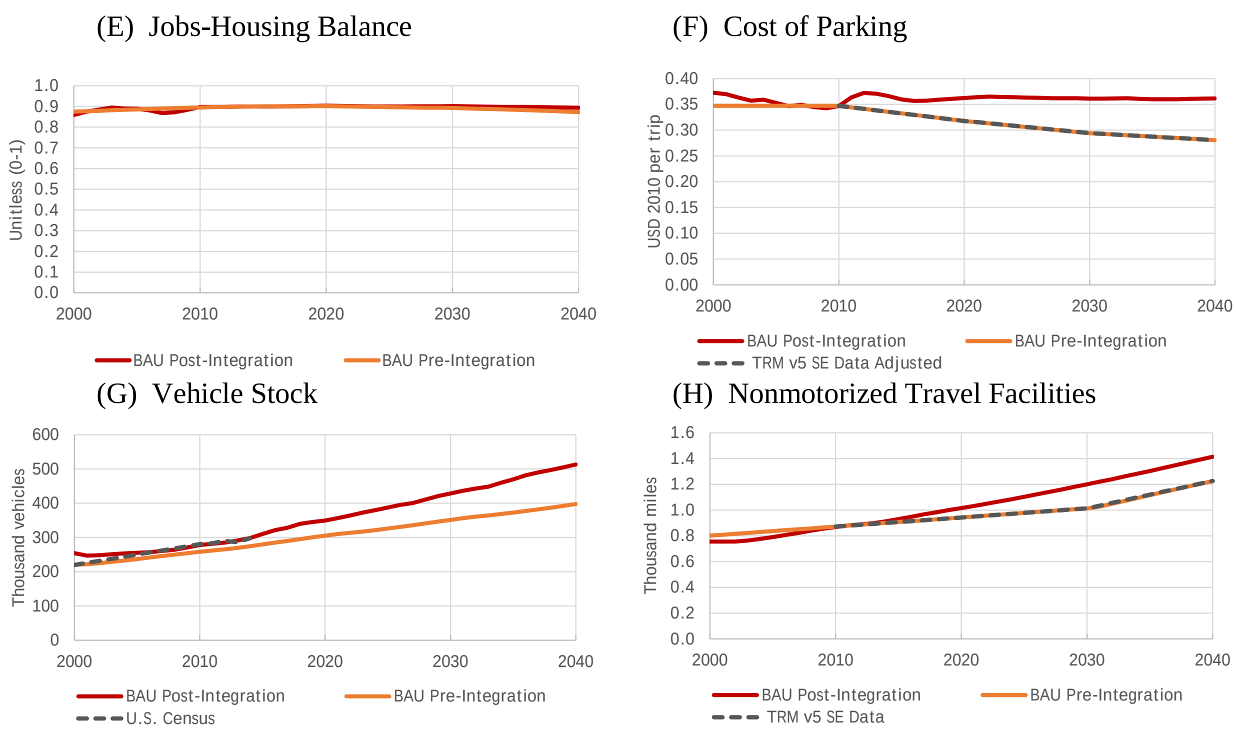


Figure 6-4 (continued). Transportation Sector in Tier 2, Before and After Sectoral Integration

Integrating the Energy Sector with Land and Transportation Sectors

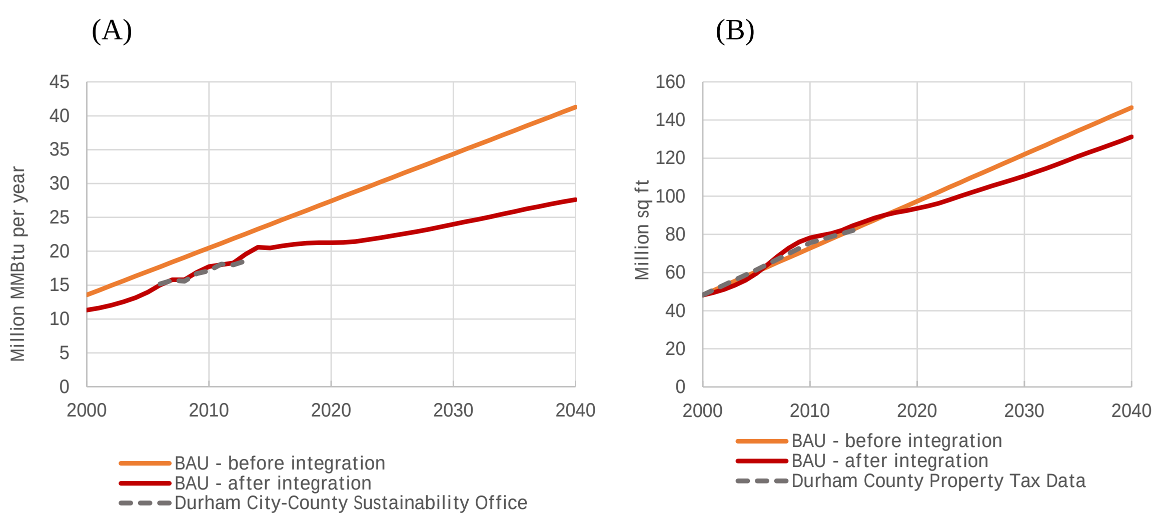


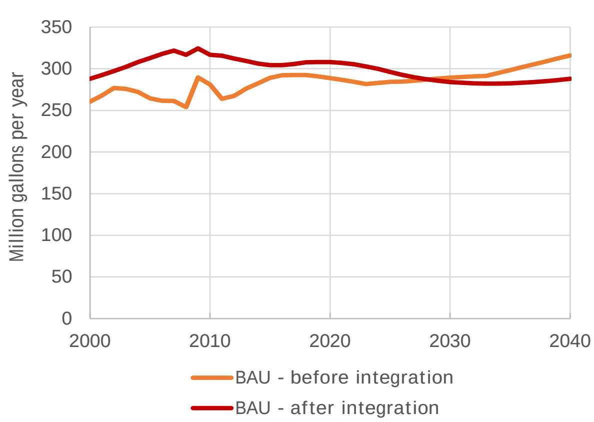
Figure 6-5. Energy Model in Tier 2, Before and After Sectoral Integration: (A) Commercial Energy Use and (B) Commercial Square Footage

Integrating the energy model with other sectors resulted in three main improvements: (1) endogenously modeled building stock, which reflects economic and land use feedbacks; (2) endogenously modeled VMT, which reflects economic and transportation feedbacks; and (3) endogenously represented feedback between the energy system and the economy. These improvements add nuance and detail to the energy sector projections. For example, before integration, commercial energy use was projected to have linear growth based on linear growth in commercial square footage (Figure 6-5A-B, orange line).

Before model integration, historical data on commercial energy use and commercial square footage do not suggest that this linear trend will change (Figure 6-5A-B, grey dashed line). After model integration, commercial energy use grows slower after 2014 partly due to slower growth in commercial square footage after 2010 (Figure 6-5A-B, red line).

As another example, before model integration, vehicle fuel consumption was based on VMT, which includes effects of population growth and elasticity to fuel price (Figure 6-6A-B, orange line). After model integration, the growth of vehicle fuel consumption is stimulated by increased GDP per capita, and includes balancing feedback from traffic congestion, in addition to the population growth, VMT, and fuel price effects found in the model before integration (Figure 6-6a-b, red line). The integrated model represents feedback between the transport and economy sectors which was not captured in the energy model before integration: economic growth (GDP) stimulates VMT, but congestion rises with VMT, giving balancing feedback to economic growth. Before integration, the energy model projected VMT by multiplying population by a constant VMT per capita, and applying an elasticity of VMT to fuel price. The integrated model is less sensitive to the drop in gasoline price in 2008, and VMT projections from the integrated model better match TRM v5 projections compared to the model before integration (Figure 6-6b). Vehicle fuel consumption declines after 2009 in the integrated model due to improvements in vehicle fuel efficiency based on EIA Annual Energy Outlook 2015 projections (Figure 6-6a). Local data were available for VMT, but not vehicle energy consumption, so we can only assess the accuracy of these fuel consumption projections in terms of their assumptions. To summarize the benefits of model integration for vehicle energy consumption: the integrated model includes feedbacks from economic growth and traffic congestion not present in the non-integrated model; and further, the integrated model has an endogenous formulation for VMT per capita, which was assumed constant in the non-integrated model.

(A)



(B)

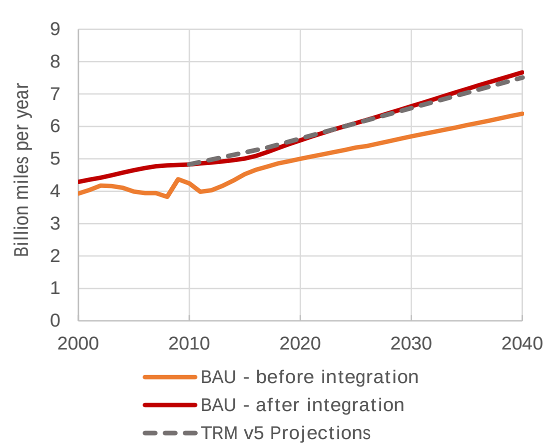


Figure 6-6. Energy Model in Tier 2, Before and After Sectoral Integration: (A) Vehicle Fuel Consumption and (B) VMT

<u>**Integrating the Economy Sector and the Population Component of the Land Use Sector**</u>

Integrating the Economy and Population sectors in Tier 1 resulted in the discovery of the need for a balancing feedback between unemployment and net migration. Formerly, Tier 1 migration was driven exclusively by changes in desired employment, as restricted by available dwelling units. However, as can be seen in Figure 6-7, when run on top of the BAU scenario, the unemployment rate rises continuously and unrealistically in Tier 1. In the Light Rail + Redevelopment scenario, unemployment drops below zero, since without a link, employment rises with the economy, reducing unemployment. The result is that before the integration was made, the BAU policy scenario was far worse in terms of unemployment and poverty rates relative to the Light Rail + Redevelopment.

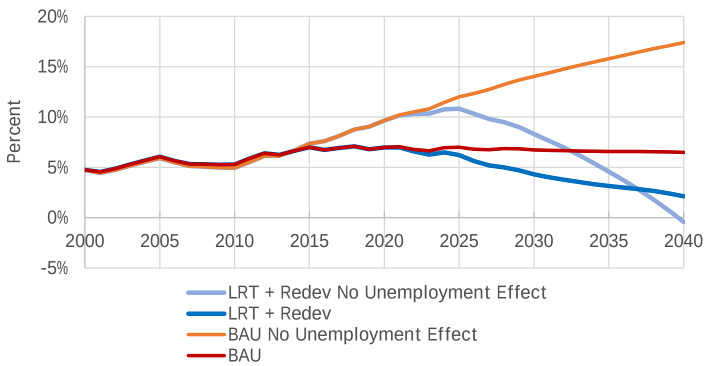


Figure 6-7. Unemployment Rate – Tier 1: Unemployment Effect on Migration in Tier 1 Removed

The addition of the effect of unemployment on migration in Tier 1 represents reality more truly by including a balancing feedback to migration - as unemployment drops very low in an area, more people move to the area for jobs, which raises the resident population, and increases unemployment until it reaches a new equilibrium. Table 6-4 displays the average yearly percent departure from the data, in comparison to the BAU, for the years data are available (2000-2014). The addition of the unemployment effect on migration in the BAU scenario improves the model fit with data for the Tier 1 unemployment rate and percent of the population in poverty. Even where the change worsens fit with the data historically, the effect is minor in comparison to the improvement in the model trends shown in Figure 6-7.

Table 6-4. Average Yearly Percent Departure from Data, 2000-2014: Unemployment Effect on Migration Tier 1 Removed

Average percent deviation from data for the years 2000, 2005-2014	BAU v Data	Unemployment Effect Removed v Data
Tier 1		
Unemployment rate Tier 1	-17.3%	-19.2%
Population Tier 1	-7.6%	-3.9%
Percent of population in poverty Tier 1	-1.8%	-2.7%
Tier 2		
Unemployment rate	0.8%	0.3%
Population	0.7%	1.4%
Percent of population in poverty	9.5%	9.3%

Model Input Characterization and Assessment

As part of the quality assurance process in developing the D-O LRP model, we assessed the quality of model inputs, both data sources and any methods used to manipulate them for use in the model. The results of this assessment are a qualitative ranking of the level of confidence in the model input (high, medium or low) and a description of the associated uncertainties. The process for determining the level of confidence in an input is based on applying a weight of evidence approach to the following criteria:

- Is the input based on information from one or more externally peer reviewed documents?
- Is there agreement in the literature or within the relevant community of practitioners about the underlying data or method for the input? Or are there conflicting viewpoints?
- Do the characteristics of the input make it suitable for use in the context of the study area? For example, is the input based on data from either Durham or Orange Counties or another area with similar characteristics; or is it based on data from another area that is highly site-specific?
- If the model input is based on manipulation of a data set, is the method used in developing the input an established and widely applied approach? If the method applies equations developed from external models, are those equations applied to local data in an appropriate manner?

A sample of the assessment results is presented in Table 6-5 (the full table can be found in Appendix C). For each input, we provide the source, how the input is used in the model, the rationale for selecting the input, and the confidence level in the input, along with a description of uncertainties associated with it.

Table 6-5. Selected Variables from Model Input Characterization Table

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Acres of developed, vacant, agricultural, and protected open space land in 2000	TJCOG. 2014. "CommunityViz 2 (CV2) Parcel Geodatabase for Place Type & Development Status Editing." Place type and development status of parcels calculated for the year 2000 by back-casting 2013 per-capita values.	Initial values for acres by category, which affects developed land.	Created in part to inform the LRP process; best inventory of current land use available for entire study area.	MEDIUM-HIGH: Each parcel was reviewed by local planning staff, but values do not quite match local comprehensive plan estimates, at least in Durham for which these were available.
Elasticity of public transit travel to fare price	McCollom, Brian E., and Richard H. Pratt. 2004. "TCRP Report 95: Traveler Response to Transportation System Changes: Chapter 12—Transit Pricing and Fares." (page 12-9)	Used to determine how much changes in the average public transit fare price affect person miles of travel by public transit. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	Source adapted this elasticity from the Simpson & Curtin formula, which is commonly used among public transit planners. Also, TCRP reports are well-regarded in their own right.	MEDIUM-HIGH: Not local.
VMT (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Used to estimate traffic congestion, fuel consumption by vehicles, and traffic accidents.	The TRM is the primary source of VMT and traffic congestion projections used by local transportation planning agencies; spatial nature allows clipping to both Tiers.	HIGH: Authoritative source with straightforward application to the study area, but the TRM only models weekday traffic. We assume that VMT on a weekend day is the same as VMT on a weekday.
Carbon dioxide (CO_2) emissions (calibration)	(1) Durham City-County Sustainability Office. 2015. (2) Freid, Tobin. Email message to authors on January 9, 2015.	CO_2 emissions is an endpoint indicator variable.	Authoritative local source; emissions are calculated by the Sustainability Office based on energy data supplied by utility companies.	MEDIUM: For buildings, only emissions from electricity and natural gas (which represent the large majority of energy use in buildings) are currently tracked.
Total water demand (calibration)	NC State Data Center. 2015. "LINC: Log Into North Carolina."	Used to determine withdrawals from water reservoirs and calculate energy used by the municipal water system.	Authoritative government source with multiple time points.	HIGH: Authoritative source for historical water demand data.
Reduction in mortality per person mile of walking for transportation per day per capita; reduction in mortality per person mile of cycling for transportation per day per capita	WHO. 2014. "Health economic assessment tools (HEAT) for walking and for cycling: Methodology and user guide, 2014 update."	Used to calculate avoided premature mortalities due to changes in the amount of walking or cycling for transportation per day per capita.	The HEAT model equations are simple and based off of many epidemiological studies and associated correlations between walking/cycling and health benefits.	MEDIUM-HIGH: The source's recommended applicable age range for walking is 20-74 and for cycling is 20-64, but we applied it to the average rate of walking and cycling for transportation over the entire population. Also, the accuracy of the HEAT calculations should be understood as estimates of the order of magnitude of the expected effect rather than the precise effect.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Shares of total employment by employment category (industrial, office, retail, service)	(1) Tier 2: Historical data (2000-2011) and projections (2012-2040) from: Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet." (2) Tier 1: Historical (2002-2009): U.S. Census Bureau. 2015. "LODES Data. Longitudinal Employer-Household Dynamics Program." (3) Tier 1: Historical data (2010) and projections (2011-2040) from: DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario."	Multiplied by total employment in the model to determine the total number of jobs by employment category which are used to calculate "total earnings," a component of "GRP," and are multiplied by employee space ratios for each employment category to determine "total nonresidential sq ft."	(1) Woods & Poole's historical data are from the BEA, but they fill in gaps in certain employment categories that the BEA omits. Projections were used by the DCHC MPO to help create employment guide totals for the CommunityViz modeling that generated the output for the TRM v5 SE data. (2) and (3) Only sources available for historical and projected employment by category at a small enough geographic scale for Tier 1.	MEDIUM-HIGH for Tier 2: High confidence level for historical data since its original source is the BEA, and medium-high confidence level for projections due to the inherent uncertainty associated with future projections.[39] MEDIUM-LOW for Tier 1: LODES data has built-in noise that distorts the data on small scales, and changes in census block group geographies between 2002 and 2009 also caused inconsistencies in the data in Tier 1. Also, TRM v5 SE data's definitions of employment categories differed from those used in the model.

[39] Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusions drawn from it are solely the responsibility of the US EPA.

Model Input Uncertainty Characterization

As an extension of characterizing model inputs, we summarized the degree of confidence in each input. Table 6-6 provides a qualitative scale of confidence for model inputs (summarized by model sector) that is meant to complement the quantitative validation and sensitivity analyses presented later in this section. In addition, this uncertainty characterization can be used by model users to target specific model inputs for scenario-specific sensitivity analyses in order to determine the extent to which uncertainty in their values can affect scenario results.

Table 6-6. Model Input Uncertainty Characterization Summary by Model Sector[40]

MODEL SECTOR	SUMMARY OF DATA INPUTS (COUNTS OF INPUTS BY LEVEL OF CONFIDENCE)					
	HIGH	MEDIUM-HIGH	MEDIUM	MEDIUM-LOW	LOW	TOTAL
Land Use	2	1	8	1	3	15
Transportation	5	13	12	5	10	45
Energy	-	4	8	-	-	12
Economy	6	10	3	1	-	20
Equity	3	-	6	4	1	14
Water	5	-	8	-	-	13
Health	-	3	1	2	-	6
Total	**21**	**31**	**46**	**13**	**14**	

Validation of Historical Simulations

The calibration of the model starts with the evaluation of the results generated when using specific parameters or equations obtained from literature. This is accomplished through the comparison of historical data and the results of the baseline simulation.

The examples provided below show the D-O LRP SD Model Business-As-Usual simulation (blue line)

[40] This table reflects the uncertainty characterization for Tier 2 inputs, except in cases where an input applied only to Tier 1. In a few cases where an input applied to both Tiers, inputs for Tier 1 had different (often lower) confidence levels assigned to them.

and historical data (red line) for the period 2000 – 2014. The model starts simulating in 2000, and runs differential equations to project results for subsequent years; it does not use historical data to generate projections. Therefore, the modeling team was able to use historical data to check whether the structure of the model is capable of reproducing the historical observed behavior.

Population

Population is driven by a combination of birth, death, and migration rates. In Tier 2, calibration was achieved through the combination of a slightly declining birth rate, constant death rate, and net migration, which was linked by an inverted-U-shaped function to the availability of residential land. In Tier 1, the team chose to calibrate more closely to the historical population trend from the U.S. Census Bureau, thus the BAU projection does not match the TRM projection in later years. The birth and death rates in Tier 1 were assumed to be identical to those used for Tier 2 (no data were available for such a small area), and net migration is driven by a link with the demand for employment and the unemployment rate, capped by the availability of dwelling units. Population in Tier 2 is calibrated very well and is within 5% of the TRM v5 SE projection in the year 2040 (Figure 6-8). In Tier 2, the R^2 equals 0.99 for the projection and 1.00 for the data, while in Tier 1, the R^2 equals 0.99 for the projected data and 0.87 for the historical data. This small difference is due to the more realistic exponential growth pattern rather than a linear one. Population in Tier 1 varies by no more than 3.5% from the U.S. Census data between 2000 and 2014. While population in BAU is about 25% lower than the TRM population projection in 2040, it is much more closely matched under the Light Rail scenario.

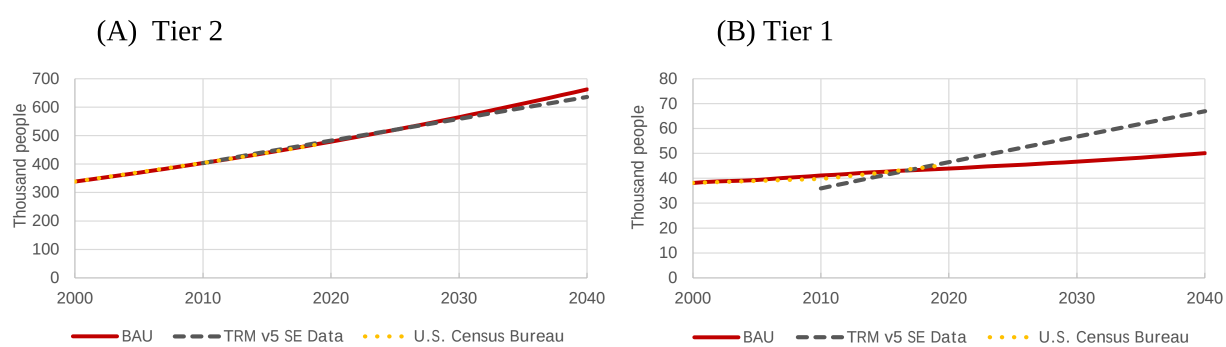


Figure 6-8. BAU Scenario vs. Historical Data for Population

Developed Land

Since there were no explicit projections of land development, developed land could not be calibrated with great confidence. The current value was derived from the CV2 Parcel Geodatabase for Place Type & Development Status Editing by summing all parcels assigned a development status of developed, minus parcels assigned a place type of protected open space. The team estimated total developed land in 2040 in two ways. The first estimate (Estimate 1) applies average floor area ratios and densities for each land use type to the employees and households added in the preferred growth scenario Imagine 2040 Grid output file, and added this to the acres of developed land in 2013. The second method (Estimate 2) calculates the acreage of grids with any allocation of employment or households. In Tier 1, Estimate 2 was in fact above the total parcel acreage (excluding protected open space), so we used that value as the maximum threshold. In both tiers, the BAU scenario is just above the lower estimate in 2040, leaving room for reasonable growth in subsequent scenarios (Figure 6-9).

In both Tiers, the R^2 equals 0.99 for both estimates. In 2040, developed land deviates by -8.1% and by 1.9% from Estimate 1 and Estimate 2 in Tier 2, respectively, and in Tier 1 by 4.4% and -27% from Estimate 1 and Estimate 2, respectively.

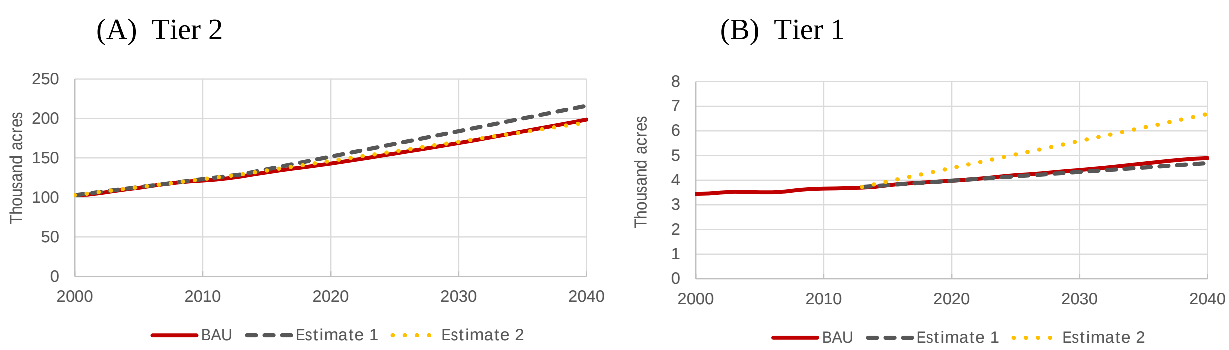


Figure 6-9. BAU Scenario vs. Historical Data for Developed Land

Nonresidential Sq. Ft.

To create a historical data series for the Tiers, data from three counties had to be combined. Most years were available for Durham County, and this accounts for the majority of nonresidential sq ft in both Tiers. For Orange and Chatham counties, we back-cast data from the 2014 estimate from the county tax administration databases using per capita rates from each county. Therefore the speed of growth shown in the data is somewhat uncertain. Since Orange and Chatham County also did not have detailed land use codes, we developed an allocation weighting scheme, which is described in the Land Use Sector description in Section 3.3, to arrive at estimates for each subcategory of square feet, including retail, office, service, and industrial. Employee space ratios for each subcategory were calculated from the final estimates and from the historical data on employment. In the model, employment and employee space ratios drive demand for development of nonresidential sq ft, leading to the close calibration seen below. Calibration of the subcategories of nonresidential square feet are similarly close, with somewhat more delays and swings visible due to the delays and feedbacks inherent in the model structure.

Total nonresidential square feet deviates by no more than 8.5% in Tier 2 from the estimate derived from the County Office of Tax Administration databases, and by no more than 2% in Tier 1 (Figure 6-10). In Tier 2, the R^2 equals 0.95 for the data, while in Tier 1, the R^2 equals 0.99 with the data.

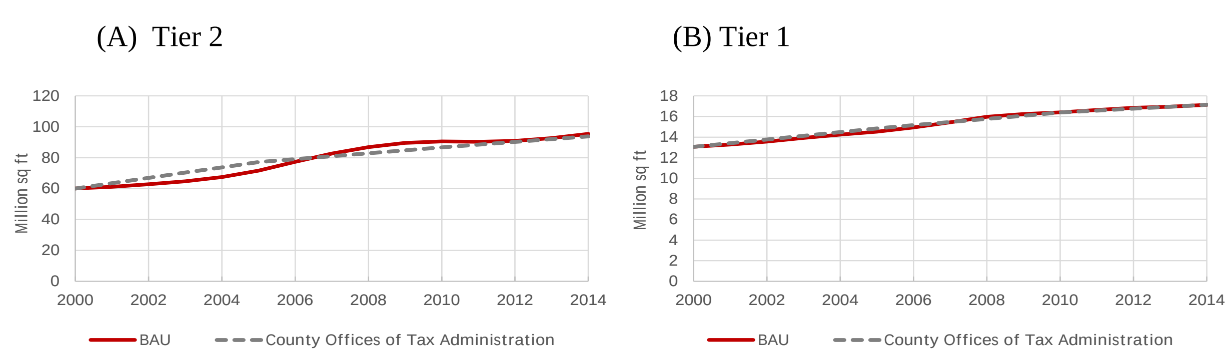


Figure 6-10. BAU Scenario vs. Historical Data for Nonresidential Sq. Ft.

Dwelling Units

Dwelling units, shown in Figure 6-11 and Figure 6-12, were calibrated in the BAU scenario to closely match the historical data (2000, 2010) and projection (2014, 2019) estimates for total dwelling units obtained from Community Analyst, following the methodology explained in Section 3.1. Total dwelling units were separated in the model into single family and multifamily stocks. The percent of dwelling units that are single and multifamily was obtained from Decennial Census 2000; SF3 DP4 and the ACS estimate 2008-2012, as clipped by Community Analyst.

Calibration of single and multifamily dwelling units to the historical data and projections used initial values of households by category, with four factors added to approximate adequate vacancy to match the data for dwelling units. First, an average housing lifetime simulates the necessary turnover due to natural degradation. Second, the percent of dwelling units that are second homes was added to single family properties, boosting the needed construction in excess of households. Third, an endogenous calculation of population growth over the next five years is used to begin construction in anticipation of demand. Finally, an effect of vacancy on equilibrium dwelling units was added. This table was made as a gentle L shape with a long tail – indicating that if vacancy is very low, there is a boost to the demand for dwelling units. As vacancy increases, demand gradually declines and eventually has a slightly negative effect. The shape of this table follows basic economic supply and demand, however the specific values were calibrated after the previous factors were established.

Dwelling units deviate by no more than 1.5% in Tier 2 and 3.2% in Tier 1 in any given year. In Tier 2, the R^2 equals 0.99 for both single family and multifamily, while in Tier 1, the R2 equals 0.95 and 0.99, for single family and multifamily, respectively.

(A) Tier 2 (B) Tier 1

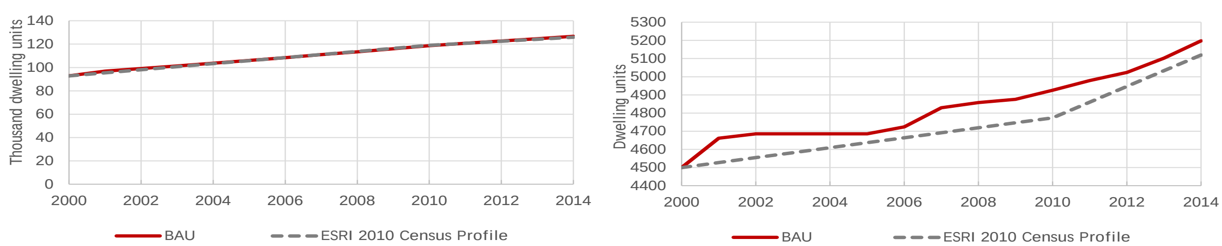


Figure 6-11. BAU Scenario vs. Historical Data for Single Family Dwelling Units

(A) Tier 2 (B) Tier 1

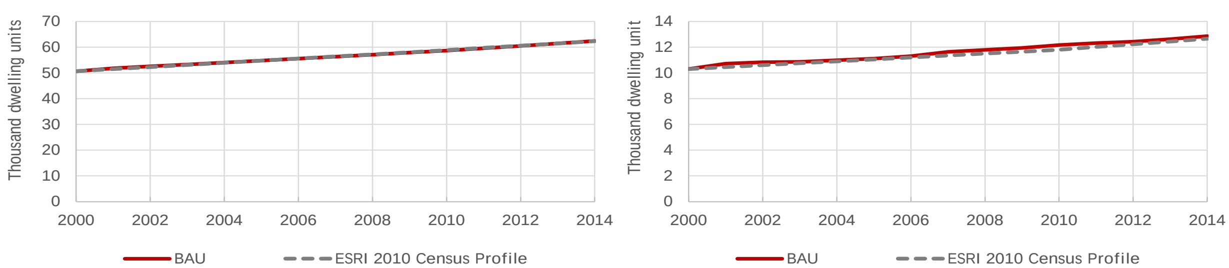


Figure 6-12. BAU Scenario vs. Historical Data for Multifamily Dwelling Units

Total Impervious Surface

To estimate impervious surfaces in the model, we used impervious surface coefficients (ISCs) for residential land use by density as reported in the Jordan Lake Stormwater Accounting Tool User's Manual (NC State Bio & Ag Engineering and NCDENR, 2011). However, coefficients for nonresidential land and roads had to be obtained from the User's Guide for the California Impervious Surface Coefficients, whose applicability to the local region is unknown. Therefore some calibration was necessary. While in Tier 1, mean values for nonresidential uses and coefficients for highway and rural roads were used as given, in Tier 2, to reach the 2010 value for total impervious surfaces, the nonresidential coefficients were reduced to 85% of the mean values. Urban roads had to be calibrated down from .91 to .7 in Tier 2 and to .8 in Tier 1. The ISC for nonmotorized travel facilities was not addressed, and therefore was assumed to be 1.

Total acres of impervious surfaces are calibrated to within 2% of the one-meter land cover data from EPA EnviroAtlas for 2010 in Tier 2, and to within 1% in Tier 1 (Figure 6-13). Since there is only one data point, an R^2 could not be obtained, and uncertainty remains regarding the speed of change in impervious surfaces over time.

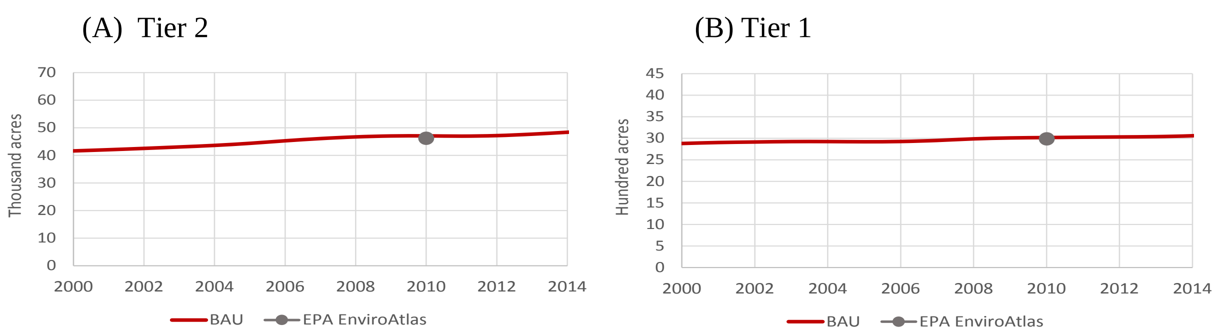


Figure 6-13. BAU Scenario vs. Historical Data for Impervious Surfaces

VMT

The largest drivers of VMT are population and GRP. Other important drivers include the disincentives to drive that come from traffic congestion (endogenous, forming a balancing feedback loop) and gasoline prices (exogenous, determined by a lookup table). Some other, less impactful drivers include parking prices, population density, and intersection densities. During the model-building process, changes occasionally resulted in the values of these various drivers, requiring us to adjust the model inputs for initial-year travel volumes (person miles) for the sake of keeping VMT calibrated to the Triangle Regional Model’s data and projections.

Version 5 of the TRM includes both a projection of future travel behavior under an official “Preferred” infrastructure-building scenario generated for the MTP and a projection of future travel behavior in an “Existing + Committed” infrastructure-building scenario. As discussed in Section 5.2, neither of these projections is entirely a match to the conditions assumed in the D-O LRP SD Model's BAU scenario.[41] These two TRM-generated scenarios only diverge from one another after the year 2017. Therefore, in the D-O LRP SD Model, we calibrated VMT principally to the values indicated by the TRM for the years 2010 and 2017, with a lower priority placed on matching it to the TRM 2040 projections. 2010, 2017, and 2040 are the only years for which the TRM provides VMT figures.

In the BAU scenario, Tier 1 and Tier 2 VMT both have an R^2 value of 0.999 with the MTP "Preferred" infrastructure case and an R^2 value of 0.997 with the "Existing + Committed" infrastructure case. In large part, these high R^2 values are due to them being based on only three points in time (2010, 2017, and 2040), in addition to the TRM's numbers having been used to calibrate VMT in this model. Tier 1 VMT deviates from the TRM's figures by +0.4% in 2010 and -2.4% in 2017; in 2040, it is 8.0% less than what the TRM projects in the Metropolitan Transportation Plan "Preferred" infrastructure case and 2.7% less than what the TRM projects in the "Existing + Committed" infrastructure case. Tier 2 VMT deviates from the TRM's figures by a margin of less than 0.1% in 2010 and by -2.6% in 2017; in 2040, it is 0.6% less than what the TRM projects in the MTP "Preferred" infrastructure case and 2.2% less than what the TRM projects in the "Existing + Committed" infrastructure case.

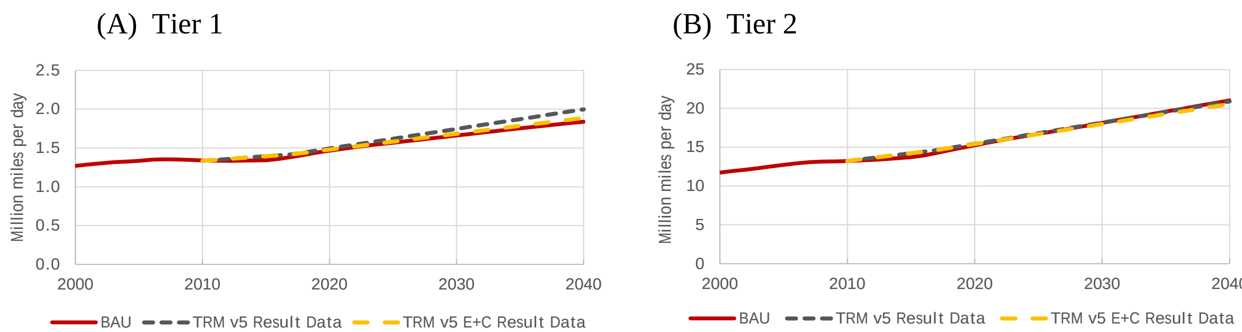


Figure 6-14. BAU Scenario vs. Projections for VMT

Congestion

In both Tiers, congestion is primarily driven by the ratio of VMT to functioning roadway lane miles, with an exogenous lookup table determining how much congestion results from a given amount of weekday peak-period VMT per lane mile. In Tier 1, congestion is also driven, to a lesser extent, by commercial floor area ratios. Since roadway lane miles are determined by exogenous policy inputs, VMT is the primary endogenous determinant of traffic congestion. Therefore, if VMT is well-calibrated, congestion is usually also well-calibrated, given that they are both calibrated to the TRM's projections.

As discussed in Section 5.2, neither the TRM's Metropolitan Transportation Plan "Preferred" infrastructure-building scenario nor its "Existing + Committed" infrastructure-building scenario is entirely a match to the conditions assumed in the D-O LRP SD Model's BAU scenario. Furthermore, the TRM does not report 2040 peak-period traffic speeds for the "Existing + Committed" scenario. Therefore, only the "Preferred" infrastructure scenario could be used to calibrate traffic congestion in

[41] The BAU scenario assumes no light rail is built and roadway lane miles will continue to be built after 2017, while the TRM "Preferred" scenario assumes that a light rail is built, and the TRM "Existing + Committed" scenario assumes that no further roadway lane miles will be built after 2017.

the D-O LRP SD Model. Regardless, since the major infrastructure-building assumptions of the TRM-generated scenarios only diverge from those of the BAU case after the year 2017, we calibrated congestion principally to the values indicated by the TRM for the year 2010, with a lower priority placed on matching it to the available TRM MTP "Preferred" infrastructure scenario 2040 projections. 2010 and 2040 are the only years for which the TRM provides congestion figures.

Because there are only two points in time at which the BAU case can be compared to data or projections (2010 and 2040), an R^2 value cannot be calculated (or, rather, the R^2 value would automatically be one). The availability of data and projections for only two points in time also obscures whether the trend of the data and projections is linear, exponential, or otherwise. Therefore, the fact that the BAU congestion forecasts in Figure 6-15 do not match the seemingly linear trend of the data lines is not meaningful. Tier 1 congestion deviates from the TRM's figures by +2.2% in 2010 and -6.3% in 2040. Tier 2 congestion deviates from the TRM's figures by a margin of less than 0.1% in 2010 and by +0.6% in 2040.

(A) Tier 1 (B) Tier 2

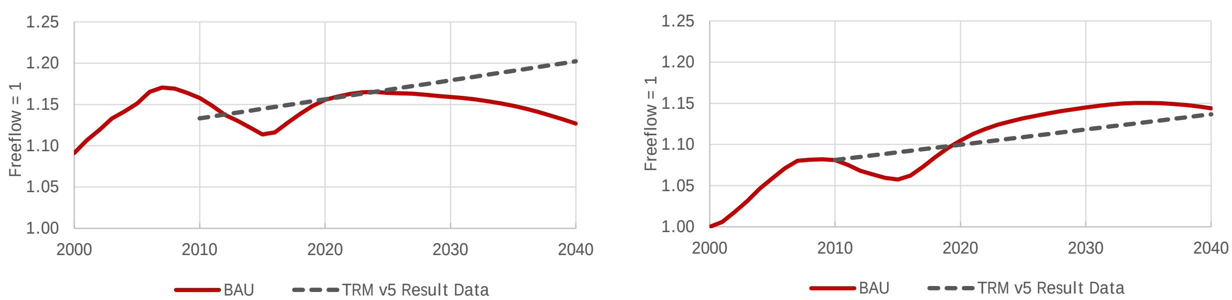


Figure 6-15. BAU Scenario vs. Projections for Congestion

Public Transit Person Miles

The largest endogenous drivers of public transit person miles are population (goes up as population goes up) and GRP (goes down as GRP per capita goes up). Like all other modal person miles, public transit person miles are significantly affected by changes in gasoline prices per mile of automobile travel (which are determined by an exogenous lookup table), as well as by the endogenous input of traffic congestion, given that congestion affects fuel efficiency. Some other, less impactful drivers include parking prices, population density, and intersection densities. In addition, public transit person miles are driven to a significant degree by the exogenous policy variables of public transit fare prices and public transit vehicle revenue miles. Meanwhile, in scenarios where a light rail line is built (unlike the BAU case), Tier 1 population and employment and Tier 2 VMT per highway lane mile assume additional, significant influence over public transit person miles per day.

In Tier 2, both historical data and projections were available during the calibration of public transit person miles. The primary basis for the calibration of this variable was historical data from the National Transit Database (NTD), which provided yearly data for the period 2000-2013. We placed top priority on calibrating to the most recent historical data, for 2013, so that the D-O LRP SD Model would project forward from an accurate representation of present-day conditions, as opposed to matching data from earlier years and extending a trend from that data that does not recreate the present. During 2000-2013, Tier 2 public transit person miles in the BAU case have an R^2 value of 0.81 with NTD data. The average percent deviation above or below NTD data during this period is 9.1% and the percent deviation in

2013, the last year for which NTD data were available, is -0.4%. The yearly percent deviation ranges from +20.4% in 2000 to -17.1% in 2008.

The only years for which the MTP provides figures on public transit use are 2010 and 2040, so, again, we could not calculate an R^2 value for projected values of this variable. In 2010, Tier 2 public transit person miles in the BAU case deviate from the TRM-generated scenarios by -1.6%. In 2040, they deviate from the TRM-generated MTP “Preferred” scenario by -15.5% and from the “Existing + Committed” scenario by +21.6%, meaning the 2040 value is in between the two projections, which differ from one another by a wide margin. Furthermore, since historical data from the NTD was the primary basis for calibrating this variable, it would not be surprising for there to be some amount of deviation between public transit person miles in the BAU case and in the TRM-generated scenarios.

In Tier 1, only one data point, for the year 2010, was available for calibrating public transit person miles per day, derived from figures reported in the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization’s Metropolitan Transportation Plan (MTP) and scaled down to Tier 1 with the help of information from version 5 of the Triangle Regional Model (TRM v5). For this reason, it was not possible to calculate an R^2 value for this Tier. Tier 1 public transit person miles in 2010 in the BAU case are 0.4% greater than this data point. Since the MTP-derived 2010 data point was the sole basis for calibrating Tier 1 public transit person miles, the percent deviation of the BAU from it is small.

(A) Tier 1 (B) Tier 2

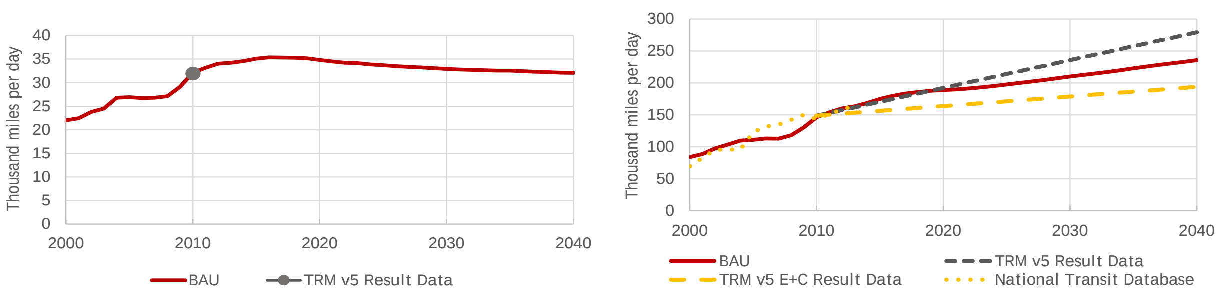


Figure 6-16. BAU Scenario vs. Data and Projections for Public Transit Person Miles

Building Energy Use

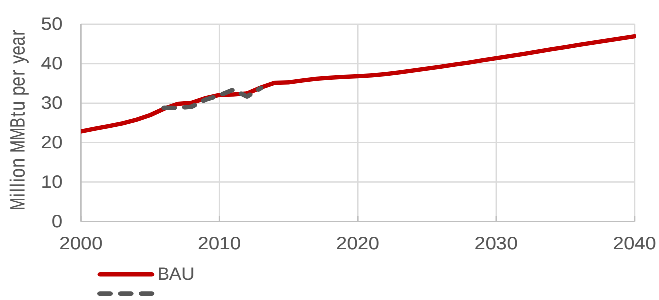


Figure 6-17. Building Energy Use - Tier 2: BAU Model Output Compared to Data

Historical data for building energy use in Tier 2 are from the Durham City-County Sustainability Office (Figure 6-17), originally sourced from local utility companies. Historical building energy use was scaled from Durham County to Tier 2 using the fraction of Tier 2 residential, commercial, and industrial square feet found in Durham County. Year-to-year variations in the data are likely due to a variety of factors, some of which are included in the model (e.g. population and sq ft) while others are not (e.g. temperature fluctuations which affect heating and cooling energy use).

In the model, building energy use is driven by the stock of dwelling units and the stock of nonresidential square feet, multiplied by the energy use intensity of each. The stock of single-family and multifamily dwelling units, as well as nonresidential square feet are each calibrated to historical data. Energy use intensities for the residential, commercial, and industrial sectors are also calibrated to historical data and projections (which are based on EIA Annual Energy Outlook 2015 projections (US EIA 2015a)).

Building energy use is calibrated to an average annual deviation of 2.0% from historical data (2006-2013),[42] and modeled building energy use matches historical data with R^2 equal to 0.87.

CO_2 Emissions

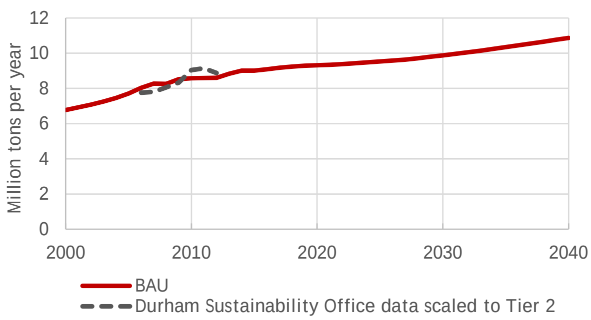


Figure 6-18. CO_2 Emissions - Tier 2: BAU Model Output Compared to Data

Historical CO_2 emissions data are from the Durham City-County Sustainability Office (Figure 6-18), based on building energy consumption data sourced from local utility companies, and based on local VMT data for vehicles. Historical CO_2 emissions were scaled from Durham County to Tier 2 using the fraction of Tier 2 building square feet found in Durham County (0.73). This scaling approach was chosen because buildings represent the majority of regional CO_2 emissions, with vehicles representing most of the remainder. As with the energy use data, year-to-year variation in the CO_2 emissions data may have a variety of causes, including increases in building square footage and VMT, which are modeled, and year-to-year temperature fluctuations, which are not modeled.

Modeled CO_2 emissions are the sum of building and vehicle emissions, as well as emissions from municipal water treatment and distribution. Vehicle emissions include buses, passenger vehicles, and light rail. Within each of these categories, CO_2 emissions are the product of energy use and a fuel-specific emissions factor. For example, burning a gallon of gasoline in a car is assumed to produce 0.00889 metric tons of CO_2 (US EPA 2015b).

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[42] This is the average absolute value of annual % deviation from data. Omitting absolute value, model projections are on average 0.91% higher than data.

CO_2 emissions are calibrated to an average annual deviation of 4.1% from historical data (2006-2012),[43] and modeled CO_2 emissions match historical data with R^2 equal to 0.81.

Total Employment

Total employment for Tier 2 and Tier 1, shown in Figure 6-19, was calibrated in the BAU scenario to closely match total employment data (2010) and projections (2011-2040) from the TRM v5 SE data files, clipped in ArcGIS to the two geographies. For the preceding model years, 2000-2009, annual employment growth trends from the U.S. Bureau of Economic Analysis (BEA) for Durham and Orange County for Tier 2 and from the U.S. Census LODES dataset (clipped to Tier 1 geography) for Tier 1 were used to back-cast total employment from the TRM v5 SE data 2010 value for total employment. The R^2 equals 1.0 for both sources of data and projections for both Tier 2 and Tier 1, with the Tier 2 average annual deviation being 0.27% between 2000 and 2009, and 0.35% between 2010 and 2040, and the Tier 1 total employment average annual deviation being 0.61% between 2000 and 2009, and 0.16% between 2010 and 2040.

Total employment (see Figure 6-19) is driven in the D-O LRP SD Model by total retail consumption, which is also calibrated to fit historical data and projections, and the exogenous input "employment per dollar of consumption," which was calculated based on historical data and projections for total employment and retail consumption in both Tier 2 and Tier 1 and adjusted slightly to improve the model fit.

(A) Tier 2

(B) Tier 1

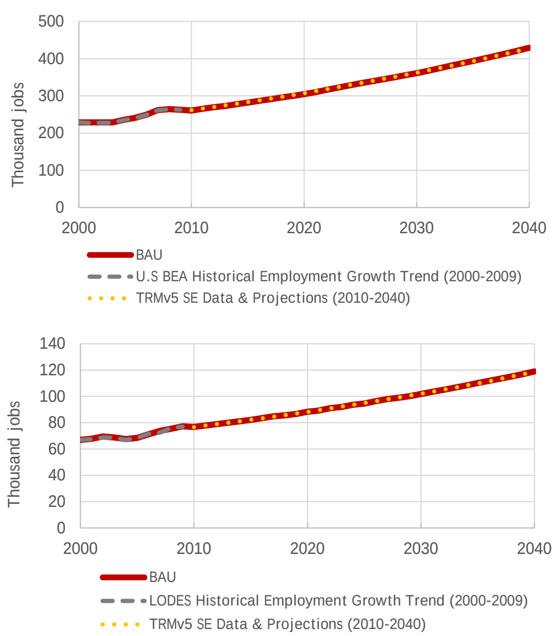


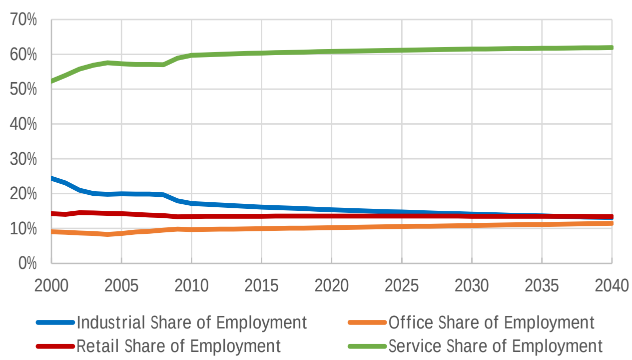
Figure 6-19. BAU Scenario vs. Historical Data and Projections for Total Employment

[43] This is the average absolute value of annual % deviation from data. Omitting absolute value, model projections are on average 0.02% higher than data.

Total Earnings

Since total employment in the model for Tier 2 and Tier 1 was calibrated to historical data and projections to match the total employment from the TRM v5 SE data, and the total employment numbers in the TRM v5 SE data were lower than total employment numbers from historical data and projection sources for Durham and Orange County combined (e.g., BEA and Woods & Poole Economics, Inc.), alternative calculations of total earnings were done to calibrate the model. Woods & Poole provide employment and average earnings per year, both historical data and projections, for each of the 20 job types that are categorized by the North American Industrial Classification System (NAICS) 2-digit code classification. We aggregated these 20 jobs types into four categories: industrial, office, retail, and service, and multiplied the total employment from the TRM v5 SE data with the share of employment that fell into each category for the entire study period (2000-2040), shown in Figure 6-20a. We then took the average earnings per employee per year in each of the four categories, shown in Figure 6-20b and multiplied them by the number of jobs in each employment category for each year and summed them up to get total earnings.

(A) Tier 1



(B) Tier 2

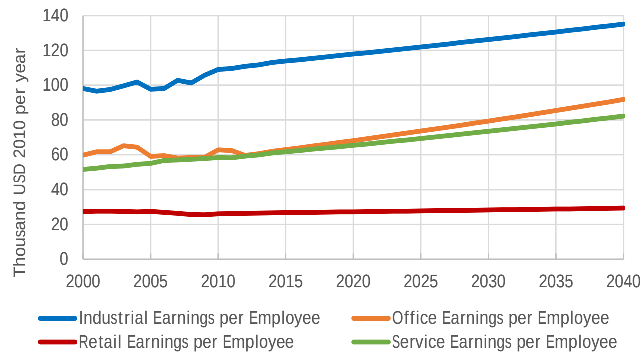


Figure 6-20. Historical Employment Data and Projections Used as Inputs in the Tier 2 Economy Model for (A) Shares of Employment by Category, and (B) Average Earnings Per Employee by Category

The same methodology that was used to calculate total earnings for Tier 2 was applied to Tier 1, but since employment by category and earnings by category from Woods & Poole are only available at the county level, a hybrid approach was used to calculate both. For Tier 1 employment by category, shown in Figure 6-21a, the percent of employment by category from the TRM v5 SE data in Tier 1 compared to Tier 2 (also from the TRM) was multiplied by the total amount of employment by category calculated from Woods & Poole data for Tier 2. For earnings per employee by category in Tier 1, the same average earnings per category were taken from Tier 2, but weighted by the number of jobs per category in the Durham and Orange County portions of Tier 1.[44]

Figure 6-22 shows the BAU scenario model output for (A) Tier 2 total earnings and (B) Tier 1 total earnings compared to the total earnings calculated from data and projections. Because total employment

[44] This was also done in Tier 2, where industrial earnings per employee were much higher in Durham County than Orange County due to the large number of high wage jobs classified as manufacturing located in RTP, NC (the outskirts of Durham County).

is the only direct endogenous connection affecting earnings in the model, the fit for total earnings is about the same as total employment, with the R^2 value being 1.0 for both Tier 2 and Tier 1 for calculated historical and projected earnings and the average % deviation being 0.26% and 0.38% for Tier 2 calculated historical and projected earnings, respectively, and 0.54% and 0.19% for Tier 1 calculated historical and projected earnings, respectively.

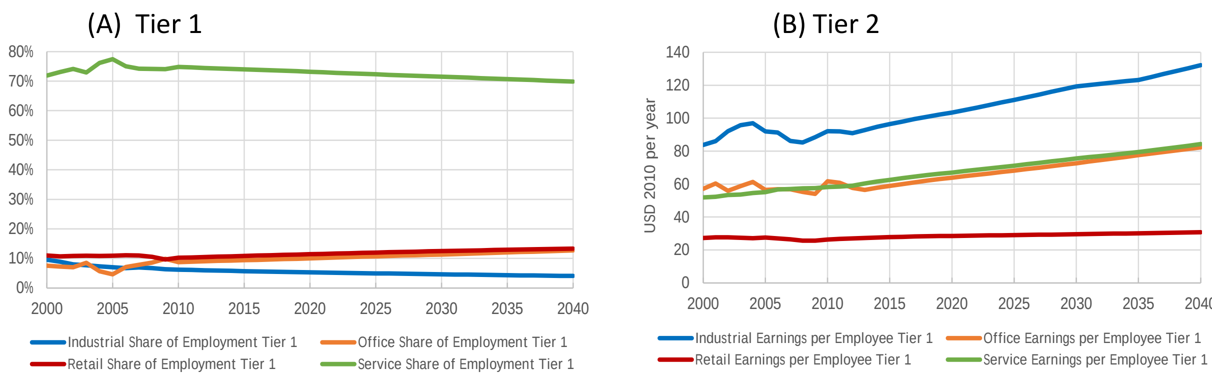


Figure 6-21. Historical Employment Data and Projections Used as Inputs in the Tier 1 Economy Model for (A) Shares of Employment by Category, and (B) Average Earnings Per Employee by Category

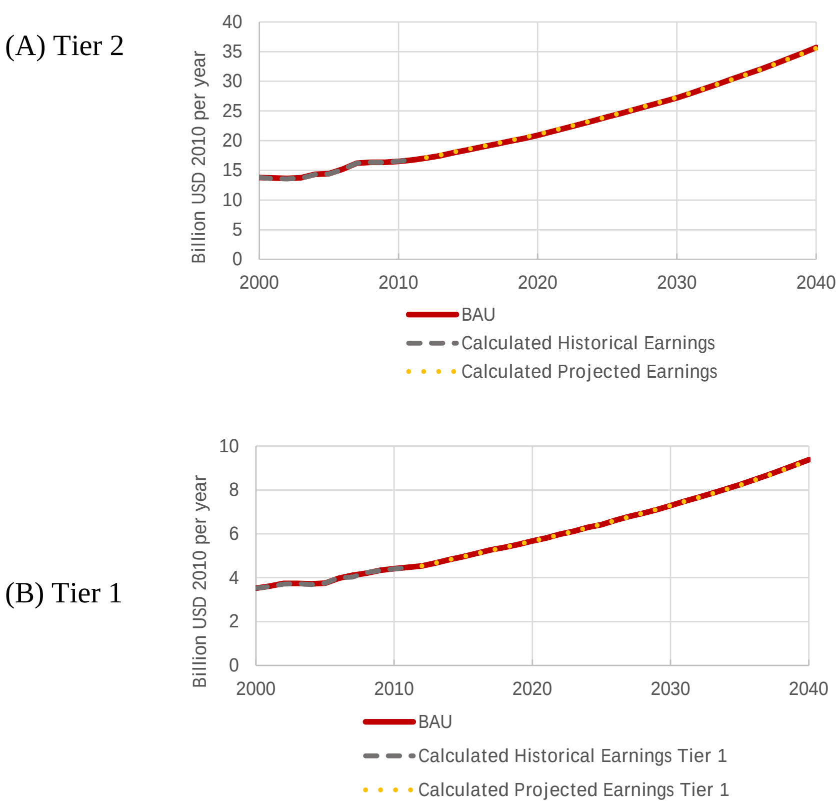


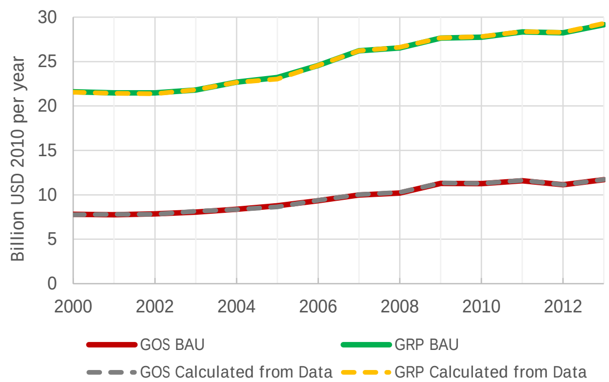
Figure 6-22. Total Earnings: Model Fit to Calculated Historical Data and Projections

Gross Operating Surplus and Gross Regional Product

To calibrate Gross Regional Product (GRP) in the model, GRP was calculated for 2000-2013 using a methodology from the BEA (Panek et al. 2007) from the calculated earnings data for Tier 2 and Tier 1. The difference between GRP and total earnings was considered the gross operating surplus (GOS). GOS is the sum of three factors in the model: (1) GOS per sq ft (multiplied by total nonresidential sq ft), (2) productivity loss by road congestion, and (3) profit gain or loss due to energy spending (relative to GRP).[45] GOS per sq ft is an exogenous lookup table and was calculated externally by dividing the calculated GOS for Tier 2 and Tier 1 (calculated from endogenously calculated GRP and total earnings) by total nonresidential sq ft for Tier 2 and Tier 1 under the BAU scenario, then adjusted so that the effects of congestion and energy spending were taken into account.

Figure 6-23 shows the BAU model output for GOS and GRP for Tier 2 (Figure 6-23A) and Tier 1 (Figure 6-23B). The R^2 value for GRP and GOS in both Tier 2 and Tier 1 is 1.0, with the average % deviation from data for Tier 2 being 0.32% for GOS and 0.28% for GRP, and the average % deviation from data for Tier 1 being 0.45% for GOS and 0.33% for GRP.

(A) Tier 2



(B) Tier 1

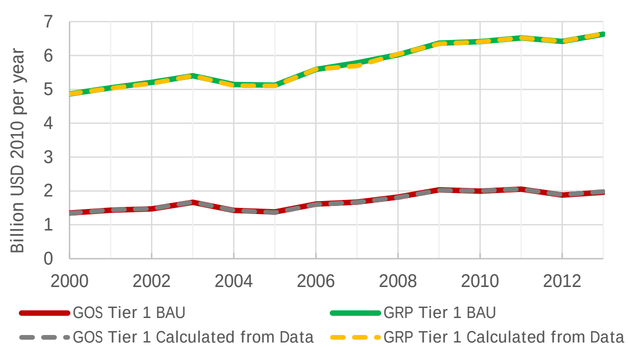


Figure 6-23. Gross Regional Product and Gross Operating Surplus: Model Fit to Values Calculated from Data

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45 The effects on GOS of removing the connections to productivity loss due to road congestion and the profit gain or loss due to energy spending are shown in Figures 6-39 through 6-42.

Total Retail Consumption

Three sources of historical retail consumption data were available for reference to calibrate the Tier 2 economy model, all with data for Orange and Durham County. The first data reference source was “total taxable sales” data for 2000-2014 from the North Carolina Department of Revenue (NC DOR). The second reference source was Woods & Poole Economics, Inc. with “total retail sales” estimates between 2000 and 2011, with 2002 and 2007 being actual historical data from the U.S. Department of Commerce. The third reference source was “total retail sales” estimates downloaded from SimplyMap for 2011-2014 (data were also downloaded from 2008-2010, but was found to be erroneous), benchmarked from the 2007 Economic Census. Since Woods & Poole’s last year of historical data was 2011, we decided to use the more up-to-date data for Tier 2 from NC DOR and apply the annual retail sales growth rate predicted by Woods & Poole for 2015 through 2040. This reference data and projections combination is shown by the green dashed line in Figure 6-24. We then calibrated the model to match (as closely as possible) the most recent reference data point (2014) from this combination by adjusting the initial value (2000) for retail consumption.

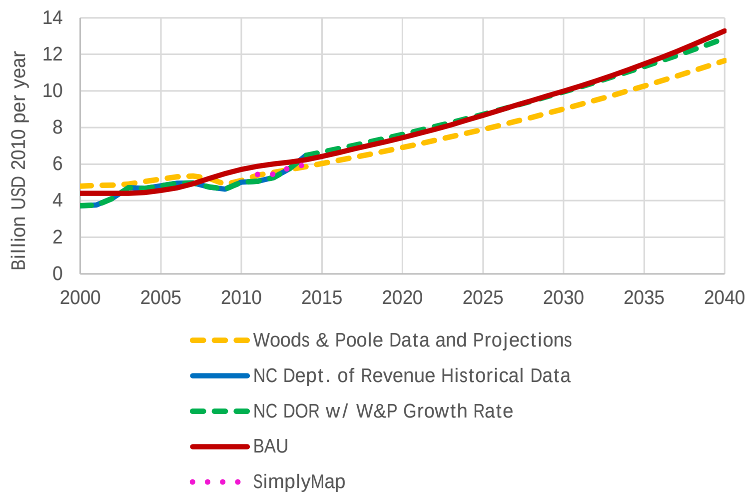


Figure 6-24. Total Retail Consumption – Tier 2: Model Fit to Historical Data and Projections

Two other factors (besides the initial value) were adjusted to calibrate Tier 2 retail consumption: (1) the elasticity of consumption to GRP, and (2) the resident percent of the working population. Together with the embedded delay function that delays the impact of relative GRP on retail consumption by two years, the slow and gradual increase of the resident percent of the working population allows for Tier 2 retail consumption in the model to reproduce historical trends and extend them into the future, though it is not able to reproduce the peaks and dips that are shown by the historical data to be typical for the region.

For the historical data (2000-2014), the R^2 value for Tier 2 total retail consumption is 0.63 with an average deviation of 8.8%. For the projections (2015-2040), the R^2 value is 1.0 with an average deviation of 1.6%.

For total retail consumption in Tier 1, only one source of historical retail sales reference data was available for calibration: SimplyMap, which takes the county-level retail sales data from the 2002 and 2007 Economic Census and uses a computer model to output retail sales at the census block group level between 2008 and 2014 based on business locations, among other variables. No projections of retail sales were available for Tier 1. Shown in Figure 6-25, the Tier 1 economy model was calibrated to match the most recent year of retail sales data for Tier 1, 2014, by adjusting the initial retail consumption value and the elasticity of consumption to GRP, which is equal to the elasticity used for Tier 2 (1.1). The R^2 value for the model fit to historical retail sales data for Tier 1 is 0.74 and the average deviation is 5.3%.

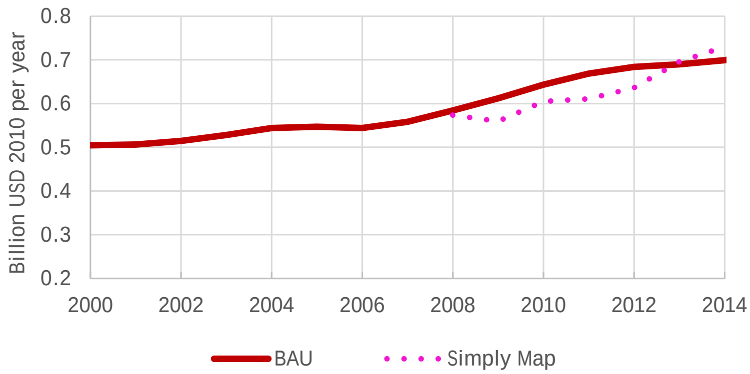


Figure 6-25. Total Retail Consumption – Tier 1: Model Fit to Historical Data

Property Values

Estimates for historical property values were derived from the Durham, Orange, and Chatham County Tax Administration Databases, as described in the Equity Sector of Section 3.3. Orange County Parcel Database (parview), and Chatham County Tax Parcel Database (ASOUTR). Nonresidential property values are expressed per square foot, obtained from the same databases. Residential property values are expressed per single or multifamily dwelling units, obtained from the ESRI 2010 Census Profile clipped by Community Analyst.

Calibration of single family, multifamily, and nonresidential property values was accomplished through a combination of a diverse set of elasticities obtained from the literature. A housing crash was also exogenously introduced, starting in 2005, to better reproduce this global phenomenon and therefore better fit data on housing costs. This adjustment reduces property values across the board by 15% by 2007, with full recovery by 2009. For a full listing of the elasticities used and explanation of the process, see the Equity Sector in Section 3.3. In a few cases, these elasticities had to be modified to fit the study area, as many studies provide elasticities for either one metro area or an average for the nation, and none were found that were specific to the study area. For details on the modifications made to elasticity values, see Appendix B.

Because property values are responsive to many factors, including both local and national, using only endogenous mechanisms available in the model led to a less than ideal fit with historical trends. Residential property values deviate from the data by an average of 9.2% in Tier 2 and 4.2% in Tier 1 for single family properties, and 10% in Tier 2 and 2.0% in Tier 1 for multifamily properties (Figure 6-26 and Figure 6-27). Nonresidential property values have more divergence, with an average absolute deviation of 12% in Tier 2 and 31% in Tier 1 (Figure 6-28). In Tier 2, the R^2 equals 0.53, 0.34, and 0.21 for single family, multifamily, and nonresidential property values, respectively, while in Tier 1, the R2 equals 0.46, 0.72, and 0.013, respectively.

(A) Single Family (B) Multifamily

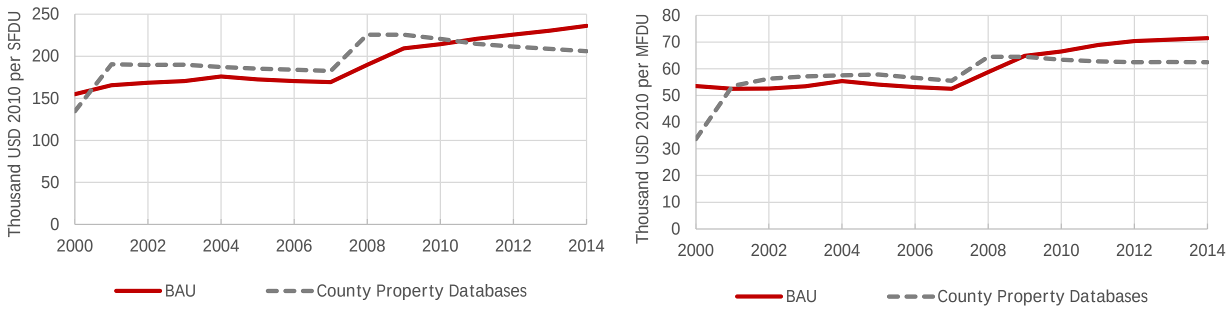


Figure 6-26. BAU Scenario vs. Historical Data for Tier 2 Residential Property Values

(A) Single Family (B) Multifamily

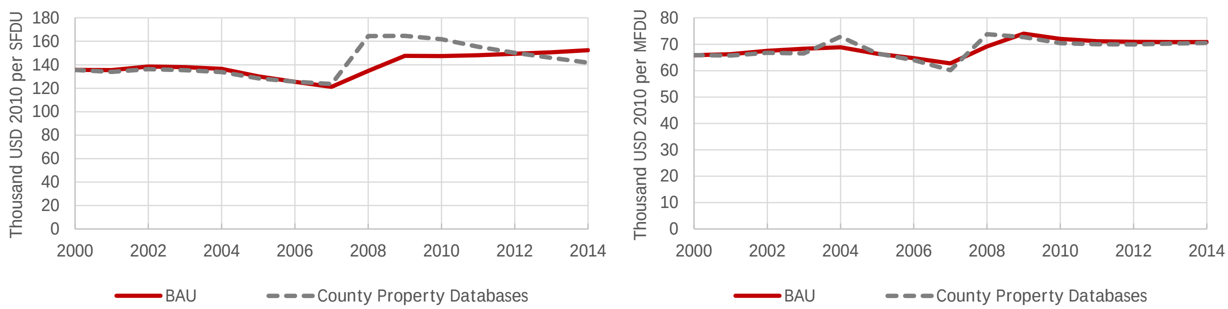


Figure 6-27. BAU Scenario vs. Historical Data for Tier 1 Residential Property Values

(A) Tier 2

(B) Tier 1

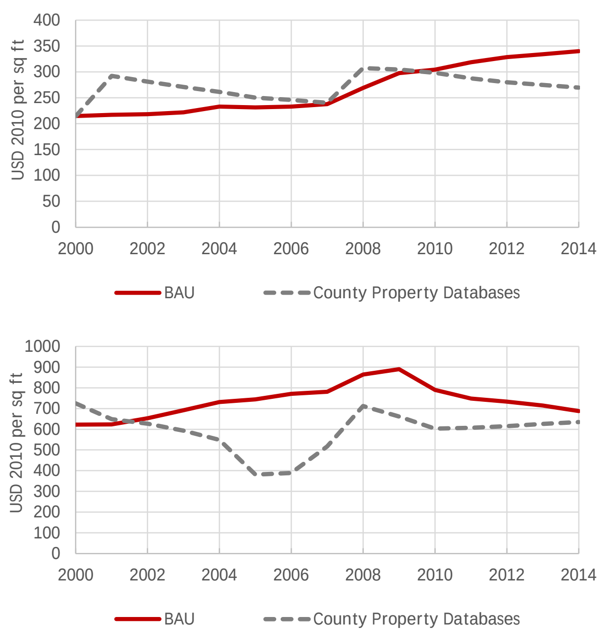


Figure 6-28. BAU Scenario vs. Historical Data for Nonresidential Property Values

Water Demand

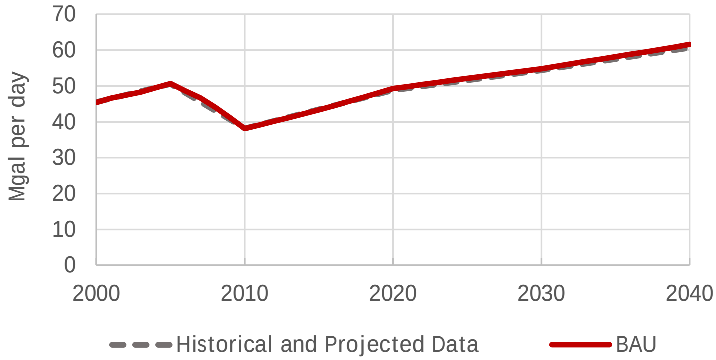


Figure 6-29. Water Demand – Tier 2: BAU Model Output Compared to Data

Historical water demand data for 2000, 2005, and 2010 are from the NC Department of Environment and Natural Resources (NC State Data Center 2015). Projected data for 2020, 2030, and 2040 are from the Triangle Regional Water Supply Plan, Vol 1 (Triangle J Council of Governments 2012).

Municipal water demand is the sum of residential, nonresidential, and nonrevenue water demand. Nonrevenue demand includes uses such as distribution system maintenance (such as line flushing), and water lost through system leakage. Each of these sectoral demands is calibrated to historical and/or projected data from the same sources as total water demand. In each case, demand is the product of an endogenously modeled stock (such as SF housing units) and a water demand intensity factor (such as water use per SF household).

Municipal water demand is calibrated to an average annual deviation of 0.64% from historical and projected data[46]. Modeled water demand matches the combined historical and projected data with R^2 equal to 0.999. The close match between modeled water demand and data is due to the assumed trend in residential water conservation ("conservation improvement residential water use") which is manually calibrated using an exogenous input.

Summary

Below, in Table 6-7 and Table 6-8, we present the R^2 and average absolute percent deviation for each of the variables discussed above, compared to both data and projections.

[46] This is the average absolute value of annual % deviation from data. Omitting absolute value, model projections are on average 0.55% higher than data.

Table 6-7. Statistical Analysis of Tier 1 Variables Compared to Historical Data and Projections

TIER 1 MODEL VARIABLE BAU SCENARIO	HISTORICAL DATA SOURCE	HISTORICAL DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM HISTORICAL DATA	PROJECTED DATA SOURCE	PROJECTED DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM PROJECTED DATA
Population	U.S. Census Bureau	0.87	1.7%	TRM v5 SE Data	0.99	13%
Developed land	Not Available	N/A	N/A	CV2 Parcel Geodatabase for Place Type & Development Status Editing	Insufficient data points	2.6%
Nonresidential sq ft	County Office of Tax Administration databases	0.99	0.57%	Not Available	N/A	N/A
Single family dwelling units	U.S. Census Bureau	0.95	2.05%	Not Available	N/A	N/A
Multifamily dwelling units	U.S. Census Bureau	0.99	1.73%	Not Available	N/A	N/A
VMT	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles	MTP "Preferred" infrastructure case: 0.999 "Existing + Committed" infrastructure case: 0.997	MTP "Preferred" infrastructure case: 3.6% "Existing + Committed" infrastructure case: 1.8%
Person miles of public transit travel per day	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles and DCHC MPO Metropolitan Transportation Plan	Insufficient data points	0.41%
Traffic congestion	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles	Insufficient data points	4.2%
Total Employment	LODES total employment growth rate (2000-2009) applied to TRMv5 SE Data total employment for 2010	1.00	0.61%	TRM v5 SE Data total employment (2010-2040)	1.00	0.16%
Total Earnings	Calculated from Woods & Poole earnings per job by category and TRM v5 SE data percent of employment by category in Tier 1	1.00	0.54%	Calculated from Woods & Poole earnings per job by category and TRM v5 SE data percent of employment by category in Tier 1	1.00	0.19%
Gross Operating Surplus	Difference between calculated GRP and Total Earnings	1.00	0.45%	Not Available	N/A	N/A
Gross Regional Product (GRP)	Calculated from BEA methodology (Panek et al. 2007)	1.00	0.33%	Not Available	N/A	N/A
Total Retail Consumption	SimplyMap (2008-2014)	0.74	5.3%	Not Available	N/A	N/A
Single family property value	County Office of Tax Administration databases	0.46	4.2%	Not Available	N/A	N/A
Multifamily property value	County Office of Tax Administration	0.72	2.0%	Not Available	N/A	N/A

TIER 1 MODEL VARIABLE BAU SCENARIO	HISTORICAL DATA SOURCE	HISTORICAL DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM HISTORICAL DATA	PROJECTED DATA SOURCE	PROJECTED DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM PROJECTED DATA
	databases					
Nonresidential property value	County Office of Tax Administration databases	0.01	31%	Not Available	N/A	N/A
Impervious surface	EPA EnviroAtlas	Insufficient data points	1.0%	Not Available	N/A	N/A

Table 6-8. Statistical Analysis of Tier 2 Variables Compared to Historical Data and Projections

TIER 2 MODEL VARIABLE BAU SCENARIO	HISTORICAL DATA SOURCE	HISTORICAL DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM HISTORICAL DATA	PROJECTED DATA SOURCE	PROJECTED DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM PROJECTED DATA
Population	U.S. Census Bureau	1.00	0.0085%	TRM v5 SE Data	0.99	1.5%
Developed land	Not Available	N/A	N/A	CV2 Parcel Geodatabase for Place Type & Development Status Editing	Insufficient data points	5.0%
Nonresidential sq ft	County Office of Tax Administration databases	0.95	3.4%	Not Available	N/A	N/A
Single family dwelling units	U.S. Census Bureau	0.99	0.42%	Not Available	N/A	N/A
Multifamily dwelling units	U.S. Census Bureau	0.99	0.22%	Not Available	N/A	N/A
VMT	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles	MTP “Preferred” infrastructure case: 0.999 “Existing + Committed” infrastructure case: 0.997	MTP “Preferred” infrastructure case: 1.1% “Existing + Committed” infrastructure case: 1.6%
Person miles of public transit travel per day	National Transit Database	0.81	9.1%	TRM v5 travel demand result shapefiles and DCHC MPO Metropolitan Transportation Plan	Insufficient data points	MTP “Preferred” infrastructure case: 8.7% “Existing + Committed” infrastructure case: 11.5%
Traffic congestion	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles	Insufficient data points	0.31%
Building energy use	Durham City-County Sustainability Office	0.87	2.8%	Not Available	N/A	N/A
CO_2 emissions	Durham City-County Sustainability Office	0.81	4.4%	Not Available	N/A	N/A
Total Employment	U.S. BEA Total Employment Growth Rate (2000-2009) applied to TRMv5 SE Data 2010 total employment	1.00	0.27%	TRM v5 SE Data Total Employment (2010-2040)	1.00	0.35%

TIER 2 MODEL VARIABLE BAU SCENARIO	HISTORICAL DATA SOURCE	HISTORICAL DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM HISTORICAL DATA	PROJECTED DATA SOURCE	PROJECTED DATA R^2 VALUE	AVERAGE PERCENT DEVIATION FROM PROJECTED DATA
Total Earnings	Calculated from Woods & Poole earnings per job by category and shares of employment by category	1.00	0.26%	Calculated from Woods & Poole earnings per job by category and shares of employment by category	1.00	0.38%
Gross Operating Surplus	Difference between GRP and Total Earnings	1.00	0.32%	Not Available	N/A	N/A
Gross Regional Product	Calculated from U.S. BEA methodology (Panek et al. 2007)	1.00	0.28%	Not Available	N/A	N/A
Total Retail Consumption	NC DOR Total Taxable Sales by County (2000-2014)	0.63	8.8%	Woods & Poole Retail Sales Growth Rate (2015-2040) applied to 2014 NC DOR Total Taxable Sales	1.00	1.6%
Single family property value	County Office of Tax Administration databases	0.53	9.2%	Not Available	N/A	N/A
Multifamily property value	County Office of Tax Administration databases	0.34	10%	Not Available	N/A	N/A
Nonresidential property value	County Office of Tax Administration databases	0.21	12%	Not Available	N/A	N/A
Impervious surface	EPA EnviroAtlas	Insufficient data points	1.8%	Not Available	N/A	N/A
Water demand	NC Dept. of Environment and Natural Resources	1.00	0.15%	Triangle Regional Water Supply Plan, Vol 1.	1.00	1.1%

6.3 Model Corroboration (Validation and Simulation)

The ultimate objective of system dynamics model validation is to establish the accuracy of model structure—that is, are the processes in the model an accurate reflection of processes in the real world? Accuracy of the model's reproduction of real behavior is also evaluated, but this is meaningful only if we first have sufficient confidence in the structure of the model. Thus, we test the validity of the model structure prior to testing its behavioral accuracy. In this Model Corroboration section, we first describe direct tests of model structure, in which equations and linkages are changed, or parameters are set at extreme values, and the resulting output is compared to data or expectations. The direct structure tests section is composed of three parts:

- *Structure Confirmation Tests*: In these tests, we changed the equations that determine the values of variables (as opposed to only changing the values of model inputs), in order to confirm that the model structure we ultimately chose to use does a better job both of reproducing data and of representing the way actual systems work.

- *Extreme-Condition Tests*: In these tests, we set the values of certain key model inputs to values far removed from what is ever likely to happen in real life, such as modeling a sudden 70% drop in population, or a spike in gasoline prices to $1,000 per gallon. Then, we assessed the plausibility of the resulting output values against the knowledge or anticipation of what would happen under a similar condition in real life.

- *Unit Consistency*: Using a functionality built into the modeling software Vensim, we confirmed that each variable calculated in the model had units assigned to it that were mathematically consistent with the units of its inputs and also represented what the variable was intended to represent (e.g., "population" has units of "person" and "developed land" has units of "acre," so "population density" has units of "person/acre").

Next, we analyze model behavior through sensitivity tests, wherein we determine how sensitive model outputs are to the values of uncertain parameters. The model behavior and sensitivity tests section has three parts, corresponding to three categories of model sensitivity:

- *Numerical Sensitivity* exists when a change in assumptions changes the numerical values of the results, without necessarily changing the trend of the output values. It is an inherent property of models to exhibit numerical sensitivity; the purpose of numerical sensitivity testing is to assure responsiveness consistent with the functions and feedbacks of the model.

- *Behavior Mode Sensitivity* exists when a change in assumptions changes the patterns of behavior generated by the model. For example, if plausible alternative assumptions changed the behavior of a model from smooth adjustment to random oscillation about a mean value or reduced the sizes of the "peaks" and "valleys" in the trend of a given output by lengthened reaction times to exogenous shocks, the model would exhibit behavior mode sensitivity.

- *Policy Sensitivity* exists when a change in assumptions reverses or heightens the impacts or desirability of a proposed policy. For example, if a change in assumptions allowed untapped demand to be realized under one scenario but not under another, the model would exhibit policy sensitivity.

With each test, we present a table showing the average percent departure from the BAU scenario (or other base case, as applicable) between 2000 and 2040, which may be either a positive or negative value (expressed as "percent above or below" in the tables). We chose to compare test results to the BAU scenario rather than to data, because we have already established the BAU fit against data, for the variables for which data are available. In some cases, in addition, we report the average *absolute-value* percent departure between 2000 and 2040. The first measure takes the percent deviation in each of the forty years (both positive and negative), and averages them. The second takes the absolute value of the percent deviation in each of the forty years, and averages them.

The two measures will have the same magnitude if the variable in question is always above or always below the BAU scenario. However, in cases where there is variation both above and below the BAU scenario, the average percent departure can obscure variation, as it averages out negative and positive differences. Figure 6-30 illustrates an example of the difference between the two measures. The arrow indicates the percent departure for a given year, and the average percent departure is the average over all years. In the figure, Run 2 values are higher than Run 1 values for about half of the time and below than Run 1 values for about half of the time, and by about the same magnitude in each case; therefore its average percent departure is zero. However, the average absolute percent departure is different from zero, since Run 2 always deviates from Run 1, except at the central time point. Therefore, we have also chosen to show the average absolute percent deviation in tests where output values vary both above and below BAU over time, resulting in differences in the magnitudes of average percent above or below BAU and average absolute percent departure from BAU. Note that the average absolute-value percent deviation can have the effect of exaggerating differences between the test case and BAU, if, for example, the test causes oscillation slightly above and below the BAU case.

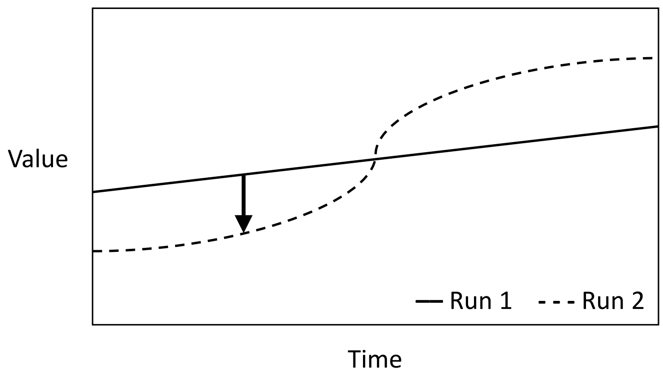


Figure 6-30. Illustration of Average Percent Departure Above or Below vs. Average Absolute Percent Departure from a Reference Run

Direct Structure Tests

Direct structure tests assess the validity of the model structure by direct comparison with knowledge about the structure of the real system. This involves assessing each relationship within the model individually and comparing it with available knowledge about the real system. Several structural tests have already been illustrated above, including the analysis of improvements resulting from model integration. The tests below include structure and parameter confirmation tests and extreme-condition tests, which test equations and data that are obtained from other sources or taken as assumed.

Structure Confirmation Tests

In this section, we present the results of structure confirmation tests for all the key variables of the model, which we tested first against existing literature and second against historical data. The comparison with available historical data in the model development phase, when exogenous assumptions were replaced with endogenous formulations, allowed the modeling team to carry out parameter confirmation tests by checking the impacts of each parameter used (regardless of the source) in the integrated structure of the D-O LRP model. We present fourteen structure confirmation tests, covering all seven sectors in the model.

Land Development Aggregated

This structural test compares early versions of the model before and after restructuring of the land sector, while running the BAU scenario at the time. The test aims to discover if disaggregating land demand and supply by land use type improve the precision of the model's estimates of land development.

Prior to restructuring, the land development sector aggregated all demand for land to feed one conversion stream, which was then allocated to different uses with static percentages based on those calculated from the CV2 Parcel Geodatabase for Place Type & Development Status Editing. This created mismatches between demand and supply and led to dramatic drops in retail density (which affected property values). The former structure also led to inconsistencies when exploring alternative scenarios. For example, reducing the percent of people in single family households lowered the demand for residential land (because multifamily homes use less land), which in turn reduced overall land development, including commercial development, since the ultimate land developed by category was not controlled by demand for that category, but instead determined by multiplying a constant percentage by the total land development flow.

In the restructured land development sector, demand for development and conversion is disaggregated by the six land use types and negative land conversion is allowed to occur. The negative land conversion implicitly represents redevelopment from one use to another, following demand. Figure 6-31 shows the change in the trajectory of acres by category; the paler lines show the former results and the darker lines show the restructured results. This makes clear that office and retail acres were under allocated throughout the simulation prior to restructuring, while service, multifamily, and single-family acres were over allocated in the short term and subsequently under allocated in the medium and longer term. Therefore, disaggregating land demand and supply by land use type does improve the precision of the model's estimates of land development.

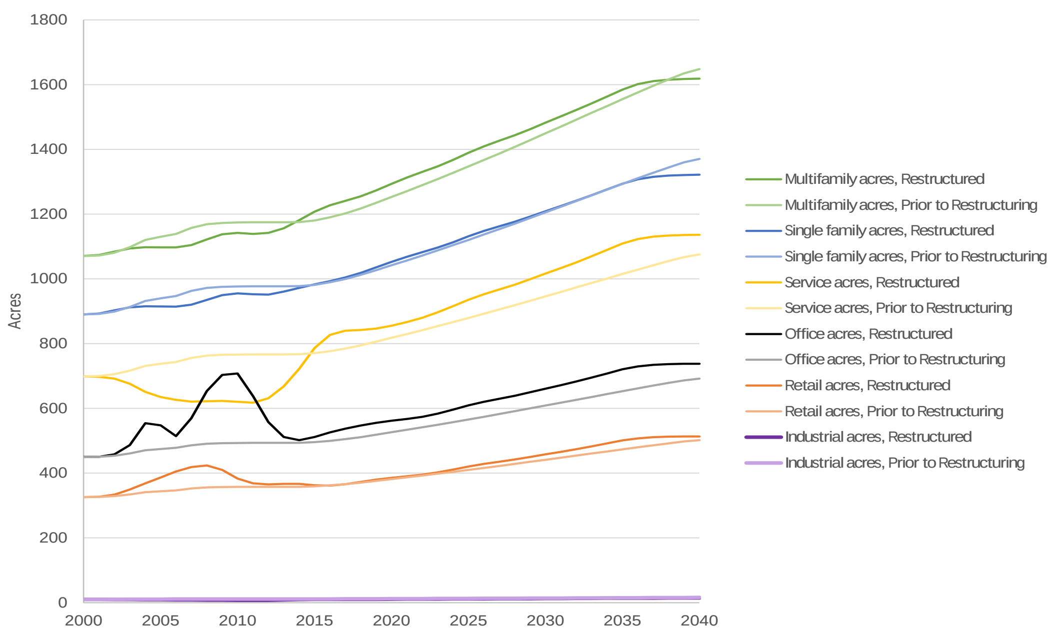


Figure 6-31. Acres by Land Use Type – Tier 1: Before and After Land Use Sector Restructuring

The change resulted in a little more nonlinearity over time in total developed land, along with more developed land overall, particularly in Tier 1. We then calibrated GOS per sq ft to bring land development back to historical levels. Figure 6-32 shows the trajectory of land development under the former structure, immediately after the restructure, and in the most recent model.

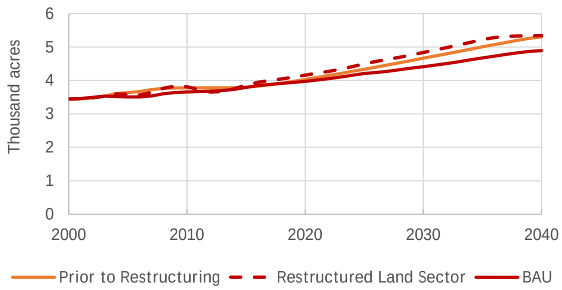


Figure 6-32. Developed Land – Tier 1: Land Development Restructure Test

In addition to improving the estimates of developed land by use, the structural change improved the consistency of other land use metrics. Table 6-9 summarizes the average yearly percent departure from BAU 2000-2040 for several affected outcomes. Nonresidential sq ft and total impervious surface follow the trend in land and are more variable, and retail density avoids the dramatic drop in density that had been artificially imposed by the constant share of acres applied, maintaining a relative constant value for the model duration. Since insufficient land had been allotted to meet growing residential demand in Tier 1, the change allowed dwelling units to increase there. As more dwelling units are available, more people may move to the area, marginally increasing net migration and population in Tier 1.

Effect of Vacancy on Single Family and Multifamily Dwelling Units Removed

This structural test removes the effect of vacancy on equilibrium dwelling units, which serves to boost dwelling unit construction when vacancy is very low, and decrease construction when vacancy is very high. This effect table was not found in the literature and was therefore calibrated to move the model projection of dwelling units closer to historical data. Since the table was based purely on assumptions, this test was performed to verify that it improves model fit and behavior.

The biggest immediate impact of this change is on multifamily dwelling units in Tier 2, as shown in Figure 6-33. The BAU scenario almost perfectly matches historical data; however, the model's estimates without the effect of vacancy on equilibrium dwelling units fall short of the BAU by an average of 4.2%. While the impact is not as large for single-family dwelling units and dwelling units in Tier 1, for consistency, the same table was applied for the other dwelling units, and always improves the fit, even if not by much.

Table 6-9. Average Yearly Percent Departure of Test from Restructured Land Sector and from BAU, 2000-2040: Land Development Structure Test[47]

Variable	Prior to Restructuring v Restructured Land Sector		Prior to Restructuring v. BAU	
	Absolute Percent Departure	Percent above or below	Absolute Percent Departure	Percent above or below
Tier 1				
Developed land Tier 1	2.4%	-1.7%	3.7%	3.6%
Retail acres Tier 1	4.1%	-4.1%	3.3%	-1.4%
Single family acres Tier 1	1.2%	0.7%	7.5%	7.4%
Nonresidential sq ft Tier 1	4.6%	-4.4%	1.1%	-0.3%
Retail density Tier 1	3.6%	-3.5%	7.0%	-6.6%
Total impervious surface Tier 1	2.2%	-1.8%	1.0%	1.0%
Total dwelling units Tier 1	0.9%	-0.7%	7.2%	6.7%
Net migration Tier 1	34%	17%	164%	148%
Population Tier 1	0.7%	-0.6%	6.0%	5.8%
Tier 2				
Developed land	1.8%	-1.8%	1.4%	-1.4%
Retail acres	10%	-10%	10%	-10%
Single family acres	1.4%	-1.4%	1.4%	-1.4%
Nonresidential sq ft	5.7%	-5.7%	4.0%	-3.8%
Retail density	10%	-10%	10%	-10%
Total impervious surface	1.3%	-1.3%	0.6%	-0.1%
Total dwelling units	0.0%	0.0%	0.1%	0.1%
Net migration	1.0%	-0.3%	4.1%	4.0%
Population	0.0%	0.0%	0.1%	0.1%

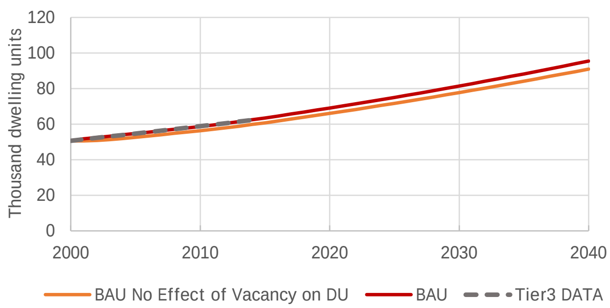


Figure 6-33. Multifamily Dwelling Units – Tier 2: Effect of Vacancy on Dwelling Units Removed

The addition of the table also improves the fit and behavior of other variables in the sector. Annual renter costs more closely fit the data with the effect of vacancy on dwelling units table included in the model, particularly in Tier 2. While the BAU deviates on average by 2.1% from the data for the years available, without the effect table, it deviates by an average of 17% in Tier 2. Table 6-10 summarizes the average yearly percent departure from BAU 2000-2040 for several affected outcomes, including the annual renter costs.

[47] Note that the large percent departure from BAU in net migration in Tier 1 is due to later corrections in the net migration rate, and not to model changes made in this test, which are instead reflected in the percent departure from the "Restructured Land Sector" scenario.

Table 6-10. Average Yearly Percent Departure from BAU, 2000-2040: Effect of Vacancy on Dwelling Units Removed

Variable	No Effect of Vacancy on DU Test v. BAU	
	Absolute Percent Departure	Percent above or below
Tier 1		
Multifamily dwelling units Tier 1	0.7%	0.7%
Single family dwelling units Tier 1	0.9%	0.9%
Multifamily vacancy rate Tier 1	7.1%	6.5%
Single family vacancy rate Tier 1	8.5%	8.5%
Annual renter costs Tier 1	0.1%	-0.1%
Tier 2		
Multifamily dwelling units	-4.2%	-4.2%
Single family dwelling units	-1.5%	-1.5%
Multifamily vacancy rate	-55%	-55%
Single family vacancy rate	-16%	-16%
Annual renter costs	19%	19%

Not Normalizing Person Miles by Mode

The heart of the transportation model sector is the calculation of mode shares, or the percentage of person miles that are taken by each transportation mode: automobile driver, automobile passenger, public transit, and nonmotorized. The model first establishes baseline projections of the number of person miles traveled per day by each mode (driven by population and real GRP per capita). These baseline values are adjusted by a series of elasticities (with respect to both exogenous and endogenous variables) and then normalized so that the total person miles of travel per day match the baseline projections. This normalization is done to keep overall person miles of travel per day within expectations and guarantee that an increase or decrease in the use of any one mode will also affect usage rates of the other modes. In this structure confirmation test (hereafter called the Travel Not Normalized test case), we compared the BAU results of the final model to what they would be if the normalization step were removed, meaning that there is no limit on how high or low the total number of person miles of travel may be and that factors that increase or decrease person miles by one mode need not necessarily also decrease or increase person miles by other modes, respectively. We did this in order to determine whether the normalization step was necessary, in this particular modeling effort, to prevent the generation of unreasonable person-mile results.

There is little difference between the trends of the modal-person-mile variables in the Travel Not Normalized test case and the BAU scenario (Figure 6-34) or between their magnitudes (Table 6-11). Therefore, leaving the person-mile-normalization step out of the model would have only required slight increases in the initial values set during the calibration process in order to match data and projections about as well as in the BAU scenario. Otherwise, given the D-O LRP SD Model's default input values and other assumptions, it may have not significantly changed the accuracy of the model to leave out the normalization step. However, if, under a given scenario, the model featured more dramatic drivers of modal person miles, leaving out the normalization step could potentially result in numbers of person miles that are either unrealistically high or unrealistically low for an area with a given population and GRP.

The greatest difference between the test case and the BAU scenario is around 2015, when, in both cases, the model is reacting to a recent period of high gasoline prices, producing a reduction in the growth rate of automobile driver person miles and increases in the growth rates of person miles by all other modes. In the BAU scenario, the normalization step moderates the negative effect on automobile driver person miles and enhances the positive effect on person miles by all other modes. This is because, before normalization, the negative elasticity of automobile driver person miles to gasoline prices has a greater magnitude than the positive elasticities of all other types of person miles to gasoline prices. After normalization, the effective elasticity of person miles by any given mode to any given input is a function of both its own pre-normalization elasticity and the pre-normalization elasticities of person miles by all of the other modes, since any increase or decrease in person miles by one mode relative to the baseline must be made up for by opposite-direction changes in person miles by one or more of the other modes. Therefore, the normalization step causes the large, negative pre-normalization elasticity of automobile driver person miles to gasoline prices to effectively be moved closer to the magnitudes of the smaller, positive pre-normalization elasticities of person miles by any other mode to gasoline prices, and vice versa. In other words, the normalization step reduces the negative effect of high gasoline prices on automobile driver person miles and increases the positive effect of high gasoline prices on all other types of person miles. As shown in Figure 6-34, in the Travel Not Normalized test case, automobile driver person miles and public transit person miles show a worse fit with data and available projections than they do in the BAU case, mostly for want of the readjustment performed by the normalization step. This suggests that the forecast generated by the normalization step improves model accuracy. The overall effect is that the Travel Not Normalized test case results in fewer person miles by all four travel modes than the BAU scenario, as shown in Table 6-11.

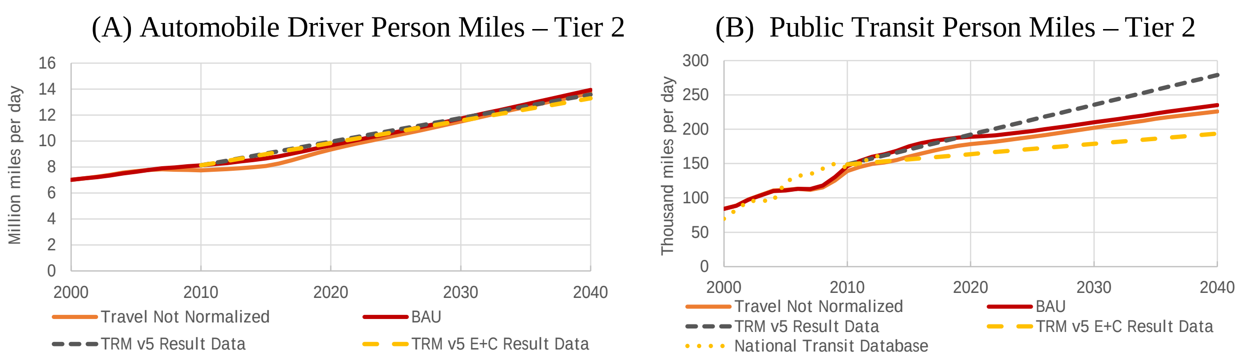


Figure 6-34. Person Miles of Travel by Different Modes Not Normalized vs. BAU

Table 6-11. Average Yearly Percent Departure from BAU, 2000-2040: Not Normalizing Person Miles by Mode

VARIABLE	AVERAGE YEARLY ABSOLUTE PERCENT DEPARTURE	AVERAGE YEARLY PERCENT ABOVE OR BELOW
Tier 1		
Automobile driver person miles	1.6%	-1.6%
Automobile passenger person miles	1.8%	-1.7%
Public transit person miles	2.4%	-2.3%
Nonmotorized person miles	2.3%	-2.2%
Total person miles	1.8%	-1.7%
Tier 2		
Automobile driver person miles	2.6%	-2.5%
Automobile passenger person miles	2.9%	-2.7%
Public transit person miles	4.0%	-3.9%

VARIABLE	AVERAGE YEARLY ABSOLUTE PERCENT DEPARTURE	AVERAGE YEARLY PERCENT ABOVE OR BELOW
Nonmotorized person miles	3.7%	-3.5%
Total person miles	2.7%	-2.6%

No Post-Normalization Congestion Effect on Automobile Driver Person Miles

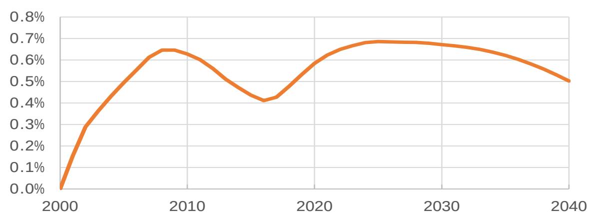
One exception to the normalization process described above is the effect of traffic congestion on automobile driver person miles. The model assumes that if traffic congestion causes driving a car to be less attractive, some people will choose to instead travel by other modes while other people will choose to reduce the amount they drive without traveling more by any other mode. Therefore, traffic congestion is modeled as leading to reduced automobile driver travel both before and after the normalization step. Before the normalization step, average vehicle speeds affect automobile driver person miles (and person miles by all other modes) through elasticity values taken from literature. After the normalization step, automobile person miles are affected further by congestion, through an S-shaped lookup function. "Congestion" is defined as the ratio of peak-period travel time to freeflow travel time, wherein a value of one represents a congestion-free state. If congestion is equal to one, no further change is made to automobile driver person miles. If congestion is equal to 1.75, the inflection point of the S-shaped function, automobile driver person miles will be reduced by 10%, with a one-year delay; if congestion is equal to 2.5 or greater, automobile driver person miles will be reduced by 20%, again with a one-year delay. In this structure confirmation test (hereafter called the No Additional Congestion Effect test case), we compared the BAU results of the final model to what they would be if this post-normalization effect of traffic congestion on automobile driver person miles were not included, in which case the effect of traffic congestion on automobile driver person miles would come entirely in the form of people switching to or from other travel modes. We did this in order to determine how much the post-normalization effect of traffic congestion on automobile driver person miles contributes to keeping person-mile trends close to projections.

As shown in Figure 6-35 and Table 6-12, the No Additional Congestion Effect test case results in slightly more automobile driver person miles of travel than the BAU scenario. In neither the BAU scenario nor either of the light rail scenarios does congestion exceed 1.27 in either Tier in any year during 2000-2040. Relative to the inflection point of the S-shaped function that determines the post-normalization effect of traffic congestion on automobile driver person miles, this is a low level of congestion. Therefore, with the model's default inputs and other assumptions, leaving out the post-normalization effect of congestion on automobile driver person miles would not have a major impact on the magnitudes or trends of model outputs. However, if congestion were much greater, the presence or absence of that post-normalization effect would make a significant difference.

In the No Additional Congestion Effect test case, automobile driver person miles are higher, meaning that VMT per lane mile is higher, which increases congestion, which reduces automobile driver and automobile passenger person miles and increases public transit and nonmotorized person miles. This feedback is an additional reason why the No Additional Congestion Effect test case and the BAU scenario do not have significantly different outputs. However, this feedback effect only partially mitigates the increase in automobile driver person miles that results from removing the post-normalization effect of congestion, so that automobile driver person miles in the No Additional Congestion Effect test case are consistently higher than in the BAU scenario, though only by a small amount. At the same time, the feedback effect exacerbates the assumption under the No Additional

Congestion Effect test case that a congestion-induced reduction in automobile driver person miles necessarily results in the same number of person miles being cumulatively added to the remaining modes. Without a post-normalization effect of traffic congestion on automobile driver person miles, an unusually high level of traffic congestion could result in unrealistically large increases in person miles by public transit and nonmotorized modes relative to population and GRP. The post-normalization effect of congestion therefore helps to make the model more consistent with expectations by avoiding such unrealistic conditions.

(A) Tier 1



(B) Tier 2

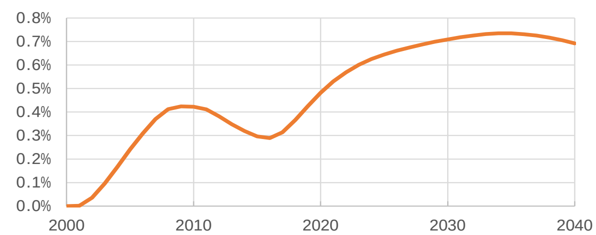


Figure 6-35. Automobile Driver Person Miles Per Day: No Post-Normalization Congestion Effect on Automobile Driver Person Miles Percent Difference from BAU

Table 6-12. Average Yearly Percent Departure from BAU, 2000-2040: No Post-Normalization Congestion Effect on Automobile Driver Person Miles

VARIABLE	NO ADDITIONAL CONGESTION EFFECT V. BAU
Tier 1	
Congestion	+0.25%
Automobile driver person miles	+0.55%
Automobile passenger person miles	-0.06%
Public transit person miles	+0.10%
Nonmotorized person miles	+0.06%
Total person miles	+0.32%
Tier 2	
Congestion	+0.28%
Automobile driver person miles	+0.48%
Automobile passenger person miles	-0.01%
Public transit person miles	+0.18%
Nonmotorized person miles	+0.12%
Total person miles	+0.36%

NMT Facility Construction Not Driven by Developed Land

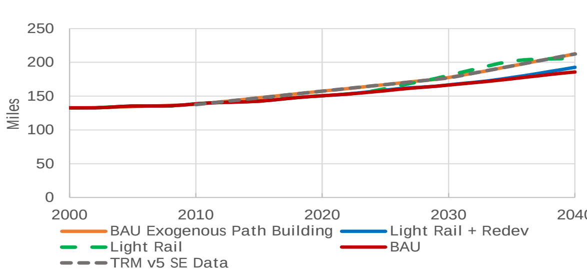
Originally, the construction of sidewalks, bike lanes, and other nonmotorized travel (NMT) facilities in the D-O LRP SD Model was driven entirely by exogenous projections from the Triangle Regional Model version 5 SE Data files. In the current model, we replaced this exogenous function with one driven by the amount of developed land. We made this change because, if NMT facility construction is completely exogenous while land development is endogenous, it could produce a scenario where the amount of NMT facilities per developed acre is unrealistic if development does not closely match levels assumed in the TRM SE Data files. We did not apply the same reasoning to make road construction driven by land development, however. We did this because roads are more likely than NMT facilities to be built through areas that are not currently developed but may be developed in the future, in accordance with transportation plans with decades-long time horizons, since land is rarely developed in the absence of motor-vehicle access. As a result, it is not unrealistic to suppose that the ratio of roads to developed acres would be greater in a low-development scenario and less in a high-development scenario. Furthermore, because NMT facilities can generally be built faster and more cheaply than roads can, NMT facilities' construction is able to be more responsive to changes in demand. In this structure confirmation test (hereafter called the BAU Exogenous Path Building test case), we examined whether keeping nonmotorized-travel-facility construction exogenous rather than endogenous would have produced unreasonable results in the model, relative to data and projections.

The TRM SE Data files feature development, population, and employment projections that are based on the assumption that the planned light rail line between Durham and Chapel Hill is built. Therefore, using that source's nonmotorized-travel-facility projections in the BAU case, wherein no light rail line is built, would produce inaccurate results. In fact, with NMT facility construction driven by developed land, the Light Rail scenario much more closely matches projections of Tier 1 NMT facilities than does the BAU scenario (Figure 6-36A). However, in Tier 2, the BAU, Light Rail, and Light Rail + Redevelopment scenarios all exceed the exogenous NMT facility projections used in the BAU Exogenous Path Building test case (Figure 6-36B). This may be attributed either to the TRM SE Data files assuming different ratios of NMT facility construction to land development than we did for this particular Tier or to the fact that the TRM SE Data files do not include projections of developed acres, such that there may be some difference between the amount of developed land implicit in that data source and the developed-land projections (calculated from Imagine 2040 outputs) that were used to calibrate the D-O LRP SD Model.

As shown in Table 6-13, no significant feedback effects are created by NMT facilities being driven by developed land in the D-O LRP SD Model: replacing this mechanism with an exogenous nonmotorized-travel-facility construction schedule does not change developed land. This lack of a meaningful feedback effect is expected, since the model assumes that the construction of NMT facilities is done in response to land development, as opposed to the other way around. Furthermore, even if the presence of sidewalks, bike lanes, and paths attracts people to an area, hence making further development in that area more attractive, people are usually only attracted by those facilities if there are already developed parcels nearby that the facilities may be used to reach.

Table 6-13 also shows the expected outcome that changing the amount of NMT facilities in an area produces a same-direction change in NMT and an opposite-direction change in automobile driver travel. However, because increases in the use of one transport mode are offset by decreases in other modes, overall person miles of travel are not affected.

(A) Tier 1



(B) Tier 2

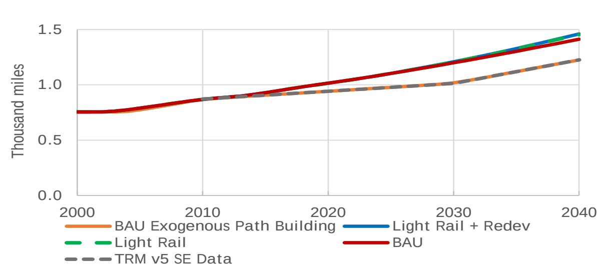


Figure 6-36. NMT Facilities

Table 6-13. Average Yearly Percent Departure from BAU, 2000-2040: Building of Pedestrian and Bicycle Facilities Driven by Exogenous Construction Schedule Based on TRM V5 SE Data

VARIABLE	BAU EXOGENOUS PATH BUILDING V. BAU
Tier 1	
NMT facilities	+4.8%
Developed land	0.0%
Nonmotorized person miles	+1.4%
Automobile driver person miles	-0.2%
Automobile passenger person miles	+0.1%
Public transit person miles	+0.9%
Total person miles	0.0%
Tier 2	
NMT facilities	-7.3%
Developed land	0.0%
Nonmotorized person miles	-2.7%
Automobile driver person miles	+0.2%
Automobile passenger person miles	-0.5%
Public transit person miles	-1.8%
Total person miles	0.0%

Light Rail Treated the Same as Bus Service for the Purpose of Determining Ridership

Adding light rail to a public transit system has the potential to attract more riders per revenue mile than adding more bus service, which, unless it is Bus Rapid Transit (BRT), does not have the advantage of traveling on an exclusive right-of-way. Originally, the D-O LRP SD Model did not contain a mechanism to account for the difference in attractiveness to travelers between light rail and bus service. Instead, the only direct effect on public transit usage of the light rail line opening in 2026 in the Light Rail and Light Rail + Redevelopment scenarios was that it represented an increase in the total number of revenue miles on the public transit system, which is one of the drivers of public transit person miles of travel. In other words, travelers were assumed to regard the light rail line in the same way that they would the opening of a new non-BRT bus route. In the current model, instead of the opening of the light rail line increasing public transit person miles through the increase in revenue miles that it represents, it activates an equation that determines the number of additional public transit person miles resulting from the light rail as a function of Tier 1 population and jobs and Tier 2 highway VMT per lane mile, derived from a spreadsheet tool found in literature (Chatman et al. 2014). The use of this equation leads to higher impacts on public transit person miles of travel from the light rail line than would assuming that additional light rail revenue miles would have the same effect as non-BRT bus revenue miles, as seen in Figure 6-37. This structure confirmation test (hereafter called the “Light Rail Treated Like Bus” test case) evaluates whether this equation produces results that are more consistent with projections from the TRM than an alternative formulation that treats light rail revenue miles like bus revenue miles.

The DCHC MPO Metropolitan Transportation Plan uses TRM v5 outputs to project how much public transit use will increase between 2010 and 2040 in a scenario where the light rail line between Durham and Chapel Hill is built, but without describing the shape of the trend between 2010 and 2040 (“TRM v5 Result Data” in Figure 6-37). In the year 2040, Tier 2 public transit person miles in the Light Rail scenario are 24.7% greater than the MTP projection, and Tier 2 public transit person miles in the Light Rail Treated Like Bus test case are 9.8% less than the MTP projection (both scenarios are calibrated to the MTP figures for 2010). One possible interpretation of this data is that the public-transit-person-mile equation used in the Light Rail and Light Rail + Redevelopment scenarios performs its intended function, representing light rail service (or any other fixed-guideway transit service) as being more attractive to travelers than bus service, but because it produces an output that deviates from projections by a greater margin than the alternative formulation, it may overestimate the attractiveness of light rail relative to bus service. This could be because the equation used in the Light Rail and Light Rail + Redevelopment scenarios to determine additional public transit person miles resulting from the light rail line does not account for public transit use in the study area before the light rail line opened. Instead, it uses population, employment, and highway VMT per lane mile to estimate the amount of demand for fixed-guideway transit services, using equations derived from data gathered from metropolitan areas across the United States. Therefore, it could be that the population of the study area is more resistant to switching to public transit than the national average and the D-O LRP SD Model fails to reflect this.

The difference between the Light Rail scenario and TRM projections shown in Figure 6-37 may also be caused by the D-O LRP SD Model assuming that the light rail line will have a larger impact on commercial development and net migration than does the MTP, which would also cause public transit person miles to be higher. To explore this possibility, the Light Rail scenario and the Light Rail Treated Like Bus test case are rerun, both with the added change of removing the assumptions that the light rail line will necessarily cause greater demand for Tier 1 commercial floor space and that net migration will necessarily be affected, renamed the Light Rail No Sq Ft Effect and Light Rail Like Bus No Sq Ft test cases, respectively, as shown in Figure 6-37. In the year 2040, Tier 2 public transit person miles in the Light Rail No Sq Ft Effect case are 18.7% greater than the MTP projection (compared to 24.7% greater for the Light Rail scenario), and Tier 2 public transit person miles in the Light Rail Like Bus No Sq Ft case are 10.7% less than the MTP projection (compared to 9.8% less for the Light Rail Treated Like Bus case). As expected, removing the assumed effects of the light rail on commercial floor space and migration brings the Light Rail scenario closer to the MTP-derived projections for public transit person miles, while making the Light Rail Treated Like Bus case farther from MTP-derived projections. However, the Light Rail Like Bus No Sq Ft case is still closer to the MTP-derived 2040 Tier 2 public transit person mile projection than is the Light Rail No Sq Ft Effect case. This suggests that, even if the figures derived from the MTP assume that the opening of the light rail will have less of an impact on land development, jobs, and population than does the D-O LRP SD Model, the D-O LRP SD Model may still overestimate how much light rail will increase public transit use, unless, conversely, the MTP's projections were to turn out to be too low in this regard.

A change in public transit person miles produces a same-direction change in nonmotorized person miles (because each unlinked, one-way public transit trip is assumed to result in an average of 0.25 miles of additional nonmotorized travel) and an opposite-direction change in automobile person miles (Table 6-14 and Table 6-15). The Light Rail Treated Like Bus test case also has fewer overall person miles of travel after 2026 than the regular Light Rail scenario, due to there being less public-transit-induced nonmotorized travel. Table 6-14 also shows that the large difference in public transit person miles between the Light Rail scenario and the Light Rail Treated Like Bus test case has relatively minor feedback effects on population, employment, and VMT per highway lane mile, the inputs that drive light-rail-induced public transit person miles in the Light Rail scenario. The small size of these feedbacks at least partially reflects the fact that public transit represents a very small proportion of overall person miles of travel, regardless of whether or not the light rail line is built. If a much larger percentage of person miles were traveled on public transit or these feedback effects were stronger, the model's results could potentially be rendered less accurate, as the underlying equation used in the model originally came from a model that did not feature feedbacks and made assumptions about the pre-light-rail public transit usage rates of areas that may differ from the study area of our model.

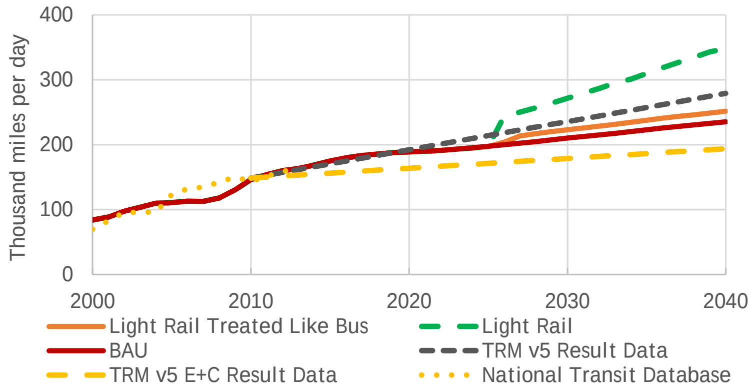


Figure 6-37. Public Transit Person Miles of Travel Per Day – Tier 2: Light Rail Scenario with Light Rail Treated Like Bus Service for Determining Transit Use vs. Regular Light Rail Scenario

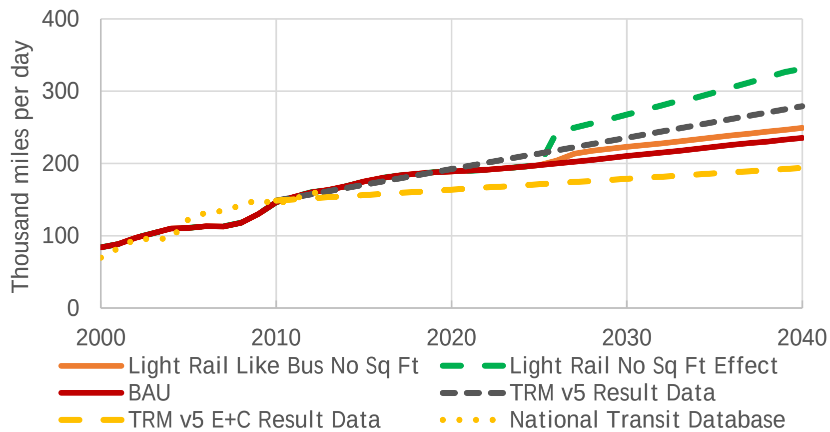


Figure 6-38. Public Transit Person Miles Of Travel Per Day - Tier 2: Light Rail Scenario with Light Rail Treated Like Bus Service For Determining Transit Use and No Assumed Direct Effect of Light Rail On Demand For Commercial Floor Space Or Migration Vs. Light Rail Scenario With Light Rail Treated Differently from Bus Service for Determining Transit Use But Still No Assumed Direct Effect of Light Rail On Demand for Commercial Floor Space or Migration

Table 6-14. Average Yearly Percent Departure from Light Rail Scenario, 2026-2040: Light Rail Treated the Same as Bus Service for The Purpose of Determining Ridership

VARIABLE	LIGHT RAIL TREATED LIKE BUS V. LIGHT RAIL
Tier 1	
Public transit person miles	-64.6%
Automobile driver person miles	+4.9%
Automobile passenger person miles	+5.0%
Nonmotorized person miles	-4.2%
Total person miles	-0.5%
Population	-0.1%
Employment	-0.2%
VMT per highway lane mile	+2.5%
Tier 2	
Public transit person miles	-21.2%
Automobile driver person miles	+0.3%
Automobile passenger person miles	+0.4%
Nonmotorized person miles	-1.3%
Total person miles	-0.1%

VARIABLE	LIGHT RAIL TREATED LIKE BUS V. LIGHT RAIL
Population	0.0%
Employment	0.0%
VMT per highway lane mile	+0.2%

Note: Difference between Light Rail scenario and Light Rail Treated Like Bus test case starts in 2026, when the light rail line opens.

Table 6-15. Average Yearly Percent Departure from Light Rail Scenario with No Assumed Direct Effect of Light Rail On Demand for Commercial Floor Space or Migration, 2026-2040: Light Rail Treated the Same As Bus Service for the Purpose of Determining Ridership + No Assumed Direct Effect of Light Rail On Demand for Commercial Floor Space or Migration

VARIABLE	LIGHT RAIL LIKE BUS NO SQ FT V. LIGHT RAIL NO SQ FT EFFECT
Tier 1	
Public transit person miles	-65.2%
Automobile driver person miles	+5.0%
Automobile passenger person miles	+5.2%
Nonmotorized person miles	-4.2%
Total person miles	-0.4%
Population	-0.1%
Employment	-0.2%
VMT per highway lane mile	+2.4%
Tier 2	
Public transit person miles	-19.5%
Automobile driver person miles	+0.3%
Automobile passenger person miles	+0.3%
Nonmotorized person miles	-1.1%
Total person miles	0.0%
Population	0.0%
Employment	0.0%
VMT per highway lane mile	+0.2%

Note: Difference between Light Rail No Sq Ft Effect and Light Rail Like Bus No Sq Ft cases starts in 2026, when the light rail line opens.

Structure of Energy-Economy Feedback

In the real world, the link between energy spending and gross regional product is complicated and difficult to summarize in a model. In two structural tests we explore alternative formulations of the energy spending-GRP link to determine the effect of this structure on our results. The current D-O LRP model assumes energy spending can have either a balancing or reinforcing effect on GRP, depending on whether energy spending grows or decreases as a fraction of GRP.[48] This structure represents energy affordability; if energy spending grows proportionately more than GRP does, energy becomes less affordable, and vice-versa. Increasing affordability of energy in the model leads to an increase in GOS, which is set to be equal to 40% of GRP.

To test the effects of this structure, we removed the connection from energy spending to GOS. This

[48] As context, other system dynamics modelers have assumed a balancing feedback between energy spending and economic growth at the US (Bassi et al. 2010) level.

removes the balancing and reinforcing feedbacks from energy spending to GRP, to determine the size of these energy spending effects.

In the current version of the model, energy spending tends to decrease GOS (and therefore GRP) between 2000 and 2022, but it increases GOS from 2023 to 2040 (red line in Figure 6-39). Unlinking energy spending from GOS therefore causes GOS to grow faster in the first half of the time series and slower in the second half, compared to BAU. Unlinking energy spending leads to less growth in GOS and GRP in the long run due to the effect of increasing energy efficiency. As building and vehicle energy efficiency increases into the future, energy spending decreases as a fraction of GRP, which in the BAU scenario leads to higher GRP growth.

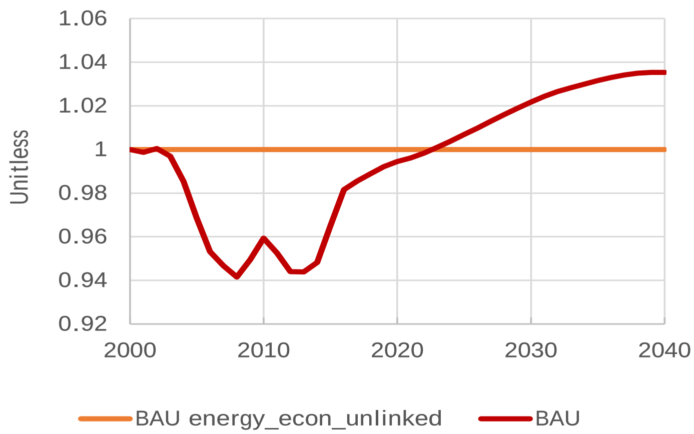


Figure 6-39. Structural Analysis for Unlinking Gross Operating Surplus from Energy Spending: Effect in Tier 2 on "Energy Spending Share of GRP Factor Affecting GOS"

Figure 6-40 shows the effect of this structural change on (a) GRP and (b) GRP growth rate in Tier 2. In (a), the orange line of unlinked GRP is larger than in BAU between 2005 and 2033, but smaller than in BAU afterward. The unlinked case differs from reference data and projections by 6% in 2010 and 4% in 2040. In contrast, the BAU scenario differs from reference data and projections by 0.3% in both years. This suggests that feedbacks from energy spending cause a 5% fluctuation in GRP in our model. These fluctuations can also be viewed in terms of growth rate; Figure 6-40B shows that the unlinked GRP (the orange line) grows faster than in BAU between 2003 and 2013, but afterward grows slower than in BAU.

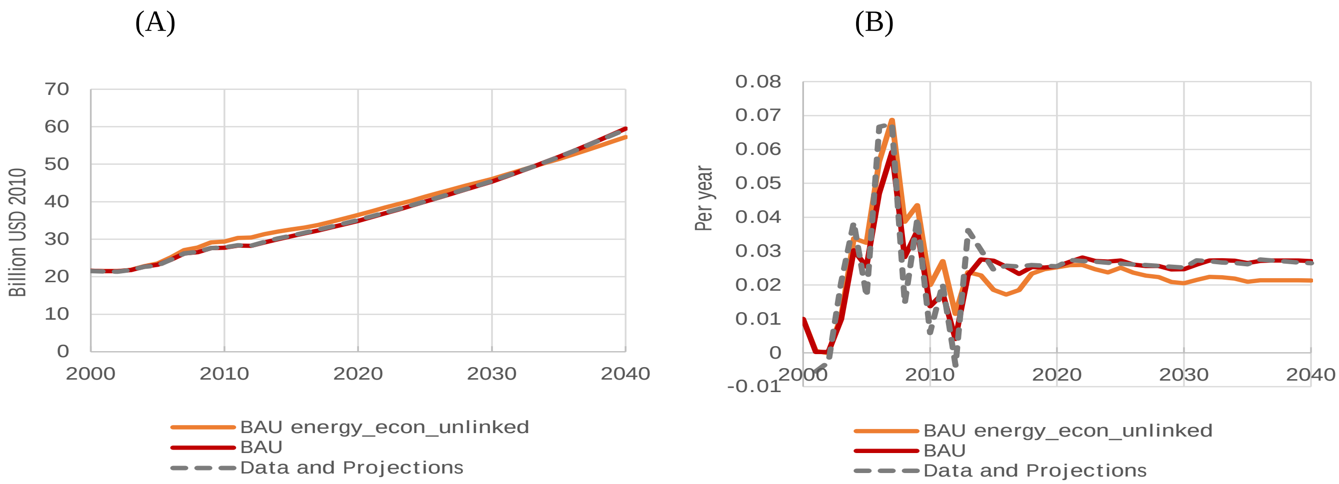


Figure 6-40. Structural Analysis for Unlinking Gross Operating Surplus from Energy Spending: Effect in Tier 2 on (A) GRP and (B) GRP Growth Rate

In a second structural test, relative energy spending, rather than energy spending/GRP, is used to create feedback from the energy sector to the economy. Again, this test explores an alternative formulation of the energy spending-GRP link to determine the effect of this structure on our results. (Here, "relative energy spending" is relative to the 2000 value of energy spending (Figure 6-41a). Using relative energy spending leads to much slower GRP growth (orange line compared to red line, Figure 6-41b), with 38% lower GRP by 2040. Reducing the elasticity of GRP to energy spending from 0.2 to 0.1 (yellow line) improves the fit to historical data for this structure, but only up to 2017.

In general, using energy spending as a fraction of GRP leads to a better fit to historical data. This suggests energy spending/GRP may better represent feedback from the affordability of energy to GRP. As the economy grows, a feedback structure using only relative energy spending would create negative feedback on GRP (Figure 6-41a), but relative energy spending/GRP can create positive feedback when GRP grows faster than energy spending. This is the case here; in the BAU scenario, energy spending grows by a factor of 2.3 between 2000 and 2040 while GRP grows by a factor of 2.75.

(A) (B)

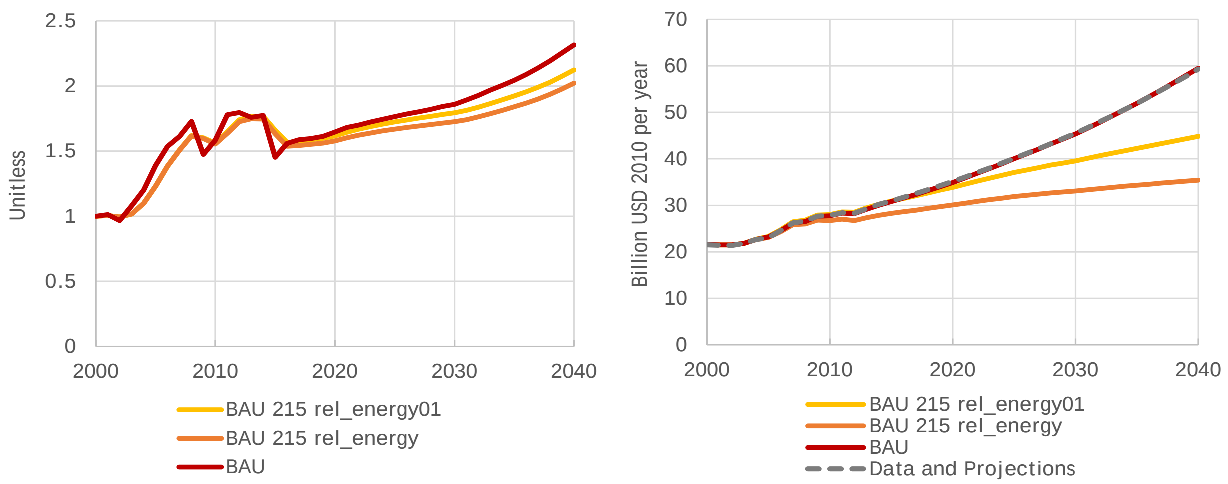


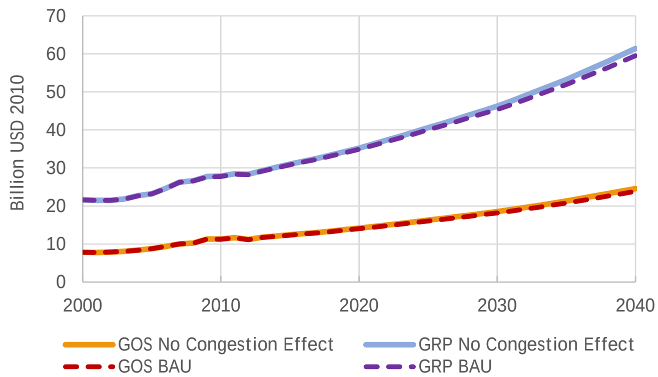
Figure 6-41. Structural Analysis for Using Relative Energy Spending, Not Energy Spending/GRP, in Feedback to GRP: Effect on (A) Relative Energy Spending and (B) GRP in Tier 2

Removing the Effect of Congestion on Productivity

Congestion negatively impacts the economy in the D-O LRP SD Model by reducing the GOS. The rationale for having congestion only impact GOS and not total GRP is that even though the earnings of salaried employees would not be affected from being stuck in traffic, the business or company that employs the worker is losing profits from the work that the employee would be doing, in addition to the profit loss from the transport of goods and services to and from the business being delayed. This structural test shows the impact of removing the effect of congestion on GOS and the subsequent effect on GRP in Tier 2 and Tier 1.

Although removing the effect of congestion seems to have a very little impact in the short term on GOS and GRP in both Tier 2 (**Figure** 6-42, Top) and Tier 1 (**Figure** 6-42, Bottom), the internal feedbacks in the economy sector (GOS → GRP → Retail Consumption → Employment → GRP, described in the economy sector narrative in Section 3.3) cause these small differences to become more substantial over time - with GRP being $1.8 Billion (2010 dollars) higher in 2040 in Tier 2 compared to the BAU scenario and GRP Tier 1 being $1.1 Billion (2010 dollars) higher in 2040 compared to the BAU scenario.

(A)



(B)

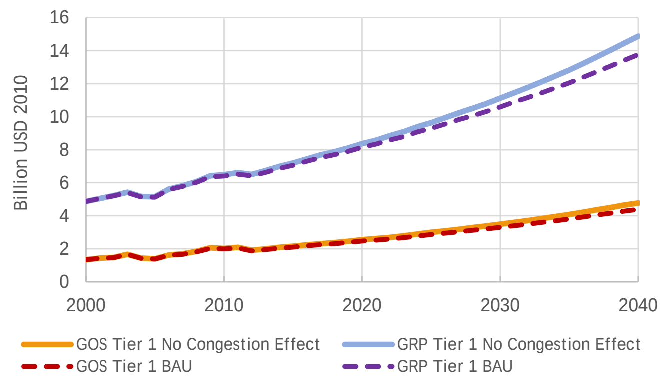


Figure 6-42. Structural Test of Removing Effect of Congestion on Economic Productivity: Comparison to BAU of Two Economic Indicators for (A) Tier 2 and (B) Tier 1

<u>Tier 1 Retail Consumption Calculation With and Without Connection to Resident % of the Working Population</u>

This section is not a quantitative structure test, but instead discusses why the Tier 1 model structure for estimating retail consumption differs from Tier 2. In Tier 2, retail consumption changes, after a two year delay, relative to an initial (2000) retail consumption value that is multiplied by two factors:

(1) The relative change in the **resident percent of the working population**, calculated exogenously based on historical data and projections for the following equation:

$$1 - \frac{(total\ employment - resident\ employment)}{population}$$

(2) The relative change in GRP (endogenous) raised to the power of a calibrated elasticity of consumption to GRP (1.1)

The first relative factor, resident percent of the working population, is meant to represent the change in the number of people that both live and work in an area, assuming that those who work in an area but don't also live there tend to do their shopping elsewhere (closer to home). Thus, as long as population grows faster than the percent of jobs that are filled by non-residents, the relative value (relative to the initial 2000 value) for resident percent of the working population will increase, allowing retail consumption to increase.

When calculating the resident percent of the working population for Tier 1, we found that, since nonresident employment (i.e. commuters) is actually higher than population in Tier 1, this parameter was negative and grew to be much more negative in the BAU scenario, shown in Figure 6-43, where total employment actually grows faster than resident employment and population. Consequently, the relative resident percent of the working population in Tier 1 decreases, changing by much more than the change observed in Tier 2. We therefore decided not to use this formulation to estimate retail consumption in Tier 1. We reasoned that, despite the decline of resident workers relative to total employment, Tier 1 residents and employees will still do their shopping in Tier 1 and continue to make up a portion of the retail consumption that happens there. As a result, we decided not to connect retail consumption in Tier 1 to the resident percent of working population in that Tier. On the other hand, if we were to create this connection, we would need to modify the formulation of retail consumption (to account for the negative and declining resident percent of working population). This would require us to divide relative GRP by the resident percent of working population, and to add an elasticity that would reduce the strength of the relationship (to account for the fact that, as mentioned above, resident population and all workers would still spend money in Tier 1).

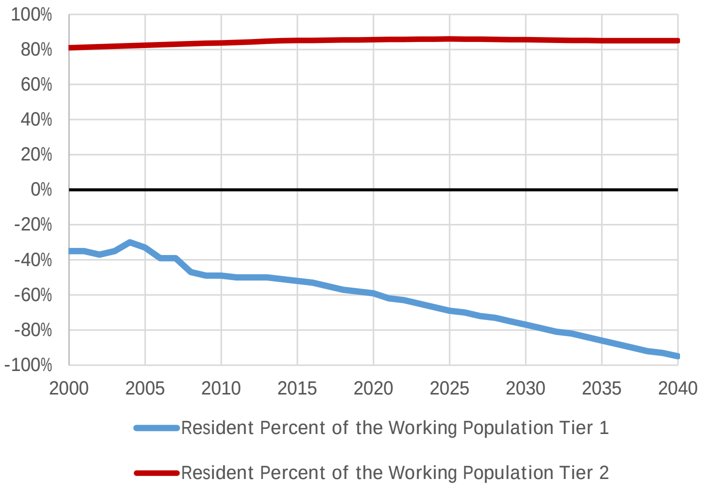


Figure 6-43. Resident Percent of the Working Population for Tier 2 and Tier 1, Calculated from Historical Data and Projections of Employment and Population

Tier 1 Resident Labor Force Calculations

The equation we chose for calculating the resident labor force in Tier 1 (Option 2 below), which directly affects unemployment rate and thus net migration to Tier 1, involved several assumptions that, at the time the model was completed, seemed to be the best assumptions. However, two other options for calculating resident labor force in Tier 1 were tested and we present here the results of all three calculations and how the different formulations affect the rest of the model.

At an early stage in model development, we simply used the same formulation for Tier 1 as in Tier 2:

Option 1: *Population Tier 1*percent of residential population in labor force Tier 1* with the percent of the residential population in the labor force Tier 1 (42%) calculated exogenously based on historical data and held constant for the entire time period.

However, since the additional employment added to Tier 1 in the Light Rail and Light Rail + Development scenarios brings additional residents to Tier 1 (compared to the BAU scenario), we decided that the family of the additional residents who were moving to Tier 1 for work should be subtracted out of the calculation for residential labor force under the assumption that it was more likely that they would either not be seeking employment or would be employed outside of the Tier 1 geographical area. Thus, we developed a second formulation for the Tier 1 labor force:

Option 2: population Tier 1*percent of residential population in labor force Tier 1-(resident employment Tier 1 - initial resident employment Tier 1)*(additional family members per worker tier 1)

After an analysis of the results of the model, we realized that this formulation actually subtracts too many residents from the labor force, decreasing the unemployment rate, which increases the population in Tier 1 and causes the "per capita" parameters in Tier 1 (e.g. resident net earnings per capita) to decrease in the Light Rail and Light Rail + Redevelopment Scenarios (relative to the BAU). As a result, we created a third option for possible use in future versions of the D-O LRP SD Model:

Option 3: (population Tier 1 – ((resident employment Tier 1 - initial resident employment Tier 1)*additional family members per worker tier 1))*percent of residential population in labor force Tier 1

Option 3 subtracts the additional family members that move along with newly employed residents from the population before multiplying that population by the "percent of residential population in labor force Tier 1."

Results of the structural tests for the three options for calculating the resident labor force in Tier 1 are shown in Figure 6-44 and Figure 6-45. For both figures, the three options are shown for the Light Rail + Redevelopment scenario, with the default option (Option 2) also shown for the BAU scenario for reference. As was mentioned previously, the unemployment rate drops very low in Tier 1 in the Light Rail + Redevelopment scenario (Figure 6-44A) when Option 2 is used to calculate resident labor force Tier 1. As a result, the population in Tier 1 increases the most with this combination (Figure 6-44b) due to the connection between unemployment rate Tier 1 and net migration to Tier 1. Consequently, the additional population in Tier 1 due to the unemployment rate being underestimated by Option 2 causes the resident per capita net earnings Tier 1 (Figure 6-45b) to decrease compared to the BAU scenario, which affects affordability in the model. This was obviously an unintended consequence of the equation that we chose for our model and one that we hope to fix in future versions of the model. Because of this, and to allow for more flexibility when using the model, a switch was added, called the "resident labor force calculation Tier 1 switch," to allow the user to easily switch between the three formulations for resident labor force and assess the outcomes of each simulation on several indicators across sectors.

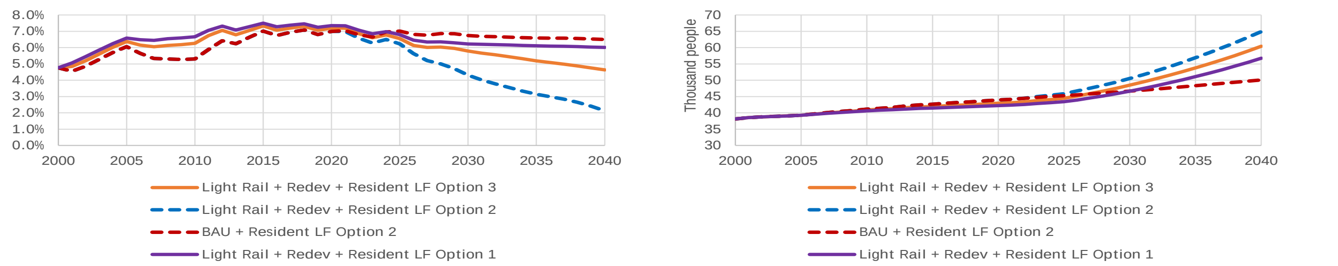


Figure 6-44. Structural Test of the Economic Effects of Three Different Formulations for Resident Labor Force Tier 1: Comparison of (A) Unemployment Rate (%) Tier 1 and (B) Population Tier 1

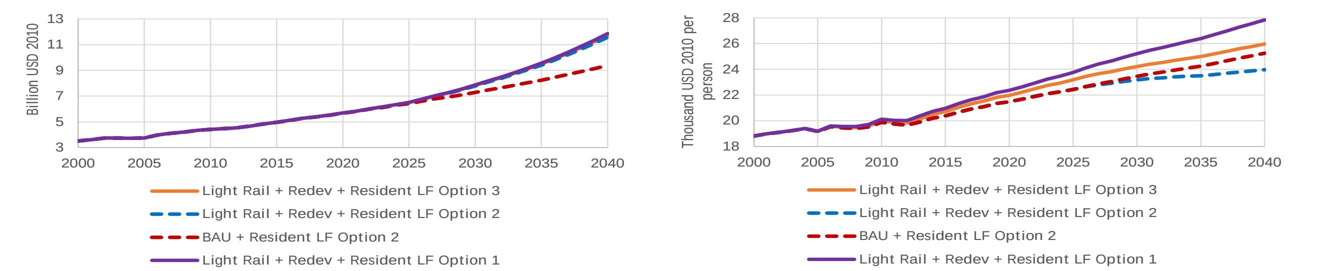


Figure 6 45. Structural Test of the Economic Effects of Three Different Formulations for Resident Labor Force Tier 1: Comparison of (A) Total Earnings Tier 1 and (B) Resident Per Capita Net Earnings Tier 1

Property Value Structure Test

This test sets all elasticities and effect tables affecting property values to the exact values found in the literature, in both Tiers, and removes any relationships that were not explicitly quantified in the literature. We ran this test due to the uncertainty of the model projection of property values and to verify the need for the multiple changes made to elasticities found in the literature during calibration. Elasticities had to be changed for various reasons including studies that were specific to very different contexts, elasticities established for one property type that had to be borrowed for another, and relationships established at the metropolitan level that were too strong for Tier 1. For example, while the elasticity of +1.09 between population growth and single family property values from a study at the metropolitan level (Jud and Winkler, 2002) worked well in Tier 2, the relationship was too strong in Tier 1 and had to be adjusted down to +0.5. Table 6-16 compares the values used in the BAU, in this test, and all those found in the literature. For the BAU scenario, values shown in orange were borrowed from literature on another building type. Values shown in red were either altered from their original literature value during calibration or were not available from the literature and were instead derived from data. These red and orange values are the ones changed during this test. No test values were given from lot size with multifamily (MF) and nonresidential (Nonres) property values, as this would have been duplicative with the relationships with building size. Values that were not changed from the literature values during the calibration process also remain the same in this test.[49]

[49] When multiple values were available from the literature, we chose values for this test from studies conducted at a similar scale (citywide rather than on a neighborhood basis). If there were multiple values available at a citywide scale, we chose the value that better matched the data.

Table 6-16. Elasticities Used to Calibrate Property Values in the BAU and the Property Value Structure Test

VARIABLE	SF (BAU)	SF (TEST)	SF (LIT)	MF (BAU)	MF (TEST)	MF (LIT)	NONRES (BAU)	NONRES (TEST)	NONRES (LIT)	SOURCES AND NOTES
Lot size (1/density)	-0.321 [50] (T1)	-0.321 (T1)	+0.005; +0.276; +0.321; +1.45	-	-	-.009; +0.06*	-	-	-0.920	(Kain and Quigley, 1970) (Srour, 2002) (Kockelman, 1997)
SF Density	+1.5 (T2)	-	-	-	-	-	-	-	-	N/A
Income	+0.17	+0.17	+0.17; +0.293; +0.45	+0.17	-	-	-	-	-	(Jud and Winkler, 2002); (Hiekkila, 1989); (Capozza et al, 2002)
Population growth	+1.09 (T2) +0.5 (T1)	+1.09	+1.09; +1.53	-	-	-	-	-	-	(Jud and Winkler, 2002); (Capozza et al, 2002
Vacant land	-0.38** (T2), 1.2 max multiplier (T1)	-0.38	-0.38	-0.38; (T2), 1.2 max multiplier (T1)	-	-	-	-	-	(Capozza et al, 2002)
Job density	+0.291	+0.291	+0.291	+0.291	-	-	-	-	-	(Srour, 2002)
Retail density	+.062	+.062	+.062; +.044	+1.44 (T2) +0.35 (T1)	+1.44	+1.44	+0.05096 (T2) +1.44 (T1)	+0.05096	+0.05096	(Kain and Quiqley, 1970) (Srour, 2002)
Building size	-	-	-	+0.994 (T2) +0.3 (T1)	-	-	+0.994	+0.994	+0.994	(Srour, 2002)
Employment	-	-	-	-	-	-	+1.09	+1.09	+.00671; +1.09; +1.92; *-1.46*	(Srour, 2002)(Dobson and Goddard, 1992)
Avg time to work	-0.343	-0.343	-0.343	-0.108	-0.108	-0.108	-	-	-	(Kockelman, 1997)

Figure 6-46 shows the effect of the changes on multifamily property values in Tier 1. Without the changes made for the BAU scenario, property values fall well below historical data, and average 20% below data over the years for which historical data are available, versus only 1.1% above the data under the BAU scenario.

[50] The elasticity of 0.321 found was for single family lot size. Since it is connected with density instead in our model, we have used the inverse, -0.321.

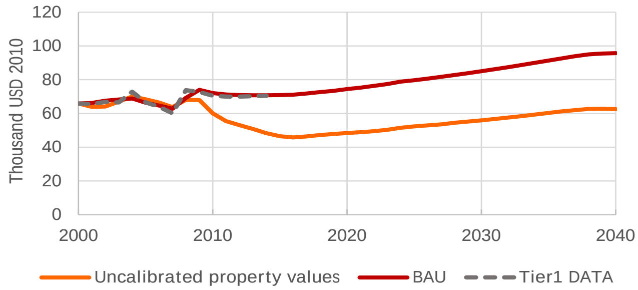


Figure 6-46. Multifamily Property Value Per MF Dwelling Unit - Tier 1: BAU and Structural Test

Finally, Table 6-17 summarizes the average yearly percent departure for the three property value classes and several variables which are affected by them from BAU 2000-2040. Since the least literature was available to support relationships with multifamily property values, the most changes had to be made and they are therefore the most affected by the test.

Table 6-17. Average Yearly Percent Departure from BAU, 2000-2040, Property Value Structure Test[51]

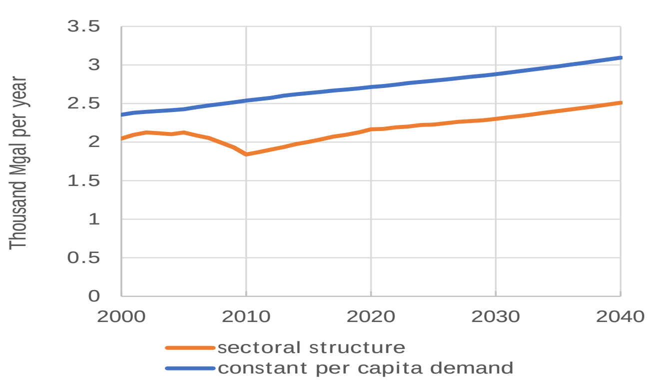
Variable	Property Value Test v BAU	
	Absolute percent deviation	Percent above or below
Tier 1		
Nonresidential property value per sq ft Tier 1	19%	16%
SF property value per SF DU Tier 1	8.6%	8.6%
MF property value per MF DU Tier 1	26%	-25%
Median annual renter costs Tier 1	14%	-13%
Tier 2		
Nonresidential property value per sq ft	0.0%	0.0%
SF property value per SF DU	10.2%	-10%
MF property value per MF DU	27.2%	-27%
Median annual renter costs	6.4%	-6.4%

<u>**Structure of Water Demand**</u>

The current model calculates municipal water demand by disaggregating demand into sectors such as residential and nonresidential demand. In this test, we compare the current sectoral structure with an earlier structure which used constant per-capita demand in order to evaluate whether the sectoral structure is more realistic. The per capita formulation is the blue line in Figure 6-47a-b, in which municipal water demand equals per-capita demand (169 gal/person/day, based on 2005 Durham County water use) times total population. In contrast, the current model estimates demand separately in the

[51] Nonresidential property value per sq ft in Tier 2 does not change because all elasticities remain the same in the test (none differed from the literature values).

residential, nonresidential, and nonrevenue sectors, then sums them. Each sector has an exogenous trend for water use intensity. In addition, residential demand is proportional to number of dwelling units, nonresidential demand is proportional to number of employees, and nonrevenue demand is proportional to population.



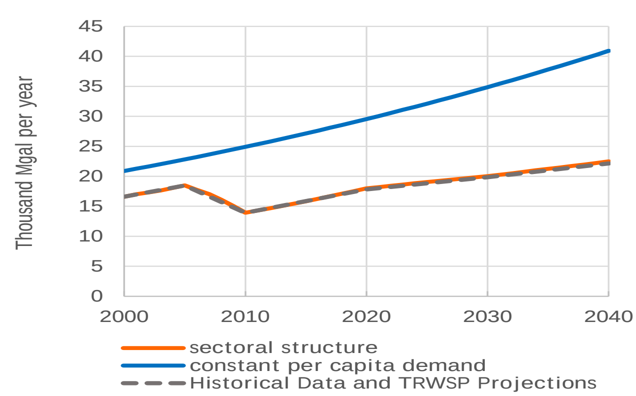


Figure 6-47. Structural Analysis for Water Demand: Sectoral Formulation Compared to Per Capita Formulation

The per capita structure yields, on average, 25% higher water demand than the sectoral structure in Tier 1, and on average 63% higher demand than the sectoral structure in Tier 2. Since the sectoral structure is calibrated to historical water demand data as well as to projected water demand in the Triangle Regional Water Supply Plan, it is not surprising that it gives a more accurate view of demand. In Tier 2, the sectoral structure differs from historical data and TRWSP projections by an average absolute value of 0.64% (Figure 6-47b). Moreover, assuming a constant per capita water demand would ignore the effects of more water efficient technology and/or conservation practices. These effects are seen in Tier 2 in the drop in demand after 2005 and the lower slope of demand growth between 2020 and 2040 in the sectoral structure compared to the per capita structure. Since historical data and projections were only available for Tier 2, the fact that the sectoral structure shows a better fit with Tier 2 data suggests that this structure is also more accurate than a per capita structure in Tier 1.

Structure of Stormwater Runoff

Our model estimates stormwater runoff using the Simple Empirical Method (Shaver et al. 2007); in this structural test we explore how aggregating vs disaggregating the stormwater structure by land use affects results. An earlier version of our model estimated stormwater N load by aggregating all land uses within each Tier and applying an aggregate percent impervious surface to calculate stormwater runoff volume and event mean concentration. The orange line in Figure 6-48 shows this aggregated form of the model. The current model disaggregates stormwater N load by land use type (SF residential, MF residential, nonresidential, etc.) and calculates stormwater runoff volume and event mean concentration separately for each land use type. The total stormwater N load for the disaggregated structure is the blue line in Figure 6-48.

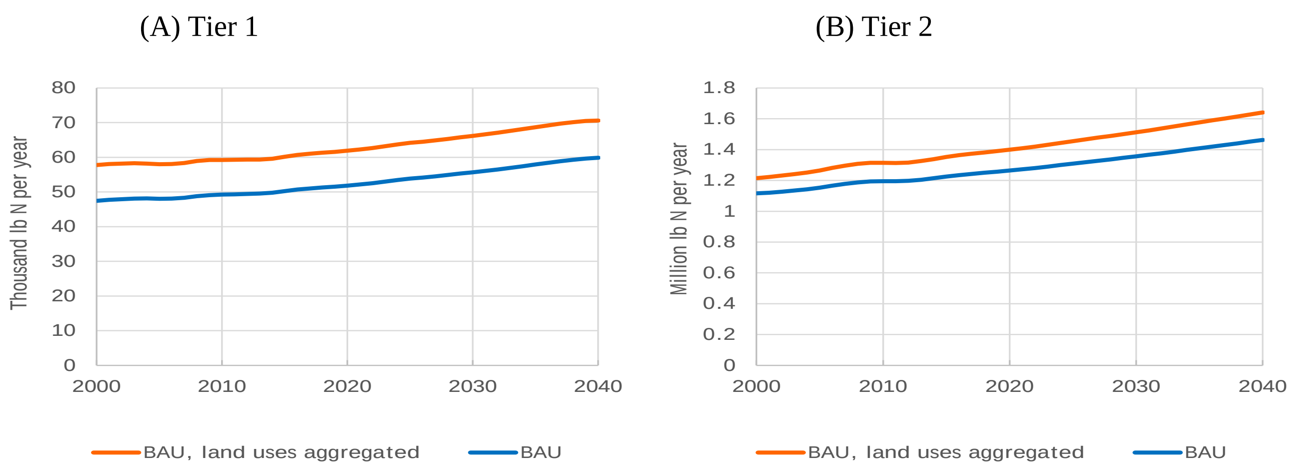


Figure 6-48. Structural Analysis for Stormwater N Load: Land Uses Aggregated Compared to Disaggregated

The two structures show similar behavior in N load over time, but N load for the aggregated structure is on average 20% higher than for the disaggregated structure in Tier 1, and 11% higher than the disaggregated structure in Tier 2. One reason for this is how event mean concentrations (EMCs) are calculated. The aggregated structure assumes all impervious cover has an EMC of 1.44 mg N/L, but the disaggregated structure has different EMCs for each land use. In the disaggregated structure, the residential and nonresidential land uses representing the majority of Tier 1 and Tier 2 stormwater N load assume 1.08 mg N/L for roofs and 1.44 mg N/L for parking lots and driveways.

Stormwater runoff volume is nearly identical in the aggregated structure compared to the disaggregated structure (graphs not shown), and this consistency is expected, given that runoff volume is modeled as a function of impervious surface. In Tier 1, runoff volume from the aggregated structure differs from the disaggregated structure by an average absolute value of 0.04%, while in Tier 2 they differ by 0.58%. We take these small differences as rounding errors, and as support that we are applying the equations consistently.

Structure of Vehicle Emissions Effects on Health

We tested several alternative structures for modeling the health effects of vehicle emissions in the D-O LRP SD Model. The EPA photochemical modeling study (US EPA 2013c) that estimated the national health benefits per ton of removing pollutants from various sources, including on-road mobile sources, used health benefit estimates from two epidemiological studies: Krewski et al. (2009) and Lepeule et al. (2012). Based on advice given by one of the authors of that report (US EPA 2013c), the default benefit-per-ton estimate chosen for the model is from the former, by Krewski et al. At first we were only going to model the difference between scenarios in avoided premature mortalities from reducing (or increasing) direct $PM_{2.5}$ emissions from vehicles; however, under the advice of the EPA report author, we included effects of NO_x emissions (a $PM_{2.5}$ precursor) from vehicles as well.

The structural tests in Figure 6-49 show the three different options for estimating the health effects of changes in vehicle emissions (relative to BAU) in the model. The Light Rail + Redev scenario (default, red) shows the combined effects of changes in $PM_{2.5}$ and NO_x vehicle emissions (relative to the BAU) on premature mortality based on Krewski et al. (2009), whereas the "Light Rail + Redev Lepeule" case (orange) uses estimates from Lepeule et al. (2012). The Lepeule values yield 123% higher premature mortalities than the Krewski values, on average, between 2020 and 2040 in Tier 2, the time period reflecting effects of the D-O LRP. The other structural test of excluding NO_x vehicle emissions effects on premature mortality (leaving only $PM_{2.5}$ effects), is shown in Figure 6-49 in yellow. The $PM_{2.5}$-only case, "Light Rail + Redev $PM_{2.5}$ only," uses the health effects estimates from Krewski et al. (2009) and produces 26% fewer premature mortalities on average during 2020-2040, compared to including both $PM_{2.5}$ and NO_x effects (Light Rail + Redev). Therefore $PM_{2.5}$ represents the majority of vehicle-emissions-related premature mortalities in this model, but leaving out NO_x emissions would significantly underestimate emissions-related premature mortalities. Further, the default Krewski et al. mortality-per-ton estimate results in roughly half the number of premature mortalities as the Lepeule et al. estimate. However, because air emissions are projected to have a very small impact on overall premature mortalities (relative to other factors such as walking and cycling), the downstream impacts of these structural changes are negligible.

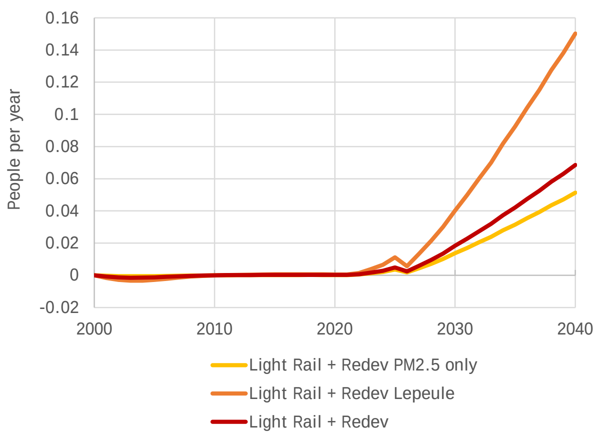


Figure 6-49. Structural Analysis for Health Effects of $Pm_{2.5}$ and No_x Vehicle Emissions: Total Premature Mortalities Relative to BAU – Tier 2

Extreme-Condition Tests

Direct extreme-condition testing is a very important step in the validation of the D-O LRP SD Model. Testing the model for extreme conditions involves evaluating the validity of the model's structure under extreme (not necessarily plausible) conditions, by assessing the coherence of the resulting values against the knowledge or anticipation of what would happen under a similar condition in real life. We present five extreme-condition tests below, including 1) Zero person miles, 2) Extreme population drop, 3) Extreme unemployment, 4) Economic crash, and 5) Extreme gas price spike.

Zero Person Mile Test

In this test, we set initial person miles of travel per day to zero for all modes of transportation. All drivers of person miles of travel in the D-O LRP SD Model are reliant upon elasticities that cause an initial value to be multiplied by a dynamically-determined product. Therefore, if person miles of travel are zero in the year 2000, we expect them to remain at zero for the entire model run. As expected, this change resulted in person miles of travel by all modes to remain at zero for the entirety of the model run. An example of this, for public transit person miles per day, is shown in Figure 6-50A. This is consistent with the real-world expectation that people's past travel behavior (or lack thereof) predicts their future travel behavior, unless events transpire to change it.

In this test, VMT is consistently reduced, but does not go to zero (Figure 6-50). This is because, even though VMT for trips that either start or end in the study area go to zero in this test case, through-traffic VMT (which, in the BAU case, is over a third of all Tier 2 VMT throughout 2000-2040) does not. In fact, due to reduced traffic congestion, through-traffic VMT (not shown) is slightly greater than BAU. As expected, because nobody does any walking or cycling in this test case, the absence of the health benefits of those nonmotorized travel modes results in far fewer premature fatalities avoided (Figure 6-50). This test case produces a GRP slightly greater than BAU, because there is no traffic congestion (Figure 6-50). This result is consistent with the fact that the model does not contain a feedback for the effect of health outcomes on the economy, as well as the fact that the model does not assume that transportation is a necessary precondition for engaging in economic activities above a certain level, both of which are limitations of the model.

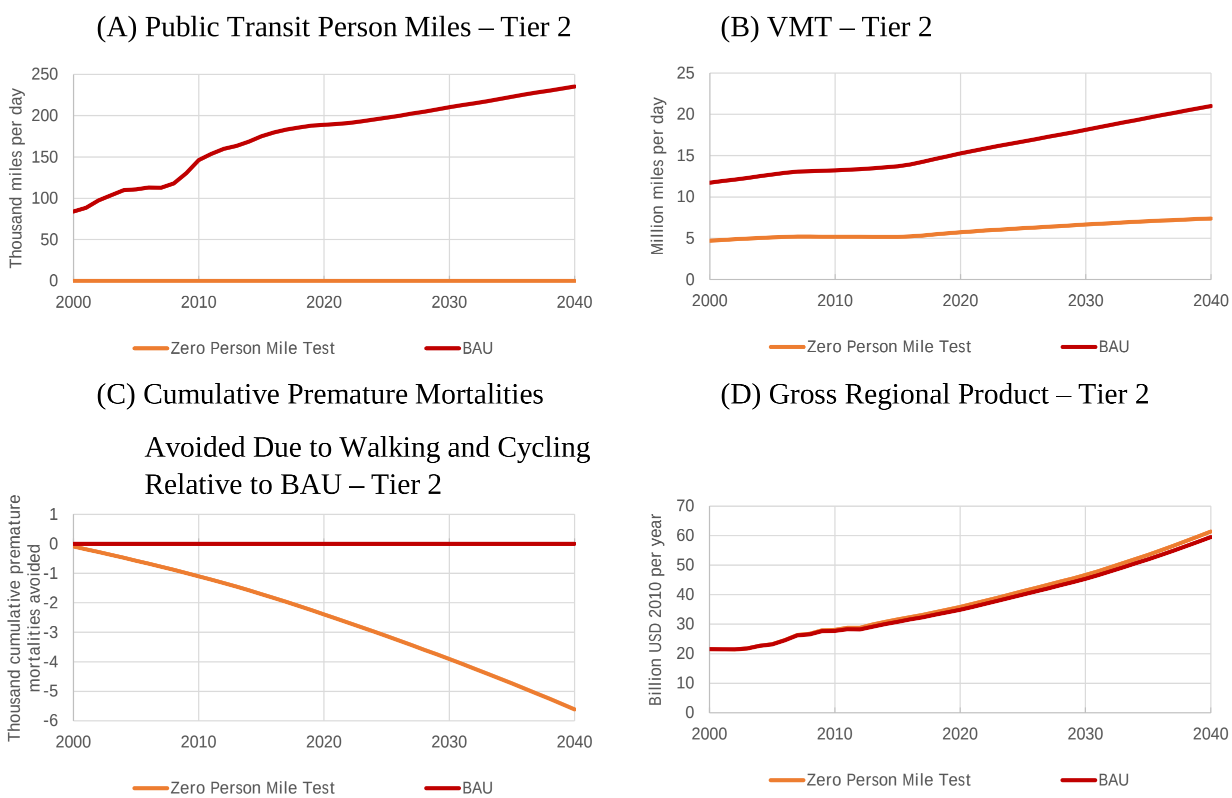


Figure 6-50. Extreme Value Test of Zero Person Miles by Any Mode from Start of Model Run vs. BAU

<u>Extreme Population Drop Test</u>

In this test, we created new outflows from Tier 1 and Tier 2 population, set to reduce population by approximately 70% around the year 2020. Births, deaths, and net migration are all functions of current population. Therefore, in this test, Tier 1 and Tier 2 population both remain far below BAU during 2020-2040. In Tier 1, this dramatic population drop has very little effect on GRP (Figure 6-51A). This is because the primary determinants of GRP are employment and nonresidential square feet (both of which exist in feedback loops with GRP), and whatever portion of Tier 1's labor force needs cannot be met by Tier 1 residents are presumed to be met by people commuting into Tier 1 . However, Tier 2 GRP is dramatically less than BAU after 2020 (Figure 6-51B). This is because the Tier 2 labor force is assumed to be a direct function of Tier 2 population, in keeping with the expectation that the larger a geographic area is, the smaller is the percentage of its workers who commute from outside the area. When population and employment drop, so do earnings, and hence GRP. As GRP drops, so does retail consumption, and hence desired employment. Around 2025, this feedback causes Tier 2 desired employment to be less than the Tier 2 labor force, which decreases employment and GRP even further. This forms a vicious cycle, such that, even after its dramatic post-2020 drop, Tier 2 GRP continues to decline through the year 2040, as opposed to increasing during 2020-2040, as it would in the BAU case. Tier 2 net migration is modeled as being mostly insensitive to economic influences, while Tier 1 net migration is sensitive to economic influences. Since Tier 1 population declines while Tier 1 GRP does not, Tier 1 unemployment goes down and the Tier 1 employment gap increases, causing an increase in Tier 1 migration. As a result, 2040 Tier 1 population is 44% of BAU, whereas 2040 Tier 2 population is 32% of BAU.

The numbers of dwelling units and square feet of nonresidential floor space do not automatically change when population changes. Therefore, the usual expectation is that a sudden drop in population will cause real estate demand to decrease relative to supply, meaning that property values will decrease. However, in this test case, the opposite occurs in Tier 1, with a sudden drop in population triggering an increase in the value of nonresidential square feet of floor space, single-family dwelling units, and multifamily dwelling units (Figure 6-51C). This is because, since Tier 1 population decreases but Tier 1 GRP does not, the amounts of jobs, earnings, and retail establishments *per capita* all become much higher in 2020 in this test case, driving up Tier 1 property values, an unrealistic outcome that represents a shortcoming of the model. In the context of Tier 1, it is reasonable that economic activity would not necessarily decline when population declines, or at least not decline by the same proportion, since, unlike in Tier 2, most Tier 1 workers and a significant portion of Tier 1 retail customers reside outside of Tier 1. Meanwhile, Tier 2 property values drop below BAU as a result of population being reduced, in keeping with expectations. However, in the case of Tier 2 multifamily dwelling units (but not single-family dwelling units or nonresidential floor space), property values are far above BAU during 2020-2021, before dropping below BAU for the remainder of the model run (Figure 6-51D). This is because the value of multifamily dwelling units is highly elastic to retail density (the number of retail establishments per capita). After population drops in 2020, retail density spikes upward, then reacts to reductions in Tier 2 employment and GRP, ultimately stabilizing at a value slightly below BAU. This follows the expectation that after people leave the metropolitan area, demand for retail goods declines, after which there is a delay of some amount of time before businesses start closing due to a lack of customers. However, the increase in multifamily dwelling unit property values during that period of delay is much less realistic.

Because of the aforementioned effects on GRP and property values, it is not surprising in this test case that Tier 1 and Tier 2 transportation and renter costs per year per household stabilize at values above and below BAU, respectively. However, in both Tiers, these costs spike upward in 2020 and take several years to come down from that spike (Figure 6-51E-F). Renter costs change because they are, in part, affected by the increase in multifamily property values described above. Transportation costs respond this way because the number of motor vehicles in the study area does not immediately respond to reductions in population, even though the excess cars are not being driven. Whereas vehicle purchases are a function of vehicle demand (such that demand is driven by population and earnings), vehicles are assumed to only be retired from the study area when they reach the end of their useful life (assumed to be an average of 17.5 years after they were purchased), rather than also moving out of the study area in the event of their owners moving away. As a result, there is a period of time during which it is assumed that all of the cars owned by the 70% of the population who moved away are still in the study area, and their fixed costs of ownership (including car payments, insurance, and maintenance, and not including fuel or parking) continue to be paid by the people who still live in the study area. However, increases in population much more immediately produce increases in vehicle stock. Therefore, in scenarios where population mostly increases over time (including the BAU, Light Rail, and Light Rail + Redevelopment scenarios), this difference between expectations and model results does not appear. This test demonstrates that the model is designed to accommodate increases in population more realistically than sharp decreases in population.

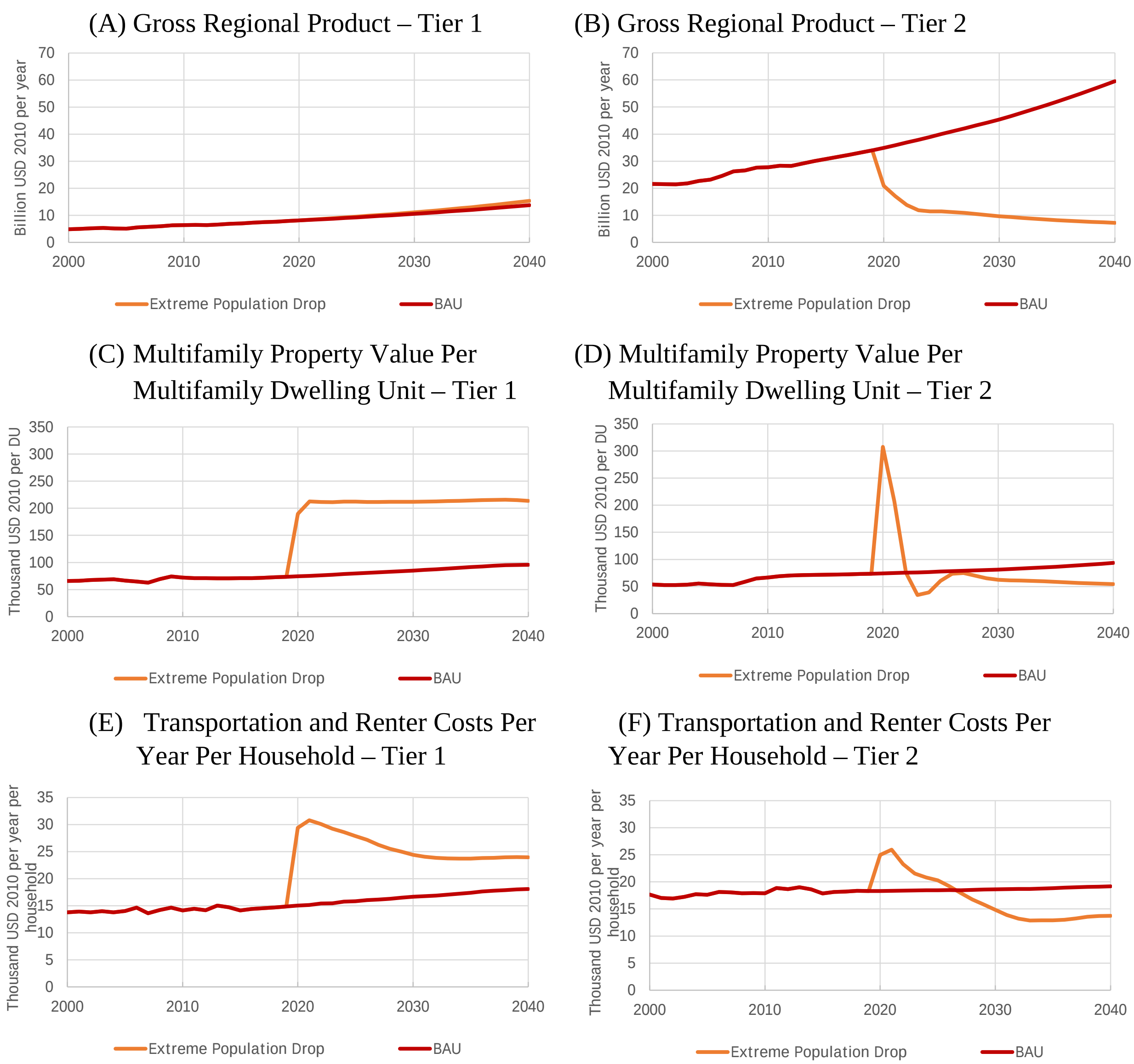


Figure 6-51. Extreme Value Test of 70% Population Drop at 2020 vs. BAU

<u>Extreme Unemployment Test</u>

In this test, we created a test case where Tier 1 and Tier 2 unemployment are both set at 50% during the period 2020-2040, regardless of the drivers that would normally cause unemployment to increase or decrease. In both Tiers, the unemployment rate directly determines the poverty rate. However, in Tier 1, it also affects net migration. In the D-O LRP SD Model, if Tier 1 unemployment is greater than 7.5%, net migration drops to zero, approximating a situation where it is no longer attractive to move to Tier 1.

Therefore, unsurprisingly, this test case causes Tier 1 population to be increasingly less than BAU after 2020 (Figure 6-52A). Since Tier 1 unemployment does not exceed 7.5% in any of the scenarios we ran outside of extreme-condition testing, the model was not designed to consider the possibility of emigration due to high unemployment. Meanwhile, because Tier 2 net migration is assumed to not be affected by unemployment rates, Tier 2 population in this test case differs from BAU by very little (Figure 6-52B).

As increased unemployment increases the poverty rate, it also increases the number of zero-car households. In the D-O LRP SD Model, zero-car households have a negative effect on VMT. However this effect is small, owing to the very small percentage of people who live in zero-car households in the BAU case. Because baseline zero-cars households are so few, the increase in such households that results from 50% unemployment has a very small effect on VMT. In Tier 1, VMT is less than BAU mostly because of population being lower (Figure 6-52). In Tier 2, VMT's difference from BAU is negligible (Figure 6-52).

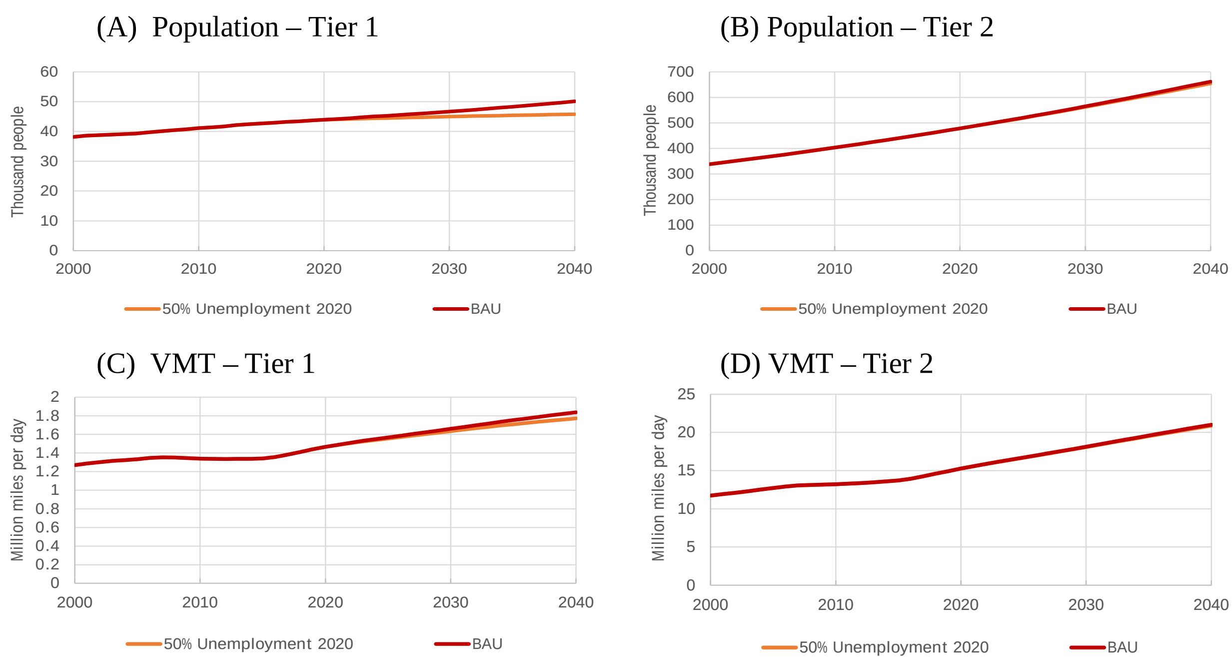


Figure 6-52. Extreme Value Test of Unemployment Becoming 50% During 2020-2040 vs. BAU

Economic Crash Test

In this test, we modeled a sudden 20% drop in GRP in the year 2020, with the assumption that the recovery from this economic crash will take at least a decade. To do this, we added an input variable to Tier 1 and Tier 2 GRP that multiplies the pre-existing GRP formula by a value that is equal to one through the year 2019, declines to 0.8 during 2019-2020, then ramps back up to one during 2020-2030. In both Tiers, GRP remains well below BAU through the year 2040 (Figure 6-53). This is because of a reinforcing feedback loop, wherein lowering GRP lowers retail consumption, which lowers desired employment, which lowers actual employment, which lowers both earnings and nonresidential floor space, hence lowering GRP, as discussed in Section 3.2. This is consistent with the expectation that a temporary economic shock may dampen economic activity for a very long time afterwards, unless other events intervene.

Although Tier 2 GRP does not get closer to BAU after the economic crash, it does continue to increase, albeit at a growth rate that is slightly less than BAU. However, Tier 1 GRP continues to decline in absolute terms after the end of the economic crash, thanks to a difference between the Tiers in how nonresidential floor space is determined. In both tiers, a reduction in overall square feet of nonresidential floor space, including retail, office, service, and industrial floor space, reduces GRP. Also in both Tiers, the addition or subtraction of office, service, and industrial land and floor space is driven by the number of office, service, and industrial workers, respectively. This makes sense, given that businesses must acquire whatever amount of floor space is necessary for the particular size of their operations, which is usually proportional to how many workers they have, depending on the type of business. However, Tier 1 and Tier 2 differ in how the amount of retail floor space is determined. Whereas the customers of businesses that use office, service, or industrial floor space may or may not be located in the same metropolitan area, the customers of retail establishments may be assumed to mostly come from the same metropolitan area, unless tourism is an unusually large proportion of the economy, which it is not in the DCHC MPO. Therefore, while other types of businesses may have an unlimited number of customers from anywhere in the world, the amount of retail that a metropolitan area can support is limited by its population. For that reason, Tier 2 retail floor space is assumed to be driven by population (i.e., the retail customer base), rather than the number of retail employees. Since the economic crash is assumed to not significantly affect Tier 2 population, it does not significantly affect Tier 2 retail floor space either, hence mitigating the reduction in overall Tier 2 nonresidential floor space that the economic crash triggers. Meanwhile, because Tier 1 is one small part of a much larger metropolitan area, its retail customers need not come from Tier 1. Therefore, in the D-O LRP SD Model, Tier 1 retail floor space is driven by employment levels in the same fashion as all other types of nonresidential floor space. That means that as the economic crash depresses Tier 1 retail employment, it also reduces the amount of Tier 1 retail land and floor space, hence pushing down Tier 1 GRP even more, in a vicious cycle that is mirrored in the cases of office, service, and industrial employment and floor space. It is because this vicious cycle only applies to three of the four major nonresidential employment/land use types that Tier 2 GRP is able to eventually assume an upward trend in the years after the economic crash, rather than continuing to decline over time, as Tier 1 GRP does. Unfortunately, because population is used as a proxy for the amount of demand for retail establishments in Tier 2, the model does not account for the possibility of the amount of retail demand per capita going down, as it would be expected to do during an economic depression. Therefore, the D-O LRP SD Model’s Tier 2 GRP results after the economic crash may be too high, even though it is also unrealistic for economic activity to decline indefinitely in the decades after a crash, as in the case of Tier 1.

Unsurprisingly, the economic crash increases the unemployment rate. However, the unemployment rate increases far more at the Tier 2 level than at the Tier 1 level (Figure 6-53). In Tier 1, prior to the economic crash, a large percentage of jobs were held by people commuting from outside of Tier 1. The model assumes, unrealistically, that the total number of jobs held by residents of Tier 1 can never decrease, making the Tier 1 unemployment rate much less than the Tier 2 unemployment rate in the event of an economic crash, reflecting the fact that the model was constructed with an aim of modeling periods of economic growth, rather than periods of economic contraction. In addition, because Tier 1 net migration declines in response to unemployment (unlike Tier 2 net migration), there come to be fewer Tier 1 residents competing for the same number of jobs. However, mirroring the GRP trends discussed above, Tier 2 unemployment eventually plateaus, whereas Tier 1 unemployment does not, since GRP drives the number of jobs in each Tier. Therefore, conceivably, if the model were extended far enough into the future, Tier 1 unemployment could eventually overtake Tier 2 unemployment, unless it eventually also plateaued.

GRP is a driver of VMT, given that economic activity provides a reason for travel and higher incomes make automobile travel more affordable. Therefore, in keeping with expectations, the economic crash causes VMT to be less than BAU in both Tiers, even though the sensitivity is small (Figure 6-53). Because the economic crash also causes Tier 1 population to decline relative to BAU, there is a greater proportional difference in Tier 1 VMT than in Tier 2 VMT.

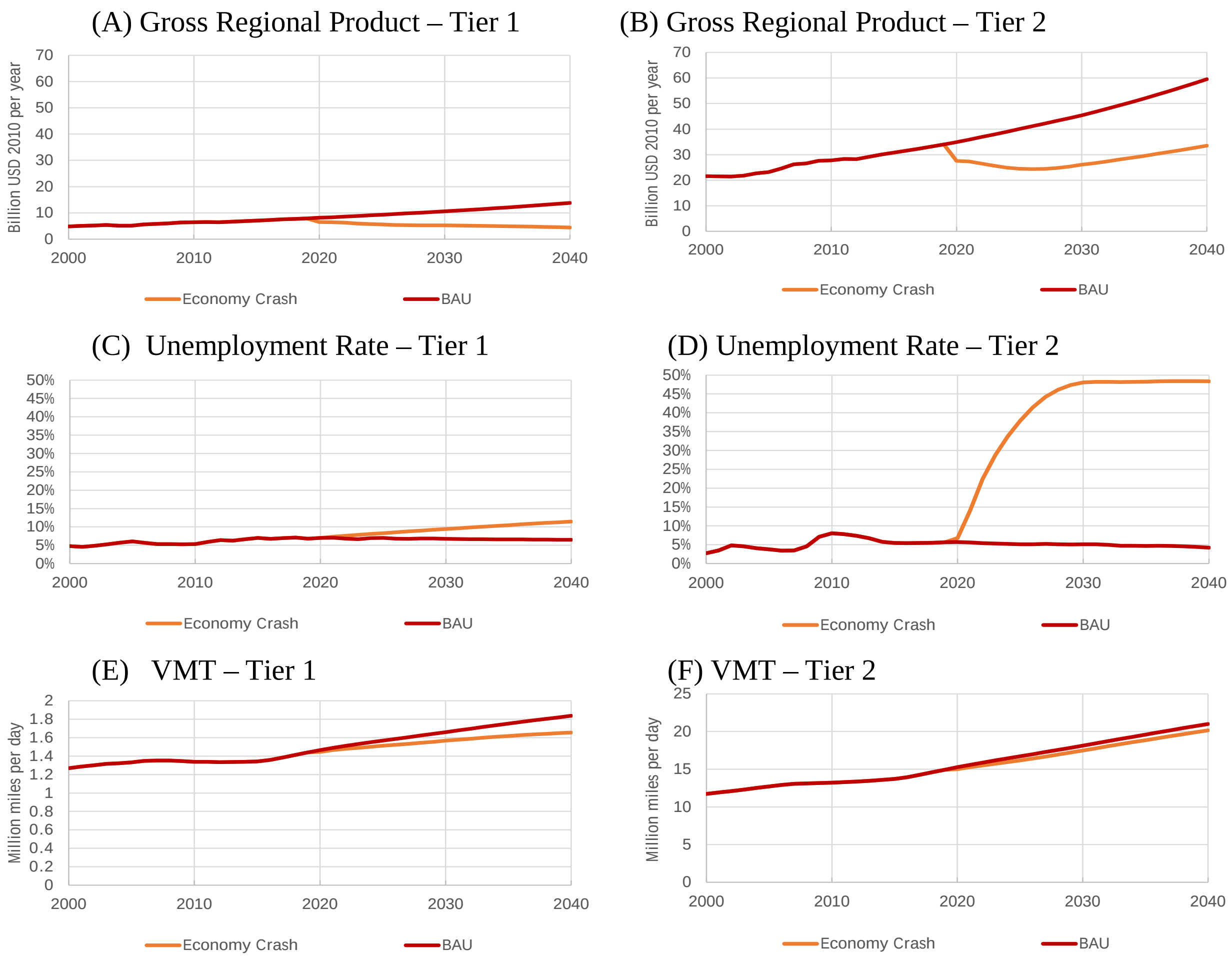


Figure 6-53. Extreme Value Test of an Economic Crash Wherein GRP Declines 20% in 2020 vs. BAU

Extreme Gas Price Spike Test

In this test, we adjusted the price of gasoline, which is exogenous in the model, to rise to $1,000 per gallon during the period 2016-2018, before dropping back down to its BAU value in 2019. Not surprisingly, this produces a large dip in VMT. After gasoline prices return to normal, VMT goes back up, but never rebounds all the way to BAU, since the shock of the fuel price spike causes a permanent contraction of the economy. This economic contraction is worse in Tier 1 than in Tier 2 for the same reasons cited in the Economic Crash Test section: retail space is sensitive to declines in employment in Tier 1 but not in Tier 2. Of greater note, however, is that the exorbitant spike in gasoline prices fails to make VMT drop to zero (or practically zero), as would normally be expected. This is because the D-O LRP SD Model assumes that the effect of fuel price changes on travel behavior is phased in over a period of five years. Since the spike in gas prices lasts less than five years, by the time VMT has fully reacted to the first year of unaffordable fuel, the return to BAU gas prices in 2019 has already started mitigating the effect of the price spike on VMT. The five-year reaction time of travel behavior to gasoline prices assumes that the elasticity value is a “long-term” elasticity (Litman 2013). If gas prices change gradually enough (relatively speaking) that people do not necessarily change their driving habits immediately (such as in the gasoline-price lookup table that is assumed for the BAU, Light Rail, and Light Rail + Redevelopment scenarios), the outputs of the D-O LRP SD Model are likely to be more realistic.

In both Tiers, the D-O LRP SD Model produces an output called the affordability index, defined as relative resident per capita net retail earnings over relative transportation and renter costs per year per household. Not surprisingly, during the period of the gas price spike, the affordability index is far lower than at any other time, since the cost of the transportation component of household spending is far greater than at any other time. However, after gasoline prices return to normal, the affordability index does not match BAU. During 2019-2040, the Tier 2 affordability index is less than BAU, and the Tier 1 affordability index is greater than BAU. In Tier 2, because the gas price spike makes the economy permanently contract without population being significantly changed, earnings per capita are far below BAU, hence reducing the numerator of the affordability index. However, it is assumed in Tier 1 that the economic contraction will first cause commuters into Tier 1 to lose their jobs, as opposed to people who both live and work in Tier 1. It is also assumed that economic downturns have more of a dampening effect on Tier 1 population than on Tier 2 population. For both of these reasons, Tier 1 earnings per capita are reduced far less relative to BAU than are Tier 2 earnings per capita, which means that the numerator of the Tier 1 affordability index is much larger than the numerator of the Tier 2 affordability index. At the same time, the denominator of the Tier 1 affordability index (relative transportation and renter costs per household) declines more relative to BAU than does that of the Tier 2 affordability index, resulting in the Tier 1 affordability index being greater than BAU during 2019-2040. This is because renter costs are driven by GRP, and the economic contraction resulting from the gas price spike is worse in Tier 1 than in Tier 2. Because the model unrealistically assumes that an economic contraction like the one in this test case cannot cause the total number of jobs held by Tier 1 residents to decline (at most, it can be made to plateau) even as overall jobs in Tier 1 decline, this test case results in a higher percent of Tier 1 jobs being held by Tier 1 residents (relative to BAU), which also increases the percent of VMT in and out of Tier 1 that is by Tier 1 residents. Therefore, even though overall Tier 1 VMT remains less than BAU for the entire period after the gas price spike and Tier 1 resident unemployment consistently grows relative to BAU for the remainder of the model run, VMT by Tier 1 residents is greater than BAU from 2024 to 2040, meaning that Tier 1 residents surprisingly end up spending more on gasoline per household than BAU, five years after fuel prices return to normal.

The inconsistent impacts of a gas price spike on overall Tier 1 VMT and VMT by Tier 1 residents described above suggest either that too weak of an elasticity is assumed for the effect of GRP on overall VMT in and out of Tier 1 (by residents and nonresidents) or that too large a percent of workers and potential workers residing in Tier 1 are assumed to also work in Tier 1. This latter possibility is especially likely when, as in this test case, the ratio of jobs in Tier 1 to the size of the Tier 1 resident labor force is particularly low (due to the economic contraction and the moderate effect it has on population, even in Tier 1). In that event, there are lower odds of any given Tier 1 resident being qualified to fill one of the subset of Tier 1 jobs that are not already held by someone else, hence making them more likely to either seek employment outside of Tier 1 or remain unemployed.

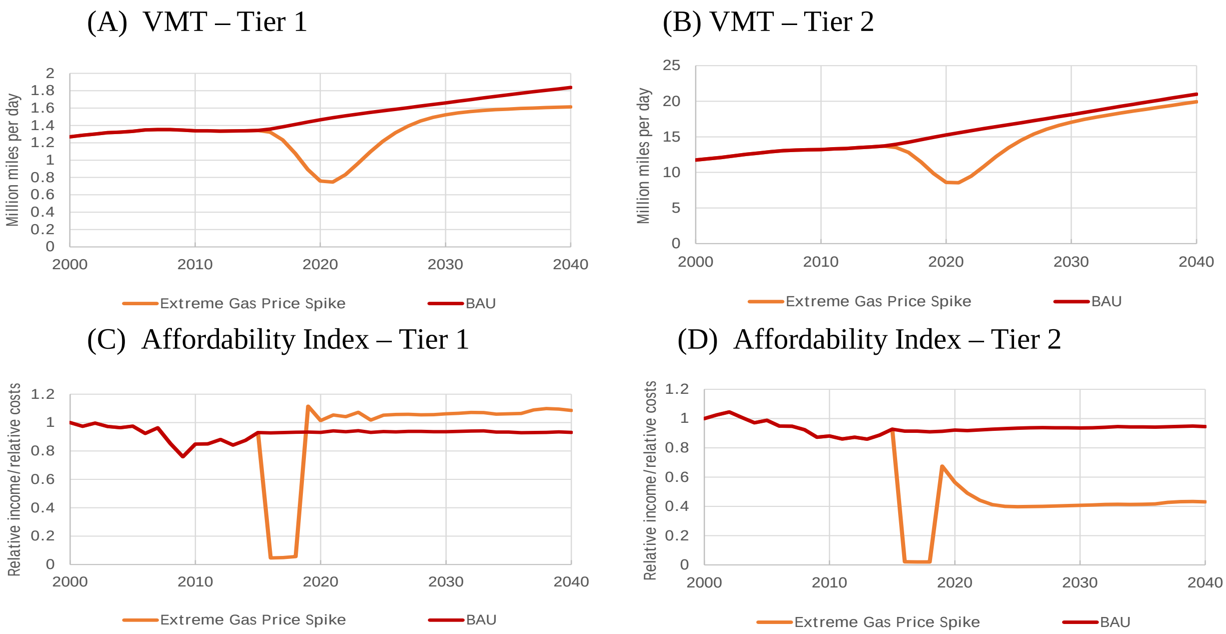


Figure 6-54. Extreme Value Test of Gas Price Spike to $1,000 Per Gallon During 2016-2018 vs. BAU

Unit Consistency

Unit consistency was checked and ensured both during model development and after the completion of the D-O LRP model. (See Table 6-18 for a list of selected indicators and their unit of measure.) Further, Vensim has a specific feature, called “units check,” that allows users to quickly identify errors or inconsistencies in the units used in the model. Still, for models of this type and size, it is very likely that Vensim will identify unit “errors” even when the units are correct. Below are examples for why this may happen, but it should be also noted that unit errors do not impact the simulations and the quality of the results generated.

- Vensim requires that every argument of an equation be represented by a variable with a unit of measure. As an example, if we use an equation such as "A = B+10," Vensim will give us a unit error because a unit for "10" is not provided. To avoid unit errors we would need to have the following equation: "A = B+C", with C=10 and the same unit specified for each of the three variables (given that we are adding B and C). This can happen when a system dynamics model uses equations based on literature without specifying a unit for each number in the equations.

- Vensim will also return a warning if a lookup table is used with an input containing units such as Time. Such warnings do not affect model behavior and are more a convention of Vensim software. To fix this, the input would need to be replaced with a unitless version of that variable (such as time divided by 1 year, so that it is unitless).

Table 6-18. Selected Quantitative Indicators and Unit of Measure

SECTOR	INDICATOR (VARIABLE NAME IN QUOTES, IF DIFFERENT)	UNIT
Land use	Population	person
Land use	Nonresidential sq ft (“Total nonresidential sq ft”)	sq ft
Land use	Developed land	acre
Economy	Total retail consumption	USD 2010/year
Economy	Employment (“Total employment”)	person
Economy	Gross regional product - GRP	USD 2010/year
Transportation	VMT	mile/day
Equity/Transportation	Zero car households	dwelling unit
Energy	Total energy spending	USD 2010/year
Energy	Cumulative CO_2 emissions (“CO_2 emissions cumulative”)	ton
Energy/Economy	CO_2 emissions per GRP	ton/USD 2010
Land use/Water	Impervious surfaces (“Total impervious surface”)	acre

Model Behavior and Sensitivity Tests

The direct structure tests discussed above are designed to evaluate the validity of the model structure. Once these tests have established an adequate level of confidence in the validity of the D-O LRP model’s structure, we apply model behavior and sensitivity tests. These examine the extent to which model behavior changes when certain parameters are adjusted, to determine which parameters influence model behavior most and least. It is crucial to note that the emphasis is on pattern prediction (periods, frequencies, trends, phase lags, amplitudes, etc.) rather than point (event) prediction. These analyses can be carried out by modifying one or more model inputs, to test the impacts of changing assumptions for several variables simultaneously. Three different types of model behavior and sensitivity analyses have been carried out to test the D-O LRP model: numerical, behavior mode, and policy sensitivity. We present sixteen tests, categorized by type, below.[52]

[52] In addition to the tests described in this report, model users can conduct additional sensitivity analyses within the Vensim software itself. For users of Vensim DSS (but not PLE), several tools are provided to evaluate behavioral validity against historical data, such as minimum, maximum, mean, median, standard deviation. This information is available in the “Statistics” tool of Vensim, and this type of result can be estimated for every variable and simulation in the model.

In conducting behavior and sensitivity tests, we have applied the same criteria as we described in the model parameterization (calibration) section above. In fact, several projections have been presented and evaluated in this document already. These include, among others:

- A modification of the structure governing land development, analyzing the impact on the distribution of land use by type, economic performance, and property values (see Figure 6-31, Figure 6-32, and Table 6-9).

- Changes in assumptions concerning the drivers of nonmotorized travel facilities, analyzing the impact on mode choice and person miles (see Figure 6-36 and Table 6-13).

- An overview of the impact of removing the link between GOS and energy spending, analyzing the impact on GRP (see Figure 6-39).

Several indicators in the model were not tested against historical data due to limitations in data availability. If additional data were to become available – either historical data or projections from other models – we could conduct additional behavior pattern tests to validate and further calibrate the model's structure. The following list provides a sample of the type of data that would allow for such tests:

Data "Wish List"

- Developed land use by type covering additional historical years;

- Single family and multifamily household sizes covering additional historical time periods;

- Property values by land use from Orange and Chatham counties covering prior years;

- Historical VMT and traffic congestion data from before 2010;

- Tier 1 data/projections for person miles of travel by mode, comparable to those provided for the DCHC MPO in the Metropolitan Transportation Plan;

- Local stormwater N and P load data as a historical time series;

- Local impervious surface data as a historical time series; and

- Local data on average passenger vehicle MPG (since MPG in the model had to be calibrated lower than the national average MPG).

Numerical Sensitivity

Numerical sensitivity exists when a change in assumptions affects the numerical values of the results. All models exhibit numerical sensitivity. We present nine numerical tests below, covering inputs in the Land Use, Transportation, Energy, Economy, Water, and Health sectors.

Sensitivity to Nonresidential Impervious Surface Coefficients

This test runs on top of the BAU scenario and tests the sensitivity of impervious surface and water quality indicators to the impervious surface coefficients (ISCs). The model applies coefficients for each of the six land use types, as well as for agricultural land, vacant and park land, and four classifications of roadways (highway, urban nonhighway, rural nonhighway, and nonmotorized travel facilities).

The Residential ISC table from the Jordan Falls stormwater load accounting tool manual fit the data on impervious surfaces better than the California residential ISC table, despite being less detailed (it was decidedly lower at each density). However no local ISCs were available for the commercial uses, so we used the values from the California source, which had to be calibrated to match the data. They were reduced from the mean values cited in the report by 15% across the board in Tier 2, though they remained the same in Tier 1. Because there was no precedent for the values chosen and historical data were very limited for purposes of verification, we ran this test to see the sensitivity of other model variables to the change.

This test sets all nonresidential ISCs to their mean values in the California report in Tier 2 to explore the effects of undoing the calibration step described above. This causes an overall increase in estimated total impervious surface and percent impervious surface, on average 4.8% higher than the BAU over the model duration (Figure 6-55). This difference is entirely due to a 17.5% higher nonresidential impervious surface projection on average over the model time frame.

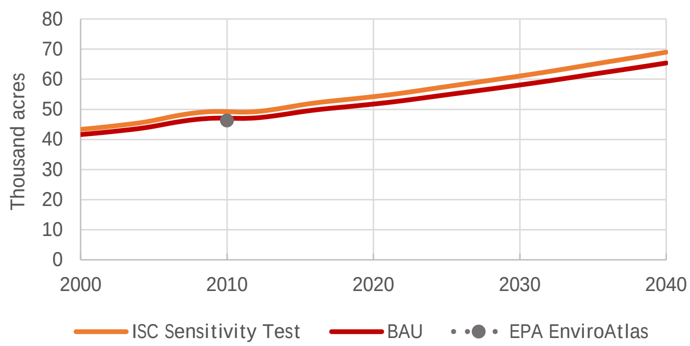


Figure 6-55. Total Impervious Surface – Tier 2: Sensitivity to Nonresidential Impervious Surface Coefficients

The test change in impervious surfaces leads to a smaller than proportional average % change in N load due to nonresidential uses, 5.4% average deviation from BAU, indicating that it is not very sensitive to the impervious surface coefficients. The volume of runoff due to nonresidential uses changes approximately proportionally, with an average deviation from BAU of 16%, compared to the 17.5% deviation of nonresidential impervious surface.

Table 6-19. Average Yearly Percent Departure from BAU, 2000-2040: Sensitivity to Nonresidential Impervious Surface Coefficients

Variable	ISC Test v BAU
Tier 2	
Total impervious surface	4.8%
Total nonresidential impervious surface	17.5%
Percent impervious surface	4.8%
N load nonresidential	5.4%
Volume of runoff nonresidential	16%

Weighting the Effects of Tier 1 and Tier 2 Congestion, Fuel Cost, and Parking Cost on Tier 1 Travel Behavior

When people decide what mode of transportation to use on the basis of traffic congestion levels (which can affect mode choices in the model either directly, through the effect of congestion on travel speed, or indirectly, by affecting vehicle fuel efficiency and overall fuel costs per VMT), conditions at any point along their entire travel route may influence their decision. Meanwhile, even though the cost of parking at someone's destination has more of an effect on their travel decisions than the cost of parking at their origin point, the D-O LRP SD Model does not distinguish between the beginnings and ends of trips, so both trip ends are assumed to be equally likely to be the destination for purposes of calculating parking costs. Because Tier 2 encompasses an entire metropolitan area, it may be reasonably assumed that most of the trips that either start or end in Tier 2 have their entire route and both of their ends within Tier 2. However, since Tier 1 is much smaller than Tier 2, it is probable that a large percentage of trips that either begin or end in Tier 1 have their other end somewhere else in Tier 2. Therefore, the D-O LRP SD Model assumes that traffic congestion, fuel costs per VMT, and parking costs in all of Tier 2 have an influence on Tier 1 modal person miles, vehicle stock, and trip distances. The model also assumes that Tier 1 travel behavior is affected more by traffic congestion, fuel costs per VMT, and parking costs in Tier 1 than by the same factors in the rest of Tier 2. To incorporate these assumptions into the model, we developed two sets of factors to represent the effects on any given variable of vehicle speed, fuel cost per VMT, and the parking cost of an average trip: one for Tier 2 and one for Tier 1 as it would be if Tier 1 travel behavior were solely a function of Tier 1 inputs. Then, we created a 50-50 weighted average factor from these two separate factors, which we applied to Tier 1 baseline values. This sensitivity test examines two cases: (1) Tier 1 travel behavior being solely a function of Tier 1 conditions (Tier 1 Weighting Factor All Tier 1 test case, with the weighting-factor parameter set to one), and (2) Tier 1 travel behavior being solely a function of conditions in all of Tier 2 (Tier 1 Weighting Factor All Tier 2 test case, with the weighting-factor parameter set to zero).

As shown in Figure 6-56 and Table 6-20, there is very little apparent sensitivity of any variable to the Tier-1-to-Tier-2 weighting factors just described. In part, this is a result of Tier 1 and Tier 2 vehicle speeds and fuel costs per VMT differing from their year-2000 values by proportions that are not far removed from one another, thanks to their comparable inputs. Meanwhile, Tier 1 and Tier 2 parking costs per trip differ from their year-2000 values by significantly different proportions over the course of 2000-2040, but modal person miles of travel have very small elasticities to the cost of parking, another cause of low sensitivity. Figure 6-56 and Table 6-20 also show that a 100% decrease in the weighting factors and a 100% increase in the weighting factors produce proportional deviations from BAU that are very near to mirror images of one another. This is an expected result, given that most variables are calculated with either the same or very similar equations in both Tiers.

Because the primary effect of high traffic congestion, low vehicle speeds, high fuel costs per VMT, and high parking costs per trip on travel behavior is to discourage automobile driver travel and encourage travel by other modes, the usual expectation is that a change in the model that increases or decreases automobile driver person miles will have an opposite-direction effect on the other modes. However, as shown in Table 6-20, the average yearly deviations of Tier 1 public transit and nonmotorized person miles from BAU in the Tier 1 Weighting Factor All Tier 1 and Tier 1 Weighting Factor All Tier 2 cases are in the same direction as the average yearly deviations of Tier 1 automobile driver person miles from BAU in those same two cases, respectively. The reason for this result may be seen in Figure 6-56. In each of these two test cases, automobile driver, public transit, and nonmotorized person miles first become either more or less than BAU, then follow a trend in the opposite direction. In keeping with expectations, the initial deviation from BAU for public transit and nonmotorized person miles is in the opposite direction from the deviation for automobile driver person miles. However, because traffic congestion and vehicle speeds have a larger and more direct impact on automobile driver person miles than on person miles by other modes, the changes in automobile person miles relative to BAU in the early years of the period 2000-2040 take longer to be entirely reversed than do the smaller early-year changes in public transit and nonmotorized person miles relative to BAU. Because the deviation from BAU for public transit and nonmotorized person miles switches polarity in an earlier year, their values after that point in time have a greater influence on their average yearly percent departure from BAU during 2000-2040 than do their values prior to that point in time. Meanwhile, the opposite is true for automobile driver person miles, which explains the fact that the average yearly percent departures from BAU are in the same direction for automobile driver, public transit, and nonmotorized person miles in Table 6-20.

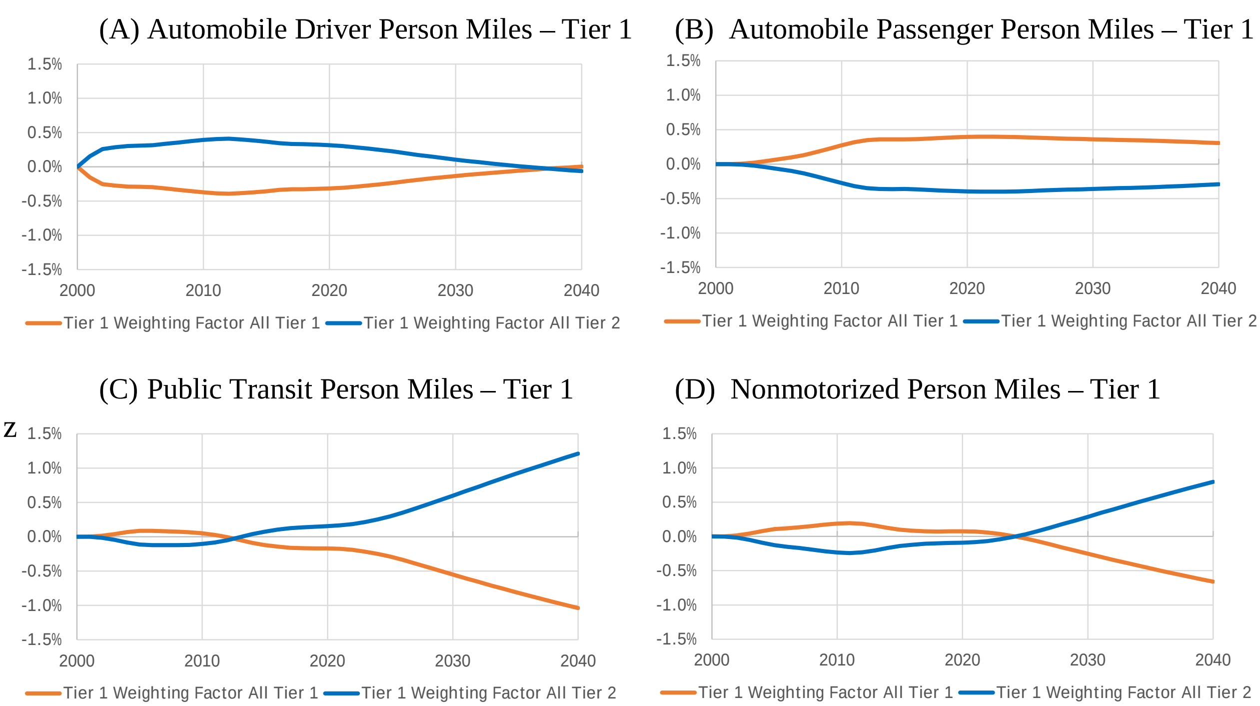


Figure 6-56. Tier 1 Person Miles Per Day by Mode: Percent Difference from BAU

Table 6-20. Average Yearly Percent Departure from BAU, 2000-2040: Sensitivity to Tier-1-to-Tier-2 Weighting Factors

VARIABLE	TIER 1 WEIGHTING FACTOR ALL TIER 1 V. BAU		TIER 1 WEIGHTING FACTOR ALL TIER 2 V. BAU	
	ABSOLUTE PERCENT DEPARTURE	PERCENT ABOVE OR BELOW	ABSOLUTE PERCENT DEPARTURE	PERCENT ABOVE OR BELOW
Tier 1				
Tier 1 to Tier 2 weighting factors	100%	+100%	100%	-100%
Vehicle speed	0.1%	0.0%	0.1%	0.0%
Fuel cost per VMT	0.0%	0.0%	0.0%	0.0%
Parking cost of average trip	0.0%	0.0%	0.0%	0.0%
Automobile driver person miles	0.2%	-0.2%	0.2%	+0.2%
Automobile passenger person miles	0.3%	+0.3%	0.3%	-0.3%
Public transit person miles	0.3%	-0.3%	0.4%	+0.3%
Nonmotorized person miles	0.2%	-0.1%	0.2%	+0.1%
Total person miles	0.1%	-0.1%	0.1%	0.0%
VMT	0.2%	+0.1%	0.2%	-0.1%
Congestion	0.2%	+0.1%	0.2%	-0.1%
Vehicle stock	0.0%	0.0%	0.0%	0.0%
Vehicle trip distance	0.6%	+0.5%	0.6%	-0.6%
GRP	0.0%	0.0%	0.1%	-0.1%
Population	0.0%	0.0%	0.0%	0.0%

Note: All Tier 2 differences from the BAU scenario in these test cases had magnitudes of less than 0.1%, both in terms of average percent above or below BAU and in terms of average absolute percent departure. Therefore, Tier 2 outputs are not shown in this table.

CO_2 Emissions Sensitivity to Increases in Energy Efficiency

The Annual Energy Outlook 2015 projects decreases in building energy intensity and increases in passenger vehicle MPG between 2015 and 2040 (US EIA 2015a). The D-O LRP model incorporates these projections, but it is useful to determine what effect they have on the BAU scenario. A test case with no building energy efficiency improvement after 2015 (yellow line, Figure 6-57) results in a 36% increase in CO_2 emissions between 2005 and 2030, compared to 28% increase over the same time in the BAU scenario (red line). The 2005-2030 timeframe is significant because the Durham County GHG Plan projects a 48% increase in CO_2 emissions during this time, in the absence of energy efficiency improvement (ICLEI 2007). In the D-O LRP model, a test case with neither building nor vehicle efficiency improvement after 2015 (orange line) closely matches the Durham County GHG Plan projections, with a 47% increase in emissions between 2005 and 2030. This consistency is expected, given that the D-O LRP model uses population and VMT projections similar to the Durham County GHG Plan to calculate energy and emissions.

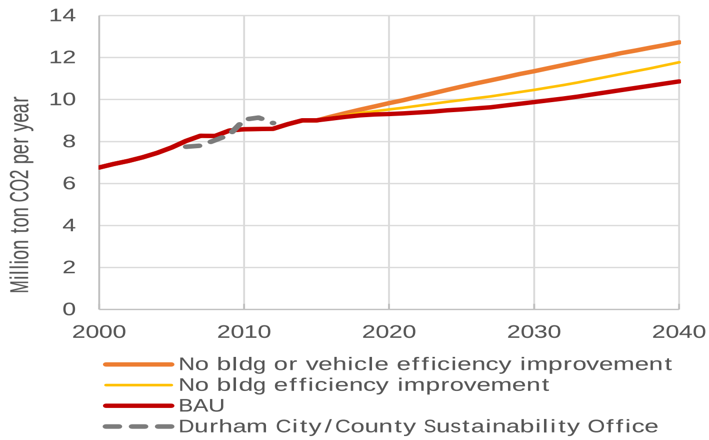


Figure 6-57. Sensitivity Analysis for Energy Efficiency: Effect on CO_2 Emissions in the BAU Scenario – Tier 2.

Elasticity of Consumption to GRP

Elasticity of consumption to GRP is an exogenous input that is used in the model to regulate the strength of the relationship between changes in GRP and retail consumption. The value chosen for both Tier 1 and Tier 2 for this elasticity was 1.1 based on the calibration of retail consumption to historical data. This sensitivity test shows the behavior of retail consumption and other economic variables when the elasticity of consumption to GRP is modified. Five different test cases were simulated, with the elasticity ranging from 1 to 1.2. Figure 6-58 below shows the variance in total retail consumption in Tier 2 as a result of the different elasticities.

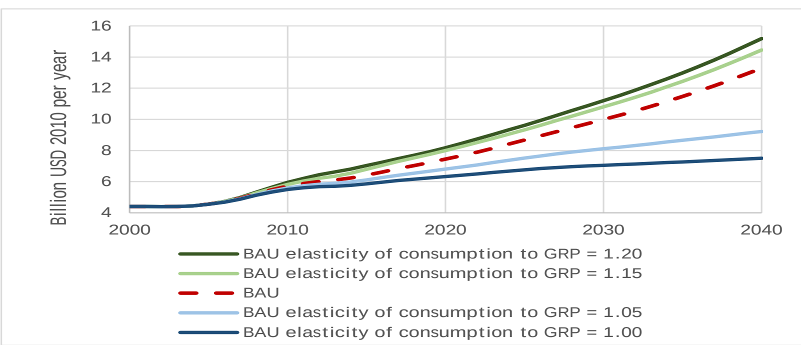


Figure 6-58. Sensitivity Analysis for Elasticity of Consumption to GRP: Effect on Total Retail Consumption – Tier 2

Changing the elasticity of consumption to GRP has a more pronounced effect on total retail consumption when the elasticity is reduced (rather than when it is increased), due to the balancing feedback that occurs in the economy sector with employment, which is calculated in the model by multiplying total retail consumption by the exogenous input “employment per dollar of consumption” (explained below). The model projects employment per dollar of consumption to decrease over time (indicating an increase in labor productivity), so because reducing the elasticity of consumption to GRP decreases retail consumption, employment, earnings, and GRP are reduced further, thus the more pronounced decline in total retail consumption and other economic variables, shown in Table 6-21.

Table 6-21. Average Yearly Percent Departure From BAU, 2000-2040

TIER 2 VARIABLE	ELASTICITY = 1.0	ELASTICITY = 1.05	ELASTICITY = 1.15	ELASTICITY = 1.2
Elasticity of Consumption to GRP	-9.1%	-4.6%	+4.6%	+9.1%
Total Retail Consumption	-17%	-11%	+5.5%	+8.4%
Total Employment	-17%	-11%	+3.1%	+3.4%
GRP	-16%	-10%	+2.9%	+3.2%

<u>Employment Per Dollar of Consumption</u>

Employment per dollar of consumption is an exogenous input to the model that drives desired employment, a variable that represents the demand for employment that could be filled if the supply of labor force workers meets the demand. Employment per dollar of consumption was calculated For Tier 2 and Tier 1 based on historical employment and retail consumption data (2000-2010) and projections (2011-2040). Since total employment projections from the TRMv5 SE data grow at a slower rate than retail consumption projections (Woods & Poole Economics, Inc.), the value for employment per dollar of consumption decreases each year between 2010 and 2040 (indicating an increase in labor productivity, as mentioned above). This simulation tests the sensitivity of the model to an alternative BAU test case where employment per dollar of consumption is held constant at its 2010 calculated value for both Tier 2 and Tier 1.

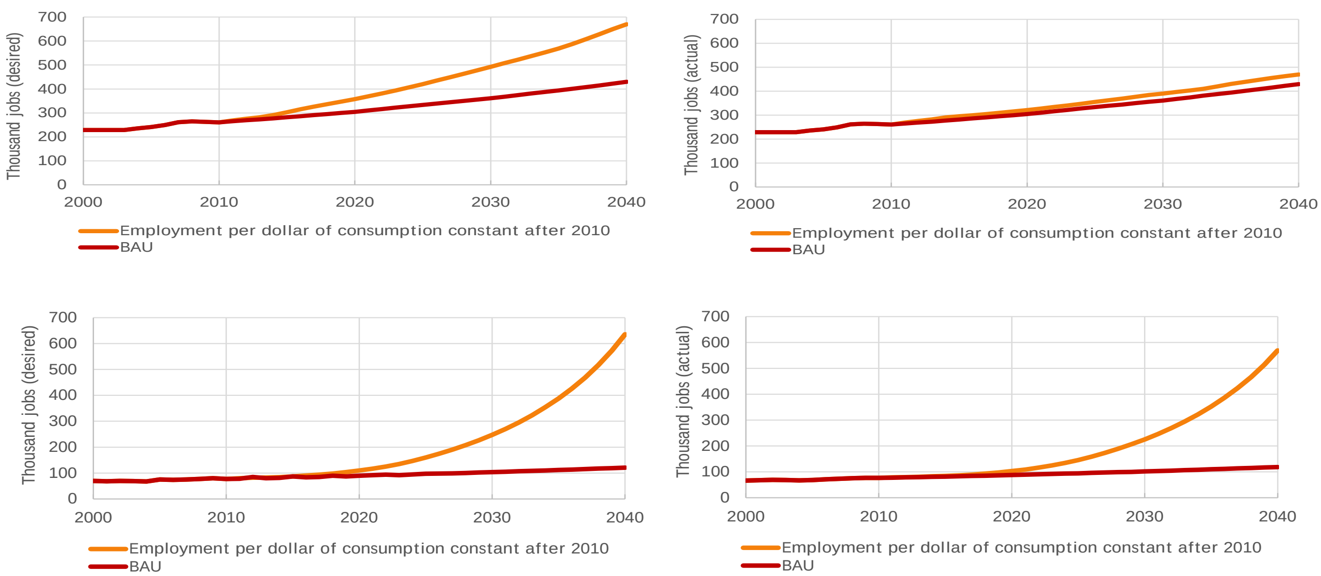


Figure 6-59. Sensitivity Analysis for Employment Per Dollar of Consumption: Effect On Desired Employment (A) and Total Employment (B) for Tier 2 (C) and Tier 1 (D)

Several interesting results emerge from this sensitivity test. First, although **desired** employment in Tier 2 increases to about 670,000 jobs in 2040 (Figure 6-59, top left), **total** employment in Tier 2 only increases to 470,000 jobs in 2040 (Figure 6-59, top right). This is because total employment is limited by total labor force and, unlike in the Tier 1 economy model, there is no link in Tier 2 that increases net migration to Tier 2 when there is a (positive) gap between desired employment and total labor force. When this feedback loop is implemented in Tier 1, employment grows considerably, reaching possibly unrealistic values. Regarding the internal consistency of the model, given that no explicit links exist between Tier 1 and Tier 2 employment, we note that employment in Tier 1 becomes larger in 2040 (570,000 jobs) than total employment in Tier 2, which encompasses Tier 1. In addition to the link between desired employment and net migration in Tier 1 (mentioned above), this is due in part to the 2010 value for employment per dollar of consumption in Tier 1 being larger than Tier 2, which causes employment to grow exponentially faster in Tier 1 due to the reinforcing feedback loop between employment, GRP, retail consumption, and again employment. In addition, despite the fact that nonresidential sq ft in Tier 1 hits a cap in this case around 2028, employment in Tier 1 continues to grow, exposing the need for a balancing loop that inhibits employment growth in Tier 1 when available nonresidential sq ft runs out. This test highlights that the model is well suited to work with values that are consistent with historical trends, and important deviations in the area of employment creation (both for Tier 1 and Tier 2, but for different reasons) have to be carefully analyzed and interpreted.

Drought Year Test

In another sensitivity test, we simulated a drought year for 2030 to determine the effect on stormwater N load. In this year, annual precipitation drops to 77% of its average value, which is equivalent to the historical drought in 2007. Because stormwater N load is a linear function of stormwater runoff volume, and therefore rainfall, stormwater N load also drops to 77% of its projected value in 2030 (Figure 6-60). In the BAU scenario this is 43,000 lb N/year, which is lower than the 2000 value of 47,000 lb N/year. Therefore the projected increase in Tier 1 N load due to increased development after 2000 is less than the variation due to a major drought.

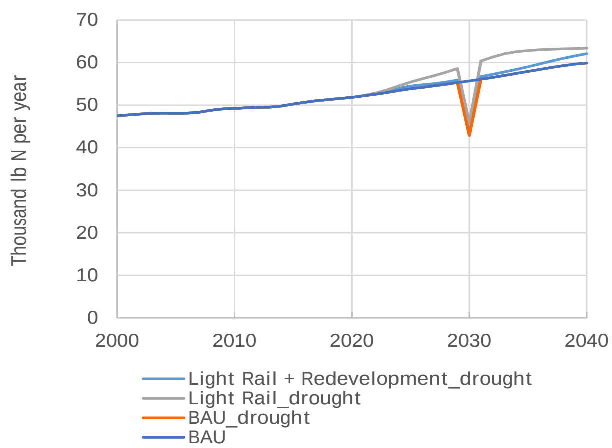


Figure 6-60. Sensitivity Analysis for Average Precipitation with Drought Year: Effect On Tier 1 Stormwater N Load

Sensitivity to Percent Impervious Surface

As another way of gauging the uncertainty in stormwater runoff, we tested how a 10% decrease or increase in impervious surface affects Tier 1 stormwater N load. A 10% decrease in impervious surface causes a 4.6% drop in stormwater N load (Figure 6-61, Table 6-22), while a 10% increase in impervious surface causes a 3.8% increase in stormwater N load. Stormwater N load is the product of stormwater runoff volume and event mean concentration. Stormwater N load changes by less than 10% because it is determined by a runoff coefficient that increases less than in direct proportion with impervious surface. Furthermore, event mean concentrations increase with a decrease in impervious surface (and vice-versa) because impervious surface is assumed to have a lower EMC (1.08 mg N/L) than open space or lawns (2.24 mg N/L).

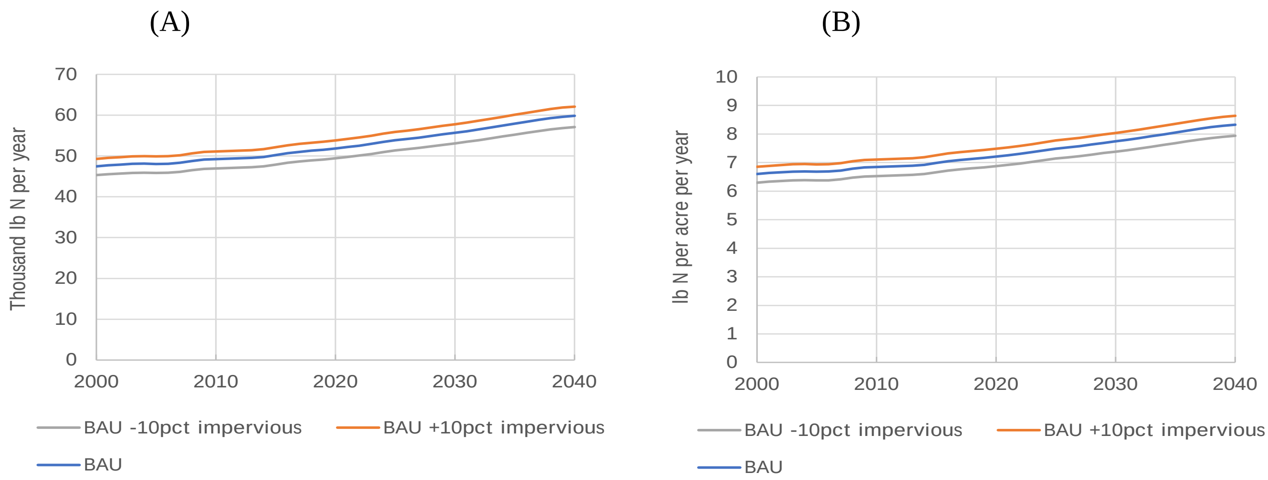


Figure 6-61. Sensitivity Analysis for Impervious Surface - Tier 1: Effect On (A) Stormwater N Load and (B) Stormwater N Load Per Acre

Table 6-22. Sensitivity of Stormwater Runoff to Impervious Surface: Average Yearly Percent Departure from BAU From 2000 to 2040

TIER 1 VARIABLE	DEPARTURE FROM BAU	
Total impervious surface Tier 1	-10%	+10%
Total N load Tier 1	-4.6%	+3.8%
Total N load Tier 1 lb per acre	-4.6%	+3.8%
Total volume of runoff Tier 1	-8.8%	+8.8%
Event mean concentration N nonresidential Tier 1	+7.3%	-7.3%
Event mean concentration N roads Tier 1	+3.8%	-3.8%

Health Benefits of NMT: Sensitivity to Miles of NMT per PTT

To test the sensitivity of modeled health benefits from nonmotorized travel, we doubled the NMT per public transit trip (PTT) from 0.25 to 0.5 miles in the Light Rail + Redevelopment scenario (Light Rail + Redev Double NMT per PTT test case). In the D-O LRP SD Model, each PTT is normally assumed to generate an average of 0.25 miles of NMT. This is meant to account for the average distance walked or biked to a bus stop or light rail station as well as the distance walked or biked to a destination once the passenger disembarks from the bus or light rail train. Both this additional NMT associated with PTTs and the NMT generated from exclusively nonmotorized trips are counted towards the model calculation of health benefits from NMT.

The results of doubling the NMT per PTT in Tier 1 are shown in Figure 6-62, compared to the three main scenarios. Values are in person miles of nonmotorized travel by residents per day (Figure 6-62A) and avoided premature mortalities due to nonmotorized travel (Figure 6-62B). Figure 6-63A and B show the results in Tier 2. Although this test was run for the Light Rail + Redevelopment scenario, the Light Rail and BAU scenarios are also presented to show how the health effects of doubling NMT per PTT compare to the increases in NMT that result from the Light Rail and Redevelopment.

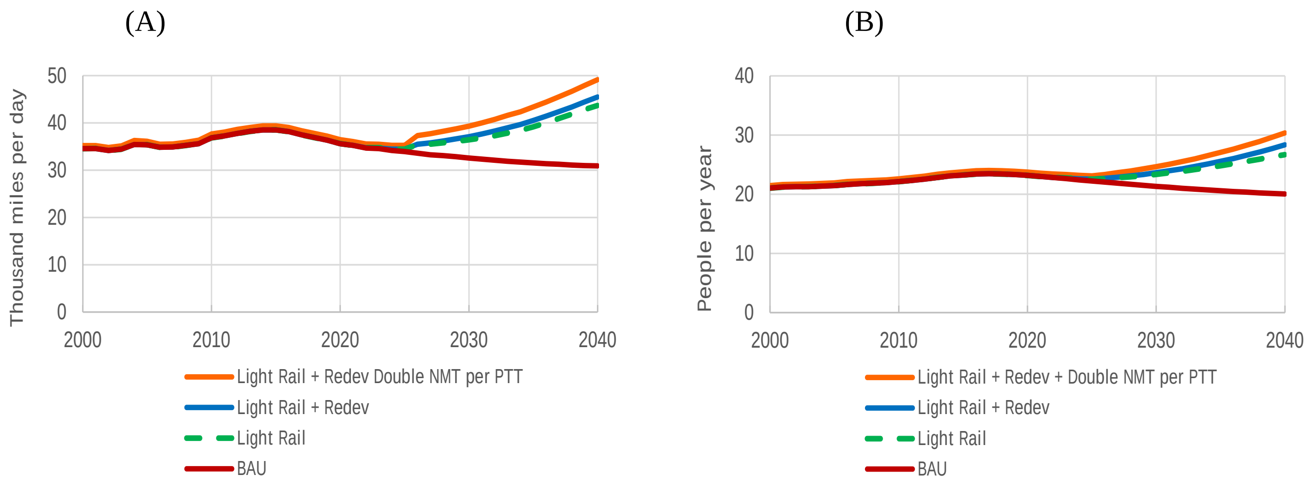


Figure 6-62 Sensitivity Analysis of Doubling the Average Person Miles of NMT Per PTT: Effect On (A) Person Miles of NMT by Residents Per Day and (B) Avoided Premature Mortality Due to NMT – Tier 1

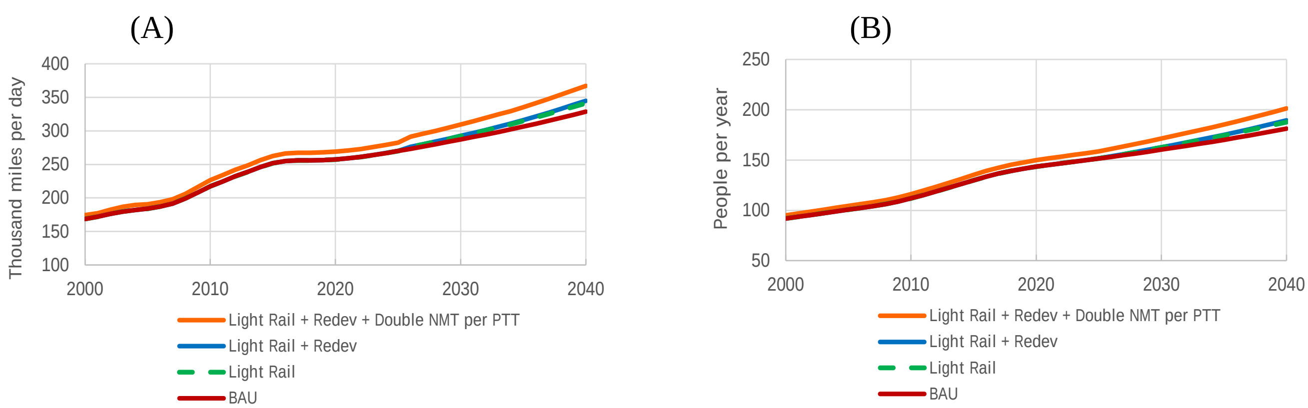


Figure 6-63. Sensitivity Analysis of Doubling the Average Person Miles of NMT Per PTT: Effect on (A) Person Miles of NMT by Residents Per Day and (B) Avoided Premature Mortality Due to NMT – Tier 2

In Tier 2, doubling NMT per PTT increases total person miles of NMT by residents per day by an average of 4.1% before the light rail line opens (2000-2025) and by an average of 6.0% after the line (2026-2040), relative to the Light Rail + Redevelopment scenario. This translates into an average increase in avoided premature mortality due to NMT of 4.0% before the light rail opens (2000-2025) and 5.6% after it opens (2026-2040), relative to the Light Rail + Redevelopment scenario. The reason that the health benefits realized from the increase in NMT are slightly less is due to a model function that delays the realization of the full health benefits of changes in NMT by 5 years. In Tier 1, doubling NMT per PTT increases total person miles of NMT by residents per day by an average of 2.2% before the light rail opens (2000-2025) and by an average of 6.6% after the light rail opens (2026-2040), relative to the Light Rail + Redevelopment scenario. This translates into an average increase in avoided premature mortality due to NMT in Tier 1 of 2.3% before the light rail opens (2000-2025) and 5.2% after it opens (2026-2040), relative to the Light Rail + Redevelopment scenario. Doubling NMT per PTT increases person miles of NMT by residents by roughly the same percent in both Tiers, because the Tiers have comparable ratios of public transit use to NMT. In the Light Rail + Redevelopment scenario, traveling to and from public transit stops represents 4.9% and 3.8% of total nonmotorized person miles in Tier 2 and Tier 1 on average, respectively.

Behavior Mode Sensitivity

Behavior mode sensitivity exists when a change in assumptions changes the patterns of behavior generated by the model. For example, if plausible alternative assumptions changed the behavior of a model from smooth adjustment to oscillation or from s-shaped growth to overshoot and collapse, the model would exhibit behavior mode sensitivity. We present three behavior mode sensitivity tests below, covering inputs into the Transportation, Economy, and Water sectors.

Lengthening Modal Person Mile Reaction Times to Drivers

We used many elasticities from literature to model relationships in the transportation sector, especially in regard to drivers of person miles of travel by mode. However, even though some of the sources of these elasticities indicated whether they were "long-term" or "short-term" elasticities, none of them made a more precise indication of what amount of time it took for a change in a given driver to produce the amount of change in a given output variable that the relevant elasticity indicates. Therefore, we adopted a rule of thumb for transportation-sector elasticities from literature whereby all elasticity-based cause-and-effect relationships are modeled as either occurring over a five-year period ("long-term" elasticities) or over a one-year period ("short-term" elasticities). However, in earlier versions of the model, we assumed that transportation-sector "long-term" elasticities were associated with a fifteen-year reaction time and "short-term" elasticities were associated with a two-year reaction time, as indicated by Sinha and Labi (2007), which we deemed to be unrealistically long reaction times for the particular relationships to which we were applying them. In this sensitivity test (hereafter called the Longer Reaction Times test case), those previous, longer reaction times are reinstated. By running this test case, we demonstrated how choosing shorter reaction times increased the model's sensitivity to shocks and shortened the time needed to recover from those shocks. Because the D-O LRP SD Model cannot run with reaction times of zero and some of the reaction times in the transportation sector are already only one year, we did not run an alternate scenario of setting reaction times to less than BAU. The eight long-term and three short-term elasticities adjusted in this test are listed in Table 6-23.

Table 6-23. Input Variable Changes Made to Test Model Sensitivity to Longer Reaction Times Associated with Elasticities, Measured in Years

VARIABLE	BAU	LONGER REACTION TIMES SCENARIO
through traffic reaction time to automobile speed	5	15
through traffic reaction time to fuel cost	5	15
vehicle trip distance reaction time to vehicle speed	5	15
mode share reaction time to automobile speed	5	15
mode share reaction time to fuel cost	5	15
mode share reaction time to parking cost	5	15
mode share reaction time to population density	5	15
mode share reaction time to intersection density	5	15
nonmotorized travel reaction time to jobs housing balance	1	2
public transit travel reaction time to fare price	1	2
public transit travel reaction time to vehicle revenue miles	1	2

Note: For this sensitivity test, input changes in Tier 1 and Tier 2 are identical

The primary effect of the Longer Reaction Times test case is to make changes in the trends of output variables occur more gradually. In the BAU scenario, during the period of approximately 2008-2015, automobile driver person miles experience a lesser growth rate than during the rest of the model run, while automobile passenger, public transit, and nonmotorized person miles have significant increases in their growth rates during that period (Figure 6-64). This occurs due to a period of mostly high gasoline prices (but still with some ups and downs during that period), with the price of a gallon of gasoline being an exogenous input. Meanwhile, in the Longer Reaction Times case, the effect of gasoline prices on transportation by mode is more muted in the short term but extends for a longer period of time.

In the BAU scenario, all modal person miles are calibrated to the most recent available historical data. Unsurprisingly, reverting to the Longer Reaction Times scenario causes the model to no longer be calibrated to these values, such that adopting those longer reaction times into the base scenario would require altering the inputs for year-2000 person miles by each mode. After such a recalibration, however, the fit of modal person miles to projections derived from the DCHC MPO's Metropolitan Transportation Plan would be slightly improved relative to the BAU scenario. On the other hand, the fit of public transit person miles to historical data from the National Transit Database for the years 2000-2013 would be worsened by reverting to longer reaction times, even after recalibration.

As shown in Table 6-24, the Longer Reaction Times test case only creates moderate average yearly deviations from BAU. The largest average yearly deviation from BAU in absolute terms is 4.2%, for Tier 2 public transit person miles per day. It is not surprising that these deviations from BAU are not large, since the only difference between the scenarios is how much time it takes for the same cause-and-effect relationships to manifest. Because any period of time when a given output variable is more or less than BAU in the Longer Reaction Times scenario is followed by a period when the opposite is true, average yearly deviations from BAU tend towards zero, given enough time.

Even though average deviations of the Longer Reaction Times test case from BAU during 2000-2040 are small, larger deviations still occur in individual years within that span (Figure 6-64 and Table 6-24). In 2015, mostly-high gasoline prices during the previous few years result in automobile driver person miles being significantly lower in the BAU scenario than in the Longer Reaction Times scenario and in person miles by all other modes being significantly greater in the BAU scenario(Table 6-24). Based on the model's exogenous inputs, gasoline prices decline sharply in the year 2015, then resume growing at a more gradual rate until 2040. During this period of increasing gasoline prices, the Longer Reaction Times scenario again lags in responding to this change, so modal-person-mile values in the BAU scenario and the test case eventually reconverge with one another. In the Longer Reaction Times test case, even though gasoline prices drop in 2015, that event is immediately preceded by a period of relatively high gas prices and is followed by a period of gradually rising gas prices. Because of the long time it takes in this case for modal person miles to respond to changes in gas prices, the effects of the 2015 drop in gas prices are felt simultaneously with the effects of the higher gas prices that exist in the years before and after 2015. Therefore, the growth rates of modal person miles during 2015-2020 in the Longer Reaction Times test case are little different from those in the preceding and following years, even though the growth rates of modal person miles in the BAU scenario experience a much more noticeable change during that same period. This is because the growth rates of modal person miles in the BAU scenario at any given point in time are reacting to the gasoline prices that existed during a narrow portion of the recent past, such that the impacts of sudden changes in fuel prices are less diluted by values in neighboring years. As a result of the mechanisms just described, the outputs of scenarios and test cases that assume different reaction times may converge more quickly after a shock to the system than the difference between their assumed reaction times would suggest (as indicated in Table 6-23, the reaction time of modal person miles to fuel prices is five years in the BAU scenario and fifteen years in the Longer Reaction Times scenario). In addition, when the D-O LRP SD Model calls for the reaction of a variable to a driver to not be immediate, we do not phase it in in a linear fashion. Instead, even though the entire indicated reaction time is needed for the effect of a change in a driver to be fully felt, the majority of the impact occurs in the first half of the indicated reaction period.

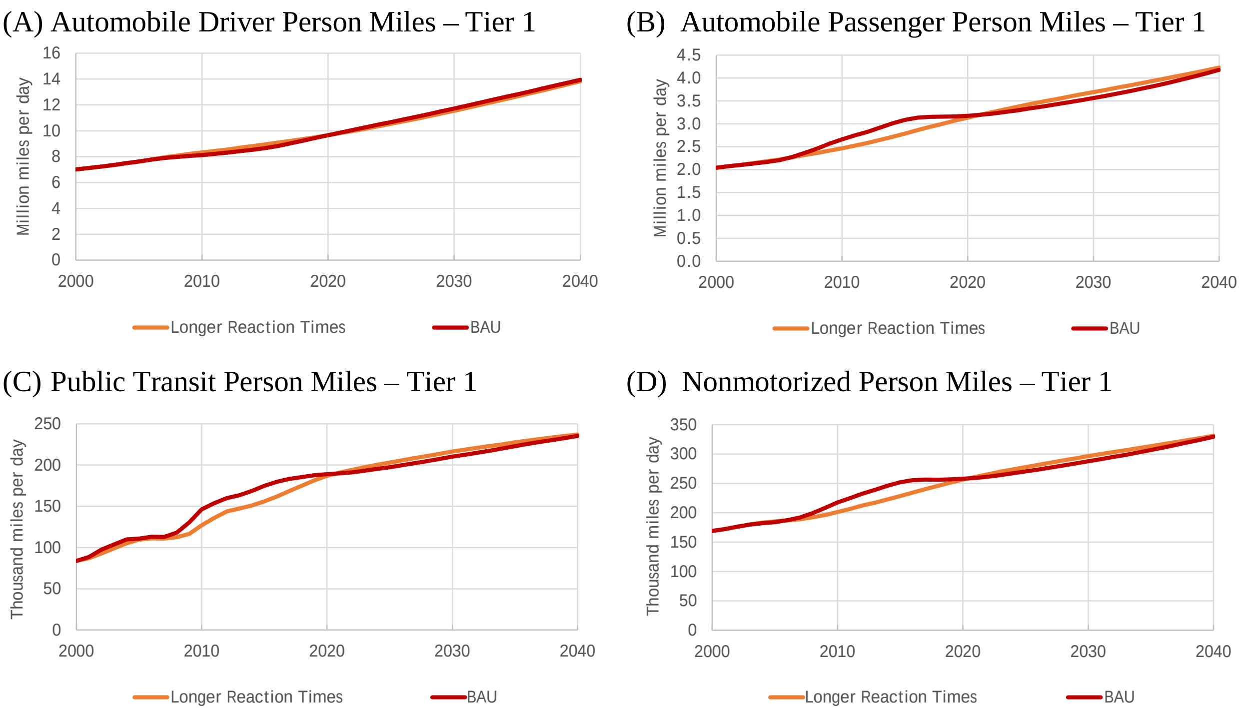


Figure 6-64. Tier 2 Person Miles Per Day by Mode: Longer Reaction Times vs. BAU

Table 6-24. Yearly Percent Departure from BAU: Sensitivity to Longer Reaction Times Associated with Elasticities from Literature in Transportation Sector

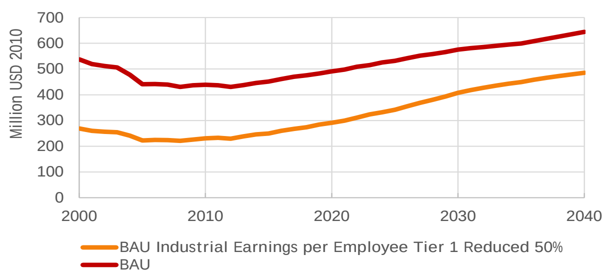
VARIABLE	AVERAGE YEARLY ABSOLUTE PERCENT DEPARTURE	AVERAGE YEARLY PERCENT ABOVE OR BELOW	2015	2020
Tier 1				
Automobile driver person miles	2.4%	-0.1%	+5.5%	-0.1%
Automobile passenger person miles	2.6%	-1.2%	-8.1%	-1.6%
Public transit person miles	3.6%	-2.1%	-9.2%	-1.2%
Nonmotorized person miles	2.7%	-1.0%	-7.9%	-0.5%
Total person miles	0.6%	-0.6%	-0.5%	-0.6%
Through traffic VMT	3.4%	+1.4%	+10.5%	+1.0%
VMT	2.9%	+0.6%	+7.8%	+0.4%
Congestion	2.9%	+0.6%	+7.8%	+0.4%
Vehicle trip distance	0.8%	+0.8%	+1.0%	-0.1%
GRP	1.5%	-1.5%	-1.2%	-1.8%
Population	0.5%	-0.5%	-0.1%	-0.5%
Tier 2				
Automobile driver person miles	1.3%	+0.1%	+3.4%	0.0%
Automobile passenger person miles	3.5%	-0.9%	-9.7%	-1.3%
Public transit person miles	4.2%	-2.1%	-10.8%	-1.1%
Nonmotorized person miles	3.2%	-1.0%	-9.4%	-0.5%
Total person miles	0.2%	-0.2%	-0.4%	-0.3%
Through traffic VMT	3.3%	+1.6%	+10.7%	+1.3%

VARIABLE	AVERAGE YEARLY ABSOLUTE PERCENT DEPARTURE	AVERAGE YEARLY PERCENT ABOVE OR BELOW	2015	2020
VMT	2.0%	+0.7%	+6.1%	+0.5%
Congestion	2.0%	+0.7%	+6.1%	+0.5%
Vehicle trip distance	1.1%	+1.1%	+1.4%	+0.3%
GRP	1.2%	-1.2%	-1.3%	-1.8%
Population	0.1%	-0.1%	0.0%	-0.1%

Earnings per Industrial Employee Tier 1 Reduced by 50%

Earnings per industrial employee Tier 1 is an exogenous input taken from historical data and projections for Durham and Orange County, since no earnings data were available at a smaller geographic scale. But due to the large amount of high wage, white-collar jobs classified as industrial in the outskirts of Durham County, average earnings per industrial employee were very high and likely not representative of the average earnings per industrial employee in Tier 1, where more blue-collar industrial jobs exist. Thus, this scenario tests the sensitivity of the model to reducing earnings per industrial employee Tier 1 by 50%, which reduces the average earnings per industrial employee in Tier 1 in 2010 from $92,000 to $46,000, during the entire model period (2000-2040).

(A)



(B)

Figure 6-65. Sensitivity Analysis for Earnings Per Industrial Employee Tier 1 Reduced by 50% Between 2000 and 2040: Effect on (A) Industrial Earnings Tier 1 and (B) Relative GRP Tier 1

Although total industrial earnings Tier 1, shown in Figure 6-65A, is considerably lower for this sensitivity scenario than the BAU throughout the study period, relative GRP Tier 1, shown in Figure 6-65B, is higher than the BAU. This is due to the formulation used to estimate GRP and its main drivers, where relative GRP (rather than absolute GRP) is used to influence other variables in the model that are impacted by economic performance, including retail consumption, which has a built-in two year delay before relative GRP begins to influence it. As a result, retail consumption, and thus employment, earnings, and GRP are not affected initially by the reduction in industrial earnings per employee, meaning that the GOS also does not change relative to the BAU simulation. Consequently, the economy remains unaffected by the initial change for two years, but because the gap between the initial GRP in 2000 and the GRP in 2001 and 2002 is larger than in the BAU scenario (because of the reduction in industrial earnings), relative GRP is larger in these years, which increases retail consumption, employment, earnings, and again GRP above the BAU values. This leads to a snowball effect on variables throughout the model, with examples shown in Table 6-25, creating an unrealistic situation where a decrease in industrial earnings actually improves overall economic performance.

This sensitivity test revealed a weakness in the model relationships that depend on relative changes in other variables following delays, which is that any scenario that causes initial (2000) model values to be reduced below levels in the BAU scenario will cause the relative values of that variable following the delay to be higher than in the BAU scenario.

Table 6-25. Average Yearly Percent Departure from BAU, 2000-2040

TIER 1 VARIABLE	AVERAGE YEARLY % DEPARTURE FROM BAU
Industrial Earnings Tier 1	-39%
Total Retail Consumption Tier 1	+24%
GRP Tier 1	+17%
Population Tier 1	+9.0%
VMT Tier 1	+5.1%

Stormwater N Load Sensitivity to Rainfall Variability

Although stormwater runoff outcomes presented the Water Sector of Section 5.4 assume constant precipitation at the historical average level, realistic rainfall varies from year to year. This test explores the impacts on stormwater N load from using randomly-generated precipitation that reflects patterns in historical data. Data from 2000-2013 show that the Northern Piedmont region receives 45 inches of precipitation per year with standard deviation of 7.0 inches per year (Figure 6-66A). Projecting this forward using a random factor causes Tier 2 stormwater N load to vary by as much as 600,000 lb N per year from the BAU level, a 41% difference (Figure 6-66B). In comparison, BAU stormwater N load grows by 350,000 lb between 2000 and 2040. Therefore the projected increase in stormwater N load due to regional development is within the range of variability due to realistic precipitation. If local data on stormwater N load were collected for management and policy purposes, it would be difficult to detect trends unless the data were adjusted for rainfall.

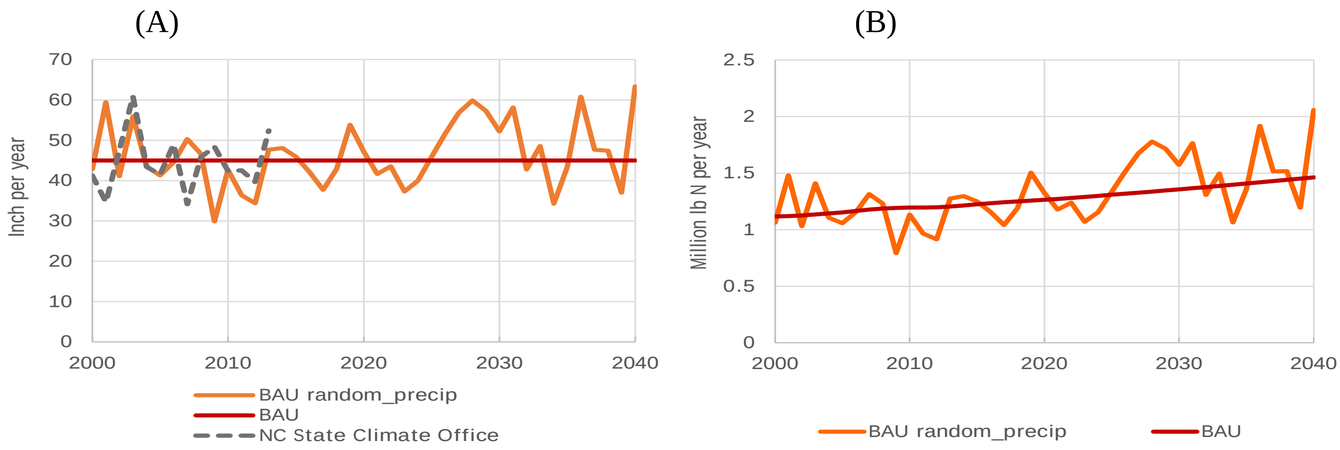


Figure 6-66. Sensitivity Analysis for Average Precipitation with Random Factor: Effect on (A) Projected Precipitation and (B) Tier 2 Stormwater N Load

Note: the effect of the random precipitation factor on stormwater N load looks nearly identical in Tier 2 (b) and Tier 1 (not shown), because rainfall volume, and therefore its variability, scales with area.

Policy Sensitivity

Policy sensitivity exists when a change in assumptions reverses the impacts or desirability of a proposed policy. We present four policy sensitivity tests below, covering inputs in the Land Use, Transportation, and Energy sectors.

Sensitivity to the Effect of the LRT on Nonresidential Square Feet Demand

This scenario is run on top of the Light Rail scenario and aims to test the sensitivity of the model to the effect of the light rail on the demand for nonresidential square feet in Tier 1, since this value is an assumption, and is intended to be modified by users. The default value in the model is 10, indicating that with the introduction of the light rail, demand for nonresidential commercial square footage will increase by 10% over the Light Rail scenario. This change is phased in during the construction of the light rail, allowing demand to begin in anticipation of its completion. Since there are so many confounding variables affecting demand for commercial space in cities, no relevant literature could be found to quantify the impact of light rail lines on the demand for nonresidential square footage in the surrounding areas.

In this test, we report the sensitivity for a minimum value (0) for the percentage increase in demand for nonresidential sq ft, a maximum value (100), and a moderate increase (20); we also display the results of a Monte Carlo simulation. The simulation was set as a random-uniform distribution with minimum of 0 and maximum of 100, run 1,000 times. Immediate effects are seen on total nonresidential square footage in Tier 1, which under the maximum value quickly hits a cap based on the maximum density and land expansion allowable, around 2025 (Figure 6-67). In the Monte Carlo simulation figures, the 50%, 75%, 95%, and 100% color-coded bands refer to the probability of the projection landing within that range, given the minimum and maximum values set, and the assumption that the likelihood of each value for the tested input variable is the same within the specified range.

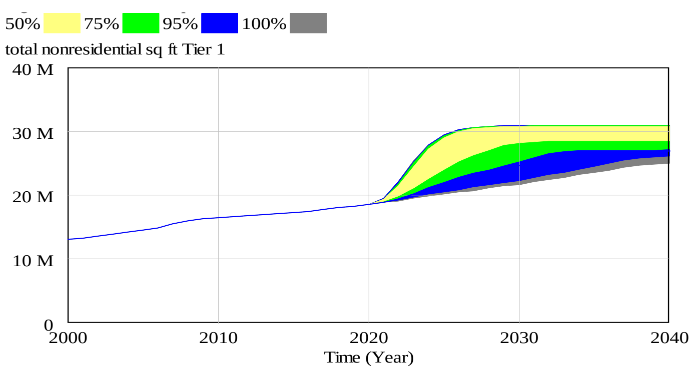


Figure 6-67. Nonresidential Sq. Ft. – Tier 1: Monte Carlo Simulation for Sensitivity to Effect of LRT on Nonresidential Sq. Ft. Demand in Tier 1

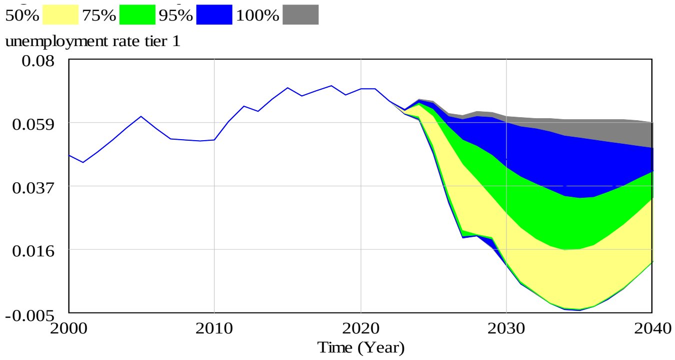


Figure 6-68. Unemployment Rate – Tier 1: Monte Carlo Simulation for Sensitivity to Effect of LRT on Nonresidential Sq. Ft. Demand in Tier 1

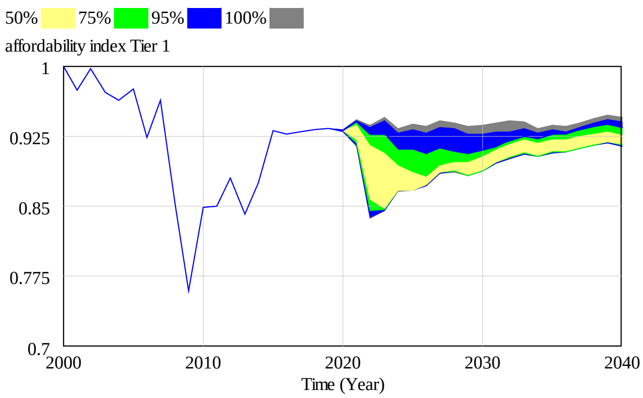


Figure 6-69. Affordability Index– Tier 1: Monte Carlo Simulation for Sensitivity to Effect of LRT on Nonresidential Sq. Ft. Demand in Tier 1

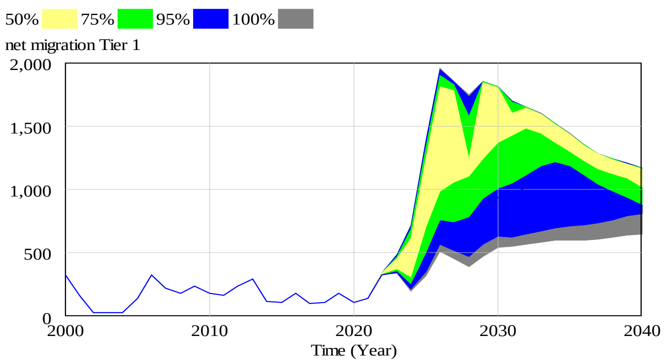


Figure 6-70. Net Migration – Tier 1: Monte Carlo Simulation for Sensitivity to Effect Of LRT on Nonresidential Sq. Ft. Demand In Tier 1

The additional portion of demand in Tier 1 is also added to Tier 2, since Tier 2 is inclusive of Tier 1, which is why effects are seen in Tier 2 as well. Nonresidential sq ft in Tier 1 diverges from the Light Rail on an average yearly basis by -4.6% in the 0% increase case, +3% in the 20% case, and +10.4% in the 100% case (Table 6-26). Unemployment is one of the most sensitive variables to this change. Since employment is strongly connected to nonresidential sq ft in the model, it increases faster than population in response, and the unemployment rate drops as the effect of the LRT on nonresidential sq ft increases, by -9.3% and -32% in the 20% and 100% cases, respectively (Figure 6-68).

The affordability index in Tier 1 also shows a sharp nonlinear reaction, with affordability spiking down dramatically soon after the effect begins in 2022, particularly in the maximum case (Figure 6-69). This is due almost entirely to a spike upwards in multifamily property values, driven primarily by the connection with retail density, which increases as nonresidential sq ft increases, and then declines as square footage is capped while population continues to grow. Therefore, despite the large swings as the light rail is introduced, even in the maximum case (a 100% increase in demand, though developed land is capped after a 67% increase in nonresidential sq ft), the average yearly percent deviation in the affordability index from the Light Rail is only -1.7% in Tier 1. Net migration in Tier 1 also displays nonlinearity. Under the maximum case, net migration spikes quickly as a result of the connection between employment and immigration. The increase in desired employment at first outpaces immigration due to the reinforcing feedback loop between the increase in nonresidential sq ft and employment, but eventually immigration catches up, leading to the subsequent drop in the employment gap and thus in net migration (Figure 6-70).

This test was also run on top of the Light Rail + Redevelopment scenario for comparison. It demonstrates that if the effect of the light rail on demand for commercial building space is much larger than assumed, the Light Rail + Redevelopment scenario becomes relatively more desirable. When the test is run on top of the Light Rail scenario, a larger effect of the light rail on demand for commercial development causes the local economy in general to improve more quickly with higher GRP and a lower unemployment rate, while diminishing affordability and increasing greenhouse gas emissions. Furthermore, the cap on developable land is hit much more quickly, indicating a much stronger case for the kind of increased density allowed in the Light Rail + Redevelopment case. By contrast, under the Light Rail + Redevelopment scenario, in the maximum case (100), GRP in Tier 1 averages 13.4% higher than the Light Rail + Redevelopment baseline, versus only 8.9% under the Light Rail maximum case. At the same time, affordability in Tier 1 is hurt less than under the light rail maximum case; 1.6% lower than the Light Rail + Redevelopment baseline on average versus 1.7% lower on average than the Light Rail baseline under the Light Rail maximum case (Table 6-26).

Table 6-26. Average Yearly Percent Departure from BAU, 2000-2040: Sensitivity Effect of LRT on Nonresidential Sq. Ft. Demand Tier 1

Variable	Min (0) v. Light Rail	Med (20) v. Light Rail	Max (100) v. Light Rail	Max (100) Light Rail + Redev v. Light Rail + Redev
Tier 1				
Nonresidential sq ft Tier 1	-4.6%	3.0%	10.4%	16.1%
Developed land Tier 1	-2.8%	1.2%	3.2%	7.0%
Total employment Tier 1	-2.9%	2.3%	8.1%	11.9%
Net migration Tier 1	-16.3%	11.0%	31.6%	33.7%
Population Tier 1	-2.0%	1.6%	4.4%	4.9%
GRP Tier 1	-3.4%	2.5%	8.9%	13.4%
Unemployment rate Tier 1	15.3%	-9.3%	-31.9%	-60.7%
Affordability index Tier 1	0.9%	-0.5%	-1.7%	-1.6%
CO2 emissions from buildings and transportation Tier 1	-3.6%	2.4%	8.1%	12.3%
Tier 2				
Nonresidential sq ft	-1.4%	1.3%	7.7%	8.9%
Developed land	-0.4%	0.4%	1.6%	1.8%
Total employment	-1.1%	0.7%	1.5%	1.6%
Net migration	-3.0%	1.9%	4.9%	6.1%
Population	-0.3%	0.2%	0.6%	0.7%
GRP	-1.3%	0.9%	4.1%	4.7%
Unemployment rate	35.3%	-13.1%	-21.6%	-22.8%
Affordability index	-0.6%	0.3%	-0.4%	-0.5%
CO2 emissions from buildings and transportation	-0.8%	0.7%	4.1%	4.7%

Sensitivity to Percent of Net Migration Due to Light Rail in Tier 1 That is from Areas External to Tier 2

This test is run on top of the Light Rail + Redevelopment scenario and tests the sensitivity of the model to changes in the percent of net migration due to the light rail in Tier 1 that is external to Tier 2, an assumed ratio for which there were no historical data available. This variable makes an assumption about how many of the people who move to the station areas are coming from outside the study region, and adds that portion to the Tier 2 population, since Tier 2 is inclusive of Tier 1. In the model, the default value is 1.5, indicating that 100% of those who move to the station areas as a result of the light rail are from outside Tier 2 (and therefore must be added to the Tier 2 population as well), and in addition, 50% more people will move into Tier 2, likely to areas near, but not within, the ½ mile station area radii. This value was chosen because it made the unemployment rate more reasonable in Tier 2; as jobs increase dramatically, population must also to some degree fill those jobs. In contrast to Tier 1, Tier 2 does not have a link between jobs and migration. Instead, the primary relationship in Tier 2 that governs migration is a link with vacant residential land, but since available land is plentiful, it doesn't increase population under the Light Rail scenarios to keep the unemployment rate above zero.

In this test, we report the sensitivity for a minimum (0) and a maximum value (3) as well as display the results of a Monte Carlo simulation. The simulation was set as a random-uniform distribution with minimum of 0 and maximum of 3, run for 1000 times. The immediate effects are seen on net migration (Figure 6-71) and population. Net migration varies from 6,920 to 10,300 people in 2040, with a percent deviance from the BAU of between -20% and +20% in the maximum case. Because population varies considerably more than total employment (see Table 6-27), the unemployment rate is significantly affected, at 11% below the BAU on average in the minimum case and 21% above in the maximum case.

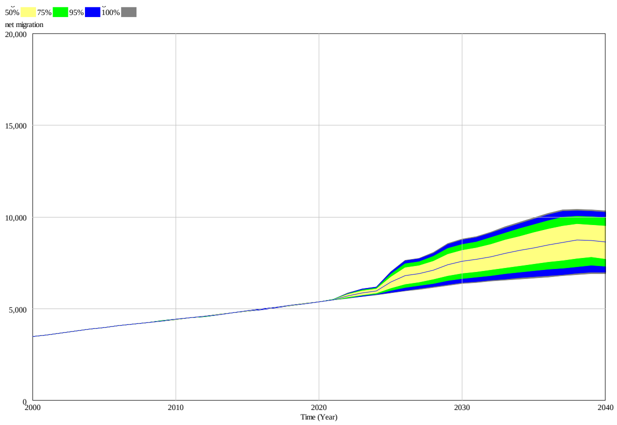


Figure 6-71. Net Migration – Tier 2: Monte Carlo Simulation for Sensitivity to Percent of Net Migration Due to Light Rail in Tier 1 That Is External to Tier 2

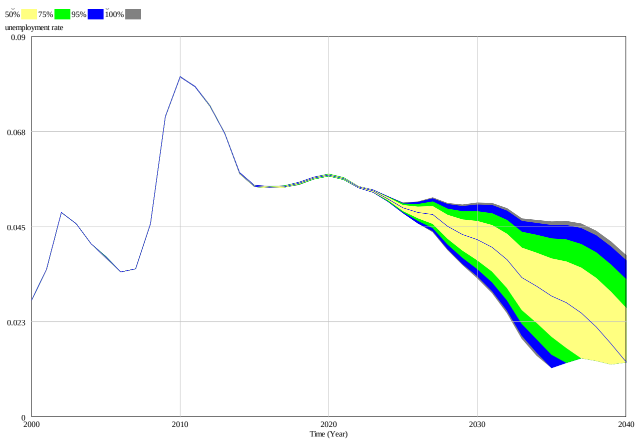


Figure 6-72. Unemployment Rate – Tier 2: Monte Carlo Simulation for Sensitivity to Percent of Net Migration Due to Light Rail in Tier 1 That Is External to Tier 2

Changes to these variables propagate throughout the model, eventually affecting the percent of the population in poverty. Smaller effects are seen in developed land, total employment, VMT, and GRP. The particularly large impact on unemployment means a low value for the percent of net migration due to the light rail in Tier 1 that is from areas external to Tier 2 makes the light rail scenarios less attractive from the perspective of the economic prospects of the residents. On the other hand, GRP, and therefore overall economic performance, is not very sensitive to changes in this variable.

Table 6-27. Average Yearly Percent Departure from BAU, 2000-2040: Sensitivity to Percent of Net Migration Due to Light Rail in Tier 1 that is External to Tier 2

Variable	Min (0) v BAU	Max (3) v BAU
Tier 2		
Net migration	-6.8%	6.7%
Population	-0.6%	0.6%
Developed land	-0.5%	0.4%
GRP	-0.2%	0.1%
Total employment	-0.3%	0.1%
Unemployment rate	-10.8%	21.4%
Percent of population in poverty	-2.1%	5.6%
VMT	-0.3%	0.3%

Congestion Per Weekday Peak-Period VMT per Lane Mile Held Constant

For both Tier 1 and Tier 2, the D-O LRP SD Model features an exogenous input variable called "congestion per weekday peak period VMT per lane mile" that determines how much traffic congestion (defined as the ratio of peak-period travel time over travel time in freeflow conditions) results from a given density of vehicles on the roadway system. Changes in its value may be due to changes in the effectiveness of traffic-control measures in the study area, but may also be due to traffic becoming more or less concentrated, both spatially across the roadway system and temporally throughout the peak travel periods. The variable consists of a lookup table, with values derived from the TRM v5 projections that were used in the DCHC MPO Metropolitan Transportation Plan. Those projections provide figures for the years 2010 and 2040, with no indication of what trend is followed between those years. Therefore, the D-O LRP SD Model assumes that congestion per weekday peak-period VMT per lane mile holds at a constant value from 2000 to 2010, then decreases linearly from 2010 to 2040, in both Tier 1 and Tier 2. For this sensitivity test, we modified the model's inputs so that the constant 2000-2010 value continues to hold constant until 2040. In Tier 1, it remains constant at 0.000388, instead of ramping down to 0.000296 during 2010-2040 (a 23.8% reduction). In Tier 2, it remains constant at 0.000483, instead of ramping down to 0.000347 during 2010-2040 (a 28.1% reduction). In order to analyze the policy implications of this sensitivity test, we examined the effects of the change in inputs on the BAU scenario, the Light Rail scenario, and the No Road Building scenario, wherein all new road construction stops after 2017, subsequently reducing the capacity of the roadway system relative to the BAU and Light Rail cases. The test cases created on the basis of these scenarios are called BAU + Cong per VMT, Light Rail + Cong per VMT, and No Road Building + Cong per VMT, respectively.

Not surprisingly, in the cases where congestion per weekday peak-period VMT per lane mile does not decline after 2010, traffic congestion is much higher during 2010-2040 than it would be with the model's default inputs (Figure 6-73). In each test case, this difference is approximately the same percentage that each test case increases congestion relative to the scenario that was modified to create it. Consequently, this sensitivity test does not change the proportion by which building roads reduces traffic congestion or the proportion by which adding a light rail line increases congestion, mostly due to the increase in Tier 1 land development that it is assumed to cause. Instead, the constant rate of congestion per weekday peak-period VMT per lane mile assumed in this test increases the baseline congestion that those policy decisions modify. If baseline traffic congestion is more severe, it makes mitigating it through road building a more attractive option and makes building a light rail line that increases congestion a less attractive option than it otherwise would be. However, the fact that the D-O LRP SD Model predicts that the building of a light rail line will increase traffic congestion is mostly due to the assumption that the presence of a light rail line will increase demand for Tier 1 commercial floor space by 10%, as well as increase the proportion of Tier 1 workers who choose to also live in Tier 1. In the absence of those assumptions, opening a light rail line would be expected to decrease traffic congestion. Furthermore, even if those assumptions are left in the model, creating a light rail line would still create economic benefits, in addition to the transportation-related effects discussed here.

The downstream effects of this sensitivity test are mostly unsurprising. Since traffic congestion is more severe in the test cases, there is also less automobile driving and more travel by public transit and nonmotorized modes (Table 6-28), indicating a greater amount of latent demand for public transit improvements, such as the addition of a light rail line. Also unsurprisingly, increased traffic congestion has a small, negative effect on GRP. From 2025 to 2040, the negative effect on Tier 2 GRP of holding congestion per weekday peak-period VMT per lane mile constant is less than the Tier 2 GRP benefit of creating the light rail line, and has less than half the magnitude of that benefit during 2032-2040. In Tier 1 (but not Tier 2), the small negative effect on GRP creates a smaller negative effect on population, by way of the unemployment rate and net migration. Table 6-28 also shows that, whereas the increased traffic congestion in this test causes Tier 1 automobile passenger miles per day to slightly decrease, it also causes Tier 2 automobile passenger miles per day to increase. This is due to fact that, in the D-O LRP SD Model, the effects of most of the drivers of modal person miles are normalized, so that overall person miles track a baseline trend that is driven by population and GRP. As a result, when person miles by one mode go up or down, an opposite-direction change must occur in person miles by one or more of the other modes. Without normalization, traffic congestion would reduce automobile passenger person miles in both Tiers, due to fewer people being willing to travel in congested conditions. However, some people are assumed to respond to traffic congestion by carpooling, so that the effect of traffic congestion on automobile passenger person miles is less than the effect on automobile driver person miles. Since congestion has a stronger effect on automobile driver travel than on any other mode and automobile driver travel accounts for the majority of person miles in both Tiers and in all scenarios and test cases, the normalization step requires that there be a net increase in person miles by all modes other than automobile driver travel. Due to how the normalization step is carried out, how much of this net increase comes from each of the remaining three modes is determined by how large of a proportion of overall person miles each of them represented to begin with. In Tier 1, public transit and nonmotorized modes account for a large enough fraction of overall person miles that the reduction in automobile driver person miles merely results in the reduction in automobile passenger person miles being partially mitigated. In Tier 2, though, public transit and nonmotorized modes account for a significantly smaller fraction of overall person miles, meaning that, after normalization, a larger percentage of the reduction in automobile driver person miles must be made up for by increased automobile passenger person miles. In effect, this means that travelers in the portion of Tier 2 that is outside of Tier 1 are more likely to start carpooling in response to greater traffic congestion than are those whose trips either begin or end in Tier 1.

Holding congestion per weekday peak-period VMT per lane mile constant has about the same effect on model outputs in the BAU, Light Rail, and No Road Building scenarios (Table 6-28). The largest exception to this is that it does not increase public transit person miles by as large of a proportion in the Light Rail + Cong per VMT test case (relative to the Light Rail scenario) as in either of the other test cases relative to their respective baselines. Since people walk or bicycle to and from transit stops, Tier 1 nonmotorized person miles are also increased less in the Light Rail + Cong per VMT scenario than in the other test cases. This happens because the increase in public transit person miles that is assumed to occur when the light rail line opens under the Light Rail scenario does not account for changes in congestion, as we define it in the model. Rather than a function that expressly mentions traffic congestion, light-rail-induced person miles are driven by Tier 1 population and employment and Tier 2 VMT per highway lane mile, in accordance with an equation from literature (Chatman et al. 2014). In this equation, the input “VMT per highway lane mile” is both an indicator of travel demand in the study area and a stand-in for traffic congestion, as decided upon by the originators of the equation. However, this way of representing traffic congestion does not account for changes (or the lack thereof) in the amount of traffic congestion that results from a given density of vehicles on the road. Therefore, adjusting congestion per weekday peak-period VMT per lane mile in scenarios where the light rail line is built may lead to unrealistic results.

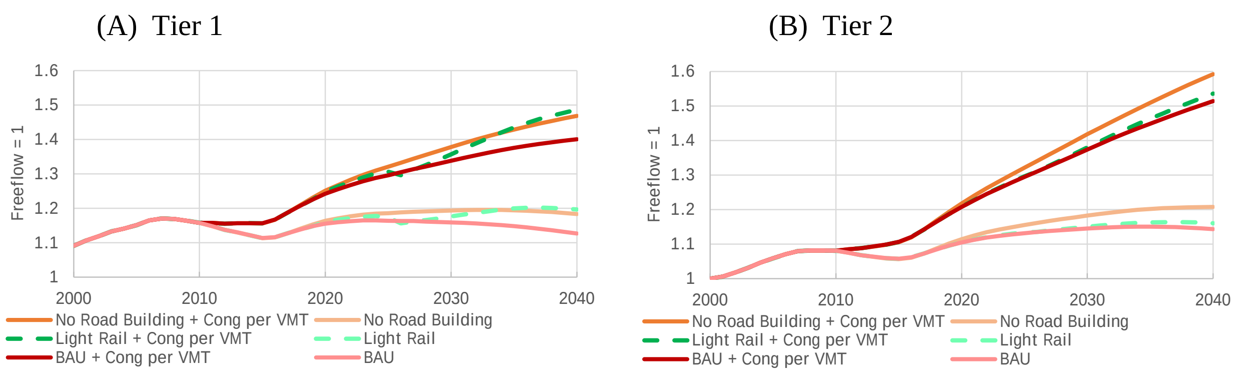


Figure 6-73. Traffic Congestion: Congestion Per Weekday Peak-Period VMT Per Lane Mile Held Constant vs. No Road Building, Light Rail, and BAU Scenarios

Table 6-28. Average Yearly Percent Departure from BAU, Light Rail, and No Road Building Scenarios, 2010-2040: Congestion Per Weekday Peak-Period VMT Per Lane Mile Held Constant

VARIABLE	BAU + CONG PER VMT V. BAU	LIGHT RAIL + CONG PER VMT V. LIGHT RAIL	NO ROAD BUILDING + CONG PER VMT V. NO ROAD BUILDING
Tier 1			
Congestion	+11.7%	+11.6%	+11.6%
VMT	-2.1%	-2.2%	-2.2%
Automobile driver person miles	-1.7%	-1.9%	-1.9%
Automobile passenger person miles	-0.1%	-0.2%	-0.1%
Public transit person miles	+3.6%	+0.8%	+3.5%
Nonmotorized person miles	+2.7%	+2.3%	+2.7%
Total person miles	-0.8%	-0.9%	-0.9%
GRP	-0.9%	-0.7%	-1.0%
Population	-0.3%	-0.4%	-0.3%
Tier 2			
Congestion	+15.1%	+15.0%	+15.0%
VMT	-1.9%	-1.9%	-2.0%
Automobile driver person miles	-1.4%	-1.5%	-1.6%
Automobile passenger person miles	+0.5%	+0.5%	+0.5%
Public transit person miles	+4.7%	+3.4%	+4.7%
Nonmotorized person miles	+3.7%	+3.6%	+3.6%
Total person miles	-0.8%	-0.9%	-0.9%
GRP	-1.0%	-1.0%	-1.0%
Population	0.0%	-0.1%	0.0%

Note: Difference between scenarios with and without constant congestion per weekday peak-period VMT per lane mile starts after 2010.

Sensitivity of Cross-Sector Indicators to Changes in the Energy Sector

In this test, we asked which energy variables had the largest proportional effect on CO_2 emissions, given the Durham County goal of reducing GHG emissions 30% from a 2005 baseline by 2030. We also examined "side effects" on variables representing travel behavior, economic performance, and impervious area. Energy variables (MPG, building energy intensity, LRT effect on person miles of public transit, desired solar capacity, and electricity emissions factor) were increased or decreased by 10% or more relative to the Light Rail + Redevelopment scenario (Table 6-29). Note that these sensitivity tests apply a constant % change to energy system variables between 2000 and 2040. This is in contrast to the policy tests described in the Energy Sector of Section 5.4, which often apply a change which starts in 2015 and gradually increases to 2040.

CO_2 emissions were most sensitive to changes to building energy intensity (MMBtu/year per sq ft or per dwelling unit) and electricity emissions factor (tons CO_2 per kWh delivered), with a 10% decrease in building energy intensity reducing Tier 2 emissions by 7.2% by 2040, and a 10% decrease in electricity emissions factor reducing Tier 2 emissions by 6.4%. The relationship between CO_2 emissions and both building energy intensity and electricity emissions factors is not 1:1 because buildings represent 73% of Tier 2 CO_2 emissions, and electricity represents about 63% of Tier 2 CO_2 emissions in the model. CO_2 emissions were next most sensitive to automobile fuel efficiency, with a 10% increase in MPG causing a 2.5% decrease in Tier 2 emissions.

GRP was most sensitive to changes in MPG and building energy intensity. Counterintuitively, a 10% increase in MPG causes a 0.51% decrease in GRP. Although this increase in MPG reduces total energy spending/GRP, the reduction is 5% in 2000 but 3.8% in 2040, so that by 2040 total energy spending/GRP is higher *relative to its updated initial (year 2000) value*, which causes the slight decline in GRP. A 10% decrease in building energy intensity causes a 0.18% increase in GRP due to declining energy cost as a fraction of GRP.

Increasing the effect of Light Rail on public transit person miles by 200% (representing an increase in rail ridership) has a slight effect on cross-sector indicators. Both VMT and congestion decrease by 0.71% in response, while GRP increases by 0.28% and impervious surface increases by 0.12%. VMT decreases due to mode shifting from automobiles to public transit, and congestion decreases as a result of VMT decreasing. GRP increases due to decreased energy spending, and impervious surface increases due to land development stimulated by increased GRP.

In summary, this set of energy system sensitivity tests demonstrates that decreases in building energy intensity and electricity emissions factor will have the largest proportional effect towards reducing GHG emissions, followed by increases in automobile MPG. Further, cross-sector side effects of changing these energy variables by 10% were negligible; GRP and impervious surface changed mostly by less than 0.2% in response (with the exception of GRP decreasing by 0.5% in response to a 10% increase in MPG). Although increasing the LRT ridership effect on public transit reduced CO_2 emissions, the effect was small; tripling the LRT effect reduced Tier 2 CO_2 emissions by less than 0.1%. Our model suggests that decreased building energy intensity, decreased electricity emissions factor, and increased MPG would make the largest proportional impact towards achieving a GHG reduction target, with minimal cross-sector side effects.

Table 6-29. Sensitivity Analysis for Energy System Variables: Effect on Cross-Sector Indicators in Tier 2 in 2040

		Cross-system indicator affected				
Energy system variable	Change	VMT	Congestion	GRP	CO2 emissions	impervious surface
MPG	+10%	-0.067%	-0.068%	-0.509%	-2.467%	-0.134%
	-10%	0.062%	0.062%	0.431%	2.992%	0.149%
Building energy intensity	+10%	-0.007%	-0.007%	-0.092%	7.230%	-0.004%
	-10%	0.013%	0.013%	0.184%	-7.246%	0.027%
LRT effect on person miles of public transit	+10%	-0.035%	-0.035%	0.014%	-0.003%	0.006%
	-10%	0.035%	0.034%	-0.014%	0.003%	-0.006%
	+200%	-0.706%	-0.707%	0.280%	-0.066%	0.116%
Solar capacity	+10%	0.000%	0.000%	0.000%	-0.024%	0.000%
	+100%	0.000%	0.000%	0.000%	-0.240%	0.000%
Electricity emissions factor	+10%	0.000%	0.000%	0.000%	6.388%	0.000%
	-10%	0.000%	0.000%	0.000%	-6.388%	0.000%

Note: orange indicates a decrease, and blue an increase, relative to the Light Rail + Redevelopment scenario.

6.4 Computational Reproducibility

Making model computations reproducible is critical to help researchers examine and use the results of simulation exercises. Further, it greatly helps in carrying out follow-up studies, saving time in identifying and interpreting the parameters used in the initial model and in subsequent scenarios. In general, computational reproducibility can be helpful in the following ways in the context of the D-O LRP project:

- It will help the technical team that has developed the D-O LRP model to reproduce scenario results and check underlying assumptions incorporated in the model. This will be particularly important as the model is used over time.

- It will also support other stakeholders who wish to use the D-O LRP model to simulate alternative scenarios or apply this type of model to other locations by allowing them to fully understand the data and relationships incorporated in it through documented code; and thereby avoid spending substantial periods of time trying to figure out how model results are produced.

In order to ensure computational reproducibility, the modeling team provided EPA with the full source code of the D-O LRP model and the Agency can make it available to qualified users. Further, model users can obtain full documentation of any scenarios they simulate, the parameters used to run them, and a summary of results from Vensim. Figure 6-74 provides an example of the Vensim documentation for the Light Rail + Redevelopment scenario, in comparison to the BAU scenario. “Runs compare” is a button at the left of the Vensim screen (see Appendix A: User Guide) which generates a list of differences between two loaded scenarios. The list may be very simple, as in Figure 6-74, or detailed if the differences are extensive.

Comparing Light Rail + Redevelopment and BAU

*******Constant differences between Light Rail + Redevelopment and BAU*******

Main policy switch - has changed in value

2	*Light Rail + Redevelopment*
0	*BAU*

Figure 6-74. Sample “Runs Compare” Report

7 Summary & Conclusions

The premise of building the D-O LRP SD Model was to demonstrate, by means of a particular but generalizable case, that integrated approaches yield a broader and more contextual basis for community decisions, and that system dynamics models are a useful tool for achieving integrated decision-making. In assessing the value added of the model, we look at both the model results and the modeling process, as evaluated against the goals of (1) better integrated and more contextual assessment processes, (2) more integrated and efficient cross-sectoral planning, and (3) enhanced community comprehension of and participation in complex decisions. Here, we discuss features of the model both as they perform in the present context of the D-O LRP, but also how they would likely perform across the spectrum of envisioned usages.

7.1 Integrated Assessments

Key features of the model that enhance its ability both to assess the success of the D-O LRP project and to evaluate its impacts include the ability to: 1) alter and test input assumptions, 2) account for feedbacks of the project on those inputs, 3) explore the effects of nonlinearities of project impacts over time and 4) characterize the nature, magnitude, and interdependencies of indirect and cumulative impacts. Regional projections of rapid population and employment growth over the next 25 years were important drivers for the local land use and transportation models used to evaluate the D-O LRP as a future transportation alternative. In the TRM v5, for example, the amount, type, and location of population and employment in 2040, along with additional assumptions, drove the total demand for transportation. However, the population projections used as inputs to the TRM, once selected, were static and not subject to endogenous feedbacks, as they were in our model. Furthermore, in our model, confidence in the causal mechanisms underlying the projections was increased by starting the model from 2000 and calibrating the model's outputs to historical data. Achieving close calibrations for drivers such as population using underlying mechanisms rather than pure data fitting increased our confidence in the model's ability to forecast the future.

Representing processes mechanistically not only allows the user to directly test assumptions about model inputs, but also permits the tracing of causal pathways by which they deliver their impacts. Endogenous population growth, based on birth, death and migration rates, allows the population assumptions to be tested, but also, perhaps more importantly, allows the population growth to respond to internal processes in other sectors of the model. For instance, premature mortalities avoided due to the positive health benefits of increased physical activity under the Light Rail scenarios feed back into the death rate, leading to fewer deaths per year than the BAU scenario. Of greater consequence, however, are the model feedbacks that impact migration rates, namely employment, housing, and the availability of residential land, which can alter population to a much greater extent.

Explicitly representing the endogenous variables that influence the drivers not only lets us alter projections and test the model's sensitivity to the altered inputs, but also allows us to separate processes that may be lumped together in a simpler model. This can be helpful in distinguishing the relative contributions of otherwise coupled processes as well as isolating leverage points in the model where policy interventions might alter the initial projected inputs. For example, while the Light Rail + Redevelopment scenario reflects what is expected to occur (in the real world) in Tier 1 should the light rail be built, there is debate as to whether the economic and transportation benefits could be realized with redevelopment to higher densities without the light rail. The model affords us the ability to examine the impacts of the light rail and redevelopment separately as well as superimpose redevelopment on top of the light rail. As a result, individually, both redevelopment and the light rail increase population and employment above BAU in Tier 1, though to varying degrees. Redevelopment by itself increases population and employment in Tier 1 slightly more than does BAU, but to a much lesser extent than the combination of redevelopment and the light rail. The attractiveness of the light rail is expected to bring more nonresidential development and jobs to the area, while at the same time decreasing VMT per capita and increasing non-motorized travel per capita relative to either BAU or redevelopment alone. Similarly, being able to isolate causal pathways associated with drivers or sectors allows us to test the effectiveness of targeted policies. For example, impacts of wage increases or non-residential rents propagate through the model from their point of intervention within the economy sector, as do the impacts of constructing non-motorized infrastructure from its transportation origins.

The temporal dynamics of the SD model are well-suited to examine changes or interventions that occur at some point in between the model start date and end date, or that change in value throughout the model period. The model could be used to assess the implications of the timing of light rail or road construction, especially for outcomes that have time lags, synergies, and/or feedbacks, such as congestion. In a similar vein, technological changes may be viewed as continuous changes of a quantity (e.g. increasing building efficiencies or vehicular fuel efficiencies) or discontinuous shifts (e.g. shift to solar power), where timing and rate of change can significantly alter outcomes. For as much as total VMT increased in all scenarios, a projected simultaneous increase in vehicle fuel efficiency meant energy use and CO_2 emissions by passenger vehicles stayed fairly level, and $PM_{2.5}$ and NO_x emissions from passenger vehicles decreased due to projected reductions in $PM_{2.5}$ and NO_x vehicle emissions per VMT.

The ability to identify and quantify indirect and cumulative benefits, singly or in combination, is an important feature of the model that could substantially enhance a comprehensive, integrated assessment of projects such as the D-O LRP. While indirect and cumulative impacts, in the context of EIAs, are usually thought of as negative, we have also demonstrated positive impacts that may lead to increased community support for a project, either as independently supported objectives or by affecting the perceived net cost-benefit of the project itself. The D-O LRP DEIS identifies a number of indirect and cumulative consequences. Some, such as visual and aesthetic impacts and impacts on historic resources, are predominantly site-specific in nature, and are not addressed by models such as ours. Others, such as consumption of water resources and production of stormwater, can be viewed in the model from the perspectives of timing and magnitude, but also of causation. Causal processes, in turn, can be viewed from a risk-benefit or cost-benefit perspective either directly from model dynamics, or by expressing outcomes as intensity measures, where the denominator of intensity measures can be selected to highlight the nature of trade-offs to be considered. So, for example, in Tier 1, although both light rail and redevelopment increase total stormwater N loadings, they decrease stormwater N loadings per capita by increasing population density. Stormwater per unit of GRP could also be a useful intensity measure that highlights possible tradeoffs or suggests a potential mitigation strategy.

7.2 Integrated Planning/Coordinated Agency Decision-Making

A project of the magnitude of the D-O LRP has a scope that extends beyond the immediate bounds of the construction of the rail itself. Its dependence on long-term demographics and economics for its success, and its ramifications in many spheres of community life by necessity invoke the participation and the coordination of numerous agencies. That scope presents a challenge to modeling. The adage to "model the problem, not the system" suggests that a model should be no more complex than it needs to be for the issue at hand. However, when a model such as the D-O LRP SD Model has a range of potential uses, and the D-O LRP itself has such a range of consequences, parsimony needs to be weighed against utility.

In the D-O LRP SD Model, we've strived to bound and structure the model to reflect not only the key causal and consequential dynamics, but also to capture key points of intervention. These points of intervention occur within sectors that are themselves the domains of agencies. In some cases, such as for the transit and planning agencies, their objectives and actions are almost inextricable, and their collaboration is a given from the inception of the project. Those interactions are captured in our three main scenarios, which reflect assumptions about drivers and magnitudes of interdependencies more than they establish novel interconnections among agencies. The expanse of the model to capture such issues as affordability, health, and resource intensity brings in agencies who had not seen themselves as central to the issue, yet whose missions could be very much impacted by it – either negatively or positively. At first glance, a health agency might not see a role for itself in a transportation issue. Yet the enhancement of nonmotorized travel that results from the transportation and land planning decisions may improve health outcomes on a level commensurate with other, more classically "in-house" health actions. Conversely, the priority of constructing additional nonmotorized travel infrastructure might fail to meet funding thresholds until the health benefits are included in the cost-benefit analysis and advocated by the health agencies. In similar fashion, the model equips the housing agencies with critical information about property values, affordability, employment and economically-driven (i.e. private sector) residential development, allowing them to elevate such issues as equity and affordability from vague concerns to projectable trends and estimates of magnitudes, subject to testable policies. In practice, we have seen the process of building the D-O LRP SD Model and testing of scenarios result in enhanced participation of housing, health, water, and sustainability agencies at the municipal and county level.

7.3 Support for Community Participation in Complex Decisions

Issues that, by either their intrinsic nature or the nature of the decision process invoked, require a high degree of public participation could also benefit from a tool like the D-O LRP SD Model. In our case, largely as a function of us beginning the modeling project during the late stages of the D-O LRP planning process, the development of the conceptual model, the vetting of the operational model, and the design of the scenarios to be tested all occurred with the input of stakeholder agencies, rather than the general public. Nevertheless, the construction of the conceptual model lends itself to public participation. Issues, concerns, and beliefs or understandings about connections can all be captured in model diagrams, for discussion in a public forum. They can then later be tested for importance or validity when developing the operational model, with feedback to the community group. Once the operational model has been constructed to incorporate community perspectives, assumptions and scenarios can be tested, either off-line or in real time. The SD model runs very fast, permitting "on-the-fly" model runs in settings such as stakeholder meetings or public fora. Having the public's questions or challenges addressed and analyzed in an open forum is helpful in demonstrating transparency, maintaining focus on the most influential issues, and developing buy-in to the decision process.

These features of the model could be even more useful if employed earlier in the design and deliberative process than occurred with the D-O LRP SD Model. In our case, the D-O LRP had already been designed and subject to a referendum for funding before the development of the SD model, with the public gradually becoming aware of the full suite of potential impacts over the course of several years. Community concerns and questions that have emerged in the planning and DEIS processes include:

1) the project planners' assumptions for population growth, ridership, and costs;
2) the impact of the project on affordability of housing, especially for the transit-dependent;
3) the likelihood of technological innovations diminishing the need/demand for fixed-guideway transit;
4) the resource carrying capacity of the region; and
5) the potential to generate public revenues through indirect impacts on jobs and property.

All of these concerns can be explored with the SD model, and while no model can pretend to head off all community objections to a project, a fuller representation of the project from the beginning would introduce transparency earlier in the process and possibly lessen the entrenched objections that arise in any project of this magnitude.

Admittedly, the construction of a model such as the D-O LRP SD Model, at least with the tools available at this time, does require considerable time and data. The effort may not be justified for all issues (although we hope, as outlined in next steps, to lower the threshold of effort required); it is more likely to be undertaken for larger projects with longer time frames. Given that it is just such projects that are most likely to invoke the requirement for an EIS, to involve multiple agencies, and to engender public concerns, we see great potential for such models to inform and enhance such projects from inception to execution. Furthermore, once built, such models can be used for years to come to evaluate policies or actions that, in and of themselves, would not have warranted the investment in a model.

7.4 Next Steps

The D-O LRP SD Model has been developed for and applied to the analysis of the Durham-Orange Light Rail Project. In its current (beta) form, with little packaging between the user and the model inputs, outputs and equations, a technically adept user can run alternate scenarios, test assumptions, and even modify data and/or equations. Less technically-oriented stakeholders can likewise interact with the model with the help of a capable intermediary.

After thorough review of the "naked" model, we do intend to develop an interface that supports easier access to the model as well as transferability to other applications. We have solicited stakeholder inputs on features that they would find desirable in a user interface, and engaged EPA's Environmental Model Visualization Lab (EMVL) in a two-stage development process. The first stage of the effort will be to develop a model interface that allows users to: 1) construct scenarios that reflect policy-driven changes or other "what-ifs" (e.g. population or economic trends) as inputs, 2) visualize and contrast scenarios with regards to multiple outputs, 3) perform sensitivity analyses on model inputs, parameters and assumptions, 4) visually explore the dynamics of causality within the model, and 5) archive scenarios with associated input and output values.

The second stage of the effort will to construct a "model builder" that will streamline and simplify the construction of this type of model for other issues, locations, or users. Many communities face similar decisions that require integration of multiple sectors, just as they also strive to maximize net benefits across social, economic, and environmental outcomes. Community-level data to populate and calibrate models are often extracted from larger scale data sets (e.g. census, economic, land cover) or are developed and held by communities in digital forms that are increasingly similar across communities (e.g. property inventories). Features of such a model builder would include: tools for structured elicitation (from users and stakeholders) of issues and linkages for conceptual model development; web-based linkages to both general and specific data and models; tools for dynamic model development; and a wrapper that combines user-interface, analytic, and visualization tools with the above.

Final Word

Ultimately, the strength of the D-O LRP SD Model is that it is a defensible, testable narrative – a narrative that speaks to a number of audiences. It allows proposed projects, policies, or aggregations of the two to be evaluated in a fully contextual mode, as required for determining net costs and benefits and sustainability. It demonstrates the connectivity and synergies of actions spread out across multiple entities, thus allowing them to develop collaborations that might not have previously existed, and to focus their efforts where net gains may have been previously undetected because they were diffuse across endpoints. And, finally, by placing the multiple concerns of agencies and stakeholders in a common frame of reference, and subjecting the connections and assumptions to rigorous testing, decisions can be made more inclusive, comprehensive, and transparent. Making synergies and conflicts more visible, and testable, early in the process ultimately benefits all and fulfills the mandate of NEPA "… to use all practical means and measures ... to create and maintain conditions under which man and nature can exist in productive harmony and fulfill the social, economic, and other requirements of present and future generations of Americans (NEPA, Sec 101(a))."

Appendices

Appendix A: Advanced User Guide for the Durham-Orange Light Rail Project System Dynamics Model

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INTRODUCTION TO THE DURHAM-ORANGE LIGHT RAIL PROJECT SD MODEL

The Durham-Orange Light Rail Project System Dynamics (D-O LRP SD) Model is a collaborative effort led by EPA's Sustainable and Healthy Communities (SHC) research program. The project uses system dynamics to explore the impact of light rail transit and associated development in the rapidly growing Research Triangle region of North Carolina. The model boundary is the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization (DCHC MPO) area. Variables in the model are simulated annually between 2000 and 2040, with a time step of 0.0625 years, allowing projections to produce relatively smooth curves. The model is designed to explore dynamic interactions among seven sectors of the urban system, including Land Use, Transportation, Energy, Economy, Equity, Water, and Health. These sectors are visualized in Figure A-1, with plus (+) signs indicating positive association, and minus (-) signs indicating negative association between two variables. Model scenarios run in a few seconds, and users can edit any variable in the model. This allows users to experiment with and test different aspects of the model's representation of a complex urban system.

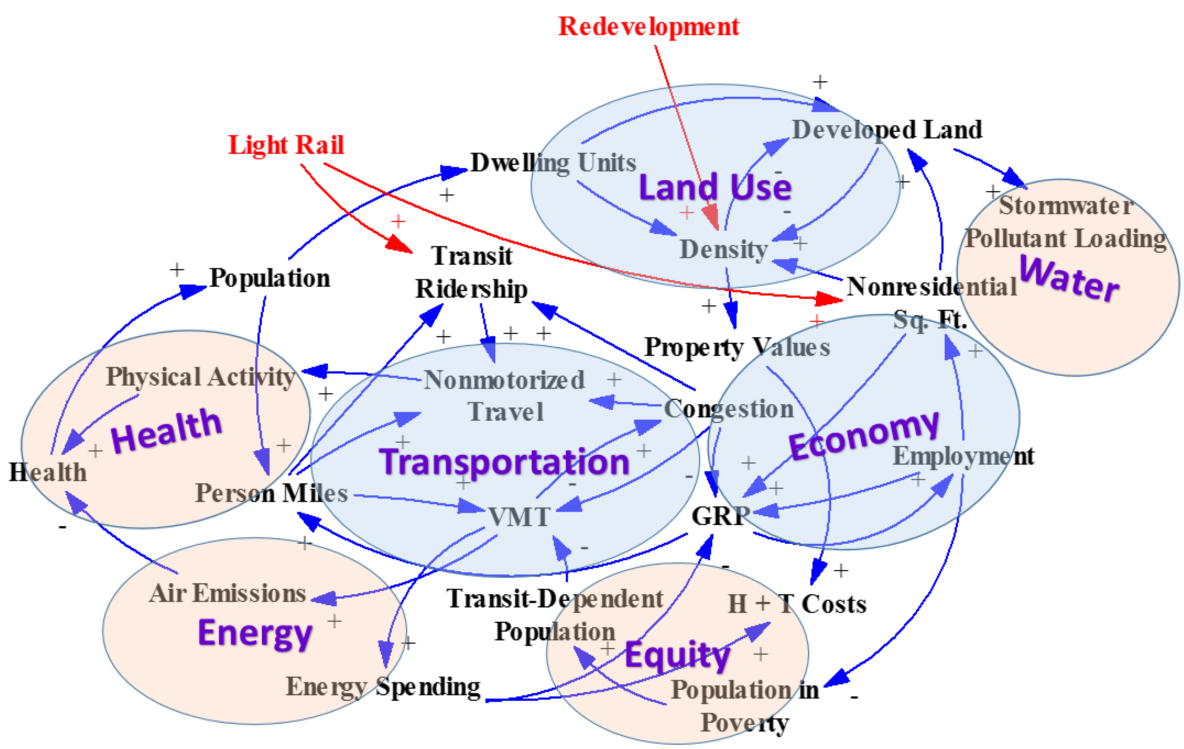


FIGURE A-1. SIMPLIFIED CAUSAL LOOP DIAGRAM (CLD) FOR THE D-O LRP SD MODEL

INSTALLATION GUIDE

INSTALLING VENSIM SOFTWARE

Vensim comes in several different versions. The D-O LRP model will run fully on the Professional Learning Edition (PLE) version of Vensim and can also be explored (without the possibility to modify variables and equations) with Vensim Reader. Vensim PLE and Reader are free for educational use and can be downloaded (in Windows or Macintosh OSX versions) from the Vensim website at http://vensim.com/download/.

***Macintosh users**: when installing Vensim, you may get a message that the program cannot be opened because it is not by a registered developer. In this case, users will need to click on the apple symbol in the navigation bar, click on "System preferences," and open "Security and Privacy." Near the bottom of the window, you should see the option to "Open anyway" the Vensim application. From this point on, Vensim and the D-O LRP model operate much the same as in Windows.*

***Advanced users**: although the model can be run and edited fully on Vensim PLE, it was built partly using Vensim DSS, which has additional functionality for model editing and sensitivity tests. Users interested in Vensim DSS should contact the authors of this report for more information.*

OPENING THE MODEL

After opening Vensim, go to the File menu → Open Model and select the model file you wish to open. If a dialog box pops up saying "The current display scaling is different from the computer the model was last modified on…," click Yes to rescale the sketch. This will pop up another box, "Rescale Sketches," and click OK to accept defaults. The model should now be open and ready to run.

VENSIM FEATURES

Figure A-2 presents an annotated illustration of the Vensim window through which the user accesses the D-O LRP model. This figure serves as a guide that will be referred to throughout this document as different features of the model and Vensim software are described. Specific features of the Vensim window are labeled with green circles, including some of the controls available on the vertical and horizontal toolbars across the top and left side of the window. These features and controls include:

1) Menu for navigating across views
2) An example of an Auxiliary/Constant variable
3) Causes Tree and Uses Tree tools
4) Equation tool
5) Where to name and run a simulation
6) Graphing tool
7) Table tool
8) Runs Compare tool
9) Control Panel
10) Loops tool
11) Causes Strip tool

NAVIGATING THROUGH THE MODEL

When first opening the model, the user may want to zoom out or zoom into the sketch. This is done by holding CTRL and turning the mouse wheel backward or forward. The user can also reposition the sketch using the scroll bars at the bottom and right edges of Figure A-2, or by holding the right mouse button and moving the mouse.

Vensim is capable of separating a large model into individual sketches or views, making it easier to organize and view a complex model. The D-O LRP model contains over 80 views which can be used to access different elements of the model. To navigate through the model by selecting a view, use the menu at the bottom left of the Vensim window, identified as 1 in Figure A-2. Views are grouped by sector; in Figure A-2, the displayed view "normalized modal person miles" is part of the Transportation sector. The next sectors are Land Use, Equity, etc. The Dashboard view at the bottom of the view navigator menu is described later in this User Guide.

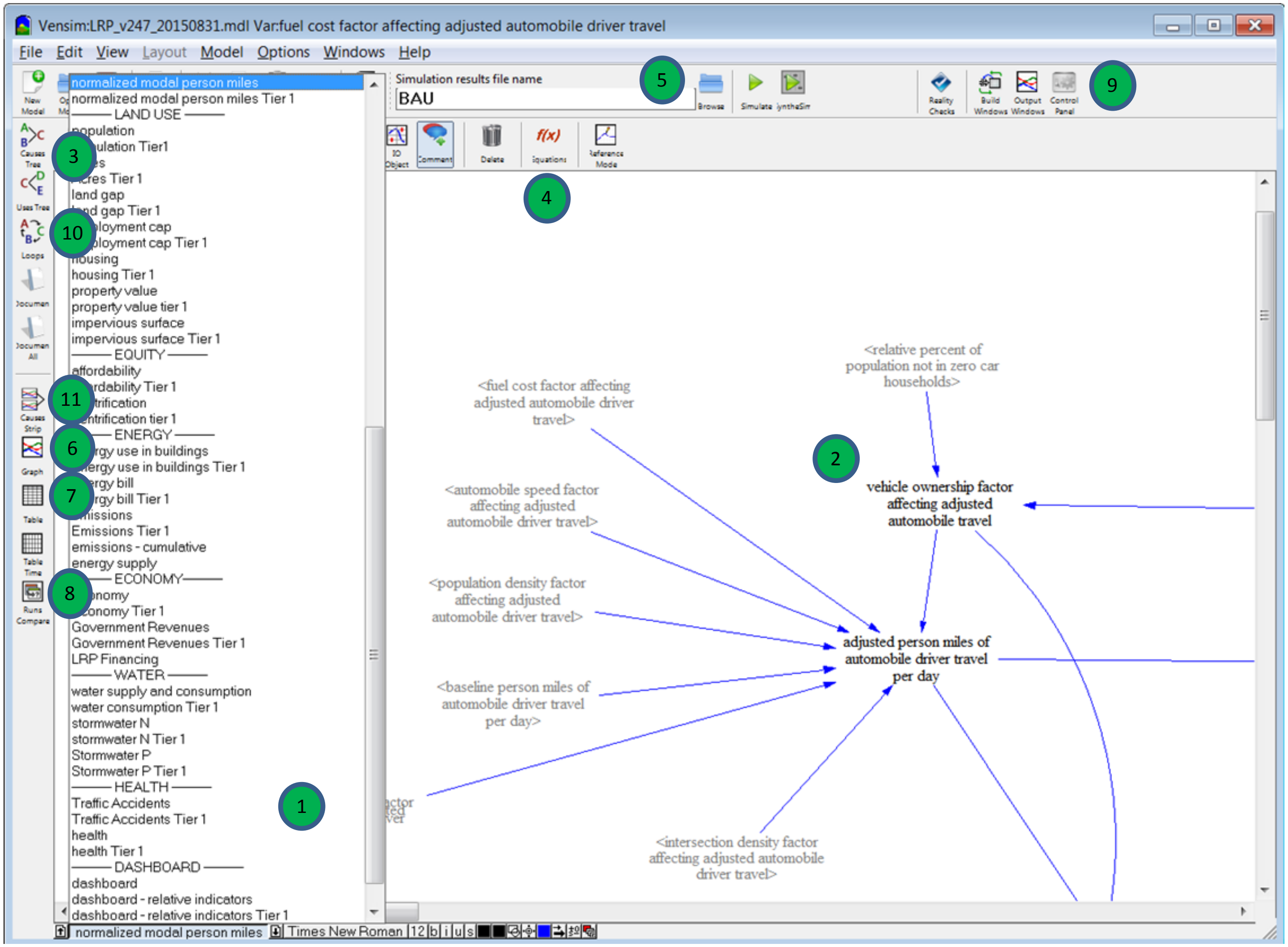


FIGURE A-2. VENSIM WINDOW

VARIABLES AND RELATIONSHIPS

There are three different types of variables in Vensim: box variables, flow variables, and auxiliary/constant variables (an example of an auxiliary/constant variable is labeled as 2 in Figure A-2). A box variable represents an accumulating quantity (or stock) and has associated inflows and outflows, which are flow variables. Auxiliary/constant variables are constants or calculated values that can affect inflows and outflows or other auxiliary/constant variables. Arrows in the model view represent relationships between variables; a given auxiliary or flow variable can be affected by all other variables with arrows pointing to it (e.g., in Figure A-2, "fuel cost factor affecting adjusted automobile driver travel" affects "adjusted person miles of automobile driver travel per day"). A variable can be located by name by going to the Edit menu → Find. To find the next instance of a variable in the model, press the F3 key.

TIER 1 AND TIER 2 OF THE MODEL

The D-O LRP SD model is divided into two geographic Tiers (Figure A-3). Tier 1 is the ½ mile radius zones around proposed light rail stations, representing the region accessible to stations by walking. Tier 2 is the entire DCHC MPO region, inclusive of Tier 1. Most views of the model are represented for both Tiers. For example, the view "normalized modal person miles" in Figure A-2 represents Tier 2, and the next view is "normalized modal person miles Tier 1." The variable at the right hand side of the screen in Figure A-2, "vehicle ownership factor affecting adjusted automobile travel," has a Tier 1 version, "vehicle ownership factor affecting adjusted automobile travel Tier 1."

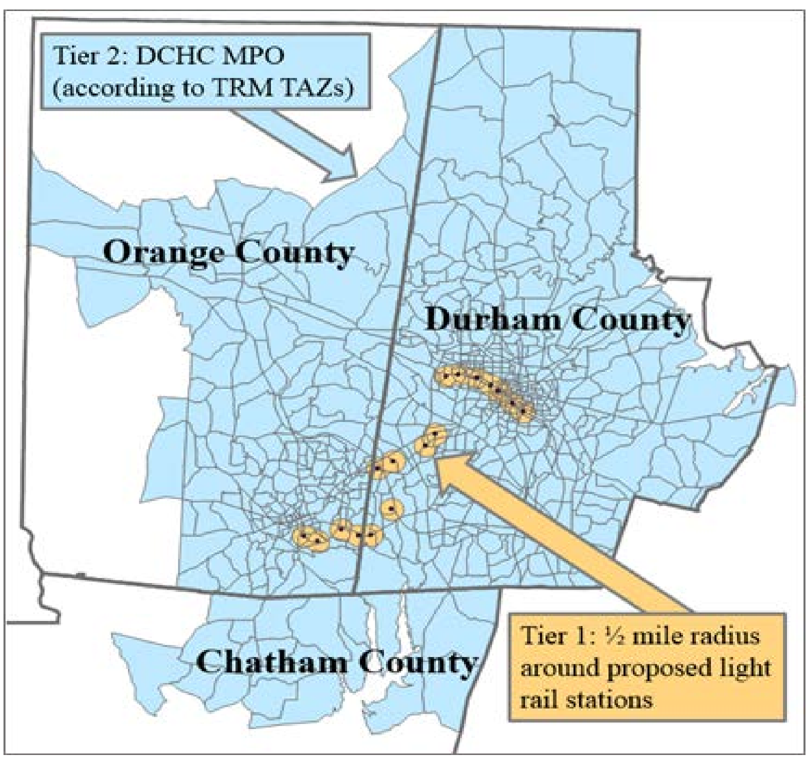


FIGURE A-3 GEOGRAPHIC BOUNDARIES OF THE MODEL

Note: in Figure A-3, TRM TAZs = Triangle Regional Model Traffic Analysis Zones

SHADOW VARIABLES AND CAUSES/USES TREES

Variables between angle brackets (<variable name>) are shadow variables, or copies of variables that are calculated in a separate view. Many of the variables in Figure A-2 are shadow variables, in addition to being auxiliaries, constants, box variables, or flows. These variables are included in a specific view because they interact with other variables in the view. Because they are calculated in another view, however, it is not immediately apparent what variables affect them. Similarly, the use of shadow variables can make it difficult to discern whether a variable in a given view influences variables in other views.

Vensim provides tools to identify which upstream variables affect a particular variable or which downstream variables are affected by it: the Causes Tree and the Uses Tree. To use these tools, click on the variable and then click on the Causes Tree or Uses Tree button, labeled as 3 in Figure A-2.

Figure A-4 and Figure A-5 show how these tools can be used to trace causes or uses up to two steps away from the variable. This is especially useful for looking at shadow variables, which can have relationships that span multiple views.

EQUATIONS AND CONSTANTS

Each variable in Vensim is defined by either an equation or a predetermined value, which may vary with time. To see how a variable is defined, first right-click on the variable name to open the variable options window, shown in Figure A-6. Clicking the equation button will open the equations window which will show either a single value, a lookup range which varies with time, an equation based on other variables, or an equation based on a built-in function. Examples of each of these types of variable definitions are provided in Figure A-7 through Figure A-11. The equations window can also be opened by clicking the equations tool, labeled as 4 in Figure A-2, and then clicking on a variable.

Lookup variables such as “county property tax rate” mentioned below, are input as tables but can be viewed as a graph for easier editing. Clicking on the “As Graph” button in Figure A-8 (circled in red) will launch the window shown in Figure A-9. The user can enter values in the Input (x axis) and Output (y axis) boxes on the left side of the window and the model will extrapolate values in a straight line between the specified points. Users can also click and drag points on the graph to change their values. When done editing, click OK to return to the main equation window.

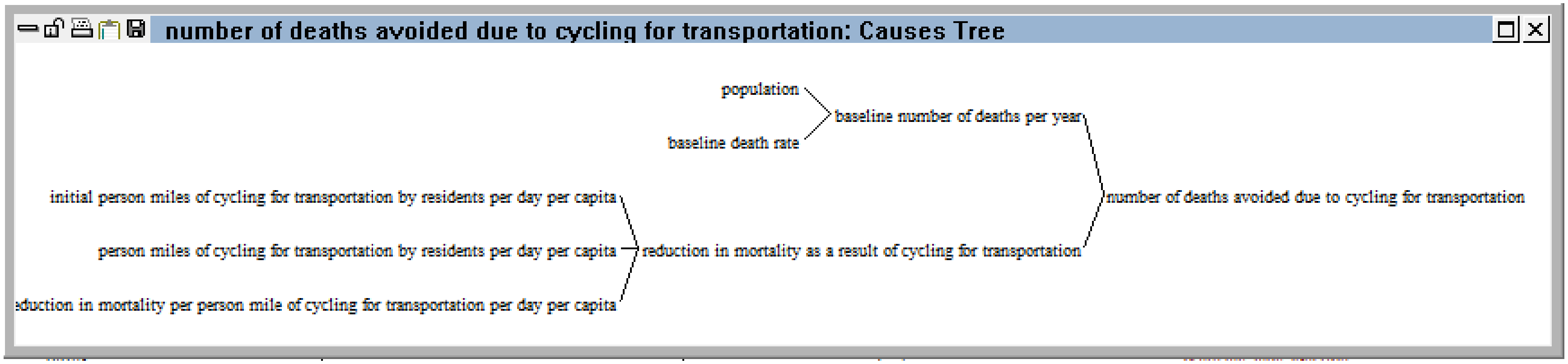


FIGURE A-4. CAUSES TREE

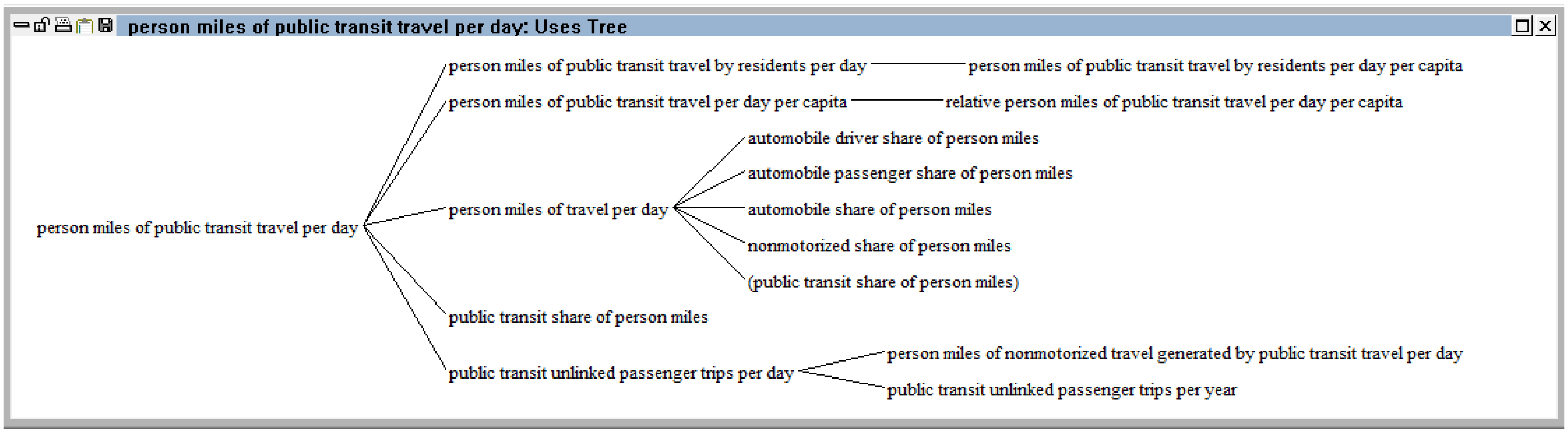


FIGURE A-5. USES TREE

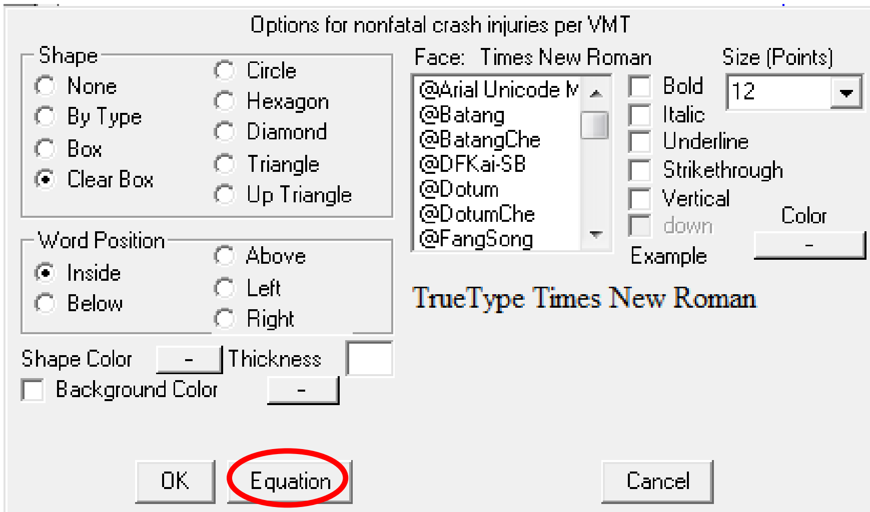


FIGURE A-6. VARIABLE OPTIONS WINDOW

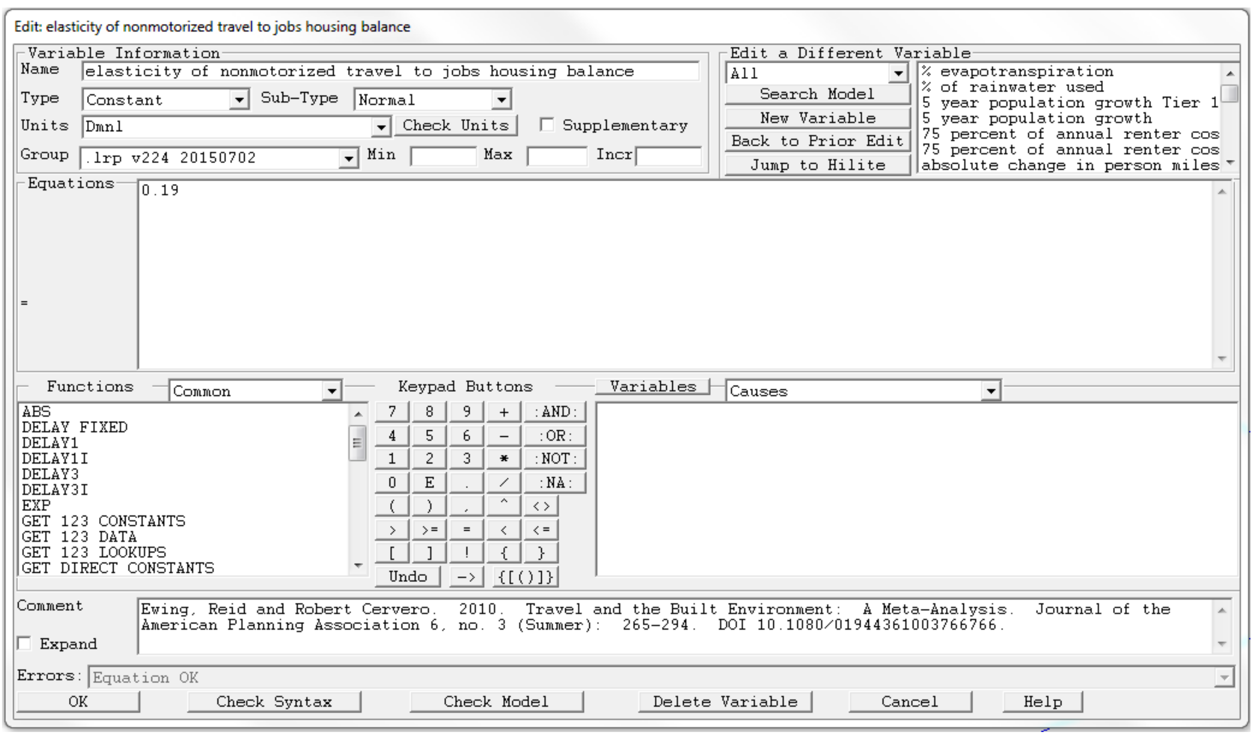


FIGURE A-7. SINGLE VALUE VARIABLE EXAMPLE

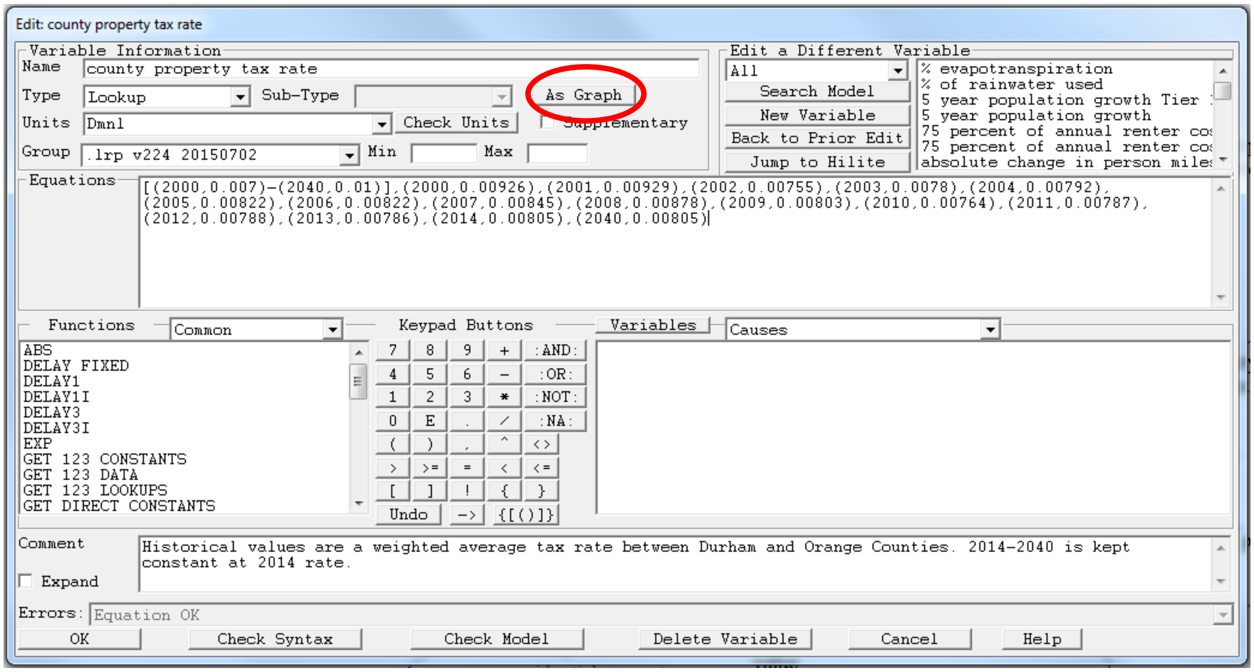


FIGURE A-8. TIME-BASED VARIABLE EXAMPLE

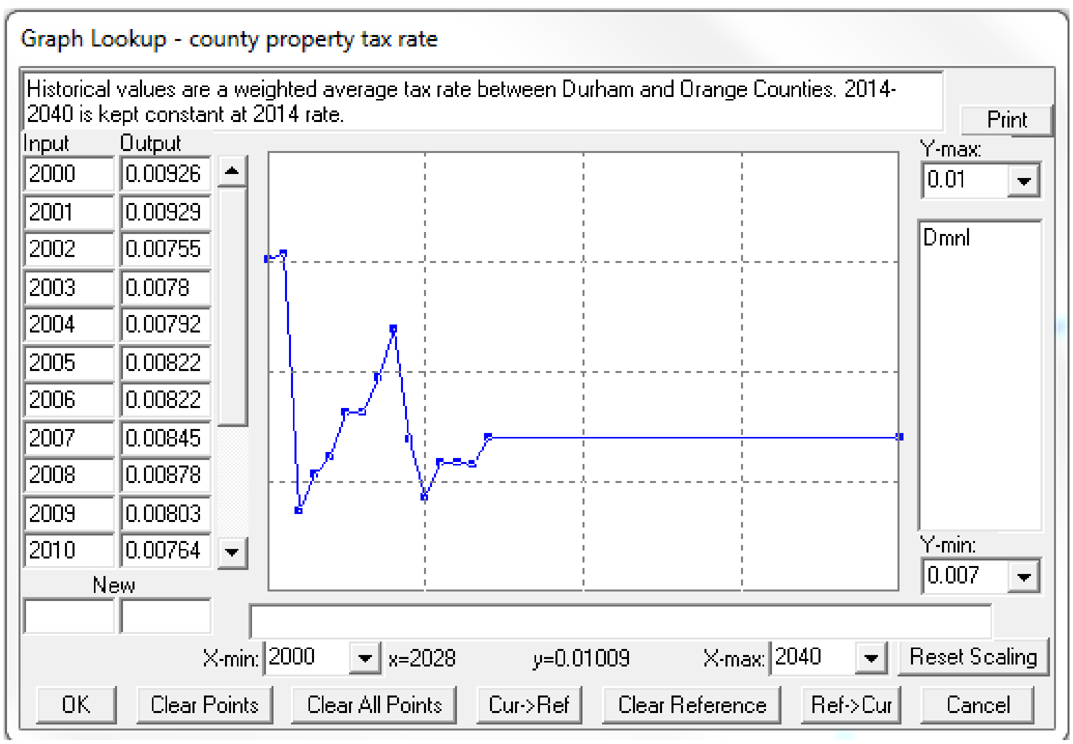


FIGURE A-9. TIME-BASED VARIABLE EXAMPLE - VIEWED AS GRAPH

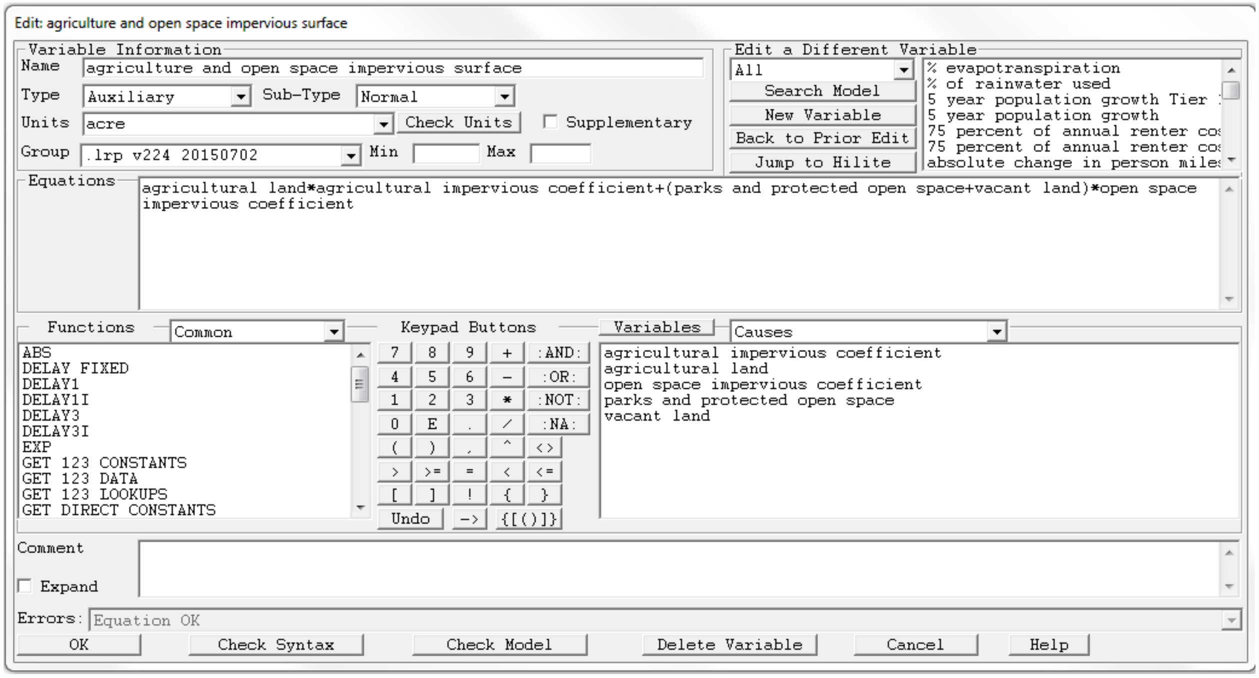


FIGURE A-10. CALCULATED VARIABLE EXAMPLE FUNCTION

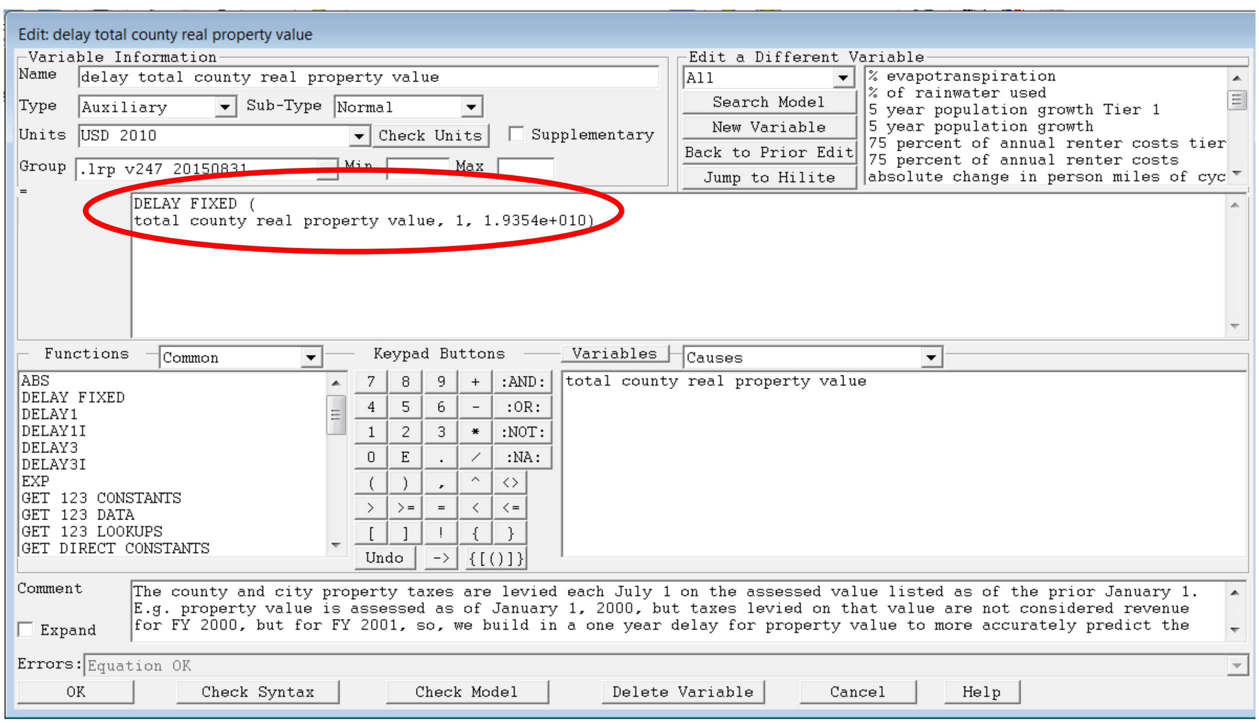


FIGURE A-11. VARIABLE USING A BUILT-IN FUNCTION

Some variables in the model use Vensim's built-in functions. Figure A-11 shows an example using the Delay Fixed function (circled in red), which is one of a variety of built-in functions. Here the function delays "total county real property value" by one year, after an initial value of 19B USD 2010.

RUNNING A SIMULATION

When the D-O LRP model is first opened, all variables are initialized to the values that define the Business As Usual (BAU) scenario. Clicking on the "Simulate" button (to the right of 5 in Figure A-2) will run this scenario. Once variables in the model are changed to define a new scenario, enter the scenario's name in the scenario name window (to the left of 5 in Figure A-2) and click the "Simulate" button. Since multiple scenarios can be stored and viewed at one time, it is useful to use a descriptive name so that they can be easily distinguished.

VIEWING RESULTS

Once a simulation has been run, results can be viewed for any variable in the model. Results for all loaded simulations can be viewed as either tables or graphs. Though Vensim provides several graphing options, this guide only describes line graphs, which display variables as a time series.

Graphs and Tables

To view a graph, first click on the desired variable and then click on the graph button (see 6 in Figure A-2). To view a table, first click on the desired variable and then click on the table button (see 7 in Figure A-2). Figure A-12 and Figure A-13 show a sample graph and table, respectively. The scenario run most recently will appear in blue. Results are shown for the Light Rail scenario (blue line and text) and the BAU scenario (red line and text). The red circle indicates the export feature that will copy the graph or table to the user's clipboard, which can then be pasted into another program on the user's computer, such as Word or Excel.

For graphs, the user can zoom in to see more detail. By holding down the shift key while clicking and dragging to the side a new time range can be set. Similarly, by holding down the control key while clicking and dragging up or down a new vertical range can be set. The selected ranges will appear once you close and reopen the graph. To refresh just the vertical range of the graph, either click the graph button again (see 6 in Figure A-2) or close and reopen the graph. The Time Axis tab in the Control Panel window (see Figure A-14) can be used to alter the time range and to reset both the time and vertical axes of output graphs. The "Reset to Full Range" button, circled in red, will make all graphs display the original full range of values.

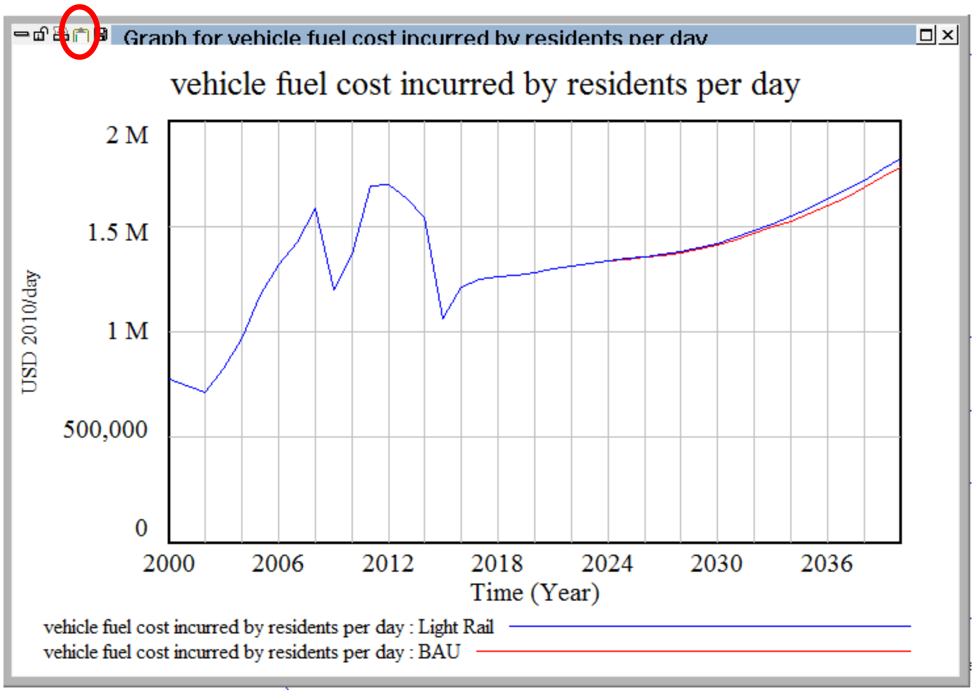
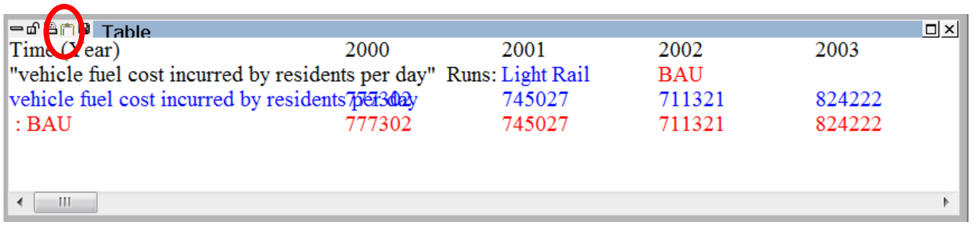


FIGURE A-12. SAMPLE GRAPH



Table

Time (Year)	2000	2001	2002	2003
"vehicle fuel cost incurred by residents per day" Runs:		Light Rail	BAU	
vehicle fuel cost incurred by residents per day	777302	745027	711321	824222
: BAU	777302	745027	711321	824222

FIGURE A-13. SAMPLE TABLE

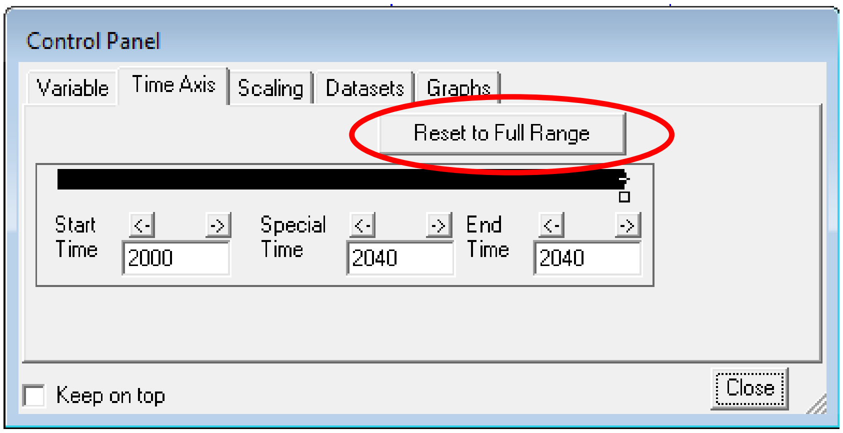
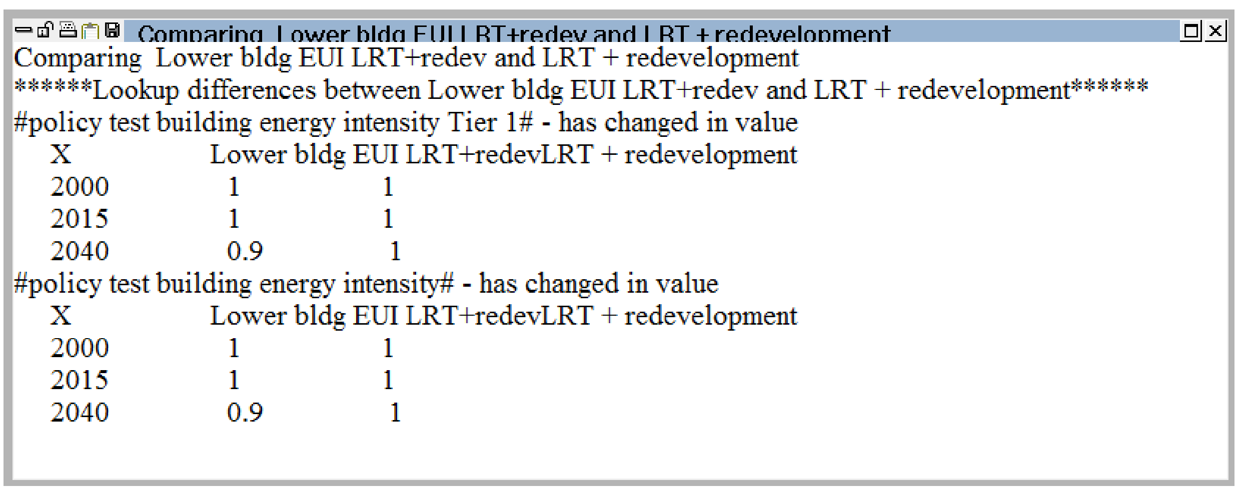


FIGURE A-14. CONTROL PANEL WINDOW – TIME AXIS TAB

Comparing Multiple Simulations

If a user has run multiple simulations, the Runs Compare tool can help track how the inputs differ between the simulations (see 8 in Figure A-2). Figure A-15 displays an example scenario with a 10% linear reduction in building energy use intensity between 2015 and 2040. The tool compares this scenario to the Light Rail + Redevelopment scenario and shows which inputs were changed when the scenario was run.



Comparing Lower bldg EUI LRT+redev and LRT + redevelopment
******Lookup differences between Lower bldg EUI LRT+redev and LRT + redevelopment******
#policy test building energy intensity Tier 1# - has changed in value

X	Lower bldg EUI LRT+redev	LRT + redevelopment
2000	1	1
2015	1	1
2040	0.9	1

#policy test building energy intensity# - has changed in value

X	Lower bldg EUI LRT+redev	LRT + redevelopment
2000	1	1
2015	1	1
2040	0.9	1

FIGURE A-15 EXAMPLE OUTPUT OF RUNS COMPARE TOOL

Users can create and save multiple D-O LRP SD model simulations in Vensim and select which of them will be included in graphs and tables. Clicking on the Control Panel button (see 9 in Figure A-2) will open the Control Panel window, which has multiple tabs; the Datasets tab will list all loaded simulations, as shown in Figure A-16. Clicking on one of the loaded simulations (red circle) will change the order of these simulations, listing the selected simulation first. The simulation listed first will appear in graphs and tables as a blue line or text. The second simulation will appear as a red line or text; and other simulations will also have standardized colors. Simulations can be moved between the "Available info" and "Loaded info" windows, and those in the "Loaded info" window will be displayed in graphs and tables. A simulation file must be located in the same folder as the model, in order to appear under "Available info."

If another simulation is required, it can be found by selecting "Load From …," which prompts a pop-up window that serves as a browser across local folders.

The last four files shown under "Available info" in Figure A-16 are actually historical datasets and projections from models other than the D-O LRP SD Model, rather than being simulations (Excel files and other datasets can be converted into Vensim simulation files (.vdf) using Vensim DSS). When any of these files are moved to "Loaded info," their numbers may be compared with model runs--especially the BAU scenario, which was calibrated to this data. Tier1 DATA and Tier2 DATA contain historical and projected data for variables in all major sectors of the model; their transportation data (VMT, congestion, road-building, public transit, nonmotorized travel) come from the Triangle Regional Model's Existing + Committed scenario (no road building after 2017 and no light rail). In contrast, Tier1RoadMTP and Tier2RoadMTP only contain data for transportation-related variables, which come from the "Preferred" scenario that the TRM generated for the DCHC MPO Metropolitan Transportation Plan. The MTP numbers assume that the light rail line will be built, unlike the BAU scenario, but they also assume the same road-building projections as the BAU. Users interested in comparing transportation variables to local data should load both the DATA and RoadMTP datasets, as no single dataset matches BAU assumptions regarding both road construction and light rail construction. Scenarios analyzed by the D-O LRP SD modeling team are described further in Chapter 4.

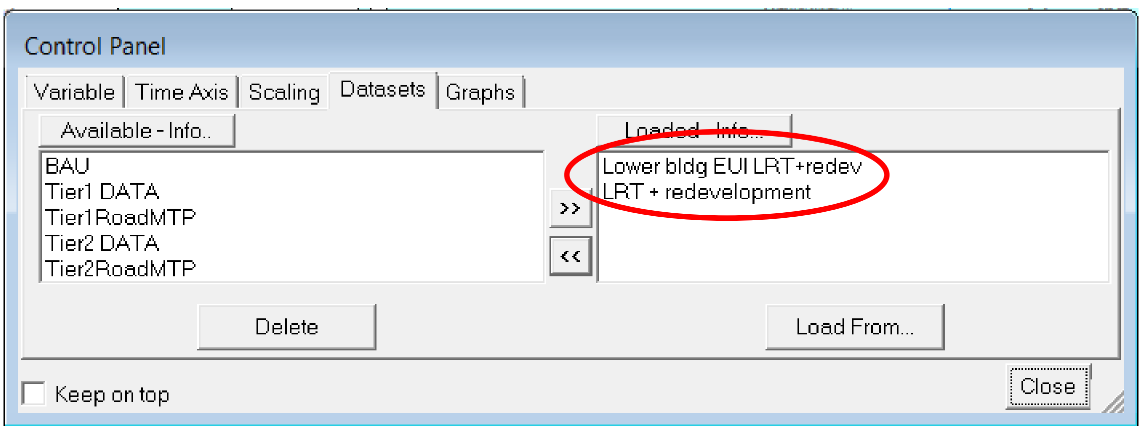


FIGURE A-16. CONTROL PANEL WINDOW - DATASETS TAB

Loops tool

The Loops tool shows the number of feedback loops that contain a selected variable (see 10 in Figure A-2). Figure A-17 displays some of the 2822 loops that population is involved in.

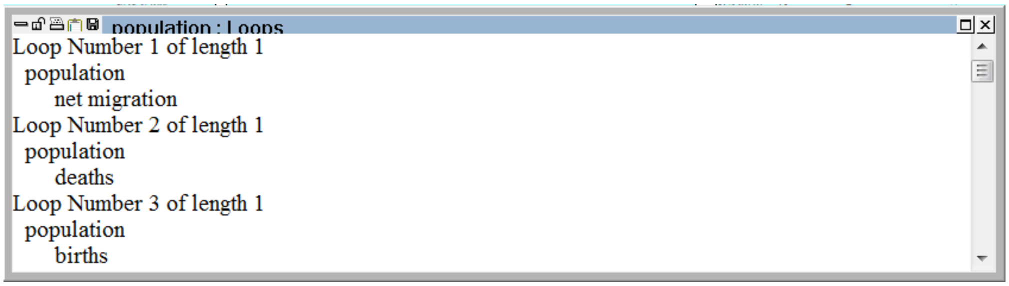


FIGURE A-17. LOOPS TOOL

Causes Strip

The Causes Strip tool shows the behavior of variables that directly affect a selected variable (see 11 in Figure A-2). This is a useful way to determine why a variable behaves the way it does. Figure A-18 shows the Causes Strip for "VMT Tier 1." Three scenarios are shown (blue, red, and green lines), and the two variables that directly affect "VMT Tier 1" are "through traffic VMT Tier 1" and "VMT of trips starting or ending in area Tier 1."

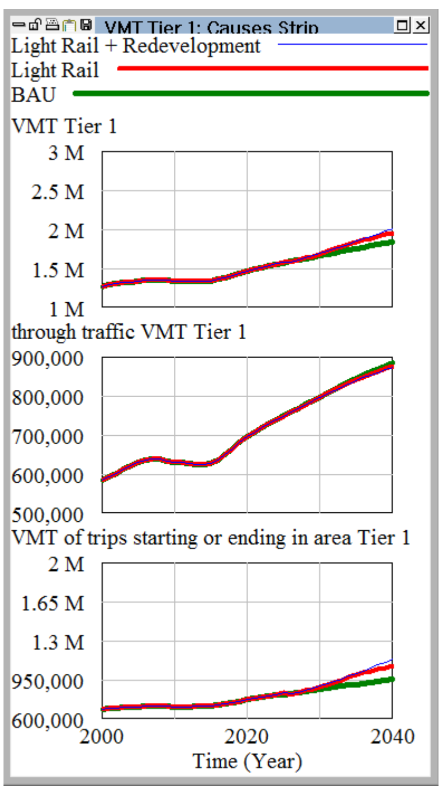


FIGURE A-18. CAUSES STRIP TOOL

DO-LRP SYSTEM DYNAMICS MODEL VIEWS

OVERVIEW

The DO-LRP SD model has separate views for different interventions, indicators, and sectors. Chapter 3 and Appendices B-C present more details about the sectors and the relationships among their variables. In addition to the sector views described above, the model includes four customized "dashboard" views that allow users to easily access the main features of the model.

INTERVENTIONS AND INDICATORS

The main "dashboard" view shown in Figure A-17 is a collection of the main input and output variables related to policy interventions and model assumptions. This dashboard makes it easier for the user to view a graph for each variable or change the value of input variables to define new scenarios. Recall that variables can be edited by right-clicking the variable and then clicking the Equation button in the Options window. The most significant output variables are organized by sector to allow the user to review scenario outcomes more easily. There are four main sections in this view (the numbers below correspond to the green circled numbers in Figure A-2):

1) **Policy switches**: These can be viewed using the equation editor to quickly review which policy interventions have been activated. In particular, "Main policy switch" is a master switch used to select among preset scenarios. Policy variables found in this section and elsewhere in the model are detailed in Table A-1 below.

2) **Key indicators**: All of the main outputs of the model are contained in this section, organized by sector. These can be viewed as tables or graphs as described in the Viewing Results section above. Key indicators colored blue summarize the behavior of a particular sector. A full list of indicator variables, together with the sustainability dimension of each variable, is presented in Table A-2 below.

3) **Redevelopment switches**: These can be viewed to quickly review or change model behavior associated with land redevelopment.

4) **Extreme value test switches**: used in model validation, these set key variables such as GRP or population to extreme values.

In addition to the main "dashboard" view, the model includes the "dashboard – relative indicators" view, the "dashboard – relative indicators Tier 1 view," and the "dashboard – intensity indicators" view. The "dashboard - relative indicators" view shown in Figure A-18 visualizes a selection of key Tier 2 indicators, relative to their value in the year 2000. The view contains a custom graph that displays results for the most recently-run scenario. The box to the right of the graph lists the relative values of key indicators in the year 2040. These values show whether a given indicator has grown faster or slower compared to other indicators. The "dashboard - relative indicators Tier 1" view (not shown) reproduces the "dashboard - relative indicators" view for Tier 1. The "dashboard – intensity indicators" view (not shown) presents some key intensities such as GRP per capita and CO_2 emissions per GRP.

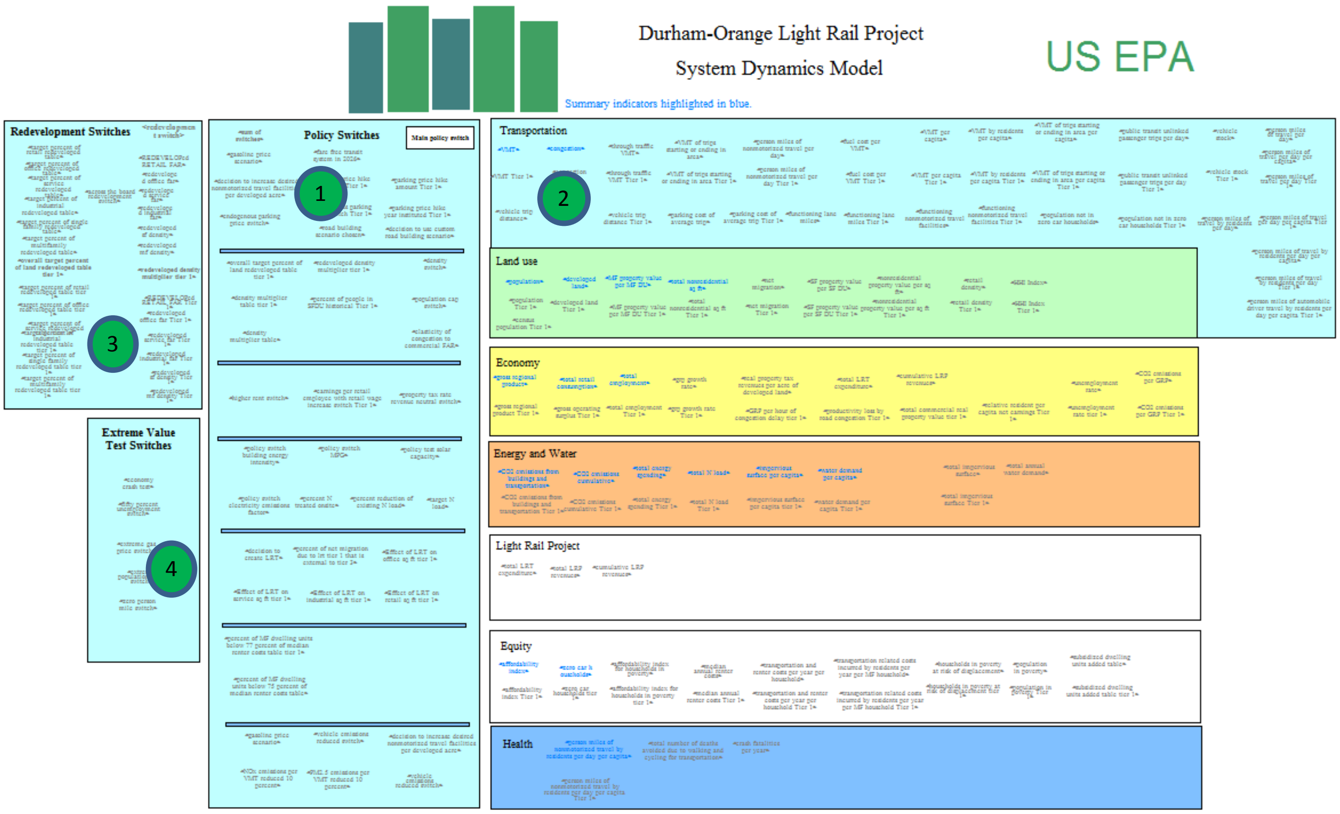
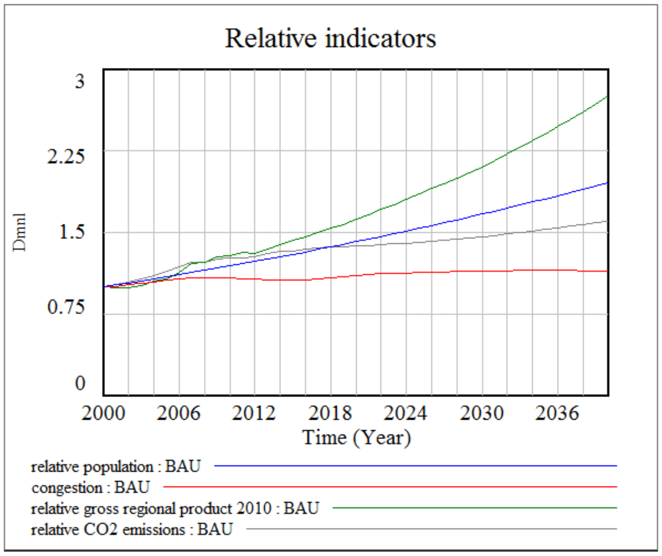


FIGURE A-17. DASHBOARD VIEW



Time (Year)	2040
relative population	1.958
congestion	1.144
relative gross regional product 2010	2.756
relative CO2 emissions	1.606

FIGURE A-18. DASHBOARD – RELATIVE INDICATORS VIEW

TABLE A-1. POLICY VARIABLES

VARIABLE NAME	TIER	NOTES
MAIN POLICY SCENARIOS		
Main policy switch	Both	0 = BAU (with MTP-prescribed amounts of road building and no light rail) 1 = Light Rail 2 = Light Rail + Redevelopment 3+ = other, less-featured scenarios
LAND USE		
Overall target percent of land redeveloped table tier 1	Tier 1 only	The portion of developed land that will be redeveloped by 2040 (e.g. 0.20 = 20%). Must be used in conjunction with a Main Policy switch setting that includes Redevelopment.
Redeveloped density multiplier Tier 1	Tier 1 only	The increase in initial density applied to redeveloped land (e.g. 3 = 200% increase)
Density switch	Both	0 = default, 1 = density multiplier table applied to new development. Must be used in conjunction with a Main Policy switch setting that includes Density.
Density multiplier table tier 1	Tier 1 only	The increase in initial density applied to newly developed land (e.g. 3 = 200% increase)

VARIABLE NAME	TIER	NOTES
More multifamily households Tier 1 switch	Tier 1 only	0=default, 1=More Multifamily Households scenario with steady decline in the percent of the household population that lives in single-family dwelling units.
Percent of people in SFDU table historical Tier 1	Tier 1 only	Allows the percent of the household population that lives in single-family dwelling units to be adjusted as desired.
TRANSPORTATION		
Main policy switch	Both	0, 1, 2, 4, 8, 9, 10, 12 = MTP-prescribed amounts of road building (otherwise, differentiated according to decisions about the light rail, redevelopment, and density) 3, 5, 6, 7, 11, 13, 14, 15 = no road building after 2017 (otherwise, differentiated according to decisions about the light rail, redevelopment, and density)
Gasoline price scenario	Both	0 = default 1 = increase in price of gasoline effective 2016
Fare free transit system in 2026	Both	0 = default fare price 1 = all public transit becomes fare-free in 2026
Decision to increase desired nonmotorized travel facilities per developed acre	Both	0 = default 1 = desired nonmotorized travel facilities per developed acre doubles in 2020, leading to increased construction of nonmotorized travel facilities
Parking price hike instituted Tier 1	Tier 1 (primary), Tier 2 (to the extent that Tier 1 is part of Tier 2)	0 = default 1 = cost of parking within Tier 1 increases by $4.00 in 2020
ECONOMY		
Higher rent switch	Both	0 = gross operating surplus per sq ft BAU 1 = gross operating surplus per sq ft REDUCED ($5 less per sq ft than BAU, starting in 2025) Gross operating surplus per sq ft represents how profitable local companies are, per unit building area.
Earnings per retail employee with retail wage increase switch Tier 1	Tier 1 only	0 = earnings per retail employee BAU Tier 1 1 = earnings per retail employee with retail wage increase Tier 1 ($1 increase in the NOMINAL hourly wage in 2016 and an additional $.25 for each year thereafter)

VARIABLE NAME	TIER	NOTES
Property tax rate revenue neutral switch	Both	0 = county/city property tax rate BAU 1 = county/city property tax rate revenue neutral 2040
EQUITY		
Percent of MF dwelling units below 77 percent of median renter costs table tier 1	Tier 1 only	The percent of multifamily dwelling units that are organically affordable (In 2010 dollars, 77% of the median housing costs equaled about 40% of the poverty threshold – the assumed maximum households in poverty could spend on housing).
ENERGY		
Policy switch building energy intensity	Tier 2 only	0 = no effect on building energy intensity trend 1 = 10% decrease in building energy intensity trend between 2015-2040
Policy switch MPG	Both	0 = no effect on MPG trend 1 = 10% increase in MPG trend between 2015-2040
Policy test solar capacity	Tier 2 only	A multiplier on the desired future solar electric capacity. 1 = no change. 2 = double, 3 = triple, etc.
Policy switch electricity emissions factor	Both	0 = no effect on electricity CO_2 emissions factor 1 = 23% reduction in electricity CO_2 emissions factor between 2022-2030 (approximates North Carolina goal within Clean Power Plan)
WATER		
Percent N treated onsite	Tier 1 only	Percent reduction in stormwater runoff N from post-2015 development due to onsite stormwater treatment
Percent reduction of existing N load	Tier 1 only	Percent reduction in stormwater runoff N from land developed before 2015, due to onsite stormwater treatment (such as retrofits).
Target N load	Tier 1 only	Desired stormwater runoff N (lb/acre/year) after onsite or offsite stormwater treatment. Offsite could include purchasing mitigation credits.
HEALTH		
Gasoline price scenario	Both	0 = default 1 = increase in price of gasoline effective 2016 Tests how gasoline price affects walking and cycling

VARIABLE NAME	TIER	NOTES
Vehicle emissions reduced switch	Both	0 = no effect on PM2.5 or NOx emissions rate 1 = 10 percent reduction in PM2.5 and NOx emission rate in new vehicles, between model year 2020 and 2040
NOx emissions per VMT with reductions	Both	Tests reductions in passenger vehicle NOx emissions between model year 2020 and 2040
PM2.5 emissions per VMT with reductions	Both	Tests reductions in passenger vehicle PM2.5 emissions between model year 2020 and 2040

TABLE A-2. KEY INDICATORS

VARIABLE NAME	TIER	SUSTAINABILITY DIMENSION(S)
LAND USE		
Population	Both	Economy, Society
Net migration	Both	Society
Developed land	Both	Economy, Environment
SF property value per SF DU	Both	Economy, Society
MF property value per MF DU	Both	Economy, Society
Nonresidential property value per sq ft	Both	Economy
HHI index	Both	Economy, Society
HHI index for nonresidential sq ft	Both	Economy, Society
Total nonresidential sq ft	Both	Economy
Retail density	Both	Economy
Total impervious surface	Both	Environment
TRANSPORTATION		
VMT	Both	Economy, Environment
VMT per capita	Both	Economy, Environment
Congestion	Both	Economy, Environment
MPG with congestion	Both	Economy, Environment
Person miles of nonmotorized travel per day	Both	Environment, Society
Public transit unlinked passenger trips per day	Both	Economy, Society, Environment
Vehicle stock	Both	Economy
Vehicle trip distance	Both	Economy
Vehicle trip duration	Tier 2 only	Economy
Parking cost of average trip	Both	Economy
Functioning lane miles	Both	Economy
Functioning nonmotorized travel facilities	Both	Economy
Population not in zero car households	Both	Economy, Society
ENERGY		

VARIABLE NAME	TIER	SUSTAINABILITY DIMENSION(S)
CO_2 emissions from buildings and transportation	Both	Environment
CO_2 emissions from buildings	Both	Environment
CO_2 emissions from passenger vehicles	Both	Environment
SF energy intensity	Both	Environment
MF energy intensity	Both	Environment
Commercial energy intensity	Both	Environment
Industrial energy intensity	Both	Environment
$PM_{2.5}$ vehicle emissions tons	Both	Environment
NO_x vehicle emissions tons	Both	Environment
Solar capacity	Tier 2 only	Environment
LFG to energy capacity	Tier 2 only	Environment
Total energy spending	Both	Environment, Economy
ECONOMY		
Gross regional product	Both	Economy
GRP growth rate	Both	Economy
Real property tax revenues per acre of developed land	Both	Economy
Total retail consumption	Both	Economy
Cumulative LRT revenues	Both	Economy
Total LRT expenditure	Both	Economy
Total employment	Both	Economy
Unemployment rate	Both	Economy
EQUITY		
Affordability index	Both	Society
Affordability index for households in poverty	Both	Society
Median annual renter costs	Both	Society, Economy
Transportation related costs incurred by residents per year per MF household	Both	Society, Economy
Transportation and renter costs per year per household	Both	Society, Economy
Population in poverty	Both	Society, Economy
Households in poverty at risk of displacement	Both	Society
Zero car households	Both	Society
WATER		
Average precipitation	Tier 2 only	Environment
Total N load, Total P load	Both	Environment
Total N load kg per ha	Both	Environment
Total volume of runoff	Both	Environment
Event mean concentration N, P (disaggregated by land use: nonresidential, SF residential, MF residential, etc.)	Both	Environment

VARIABLE NAME	TIER	SUSTAINABILITY DIMENSION(S)
Total water demand	Both	Environment
Residential water use, Nonresidential water use, Nonrevenue water use	Both	Environment
SF water use per household	Both	Environment
MF water use per household	Both	Environment
HEALTH		
Total number of deaths avoided due to walking and cycling for transportation	Both	Society
Delta premature mortality PM2.5 + NOx Krewski Lepeule	Both	Society
Crash fatalities per year	Both	Society

Appendix B: Detailed Data Documentation

Please see the accompanying spreadsheet (separate file) for detailed documentation of the model's data and relationships. The three tabs in this spreadsheet include:

- **Calibrated Variables**: contains information on variables in each sector that were calibrated to external data sources, including historical data and projections.

- **Exogenous Inputs**: contains information on variables in each sector that were drawn from exogenous sources.

- **Equations from Literature**: contains information on equations used in the model to calculate selected variables, in cases where the equations themselves (rather than parameter values or calibration targets) were drawn from external sources.

For each variable in the Calibrated Variables and Exogenous Inputs tabs, the appendix provides information on the variable's units, the data source(s) used for initial, historical, and/or projected values, and notes on subcategories, data processing, and calibration. For each equation in the Equations from Literature tab, the appendix provides information on the variable calculated, the variable's units, the equation itself, notes on the calculation process, and the data source from which the equation was drawn.

Appendix C: Model Input Characterization Tables

MODEL INPUT CHARACTERIZATION AND ASSESSMENT

To assist users of the D-O LRP SD Model, the project team assessed the quality of key model inputs, both data sources and any methods used to manipulate them for use in the model. The results of this assessment are an indicator of the confidence level in the model input (high, medium or low) and a description of the uncertainties associated with it. Following the Quality Assurance Project Plan, the process for determining the confidence level in an input are based on applying a weight of evidence approach to the following criteria:

- Is the input based on information from one or more externally peer reviewed documents?
- Is there agreement in the literature or within the relevant community of practitioners about the underlying data or method for the input? Or are there conflicting viewpoints?
- Do the characteristics of the input make it suitable for use in the context of the Durham-Chapel Hill-Carrboro MPO? For example, is the input based on data from either the DCHC MPO or another area with similar characteristics; or is it based on data from another area that is highly site-specific?
- If the model input is based on manipulation of a data set, is the method used in developing the input an established and widely applied approach? If the method applies equations developed from external models, are those equations applied to local data in an appropriate manner?

The assessment results are presented in Tables C-1 through C-7. For each input, we provide the source, how the input is used in the model, the rationale for selecting the input, and the confidence level in the input, along with a description of uncertainties associated with it. If the model input is used for calibration purposes, that fact is noted in the “Model Input” column.

This information is made available to users of the model so that they can evaluate the relative confidence level in model results. For example, for any output indicator produced from a scenario run, it is possible to determine how many of the model inputs that are causally linked to it are classified as having high, medium or low confidence levels. In addition, the assessment results can be used to help target specific model inputs for sensitivity analyses that can help determine the extent to which uncertainty in their values can affect the model results.

TABLE C-1. MODEL INPUT CHARACTERIZATION FOR THE LAND USE SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Acres of developed, vacant, agricultural, and protected open space land in 2000	TJCOG. 2014. "CommunityViz 2 (CV2) Parcel Geodatabase for Place Type & Development Status Editing." Place type and development status of parcels calculated for the year 2000 by back-casting 2013 per-capita values.	Initial values for acres by category, which affects developed land.	Created in part to inform the LRP process; best inventory of current land use available for entire study area.	MEDIUM-HIGH: Each parcel was reviewed by local planning staff, but values do not quite match local comprehensive plan estimates, at least in Durham for which these were available.
Division of developed commercial acres by category (retail, office, service, and industrial) and residential acres by category(single-family and multifamily)	TJCOG. 2013. "Imagine 2040: The Triangle Region Scenario Planning Initiative Final Summary Document." Used in the Imagine 2040 CommunityViz model.	Initial values for acres of developed land by category. Also used to calculate floor area ratios (FAR) by land use type, and residential density per acre, which affect the rate of land development.	Created in part to inform the LRP process; best inventory of current land use available for entire study area.	MEDIUM-LOW: Each parcel was reviewed by local planning staff, but the dataset was still in editing at the time of analysis, and the land use tables are broad estimates for each jurisdiction's zoning classifications, and therefore do not necessarily reflect use.
Developed land estimates in 2040 (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario and travel demand result shapefiles." We developed two estimates of total developed land based on data from TRMv5: 1) projected jobs and dwelling units multiplied by average space needed per unit of each, 2) acreage of all parcels with either employment or dwelling units allocated in 2040.	Used to calibrate land development to within reasonable range, which affects impervious surfaces and non-motorized facilities.	Created in part to inform this LRP process; best inventory of current land use available for entire study area.	LOW: Development status was never assigned for future projections in Imagine 2040, so we had to derive estimates consistent with Imagine 2040 projections based on allocations that weren't meant to estimate land development.
Total impervious surface (calibration)	US EPA. 2013. "EnviroAtlas."	Affects loadings of phosphorus and nitrogen from storm water runoff.	Provided the broadest coverage of the study area; consistent with impervious surface data for the City of Durham shared by the Durham City/County Planning Department, which excluded impervious surfaces from roads.	MEDIUM: Input comes from an authoritative source for land cover data, but it does not cover the entire study area and was only available for one year (2010).

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Population, households, and housing units (calibration)	ESRI Community Analyst. 2014. "Census Data 2000, ACS 1-yr and 5-yr Estimates 2005-2013, and ESRI Demographic Projections for 2014 and 2019"	Initial values and calibration for population, drivers of demand for residential land.	Community Analyst uses Census and ACS data, and the clipping method weights it by block level population data, making it more accurate than personally downloading Census data and performing area-based weighting in excel.	HIGH: The U.S. Census Bureau is the authoritative source for demographic data and the Community Analyst clipping method more accurate than by hand.
Birth, death, and migration rates	NC Department of Health and Human Services Vital Statistics Database. 2015. "Resident Live Births, Deaths, and Estimated Net Migration 2000-2014." NC State Data Center, Accessed from Log Into North Carolina (LINC) (Durham/Orange County average)	Average death rate is held constant throughout the model period; the average historical birth rate trend is extended into the future.	Most geographically specific data source with longest time series.	MEDIUM: the population levels simulated by using historical birth, death, and migration rates did not match historical population trends, so additional calibration was applied to birth and migration rates.
Proportion of dwelling units that are single-family	U.S. Census Bureau. 2000. "Census 2000, Summary File 3." And ESRI Community Analyst. 2014. "Census Data 2000, ACS 1-yr and 5-yr Estimates 2005-2013, and ESRI Demographic Projections for 2014 and 2019."	Used, along with household sizes to calculate the percent of people in single-family dwelling units, which affects residential land usage and energy efficiency.	Only source found; property database doesn't include number of units in multifamily structures.	MEDIUM: The U.S. Census Bureau is the authoritative source for this input, but the data were only available for two years, so a consistent trend could not be established.
Single-family and multifamily household sizes	Hodges-Copple, John. 2012. "FINAL 2040 Population Forecast by County for CommViz –EPA,"(Year 2010, based on ACS 2010 data by county) .	Used, along with the percent of people in single-family dwelling units, to calculate demand for single-family and multifamily dwelling units based on population.	Only sources available for the study area.	HIGH for Tier 2; MEDIUM for Tier 1 as there are no good benchmarks to check the distribution except estimates of owner-occupied and renter-occupied household sizes.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Retail, industrial, office, and service building square feet (calibration)	Durham County Tax Administration. 2000-2014. Durham County Tax Administration Real Property Database, Orange County Tax Administration. 2014. Orange County Parcel Database, Chatham County Tax Administration Office. 2014. Chatham County Tax Parcel Database	Initial year 2000 values and calibration. Also used to calculate employee space ratios.	Most detailed source; used by Tax Office and Planning departments.	MEDIUM: According to Durham Planning Department representative Laura Woods, the data may underestimate actual values; there are some blank properties in database, as well as duplicate records and inaccuracies.
Effect of developed portion of residential land on migration table	Vina-Arias, Laura Beatriz. 2013. "Understanding Patterns of Growth at Kendall Square Using a System Dynamics Approach."	Used in Tier 2 to relate land supply to immigration.	Only source found to address the relationship between land development and immigration; used elsewhere in a system dynamics model.	LOW: First, the effect table was originally used to relate land supply to residential construction rather than migration - showing the attractiveness of construction increases gradually until land becomes very scarce, when it gradually decreases (sharper than increase). Second, the context is very different – an urban core, rather than a suburban metro area. Finally, the strength of the relationship had to be decreased during the calibration process.
Effect of unemployment on net migration Tier 1	N/A	Used in Tier 1 to relate the unemployment rate to immigration.	No literature found quantifying the topic.	LOW: No source available, calibrated to historical data on population.
Average housing lifetime	US EPA. 2013. Analysis of the Life Cycle Impacts and Potential for Avoided Impacts Associated with Single-Family Homes. Page 4.	Used as in input to the calculation of single family dwelling units.	Authoritative source that reviewed the research on the topic to provide a reasonable range.	MEDIUM: The meta-analysis provided a wide range of estimates which were only given on a national scale. We chose the lowest estimate.
Percent second homes	Economic and Strategic Research. 2014. "Second homes: Recovery post financial crisis."	Used as an input to the calculation of single-family dwelling units.	Authoritative source that reviewed the research on the topic to provide a reasonable range.	MEDIUM: Value is an average for 1998-2014 for the nation and includes both single-family and multifamily homes with a mortgage, while we used the value only for single-family homes.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Residential impervious surface coefficients	NCDENR. 2011. *Jordan Lake Stormwater Load Accounting Tool User's Manual*. See Table 5 on page 20.	Used to calculate impervious surface due to residential land use.	This source relates residential density to impervious surface cover based on GIS land cover data from several counties in MD, VA, and PA for use in the Triangle region of North Carolina. More representative of the local context than source used for nonresidential and road impervious surface (Washburn et al, 2010).	MEDIUM: The most comprehensive local source, but values are averages for broad categories of land use.
Nonresidential and road impervious surface coefficients	Washburn, Barbara, Katie Yancey, and Jonathan Mendoza. 2010. User's Guide for the California Impervious Surface Coefficients. See pages 20-17.	Used to calculate impervious surface due to land use of nonresidential uses and roads.	Cited in the Imagine 2040 model documentation; best available source for coefficients for nonresidential uses.	MEDIUM: Used in local regional planning efforts, but based upon California land uses, which may not be representative of land uses in the study area.

TABLE C-2. MODEL INPUT CHARACTERIZATION FOR THE TRANSPORTATION SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
(1) Annual change in desired vehicle ownership per person not in a zero-car household that is independent of explicit inputs (i.e., not attributed to any specific cause) and (2) Elasticity of desired vehicle ownership per person not in a zero-car household to per-capita income	International Energy Agency and World Business Council for Sustainable Development. 2004. "IEA/SMP Transportation Model." Spreadsheet model discussed in: Fulton, Lew, and G. Eads. 2004. "IEA/SMP Model Documentation and Reference Case Projection."	(1) Used to account for factors influencing vehicle stock other than resident per capita net earnings and fuel cost; and (2) Used to determine how much influence resident per-capita net earnings has on vehicle stock. Vehicle stock helps drive household transportation costs and vehicle registration fee revenue.	Best identified equation for estimating desired vehicle ownership; produces results consistent with other data sources used in the model.	LOW: The equation was created for the combined area of the U.S., Canada, and Mexico, so it may not be representative of the study area. As part of the downscaling, we assumed resident per-capita net earnings could be used instead of GDP per capita. We also assumed that counting the effect of fuel cost separately would not be double-counting. Whereas the source's equation was for vehicles per capita, it is included in the D-O LRP SD Model in terms of vehicles per person not in a zero-car household.
Baseline rate of change in through-traffic VMT	NC Office of State Budget and Management. 2015. "Population Estimates and Projections."	Since through-traffic VMT is, by definition, largely the result of factors external to any given study area, this rate of change serves as a stand-in for those external factors. VMT is used to estimate traffic congestion, fuel consumption by vehicles, and traffic accidents.	Baseline rate of change is based on the rate of population change in North Carolina, since VMT and population tend to follow similar trends. Local data on through-traffic VMT is scarce. Produces VMT results that are consistent with projections.	LOW: The relationship between through-traffic VMT and North Carolina population is assumed, not based on empirical evidence.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Change in person miles of public transit travel per year due to adding fixed guideway transit	"Draft Spreadsheet Tool: Estimated Ridership and Cost of Fixed-Guideway Transit Projects," created as part of TCRP Project H-42: Chatman, Daniel G., Robert Cervero, Emily Moylan, Ian Carlton, Dana Weissman, Joe Zissman, Erick Guerra, Jin Murakami, Paolo Ikezoe, Donald Emerson, Dan Tischler, Daniel Means, Sandra Winkler, Kevin Sheu, and Sun Young Kwon. 2014. "TRCP Report 167: Making Effective Fixed-Guideway Transit Investments: Indicators of Success."	Equation from literature used to dynamically determine new public transit person miles of travel resulting from the LRT line. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	TCRP is a well-respected source; the equation produces results that appear reasonable when compared to the projections in the Metropolitan Transportation Plan.	MEDIUM: The equation is not specific to this particular study area and does not account for the number of revenue miles run on the new LRT line. The equation is also for fixed-guideway transit in general, as opposed to LRT specifically. Finally, the equation does not factor in any change over time.
Congestion (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Used to estimate vehicle speed, which affects daily modal person miles using elasticities. Modal person miles affect household transportation costs, traffic accidents, fuel consumption, and health outcomes.	GIS format, highly detailed, with per-link variables for traffic volume, capacity, and freeflow and peak-period travel speeds. Also, it is the official travel-behavior model for the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization.	HIGH: It is an authoritative source, but many modeling assumptions go into the numbers. "Congestion" is defined here as the ratio of freeflow speed on a road link to the traffic speed on that link during "peak" periods (6-10 AM and 3:30-7:30 PM on weekdays), weighted by the peak-period VMT on each link. This definition does not account for congestion during the rest of the day, or for variations in congestion or traffic volumes during the designated "peak" periods.
Congestion per weekday peak period VMT per lane mile	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Used to translate modeled peak-period-VMT and lane-mile figures into a measure of traffic congestion that can feed back into the model.	GIS format, highly detailed, with per-link variables for traffic volume, capacity, and freeflow and peak-period travel speeds. Also, it is the official travel-behavior model for the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization.	MEDIUM: We took ratios between congestion and peak period VMT per lane mile in 2010 and 2040 and assumed a direct, causal, proportional relationship. Other factors influencing congestion are ignored.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Construction cost per lane mile; maintenance cost per lane mile per year; construction cost per nonmotorized facility mile	CAMPO and DCHC MPO. 2013. "2040 Metropolitan Transportation Plans." (MTP); DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario and travel demand result shapefiles." (TRM)	Constant values are multiplied by numbers of roadway lane miles to arrive at transportation facility expenditure totals.	Resulting values for costs per lane mile are comparable to what transportation planners in the local MPO use.	MEDIUM-HIGH: Does not disaggregate the cost of urban vs. rural roadwork, the cost of highway vs. nonhighway roadwork, or facilities built by the government vs. by developers. Does not account for variations in the cost of right-of-way acquisition. We assume that the MTP's anticipated nonmotorized-facility spending is all construction and not maintenance (due to sidewalks being the responsibility of private land owners).
Elasticity of congestion to commercial FAR Tier 1	N/A	Used to estimate the effect of average building floor area ratio (FAR) on traffic congestion in Tier 1. Traffic congestion reduces VMT and increases the use of other travel modes. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	No source available. Although the model also has a relationship wherein VMT increases traffic congestion, Tier 1 traffic congestion is also affected by nonmotorized traffic, including nonmotorized travel within Tier 1 by people who entered Tier 1 by automobile. FAR is used as a proxy for these more immediate drivers. This effect is represented only in Tier 1 because Tier 2 nonmotorized travel is very low, so it is assumed to have a negligible effect on Tier 2 congestion.	LOW: No source available.
Elasticity of desired vehicle ownership per person not in a zero car household to fuel price	Johansson, Olof, and Lee Schipper. 1997. "Measuring the long-run fuel demand of cars: Separate estimations of vehicle stock, mean fuel intensity, and mean annual driving distance."	Used to determine how much influence fuel price per VMT has on vehicle stock, which helps drive household transportation costs and vehicle registration fee revenue.	Best available equation for this purpose; produces results consistent with other data sources used in the model.	LOW: Came from a study that looked at entire countries, including countries that are much farther from vehicle-ownership saturation than the U.S.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Elasticity of person miles of travel per day per capita to GRP per capita (separate values for automobile driver, automobile passenger, nonmotorized, and public transit travel)	(1) BEA. 2014. "Gross Domestic Product (GDP) by Metropolitan Area: Per Capita Real GDP, 2001-2013, for the Durham-Chapel Hill, NC Metropolitan Statistical Area (MSA)." (2) CAMPO and DCHC MPO. 2013. "2040 Metropolitan Transportation Plans." (MTP) (3) DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM) (4) NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (5) ESRI Community Analyst. 2014. "ACS 1-yr and 5-yr Estimates 2005-2013."	Used to create a baseline of overall modal person miles of travel that fits projections and which all other drivers of modal person miles may modify in a process where most other inputs serve to change the mode shares, as opposed to the overall quantity of person miles across modes. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	(1) BEA is an authoritative government source that looks at individual metropolitan areas (as Metropolitan Statistical Areas). (2) The Metropolitan Transportation Plan (MTP) is the authoritative transportation planning document in the DCHC MPO. Produces results consistent with other data sources used in the model. (3) The TRM is the primary source of travel-behavior projections for the MTP. (4) The Household Travel Survey Final Report is one of the TRM's key inputs. (5) Community Analyst is able to clip ACS data from the U.S. Census Bureau to specific geographic areas.	MEDIUM-LOW: This is a custom-made elasticity, calculated by assuming that two separate projections will both come to pass. As such, the actual elasticity between person miles of travel per capita and GRP per capita might be greater or lesser, with the apparent outcome shown here being the result of the effects of that elasticity being either offset or compounded by other factors not accounted for in the model. Furthermore, it is unconfirmed whether the two projections used here are based on compatible sets of assumptions.
Elasticity of public transit travel to fare price	McCollom, Brian E., and Richard H. Pratt. 2004. "TCRP Report 95: Traveler Response to Transportation System Changes: Chapter 12—Transit Pricing and Fares." (page 12-9)	Used to determine how much changes in the average public transit fare price affect person miles of travel by public transit. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	Source adapted this elasticity from the Simpson & Curtin formula, which is commonly used among public transit planners. Also, TCRP reports are well-regarded in their own right.	MEDIUM-HIGH: Not local.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Elasticity of public transit travel to vehicle revenue miles	Sinha, Kumares Chandra, and Samuel Labi. 2007. *Transportation Decision Making: Principles of Project Evaluation and Programming*. (page 55)	Used to determine how much changes in the number of daily public transit vehicle revenue miles affect person miles of travel by public transit. Greater public transit ridership reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	Provided an elasticity between a variable that data could easily be obtained for (revenue miles) and public transit use.	MEDIUM: Results appear reasonable, but we do not possess information on the original study that produced the elasticity.
(1) Elasticity of through traffic to automobile speed; (2) Elasticity of through traffic to fuel cost	Litman, Todd. 2013. "Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior."	Used to determine how much changes in (1) average vehicle speed and (2) fuel cost affect through-traffic VMT. VMT is used to estimate traffic congestion, fuel consumption by vehicles, and traffic accidents.	Same source provided multiple related elasticities for this model, creating a greater likelihood of consistency. Comes with note reading "in areas with high vehicle ownership (more than 450 vehicles per 1,000 population)," which suggests it is applicable to the study area for this model.	MEDIUM-LOW: Elasticity is not specific to this region. Also, using this parameter for through-traffic VMT implies that VMT of trips originating outside of the study area are just as sensitive to average vehicle speeds and the cost of vehicle fuel per VMT in the study area as VMT of trips starting or ending in the study area.
Elasticity of travel to (1) automobile speed, (2) fuel cost, and (3) parking cost (separate values for automobile driver, automobile passenger, nonmotorized, and public transit travel)	Litman, Todd. 2013. "Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior."	Used to determine how much changes in (1) average vehicle speed, (2) fuel cost, and (3) parking cost affect person miles of travel by mode. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Same source provided multiple related elasticities for this model, creating a greater likelihood of consistency. Comes with note reading "in areas with high vehicle ownership (more than 450 vehicles per 1,000 population)," which suggests it is applicable to the study area for this model	MEDIUM: Elasticities are not specific to this region.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Elasticity of travel to (1) intersection density and (2) population density (separate values for automobile driver, nonmotorized, and public transit travel); (3) elasticity of nonmotorized travel to jobs housing balance	Ewing, Reid and Robert Cervero. 2010. "Travel and the Built Environment: A Meta-Analysis."	Used to determine how much changes in (1) the density of intersections that are not entirely automobile-oriented, (2) population density, and (3) the jobs-housing balance affect person miles of travel by mode. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Journal article synthesizes results of multiple studies on the same causal relationship(s) and is a highly regarded work by highly regarded researchers in the transportation planning field.	MEDIUM: Distinctions made in individual studies are obscured by composite numbers, possibly leading to misuse.
Elasticity of vehicle trip distance to vehicle speed	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM); CAMPO and DCHC MPO. 2013. "2040 Metropolitan Transportation Plans."	Used to help determine the average distance of a vehicle trip. Along with a separate calculation of overall VMT by residents, this is used to arrive at an aggregate number of vehicle trips by residents, which drives how much residents spend on parking.	We employed this ad-hoc elasticity because we could not find an elasticity or formula for the distance of an average trip, as opposed to number of trips or cumulative distance of trips. Because this elasticity was created from TRM/MTP data, it replicates the trends in that data.	LOW: The elasticity produces results consistent with TRM/MTP data, but it is still an ad-hoc elasticity lacking the usual rigor of a scientific study.
Finished LRT line miles	Triangle Transit. 2015. "Our Transit Future."	Used in calculating the land use of the LRT, its building expense, its revenue miles, and the amount of roadway lane miles that are disrupted during LRT construction, which affects traffic congestion.	Source is the agency in charge of planning the light rail line.	HIGH: Most of the LRT alignment has been determined at the time of this writing.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Off-peak-period vehicle speed; freeflow speed of the roadway link on which the average peak period vehicle mile of travel is performed	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Freeflow speed and congestion are used to estimate peak period vehicle speed, which, together with off-peak-period vehicle speed, determines average vehicle speed. Higher vehicle speeds increase automobile travel and reduce public transit and nonmotorized travel, affecting fuel consumption, household transportation costs, and health outcomes.	The TRM is the primary source of VMT and traffic congestion projections used by local transportation planning agencies; spatial nature of the data allows clipping to both Tiers.	HIGH: Authoritative source with straightforward application to the study area.
Functioning lane miles	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Along with VMT, this is used to calculate traffic congestion. It is also used to determine land use and impervious surface area due to roadways.	The TRM result GIS shapefiles provide detailed counts of both existing lane miles and those planned to be built by 2040, according to the MTP.	MEDIUM-HIGH: Some lower-order roads are represented as "centroid connectors," which only estimate their cumulative lane miles.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Functioning nonmotorized travel facilities (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario shapefiles." (TRM)	Used to drive roadway intersection density (excluding those that are purely automobile oriented), which affects modal person miles. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Best available source that quantifies miles of nonmotorized facilities; spatial nature of the data allows clipping to both Tiers.	MEDIUM-HIGH: Does not distinguish between sidewalks, bike lanes, etc., even though these different types of facilities attract different amounts of nonmotorized person miles, with different proportions of those person miles being walking or cycling. Does not indicate how well-connected the nonmotorized travel facilities are, even though well-connected facilities are much more likely to drive nonmotorized travel than disconnected facilities. When clipping data to the Tier 1 boundary, it was necessary to assume that nonmotorized facilities were evenly distributed throughout any given Traffic Analysis Zone that was clipped.
Indicated percent reduction in driver person miles due to congestion	N/A	Used to determine how much changes in traffic congestion affect person miles of automobile driver travel. Automobile driver person miles affect household transportation costs, traffic accidents, fuel consumption, and health outcomes, as well as have a feedback effect on traffic congestion.	No source was available that indicated the degree to which traffic congestion causes people to drive less without traveling more by other modes, as opposed to traffic congestion causing people to switch travel modes (for which a source was used).	LOW: No source available.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Initial nonmotorized travel facilities per developed acre	(1) DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario shapefiles." (TRM) (2) TJCOG. 2014. "CommunityViz 2 (CV2) Parcel Geodatabase for Place Type & Development Status Editing." Estimates of developed land in 2013 are obtained for the CV2 parcels assigned a development status of developed, minus parcels assigned a place type of POS (Protected Open Space).	Multiplied by initial developed land to get initial functioning nonmotorized travel facilities. Used as the default value for desired nonmotorized travel facilities per developed acre. Nonmotorized travel facilities drive the density of intersections that are not purely automobile-oriented, helping to increase nonmotorized and public transit person miles and decrease VMT, affecting fuel consumption, household transportation costs, and health outcomes.	(1) Best available source that quantifies miles of nonmotorized facilities; spatial nature allows clipping to both Tiers. (2) Provided the most detailed accounting of land usage by acres that was available for the entire study area; provided a consistent categorization system for the study area, and was used in the development of the Imagine 2040 model, and therefore was assumed to be consistent with the data and projections used for the transportation sector.	MEDIUM-LOW: For the sake of calibration, this value had to be adjusted in Tier 2 (but not in Tier 1). Some interpolation was required to get the numerator and denominator values to be for the same year. Due to a lack of land development data from prior to 2013 and a lack of nonmotorized facility data from prior to 2010, we had to back-cast to estimate a value for 2000.
Intersections excluding those that are purely automobile-oriented (calibration)	US EPA, Office of Policy, Office of Sustainable Communities. 2013. Smart Location Database version 2.0. (SLD)	The density of intersections affects modal person miles through elasticities. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Provides a tally of intersections that excludes purely automobile-oriented ones, which makes it more useful for examining effects on mode choice; spatial nature allows clipping to both Tiers.	MEDIUM-HIGH: Block Groups are a courser unit than TAZs; data are available for 2010 only
Land use per lane mile (separate values for rural highways, rural nonhighways, urban highways, and urban nonhighways)	NC DOT. 2007. Roadway Design Manual. (Part II, Chapter 9: Right of Way)	Used to determine the land use of roadways in the area and the amount of impervious surface (and hence runoff) that they contribute.	Authoritative source on road rights-of-way.	MEDIUM: The source is authoritative, but we did not check it against actual local conditions, and the source provides wide allowable ranges that apply to new road construction.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Land use per LRT line mile	N/A	Used to determine the land use of the light rail line, which is a component of impervious surface, which determines runoff volumes.	No source available. Estimated from an assumed right-of-way width.	LOW: No source available.
LRT construction cost per line mile; LRT O&M cost per year	Triangle Transit, Chapel Hill Transit, Orange County, DCHC MPO, and Orange County Public Transportation. 2012. "The Bus and Rail Investment Plan in Orange County." DCHC MPO, Triangle Transit Board of Trustees, and Durham Board of County Commissioners. 2011. "The Durham County Bus and Rail Investment Plan."	Used to quantify spending on construction and operation of the light rail line.	Authoritative planning documents for matters of public transit spending.	HIGH.
LRT revenue miles per line mile per day	Triangle Transit. 2015. "Our Transit Future."	Contributes to overall public transit revenue miles, which affects public transit person miles; drives LRT electricity use.	Source is the agency in charge of planning the light rail line.	MEDIUM: This input is from a back-of-the-envelope calculation based on anticipated service hours and frequencies for the future LRT line. This calculation has not been verified by the transit agency that will operate the line.
Ownership and maintenance costs for one automobile for one year	Litman, Todd Alexander, and Eric Doherty. 2009. "Transportation Cost and Benefit Analysis: Techniques, Estimates and Implications." 2nd ed. (Chapter 5.1: Vehicle Costs)	Used to estimate vehicle ownership and maintenance costs per capita, which is one component of annual per-capita transportation related costs incurred by residents.	Best available source that disaggregates fuel- and non-fuel-related vehicle costs and reduces purchase costs to an average per year instead of a one-time expense every several years.	MEDIUM: The source uses non-local data from 2007.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Parking cost of average trip (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario shapefiles." (TRM); TRM Service Bureau and TRM Team. 2012. "Triangle Regional Model Version 5 Model Documentation Report."	Affects modal person miles through elasticities. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Best available source that quantifies the average cost per trip of parking; spatial nature allows clipping to both Tiers.	MEDIUM-LOW: Source does not account for the opportunity cost that is felt when parking is free yet scarce. Processed data used here assumes that the only source of change in "parking cost of average trip" during 2010-2040 is the proportion of trips that end in existing paid-parking areas, as opposed to new paid-parking areas being created or prices in the existing paid-parking areas increasing at a rate that is not equal to the inflation rate.
Peak period percent of VMT	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Determines how much of the modeled VMT is taken to be during peak periods, which drives congestion. Congestion decreases VMT and increases the use of public transit and nonmotorized modes.	GIS format, highly detailed, with per-link variables for traffic volume, capacity, and freeflow and peak-period VMT and travel speeds; the source is the official travel-behavior model for the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization.	MEDIUM: By using this input and determining the value of this variable through a lookup table, we assume that it is entirely exogenous, even though there likely are additional factors within the model that would cause people to do more or less of their driving during peak periods.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Percent of person miles of public transit travel that is on transit systems entirely contained within the DCHC MPO	FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward); Green, Jennifer. 2014. "FY2014 TTA Stats by County.xlsx." (data on the percent of Triangle Transit boardings attributed to any given county; Triangle Transit is now known as GoTriangle)	Used in Tier 2 only; helps determine the percent of public transit travel starting or ending in area that is by residents, which is used with projections of overall public transit use to determine public transit use by residents, which determines the public-transit-fare component of household transportation spending. Also, resident public transit travel increases resident nonmotorized travel, which drives health outcomes.	The NTD provides detailed service and usage data on most of the public transit systems in the U.S. However, additional data from Jennifer Green at Triangle Transit (now known as GoTriangle) was needed to estimate how many of their person miles are in the DCHC MPO.	MEDIUM-HIGH: We assume that the value of this variable remains constant after 2013.
Percent of VMT that is on highways	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM, 2010 value held constant going forward)	Used to calculate VMT per highway lane mile, which helps determine the change in person miles of public transit travel per year due to adding fixed-guideway transit. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	The TRM is the primary source of VMT and traffic congestion projections used by local transportation planning agencies; spatial nature allows clipping to both Tiers.	MEDIUM: We assume that the value of this variable remains constant over time, though it is likely affected by other variables in the model.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Person miles of automobile driver travel per day; through-traffic VMT; person miles of automobile passenger travel per day; person miles of nonmotorized travel per day (calibration)	(1) CAMPO and DCHC MPO. 2013. “2040 Metropolitan Transportation Plans.” (MTP); (2) DCHC MPO. 2013. “Triangle Regional Model version 5: Travel demand result shapefiles.” (TRM); (3) NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (conducted for the TRM); (4) ESRI Community Analyst. 2014. “ACS 1-yr and 5-yr Estimates 2005-2013.”	Person miles of automobile driver travel per day and through-traffic VMT drive VMT; person miles of automobile driver and passenger travel per day determine average vehicle occupancy; person miles of nonmotorized travel per day determines walking and cycling activity by residents and associated health benefits.	(1) The MTP is the authoritative transportation planning document in the DCHC MPO. (2) The TRM is the primary source of travel-behavior projections for the MTP; spatial nature allows clipping to the Tiers. (3) The Household Travel Survey Final Report is one of the TRM’s key inputs. (4) Community Analyst is able to clip ACS data from the U.S. Census Bureau to specific geographic areas.	Tier 2 = MEDIUM; Tier 1 = LOW: A long sequence of processing steps was required in order to convert the modal trip counts in the MTP into person-mile counts, as well as to scale the data to Tier 1, requiring several assumptions that may not be correct. For example, we used average carpool sizes from the ACS, which are specific to journey-to-work trips, as opposed to travel for all purposes. In addition, for Tier 1 scaling, we assume that there is a proportional relationship between the percent of VMT that is through traffic and the percent of VMT that is on highways.
Person miles of nonmotorized travel generated by average public transit trip	N/A	Used to estimate how much nonmotorized travel is increased by public transit travel, through people walking or biking to and from public transit stops. Nonmotorized travel affects health outcomes.	No source available. Input value is in keeping with general rules of thumb employed by public transit planners and researchers.	MEDIUM-LOW: No source available, but input value is in keeping with general rules of thumb employed by public transit planners and researchers.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Person miles of public transit travel per day (calibration)	**Historical Values (Tier 2 only):** (1) FTA. 2015. National Transit Database. (NTD) (2) Green, Jennifer. 2014. “FY2014 TTA Stats by County.xlsx.” **2010 (Tier 1 only) and Projected Values (Tier 2 only):** (3) CAMPO and DCHC MPO. 2013. “2040 Metropolitan Transportation Plans.” (MTP) (4) DCHC MPO. 2013. “Triangle Regional Model version 5: Travel demand result shapefiles.” (TRM) (5) NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (conducted for the TRM) (6) ESRI Community Analyst. 2014. “ACS 1-yr and 5-yr Estimates 2005-2013.”	Used to estimate public transit ridership and the amount of additional nonmotorized travel that results from traveling to and from public transit stops. Greater public transit use reduces VMT, and hence congestion, fuel consumption, and traffic accidents. Greater nonmotorized travel drives physical activity, with its associated health benefits.	(1) The NTD provides detailed service and usage data on most of the public transit systems in the U.S., provided by public transit agencies themselves to the federal government (supplemented by data from personal communication with (2) Jennifer Green at Triangle Transit, now known as GoTriangle). (3) The MTP is the authoritative transportation planning document in the DCHC MPO. (4) The TRM is the primary source of travel-behavior projections for the MTP. (5) The Household Travel Survey Final Report is one of the TRM’s key inputs. (6) Community Analyst is able to clip ACS data from the U.S. Census Bureau to specific geographic areas.	Tier 2 = MEDIUM-HIGH (Historical = High; Projected = Medium) Tier 1 = LOW (Historical only) A long sequence of processing steps was required in order to convert the modal trip counts in the MTP into person-mile counts, as well as to scale the data to Tier 1, requiring several assumptions that may not be correct. For example, to convert the MTP’s weekday-only transit-use projections to an average of all seven days of the week, we held the NTD’s reported 2013 ratio of weekend-day transit use to weekday transit use constant until 2040.
Public transit fare price	FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward); supplemented by: Green, Jennifer. 2014. “FY2014 TTA Stats by County.xlsx.” (data on the percent of Triangle Transit boardings attributed to any given county, obtained so that that transit agency’s ridership in the study area could be compared to that of other transit agencies in the study area to arrive at a weighted average of their fare prices; Triangle Transit is now known as GoTriangle)	Helps determine person miles of public transit travel per day, through an elasticity; directly affects public transit fare revenue per year. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity.	The NTD provides detailed service and usage data on most of the public transit systems in the U.S., provided by public transit agencies themselves to the federal government. However, additional data from Jennifer Green at Triangle Transit was needed to estimate how many of their boardings are in the DCHC MPO, in order to create a weighted average.	MEDIUM-HIGH: We assume that the value of this variable remains constant after 2013, though it may change in response to changes in ridership or operation costs.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Public transit nonfuel expenditure per road based VMT	FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward); supplemented by: Green, Jennifer. 2014. "FY2014 TTA Stats by County.xlsx." (data on the percent of Triangle Transit revenue miles attributed to any given county; Triangle Transit is now known as GoTriangle)	Used to estimate one component of annual public transit operating expenditure.	The NTD provides detailed service, usage, and operations data on most of the public transit systems in the U.S., provided by public transit agencies themselves to the federal government. Additional data from Jennifer Green at Triangle Transit was needed to estimate how many of their revenue miles and VMT are in the DCHC MPO.	MEDIUM-HIGH: The calculation in the model subtracts an estimate of public-transit-vehicle fuel (based on NTD fuel-consumption data and Energy Information Administration figures for gasoline and diesel prices at a national level) from NTD operating expenditure figures, so it combines local and non-local data.
Public transit road-based vehicle revenue miles per day; ratio of VMT to revenue miles for public transit road based vehicles	(1) FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward) (2) Green, Jennifer. 2014. "FY2014 TTA Stats by County.xlsx." (data on the percent of Triangle Transit revenue miles attributed to any given county; Triangle Transit is now known as GoTriangle); (3) Triangle Transit, Chapel Hill Transit, Orange County, DCHC MPO, and Orange County Public Transportation. 2012. "The Bus and Rail Investment Plan in Orange County."; (4) DCHC MPO, Triangle Transit Board of Trustees, and Durham Board of County Commissioners. 2011. "The Durham County Bus and Rail Investment Plan."	Revenue miles influence person miles of public transit travel per day through an elasticity. Greater public transit use reduces VMT (and hence congestion, fuel consumption, and traffic accidents) and helps drive nonmotorized travel, and hence physical activity. The product of public transit road-based vehicle revenue miles per day and the ratio of VMT to revenue miles for public transit road based vehicles determines road-based public-transit VMT, fuel use, and operating costs.	The NTD provides detailed service and usage data on most of the public transit systems in the U.S., provided by public transit agencies themselves to the federal government (supplemented by data from personal communication with Jennifer Green at Triangle Transit,). County Bus and Rail Investment Plans are authoritative planning documents for public transit spending.	MEDIUM-HIGH: The input comes from an authoritative source, but we needed to convert gross revenue-hour figures from the county bus and rail investment plans to road-based revenue miles by assuming the NTD's 2013 ratio of road-based revenue miles per revenue hour will hold constant.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Public transit trip distance	FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward); supplemented by: Green, Jennifer. 2014. "FY2014 TTA Stats by County.xlsx." (data on the percent of Triangle Transit boardings attributed to any given county; Triangle Transit is now known as GoTriangle)	Used to estimate daily public transit passenger trips from person miles of public transit travel per day. The number of public transit trips drives public transit fare revenue and nonmotorized travel to and from transit stops, which contributes to physical activity, with its attendant health benefits.	The NTD provides detailed service, usage, and operations data on most of the public transit systems in the U.S., provided by public transit agencies themselves to the federal government. Additional data from Jennifer Green at Triangle Transit was needed to estimate how many of their boardings and person miles are in the DCHC MPO.	MEDIUM-HIGH: The input comes from an authoritative source and does not require any assumptions to apply to the model, except that we assume that the value of this variable remains constant over time.
Reaction times of modal person miles and vehicle trip distance to (1) vehicle speed, (2) fuel cost, (3) parking cost, (4) population density, (5) jobs-housing balance, (6) intersection density, (7) public transit fares, and (8) public transit revenue miles.	N/A	Used to determine effects on person miles of travel by mode and vehicle trip distance. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes. VMT by residents is divided by vehicle trip distance to arrive at vehicle trips per resident, which determines parking spending per resident.	Sources of elasticity values for these relationships did not indicate specific amounts of time that it takes for a given output to react to changes in a given input. Indications were only provided of whether the elasticities were "long-term" or "short-term."	LOW: No source available. Instead, inputs are based on system-dynamics rules of thumb for what to consider "long-term" versus "short-term" elasticities.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Tier 1 to Tier 2 weighting factors for effect of (1) congestion (2) vehicle speed, (3) fuel cost, and (4) parking cost on Tier 1 desired vehicle ownership per person not in a zero-car household, vehicle trip distance, through-traffic VMT, and modal person miles (separate values for automobile driver, automobile passenger, nonmotorized, and public transit travel).	N/A	Used to determine how much changes in Tier 1 and Tier 2 (1) traffic congestion (2) average vehicle speed, (3) fuel cost, and (4) parking cost affect Tier 1 person miles of travel by mode, VMT, trip distances and vehicle ownership. These outputs affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	Sources were not available that estimated how much Tier 1 travel behavior and vehicle ownership are affected by neighborhood-scale (Tier 1) congestion, vehicle speed, fuel cost, and parking cost, relative to the metropolitan-area scale (Tier 2). We decided that both of these scales were important for the relationships discussed here.	LOW: No source available.
Urban nonhighway lane miles disrupted per LRT line mile under construction	N/A	Used to estimate reductions in functioning roadway lane miles resulting from light rail line construction. Temporarily reducing functioning lane miles increases traffic congestion, which reduces VMT and increases the use of other travel modes. Modal person miles affect household transportation costs, traffic accidents, congestion, fuel consumption, and health outcomes.	No source available. Used an assumed value.	LOW: No source available.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Vehicle lifespan	International Energy Agency, Directorate of Sustainable Energy Policy and Technology. 2009. *Transport, Energy, and CO_2: Moving Toward Sustainability*. (Table 3.1)	Each addition to the stock of vehicles is eventually removed (unless the end of the model run intervenes) after the average vehicle lifespan. Vehicle stock helps drive household transportation costs and vehicle registration fee revenue.	The International Energy Agency is an authoritative source; the result is consistent with information found in other sources.	MEDIUM-HIGH: Data are not specific to the study area (so we assume that average vehicle lifespans in the study area are the same as national averages) and are drawn from the period 2000-2005.
Vehicle stock (calibration)	Geographic Research Inc. 2015. "Census Data 2000, ACS Estimates 2008-2014." (data by Census Block Group)	Multiplied by vehicle ownership and maintenance costs to form one component of transportation costs incurred by residents; also drives vehicle registration fee revenues.	Chosen because it provides multiple years' data up to 2014. Unlike the Smart Location Database (which only has one year's data), counts households with 0, 1, 2, 3, or 4+ vehicles, as opposed to just households with 0, 1, or 2+ vehicles.	MEDIUM-HIGH: Only counts vehicles belonging to households. Clipping Census Block Groups to the Tiers assumes that vehicles are evenly distributed within any given block group. Does not count any vehicles in a household beyond four.
Vehicle trip distance (calibration – Tier 2 only)	(1) CAMPO and DCHC MPO. 2013. "2040 Metropolitan Transportation Plans." (MTP); (2) DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM); (3) NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (conducted for the TRM); (4) ESRI Community Analyst. 2014. "ACS 1-yr and 5-yr Estimates 2005-2013."	Used along with VMT by residents to determine the number of resident vehicle trips. The number of vehicle trips by residents and the average cost of parking determine overall and parking expenditures, a component of household transportation costs.	Same collection of sources and data processing steps used to arrive at data for person miles of travel by mode per day, which helps impart consistency. (1) The MTP is the authoritative transportation planning document in the DCHC MPO. (2) The TRM is the primary source of travel-behavior projections for the MTP. (3) The Household Travel Survey Final Report is one of the TRM's key inputs. (4) Community Analyst is able to clip ACS data from the U.S. Census Bureau to specific geographic areas.	MEDIUM: A long sequence of processing steps was required in order to convert the average distance of all person trips reported in the MTP into average person-trip distances by mode, requiring several assumptions that may not be correct. For example, we used average carpool sizes from the ACS, which are specific to journey-to-work trips, as opposed to travel for all purposes. We also assumed that the ratios between average trip distances by different modes reported in the Household Travel Survey could be held constant going forward for the purpose of calculating vehicle trip distances to calibrate to.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
VMT (calibration)	DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM)	Used to estimate traffic congestion, fuel consumption by vehicles, and traffic accidents.	The TRM is the primary source of VMT and traffic congestion projections used by local transportation planning agencies; spatial nature allows clipping to both Tiers.	HIGH: Authoritative source with straightforward application to the study area, but the TRM only models weekday traffic. We assume that VMT on a weekend day is the same as VMT on a weekday.

TABLE C-3. MODEL INPUT CHARACTERIZATION FOR THE ENERGY SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Carbon dioxide (CO_2) emissions (calibration)	(1) Durham City-County Sustainability Office. 2015. (2) Freid, Tobin. Email message to authors on January 9, 2015.	CO_2 emissions is an endpoint indicator variable.	Authoritative local source; emissions are calculated by the Sustainability Office based on energy data supplied by utility companies.	MEDIUM: For buildings, only emissions from electricity and natural gas (which represent the large majority of energy use in buildings) are currently tracked.
Building energy use (calibration)	(1) Durham City-County Sustainability Office. 2015. (2) Freid, Tobin. Email message to authors on January 9, 2015.	Used to estimate CO_2 emissions and energy costs.	Authoritative local source; energy data is supplied by utility companies.	MEDIUM: For buildings, only emissions from electricity and natural gas (which represent the large majority of energy use in buildings) are currently tracked. We assume that the data collection methods used by the companies (their definition of county boundaries, etc.) are consistent year-to-year.
Energy use intensity – buildings (calibration)	(1) US EIA. 2009. "Residential Energy Consumption Survey (RECS)." (2) Durham County Property Tax Database. 2000-2014. (3) US DOE. 2008. "Energy Efficiency Trends in Residential and Commercial Buildings." (4) US EIA. 2015. "Annual Energy Outlook 2015."	Historical and projected trends in building energy use intensity are multiplied by local data on housing stock and building square footage to calculate building energy use. A calibration factor is applied to better fit building energy use to historical data.	EIA and DOE are authoritative national sources for energy data and projections. Durham County Property Tax Database is a comprehensive and detailed record of buildings in Durham County.	MEDIUM. We assume that regional or national trends are appropriate for the study area.
Light rail electricity use	FTA and CATS. 2011. "Lynx Blue Line Extension, Northeast Corridor Light Rail Project, Charlotte-Mecklenburg County, North Carolina, Final Environmental Impact Statement."	Used to estimate CO_2 emissions and energy costs of the light rail.	This environmental impact statement is for light rail in the same state as the D-O LRP.	MEDIUM. We assume that the D-O LRP rail will consume electricity at the same rate per vehicle mile traveled as the Charlotte Lynx Blue Line.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Energy prices: gasoline, diesel, natural gas, electricity	(1) US EIA. 2015. "Weekly Retail Gasoline and Diesel Prices." (2) US EIA. 2015. "Annual Energy Outlook 2015." (3) US EIA. 2015. "North Carolina Price of Natural Gas Delivered to Residential Customers." (4) US EIA. 2015. "Electricity: Sales (consumption), revenue, prices & customers."	Used to calculate historical and projected energy spending	US EIA is an authoritative national source on historical and projected fuel prices.	MEDIUM-HIGH: Historical prices: HIGH. Future prices: MEDIUM. Projections are inherently uncertain.
CO_2 emissions factors	US EPA. 2015. "Clean Energy, Calculations and References."	Used to calculate CO_2 emissions by fuel type	Authoritative national source on pollutant emissions factors.	MEDIUM-HIGH: Authoritative source with straightforward application to the model, but local emission factors (such as for electricity generation) may differ from the regional average.
$PM_{2.5}$ emissions per VMT; NO_x emissions per VMT	(1) Cai et al. 2013. "Updated Emission Factors of Air Pollutants from Vehicle Operations in GREET[TM] Using MOVES." (GREET = Greenhouse gases, Regulated Emissions, and Energy use in Transportation model. MOVES = Motor Vehicle Emission Simulator) (2) Jackson, Tracie R. 2001. "Fleet Characterization Data for MOBILE6: Development and Use of Age Distributions, Average Annual Mileage Accumulation Rates and Projected Vehicle Counts for Use in MOBILE6."	Used to calculate $PM_{2.5}$ and NO_x emissions from passenger vehicles, which affect premature mortality.	In the absence of local data for vehicle fleet emissions, we chose to use the most recent available data on average $PM_{2.5}$ and NO_x emissions per VMT by vehicle model year (1) and weight each model year by the only U.S. vehicle fleet distribution data by vehicle age that we could find (2).	MEDIUM: MEDIUM-HIGH for historical data since the two studies are peer-reviewed and highly regarded, but we assume that national averages are appropriate for the study area. MEDIUM-LOW for projections because Cai et al. (1) shows $PM_{2.5}$ emissions per VMT flat-lining for vehicle model years after 2010, which may not be accurate based on more recent vehicle emissions reductions, and the study only goes until 2020, so emissions per VMT for NO_x and $PM_{2.5}$ were extrapolated to 2040.
Vehicle fuel efficiency (MPG)	US EIA. 2015. "Annual Energy Outlook 2010-2015."	Used to calculate passenger vehicle energy use, fuel costs, and emissions	Authoritative national source for energy data and projections.	MEDIUM: Projections are inherently uncertain.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Additional fuel consumed per hour of congestion delay	Sinha, Kumares Chandra, and Samuel Labi. 2007. *Transportation Decision Making: Principles of Project Evaluation and Programming*. (page 389, citing FHWA)	Used to determine how much additional vehicle fuel is consumed as a result of the reduced fuel efficiency that results from traffic congestion.	Cites an authoritative source and uses inputs that are easily calculated in the model.	MEDIUM: Does not account for changes in vehicle technology (that might affect fuel efficiency) over time.
Ratio of fuel consumption per public transit road-based VMT over gasoline gallon equivalent consumption per non-public transit VMT	(1) FTA. 2015. National Transit Database. (NTD, 2013 value held constant going forward); supplemented by: Green, Jennifer. 2014. "FY2014 TTA Stats by County.xlsx." (data on the percent of Triangle Transit revenue miles attributed to any given county; Triangle Transit is now known as GoTriangle); (2) US EIA. 2015. "Annual Energy Outlook 2010-2015."	Used to estimate public transit vehicle diesel and gasoline consumption per VMT (of buses and demand-response/vanpool vehicles, respectively), after accounting for different fuel efficiencies by vehicle type.	(1) The NTD provides detailed service, usage, and operations data on most of the public transit systems in the U.S., provided by transit agencies themselves to the federal government (supplemented by data from personal communication with Jennifer Green at Triangle Transit). (2) The US EIA is an authoritative source on fuel efficiency.	MEDIUM-HIGH: The input comes from authoritative sources, but we implicitly assume that local public transit vehicle fuel efficiency will increase along a similar trend to U.S. light-duty-vehicle fuel efficiency.
Solar capacity	NC Sustainable Energy Association. 2015. "Installed solar projects in NC."	Used to determine the historical trend of solar electricity installation, and its effect on CO_2 emissions in Tier 2.	NCSEA has a comprehensive state-wide database of solar energy installations, which we used to calculate solar capacity in Tier 2.	MEDIUM-HIGH: The source is comprehensive and regularly curated. Data are available by county, and the sum of solar capacity in Durham and Orange county was taken to approximate the solar capacity of Tier 2.
LFG energy capacity	(1) Duke Energy. 2008. "Duke Energy Carolinas signs deal to turn landfill gas into energy." (2) City of Durham. 2009. "Durham landfill gas-to-energy green power project."	Used to determine the effect of current renewables on CO_2 emissions in Tier 2	Duke Energy is a major electricity utility in the region. The City of Durham is a partner in this LFG project, and reference (2) is a press release.	MEDIUM: An alternate source states that the landfill will generate 3MW rather than 2MW: http://icma.org/en/icma/knowledge_network/documents/kn/Document/102318/Durham_Landfill_GastoEnergy_Green_Power_Project

TABLE C-4. MODEL INPUT CHARACTERIZATION FOR THE ECONOMY SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Total employment (calibration)	(1) Tier 2: Historical (2000-2009) employment growth rate calculated from: BEA. 2014. "Local Area Personal Income and Employment: Table CA25N, Total Full-Time and Part-Time Employment by NAICS Industry, 2001-2013, for Durham and Orange County, NC." (2) Tier 2: Historical data (2010) and projections (2011-2040) from: DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario." (3) Tier 1: Historical (2002-2009) employment growth rate calculated from: U.S. Census Bureau. 2015. "LODES data. Longitudinal Employer-Household Dynamics Program." (4) Tier 1: Historical data (2010) and projections (2011-2040) from: DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario."	Total employment is one of the main drivers of economic growth in the model, generating earnings, the largest component of GRP, which has cascading impacts throughout the model.	(1) The BEA is a prominent government source for historical economic data and updates historical employment data regularly. (3) Only source of employment data available at a small enough geographic scale for Tier 1. (2) and (4) TRM v5 SE data total employment are the benchmark we wanted to match because these employment numbers were used to generate travel demand in the TRM v5. In addition, the data are output by traffic analysis zones (TAZs) which are small enough in the proposed light rail station areas to use for Tier 1.	HIGH for Tier 2: (1) The most accurate, up-to-date source for total employment data by county, which was verified to be a good surrogate for Tier 2 by calculating total employment from TRM v5 SE data for Durham and Orange County, which was less than 1% different than total employment for Tier 2. (2) HIGH for historical data (2010) and MEDIUM-HIGH for projections due to the inherent uncertainty associated with future projections. MEDIUM-HIGH for Tier 1: (3) LODES data has built-in noise that distorts the data on small scales, but total employment values were mostly consistent year-to-year. (4) HIGH for historical data (2010) in Tier 1, but MEDIUM-HIGH for the projections because, although the regional employment growth projections were estimated by local planners, a model (CommunityViz) was used to allocate that employment growth to smaller geographies (TAZs) based on a subjective measure of the attractiveness of those areas.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Shares of total employment by employment category (industrial, office, retail, service)	(1) Tier 2: Historical data (2000-2011) and projections (2012-2040) from: Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet." (2) Tier 1: Historical (2002-2009): U.S. Census Bureau. 2015. "LODES Data. Longitudinal Employer-Household Dynamics Program." (3) Tier 1: Historical data (2010) and projections (2011-2040) from: DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario."	Multiplied by total employment in the model to determine the total number of jobs by employment category, which are used to calculate "total earnings," a component of "GRP," and are multiplied by employee space ratios for each employment category to determine "total nonresidential sq ft."	(1) Woods & Poole's historical data are from the BEA, but they fill in gaps in certain employment categories that the BEA omits. Projections were used by the DCHC MPO to help create employment guide totals for the CommunityViz modeling that generated the output for the TRM v5 SE data. (2) and (3) Only sources available for historical and projected employment by category at a small enough geographic scale for Tier 1.	MEDIUM-HIGH for Tier 2: HIGH for historical data since its original source is the BEA, and MEDIUM-HIGH for projections due to the inherent uncertainty associated with future projections.[53] MEDIUM-LOW for Tier 1: LODES data have built-in noise that distorts the data on small scales, and changes in census block group geographies between 2002 and 2009 also caused inconsistencies in the data in Tier 1. Also, TRM v5 SE data's definitions of employment categories differed from those used in the model.
Percent of jobs earning $3,333 per month in 2010 USDs Tier 1	Historical (2010): U.S. Census Bureau. 2015. "LODES Data. Longitudinal Employer-Household Dynamics Program."	Used to determine the change in person miles of public transit travel per year due to adding fixed-guideway transit.	LODES is based on Census Bureau data, clipped to the study area.	MEDIUM-LOW: We assume that this source was using 2010 USDs but were unable to verify this assumption. We also assume that this value remains constant over time, though it is likely to change in response to other factors in the model.

[53] Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusions drawn from it are solely the responsibility of the US EPA.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Ratio of entertainment jobs to retail jobs Tier 1	Historical (2010): U.S. Census Bureau. 2015. "LODES Data. Longitudinal Employer-Household Dynamics Program."	Is a component of retail plus entertainment employment in Tier 1, which is used to determine the change in person miles of public transit travel per year due to adding fixed-guideway transit.	LODES is based on Census Bureau data, clipped to the study area.	MEDIUM: Entertainment jobs are technically a subset of service employment, but we estimate them using a ratio to retail employment. In addition, we assume that this ratio remains constant over time.
Earnings per employee by employment category	Historical data (2000-2011) and projections (2012-2040) from: Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet."	Multiplied by employment by category to estimate the total earnings by category, which is then summed to yield total earnings.	Historical earnings data (2000-2011) from Woods & Poole is from the U.S. Bureau of Economic Analysis (BEA), but fills in gaps in certain earnings categories that the BEA omits. No earnings per employee by employment category data were available at the Tier 1 level, so earnings by category for Orange and Durham County were used, weighted by the number of Tier 1 jobs in each county.	HIGH for Tier 2: The historical data are reported by employers, not employees, and the projections in real dollars are reasonable when compared with historical trends. MEDIUM-LOW for Tier 1: Using county-level earnings per employee estimates likely overestimates earnings per employee for industrial jobs in Tier 1, because the North American Industrial Classification System (NAICS) considers high-wage jobs in RTP to be manufacturing.
Percent of residential population in labor force	(1) Tier 2: NC ESC. 2014. "Local Area Unemployment Statistics, 2000-2014 for Durham and Orange County, NC. " (2) Tier 1: Labor force statistics by block group from: Geographic Research Inc. 2015. "Census Data 2000, ACS Estimates 2008-2014." Accessed from SimplyMap Database.	Multiplied by total population to determine the civilian labor force in Tier 2 and Tier 1, which is used to determine the unemployment rate of residents.	(1) Best available source that had county-level data for all years covered by the model (U.S. Bureau of Labor and Statistics only had data from 2004 onward). (2) Only labor force data at small enough geographies for Tier 1 (census block group) and Simply Map provides the data from both sources in one convenient download.	HIGH: Both historical data sources have high accuracy and reliability. The only small source of uncertainty is for Tier 1 because the ACS warns that the 5-year average data may not be comparable to the data from the decennial census, though Simply Map accounts for this in their methodology.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Percent of employment held by commuters (Tier 2 only)	(1) NC ESC. 2014. "Local Area Unemployment Statistics, 2000-2014 for Durham and Orange County, NC." (2) Calculated "total employment" (see above).	Used to determine the number of people that work AND live in the region, which is used to determine the unemployment rate of residents.	(1) Best available historical data source for unemployment statistics. (2) No single data source gave employment statistics for the number of jobs held by residents of a particular area, so total employment was used.	MEDIUM: While confidence in the historical data for employed residents is high, we divide these historical data by our calculated total employment data to determine the percent of employment held by commuters. Assumptions that introduce uncertainty in this calculation are: (1) that all employed residents work within the study area, and (2) that all employed residents hold only one job. Since our total employment numbers include both part-time and full-time employment, it is likely that some residents hold multiple jobs, thus the percent of employment held by commuters is likely over-estimated.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Total retail consumption (initial value and calibration)	(1) Tier 2: Historical data (2000-2013) from: NC DOR. 2013. Table 37A. State Sales and Use Tax: Retail Taxable Sales by County. 2014 value from: NC DOR. 2014. "Gross Retail Sales for Durham and Orange County, FY 2014." (2) Tier 2: Historical retail sales data (2000-2011) and projected retail sales growth rate (2012-2040) from: Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet." (3) Tier 1: Historical data from: Geographic Research Inc. 2015. "Total Retail Sales (2008-2014) by Census Block Group."	Used to determine "desired employment" which adds additional employment yearly in the model, and to determine all sales tax revenues.	(1) and (2): The initial retail consumption value used was in between both sources of historical retail sales data for 2000 since the NCDOR data (total taxable sales) slightly under-estimates total retail sales, and total retail sales from Woods & Poole slightly over-estimates the amount for tax purposes historically, though the two data sources converged around 2010. Woods & Poole was the only source of retail sales projections. (3) Retail sales data are only output by the Economic Census by county, but Simply Map estimates retail sales by block group using a computer model.	HIGH for Tier 2: (1) Historical data for retail sales for Durham and Orange County are a very reasonable substitute for Tier 2 since almost all of the retail businesses in Tier 2 are located in those counties. (2) Woods & Poole retail sales growth rate projections are modest compared to the high growth rates in retail sales for Durham and Orange County over the past couple of years, but this balances out with other periods of slow growth or decline over the past 15 years. MEDIUM-HIGH for Tier 1: (3) Retail sales data at the Tier 1 level (Simply Map) are estimated by a computer model, so it is not directly from the source (businesses).
Elasticity of consumption to GRP	N/A	Used to determine the magnitude of the annual increase of retail consumption based on the relative increase in GRP.	No particular source was available for this elasticity, thus the value for both Tier 2 and Tier 1 (1.1) was determined through the calibration.	MEDIUM-HIGH: The elasticity was calculated based on historical data.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
GRP (calibration)	Historical GRP (2000-2014) calculated using a top-down methodology from: Panek, Sharon D., et al. 2007. "Introducing New Measures of the Metropolitan Economy: Prototype GDP-by-Metropolitan-Area Estimates for 2001-2005," using NC State GDP from: BEA. 2014. "Gross Domestic Product (GDP) by State: GDP in Current Dollars, 2000-2013, for North Carolina." And earnings data from: BEA. 2014. "Annual State Personal Income and Employment: Table SA05N - Personal Income by Major Source and Earnings by NAICS Industry, 2000-2013, for North Carolina." Local earnings data were calculated for Tier 2 and Tier 1 using "total employment," the "share of jobs by employment category," and "earnings per employee by category," (see above).	GRP influences many model variables, most directly total person miles (all modes), CO_2 emissions, and stormwater pollutant loadings.	The methodology provided allowed us to calculated GRP based on our own employment data and earnings calculations, rather than using GRP directly from the BEA or Woods & Poole (See Appendix D: Data Sources Not Used).	MEDIUM-HIGH: This methodology is used by the BEA to calculate GDP (GRP) by county, which is very difficult to calculate based on a "bottom-up" approach. For the purposes of this model, the GRP we calculated is the best possible fit.
Elasticity of GRP to energy spending	Bassi, Andrea M., Robert Powers, and William Schoenberg. 2010. "An integrated approach to energy prospects for North America and the rest of the world." *Energy Economics* no. 32 (1): 30-42.	Used to determine the magnitude of the influence of relative increases in energy spending on "gross operating surplus," which is one component of GRP.	Most relevant source for the data needed and gives a range of values for the magnitude of the elasticity.	MEDIUM: The range for this value given in the report was 0.1-0.3, so we chose 0.2, but the actual impact for our study area is unknown.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
GRP deflator 2010	(1) Historical (2000-2014): BEA. 2015. "National Income and Product Accounts Tables: Section 2 - Table 2.3.4. Price Indexes for Personal Consumption Expenditures (PCE), Annual Data for 2000-2014." (2) Projected (2015-2040): Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet."	Used to convert 2010 constant dollars to current (nominal) dollars, and was also used for all data sources to convert historical dollar values that were not adjusted for inflation to 2010 dollars.	The PCE index, rather than the CPI index, is used by Woods & Poole for historical data, though we downloaded the more recent PCE from the BEA website since it is updated regularly.	MEDIUM-HIGH: (1) The PCE is a national price index, but is a widely used price index that can apply to different consumption categories, making it ideal for our model rather than using several different price indexes. (2) Woods & Poole projects future inflation indices based on historical trends among many other predictive variables making it the best available source for a variable that has a wide range of uncertainty in the future.
Social insurance contribution	(1) Tier 2: Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet." (2) Tier 1: BEA. 2014. "Local Area Personal Income Methodology."	Reduces "earnings per capita" along with a residence adjustment to determine "resident net earnings per capita," which affects vehicle ownership and property values.	(1) Woods & Poole provide historical data and projections of social insurance contributions for Orange and Durham County. (2) No data was available at the Tier 1 level, so a national average from 2013 (11%) was used for the entire study period from the BEA.	MEDIUM-HIGH: The percent social insurance contribution did not vary widely historically for Durham an Orange County, providing a reasonable assumption that it will not vary widely in the future, however, in Tier 1 where per capita income is lower, the national average percent may be slightly high.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Percent of tax exempt nonresidential property value; total nonresidential property value (calibration); total MF property value (calibration); total SF property value (calibration); total commercial real property value (calibration)	(1) Total tax-exempt commercial and residential (SF only) property values from: NC DOR. 2004-2014. "County Taxable Real Property Valuations" for Durham and Orange County. (2) Breakdown of total commercial property value into multifamily and single-family housing from: "Durham County Tax Administration Real Property Tax Database." 2000-2014.	Used to determine the amount of taxable real property value in Tier 2 and Tier 1, which affects property tax revenues.	The data from the NC DOR give % residential and % commercial real property value, but they do not divide commercial into multifamily housing (apartments) and nonresidential property value. The Durham County property tax database did not make it easy to separate tax exempt and non-tax exempt property, therefore, both datasets were necessary to determine the amount of non-residential property value that was tax exempt.	MEDIUM-HIGH for Tier 2, with the only sources of error being the limited amount of property value available for Orange and Chatham County (2014 only) and the use of Orange County entire for the combined portions of Orange and Chatham County in the DCHC MPO for the NC DOR data. MEDIUM-LOW for Tier 1, with quite a bit of uncertainty around these calculations with data unavailable at the Tier 1 level.
County property tax rate; city property tax rate; percent of county real property value in cities (Tier 2 only), total county real property value (calibration)	Durham County, Orange County, City of Durham, and Town of Chapel Hill Comprehensive Annual Financial Plans (AFPs) for FY 2009 and 2014.	Used to determine property tax revenues for the county and city local government budgets.	AFPs are the official city and county financial documents, making them the most reliable, direct source for tax revenue information and each AFP provided 10-year summary tables of property tax information, requiring only 2 documents to be downloaded (2009 and 2014) to collect historical data for 2000-2014.	MEDIUM-HIGH: HIGH for historical property value and tax rate data for Tier 2 and MEDIUM for projected values because tax rates are held constant at 2014 values for 2015-2040 even though tax rates are highly variable historically.
Combined sales tax rate; local sales tax rate; percent of collected local option sales tax distributed	(1) NC DOR. 2013. "Table 36A. State Sales and Use Tax: Gross Collections by County, FY 2000-2013." (2) NC DOR. 2003-2013. "Table 56. Summary of Local Sales and Use Tax Collections, Tax Allocations, and Distributable Proceeds by County."	Used to determine state and local sales tax collected and local sales tax revenues received back from those collections for the county and city local government budgets.	Only NC DOR had data on the amount of state and local sales and use tax collected AND distributed.	HIGH: Authoritative government source.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Transit sales tax share of local option sales tax revenues	(1) NC DOR. 2013. "Table 60A. Article 43 Local Government Sales and Use Taxes for Public Transportation for FY 2013." (2) Triangle Transit. 2014. "Durham and Orange County Bus and Rail Investment Progress Reports for FY 2014."	Used to calculate "half cent transit sales tax revenues," a component of "total LRP revenues," which is used to calculate the D-O LRP budget.	NC DOR has not yet released data for FY 2014, but Triangle Transit did report the half cent transit tax revenues for FY 2014, so FY 2013 was checked for both sources to make sure the values matched.	MEDIUM-HIGH: While confidence is high for the historical years of data available (2013 and 2014), 2014 was the only full fiscal year that the transit tax was collected, thus only providing one data point for forecasting future values of this model input.
County share of local option sales tax revenues; city share of local option sales tax revenues (both Tier 2 only)	NC DST. 2015. "Local Government Revenues by Source: Local Option Sales Tax Revenues for Chapel Hill and the City of Durham, FY 2000-2014."	Used to divide local option sales tax revenues into county and city revenues for the county and city local government budgets.	Several different sources, including county and city AFPs and annual budgets, had conflicting values for these percentages, but NC DST reviews AFPs and budgets to compile their statistics.	MEDIUM-HIGH: Authoritative government source, however a large amount of variability historically makes projecting these percentages less certain.
Rental car tax revenues (Tier 2 only)	(1) Triangle Transit. 2014. "Durham and Orange County Bus and Rail Investment Progress Reports for FY 2014." (2) Triangle Transit et al. 2012. "The Bus and Rail Investment Plan in Orange County." (3) DCHC MPO et al. 2011. "The Durham County Bus and Rail Investment Plan."	A component of "total LRP revenues," which is used to calculate the D-O LRP budget.	(1) Only source for rental car tax revenues collected for the D-O LRP in 2014 (the first year it was collected). (2) and (3) Bus and rail investment plans gave an expected annual growth rate for rental car tax revenues collected in both Durham and Orange County (4.0%).	MEDIUM-HIGH: Only one year of actual collected data was available (2014), but Triangle Transit does extensive budgets using historical data.
Nominal revenues per vehicle (Tier 2 only)	(1) NC DOT. 2014. "Auto and Truck Registrations in Durham County and Orange County, 2014." (2) Triangle Transit. 2014. "Durham and Orange County Bus and Rail Investment Progress Reports for FY 2014." (3) Triangle Transit. 2015. "FY 2015 Annual Budget & Capital Investment Plan: XI. Durham-Orange Bus and Rail Investment Plan."	Used to calculate "vehicle registration fee revenues," a component of "total LRP revenues," which is used to calculate the D-O LRP budget.	(1) and (2) were used to calculate the revenues collected for the year 2014, and were the most authoritative sources for both data needs. The Triangle Transit 2015 budget (3) gave an estimate of vehicle registration fee revenues for Durham and Orange County in 2015, the first full year in which the fees were collected, with one vehicle registration fee being $7 per vehicle and another being $3 per vehicle, for a combined total of $10.	HIGH: Calculated from historical data for 2014 and no reason to believe it will change from $10 total per vehicle between 2015 and 2040.

TABLE C-5. MODEL INPUT CHARACTERIZATION FOR THE EQUITY SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Property values (calibration)	Durham County Tax Administration. 2000-2014. Durham County Tax Administration Real Property Database, Orange County Tax Administration. 2014. Orange County Parcel Database, Chatham County Tax Administration Office. 2014. Chatham County Tax Parcel Database.	Used to determine affordability and property tax revenue.	Most detailed sources; used by Durham planning department for their comprehensive plan	HIGH: Authoritative source used for property taxation.
Median annual renter costs (calibration)	Geographic Research Inc. 2015. "Census Data 2000, ACS Estimates 2008-2014." Accessed from SimplyMap Database by county and block group; U.S. Census Bureau. 2000. "Census 2000, Summary File 3" by block group; U.S. Census Bureau American Community Survey. 2014. American Community Survey 1-yr estimates by county and 5-yr Estimates by block group 2005-2013.ACS 5- yr estimates by block group; Zillow by zip code	Used to determine affordability.	Multiple sources were used to corroborate trends, since each source had either the right spatial or temporal scale, not both.	MEDIUM: Different sources show different values and somewhat different trends.
Percent of population in poverty (calibration)	Geographic Research Inc. 2015. "Census Data 2000, ACS Estimates 2008-2014." Accessed from SimplyMap Database by block group; U.S. Census Bureau. 2000. "Census 2000, Summary File 3" by block group; U.S. Census Bureau American Community Survey. 2014. American Community Survey 1-yr estimates by county and 5-yr Estimates by census tract 2005-2013.	Used to determine the population in poverty and zero-car households.	Multiple sources were used to corroborate trends, since each source had either the right spatial or temporal scale, not both.	MEDIUM: Different sources show different value and somewhat different trends.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Zero-car households (calibration)	Geographic Research Inc. 2015. "Census Data 2000, ACS Estimates 2008-2014." Accessed from SimplyMap Database by block group.	Used to determine transit-dependent population which affects transportation mode choice.	Consistent with the source used for the population in poverty.	HIGH: The U.S. Census Bureau is the authoritative source for demographic data.
Percent of multifamily dwelling units below 75 percent of median renter costs	U.S. Census Bureau American Community Survey. 2014. American Community Survey 1-yr Estimates 2005-2013 at county level	Used to indicate organically affordable units, which affects the "housing gap for households in poverty;" in the absence of reliable projections for this value, model users can vary this estimate going forward.	Consistent with data source for renter housing costs	LOW: The initial value has high confidence, but we were unable to identify either reliable projections or a modeling method for estimating how the distribution of rental units at various cost units will change over time. Accordingly, we have designated this variable as a user-specified input.
Subsidized total dwelling units	Bearden, Ben. 2015. Durham and Orange County Subsidized Housing Point Shapefiles received from Ben Bearden at Triangle J Council of government.	Initial value for a user-modifiable table which determines the number of households not at risk for displacement.	Most comprehensive list of publicly subsidized housing units maintained by governments in Durham and Orange county.	MEDIUM: Data are only available for the current year; an undetermined percentage of units are not guaranteed to remain subsidized in the future, so we are unable to project changes in this variable over time.
Poverty threshold	U.S. Census Bureau. 2013. "National Poverty Standards for 2013 by Size of Family and Number of Related Children Under 18 Years."	Forty-five percent of this value is used as the budget/income value in the affordability index for households in poverty.	The U.S. Census Bureau uses an absolute poverty threshold, which allows comparison over time.	HIGH: Authoritative source for defining the poverty threshold.
Elasticity of single-family (SF) property value to SF density (Tier 1); elasticity of nonresidential property value to building size; elasticity of SF property value to job density; elasticity of nonresidential property value to retail density (Tier 2)	Srour, Issam M., Kara M. Kockelman, and Travis P. Dunn. 2002. "Accessibility indices: Connection to residential land prices and location choices."	Used to relate several variables (including density, a building size proxy, and a retail density proxy) to property values, calibrated to match historical trends.	Clear elasticities available for a variety of variables we estimate in the model. One of best sources for nonresidential property values.	MEDIUM-LOW: The study examined Dallas-Fort Worth during the 1990s and derived elasticities on a neighborhood basis. Elasticities from the study therefore reflect variation across locations, but we apply them in the model to variation over time.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Elasticity of single-family (SF) property value to income; elasticity of SF property value to population	Jud, G. Donald, and Daniel T. Winkler. 2002. "The dynamics of metropolitan housing prices."	Used to relate income and population to property values, calibrated to match historical trends.	Values provided by this source yielded a better fit to historical trends than other available sources (e.g., Srour, 2002).	MEDIUM: The study derived elasticities for 130 metro areas around the U.S., so values may not be representative of the study area.
Elasticity of single-family (SF) and multifamily (MF) property value to vacant land (used to create the effect table of vacant land on SF property value (in Tier 1)	Capozza, Dennis R., Patric H. Hendershott, Charlotte Mack, and Christopher J. Mayer. 2002. "Determinants of real house price dynamics."	Used to relate vacant land to property values, calibrated to match historical trends.	Best available source that characterized this relationship.	MEDIUM: The study derived elasticities for 62 metro areas around the U.S., so values may not be representative of the study area.
Elasticity of single-family (SF) property value to retail density; elasticity of multifamily (MF) property value to retail density; elasticity of nonresidential property value to retail density (Tier 1)	Kain, John F., and John M. Quigley. 1970. "Measuring the value of housing quality."	Used to relate a retail density proxy to property values, calibrated to match historical trends.	Values provided by this study yielded a better fit to historical trends than other available sources, particularly in Tier 1.	MEDIUM-LOW: The study examined St. Louis in the 1970s and derived elasticities on a neighborhood basis. Elasticities therefore reflect variation across locations, but we apply them in the model to variation over time.
Elasticity of single-family (SF) property value to commute time; elasticity of MF property value to commute time	Kockelman, K. M. 1997. "The effects of location elements on home purchase prices and rents: Evidence from the San Francisco Bay Area. "	Used to relate a commute time proxy to property values, calibrated to match historical trends.	Best available source that characterized this relationship separately for renter-occupied and owner-occupied housing.	MEDIUM-LOW: The study examined San Francisco in the 1990s and derived elasticities on a neighborhood basis. Elasticities therefore reflect variation across locations, but we apply them in the model to variation over time.
Elasticity of nonresidential property value to employment	Dobson, S.M., and J. A. Goddard. 1992. "The determinants of commercial property prices and rents." (Dobson and Goddard)	Used to relate employment growth to property values, calibrated to match historical trends.	Best available source that characterized the relationship over time, consistent with the intended use in the model.	MEDIUM-LOW: The study examined Great Britain in the 1970s-80s, though the elasticities were derived to reflect change over time in response to changes in employment.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Elasticity of housing costs to renter vacancy	Rosen, Kenneth T., and Lawrence B. Smith. 1983. "The price-adjustment process for rental housing and the natural vacancy rate."	Used to relate renter vacancy to renter housing costs, calibrated to match historical trends.	Best available source that characterized this relationship for renter-occupied housing.	MEDIUM: The study derived elasticities for 17 metro areas around the U.S. (we use the median reported value), so values may not be representative of the study area.

TABLE C-6. MODEL INPUT CHARACTERIZATION FOR THE WATER SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Historical precipitation	State Climate Office of North Carolina. 2015. "Historical Data."	Used to calculate drinking water reservoir volume and stormwater runoff	Authoritative government source with regional data.	HIGH: Authoritative source at the same geographic scale as the study area.
Percent evapotranspiration	Wilson. 2011. *Constructed Climates: A Primer on Urban Environments*. Chicago: The University of Chicago Press.	Used to calculate drinking water reservoir volume	Authoritative local source; author is a professor at a local university.	MEDIUM: Water lost by evapotranspiration will vary due to many site-specific factors that are not accounted for in this estimate.
Impervious Surface Area	US EPA. 2015. "EnviroAtlas."	Used to calculate stormwater runoff and stormwater pollutant loading. (Impervious surface area is calibrated within the land use sector.)	Authoritative national source with 1-meter-resolution land cover.	MEDIUM: The 1-meter land cover generally follows the Durham study area but does not extend into Chapel Hill.
Event mean concentration (EMC) for nitrogen and phosphorus	NCDENR. 2011. *Jordan Lake Stormwater Accounting Tool User's Manual (Version 1.1.).*	Used to calculate stormwater pollutant loading.	Authoritative local source. The Jordan Lake Stormwater Accounting Tool is a spreadsheet tool used to calculate the stormwater runoff impact of new local development.	MEDIUM: Data from this source are based on local and national sources, but EMCs have large variability due to fine-scale differences in land cover. Our use of EMCs for different land use types approximates that variability.
Energy intensity for water treatment and distribution	American Council for an Energy-Efficient Economy. 2010. "North Carolina's Energy Future: Electricity, Water, and Transportation Efficiency. Report E102."	Used to calculate energy used by the municipal water system.	Authoritative source that applies national numbers on the energy intensity of water systems to North Carolina.	MEDIUM: The source provided two energy intensity estimates: 3,972.5 kWh/Mgal and 3,239 kWh/Mgal. We adopted a conservative approach in the context of reducing CO_2 emissions, using the higher of the two intensity estimates to prevent underestimating CO_2 emissions.
Total water demand (calibration)	NC State Data Center. 2015. "LINC: Log Into North Carolina."	Used to determine withdrawals from water reservoirs and calculate energy used by the municipal water system.	Authoritative government source with multiple time points.	HIGH: Authoritative source for historical water demand data.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Durham reservoirs - days of supply (calibration)	City of Durham Department of Water Management. 2015. "Water Supply Status." Available at: http://durhamnc.gov/ich/op/dwm/Pages/Water-Supply-Status.aspx	Used (together with water demand) to determine water reservoir volume. In addition, future trends in reservoir volume are modeled, assuming a constant water supply rate but a growing demand.	Authoritative government source.	HIGH: Authoritative source for historical reservoir supply data.
Durham reservoirs - average demand (calibration)	City of Durham Department of Water Management. 2015. "Water Supply Status." Available at: http://durhamnc.gov/ich/op/dwm/Pages/Water-Supply-Status.aspx	Used (together with reservoir levels) to determine water supply.	Authoritative government source.	HIGH: Authoritative source for historical water demand data.
Projected water demand - Durham and other counties (calibration)	TJCOG. 2012. "Triangle Regional Water Supply Plan, Vol I: Regional Needs Assessment."	Used (together with reservoir levels) to determine water supply. Total water demand is also used to calculate energy and emissions for the municipal water system.	Authoritative government source.	MEDIUM: Future projections are inherently uncertain.
Single-family residential water use rate per person (calibration)	US DOE. 2011. *2010 Buildings Energy Data Book*.	Used to calculate residential water use, which is the largest component of local drinking water demand.	Authoritative government source.	MEDIUM: Source provides a national average that may not be representative of our study area.
Multifamily water use rate per household (calibration)	US DOE. 2011. *2010 Buildings Energy Data Book*.	Used to calculate residential water use, which is the largest component of local drinking water demand.	Authoritative government source.	MEDIUM: Source provides a national average that may not be representative of our study area.
Elasticity of water use to residential density	Chang et al. 2010. "Spatial variations of single-family residential water consumption in Portland, Oregon." *Urban Geography* 31, 7, 953-972.	Used to relate residential density to residential water use.	Has data relating single-family residential density (DU/acre) to household water consumption.	MEDIUM: Source examined Portland, OR, so the relationship it estimates may not be representative of our study area.
Nonresidential use rate (calibration)	TJCOG. 2012. "Triangle Regional Water Supply Plan, Vol I: Regional Needs Assessment."	Used to calculate nonresidential water use, the second largest component of local drinking water demand.	Authoritative government source	HIGH: Authoritative local government source for nonresidential water use.

TABLE C-7. MODEL INPUT CHARACTERIZATION FOR THE HEALTH SECTOR

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Mortality cases per ton of $PM_{2.5}$; morbidity cases per ton of $PM_{2.5}$; Mortality cases per ton of NO_x; morbidity cases per ton of NO_x	US EPA. 2013. "Technical support document: estimating the benefit per ton of reducing $PM_{2.5}$ precursors from 17 sectors."	Used to estimate the mortality and morbidity impacts of changes in $PM_{2.5}$ and NO_x emissions from vehicles (positive or negative) relative to the BAU scenario.	Source involved extensive health benefits research and source apportionment photochemical modeling; most current available study with estimates of health impacts of $PM_{2.5}$ and NO_x emissions from vehicles, expressed in cases per ton.	MEDIUM-LOW: Though these are the best available estimates for health impacts per ton of $PM_{2.5}$ and NO_x emissions reduced from vehicles, they are national averages intended to be used for a scoping-level analysis and may therefore not be appropriate at the scale used in our model.
Reduction in mortality per person mile of walking for transportation per day per capita; reduction in mortality per person mile of cycling for transportation per day per capita	WHO. 2014. "Health economic assessment tools (HEAT) for walking and for cycling: Methodology and user guide, 2014 update."	Used to calculate avoided premature mortalities due to changes in the amount of walking or cycling for transportation per day per capita.	The HEAT model equations are simple and based off of many epidemiological studies and associated correlations between walking/cycling and health benefits.	MEDIUM-HIGH: The source's recommended applicable age range for estimating benefits from walking is 20-74 and for cycling is 20-64, but we applied it to the average rate of walking and cycling for transportation over the entire population. Also, the accuracy of the HEAT calculations should be understood as estimates of the order of magnitude of the expected effect rather than the precise effect.
People in traffic accidents per year; crash injuries and fatalities per year; crash fatalities per year; nonfatal crash injuries per year (calibration, Tier 2 only)	Highway Safety Research Center at UNC Chapel Hill. 2015. "NC Crash Data Query Web Site."	Used to estimate mortality and morbidity impacts due to changes in transportation by vehicles.	Based on official crash statistics from the North Carolina government (2001-2013), which are highly detailed and able to be parsed out in numerous ways.	MEDIUM-HIGH: Statistics are for Orange and Durham Counties combined, as opposed to the exact extent of the study area. Data are limited to "reportable" crashes, defined as those that occur on publicly-maintained roadways and which also result in at least $1,000 worth of damage.

MODEL INPUT	SOURCE	HOW INPUT IS USED IN THE MODEL	RATIONALE FOR SELECTING SOURCE	CONFIDENCE LEVEL NOTES
Percent of people in traffic accidents that are injured or killed; fatal percent of crash injuries	Highway Safety Research Center at UNC Chapel Hill. 2015. "NC Crash Data Query Web Site."	Used to determine crash fatalities and injuries per year from the overall number of people in crashes during a year.	Data come from official source and are highly detailed.	Tier 2 = MEDIUM-HIGH; Tier 1 = MEDIUM: The numbers are for all of Durham and Orange Counties. It is assumed that the Durham + Orange figure will be fairly close to the MPO figure. In the absence of data for Tier 1, we assume that values for Tier 1 are equal to those for Tier 2.
People in traffic accidents per VMT	(1) Highway Safety Research Center at UNC Chapel Hill. 2015. "NC Crash Data Query Web Site."(numerator); (2) DCHC MPO. 2013. "Triangle Regional Model version 5: Travel demand result shapefiles." (TRM) (denominator)	Used to estimate the number of people in traffic accidents per year, from which are calculated the numbers of people killed and injured in traffic accidents per year.	(1) Data come from official sources and are highly detailed. (2) Primary source of VMT and traffic congestion projections used by local transportation planning agencies; spatial nature allows clipping to both Tiers.	Tier 2 = MEDIUM-LOW; Tier 1 = LOW: Data were only available from both sources in 2010; therefore, we assumed the 2010 ratio to hold constant for all model years. Statistics are for Orange and Durham Counties combined, as opposed to the exact extent of the study area. Data are limited to "reportable" crashes (defined as those that occur on publicly-maintained roadways and which also result in at least $1,000 worth of damage), so they may underestimate total traffic accidents with health risks. In the absence of data for Tier 1, we assume that values for Tier 1 are equal to Tier 2.
Percent of person miles of nonmotorized travel by residents that is cycling	(1) US DOT, Federal Highway Administration. 2009. "2009 National Household Travel Survey." (2) ESRI Community Analyst. 2014. "ACS 1-yr and 5-yr Estimates 2005-2013." (Tier 1 only)	Used to divide nonmotorized person miles by residents into walking and cycling miles, which the model uses to estimate health benefits from walking and cycling (using the HEAT model).	(1) Authoritative source with detailed data; (2) Community Analyst is able to clip ACS data from the U.S. Census Bureau to specific geographic areas.	MEDIUM: Data are not specific to the study area, so we assume that the value for this variable for the DCHC MPO matches the national average. Community Analyst/ACS data that were used to scale NHTS data to Tier 1 only examine journey-to-work trips, and do not consider the number of miles traveled.

Appendix D: Data Sources Not Used

As we developed the D-O LRP SD Model, we identified several data sources that we were not able to include in the model, either because they were inferior to other data sources or because they did not contain data at the appropriate scale for our model's purposes. The table presented in this appendix lists data sources that we did not use to develop the model, together with the rationale for excluding each data source.

TABLE D-1. DATA SOURCES NOT USED

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Land Use	Acres by land use type	(1) Durham County Tax Administration. 2000-2014. Durham County Tax Administration Real Property Database. (2) Orange County Tax Administration. 2014. Orange County Parcel Database. (3) Chatham County Tax Administration Office. 2014. Chatham County Tax Parcel Database.	When we examined the data from the tax property databases, we found that they showed that total developed acres declined between 2001 and 2014, contrary to common sense. Laura Woods at the Durham County Planning Department, who has analyzed the same dataset, mentioned that many errors, particularly in earlier years, were evident. Finally, Orange and Chatham counties did not have nearly as detailed information as Durham, whereas the CV2 database was of equal detail for the whole study area.
	Developed nonresidential square feet by type	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario"	Imagine 2040's projections for developed nonresidential square feet by type are based on many strong assumptions (including constant employee space ratios), and only provide estimates for 2040
	Single-family home values	U.S. Census Bureau American Community Survey. 2014. "American Community Survey 1-yr and 5-yr Estimates 2005-2013."	Since property values of multifamily homes and nonresidential properties were only obtainable from the County Property Tax Databases, we obtained values for single-family homes from the same source for the sake of consistency.
	Employee space ratios	TJCOG. 2013. "Imagine 2040: The Triangle Region Scenario Planning Initiative Final Summary Document" (p115-117).	Uses constant employee space ratios from the literature that were very inconsistent with those calculated from our data sources for employment and square feet.
Transportation	Congestion	CAMPO and DCHC MPO. 2013. 2040 Metropolitan Transportation Plans.	Though it provides measures of congestion, this source does not provide the specific measure of congestion that was ultimately chosen for the model (namely, the ratio of peak-period travel time to freeflow travel time, weighted by VMT on each road link).

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Transportation	Construction cost per lane mile	American Road and Transportation Builders Association. 2014. "Transportation FAQs."	We chose to use the Metropolitan Transportation Plan, which is both authoritative and local, instead of this source, which only provides data from other states.
	Elasticity of desired vehicle ownership per person not in a zero-car household to per-capita income	Johansson, Olof, and Lee Schipper. 1997. "Measuring the long-run fuel demand of cars: Separate estimations of vehicle stock, mean fuel intensity, and mean annual driving distance."	The elasticity value estimated by this source is much higher than the value we used, largely because it comes from a study that included many developing nations, which are much farther from vehicle-ownership saturation than the United States is.
	Elasticity of public transit travel to fare price	Sinha, Kumares Chandra, and Samuel Labi. 2007. *Transportation Decision Making: Principles of Project Evaluation and Programming* (page 55).	Though we considered using the elasticity provided by this source, we instead followed the recommendation of a staffer from a local planning agency to use a formula based on the Simpson & Curtin formula, which is commonly used by public transit planners.
	Functioning lane miles	CAMPO and DCHC MPO. 2013. 2040 Metropolitan Transportation Plans.	This source only provides data for the DCHC MPO as a whole and not at a scale that could be used for Tier 1, so we used data from the TRM instead. While this source's numbers are based on the TRM, it does not count the TRM's "centroid connectors," which serve as stand-ins for a variety of lower-order roadways.
	Functioning lane miles	US EPA, Office of Policy, Office of Sustainable Communities. 2013. Smart Location Database version 2.0. (SLD)	This source only provides densities of road miles within Census Block Groups and does not provide the number of lanes on the average roadway. Rather than clipping Block Groups to the study area (which could introduce error), we used road-link-based data from the Triangle Regional Model.
	LRT construction cost per line mile	Triangle Transit. 2015. "Our Transit Future."	This source provides numbers for the casual observer without much explanation, in contrast to the planning documents that we used for this variable.

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Transportation	Person miles of <insert mode> travel per day	US DOT, Office of Policy, Office of Transportation Policy, Office of Economic and Strategic Analysis. 2014. The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations Revision 2 (2014 Update).	This source provides estimates of the monetary values that people place on the time they spend traveling. These values could be used to calculate what the appropriate ratio should be between the respective effects of travel time and monetary travel costs on mode choice. The source is authoritative, but not local, and it does not provide a clear equation to input, but just numbers that could be used to figure out such an equation. Because of these limitations, we chose not to expressly include the tradeoff between travel time and monetary costs in the model, although modal person miles are partially driven by factors that influence travel time and monetary costs of travel.
	Public transit trip distance	NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (study conducted to generate inputs for the Triangle Regional Model)	The National Transit Database contains more recent and more detailed data for this variable.
	Public transit unlinked passenger trips per day	Ramsey, Kevin, and Alexander Bell. 2014. Smart Location Database Version 2.0 User Guide.	The National Transit Database provides data for this variable that covers multiple years, is more detailed, and is authoritative.
	Vehicle stock	US EPA, Office of Policy, Office of Sustainable Communities. 2013. Smart Location Database version 2.0. (SLD)	For this variable, we relied on SimplyMap, which provides calibration data for multiple years, whereas the SLD only provides data for a single year. Both SimplyMap- and SLD-derived vehicle stock figures are based on counts of households with given numbers of vehicles, but SimplyMap includes more categories (up to 4+ vehicles) than SLD (up to 2+ vehicles), making it a more accurate source for our purposes.
	Vehicle trip distance	NuStats. 2006. Greater Triangle Travel Study, Household Travel Survey Final Report. (study conducted to generate inputs for the Triangle Regional Model)	The values provided by this source are inconsistent with the Metropolitan Transportation Plan (MTP), which, although partially based on this source, also contains more recent data. We calculated the values to which this variable is calibrated primarily on the basis of the MTP, instead.

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Energy	VMT	CAMPO and DCHC MPO. 2013. 2040 Metropolitan Transportation Plans.	For this variable, we relied on direct outputs from the Triangle Regional Model (which the numbers in this source are based on). Doing so allowed us to get data in both Tiers, instead of just Tier 2.
	Developed nonresidential floor area (square feet)	(1) Durham City-County Sustainability Office. 2015. (citing Durham City-County Planning Department data) (2) TJCOG. 2014. CommunityViz 2.	For developed nonresidential floor area, we relied on data from the Durham County property tax database over data from the Durham planning department due to longer coverage (2000-2014 vs. 2005-2012). We also considered using projections from CommunityViz 2, but those values would have been calculated based on general floor area ratios rather than being based on data.
	Vehicle Fuel Efficiency (MPG)	US DOT. 2013. "New and Small Starts Evaluation and Rating Process Final Policy Guidance."	Does not equate Btu/VMT to gallons of fuel/VMT. We instead needed to calculate gallons of fuel to model energy spending. For this, we relied on data from the Energy Information Administration's Annual Energy Outlook (AEO), which has projected MPG every year from 2012-2040. The "New and Small Starts" document, by contrast, only projects 10 and 20 years into the future.
	$PM_{2.5}$ and NO_x emissions per VMT	US DOT. 2013. "New and Small Starts Evaluation and Rating Process Final Policy Guidance."	The New and Small Starts document gives $PM_{2.5}$ and NO_x emissions rates for three years only (2013, 2023, 2033), and while the NOx emissions rates decrease over that time period, the PM2.5 emissions rates remain constant. We were advised through personal correspondence with Dr. Amy Lamson that this was erroneous and we instead calculated annual emissions rates using GREET model emissions rates and a US fleet age distribution, which shows a steady decline in PM2.5 emissions rates.
	Solar capacity	(1) Oleniacz. 2014. "Company Puts Last Panel on Durham County Solar Farm." The Herald Sun (local newspaper) (2) Crowley and Quinlan. 2011. *North Carolina Clean Energy Data Book*. p. 55	These two sources provided numbers for local solar capacity at two years within the D-O LRP model timeframe. However, the North Carolina Sustainable Energy Association more recently provided county-level data on solar capacity, 2005-2014, which we used instead.

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Economy	GRP & GRP Growth Rate	Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet."	GRP: Woods & Poole use their own formulation to calculate GRP by county based on their earnings data, but do not disclose this formula. Because our calculated earnings estimates were less than Woods & Poole (our employment numbers were lower), we could not use Woods & Poole's GRP without knowing their methodology. GRP Growth Rate: Woods & Poole's projected GRP growth rate (2014-2040) of about 3% per year could not be applied to our historically calculated GRP in 2013 because this would cause GRP to grow faster than calculated "total earnings" between 2014 and 2040, with the share of earnings decreasing from 60% in 2013 to less than 55% of GRP in 2040. Without knowing Woods & Poole's rationale for why GRP would grow faster than earnings, we decided instead to hold the earnings share of GRP constant at 60% between 2014 and 2040 for the BAU scenario (Tier 2), and use this calculated GRP to calibrate the Tier 2 GRP in the model.
	GRP & GRP Growth Rate	BEA. 2014. "Gross Domestic Product (GDP) by Metropolitan Area: GDP in Current Dollars, 2001-2013, for the Durham-Chapel Hill, NC Metropolitan Statistical Area (MSA)."	Historical GDP data from the BEA could not be used for Tier 2 because they were only available by Metropolitan Statistical Area (MSA), not by county.
	Total Employment	Woods & Poole Economics, Inc. Copyright 2014. "Durham and Orange County, NC Data Pamphlet;" BEA. 2014. "Local Area Personal Income and Employment: Table CA25N, Total Full-Time and Part-Time Employment by NAICS Industry, 2001-2013, for Durham and Orange County, NC."	We could not use Woods & Poole's historical or projected data for total employment (historical employment data from Woods & Poole are from the BEA), even for the model years not covered by the TRMv5 (2000-2009), because Woods & Poole (BEA) total employment numbers are much higher in 2010 than the TRMv5 SE data total employment numbers. This difference is because they measure more kinds of employment, including proprietors, private household employees, and miscellaneous workers, which the data collection for the TRMv5 did not include.

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
	Employment by Job Category	DCHC MPO. 2013. "Triangle Regional Model version 5: Socioeconomic data and projections for the preferred growth scenario."	The TRMv5 SE data provided employment by job categories, however some job types within a certain 2-digit NAICS category were divided among job categories in the TRM, making it impossible to combine these jobs by category with earnings per job by category data from Woods & Poole to get total earnings. E.g. The job type "Library & Archives," which is categorized by NAICS as an information job (2-digit NAICS code = 51), is considered a service job in the TRMv5 SE data, while the job type "Newspaper Publishers," also categorized as an information job with a 2-digit NAICS code of 51, is considered an industrial job in the TRMv5 SE data.
Equity	Elasticities of property values to housing age, home sq ft, # of rooms, and interest rates	Dobson, S.M., and J. A. Goddard. 1992. "The determinants of commercial property prices and rents." Heikkila, E., P. Gordon, J.I. Kim, R.B. Peiser, and H.W. Richarson. 1989. "What happened to the CBD-distance gradient?: Land values in a policentric city." Kain, John F., and John M. Quigley. 1970. "Measuring the value of housing quality." Kockelman, K. M. 1997. "The effects of location elements on home purchase prices and rents: Evidence from the San Francisco Bay Area." Srour, Issam M., Kara M. Kockelman, and Travis P. Dunn. 2002. "Accessibility indices: Connection to residential land prices and location choices."	While these variables are significantly associated with single-family or nonresidential property values in the literature, they were either not associated with property values in our time series data (e.g., housing age did not correlate with property values over time and had very low R^2), or were not likely to show any changes in response to other variables in our model, so we decided not to include these relationships.
	Median Rent	Zillow Real Estate Research. 2010-2014. "Median Rent by County and Zip Code."	The data were only available for a short timespan, were based on advertised rent rather than rent paid, and were not standardized as to the costs they include (e.g. utilities), as are renter costs reported by the U.S. Census Bureau.

SECTOR	MODEL INPUT	DATA SOURCE	WHY NOT USED
Water	Average Precipitation	NOAA. 2015. Durham, NC station 312515	NOAA's precipitation data for the region comes from a single weather station in the city of Durham. Because the model is regional in scope, we instead chose a data source that provided regional precipitation data.
	Per Capita Water Use	USGS. 2015. "Water use in North Carolina: 2005 data tables." http://nc.water.usgs.gov/infodata/wateruse/data/Data_Tables_2005.html	The USGS source has data for 2005 only. In addition, the source that we used for this model input provided separate water use intensities for different land use types (namely, single-family, multifamily, and nonresidential).
	Lake Water Quality	NCDENR. 2015. "Falls Lake and Jordan Lake monitoring." http://portal.ncdenr.org/web/wq/fallsjordan	The NC DENR source includes data on nitrogen (N) and phosphorus (P) concentrations in the lakes receiving stormwater runoff from Tier 2, which is different (though related to) the N and P loading calculated by the model (estimated as lbs N or lbs P/year).
Health	Premature mortality and morbidity per ton for $PM_{2.5}$ and NO_x	Chan and Jackson. 2011. http://www.lung.org/associations/states/california/assets/pdfs/advocacy/smart-growth/tiax-full-technical-slides.pdf	We relied on incidence-per-ton estimates from EPA's technical support document (EPA 2013) because they are more recent and cover a larger time period (2016-2030, compared to 2025 only in Chan and Jackson 2011).

Appendix E: Stakeholder Meeting Materials

FIRST STAKEHOLDERS MEETING ON FEBRUARY 24, 2014 AT EPA RTP

Meeting Announcement and Agenda

Workshop on Developing Integrated Approaches to Sustainability
EPA's Research Program in Sustainable and Healthy Communities (SHC) – Durham Pilot Project

Feb 24, 1:00 – 4:30 pm

EPA RTP Campus Room C400A

Objective: To design an approach that uses dynamics systems modeling to explore the interplay among actions and decisions that lead to (or fail to lead to) healthier and more sustainable communities.

Background: EPA is engaging with its Federal (Department of Transportation and Housing and Urban Development) and local partners to develop approaches that enable communities to better consider interactions among decisions in the context of sustainability. Durham has been selected as one of the communities where approaches are developed and applied to real-world issues.

The present activity focuses on the proposed Durham-Orange Light Rail plan as a driver for these interactions – within the context of projections for regional demographic and economic growth - and Durham's goals for a sustainable and healthy community.

1:00 – 1:15	Welcome and Overview of SHC	Rochelle Araujo, EPA ORD
1:15 – 1:30	Systems Approaches to Sustainability	Joseph Fiksel, EPA ORD
1:30 – 1:45	Durham/Chapel Hill Sustainability Goals	Tobin Freid, Durham Sustainability Office
1:45 – 2:00	Overview of Durham – CH Light Rail	Jeff Weisner, URS
2:00 – 2:15	Population and Economic Growth in the Region	Felix Nwoko, DCHC MPO
2:15 – 2:30	Infrastructure and Growth – Structural and Fiscal Issues	John Hodges-Copple, Triangle J
2:30 – 2:45	Break	
2:45 – 3:00	Strategic Planning for Infrastructure Improvements	Hannah Jacobson, Durham City-County Planning
3:00 – 3:15	Urban Growth, Watersheds and Water Resources	Sarah Bruce and Heather Saunders, Triangle J
3:15 – 3:30	Transportation, Energy and Air Quality	Brennan Bouma, Triangle J
3:30 – 4:30	Discussion – Key Interactions	ALL

Meeting Attendees – February 24, 2014

EPA

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SECOND STAKEHOLDERS MEETING ON JUNE 4, 2014 AT TRIANGLE J COUNCIL OF GOVERNMENTS

Meeting Announcement and Agenda

EPA Project – Integrated Approaches to Sustainability:
Developing a Dynamic Systems Model

Focus: Durham-Chapel Hill Light Rail Project
Event: Stakeholders Meeting
Wednesday, June 4th 1:00pm
Large Conference Room, Triangle J Council of Governments
4307 Emperor Blvd, Suite 110 Durham, NC 27703

Purpose:

- An update on the progress of our conceptual model since our first stakeholders meeting (February 24th, 2014).
- Updates on the light rail project development phase and draft environmental impact statement.
- An interactive discussion on:
    - How well our conceptual model represents the system holistically.
    - Aligned decisions or policies that could be tested in our model and what we can do to incorporate them.
    - Availability of local data that could be useful to our model.
    - How we can make our model useful to the stakeholders.

Schedule:

1:00 – 1:10 Welcome and Introductions
1:10 - 1:20 Meeting Objectives, Project Overview and Approach (Araujo)
1:20 – 1:40 Demo of 3VS Model (Bassi)
1:40 – 1:45 Model organization, Outline of Desired Stakeholder Input (Araujo, Kolling)
1:45 – 2:00 Land use change, Equity (Cox)
2:00 – 2:10 Stakeholder Inputs to Land use change, equity
2:10 – 2:20 Water resources and infrastructure (Almeter)
2:20 – 2:30 Stakeholder Inputs to water resources and infrastructure
2:30 – 2:45 Health, quality of place, economics (Kolling)
2:45 – 3:00 Stakeholder inputs to health, quality of place, economics
3:00 – 3:10 Transportation, Energy (Flanders)
3:10 – 3:20 Stakeholder input to Transportation, Energy
3:20 – 3:30 Update on light rail project, draft EIS and other potential model uses
3:30 – 4:00 Group discussion on model structure, data sources, applications, future interactions

EPA

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LRP Stakeholder Feedback Sheet

Tentative Key Indicators

Land:
- relative change in developed land
- developed land per capita
- agricultural land converted to developed use
- quantity of multifamily housing and compact development
- degree of mixed-use

Equity:
- displacement of poorer residents
- housing affordability
- transportation affordability
- access to jobs

Water:
- pollutant Loading
- water Consumption
- water Treatment Cost
- infrastructure Cost

Economy:
- public revenues due to increased sales tax revenues, property tax, and public transport fees
- economic productivity gains due to increase in public transport trips and reduced congestion
- public expenditure changes due to reduced infrastructure costs
- private spending changes due to housing and transportation affordability

Health:
- air emissions
- traffic collisions
- physical activity increases from compact development and public transportation trips
- stress

Quality of Place:
- walkability
- housing and transportation affordability
- traffic collisions
- access to …
- public transportation capacity and trips

Transportation:
- relative change in Vehicle Miles Traveled (VMT)
- traffic congestion
- public transportation trips
- non-motorized trips
- transportation-related government expenditures

Energy:
- total energy consumption
- air emissions
- spending on motorized transportation
- electricity spending

Questions for stakeholders:

1. **Are these indicators of interest?**

2. **Which other indicators would be valuable to your organization?**

3. **Which elements or assumptions do you expect to be the most significant drivers of change due to the light rail? Have we addressed them?**

Possible interventions that could be testable

- Land and Equity:
    - reduced parking requirements for affordable TOD
    - increased height/density allowances for affordable housing in the ½ mile zone
    - flexible-use zoning near rail stations
    - expedited approval processes for mixed-use development
    - agricultural land conservation strategies
- Water:
    - green infrastructure incentives
- Economics:
    - strategies to promote vibrant walkable places
- Health and Quality of Place:
    - strategies to increase walkability of the station areas
- Transportation:
    - improved pedestrian and bicycle facilities
    - expanding/improving bus services that connect with the light rail line
    - increasing the level of traffic congestion that must be projected in order to warrant roadway-system capacity expansions, based on the assumption that some travelers will switch to either public transit or non-motorized transportation
- Energy:
    - actions by local government agencies to reduce energy consumption in their operations, such as drinking water and wastewater conveyance and providing public transit services
    - strategies promote energy-efficiency of buildings near light rail stations, through compact design

Questions for stakeholders:

1. **Are the system-wide impacts of these strategies and interventions of interest?**

2. **What specific interventions would be valuable to your organizations to test?**

Meeting Announcement and Agenda

EPA Project – Integrated Approaches to Sustainability:
Developing a Dynamic Systems Model

Focus: Durham-Orange Light Rail Project
Event: Stakeholders Review of Model Development and Analyses
Wednesday, May 13th 1:00pm
Large Conference Room, Triangle J Council of Governments
4307 Emperor Blvd, Suite 110 Durham, NC 27703

Purpose:

- To present and discuss the "beta" version of the working integrated systems model for Durham –Orange Light Rail and associated regional and local issues:
    - integrated, calibrated and tested interactions for land use, economic, and transportation sectors.
    - pathways, available information and potential model representation of energy, air emissions, water quantity, stormwater runoff, health, equity and quality of place.
- To discuss scenarios or policy options for use of the model.
- To discuss ways of interacting with the model (inputs/outputs/interfaces) and setting in which model can be most useful.

Schedule (Approximately):

1:00 – 1:10 Welcome and introductions
1:10 - 1:20 Meeting objectives, project overview and approach
1:20 – 2:15 Model Demo with land and transportation scenarios
2:15 – 2:30 Discussion of model construction
2:30 – 2:45 Break
2:45 – 3:30 Discussion of policies, scenarios
3:30 – 3:45 Demonstration of interfaces developed for similar models
3:45 – 4:00 Discussion - Interfaces, General

The team can be available for an additional half hour after the meeting for folks to "poke around under the hood". Similarly, we will be distributing comment sheets for attendees to use – either at the meeting – or to send along later – to provide feedback on the model, data/projections/models used, scenarios to be analyzed, additional functionalities desired of the model, etc.

In Person: Llael Cox, Jenna Kolling, Nick Flanders, Andrew Procter, Rochelle Araujo (EPA ORD); Nadav Tanners (IEc); Hannah Jacobson (Durham City/County Planning Dept); Patrick McDunnough (GoTriangle); Katherine Eggleston (GoTriangle); Geoff Green (GoTriangle); David Bonk (Chapel Hill); Mila Vega (Chapel Hill Transit); Jeff Weisner (AECOM); Marissa Mortiboy (Durham County); Helen Youngblood (Durham City/County Planning); Mike Shiflett (Coalition for Affordable Housing & Transit); Roy LeGard (Chapel Hill); Chris Dickey (Durham); Constance Stancil (City of Durham); Andy Henry (MPO); Andy Gillespie (EPA ORD); Elizabeth Doran (Grad Student at Duke); Todd BenDor (UNC Chapel Hill); John Hodges-Copple (Triangle J); Laura Jackson (EPA ORD);

On the Phone: Andrea Bassi (KnowlEdge Srl); Marilyn Ten Brink (EPA ORD); Melissa McCullough (EPA ORD); Gary Foley (EPA ORD); Kate Mulvaney (EPA ORD)

EPA D-O LRP System Dynamics Model

Summary of main assumptions in current model scenarios – May 13, 2015

BAU (Business as Usual)

Land

- Share of acres in each land use type held constant at 2013 values (from CV2 Parcel Geodatabase)
- Floor area ratios and dwelling units per acre remain steady at 2013 values (acres from CV2 Parcel Geodatabase, sq ft from County Tax Property Databases, and dwelling units from the Census)
- Employee space ratios remain relatively steady at 2013 value, except for:
    - industrial which declines following the historical trend
    - retail and office in Tier 1, which rise following the historical trend
- The percent of people in single and multi-family dwelling units are held constant at 2014 values
- Single family and multifamily household sizes are held constant at the 2014 value

Economy

- Total employment calibrated to match employment in the TRM v5 SE Data
- Total earnings is 60% of GRP, while gross operating surplus is 40%
- Share of employment by category and earnings per job by category from Woods & Poole Economics, Inc.

Transportation

- No light rail built
- No road building after 2017
- Bus system expansion conforms to Orange County and Durham County public transit plans
- Sidewalk building conforms to Triangle Regional Model projections

Energy and Water

- Passenger vehicle MPG increases according to US Energy Information Administration projections
- Annual precipitation stays constant over time
- Water consumption rates (per dwelling unit or per job) are taken from literature, including Triangle Regional Water Supply Plan

Light Rail

- Light Rail service begins 2026
- Tier 1 commercial sq ft increases in 2020 (10% increase in desired retail/office/service sq ft)

Light Rail + Density

- Increases density of new development (sq ft per acre and dwelling units per acre), by:
    - 10% in Tier 3 (DCHC MPO)
    - 20% in Tier 1 (combined 1/2 mile radius of all proposed rail stations)

Light Rail + Road Building

- Future road building increased, conforming to DCHC MPO 2040 MTP "Preferred Scenario"
- Still introduce light rail in 2026, but no increased density

Light Rail + Density + Road Building

- Light Rail service begins 2026
- Tier 1 commercial sq ft increases in 2020 (10% increase in desired retail/office/service sq ft)
- Increases density of <u>new</u> development (sq ft per acre and dwelling units per acre), by:
    - 10% in Tier 3 (DCHC MPO)
    - 20% in Tier 1 (combined 1/2 mile radius of all proposed rail stations)
- Future road building increased, conforming to DCHC MPO 2040 MTP "Preferred Scenario"

System Dynamics Model Stakeholder Feedback Sheet – May 13, 2015

Name and contact: ____

Organization: ____

We plan to add the ability to test several policies, interventions, or future trends in the model. Please rank the top *three* options in order of importance to your organization (1 as most important).

___ Redevelopment that changes density and use of existing land
___ Green infrastructure and its effect on impervious surface and stormwater
___ Land conservation strategies
___ Reduced parking requirements and the effect on affordability and VMT
___ Telecommuting and the effect on congestion
___ Other: ____
___ Other: ____

Please rank your *three* highest priority indicators to add to the model (1 as most important).

___ Income brackets and housing costs brackets to better assess household budgets and affordability
___ Health outcomes in terms of morbidity
___ Health outcomes in dollar terms
___ Quality of place index
___ Other: ____
___ Other: ____
___ Other: ____

Many assumptions about future trends are already easily modifiable in the model, such as those below. Are there other future trends that we might want to consider?

1. Densification (retail, office, service, industrial, single family, and multifamily separately)
2. Increase in nonmotorized facilities
3. Shifts in the share of employment
4. Increases in energy efficiency

What features of a user interface would you find most useful?

In what settings could you imagine using this model?

Please let us know any other feedback you have (feel free to elaborate on the back)

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