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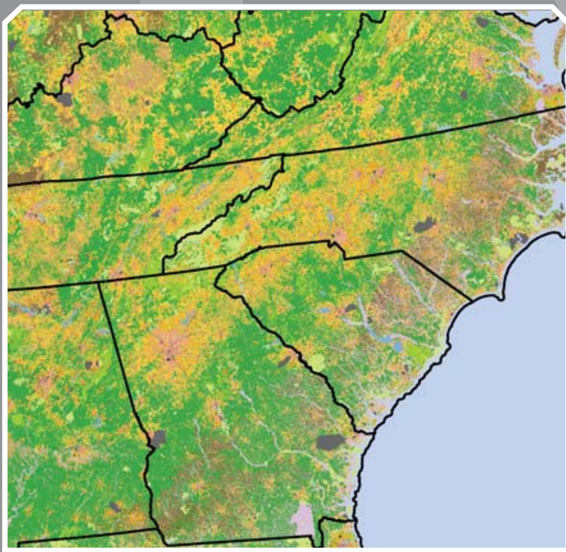
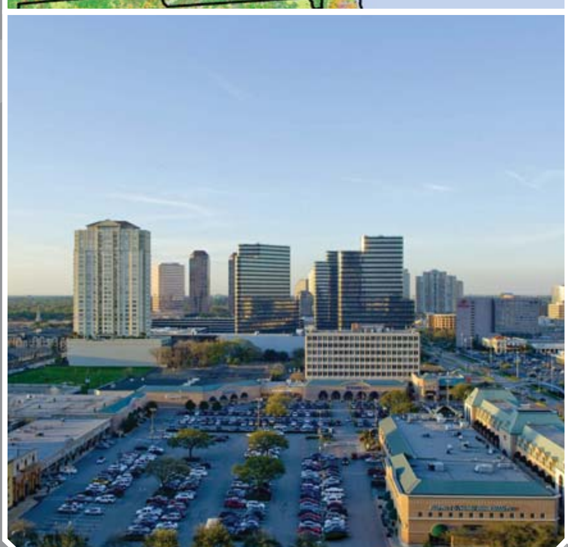
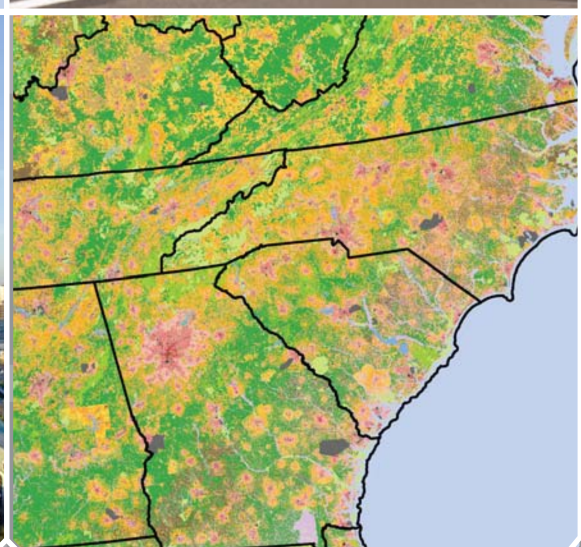
Updates to the Demographic and Spatial Allocation Models to Produce Integrated Climate and Land Use Scenarios (ICLUS) Version 2



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DISCLAIMER

ABSTRACT

The first version of the Integrated Climate and Land Use Scenarios (ICLUS) project modeled population, residential development, and impervious surface cover changes by decade to the year 2100 consistent with four Intergovernmental Panel on Climate Change (IPCC) emissions scenarios and a baseline. This report discusses improvements to the underlying demographic and spatial allocation models of the ICLUS that result in version 2 (v2) consistent with two of the new Shared Socioeconomic Pathways (SSPs) and two Representative Concentration Pathways (RCPs). Improvements include the use of updated data sets, integration of changing climate variables within the migration model, inclusion of transportation network capacity and its increase over time, growth in commercial and industrial land uses, and the use of population density-driven demands for residential housing, commercial development, and industry. This report demonstrates the effect of these improvements by comparing national and regional results among the SSP and RCP combinations and the two climate models selected. ICLUS v2 shows differences in population migration patterns by including climate variables that change over time rather than ones that are static. Additionally, changing commercial and industrial land uses can drive patterns of new urban growth with consequences for many environmental endpoints.

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CONTENTS

CONTENTS (CONTINUED)

LIST OF TABLES

LIST OF FIGURES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

BCSD	bias-correcting and spatial-downscaling
CI	confidence interval
CMIP	Coupled Model Intercomparison Project
df	degrees of freedom
DUA	dwelling units per acre
EPA	U.S. Environmental Protection Agency
FASOM	Forestry and Agricultural Sector Optimization Model
FIO-ESM	First Institute of Oceanography-Earth System Model
FIPS	Federal Information Procession Standard
FORESCE	FOREcasting SCEnarios
GAM	generalized additive model
GCM	general circulation model
GHG	greenhouse gases
GU	geographic unit
HadGEM2-AO	Hadley Global Environment Model 2 Atmosphere-Ocean
ICLUS	Integrated Climate and Land Use Scenarios
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
IRS	Internal Revenue Service
LUC	land use class
MIGPUMA	Migration Public-Use Microdata Area
MSA	metropolitan statistical area
NLCD	National Land Cover Database
US-NLUD	National Land Use Dataset
OMB	Office of Management and Budget
OR	odds ratio
ORD	Office of Research and Development
P	population density, pixel
PUMA	Public Use Microdata Area
PUMS	Public Use Microdata Sample
RCP	Representative Concentration Pathway
SERGoM	Spatially Explicit Regional Growth Model
SRES	Special Report on Emissions Scenarios
SSP	Shared Socioeconomic Pathway
TIGER	Topologically Integrated Geographic Encoding and Referencing
USGS	U.S. Geological Survey
v1	version 1
v2	version 2
WCRP	World Climate Research Programme

LIST OF TECHNICAL TERMS

Climate Amenities: Climate variables in association with their perceived value and putative influence on migration decisions. For example, the climate variables selected to represent climate amenities in ICLUS v2 are average monthly humidity-adjusted temperature and average seasonal precipitation for both summer and winter.

County-to-County Migration: The permanent or semipermanent change of residence from one county to another. In ICLUS v2, many county-to-county migration flows are modeled in aggregate based on U.S. Census statistical area definitions.

Emission Scenario: A storyline providing assumptions on future releases of greenhouse gases (GHGs) and other aerosols or atmospherically active substances into the atmosphere based on postulated economic patterns, used as input into a climate model and a precursor to Shared Socioeconomic Pathways (SSPs).

Endpoint: An outcome used to assess risk to ecosystems and environmental health.

GU (Geographic Unit): An important county-based spatial unit of analysis used in ICLUS v2. Includes aggregations of counties (i.e., metropolitan statistical areas and micropolitan statistical areas) defined by the U.S. Census Bureau. Many rural or less-populated counties are not included in either of those statistical area types, and remain standalone units.

Land Use: The human-induced activities on a unit of land.

Land Use Change: A transition to a different human-induced activity. May include changes in management or environmental condition.

Land Use Class (LUC): The primary land use at a given location. In ICLUS v2, land use is defined and tracked at a spatial resolution of 90 m × 90 m.

Observed Climate: Climate variables measured and recorded by instruments. Includes derivative or composite climate products.

LIST OF TECHNICAL TERMS (CONTINUED)

Projected Climate: Future climate variables produced by computer simulation models. These simulations are based on a set of assumptions (e.g., future global emissions of greenhouse gases) and do not perfectly replicate the observed climate.

Patch: A contiguous area composed of one or more pixels of the same land-use class. In ICLUS v2, land use change is modeled by placing new patches on the existing landscape.

Pixel: A single nonoverlapping member of a uniform grid. In ICLUS v2, the conterminous United States is represented as a grid where each pixel measures 90 m × 90 m.

Region: A geographic area defined by similar climatic, demographic, and land use patterns.

Representative Concentration Pathways (RCPs): Used by climate modelers to standardize experiments, a set of four forcing pathways or trajectories for GHG concentrations based on underlying socioeconomic assumptions.

Shared Socioeconomic Pathways (SSPs): Narratives that qualitatively describe future changes in demographics, human development, economy and lifestyle, policies and institutions, technology, and the environment.

Spatial scale: The geographic area at which a response associated with a process or pattern is examined. For example, in ICLUS v2, climate variables are resolved at the scale of GU to examine the influence of climate on human migration.

Static Climate Variables: Climate variables that remain constant throughout the modeling period. ICLUS v1 used only static climate variables, taken from observed climate records.

Dynamic Climate Variables: Climate variable that change over time. ICLUS v2 uses dynamic climate variables taken from projected future climate conditions.

PREFACE

This report was prepared jointly by the Office of Research and Development (ORD) at the U.S. Environmental Protection Agency (EPA), ICF International, Colorado State University, and Conservation Science Partners. The report describes the updates to data sets and models that constitute ICLUS version 2 (v2). Because this is an update to ICLUS version 1 (v1), many of the concepts and models build on the original report (U.S. EPA, 2009). Users familiar with ICLUS v1 can use this report as a reference guide to understand what changes have been made and the implications for the resulting data sets and maps. Output data sets and maps are intended to be used in a scenario context to assess the risks, vulnerabilities, impacts, and adaptation options of climate change.

AUTHORS AND REVIEWERS

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EXECUTIVE SUMMARY

The Integrated Climate and Land Use Scenarios (ICLUS) version 1 (v1) furthered land change modeling by providing nationwide housing development scenarios to 2100. ICLUS version 2 (v2) builds on this modeling approach by updating population and land use data sets and addressing two sets of limitations identified in ICLUS v1. This report documents the changes made to the underlying data sets used for model parameterization and to the demographic and spatial allocation models. The purpose is to address limitations encountered in ICLUS v1 and identified, in part, by the ICLUS user community.

The first set of limitations is within the ICLUS v1 migration component of the demographic model, which incorporated only five years of human migration data, only road-based connections among counties, and a static climate variable. To address these limitations, ICLUS v2 uses a data set from the Internal Revenue Service (IRS) of county-to-county migration from 1991−2000 to parameterize the migration model. Intercounty connectivity calculations include fixed mass transit as well as roads.

Another update to the migration model is the inclusion of dynamic climate variables as part of the amenity parameters. ICLUS v1 used static amenity variables, including older county-level historical climate data. ICLUS v2 now parameterizes the model with updated historical climate data (1981−1999) and includes projected climate variables for each time step to 2100. Analyses in this report use two different climate models: (1) the First Institute of Oceanography-Earth System Model (FIO-ESM) and (2) the Hadley Global Environment Model 2 Atmosphere-Ocean (HadGEM2-AO) to illustrate the effect of dynamic climate variables on migration patterns. Specific climate variables include January and July humidity-adjusted temperature and summer (June, July, August) and winter (December, January, February) precipitation incorporated as the running average of the previous 10 years of climate model output. Comparisons of the results with and without projected climate variables show that differences in regional migration patterns occur when dynamic climate variables are included. Differences in the distribution of population between model runs using climate variables and results of model runs using static climate variables are more similar to each other than are differences in migration patterns between combinations emissions and demographic scenarios. Different fertility and migration rates in the scenarios exert much larger influences on the overall migration patterns than changes in climate amenities.

Several additional changes in the ICLUS v2 demographic model resulted from updates of data sets. The use of the 2010 U.S. Census Bureau's data in the demographic model results in new national population projections for each of the scenarios documented in this report. Because the IRS database does not contain demographic information, the migration model in ICLUS v2 combines all age groups into a single population, whereas ICLUS v1 recorded separate migration information for populations under and over 50 years old.

The second set of limitations identified was within the ICLUS v1 spatial allocation model, which used population to calculate housing density based on household size, while all other land use classes remained static. ICLUS v2 uses statistical relationships between population density, road capacity, and land use classes to allocate new land uses at the next time step based on the demands of the growing population. Demand calculations are done nationally for each developed land use class and transition probabilities from one land use to another incorporate differences in growth patterns for each of seven regions of the conterminous United States, similar to U.S. Census Bureau divisions. In addition to residential housing classes, commercial and industrial land uses also change at each time step.

The spatial allocation model also incorporates updated data sets for land use (a new U.S. National Land Use Dataset [US-NLUD] based on the 2011 National Land Cover Database [NLCD] and many other detailed data on land use), transportation (roads and fixed mass transit), and developable area derived from the 2012 U.S. Geological Survey (USGS) Protected Areas Database. The model uses land use transitions from 2000 to 2010 as the basis for all future land use changes. The spatial allocation model projects transitions for five residential housing classes and commercial and industrial land uses. The sequence of land use class changes is based on the theory that the highest and best use prevails, generally as determined by land value. The spatial allocation model uses output from the demographic model to calculate demand for each land use class in relation to population density. New land uses are allocated as patches that reflect a region-specific distribution of sizes and shapes. Patch placement is determined by the antecedent land use class and accessibility, and placement of residential patches also takes into account distance to commercial areas.

The resulting land use allocation replaces low-density residential development by higher density land uses as a population grows within ICLUS geographic units. Low-density development generally expands outward. The development of higher density residential, commercial, and industrial classes levels off in terms of demand at high population densities, exhibiting a threshold effect. This threshold shows that these land use classes are not rapidly replaced once developed, and that there are observed limitations in the density of particular land use classes in dense metropolitan areas. Similarly, transportation capacity also reaches a threshold. Dense cities add new road capacity more slowly than do smaller cities.

The emergence of new socioeconomic and emissions scenarios (e.g., SSPs and RCPs) utilized in ICLUS v2, as opposed to the previous emissions storylines used in ICLUS v1, limits the usefulness of direct comparisons between outputs from both ICLUS versions. Instead, this report compares results from the SSP-RCP combinations implemented in ICLUS v2.

Improvements in ICLUS v2 allow discussions of results in terms of national changes, as well as regional and subregional changes over time.

The output of the demographic model is similar to globally based population estimates for the United States that are consistent with the SSPs. ICLUS v2 population estimates for the United States by 2100 are slightly higher for both SSP1 and SSP5 than those derived by KC and Lutz (2014) for SSP1 and SSP5 from the global estimates for the United States, although the relative difference in population between the scenarios in 2100 is similar. The use of two population estimates, one higher and one lower, allows for an interpretation of differences in impacts between the two scenarios. By using population estimates that are consistent with the SSPs, the resulting impacts can be put into a context consistent with other efforts using those socioeconomic storylines. Regionally, differences in population growth are greater between the SSPs than differences between climate models used with the same SSP. However, comparisons between model runs with dynamic climate variables and static climate show regional differences in population of up to 4%. Subregionally, there are additional differences that are reinforced by the choice of climate model used in the migration model. These differences are more distinct at higher population densities and during the last half of the century, especially when using SSP5, which has higher fertility rates than SSP1.

The national-scale land use projections show nearly identical trends when comparing outcomes under the same SSP assumption; the choice of climate model has no discernible effect on the overall amount of projected development. However, there are differences in amount and allocation of land uses when comparing between SSPs and examining changes regionally. Regional allocation patterns reflect existing differences across the conterminous United States that continue to shape patterns into the future. While nearly all developed land use classes increase in nearly all regions, the magnitude of changes reflects current trends, such that low-density residential classes continue to increase in the Intermountain West more so than in other regions, and regions with higher densities continue to increase their urban land uses.

Overall, ICLUS v2 provides users with the ability to model population and land use changes consistent with SSP and RCP scenarios and specific climate models to improve integrated climate and land use assessments. While this report only uses SSP1-RCP4.5 (lower population growth, lower emissions) and SSP5-RCP8.5 (higher population growth, higher emissions) scenarios in conjunction with two climate change models, FIO-ESM and HadGEM2-AO, to illustrate ICLUS v2 improvements, the model structure allows users the flexibility to select any SSP, RCP, and climate model combination. The use of statistically based transition and demand models also allows users to change parameters for further scenario explorations that alter development pathways from current trajectories. Improvements in ICLUS v2 facilitate the analysis of scenarios of climate change impacts, vulnerability, and adaptation options, including the use of ICLUS v2 outputs in models projecting emissions from developed land uses to determine consequences for water and air quality endpoints, as well as human health.

1. INTRODUCTION

Changes in climate and land use are global drivers of environmental impacts. The interactions between climate and land use changes are complex and can result in challenges for ecosystems and environmental health. The motivation for the U.S. Environmental Protection Agency (EPA) Integrated Climate and Land Use Scenarios (ICLUS) project originated with the recognition of this complex relationship and the absence of an internally consistent set of land use scenarios that support national assessments of climate change effects. This report describes updates to the ICLUS model data, methods, and outputs described in *Land-Use Scenarios: National-Scale Housing-Density Scenarios Consistent with Climate Change Storylines* (U.S. EPA, 2009).[2] The goal of the current report is to describe the changes between the ICLUS version 1 (v1) data sets and modeling approach and ICLUS version 2 (v2) that are intended to improve on the demographic and spatial model outputs.

ICLUS v1 developed future scenarios of population, housing density, and impervious surfaces that were consistent with the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) storylines (Nakicenovic and Swart, 2000). ICLUS v1 integrated two main components: a demographic model and a spatial allocation model (see Figure 1). ICLUS v1 helped advance land change modeling by providing nationwide development scenarios to 2100. ICLUS v2 builds on this modeling approach by addressing two sets of limitations. First, the demographic model in v1 incorporated a limited timeframe of movement data, intercounty connectivity solely based on roads, and a static climate variable in its migration model. Second, the spatial allocation model used population to calculate housing density based on household size, while all other land use types remained static, including commercial and industrial uses. In addition to addressing these limitations, ICLUS v2 incorporates updated data sets of population, land use, and land cover. The addition of dynamic future climate variables draws on the most recent climate data, which use Representative Concentration Pathways (RCPs) rather than SRES storylines (van Vuuren et al. 2011). The RCPs are targets of greenhouse gas concentrations that general circulation models reach by the year 2100 to depict a range of climate change outcomes. Thus, ICLUS v2 is now consistent with the most recent suite of climate change scenarios, linking RCP-driven climate model output with Shared Socioeconomic Pathways (SSPs; O'Neill et al. 2014). Though the effect of dynamic future climate variables on migration is small, the cumulative changes yield different settlement patterns that enable scenario-based analyses of impacts and vulnerabilities of environmental endpoints.

[2] Download the ICLUS version 1 report: https://cfpub.epa.gov/ncea/global/recordisplay.cfm?deid=203458.

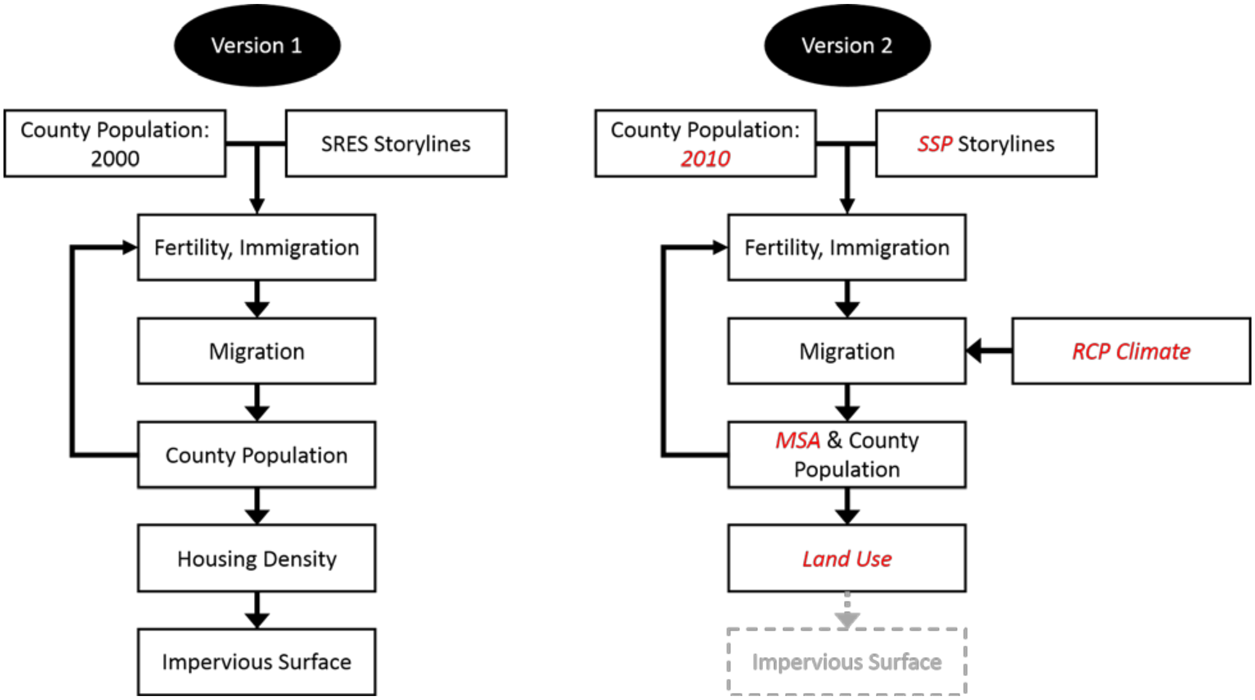

Figure 1. Comparison of ICLUS v1 and ICLUS v2. The two model versions are conceptually very similar. ICLUS v2 reflects substantial updates to key inputs as well as a modified geographic framework. Estimates of percentage impervious surface change for ICLUS v2 will be produced subsequent to this report.

This report covers the updates to the demographic model in Section 2 and the spatial allocation model in Section 3. Figure 2 provides an orientation of the flow of data and processes within ICLUS v2. The output of the demographic model, the population data, is one input to the data sets further described in Section 3. Section 4 focuses on model outputs, both demographic and land use, and compares these outputs among the scenarios implemented. Descriptions of the updates and analyses of v2 outputs are intended to assist users of the ICLUS data sets and maps to understand which changes were made, why, and what the consequences for the outputs are.

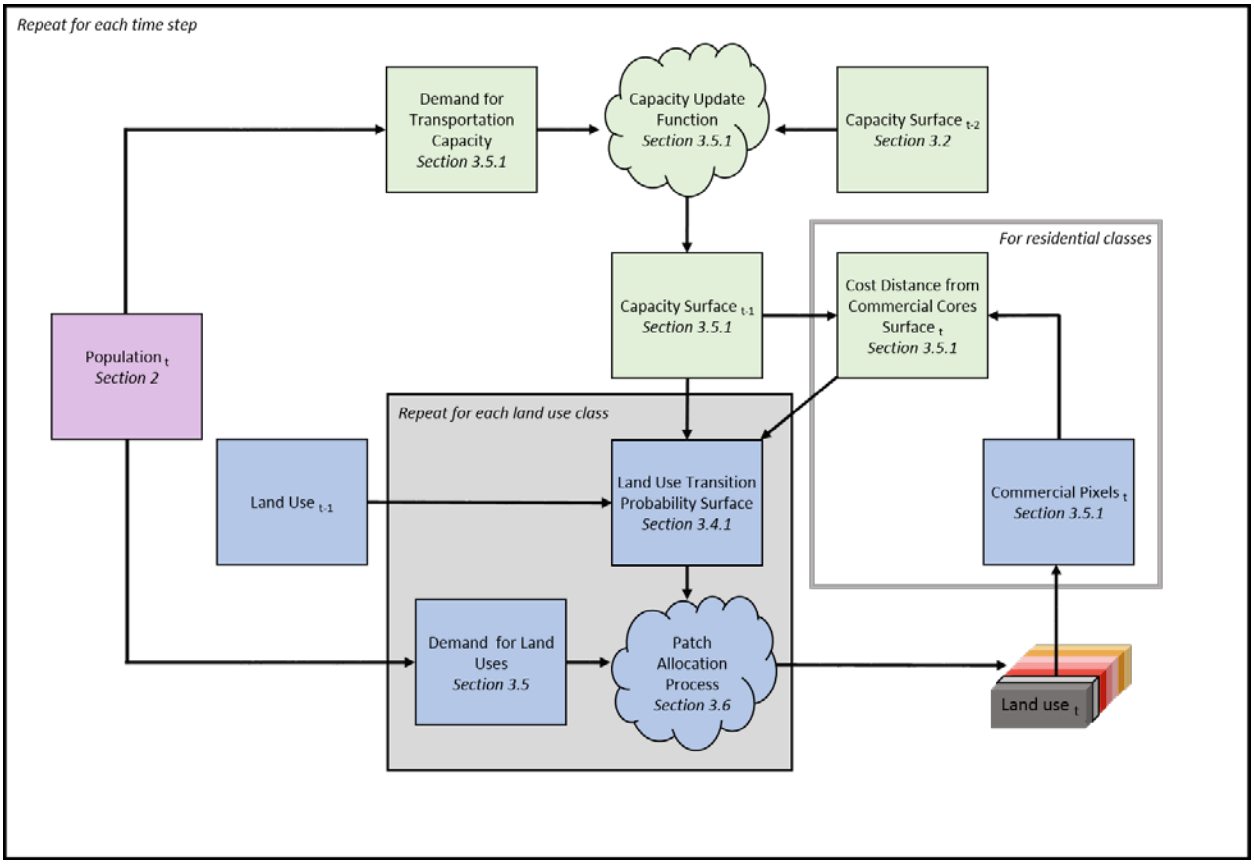

Figure 2. ICLUS v2 spatial allocation flow diagram. Land use change is modeled by allocating new patches (comprised of 90 m × 90 m pixels) until the demand for new pixels of each land use is satisfied. The likelihood of an existing pixel converting to a new land use is a function of both transportation capacity (i.e., the accessibility of the pixel) and the existing land use. For residential classes, proximity to commercial pixels is treated as an amenity and will attract new growth. Transportation capacity grows in relation to population density (green boxes). Likewise, the demand for new pixels is driven by population growth (blue boxes).

2. UPDATES TO THE MIGRATION MODEL

The ICLUS demographic model consists of a cohort-component model and a migration model that project county-level population for the conterminous United States on an annual basis from 2010 to 2100 for a number of socioeconomic scenarios and climate projections. The cohort-component methodology projects fertility, mortality, and international migration. The model also includes a submodel to project county-to-county domestic migration influence by amenity variables such as climate (U.S. EPA, 2009).

The baseline population and demographic characteristics in ICLUS v2 use the most recent 2010 U.S. Census Bureau data (NCHS, 2011) but the same fertility and migration rates as ICLUS v1. The combinations of demographic components of change (i.e., fertility, mortality, migration) was revisited for ICLUS v2 to be consistent with published descriptions of RCPs and SSPs (Samir and Lutz, 2014; van Vuuren and Carter, 2014). Model updates discussed in this report use combinations of RCPs and SSPs that succinctly demonstrate a range of possible ICLUS v2 projections with respect to climatic changes and population growth. We used a peer-reviewed crosswalk of the SSPs and RCPs to the SRES scenario framework to identify combinations of SSPs and RCPs (van Vuuren and Carter, 2014) that resemble the bounding scenarios used to demonstrate the range of impacts explored with ICLUS v1 (e.g., Bierwagen et al., 2010; Voorhees et al., 2011; Georgescu et al., 2014). We selected the combination of SSP5 and RCP8.5 to represent a high emissions, high population-growth scenario, and the combination of SSP1 and RCP4.5 as a lower emissions, lower population-growth scenario. Like ICLUS v1, the population-growth scenarios were generated using projections of immigration, fertility, and mortality produced by the U.S. Census Bureau (2000). Specifically, the SSP5-RCP8.5 scenario uses the U.S. Census Bureau's high fertility, high domestic migration, and medium immigration rates; SSP1-RCP4.5 uses medium fertility, high domestic migration, and medium immigration. These combinations are qualitatively consistent with rates for high-income countries globally (Samir and Lutz, 2014) and generally correspond to the SRES A1Fi (high emissions) and B1 (low emissions) scenarios, respectively (van Vuuren and Carter, 2014).

The focus of the remainder of Section 2 is on implementing the migration model within the cohort-component model. The following subsections describe changes to the migration component of the ICLUS v1 demographic model, including updates to domestic movements and the incorporation of climate change projections. Section 4.1 shows the results of the updated model and compares these to ICLUS v1 outputs.

2.1. UPDATING THE MIGRATION MODEL

The demographic component in ICLUS v1 included a migration model that simulated domestic migration by estimating flows between pairs of counties. ICLUS v2 updates the underlying data used to parameterize the migration model, adds new independent variables, incorporates a county-to-county migration data set that covers a longer historical time period than the data set in ICLUS v1, and aggregates some counties into metropolitan and micropolitan statistical areas, defined as 50,000 people or more in an urban area and at least 10,000 but less than 50,000 people, respectively. Finally, amenity variables use recent climate data for model calibration and update these data each decade with model output of future climate variables.

2.1.1. Parameterizing Domestic Migration

ICLUS v2 incorporates definitions of both metropolitan and micropolitan statistical areas (OMB, 2010) and aggregates counties into geographic units accordingly.[3] This change effectively reduces the number of migration origin and destination locations and simplifies analysis of the historic migration information by excluding many short-distance moves (i.e., moves within metropolitan or micropolitan statistical areas). In addition, a small number of independent cities that were not absorbed into metropolitan or micropolitan areas were merged with an adjacent county. The resulting geographic framework consists of 2,256 units, composed of metropolitan and micropolitan statistical areas and stand-alone rural counties, referred to hereafter as ICLUS geographic units (GUs; see Figure 3).

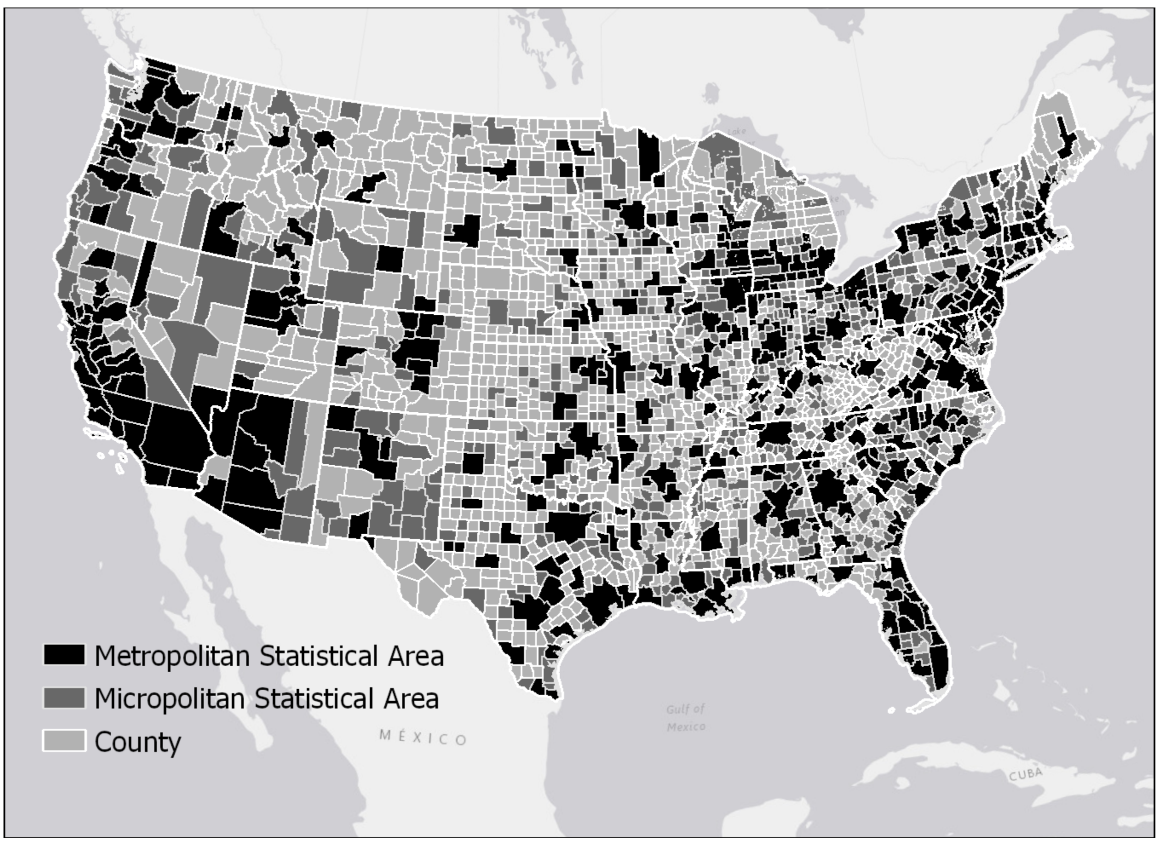

Figure 3. ICLUS v2 geographic units include metropolitan statistical areas (MSAs), micropolitan statistical areas, and stand-alone counties.

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[3] Metropolitan and micropolitan statistical areas are delineated by the U.S. Office of Management and Budget (OMB) and are the result of the application of published standards to Census Bureau data. A metropolitan statistical area contains a core urban area of population 50,000 or more, and a micropolitan statistical area contains an urban core of at least 10,000 (but less than 50,000). Metro or micro areas represent larger regions to reflect broad social and economic interactions (as measured by commuting to work) within the urban core.

The ICLUS v1 migration model used a temporally limited data set to parameterize county-to-county movements across the conterminous United States, specifically the 1995 to 2000 Public Use Microdata Samples (PUMSs; U.S. Census Bureau, 2003). Although this data set includes millions of migration records (n = 2,397,007), it covers just a single 5-year time span. ICLUS v2 uses 10 years (1991 to 2000) of the IRS (2014) county-to-county annual migration data to parameterize the migration model[4]. The values in the migration data set, combined with specific county-level information, such as population size, growth rates, climate, and connectivity to other counties, are used to parameterize the updated migration model. The decade of IRS data chosen to calibrate the migration model captures relatively recent responses to climate and overlaps with the climate data used in model parameterization described in Section 2.1.3.

The IRS data set provides a full count of all income tax filers based on year-to-year changes in or continuity of address reported on individual income tax returns. Data are expressed in terms of inflows (the number of new residents who moved to a county and where they originated) and outflows (the number of residents leaving a county and where they went). The data set covers all counties in the United States but only reports county-to-county migrations when 10 or more such migrations occurred.

The IRS data present multiple advantages over the PUMS data. First, unlike the PUMS migration data used in ICLUS v1, the IRS migration data are true county-to-county records. The PUMS migration data represent migrations between Migration Public-Use Microdata Areas (MIGPUMAs). This required a two-stage conversion, from MIGPUMA to Public Use Microdata Areas (PUMAs), and then from PUMAs to counties. Second, the IRS data represent full counts of all income tax filers, while the PUMS data are based on a statistical sample. Third, and most importantly, the IRS data used in this analysis are annual data for the years 1991−2000, compared with a single 5-year period of PUMS data.

However, the IRS data has a different set of limitations not present in the PUMS data. First, age is not included in the IRS data. The ICLUS v1 migration model consisted of two age groups (ages 0−49 years and ages 50 years and older). ICLUS v2, therefore, does not separate the model into different age groups. Second, the IRS data are based on the number of income tax filers and exemptions, not the number of people. The number of exemptions, however, closely matches the number of people (IRS, 2014). Consequently, people who did not file income tax returns are excluded from the IRS data, and their migrations would not be captured in ICLUS v2. Third, in cases where fewer than 10 migrations were recorded between any county pair, migration flows are aggregated in the IRS data. Flows of fewer than 10 migrants represent about

[4] These data are available for public download: http://www.irs.gov/uac/SOI-Tax-Stats-Migration-Data.

7% of total migrations but were not included in the analysis due to lack of specific origin/destination pairing.

From the IRS data set, we extracted two key variables used in this analysis: (1) total outflow expressed as a percentage of the county population and (2) individual county-to-county migration records.

2.1.2. Functional Connectivity

ICLUS v2 also includes updated measures of connectivity. Like ICLUS v1, population-weighted centroids were generated for each of the 2,256 geographic units. Centroids for a few units were manually moved inside of their respective geographic boundaries. To evaluate the connectedness of each geographic unit, a network-based travel time was calculated for every possible origin-destination combination. Travel times were estimated using StreetMap North America[5] and the Network Analyst extension for ArcGIS 10.3. The population-weighted centroids were snapped to the nearest network feature, including regular ferry routes where applicable.

2.1.3. Historic Climate Amenities

Linkages between climate variables and human migrations are reported in the literature (e.g., Alonso, 1971; Cragg and Kahn, 1996; Rappaport, 2007; Feng et al., 2010; Maxwell and Soulè, 2011; Sinha and Cropper, 2013) and form the basis for our exploration of including changing climate variables in the migration model. The influence of climate on migration decisions is only one of many possible amenity-based influences and is smaller than other factors like jobs, housing costs, and family, which are implicitly represented in our migration model. The explicit inclusion of climate variables allows for the development of land use scenarios that incorporate climate change model output and are consistent with SSPs and RCPs. ICLUS v1 used a static set of 30-year average climate data based on 1941−1970 records (McGranahan, 1999). ICLUS v2 improves on the inclusion of a climate amenity value in two ways. First, the historic climate data were updated to cover the 1981−1999 time period, which coincides with the IRS migration data. Second, future projections of climate change are used to update these amenity values at each time step of the migration model. Together, these improvements allow the ICLUS v2 migration model to better reflect the human responses to climatic changes based on the historical estimate of such responses.

[5] http://resources.arcgis.com/en/help/main/10.1/index.html#/About_StreetMap_North_America/001z00000039000000/.

In order to incorporate both observed and projected climate amenity values in the migration model, data covering the observed historical period and future time period need to be consistent. ICLUS v1 used January temperature, January sunlight, July temperature, and July humidity as the climate amenity variables. However, sunlight variables generally are not available as output from general circulation models (GCM) used to model climate change and therefore were not used in ICLUS v2. Furthermore, results from Sussman et al. (2014) suggest that precipitation is a key climate amenity driving housing prices and should not be omitted in a migration model. Results from Sussman et al. (2014) informed the ultimate selection of climate variables to include in ICLUS v2.

Climate variables also need to be resolved at the spatial scale of ICLUS geographic units (or smaller) for consistency with the migration model. While raw GCM output covers much larger geographic areas, the use of downscaled products reduces the spatial resolution. Historical and projected climate data are available for download from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 5 (CMIP5) multimodel data set with bias-correcting and spatial-downscaling (BCSD) methodology applied (Wood et al., 2004; Maurer et al., 2007).[6] The BCSD methodology uses statistical bias correction to interpret GCM output over a large spatial domain based on current observations. The principal potential weakness of this approach is an assumption of stationarity (i.e., the relationship between large-scale precipitation and temperature and local precipitation and temperature in the future will be the same as in the past). Thus, the method can successfully account for orographic effects that are observed in current data, but not for impacts that might result from the interaction of changed wind direction and orographic effects. A second assumption included in the bias-correction step is that any biases exhibited by a GCM for the historical period will also be exhibited in simulations of future periods.

The variables selected for use in the migration model were average monthly humidity-adjusted temperature (January and July) and average seasonal precipitation (December through February, or "winter," and June through August, or "summer"), although a number of permutations were tested to maximize model fit. These included:

- Comparing the role of absolute temperature versus changes in temperature relative to the mean;
- Comparing the role of absolute precipitation versus changes in precipitation relative to the mean;

[6] Bureau of Reclamation/Santa Clara University/Lawrence Livermore archive of downscaled IPCC model runs available at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/.

- Considering the impact of including temperature-squared and precipitation-squared terms as quadratic terms;
- Comparing temperature versus humidity-adjusted temperature (a function of temperature and humidity); and
- Considering alternative specifications of precipitation (monthly, seasonal, annual, etc.).

The precipitation variables used in ICLUS v2 were calculated from climate model output downscaled using the BCSD methodology. Humidity-adjusted temperature is generally not available as a downscaled climate model output. Instead, this variable was calculated using a polynomial equation (eq 1-1) relating humidity-adjusted temperature to absolute temperature and relative humidity (Rothfusz, 1990):

Humidity-adjusted temperature is calculated by:

$$\begin{aligned} T_H \;=\; & -42.379 + (2.04901523 \times T) + (10.1433127 \times RH) - (0.22475541 \times T \times RH) \\ & - (0.00683783 \times T^2) - (0.05481717 \times RH^2) + (0.00122874 \times T^2 \times RH) \\ & + (0.00085282 \times T \times RH^2) - (0.00000199 \times T^2 \times RH^2) \end{aligned} \tag{1-1}$$

Where:

T_H = average monthly humidity-adjusted temperature

T = average monthly air temperature in degrees Fahrenheit

RH = average monthly relative humidity

Humidity-adjusted temperature (T_H) was calculated only when absolute temperature (T) was greater than 80°F and relative humidity was greater than 40%. When either of those conditions was not met, unadjusted T was used.

2.1.4. Climate Change Model Selection

The selection of climate data for the migration model is another opportunity for consistency with the SSP and RCP scenarios. For each of the RCP8.5 and RCP4.5 emission scenarios, we identified two climate change projections that generally capture the range of potential climate change for the contiguous United States. We constructed scatterplots of all climate projections in the BCSD CMIP climate projection archive using climate amenity descriptions to form axes of “summer” and “winter” scatterplots and duplicated those scatterplots for both emissions scenarios. As shown in Figure 4 below, the scatterplots provide a simple, visual heuristic device to identify climate projections that bracket a broad range of future climate change uncertainty. Using the plots in Figure 4, we selected projections from the HadGEM2-AO and FIO-ESM climate models for the analyses included in this report. The selection of these two climate models accomplished two goals: first, we wanted to represent the range of temperature and precipitation changes in terms of a high and a low model, and second, we wanted to use the same two models for both RCP 4.5 and RCP 8.5. Therefore, while the two climate models selected do not always have the minimum or maximum temperature or precipitation values in the scatterplot, they are the two models that balance our two goals most effectively.

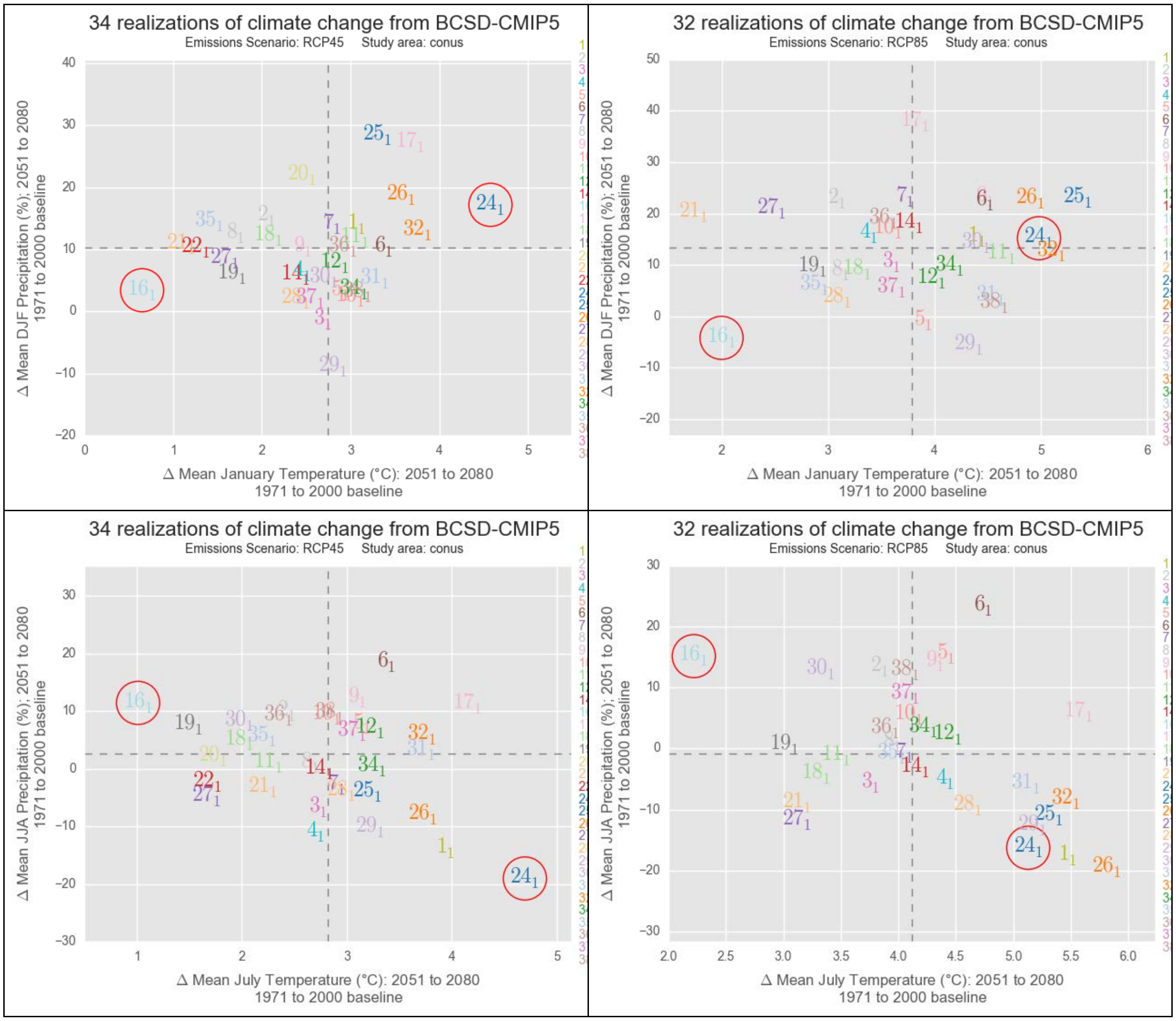

Figure 4. Scatterplots used to select climate projections used in this report. Dashed lines show median values. The HadGEM2-AO and FIO-ESM climate projections circled in red were selected for this report because they generally spanned the range of climate outcomes regardless of emissions scenario (RCP4.5 and RCP8.5) or season (winter precipitation/January temperature and summer precipitation/July temperature).

2.1.5. Redesign and Recalibration of the Migration Model

Each of the updated data sources required some modification to the migration model. In order to accommodate the IRS data, the two age groups (under or over 50) used in ICLUS v1 were combined into a single population for ICLUS v2. The migration model also calculates migrations annually because the IRS data are based on single-year records. ICLUS v1 was based on 5-year migration records.

In addition, an important constraint was introduced to the updated migration model that gives more reasonable population projections across the ICLUS v2 geographic framework. The IRS migration records for 1991−2000 were grouped such that total migration between and among metropolitan statistical areas (MSAs), micropolitan statistical areas, and stand-alone (rural) counties could be quantified. The relative proportions shown in Figure 5 are used at each annual time step to adjust the raw migrations calculated by the migration model. For example, at each annual time step migration flows between MSAs are rescaled to equal 70% of the national migration total; total annual migration from rural counties to micropolitan statistical areas will make up 1.6% of the national total, as depicted by each of the flows in Figure 5.

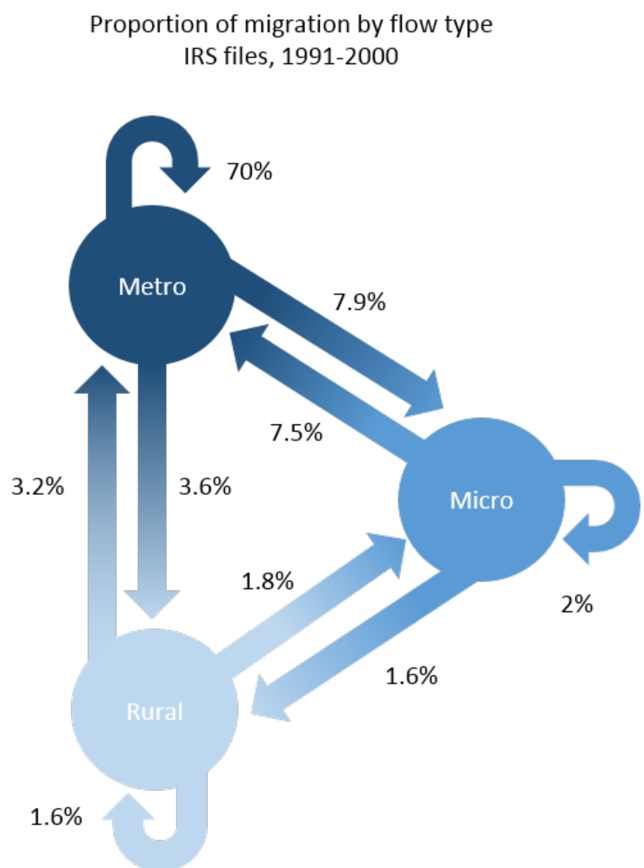

Figure 5. Proportion of total migration between MSAs, micropolitan statistical areas, and rural counties.

The migratory flows shown in Figure 5 are consistent with U.S. Census Bureau data reported for the 1995–2000 time period (U.S. Census Bureau, 2003). Incorporating these values into the ICLUS v2 migration model provides two important advantages. First, we are able to capture important macro-level trends, such as a net migration deficit for MSAs. Second, these values serve as useful parameters for scenario exploration in future phases of ICLUS development.

2.1.5.1. *Revised functional form and model statistics*

The historical migration records and historical climate amenities discussed above were combined so that a record in the migration data table contained the number of migrations from one ICLUS Geographic Units (GU) to another, the attributes of the origin unit, the attributes of the destination unit, and the functional distance between them. Attributes of the GUs include population density, growth rate in the previous time period, developable area, and climate variables. Equation 2-1 shows the variables used in the migration model. To estimate the number of migrants, we used negative binomial regression with a natural log link. Predictor variables were transformed as needed to control for skewness or heavy tails and were standardized (Schielzeth, 2010). Because we expected that the amenity values associated with temperature would depend on precipitation, we included interactions between those terms for both summer and winter origin and destination units. As suggested by Dormann et al. (2013) and to avoid the effects of collinearity, we used only predictor variables with absolute correlations less than 0.70 (all correlations except those for summer and winter temperature were less than 0.40). The migration model equation used balances theoretical considerations with overall performance.

The migration model calculation is:

$$\ln(F_{ij}) = \beta_0 + \beta_1 \times \ln(D_{ij}) + [\beta_2 \times \ln(P_i) + \beta_3 \times \ln(P_j)] +$$

$$[\beta_4 \times G_i^{-4} + \beta_5 \times G_j^{-4}] + [\beta_6 \times \ln(A_i) + \beta_7 \times \ln(A_j)] +$$

$$[\beta_8 \times SH_i + \beta_9 \times SH_j] + [\beta_{10} \times WH_i + \beta_{11} \times WH_j] +$$

$$[\beta_{12} \times SP_i + \beta_{13} \times SP_j] + [\beta_{14} \times WP_i^{1/2} + \beta_{15} \times WP_j^{1/2}] +$$

$$[\beta_{16} \times SH_i \times SP_i + \beta_{17} \times SH_j \times SP_j] +$$

$$[\beta_{18} \times WH_i \times WP_i^{1/2} + \beta_{19} \times WH_j \times WP_j^{1/2}]$$

(2-1)

Where:

i = origin

j = destination

F_{ij} = people migrating from unit i to unit j between year n and $n + 1$

β_k = intercept or slopes quantifying the relationship between the parameters and number of migrants

D_{ij} = functional distance between unit i and j

P = population density

G = population growth rate, previous time step

A = developable land area

SH = mean summer (July) apparent temperature, 10 year running average

SP = mean summer (June, July, August) precipitation, 10 year running average

WH = mean winter (January) apparent temperature, 10 year running average

WP = mean winter (December, January, February) precipitation, 10 year running average

2.2. MIGRATION MODEL INTERPRETATION

The migration model parameters are derived from a generalized linear modeling approach, so common measures of model performance are not available. However, Nagelkerke's R^2 was equal to 0.62 for the final model specification (Faraway, 2006).

Interpretation of the role of climate variables in the model is difficult, largely because both origin and destination locations are affected simultaneously. Furthermore, migration is calculated between all possible origin-destination pairs, meaning the observed net migration is the difference between two opposing flows. Despite this complexity, the effects of variables in the migration model may be characterized three ways.

First, the sign and magnitude of the coefficient indicates whether a variable will tend to generally increase or decrease migrations. For example, winter temperature (WH) has a positive coefficient for both the origin (WH_i = 0.141) and destination (WH_j = 0.207) locations. If all other variables were held constant, more total migrations would occur between places with warm winters, relative to places with cold winters in our model, though this is not a cause and effect relationship of the climate variables. The magnitude of this influence is less than that of population density (P_i = 0.530 and P_j = 0.430), which exerts the largest influence on migration (see Table 1).

Second, comparing the origin and destination coefficients indicates the net directional influence of that variable. For example, if all other factors are equal, the net flow of migrants will be to locations with warmer winter temperatures ($WH_i < WH_j$) and less winter precipitation ($WP_i > WP_j$; see Table 1).

Table 1. Migration model results. Parameters are sorted by whether they applied to origin or destination county (*i* or *j*), and matching pairs of parameters share a row. Differences in slope estimates between matching pairs of parameters are provided in the last column. Variables are defined in Equation 2-1. $\widehat{\beta_k}$ is the estimate of the variable.

Parameter	$\widehat{\beta_k}$	p	Parameter	$\widehat{\beta_k}$	p	$\lvert\widehat{\beta_{ki}} - \widehat{\beta_{kj}}\rvert$
Intercept	4.472	<0.0001				
D_{ij}	−1.048	<0.0001				
P_i	0.530	<0.0001	P_j	0.430	<0.0001	0.100
G_i	0.027	<0.0001	G_j	−0.051	<0.0001	0.078
A_i	0.385	<0.0001	A_j	0.352	<0.0001	0.033
SH_i	−0.080	<0.0001	SH_j	−0.042	<0.0001	0.038
WH_i	0.141	<0.0001	WH_j	0.207	<0.0001	0.066
SP_i	−0.088	<0.0001	SP_j	−0.082	<0.0001	0.006
WP_i	−0.077	<0.0001	WP_j	−0.101	<0.0001	0.024
$SH_i \times SP_i$	0.022	<0.0001	$SH_j \times \mathrm{SP_j}$	0.019	<0.0001	
$WH_i \times WP_i$	0.002	0.3040	$WH_j \times WP_j$	0.040	<0.0001	

Lastly, the relative contribution of each climate variable to net migration patterns is also related to the absolute difference between the origin and destination coefficients (the last column in Table 1), although we did not test the significance of this different. For example, winter temperature is the most influential climate variable in the ICLUS v2 migration model, given both the relative size of the absolute difference between the origin and destination coefficients and the size of the coefficients relative to other climate variables. Summer temperature, winter precipitation, and summer precipitation variables follow winter temperature in influence on net migration.

3. UPDATES TO THE SPATIAL ALLOCATION MODEL

ICLUS v1 used the Spatially Explicit Regional Growth Model (SERGoM) to project future increases of housing density at a relatively fine spatial resolution (Theobald, 2005; Bierwagen et al., 2010). This update to the spatial allocation model addresses reviewers' comments on ICLUS v1 and incorporates advances in the literature on land use change modeling. The new literature suggests that land use models should (1) incorporate spatial dynamics[7] and multiple sources of spatial heterogeneity, (2) explicitly describe transitional dynamics of urban land use, (3) incorporate direct effects of market adjustments, (4) use local-scale heterogeneity to determine urban spatial dynamics (Irwin, 2010), and (5) integrate top-down and bottom-up methods that incorporate the effects of national and global drivers of change while also accounting for local drivers of change and feedbacks (Sohl et al., 2010). For ICLUS v1, SERGoM met the conditions for (1), (4), and partially (5). The revised allocation model in ICLUS v2 addresses (2) by using a transition probability model, partially addresses (3) by incorporating an assumption of maximum utility of land use (Alonso, 1964), and strengthens (5) by using a finer spatial and thematic resolution. Another major change in ICLUS v2 is that the land use modeled in ICLUS v1 was the dynamic growth of a single (residential) land use in ICLUS v1, although commercial and industrial lands were identified and held constant through time. ICLUS v2 uses a deterministic demand-allocation approach, similar to SERGoM, which assumes many aspects of future growth will resemble the recent past (i.e., 2000 to 2010), though over time land use changes would result in different overall patterns. Different from ICLUS v1, v2 sequentially allocates patches from seven of the 19 discrete land use classes (LUC) used in ICLUS v2: five levels of residential, plus commercial and industrial. Thus, in ICLUS v2 commercial and industrial LUCs no longer remain constant.

3.1. OVERVIEW OF THE UPDATED SPATIAL ALLOCATION MODEL

The updated spatial allocation model incorporates information from multiple spatial scales. At the national scale, all 2,256 ICLUS GUs (see Figure 3) in the conterminous United States were used to construct a statistical model that generates local demands for new pixels (90 m × 90 m) of land use based on changes in population density. The demand model captures a log-log relationship that is consistent with a theory of city growth broadly relevant to many aspects of city form and function (Bettencourt et al., 2007; Bettencourt, 2013; Batty, 2013). Satisfying the demands for new land use involves using transition probabilities and land use patch size and shape distributions that are region specific. Finally, local patterns of

[7] A spatially dependent dynamic process is one in which a change over time at one location is dependent on the state or changes in the state at other locations.

transportation capacity and accessibility to commercial areas inform future spatial patterns of growth. Figure 2 (see Section 1) illustrates the spatial allocation process and references specific sections for each step in the flow diagram. The areas used to calculate regionally specific distributions and demands are similar to U.S. Census Bureau regions (see Figure 6).

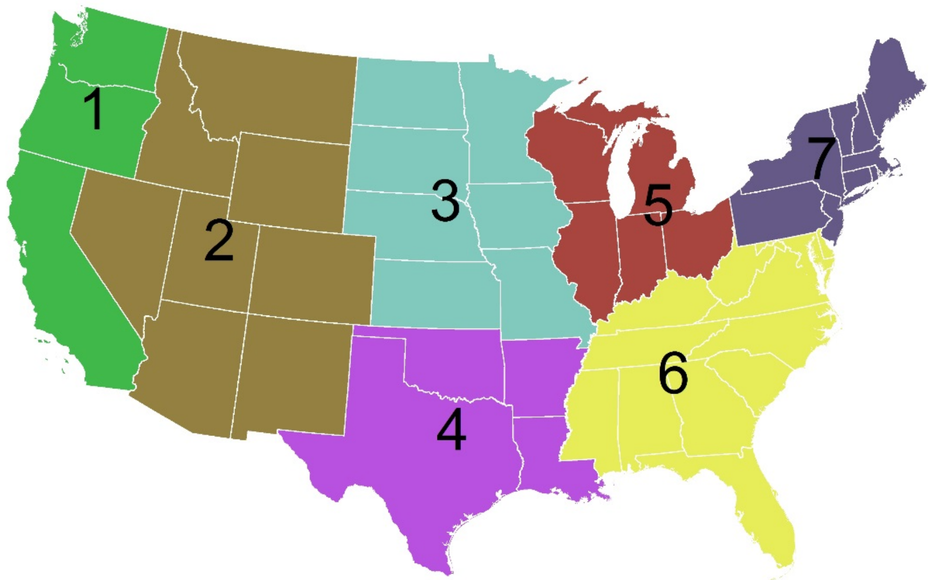

Figure 6. Regions used in ICLUS v2. Region 1–West Coast; Region 2–Intermountain West; Region 3–North Central; Region 4–South Central; Region 5–Great Lakes; Region 6–Southeast; Region 7–Northeast.

The application of regions within ICLUS v2 is intended to maintain differences in land use patterns across the country and over time. Within each region (see Figure 6), patterns of land use change between 2000 and 2010 were summarized to form a land use transition matrix that captured the probability of a given pixel converting to a specific land use category given (1) the antecedent LUC and (2) the accessibility of the pixel.[8] ICLUS v2 prioritizes pixels by transition probability in order from highest to lowest. We similarly allocate new land use pixels beginning with highest value land uses (e.g., Industrial, Commercial) and continuing in order to the lowest value land uses (i.e., exurban-low). The process of allocating new land use pixels to the most

[8] Accessibility is defined using the capacity (i.e., people per hour) of transportation infrastructure, and is updated at each time step. This aspect of the model is elaborated later, in Sections 3.2 and 3.5.1.

likely remaining location continues until demand for each LUC has been satisfied. While somewhat simplistic, this approach nevertheless reflects classic land use theory, that is, a pattern of transition to the highest and best use for a given location (Chisolm, 1962). New land uses are then allocated as patches using a distribution of patch shapes and sizes for each LUC unique to each region. These patches are used in ICLUS v2 at each time step such that the size, shape, and frequency of new patches within a region reflect the new patches observed when comparing 2010 land use to 2000 land use.

The allocation of residential land use patches also considers accessibility to commercial areas. This consideration holds to the precept that people will generally prefer to live close to areas that offer employment opportunities, as well as the goods, services, and other amenities associated with commercial development. A similar concept was used in ICLUS v1 and yields a modeling framework that is responsive to emergent urban areas.

3.2. CREATING THE INITIAL ACCESSIBILITY-CAPACITY SURFACE

When allocating new housing units, ICLUS v1 used a nationwide surface of travel time to preferentially weight new growth in areas most accessible to existing development, including transitions to higher density development and new development. A key limitation of the ICLUS v1 model was that this travel time surface was static at each time step, and therefore was not updated to reflect improvements to transportation networks. ICLUS v2 uses a more sophisticated surface of accessibility that incorporates the capacity of roads and fixed mass transit (i.e., people per hour), and is also updated at each time step. We refer to this as the capacity surface.

The spatial allocation model is initialized with a capacity surface for the year 2010. To generate the capacity surface, we follow methods outlined in Theobald (2008), which are summarized here. Conceptually, this followed three steps, with details about each step in the following paragraphs. First, we identified urban cores (e.g., central business districts) at multiple resolutions. Second, we calculated the travel time to the nearest urban core for each pixel, which reflects the polycentric nature of modern human settlements. For road infrastructure, we assume travel speeds occur at typical speed limits for different road types, including fixed mass transit, and for off-road pixels we used walking speeds. We then calculated the travel time from the centroid of each urban core through the transportation infrastructure using cost-distance analysis as determined by distance and travel time. This calculation was performed for each pixel. Finally, we incorporated the different capacity of roads by increasing accessibility linearly by the number of highway lanes.

Urban cores were built directly on the LUCs by converting developed LUCs to the following weights: exurban high = 1; suburban and institutional (only where the National Land

Cover Database [NLCD] identified developed areas with values of 23 or 24) = 5; urban low and transportation = 8; and urban high and commercial = 10. These values were then aggregated by summing their values to 270-m resolution. We then identified the upper half of values (greater than mean of 136) and calculated a kernel density on these cells with a radius of 1 mile. Then, we identified the cells resulting from the kernel-density operation that have values in the upper half of values. To get at urban areas as a multiscale phenomenon, we generated urban core areas at six spatial scales using the natural log of the number of cells. These areas of urban clusters range from: 1.2, 3.2, 8.8, 23.9, 64.7, and 175.0 km^2. We then identified the centroid of each of these clusters at the six different scales and used these as the starting location from which to calculate travel time. The benefit to this approach is that the centroid of the urban area is defined by the land use pattern.

The next step was to create the cost weights that reflect the assumed travel speeds through the transportation infrastructure. We assumed the same travel speeds as in ICLUS v1 but updated the transportation infrastructure to the U.S. Census Bureau Topologically Integrated Geographic Encoding and Referencing (TIGER) 2010 roads.[9] For each of the six urban cluster starting locations, we generate a cost-distance layer that reflected the travel time from the urban core through the infrastructure. We then combine the six time travel surfaces by averaging them to generate a travel time surface.

The accessibility surface provides a platform on which to allocate new growth, but it does not yet account for differences and changes in the capacity of the infrastructure. That is, most infrastructure changes are simply to widen or increase the number of lanes on a given road, rather than to generate a brand new highway through a roadless area. New, typically low-density development can, and does, occur in large, roadless, previously undeveloped tracts of land even though the model does not explicitly add roads to the landscape (further described below in Section 3.4.1 and Figure 8).

To transform the travel time surface into a capacity surface (measured as passenger cars per hour per lane), we calculated the number of cars that could be handled by converting travel time to units of hours, then multiplying by the number of lanes of road. State and U.S. highways and interstates that had information on the number of lanes in the National Transportation Atlas Database[10] were used, otherwise we assumed only a single lane (each way). We also accounted for fixed mass transit (i.e., light rail). We assumed that a light rail system added the equivalent in capacity as a single lane of interstate highway (roughly 2,000 passenger cars per hour per

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[9] ftp://ftp2.census.gov/geo/tiger/TIGER2010/ROADS/.

[10] http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_atlas_database/index.html.

lane)[11] because we did not have individual transit information on the number of cars, number of passengers carried in each car, and other pertinent data.

We converted the continuous capacity surface into a series of eight capacity classes. To identify the class thresholds, we calculated class breaks using the "Natural Breaks (Jenks)" method in ArcGIS and then modified class breaks slightly using visual analysis of five "representative" urban areas: San Francisco, Portland, Denver, Atlanta, and New York City. The classes are at breaks of: 1 > 1,300; 2 = 900 to 1,300; 3 = 600 to 900; 4 = 300 to 600; 5 = 200 to 300; 6 = 150 to 200; 7 = 100 to 150; and 8 = ≤ 100. We used these classes to compute the transition probabilities of growth as a function of the broader neighborhood location of change, rather than the more local scale that the strict LUC transitions provided. That is, for each land use type, we found the transition probabilities for each capacity class independently (or jointly). The capacity class values for time step $t - 1$ are combined with the land use surface from $t - 1$ to yield a transition probability surface at time step t (see Figure 2).

3.3. ICLUS V2 LAND USE CLASSES

In ICLUS v2 land use is represented by 19 discrete categories delineated in the U.S. National Land Use Dataset (US-NLUD; Theobald, 2014). The US-NLUD contains high-resolution (90 m × 90 m pixels) land use information for the years 2000 and 2010 and provides the statistical underpinnings for ICLUS v2 land use change probabilities. The US-NLUD synthesizes data from multiple sources, including remotely sensed data, to map the primary land use at a given location. Parameterization of ICLUS v2 is based on land use transitions from 2000 to 2010, which may not remain constant over time. Changes to transition probabilities are not explored in this report, but may be implemented in a scenarios context within the ICLUS v2 framework.

From the US-NLUD, we retained four nonresidential land use categories (commercial, industrial, institutional, and transportation) within the developed land use group, and further subdivided the residential-urban and residential-rural subgroups to form five categories of residential intensity. Urban residential uses are defined at the 1.6-dwelling units per acre (DUA; 3.95 units per hectare) threshold based on the U.S. Census Bureau definition of urban population of 1,000 people per square mile (Theobald, 2001). The urban high category is greater than 10 DUA based on typical densities at which public transportation is viable (Ewing and Cervero, 2010). Suburban areas have residential densities below the urban low threshold but greater than the 0.4 DUA threshold, which is commonly the density at which services such as municipal sewer and water supply are provided. Lower densities are split into two additional categories

[11] http://www.fhwa.dot.gov/ohim/hpmsmanl/appn2.cfm.

with exurban high as 0.1−0.4 DUA and exurban low as 0.02−0.1 DUA. We also included nine other land use/land cover categories that can be converted into developed land uses, such as cropland, grazing, and timber. The complete list of LUCs used in ICLUS v2 is shown in Table 2. Further detail on the entire US-NLUD can be found in Theobald (2014).

Table 2. Land Use Classes used in the ICLUS v2 model.

Code	Group	Class Name
0	**Water**	Natural water
1		Reservoirs, canals
2		Wetlands
3	**Protected**	Recreation, conservation
4	**Working/production**	Timber
5		Grazing
6		Pasture
7		Cropland
8		Mining, barren land
9	**Developed**	Parks, golf courses
10		Exurban, low density
11		Exurban, high density
12		Suburban
13		Urban, low density
14		Urban, high density
15		Commercial
16		Industrial
17		Institutional
18		Transportation

3.3.1. Quantifying Land Use Changes, 2000−2010

To examine relative changes in land use between 2000 and 2010, we estimated the amount of land assigned to each of the seven developed LUCs and used the counts in 2000 and 2010 as observed values in chi-squared goodness-of-fit tests. For this analysis, the 90 m pixels were aggregated to 1 km pixels for computational efficiency. As the first step in the analysis, both nationally and in each ICLUS region, we tested whether the total percentage of land in developed LUCs increased from 2000 to 2010. Then we tested whether or not the percentage of developed land assigned to the seven individual developed LUCs changed between 2000 and 2010. Only allowable transitions (see Table 3) were considered. The results of these statistical tests show whether development increased significantly (p <0.05) between 2000 and 2010 nationally and for each region and whether development patterns (i.e., relative proportions of the developed classes) changed significantly over the same period (p <0.05). Appendix A presents results for each of the seven ICLUS regions.

If development patterns changed significantly, we examined the changes among the seven developed classes for which ICLUS v2 models transitions. We first compared the odds that a unit of land remained in the same developed LUC from 2000 to 2010 to the odds that it transitioned to a different developed LUC for 2010. If the confidence interval (CI) of the calculated odds ratio (OR) spanned zero, the percentage of developed land assigned to that particular class did not change significantly between the two time periods. If the OR was statistically significantly greater or less than zero, then the percentage of developed land assigned to that particular class increased or decreased in 2010, respectively.

We compared the odds that a unit of land remained in the same residential LUC from 2000 and 2010 to the odds that it transitioned to the next most developed residential class for 2010. The five residential classes are only allowed to transition in one direction: progressively from exurban low to urban high. This resulted in four comparisons: (1) exurban high versus exurban low, (2) suburban versus exurban high, (3) urban low versus suburban, (4) urban high versus urban low. If the CI of the calculated OR spanned zero, the relative amount of land assigned to the two residential classes did not differ between 2000 and 2010 (i.e., the amounts of the two residential classes were not distinguishable). If the OR was significantly greater or less than zero, relatively more or less land, respectively, was assigned to the higher density residential class in 2010. To correct for multiple comparisons and keep the family-wise error rate at 0.05, confidence intervals of 98.3% were used. Furthermore, because the data were aggregated at a 1-km^2 resolution rather than at 8,100 m^2 (the native resolution of the model), our results should be considered conservative.

Combining the data from all ICLUS regions, both the percentage of land assigned to developed use classes (χ^2 = 34,501.40, [degrees of freedom] df = 1, p <0.0001; Table 3, A; Figure 7, C) and the relative amount of land assigned to each of the seven developed LUCs (χ^2 = 276.07, df = 8, p <0.0001; Table 3, B) increased between 2000 and 2010. Among the developed classes, the proportion of developed land in the urban low, commercial, and industrial LUC decreased, the proportion of developed land in the exurban low, suburban, and urban high

LUCs increased between 2000 and 2010, and the proportion of developed land in the exurban high LUC did not change significantly between 2000 and 2010 (see Figure 7, A). Relative growth in the urban high LUC was significantly larger than in the urban low LUC (see Figure 7, B). Conversely, relative growth in the urban low LUC was significantly less than in the suburban LUC. The relative growth in the suburban LUC tested statistically was not significantly different than exurban high LUC, and growth in the exurban high LUC was not significantly different than the exurban low LUC (see Figure 7, B).

Table 3. Goodness-of-fit test results comparing Land Use Classes in 2000 and 2010, nationally. Values are limited to developable area and Land Use Classes that transition in the model. (A) Land assigned to developed and undeveloped Land Use Classes. (B) Percentage developed land assigned to the seven developed Land Use Classes.

(A) Land Use Type	**2000**	**2010**
Developed	12.60%	16.61%
Undeveloped	87.40%	83.39%
χ^2 = 34,501.40	**df:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	53.04%	53.33%
Exurban high	26.00%	26.14%
Suburban	8.93%	9.11%
Urban low	7.81%	7.48%
Urban high	0.44%	0.52%
Commercial	2.38%	2.22%
Industrial	1.40%	1.20%
χ^2 = 276.07	**df:** 8	***p*-value:** <0.0001

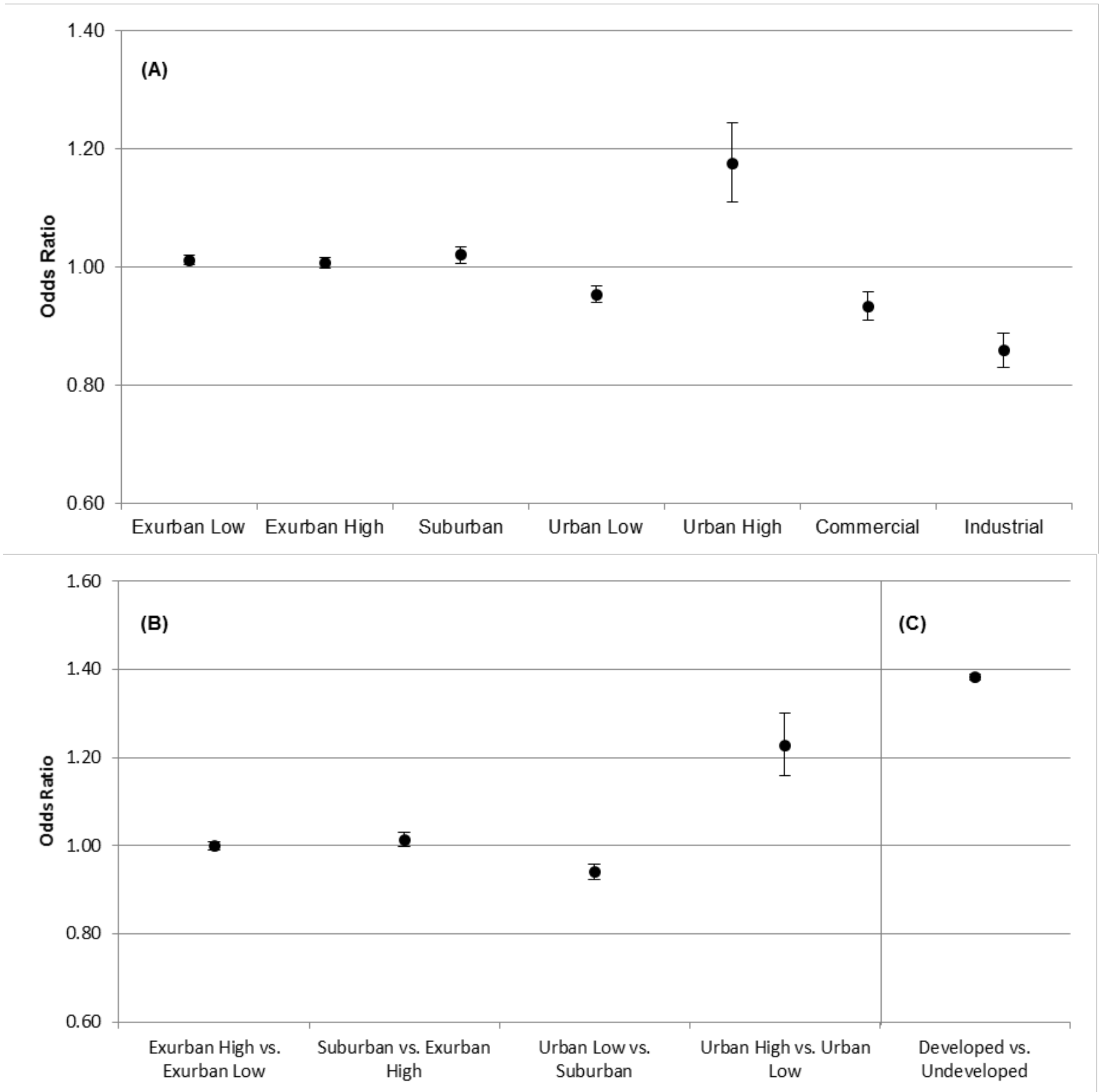

Figure 7. Land use comparisons between 2000 and 2010, nationally. (A) Odds ratios (ORs) and confidence intervals that a unit of land stayed in the same developed LUC from 2000 to 2010 compared to the odds that it switched to a different developed LUC for 2010; (B) ORs and confidence intervals that a unit of land stayed in the same residential LUC from 2000 and 2010 compared to the odds that it switched to the next most developed residential class for 2010; and (C) OR comparing developed and undeveloped LUCs.

3.4. TRANSITION-PROBABILITY MODEL

We calculated the transition probabilities between LUCs empirically from the baseline change layers (i.e., 2000 and 2010 land use layers). We identified transitions that were plausible and then further identified transitions that were plausible but could not be supported by the underlying data (see Table 4) to correct for spurious changes that resulted from artifacts in the various data sets. For example, the institutional land use data set does not contain information about the year that land use first appeared; therefore, we could not infer any change in the institutional category. Furthermore, as in ICLUS v1, land uses transition to *increasing* intensity and, therefore, “backwards” transitions are excluded (e.g., urban to suburban). Note that this also requires generation of a modified land use data set for 2000, such that the classes are consistent logically with 2010. In ICLUS v2, 2010 is the base year for future projections; thus, the 2000 data set needed to be consistent with 2010 information.

Table 4. Land Use Classes transitions from 2000 (rows) to 2010 (columns) incorporated into ICLUS v2. Filled circles (●) denote transitions that were included in the model; shading is added for emphasis. Empty circles (○) denote plausible transitions that were excluded for the purpose of model simplification. Hatches (x) denote plausible transitions that were excluded from the model because temporal data were not available. Unmarked transitions were excluded from the model because they were considered unlikely or infrequent and temporal data were not available.

	Water	Wetland	Rec Con	Timber	Graze	Pasture	Crop	Mining	Parks	Exurb L	Exurb H	Suburb	Urban L	Urban H	Comm	Indust	Inst	Trans
Water		x																
Wetland	x			x	x	x	x	x	x	●	●	●	●	●	●	●	x	x
Recreation and Conservation				x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Timber		x	x		○	○	○	x	x	●	●	●	●	●	●	●	x	x
Grazing		x	x	○		○	○	x	x	●	●	●	●	●	●	●	x	x
Pasture			x	○	○		○	x	x	●	●	●	●	●	●	●	x	x
Cropland			x		○	○		x	x	●	●	●	●	●	●	●	x	x
Mining			x						x	x	x	x	x	x	x	x	x	x
Parks and Open Space								x		x	x		x	x	x	x	x	x
Exurban Low				○	○	○	○	x	x		●	●	●	●	●	●	x	x
Exurban High								x	x	○		●	●	●	●	●	x	x
Suburban			x					x	x	○	○		●	●	●	○	x	x
Urban Low			x						x	○	○	○		●	●		x	x
Urban High			x						x	○	○	○	○		●		x	x
Commercial			x						x	○	○	○	○	○		●	x	x
Industrial and Utility			x					x	x	○	○	○	○	○	○		x	x
Institutional			x					x	x			x	x	x	x	x		x
Transportation			x						x									

3.4.1. Empirical Estimation of Transition Probabilities

A series of multinomial generalized additive models (GAMs) were used to model LUC transitions using the VGAM package in R (Yee, 2010; R Core Team, 2015). The GAMs predict the probability that a pixel transitioned from one LUC to another between 2000 and 2010 by transportation capacity class. Capacity class here is determined by binning raw capacity values into eight ordinal values, 1−8, where lower values represent higher transportation capacity (described in Section 3.2). The 53 possible transitions between LUCs were modeled in two stages. First, for each ICLUS region, we modeled the probability that a pixel transitioned into each LUC, $p(\mathrm{LUC}_j)$, by capacity class, where subscript j is the LUC in 2010. These seven regional, "marginal" models had capacity class as their predictor variable and LUC_j as a categorical response variable (seven levels: exurban low, exurban high, suburban, urban low, urban high, commercial, and industrial; see Figure 8). Second, seven "conditional" models for the LUC_j in each region model the probability that a pixel transitioned from a LUC in 2000 (represented as subscript i) if it transitioned into LUC_j in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. Each of these models had capacity class as its predictor variable and $\mathrm{LUC}_{i|j}$ as a categorical response variable (up to ten levels depending on the region and LUC_j: wetland, timber, grazing, pasture, cropland, exurban low, exurban high, suburban, urban low, urban high, and commercial).

These sets of models are the basis for probability calculations that a pixel transitioned from one LUC to another by multiplying the corresponding two model predictions together, that is, for a given capacity class and region, the probability that a LUC transitioned from LUC_i to LUC_j is $p(\mathrm{LUC}_{ij}) = p(\mathrm{LUC}_j) \times p(\mathrm{LUC}_{i|j})$. Pixels that did not transition and response categories with zero pixels were not included in the analysis and were given transition probabilities of zero. The many transitions containing a small number of pixels required limiting the degrees of freedom used in the smoothing function to three. Each multinomial GAM used a logit link, and the LUC with the largest number of pixels was set as the reference category for comparison purposes.

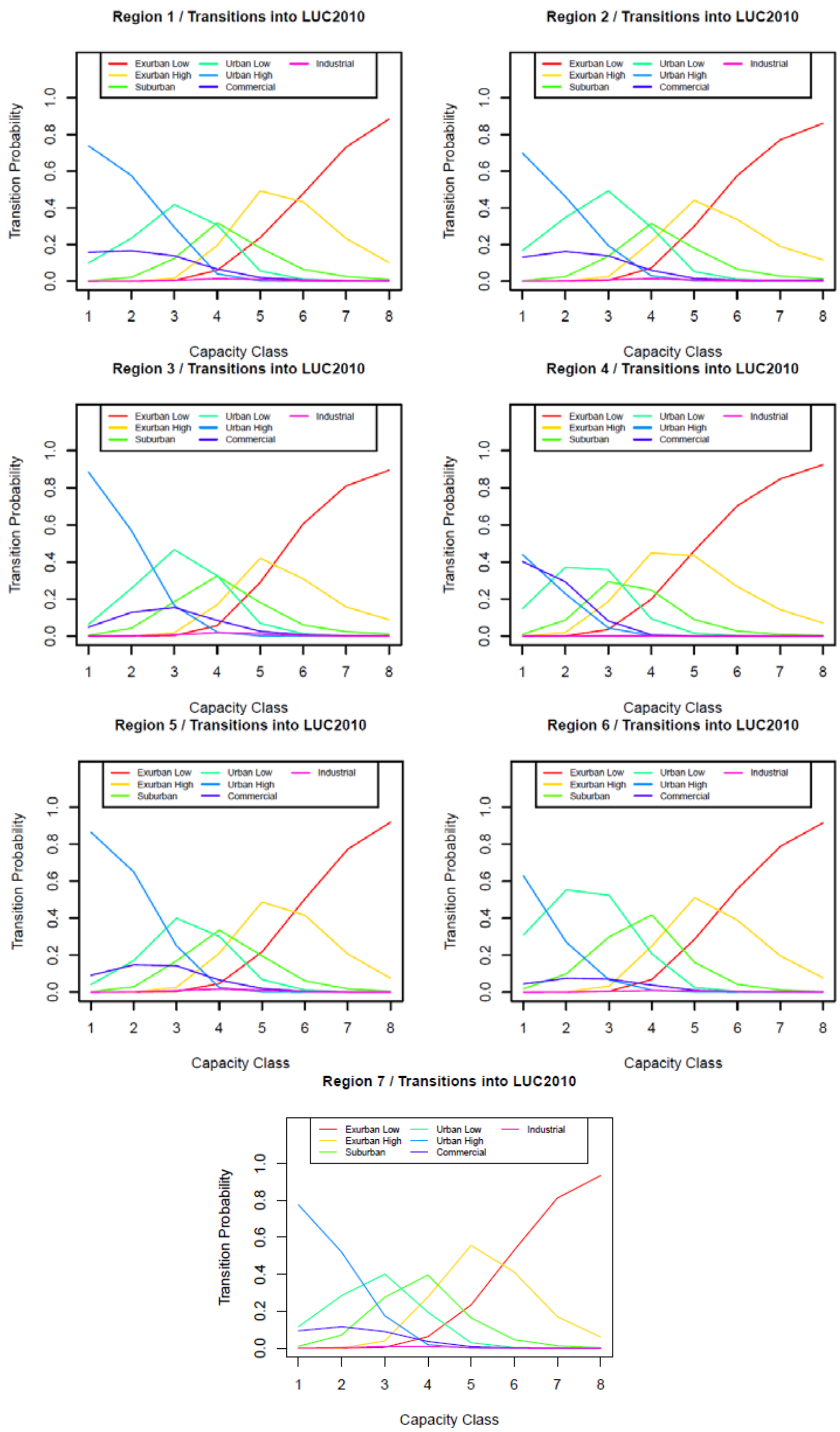

Figure 8. Predicted transition probability by capacity class into Land Use Classes in 2010. Each panel shows the probability of a pixel transitioning to each of seven land uses based on observed 2000 to 2010 changes.

Due to the large number of models, Tables B-1 to B-7 (see Appendix B) show only model outputs with statistically significant individual smoothing terms and global tests. Global test results, which compare models with capacity class as a predictor variable to intercept only models using the difference in the deviance and residual df between models, showed that capacity class was a highly significant predictor of transition probability overall (p <0.0001 in all cases, Tables B-1 to B-7). Figure 8 shows the relationships between the probability of transitioning into LUC_j in 2010 and capacity class for the seven regional, marginal models. Figures B-1 to B-7 (see Appendix B) also show the full regional transitional probabilities, created by multiplying the marginal and conditional models together. Generally, pixels were more likely to transition into higher density residential classes at lower capacity class values and vice versa with some regional variability on that overall pattern (see Figure 8 and Appendix B). The intermediate density residential LUC showed unimodal responses, while the probability of transitioning into urban high and exurban low monotonically decreased and increased in higher capacity classes, respectively. Transitions into the commercial LUC displayed more regional variability, with some monotonically decreasing with capacity class or displaying unimodal behavior. Industrial transitions, however, were relatively low overall. The transition probabilities do allow for irregular growth patterns that do not always follow the most likely pattern (Appendix B). For example, the suburban LUC can transition into the commercial LUC, which then becomes a new commercial core and an attractor for new residential growth. Although the general pattern of transitions into the seven LUC held across the regions, we expect the regional variability in observed transitions to produce different growth patterns over the 80-year projection period.

3.5. LAND USE AND CAPACITY DEMAND MODELS

To estimate LUC demands and changes in capacity, we created eight GAMs to predict LUC density from population density within each ICLUS GU (see Figure 2 for representation of ICLUS GUs). Capacity and each of the seven developed LUCs has its own GAM, created using the *mgcv* package in R (Wood, 2004; R Core Team, 2015). Each model includes population density, ln((people + 1) km^{-2}), as its primary predictor variable and either capacity density per km^{-2}, ln(capacity km^{-2}) or LUC pixel density, ln((pixels + 1) km^{-2}), as its response variable. Density calculations use both 2000 and 2010 population data within each ICLUS GU and the developable area for each ICLUS GU, estimated from the 2010 U.S. Census and USGS Protected Areas Database of the United States (USGS, 2012), respectively.

Comparison of the difference in estimated number of pixels for each LUC or capacity, the dependent variables of the eight GAMs, between adjacent time periods is the basis of the demand calculation for each decade from 2020 to 2100. For example, 2050 demands were calculated by subtracting modeled 2040 from 2050 pixel counts or capacity. The pixel counts and capacity for each ICLUS GU and decade were calculated by back transforming the value $\hat{y}_{i,t} + \varepsilon_{i,2010}$, where $\hat{y}_{i,t}$ is the modeled response for a specified ICLUS GU and decade, and $\varepsilon_{i,2010}$ is the raw residual associated with the 2010 measurement for that GAM and ICLUS GU. Adding the raw residual for 2010 ensured that all ICLUS GU densities were scaled to their actual densities in 2010, and that each GU followed a course parallel to the estimated density curve over time on the log scale. In effect, this can be thought of as estimating proportional changes in LUC density or capacity from proportional changes in population density. ICLUS v2 does not generate LUC or capacity demands for counties that are projected to lose population, meaning land use patterns in these counties do not change.

Table C-1 (see Appendix C) presents summary results of the GAMs with a brief overview presented here. Smoothing terms of the eight models are highly significant (p <0.0001 for all cases) and the adjusted R^2 of the curves ranges from 0.550 for the exurban low model to 0.889 for the suburban model. Relationships between ln(population density) and ln(pixel density) are displayed in Figure 9. For all exurban low and high classes, the relationship between population and pixel density was unimodal, and monotonically increasing for all others. This matched our expectation regarding urban land use succession (i.e., higher density pixels should displace lower density pixels at high accessibility locations, while low-density pixels displace nonurban land uses at the urban fringe). Urban high, the highest density class, continues to increase rapidly with population density, while the rates of increase for other classes level off. Generally, the persistence of high-density residential classes at high population densities suggests urban areas are either better mixed (less likely to be replaced with growth) or that expansion and replacement rates of these classes balance as cities expand outward. Similar to high density residential classes, commercial and industrial classes tend to level off in counties with high population densities. This leveling off indicates that these classes are not rapidly replaced or that growth and replacement rates balance as counties grow. Similar to the urban high residential class, transportation capacity initially increases approximately exponentially and then linearly at higher population densities.

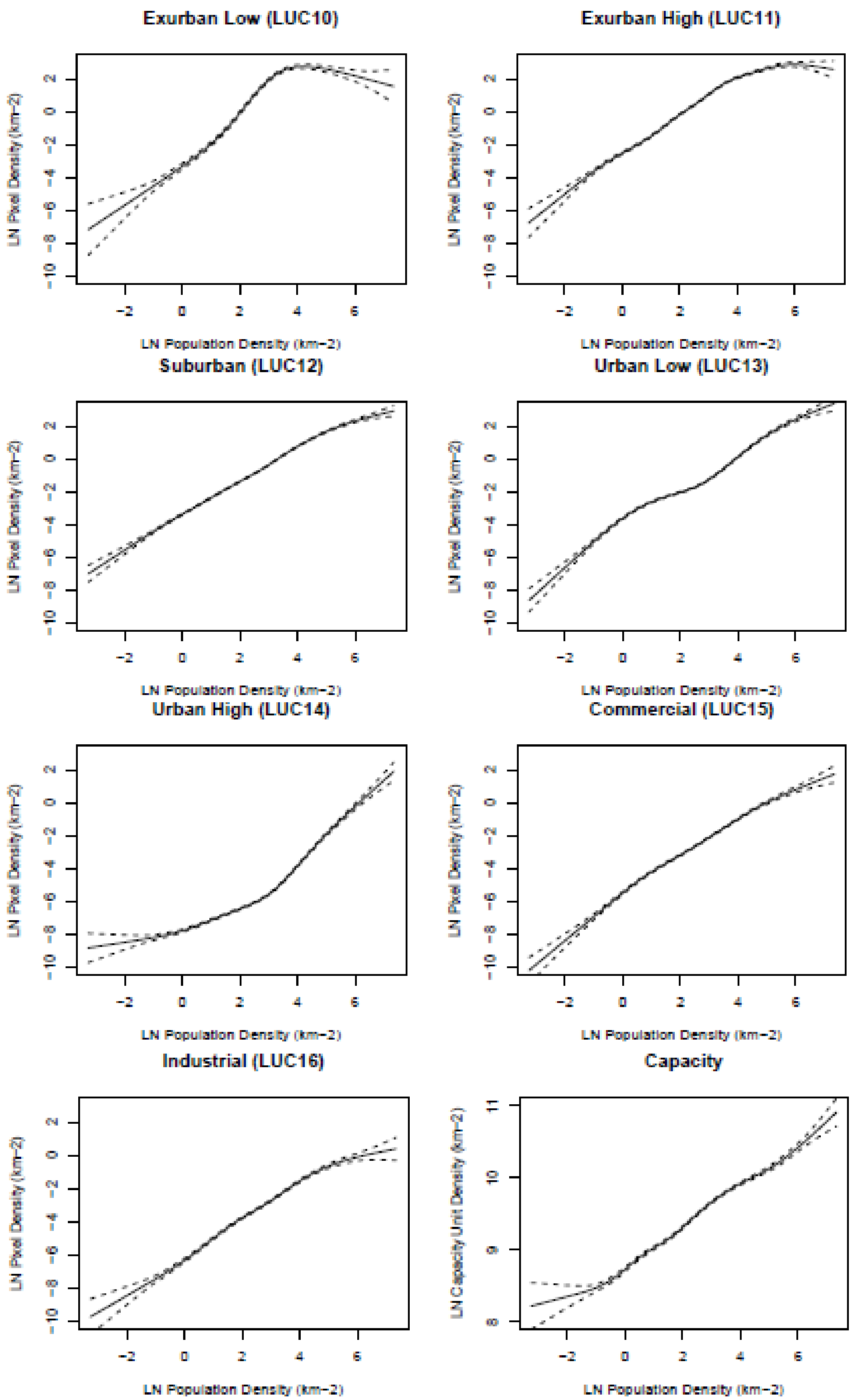

Figure 9. Predicted log transformed pixel or capacity density (km^{-2}) (± 2 SE) by log transformed population density (km^{-2}). Each panel shows a smooth curve for a different Land Use Classes or for mean capacity nationally.

3.5.1. Updating the Accessibility-Capacity Surface

As shown in Figure 2, the surface of continuous capacity values at time step $t - 2$ is updated and used to form a surface of land use transition probabilities at time step t. To complete this update, we generate demand for new capacity units as a function of population density and proportionally allocate that demand using region-specific weights calculated from the 2000 and 2010 capacity surfaces. These weights are specific to each combination of LUC i and region k. First we calculated the sum of capacity units $\hat{C}$ by land use and region, averaged across 2000 and 2010:

$$\hat{C}_{i,k} = \frac{C_{2000\,i,k} + C_{2010\,i,k}}{2} \tag{3-1}$$

Next, we calculated a relative weight W for each LUC, where $\hat{C}_{MAX}$ is the maximum result from Equation 3-1 for region k and $0 \leq W_{i,k} \leq 1$:

$$W_{i,k} = \frac{\hat{C}_{i,k}}{\hat{C}_{MAX}} \tag{4-1}$$

Equation 4-1 yields the final weights used to allocate new capacity units through time. Each time the capacity update function is called, new capacity units U for pixel P are given as:

$$U_P = \frac{W_P}{W_T} \times D_T \tag{5-1}$$

where W_P is the weight value from Equation 4-1; W_T is the sum of pixel weights for the entire geographic unit being processed; and D_T is the countywide demand for new capacity units. Equation 5-1 represents the culmination of the capacity update function.

3.6. LAND USE PATCH ALLOCATION PROCESS

At each time step, the allocation of new land use pixels occurs on a county-by-county basis. Industrial pixels are allocated first, based on the reasoning that fundamental services such as water and electric utilities have the least flexibility in terms of location siting. Commercial is allocated next, and the process continues iteratively through the urban, suburban, and exurban residential classes following the highest-to-lowest order of land use intensity and value. After the allocation of commercial patches, the model calculates a cost-distance surface such that each pixel in the county is assigned a functional distance from commercial areas. All five residential LUCs include this cost-distance surface as a spatial allocation weight for new patches. The order in which LUCs are allocated, and the inclusion of accessibility to commercial pixels as an amenity for residential classes, results in a land use change pattern that is generally consistent with classic land use economic theory (Alonso, 1964). This process also allows new commercial and urban centers to form that alter the cost-distance surface in the next time step.

ICLUS v2 uses the observed set of land use patches as an analog for future development patterns. That is, for each LUC-region combination, a patch is drawn at random from the set of patches that appeared between 2000 and 2010. That patch is compared against the transition probability surface and placed at the location of the highest median probability, with the constraint that all probabilities considered must be greater than zero. In the case of ties between two or more locations, one location is selected at random. This process is repeated until the demand for each land use is satisfied. If there are no remaining pixels with a greater-than-zero probability of being converted, then any remaining demand is carried over to the next time step.

As in ICLUS v1, we assume that the vast majority of land use changes will be to a higher intensity or value, and thus restrict new patches of land use from replacing pixels of a higher use. There is no “undevelopment” in either ICLUS v1 or ICLUS v2, although we recognize that in a few urban areas (e.g., Detroit, Michigan) recent and unprecedented economic conditions have resulted in conversion of higher density areas to less developed land uses.

The patch allocation process uses morphological functions from the Python programming language,[12] specifically the SciPy[13] package (Jones et al., 2001). An important change in this new version of the ICLUS model is the use of pseudorandom numbers at two stages of the patch allocation process: (1) patch selection and (2) choosing between locations of equal probability. It is not the goal of the ICLUS project to generate probabilistic forecasts of land use change; therefore, stochastic processes were not incorporated into any phase of the model. Instead,

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[12] www.python.org.
[13] The *binary_hit_or_miss* function from scipy.ndimage is used to identify valid locations for a new patch. The *median_filter* function is then used to identify the valid location(s) of the highest median transition probability.

Python's random number generator was "seeded" at the start of the initial patch allocation process for each county. For this, we used the integer version of the five-digit county Federal Information Procession Standard (FIPS) code. This step ensures that, holding all other parameters constant, consecutive runs of the model will yield identical results.[14]

4. RESULTS

This section discusses the consequences of the data set and model updates for ICLUS v2. Similar to the overall model flow, Section 4.1 provides results for the demographic model, and Section 4.2 describes land use changes.

The discussion of the demographic model begins at the national level, then examines regional population trends including the effect of changing climate variables in the migration model. This subsection delves into further detail on the influence of climate on domestic migration by ICLUS geographic units in relation to climate variables. These maps demonstrate the absolute and relative influence that climate change has on domestic migration in the ICLUS v2 modeling approach. The discussion on migration concludes with an analysis of the relative contribution of the different scenarios, climate models, and regions on migration patterns.

The discussion of land use changes initially focuses on the addition of commercial and industrial classes to the set of transitioning land uses. This section also examines growth in all developed LUCs by region over time. Finally, comparisons of standardized LUCs between ICLUS v1 and v2 show the overall differences in output that result from all of the data set and model updates.

4.1. POPULATION PROJECTIONS

4.1.1. National Projections

Figure 10 shows projections of total population for the conterminous United States. Nationally, the ICLUS SSP5 scenario results in the highest total population because of higher fertility rates than the ICLUS SSP1 scenario. The relative difference in population in 2100 between ICLUS SSP1 and 5 (229 million) is similar to the relative difference between the International Institute for Applied Systems Analysis (IIASA) SSP1 and 5 scenarios (247 million), allowing qualitative comparisons and exploration of differences in impacts

[14] Results shown in this report were generated on a computer using Windows 7 (64-bit) and Python version 2.7.10 and SciPy version 0.16. Executing the ICLUS v2 model on computers with different software will yield different random number draws, despite the "seeding" process described above.

between scenarios. Both SSP scenarios fall within the range of the U.S. Census Bureau's 2000 projections (see Figure 10).

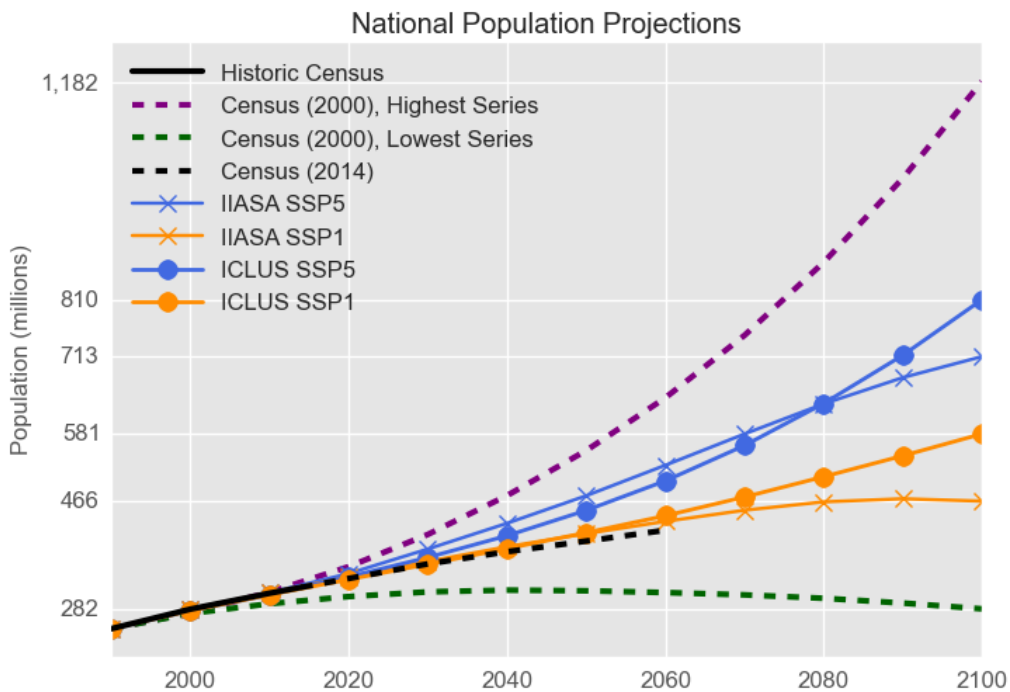

Figure 10. Total population for the conterminous United States to 2100 showing projections for ICLUS v2. For comparison, historic and projected population from the U.S. Census Bureau, and projected population from the International Institute for Applied Systems Analysis (IIASA)[15] are shown. The most recent census projection (2014) aligns well with the SSP1 projection used in this report through 2060.

4.1.2. Regional Projections

By region, ICLUS v2 total population projections are similar within the same SSP-RCP combination but use different climate model output in the migration model (see Figure 11). Even when climate change projections are selected to maximize differences, regional population projections will largely reflect demographic parameters such as fertility rates, net immigration assumptions, and so forth. Section 4.1.4 discusses differences between scenarios at the subregional scale that arise from the spatial allocation model.

[15] These population projections are available at https://secure.iiasa.ac.at/web-apps/ene/SspDb.

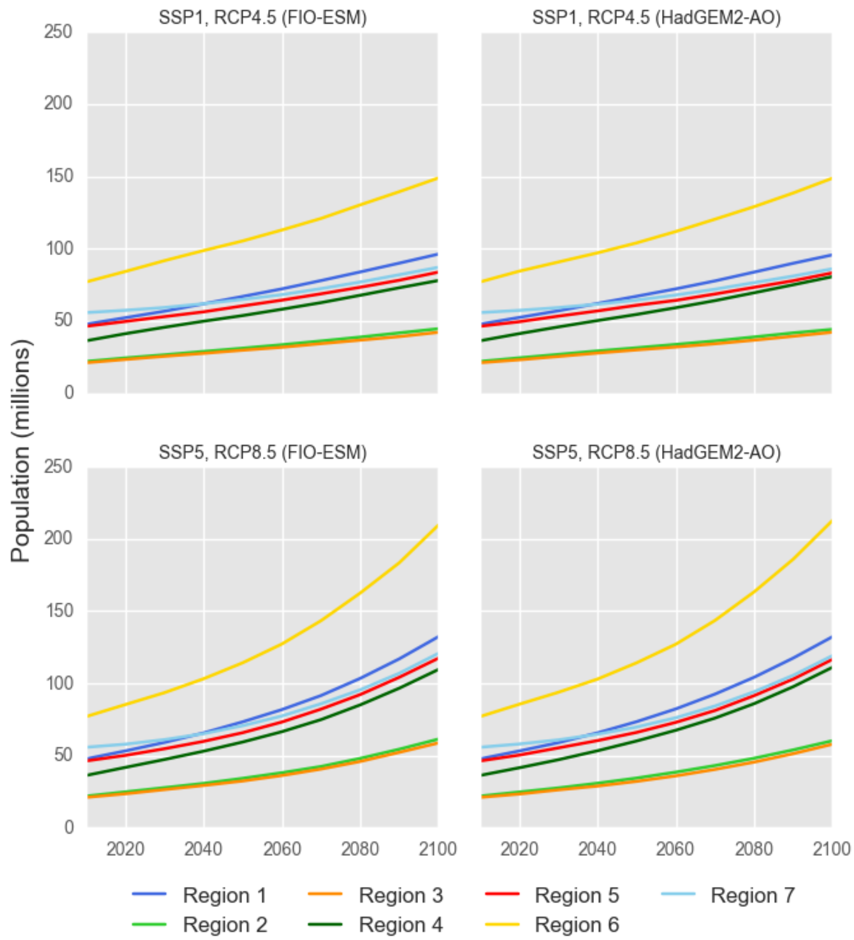

Figure 11. Total population for each ICLUS region to 2100 under four scenario assumptions. SSP1 is low population growth, SSP5 is high population growth; RCP 4.5 is low carbon emissions, RCP8.5 is high carbon emissions. With respect to temperature increases over the United States, FIO-ESM and HadGEM2-AO are among the models least and most sensitive to global emissions, respectively.

4.1.3. The Effect of Changing Climate Amenities

A key feature introduced in ICLUS v2 is the integration of climate change as an amenity (or *dis*-amenity) in the migration model equation used to simulate domestic migration at each annual time step (see Section 2.1.4). Using this additional information means that a wider range of spatial patterns are theoretically possible with respect to population distribution because each unique climate change projection should produce a unique pattern of domestic migration. Moreover, small differences between two similar climate change projections could yield pronounced differences in migration patterns as the cumulative effect of simultaneously adjusting amenity values for each geographic unit at each annual time step plays out over time.

Figure 12 shows the effect of climate change-induced migration by ICLUS region and scenario relative to a migration model that, like ICLUS v1, holds climate amenity variables constant over time for all scenarios. There were no entirely consistent patterns with respect to population differences, as five regions (1, 3, 4, 6, and 7) had either higher or lower total populations by 2100 depending on the scenario. The total population of Region 5 (Great Lakes) was higher relative to the no climate change model regardless of scenario, while in Region 2 (Intermountain West) the opposite was true, especially under the ICLUS SSP5-RCP8.5 scenarios. Across all scenarios explored in this report, the effect of climate change-induced migration on total population for any ICLUS Region was no more than about ± 2,500,000 people (see Figure 12).

This diversity of outcomes is not surprising given the complexity of the underlying model. Each climate change projection presents a unique spatiotemporal pattern of migration model inputs. These patterns in turn alter the spatial distribution of population over time and across the modeling domain and enhance or diminish migration feedbacks via other variables in the migration model equation (i.e., population density or growth rate). While the relative net effect of these interactions may total millions of people for a given region, we note that these differences are a small fraction of total population. Figure 13 shows that, in relative terms, the effect of climate change-induced migration is no more than ~4% of the regional population, as seen in Region 2 under SSP5-RCP8.5 using the HadGEM2-AO climate data. Most differences are between ± 2% of the regional population regardless of scenario and climate model.

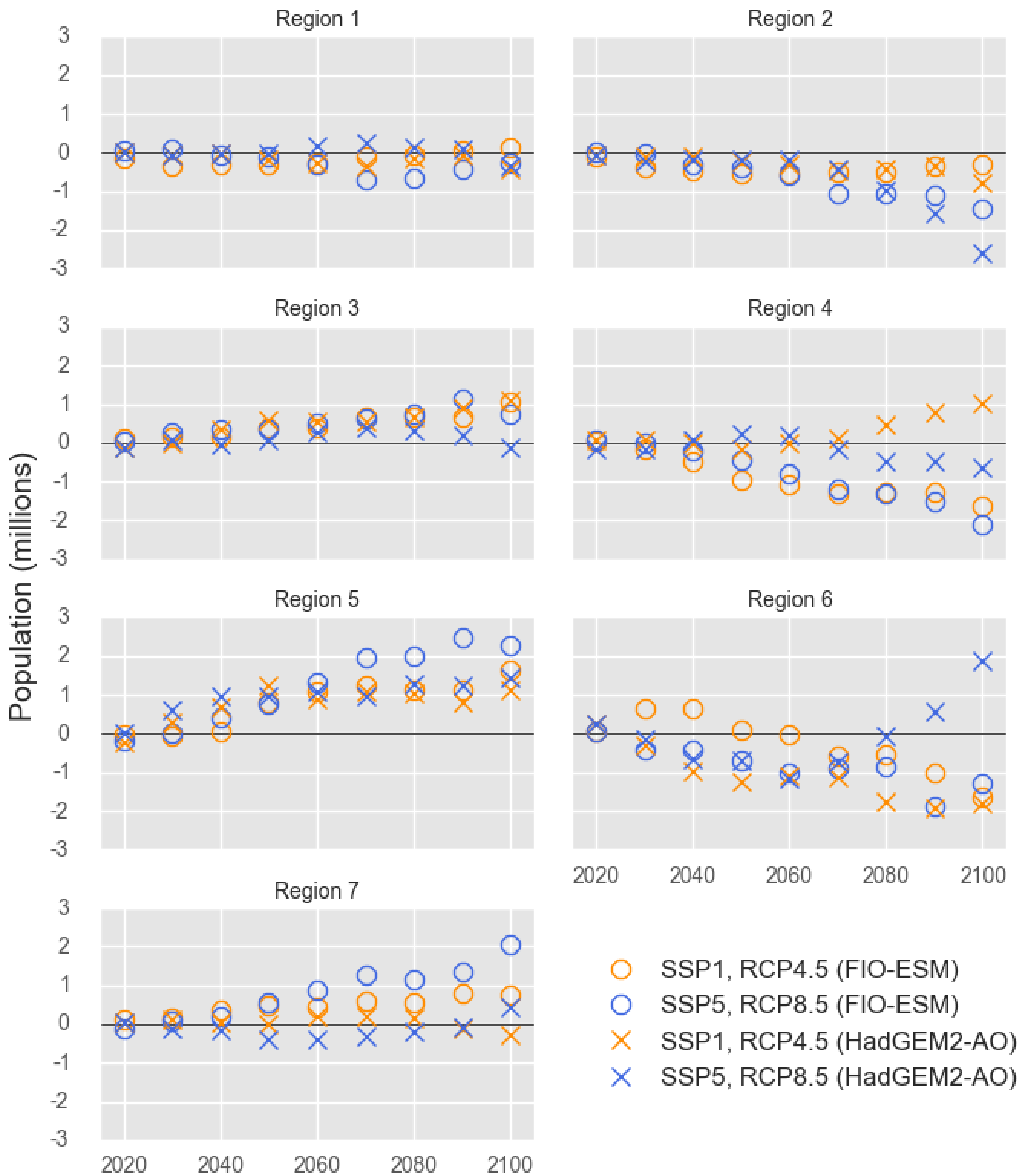

Figure 12. The effect of climate change-induced domestic migration expressed as differences in millions of people. Differences in regional population projection by emissions scenario and climate model are shown. Values are expressed as the difference from a "no climate change" version of the migration model. SSP1 is low population growth, SSP5 is high population growth; RCP 4.5 is low carbon emissions, RCP8.5 is high carbon emissions. With respect to temperature increases over the United States, FIO-ESM and HadGEM2-AO are among the models least and most sensitive to global emissions, respectively.

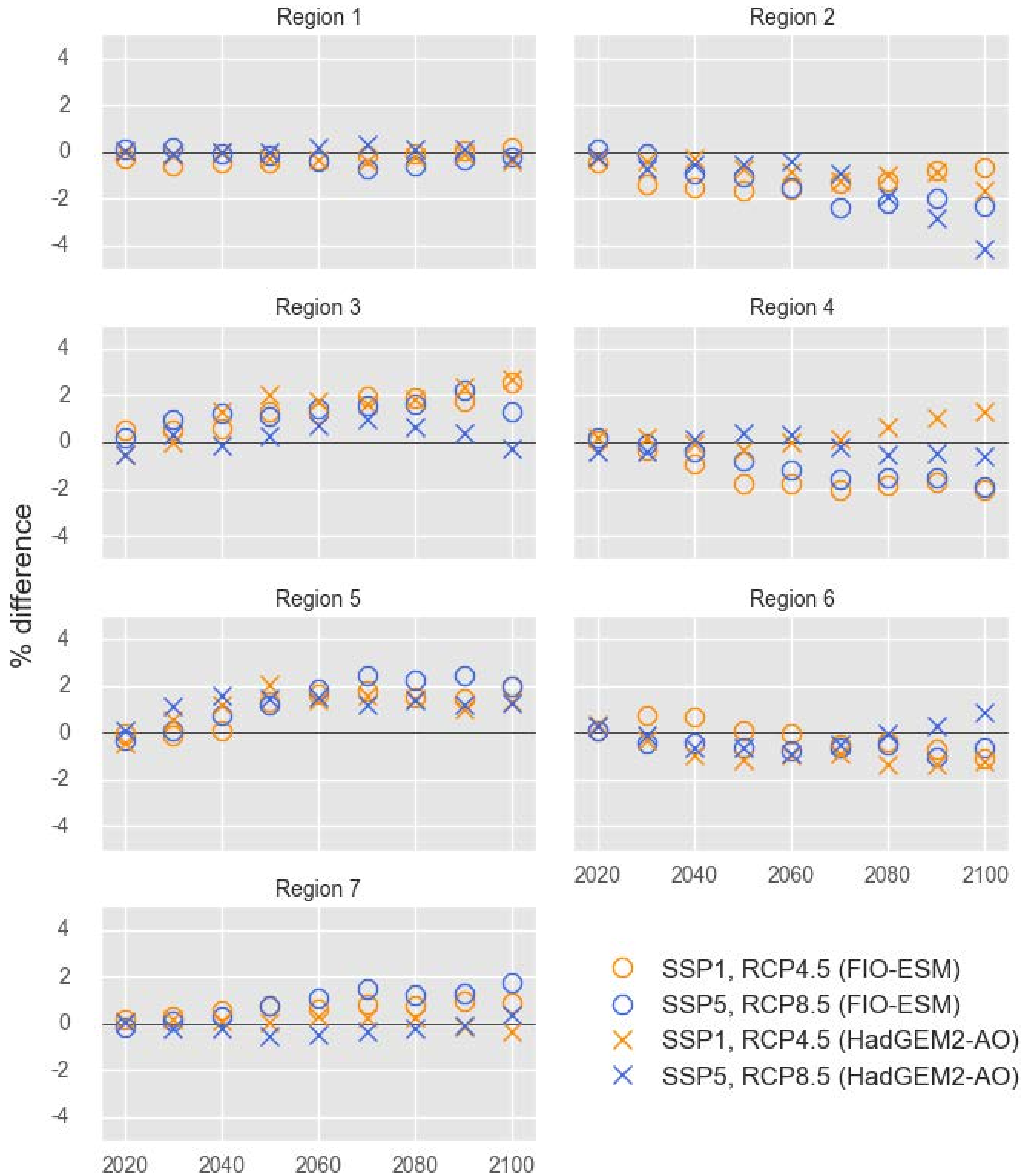

Figure 13. The effect of climate change-induced domestic migration expressed as percentage differences. Relative differences in regional population projection by emissions scenario and climate model are shown. Values are expressed as the percentage difference from a "no climate change" version of the migration model. SSP1 is low population growth, SSP5 is high population growth; RCP 4.5 is low carbon emissions, RCP8.5 is high carbon emissions. With respect to temperature increases over the United States, FIO-ESM and HadGEM2-AO are among the models least and most sensitive to global emissions, respectively.

4.1.4. Subregional Projections

The effect of climate change on ICLUS v2 population projections can be further illustrated with difference maps comparing climate variables derived from the FIO-ESM and HadGEM2-AO climate projections and their respective population projections. An examination and interpretation of the migration model is provided in Section 2.2; however, some general spatial relationships between climate variable differences and population differences are apparent.

For example, under the SSP5-RCP8.5 scenario assumptions, total population in Region 6 (Southeast) is generally higher when the migration model is driven by the HadGEM2-AO climate projection (see Figures 14, A and B, green areas). In this comparison, all parameters and assumptions are identical except for the annual climate amenity values; therefore, differences in the spatial pattern of population are the cumulative result of migration differences where and when the climate projections diverge.

The difference between the two climate models in terms of winter precipitation seems to play an important role in this particular spatial pattern. While relatively warmer winter temperatures are projected by the HadGEM2-AO model over most of the country, the southeastern United States is one of the few areas to show relatively dryer winters by HadGEM2-AO. The effect of markedly warmer winters (which would attract more migrants) projected by HadGEM2-AO across the northern plains is difficult to discern because of generally smaller, fewer, and more distant high-population areas relative to the southeastern United States. In addition, relatively more winter precipitation would also work to slow migration into and within the northern plains area.

A comparison of population difference maps in Figures 14 and 15 shows somewhat larger migration differences under RCP4.5—the *lower* emissions scenario of the two. This somewhat counterintuitive result is explained by the relatively larger difference between the two climate models as shown in the climate maps. The spatial extent and magnitude of divergent projections is clear for virtually all combinations of variables and years. The cumulative effect of these comparatively larger differences in climate variables results in comparatively larger migration differences.

These maps demonstrate some implications of the ICLUS v2 modeling approach; however, care should be taken to avoid over-simplifying the apparent spatial relationship between climate variables and population shown in Figures 14 and 15. The suite of interactions and feedbacks present in the migration model extends beyond the figures presented here, and cannot be exhaustively characterized by examples presented in this report.

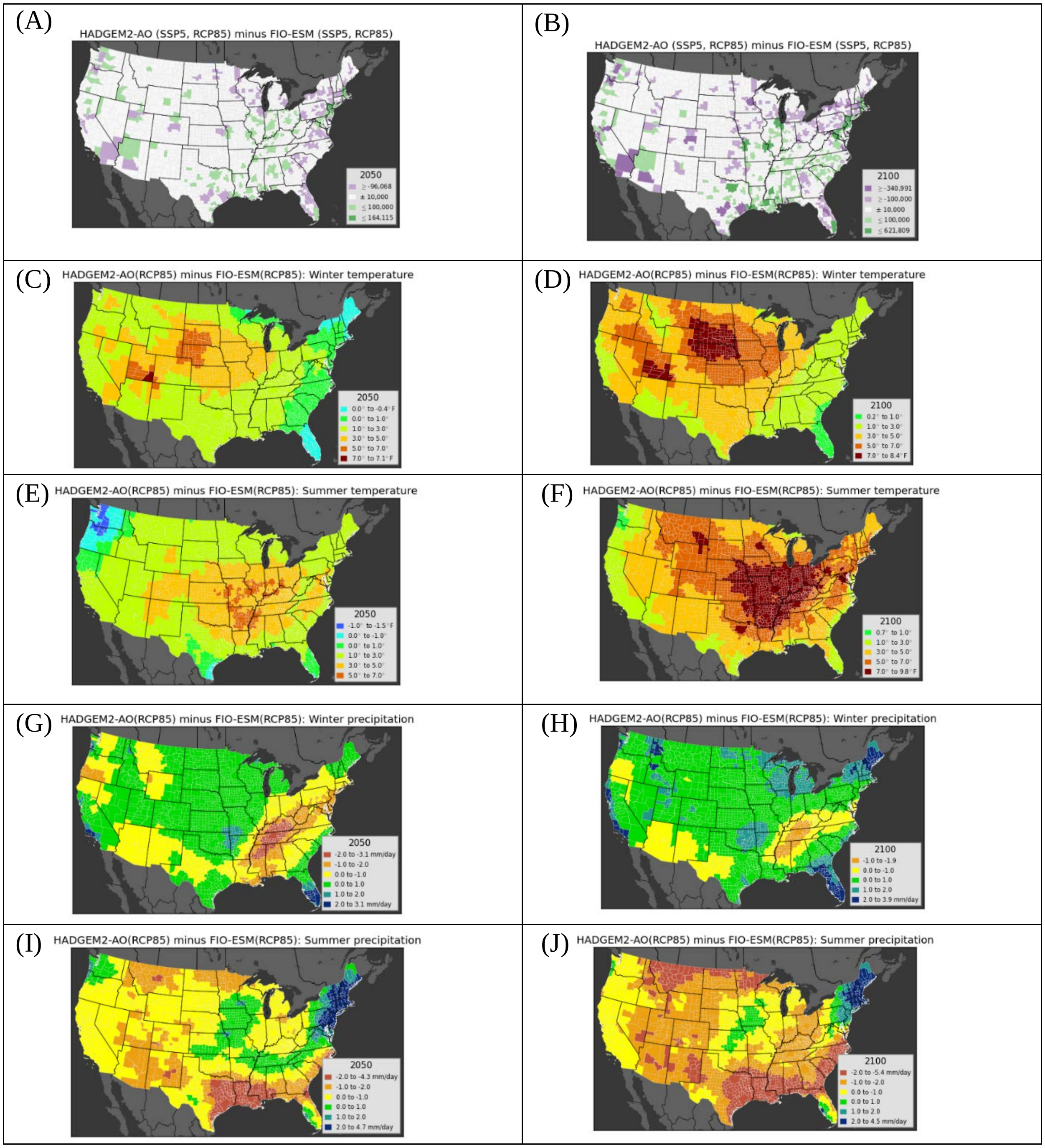

Figure 14. Differences in population and climate change projections driven by FIO-ESM and HadGEM2-AO under SSP5 and RCP8.5 assumptions for 2050 and 2100. (A) Population differences by ICLUS GU in 2050 and (B) in 2100; (C) differences in change in winter temperature in 2050 and (D) in 2100; (E) differences in change in summer temperature in 2050 and (F) in 2100; (G) differences in change in winter precipitation in 2050 and (H) in 2100; (I) differences in summer change in precipitation in 2050 and (J) in 2100.

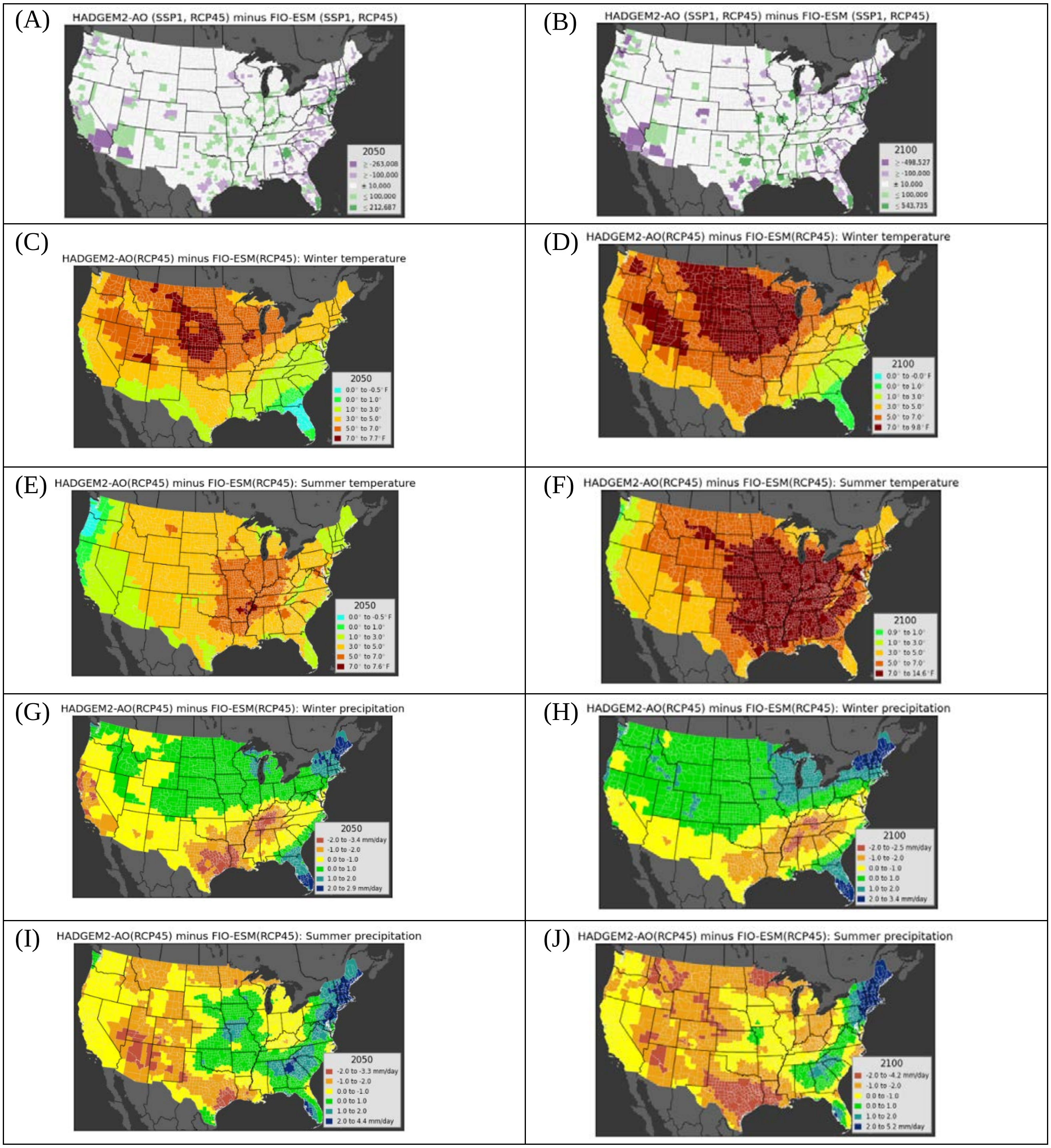

Figure 15. Differences in population and climate projections driven by FIO-ESM and HadGEM2-AO under SSP1 and RCP4.5 assumptions for 2050 and 2100. (A) Population differences by ICLUS GU in 2050 and (B) in 2100; (C) differences in change in winter temperature in 2050 and (D) in 2100; (E) differences in change in summer temperature in 2050 and (F) in 2100; (G) differences in change in winter precipitation in 2050 and (H) in 2100; (I) differences in change in summer precipitation in 2050 and (J) in 2100.

To further investigate the differences among scenario, climate model, and region, we developed a fully factorial generalized least squares model to test the influence of these variables and their interactions on mean 10-year changes in population density. The categorical independent variables include ICLUS GU initial population density (people per km^2 in five size bins, P1: ≤5.0; P2: 5.1−15.0; P3: 15.1−45.0; P4: 45.1−135.0; P5: ≥135.1; see Figure 16), ICLUS region (seven regions; see Figure 6), SSP (two scenarios: SSP1, SSP5), and climate model (three levels: no climate change, FIO-ESM, HadGEM2-AO). The model also includes all possible 2-way, 3-way, and 4-way interactions among the variables. To meet the assumption of homogeneity, we allowed each county size class to have its own residual variance (Zuur et al., 2009). We ran separate models to look at population differences between 2010−2050 and 2060−2100 because results suggest higher divergence in populations by the end of the century (see Figures 14 and 15).

During the initial decades modeled, 2010−2050, the magnitude of population change depends on the initial population density, which varies by region (single 2-way interaction; see Table 5, left). ICLUS GUs with higher initial population densities have larger increases in population density overall and show the most distinct regional differences (see Figure 16, A). In the second half of the century, 2060−2100, the magnitude of population change still depends on the initial population density, but varies by both region and SSP (two 2-way interactions; Table 5, right). As in the initial decades, ICLUS GUs with higher initial population densities have larger increases overall and show the most distinct regional differences (see Figure 16, B). Similarly, differences between SSPs are more distinct at higher population densities (see Figure 16, C), in part because SSP5 uses a higher fertility rate and therefore has more people to distribute across ICLUS GUs. The addition of the SSP variables in the late-century model shows that the pathways diverge during this time period, but are similar during the first half of the century.

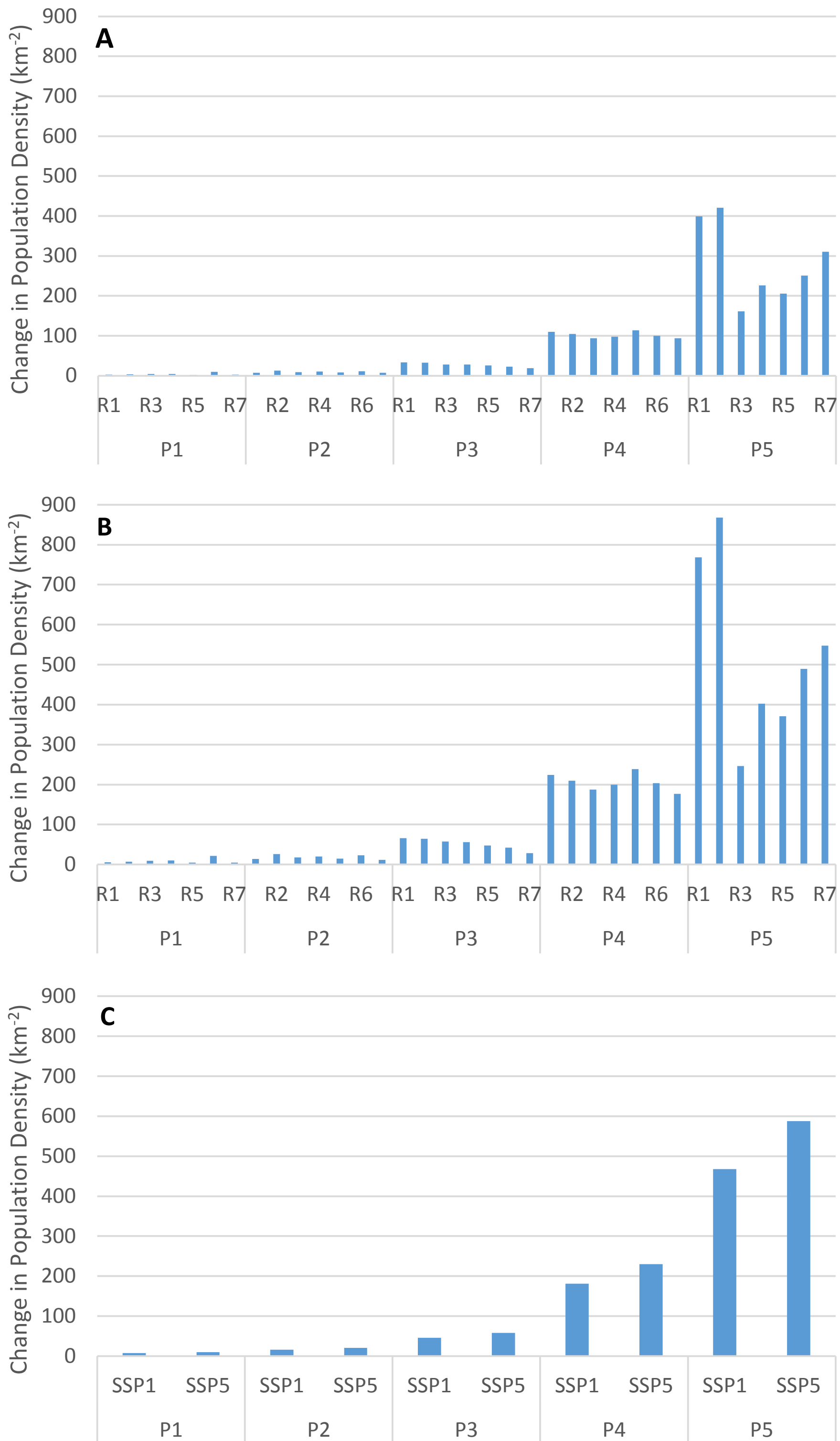

Figure 16. Average ICLUS GU 10-year population change by (A) starting population density and ICLUS region from 2010−2050, (B) starting population density and ICLUS region from 2060−2100, (C) starting population density and SSP from 2060−2100. P1: ≤5.0; P2: 5.1−15.0; P3: 15.1−45.0; P4: 45.1−135.0; P5: ≥135.1 people per km^2.

Table 5. GLS model results. Model output includes degrees of freedom (df), F-statistic, and significance (*p*). Nonsignificant terms (including interactions) are included for completeness.

Change in population density: 2010−2050	**df**	**F**	***p***	**Change in population density: 2060−2100**	**df**	**F**	***p***
Initial population density	4	97.706	<0.0001	Initial population density	4	119.594	<0.0001
ICLUS region	6	20.639	<0.0001	ICLUS region	6	34.111	<0.0001
Socioeconomic pathway	1	0.183	0.6686	Socioeconomic pathway	1	1.534	0.2156
Climate model	2	0.055	0.9462	Climate model	2	0.024	0.9761
$P \times R$	24	7.240	<0.0001	$P \times R$	24	13.929	<0.0001
$P \times S$	4	0.343	0.8493	$P \times S$	4	3.750	0.0047
$R \times S$	6	0.053	0.9994	$R \times S$	6	1.441	0.1944
$P \times M$	8	0.071	0.9998	$P \times M$	8	0.084	0.9996
$R \times M$	12	0.094	1.0000	$R \times M$	12	0.246	0.9959
$S \times M$	2	0.008	0.9919	$S \times M$	2	0.007	0.9929
$P \times R \times S$	24	0.050	1.0000	$P \times R \times S$	24	0.501	0.9797
$P \times R \times M$	48	0.034	1.0000	$P \times R \times M$	48	0.059	1.0000
$P \times S \times M$	8	0.020	1.0000	$P \times S \times M$	8	0.007	1.0000
$R \times S \times M$	12	0.017	1.0000	$R \times S \times M$	12	0.028	1.0000
$P \times R \times S \times M$	48	0.008	1.0000	$P \times R \times S \times M$	48	0.009	1.0000

P: Initial population density
R: ICLUS Region
S: Socioeconomic pathway
M: Climate model

4.2. LAND USE PROJECTIONS

4.2.1. National Projections

The national-scale land use projections show nearly identical trends under the same SSP assumption; the choice of climate model has no discernible effect on the overall amount of projected development at the national level (see Figure 17). Relative to SSP1, the larger national population under SSP5 drives more development overall, particularly with respect to exurban residential density (yellow wedge in all panels in Figure 17). By 2100, the area of developed land in the conterminous United States increases by more than 80% of the 2010 value, yielding a total of more than 1.6 million square kilometers under the SSP5 scenario. Under the SSP1 scenario, the increase is nearly 50%, and yields more than 1.3 million square kilometers of developed land by 2100 (see Figure 17).

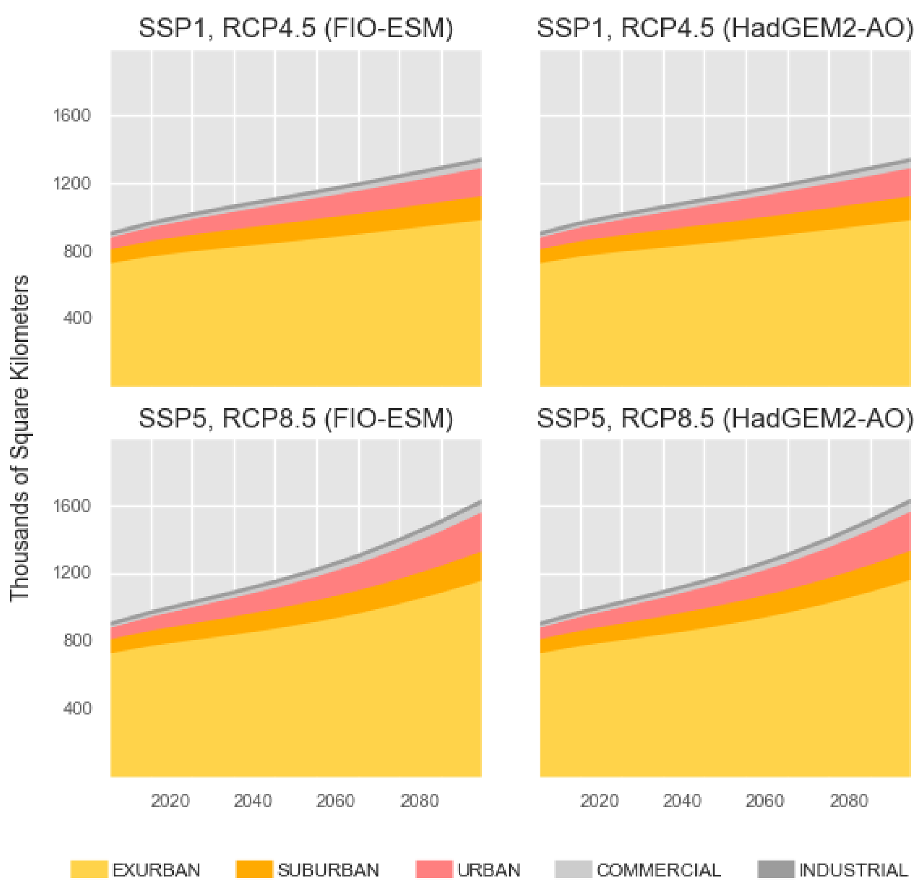

Figure 17. National land use projections from ICLUS v2 to 2100. Trends in total area of exurban (exurban low + exurban high), suburban, urban (urban low + urban high), commercial, and industrial lands are shown under four scenarios.

Differences in the percentage changes in each of the LUCs emerge nationally when comparing SSP1-RCP4.5 and SSP5-RCP8.5 (see Figure 18). The SSP1-RCP4.5 projection using FIO-ESM climate data has the smallest increases over time in terms of land use changes, as compared to the SSP5-RCP8.5 projection using HadGEM2-AO climate data. These two scenario combinations represent the extremes explored in ICLUS v2 in terms of demographic and climatic change rates. For SSP1-RCP4.5, only the combined urban category increases by more than 100% in 2100 and commercial land uses increase nearly that much. This scenario consists of a relatively lower national population (SSP1) and lower anthropogenic perturbation of the climate system (RCP4.5) modeled with a demonstrably less sensitive climate model (FIO-ESM).

Conversely, the SSP5-RCP8.5 (HadGEM2-AO) projection models more than a 100% increase in the extent of all developed LUCs already by 2050. The extent of urban land increases by more than 200% by 2050 under this scenario, and more than quadruples by 2100. This projection uses a very high population scenario (SSP5) and climate scenario of high anthropogenic forcing (RCP8.5) modeled with a demonstrably more sensitive climate model (HadGEM2-AO). This combination of model variables leads to greater changes in the extent of developed lands than the SSP1-RCP4.5 (FIO-ESM) combination, even though the initial land use demands and transition probabilities are the same. Changes in land use demands and transition probabilities represent a future pathway to explore further differences among ICLUS v2 scenarios.

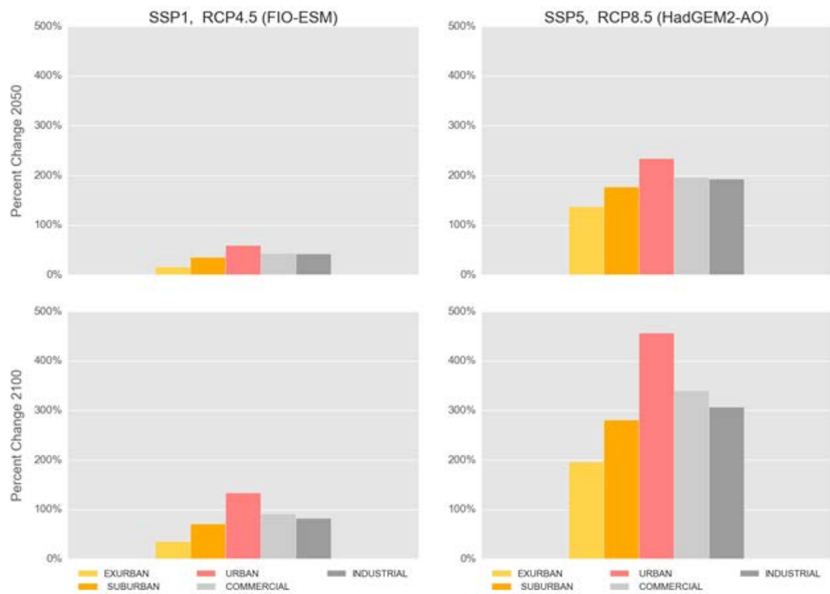

Figure 18. Relative increases in the area of developed LUCs nationally at 2050 (top row) and 2100 (bottom row). The left column shows results for SSP1-RCP4.5 using FIO-ESM climate data; the right column shows results for SSP5-RCP8.5 using HadGEM2-AO climate data. The SSP × RCP × climate model combinations shown at the top of the graphs bracket the range of national population projections, emissions scenarios, and climate model sensitivity, respectively, of all combinations considered in this report.

4.2.2. Regional Projections

Summarizing the ICLUS v2 land use projections by region illustrates substantial differences between the SSP1-RCP4.5 and SSP5-RCP8.5 scenarios. In almost every scenario run, developed land use categories in all regions increase (see Table 6). The magnitudes of those increases vary based on the SSP (i.e., population) assumption being considered.

ICLUS v2 projects a net decrease in the lowest residential density class (exurban-low) in Region 7 (Northeast) by 2100 under the SSP5-RCP8.5 (HadGEM2-AO) scenario (see Table 6). This singular instance of an extent decrease reflects the relatively high population density of the northeastern United States, and the concomitant demand for higher density residential development. In that case, the conversion of exurban-low pixels to other developed uses has outpaced the demand for low-density residential pixels.

The urban-high LUC shows the greatest percentage increase by 2050 in both SSPs considered, although smaller increases occur in Region 7 (Northeast) and, under SSP1-RCP4.5 (FIO-ESM), in Region 5 (Great Lakes). Substantial increases in commercial and industrial land uses occur in Regions 2−4 under both SSPs by 2050, with more moderate increases in the remaining regions. Region 2 (Intermountain West), which is currently less densely developed than most other regions, also has greater percentage increases in both exurban classes under both SSPs by 2050. In 2100, this remains true for SSP1-RCP4.5 (FIO-ESM), although Regions 3 and 4 have the next highest percentage increases compared to the other regions, while the increases in Regions 3 and 4 under SSP5-RCP8.5 (HadGEM2-AO) are more similar to Region 2 and larger than the other regions (see Table 6). The overall regional pattern across both SSPs is that urban-high increases sooner than lower density land uses, and that generally the pattern of increases follows the density classes from urban-high to exurban-low.

Table 6. Cumulative change in developed land use classes for 2050 (top row) and 2100 (bottom row) by Shared Socioeconomic Pathways (SSPs), Representative Concentration Pathways (RCPs) and climate model (in parentheses). Values shown represent the change in square kilometers for each LUC since 2010. Shading is used to describe that change as a percentage, with the darkest gray indicating a >100% change, medium gray 50−100% change, light gray 0−50% change, and peach <0% change.

	SSP1, RCP45(FIO-ESM)							SSP5, RCP85(HadGEM2-AO)						
2050														
ICLUS REGION	EXURBAN LOW	EXURBAN HIGH	SUBURBAN	URBAN LOW	URBAN HIGH	COMMERCIAL	INDUSTRIAL	EXURBAN LOW	EXURBAN HIGH	SUBURBAN	URBAN LOW	URBAN HIGH	COMMERCIAL	INDUSTRIAL
1	36	321	245	584	112	101	58	55	393	310	764	152	132	73
2	1,531	791	305	488	45	133	68	2,013	993	383	642	62	171	86
3	1,344	804	306	492	36	157	91	1,590	933	338	588	44	182	105
4	2,859	1,284	595	778	66	226	128	3,881	1,663	767	1,031	92	296	164
5	262	769	441	813	64	150	75	300	887	518	982	83	181	89
6	2,027	2,412	1,472	1,347	122	298	144	2,608	2,788	1,717	1,572	152	353	166
7	147	223	190	230	87	42	15	99	213	221	272	113	50	17
2100														
ICLUS REGION	EXURBAN LOW	EXURBAN HIGH	SUBURBAN	URBAN LOW	URBAN HIGH	COMMERCIAL	INDUSTRIAL	EXURBAN LOW	EXURBAN HIGH	SUBURBAN	URBAN LOW	URBAN HIGH	COMMERCIAL	INDUSTRIAL
1	131	497	437	1,294	333	224	111	549	728	651	1,889	645	366	161
2	3,799	1,605	712	1,153	130	292	139	6,657	2,433	1,082	1,885	251	461	209
3	3,286	1,720	712	1,125	99	341	195	5,615	2,592	1,072	1,812	183	525	293
4	7,000	2,619	1,242	1,735	184	484	252	12,348	4,082	2,027	2,978	381	813	393
5	751	1,254	859	1,666	170	301	138	1,761	1,719	1,292	2,619	331	470	205
6	4,644	4,169	2,804	2,787	348	607	261	8,619	6,380	4,515	4,612	705	1,039	411
7	51	262	395	497	257	94	32	-21	270	530	851	506	164	56

Percent Change
- < 0%
- 0 - 50%
- 50 - 100%
- > 100%

4.2.3. Subregional Projections

Decadal land use maps show changes for three selected metropolitan areas (see Figures 19−24). Net changes in other land uses classes (e.g., agriculture, recreation) are only negative and only occur as a result of transitions into developed classes. For example, in the Portland, OR-Vancouver, WA metropolitan area most of the growth in low-density urban land uses results from conversion of suburban and exurban areas, although more conversions of cropland to urban low occur in the decades from 2050−2100 than the earlier time period under both SSPs (see Figures 19 and 20). Similar trends also occur in cities in other regions (e.g., Springfield, MO; see Figures 21 and 22). In contrast, some metropolitan areas that already have multiple high-density urban centers throughout the area (e.g., Washington, DC metropolitan area) and have high population growth convert more of the existing residential land uses to additional high-density urban areas under both SSPs (see Figures 23 and 24). These three metropolitan areas exemplify changes nationally in such areas and illustrate the spatial patterns produced using ICLUS v2.

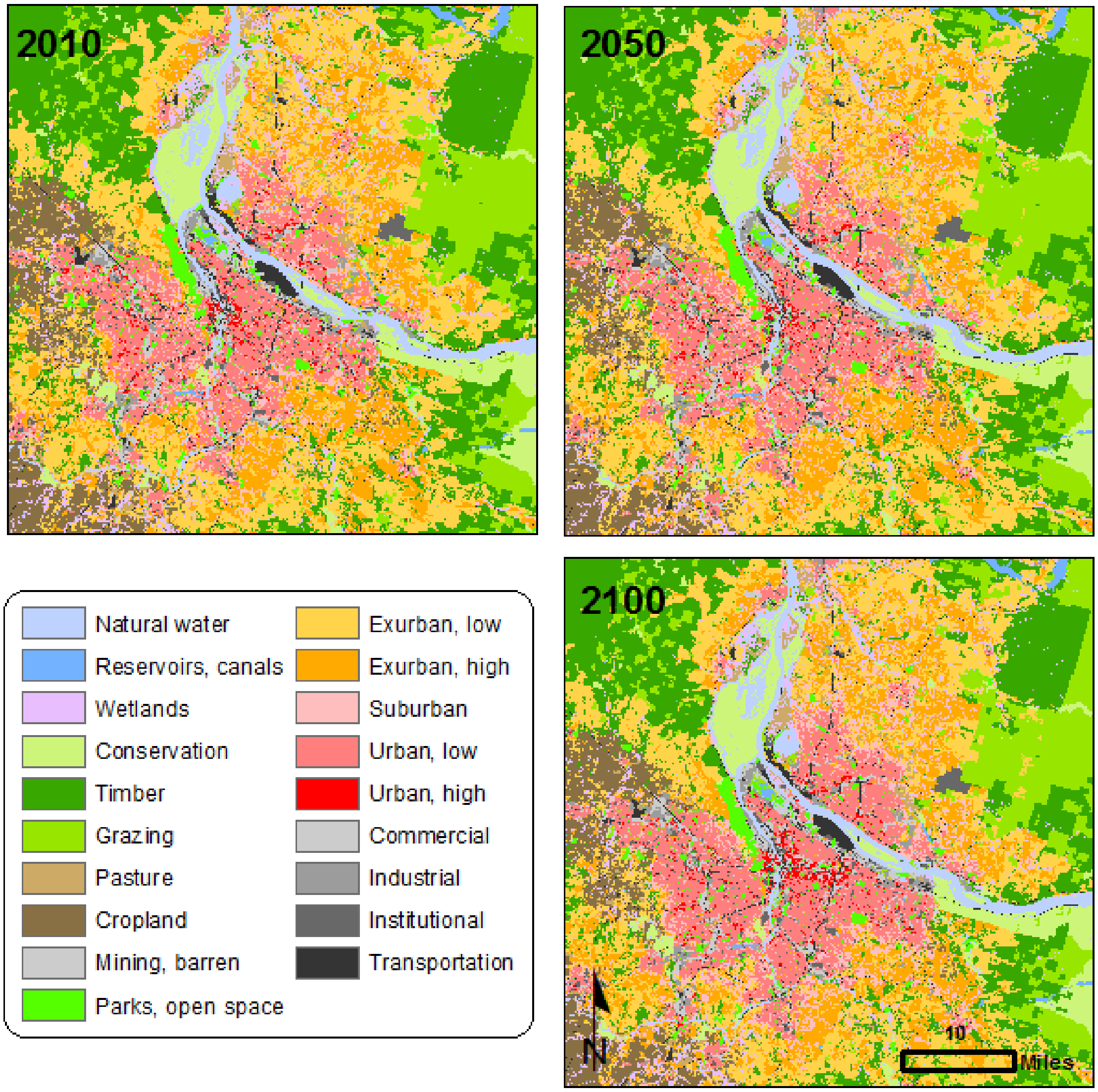

Figure 19. Land use change in the vicinity of the Portland, OR-Vancouver, WA Metro Area under the SSP1-RCP4.5 (FIO-ESM) scenario: 2010, 2050, and 2100.

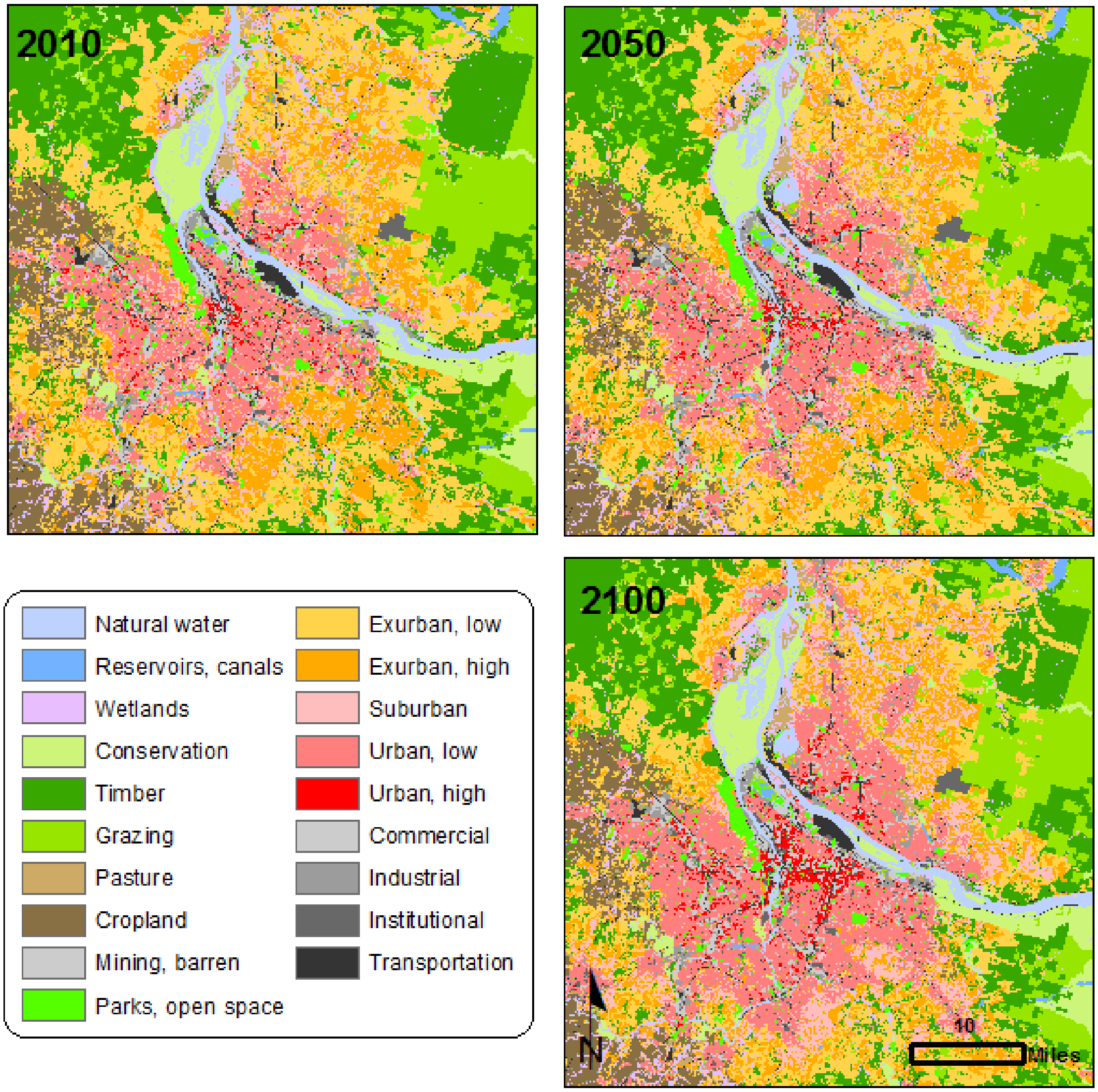

Figure 20. Land use change in the vicinity of the Portland, OR-Vancouver, WA Metro Area under the SSP5-RCP8.5 (HadGEM2-AO) scenario: 2010, 2050, and 2100.

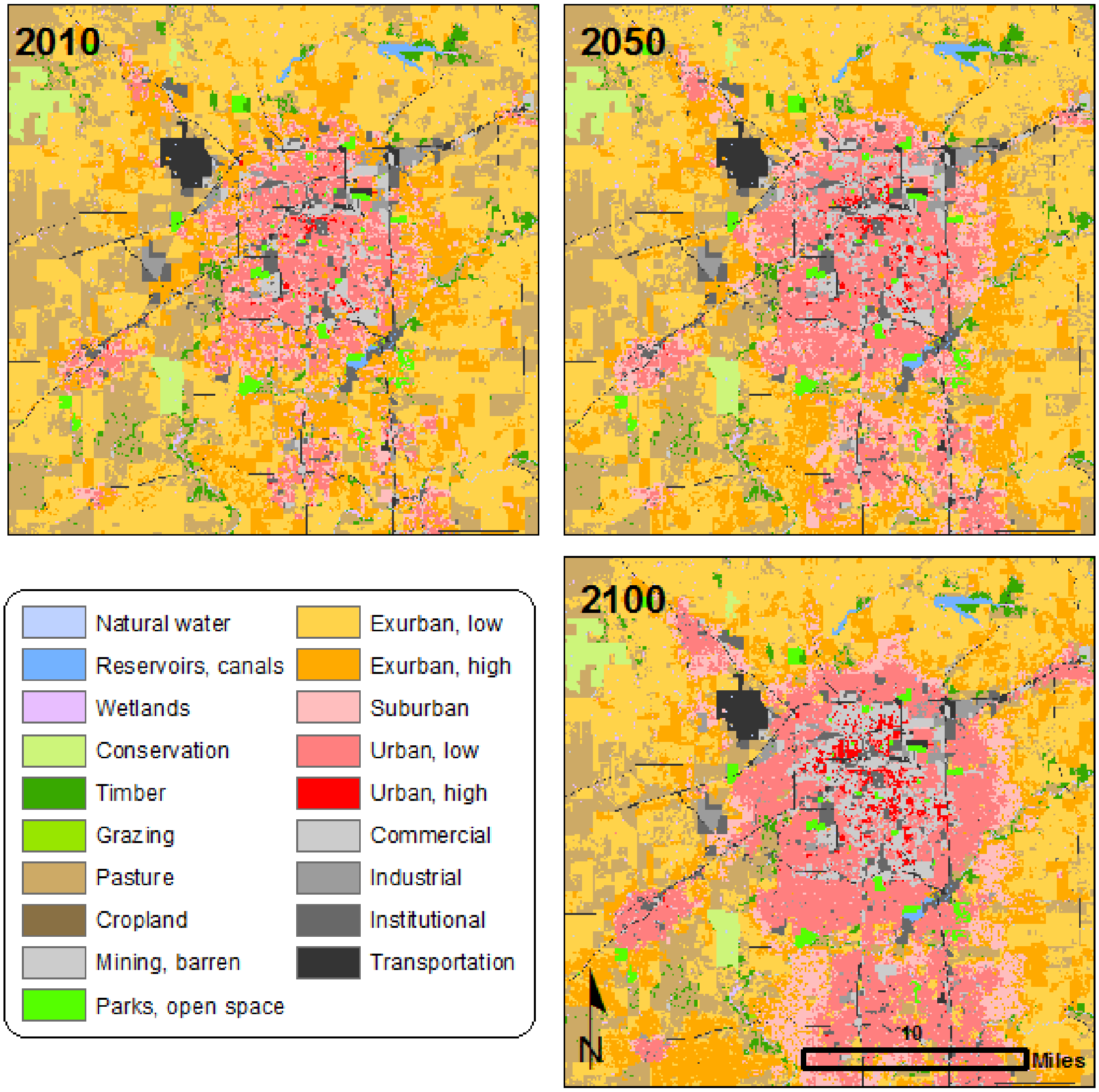

Figure 21. Land use change in the vicinity of the Springfield, MO Metro Area under the SSP1-RCP4.5 (FIO-ESM) scenario: 2010, 2050, and 2100.

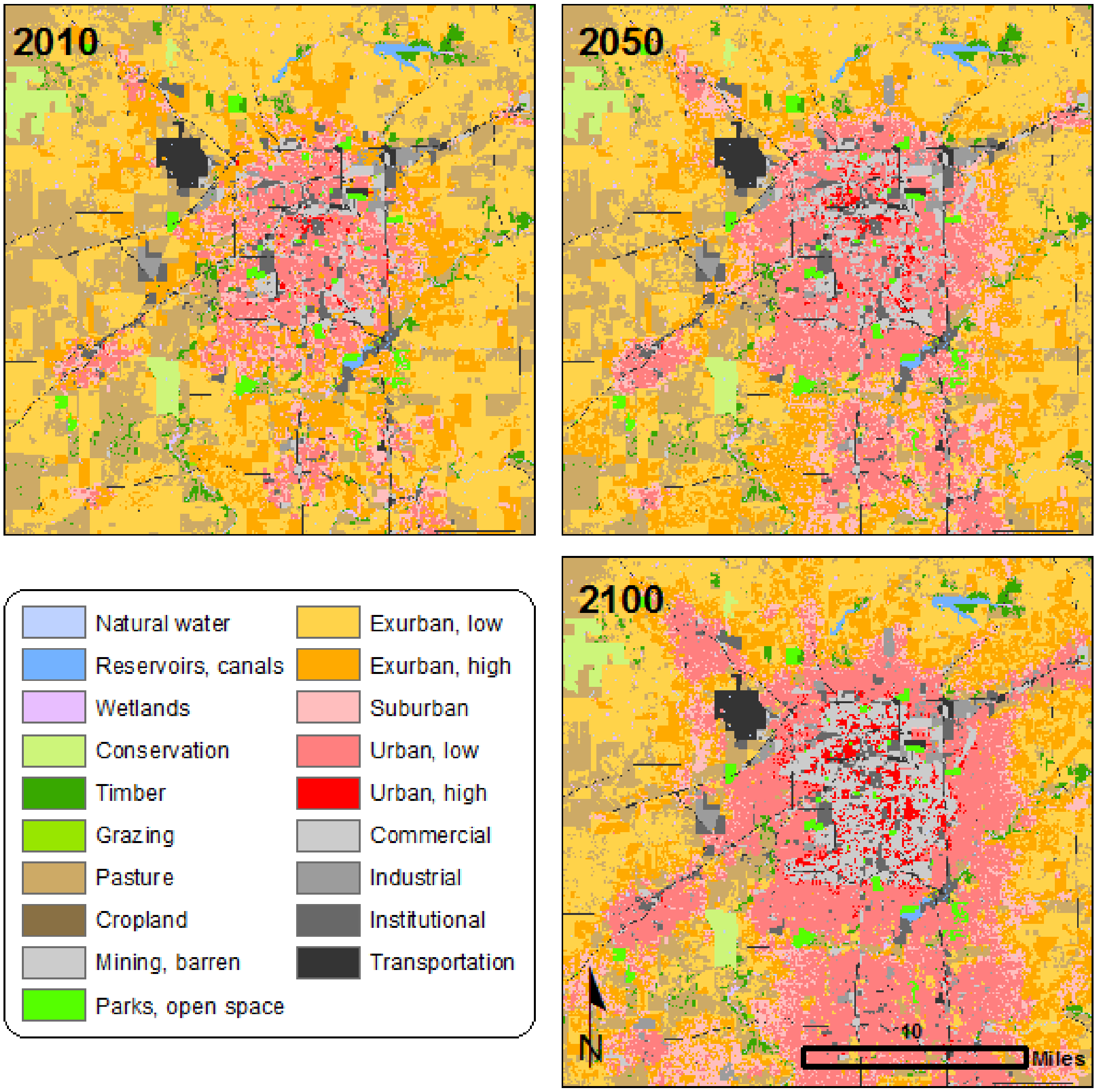

Figure 22. Land use change in the vicinity of the Springfield, MO Metro Area under the SSP5-RCP8.5 (HadGEM2-AO) scenario: 2010, 2050, and 2100.

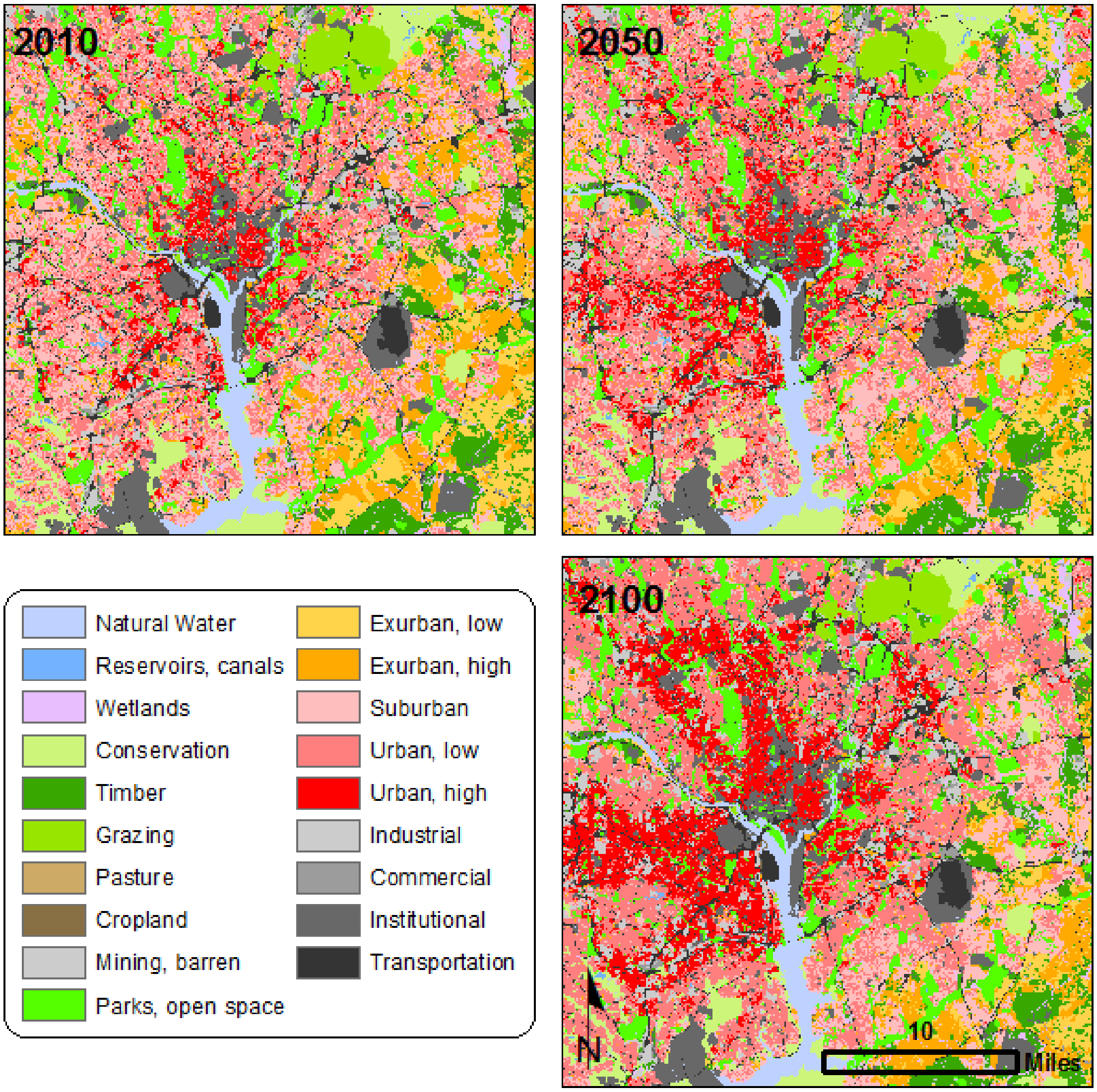

Figure 23. Land use change in the vicinity of the Washington-Arlington-Alexandria, DC-VA Metro Area under the SSP1-RCP4.5 (FIO-ESM) scenario: 2010, 2050, and 2100.

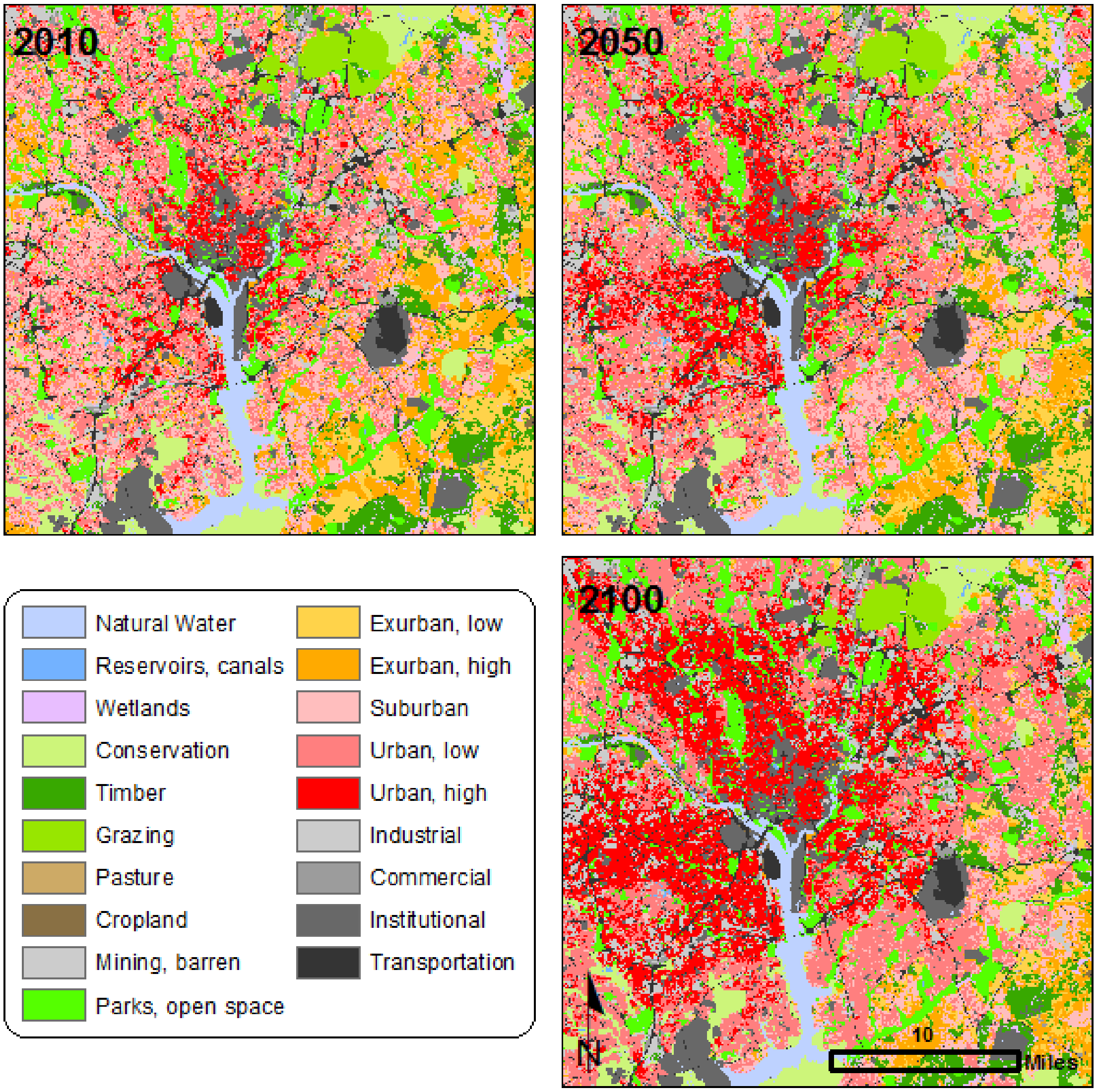

Figure 24. Land use change in the vicinity of the Washington-Arlington-Alexandria, DC-VA Metro Area under the SSP5-RCP8.5 (HadGEM2-AO) scenario: 2010, 2050, and 2100.

5. CONCLUSION

The updated data sets and underlying statistical and spatial methods result in realizations of future land use changes that are substantially different from ICLUS v1. The revisions made for ICLUS v2 have many advantages, particularly for assessments of future climate change impacts, vulnerabilities, and adaptation options. These advantages include the ability to (1) develop future scenarios that include changes in commercial and industrial land uses,

(2) examine the effect of changes in transportation capacity through additional lane miles or added fixed mass transit, (3) examine trends in land use changes regionally, and (4) assess differences among scenarios consistent with current socioeconomic and emissions storylines (i.e., SSPs and RCPs). However, some of the updates have disadvantages. For example, the use of the IRS migration data set requires collapsing all age classes from the cohort component model into one population, compared with the two age groups used in ICLUS v1. The loss of this demographic information theoretically results in less useful model outputs because the assessment of future health impacts related to climate change typically is improved by using segmented age groups. This limitation is somewhat mitigated by the fact that ICLUS v1 only retained two broad population segments, over 50 and under 50. An additional limitation of a single population is that people of different ages move in different patterns (e.g., Voorhees et al., 2011) and may respond differently to future climate. These behaviors are likely to have repercussions in the population and land use patterns generated by ICLUS v2. Methods to add more detailed demographic information back into the migration model would make the population outputs from ICLUS v2 more useful for the health impacts communities, research on vulnerable populations, and examinations of potential environmental justice issues.

ICLUS v2 represents significant progress in the development of land use change scenarios that are consistent with emissions story lines and has the flexibility to adapt to other emerging storylines from the climate change modeling community. For example, land use transitions can be altered by changing the population density and land use demand relationships. The current transitions are based on a limited temporal segment of land use data (2000−2010) and remain constant over time. These transition probabilities may change over time, and this change currently is not represented in the model. There are several options for exploring changes in transitions over time. For example, new land use change information can be used to compared predicted land uses to actual land uses in 2015. This would yield information on deviations from near-term trends. Exploring longer term implications of changes in land use transitions can employ a scenarios approach. Both of these approaches can inform on potential trajectories and environmental impacts.

The current ICLUS v2 land use transitions follow an expected development path from low to high densities, generally expanding outwards from population centers. Higher density residential classes, commercial, and industrial development exhibit a threshold effect at high population densities, such that these land uses generally are not replaced once they are developed. This tendency has implications in terms of the continuity of urban form, redevelopment patterns, creation of park and recreation areas, and other “undevelopment” (e.g., transitions from higher land use classes to lower ones as a result of declining population), which in turn influences subsequent development patterns. One potential consequence of not allowing LUCs to transition to lower density or nondeveloped uses is that these data sets overestimate impervious surface cover and its impacts, even though such surfaces may remain for many years following population loss from an area. Alternatively, some industrial sites may be redeveloped into lower use classes such as residential housing, in this case also altering the impervious surface cover estimates and population densities. While the current model does not explicitly include these types of transitions, the model structure does allow for the future exploration of these phenomena through scenarios.

ICLUS v2 also makes significant progress in providing future estimates of commercial and industrial land use changes. These estimates serve as inputs to a variety of environmentally relevant models that project changes in emissions and other air quality factors. Additional research into the emergence of new commercial areas and densities and occurrences of mixed commercial and residential buildings in urban areas would be useful inputs into future ICLUS updates and land use change scenarios. Data on the emergence of new commercial and industrial centers, as well as associated impervious surface cover, are critical for modeling future changes in a variety of air and water quality endpoints, including emissions of criteria air pollutants, greenhouse gases, and stormwater runoff.

Another important advancement of ICLUS v2 is the inclusion of future climate change variables in the migration model. While climate variables represent a relatively small instantaneous influence on migration, the cumulative effect of this influence through time on a process as complex as human migration results in meaningful spatial variability of population projections across the ICLUS GUs. The strength of this influence also can be explored through scenarios that alter migration responses to climate change over time. Additionally, differences in migration patterns can be explored as other climate model data are incorporated.

The use of changing climate variables in the migration model does produce some differences in population distribution. Differences in regional populations between static and dynamic climate variables are no more than approximately 4%. Most differences are ±2% of the regional population, regardless of scenario and climate model combination. Nationally, the choice of climate model has little effect on the overall development pattern. However, this report only used two climate models as examples to implement the changes in the ICLUS v2 models. Other climate change models may have more extreme temperature or precipitation values in certain regions that may exert larger influences on population migration. ICLUS v2 users can explore impacts of other climate change model values as part of scenario and sensitivity analyses. However, as projected temperatures and precipitation amounts become more extreme in some models, these values will be outside of the range of the data used to parameterize the migration equation.

The results presented in this report cover only two of the many possible GCMs and two emissions scenario. Data from other climate change models can be incorporated easily into the migration model. Additional emissions scenarios also can be explored. Transition probabilities and land use and capacity class relationships can be modified to create land use patterns consistent with SSP and RCP combinations not explored in this report.

As in ICLUS v1, this version focuses on developed land uses. It would be useful to integrate ICLUS v2 with models using similar principles that change other land uses, such as agriculture and forestry—particularly for more comprehensive assessments of impacts, vulnerabilities, and adaptation options related to climate change. The composition of agricultural, forest, and natural landscapes has changed and will continue to change over time in response to human, climatic, and other factors. A large body of research exists that models changes in various species distributions under the SRES storylines (e.g., Thomas et al., 2012). These types of analyses can make use of the changing development patterns from the ICLUS output, and provide feedbacks from changes in the undeveloped landscape that can be incorporated into the ICLUS modeling structure. Several models exist that can easily integrate ICLUS data and vice versa. For example, the FOREcasting SCEnarios of Land-use Change model (FORESCE; Sohl et al., 2007) also uses scenario assumptions to examine changes in forest composition in the future, while the Forestry and Agricultural Sector Optimization Model (FASOM) can integrate changes in the available agricultural and forest land area to develop projections of future markets based on population demands (Zhang et al., 2014). These types of feedbacks and interactions among changes in land use and land cover are an active area of research that are likely to improve future version of ICLUS output.

The data sets resulting from ICLUS v2 can serve as inputs for other models to further investigate changes in environmental and human health endpoints. Many models use population as a critical variable, and ICLUS v2 enables scenario-based explorations of the endpoints of such models. These types of analyses also can explore such endpoints in the context of the global SSPs and RCPs because of the consistency of the ICLUS v2 outputs with those scenarios. Other models also use a combination of population and land use variables for which ICLUS v2 can provide inputs. In some cases, the scenarios of land use change provided by ICLUS v2 can add a novel forward-looking component to other models and further analyses of feedbacks among land uses or influences from land use changes on specific endpoints. The range of data sets and the consistency of the data sets with SSPs and RCPs facilitates the use of ICLUS v2 in many applications.

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APPENDIX A. REGIONAL LAND-USE CHANGES FOR 2000−2010

A.1. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 1 (PACIFIC) LAND USE CHANGES

In the Pacific region (Integrated Climate and Land Use Scenarios [ICLUS] Region 1), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-1, A, Figure A-1, C). Over the same period, the relative amount of land assigned to each of the seven developed land use classes (LUCs) also changed (see Table A-1, B). Among the developed classes, the proportion of developed land in the urban low LUC decreased, while the proportion of land in the urban high LUC increased between 2000 and 2010 (see Figure A-1, A). The relative amount of developed land in the exurban low, exurban high, suburban, commercial, and industrial LUCs did not change statistically significantly between 2000 and 2010. Relative growth in the urban high LUC was larger than in the urban low LUC (see Figure A-1, B). The relative amount of growth in paired comparisons of exurban high with exurban low, suburban with exurban high, and urban low with suburban LUCs show no statistically significant differences.

Table A-1. **Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 1 (Pacific).** Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	13.33%	15.72%
Undeveloped	86.67%	84.28%
χ^2**:** 873.48	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	39.28%	39.11%
Exurban high	25.67%	26.44%
Suburban	11.10%	10.70%
Urban low	16.86%	16.27%
Urban high	1.23%	1.60%
Commercial	3.58%	3.76%
Industrial	2.28%	2.12%
χ^2**:** 47.74	**DF:** 8	***p*-value:** <0.0001

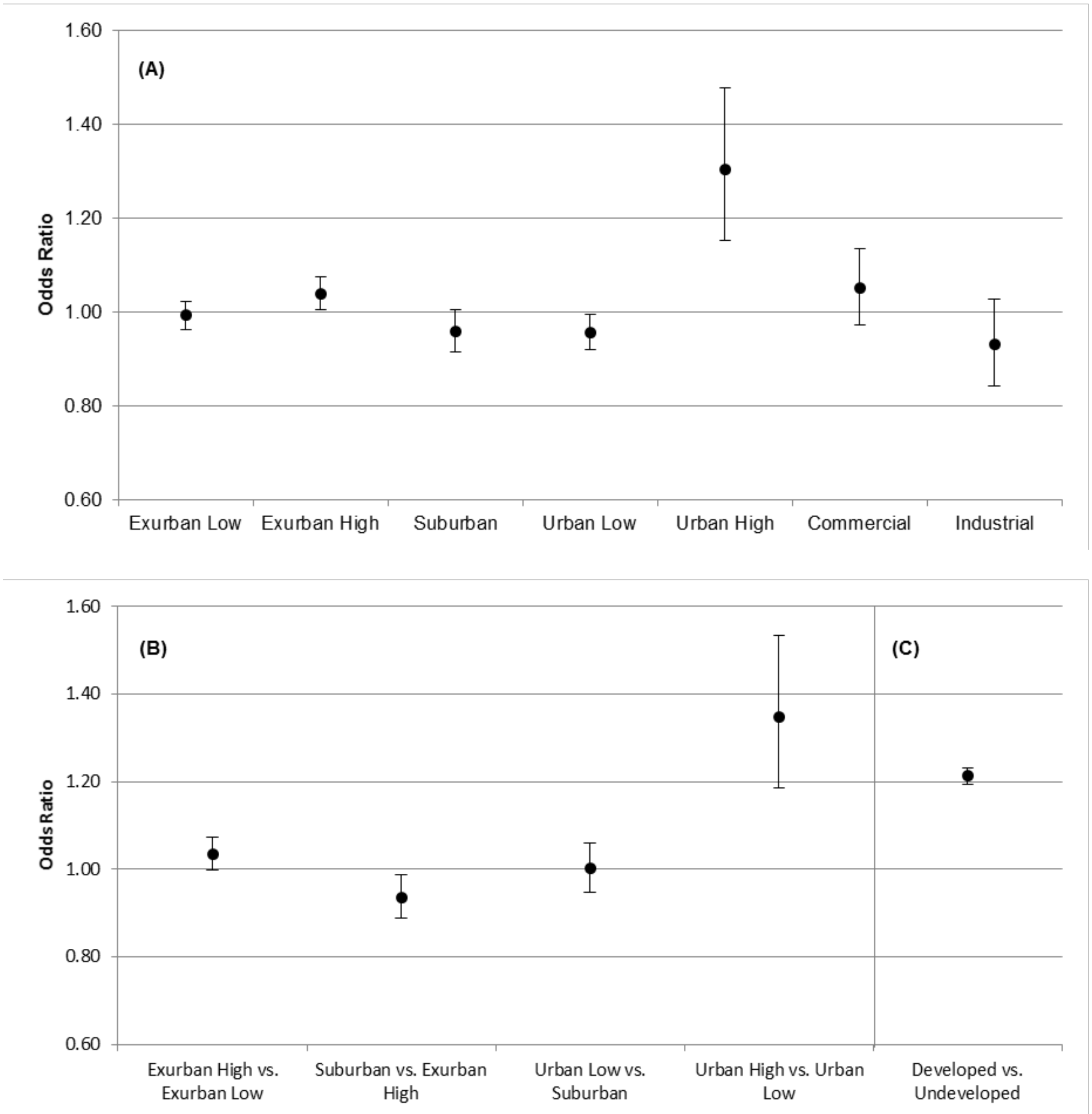


Figure A-1. Land use comparisons between 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 1 (Pacific). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.2. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 2 (INTERMOUNTAIN WEST) LAND USE CHANGES

In the Intermountain West region (ICLUS Region 2), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-2, A, Figure A-2, C).

Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed (see Table A-2, B). Among the developed classes, the proportion of developed land in the exurban high, urban low, and industrial LUC decreased, while the proportion of developed land in the exurban low and urban high LUCs increased between 2000 and 2010 (see Figure A-2, A). The relative amount of developed land in the suburban and commercial LUCs did not change significantly between 2000 and 2010. Relative growth in the urban high LUC was larger than the urban low LUC (see Figure A-2, B). However, relative growth in the exurban high LUC was less than the exurban low LUC. The relative amount of growth in the suburban LUC was not significantly different from the exurban high LUC, and the relative amount of growth in the urban low LUC was not significantly different from the suburban LUC.

Table A-2. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 2 (Intermountain West). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	3.41%	4.53%
Undeveloped	96.59%	95.47%
χ^2**:** 1,557.17	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	37.39%	40.62%
Exurban high	29.45%	27.92%
Suburban	12.05%	11.67%
Urban low	13.86%	13.01%
Urban high	0.58%	0.77%
Commercial	4.39%	4.07%
Industrial	2.28%	1.94%
χ^2**:** 99.84	**DF:** 8	***p*-value:** <0.0001

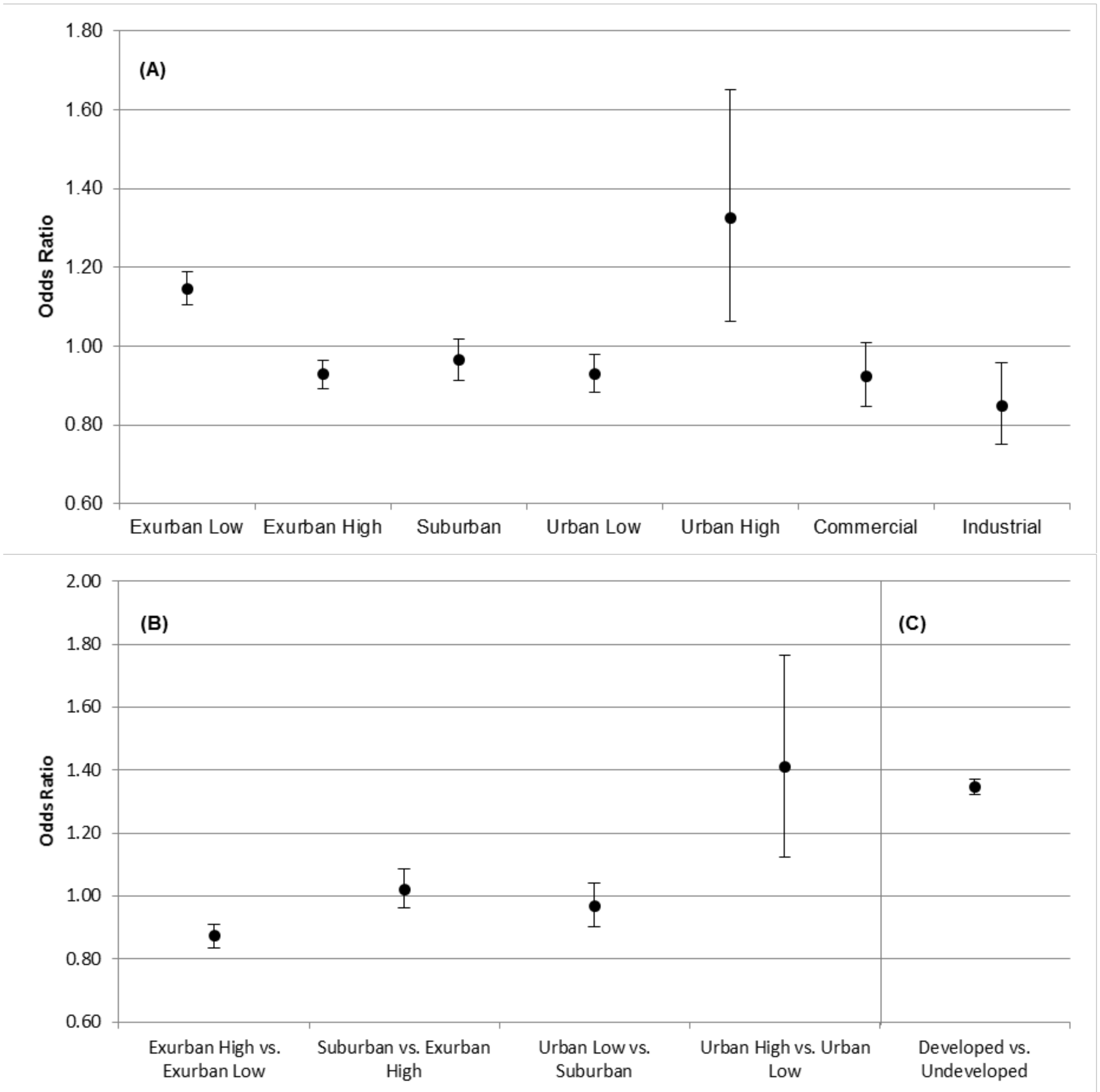


Figure A-2. Land use comparisons between 2000 and 2010 in ICLUS Region 2 (Intermountain West). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.3. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 3 (NORTH CENTRAL) LAND USE CHANGES

In the North Central region (ICLUS Region 3), the percentage of land assigned to developed use classes increased between 2000 and 2010 (χ^2 = 1,507.45, DF = 1, p < 0.0001; see Table A-3, A, Figure A-3, C). Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed ($\chi^2 = 149.09$, DF = 8, $p < 0.0001$; see Table A-3, B). Among the developed classes, the proportion of developed land in the exurban high, suburban, urban low, and industrial LUC decreased, while the proportion of developed land in the exurban low and urban high LUCs increased between 2000 and 2010 (see Figure A-3, A). The relative amount of developed land in the commercial LUC did not change significantly for the same period. Relative growth in the urban high LUC was larger than the urban low LUC (see Figure A-3, B). Conversely, relative growth in the exurban high LUC was less than the exurban low LUC. The relative amount of growth in the suburban LUC was not significantly different than the exurban high LUC, and the relative amount of growth in the urban low LUC was not significantly different than the suburban LUC.

Table A-3. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 3 (North Central). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	4.05%	5.10%
Undeveloped	95.95%	94.90%
χ^2**:** 1,507.45	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	47.01%	50.55%
Exurban high	27.72%	25.51%
Suburban	9.17%	8.61%
Urban low	9.93%	9.49%
Urban high	0.24%	0.32%
Commercial	3.62%	3.47%
Industrial	2.31%	2.05%
χ^2**:** 149.09	**DF:** 8	***p*-value:** <0.0001

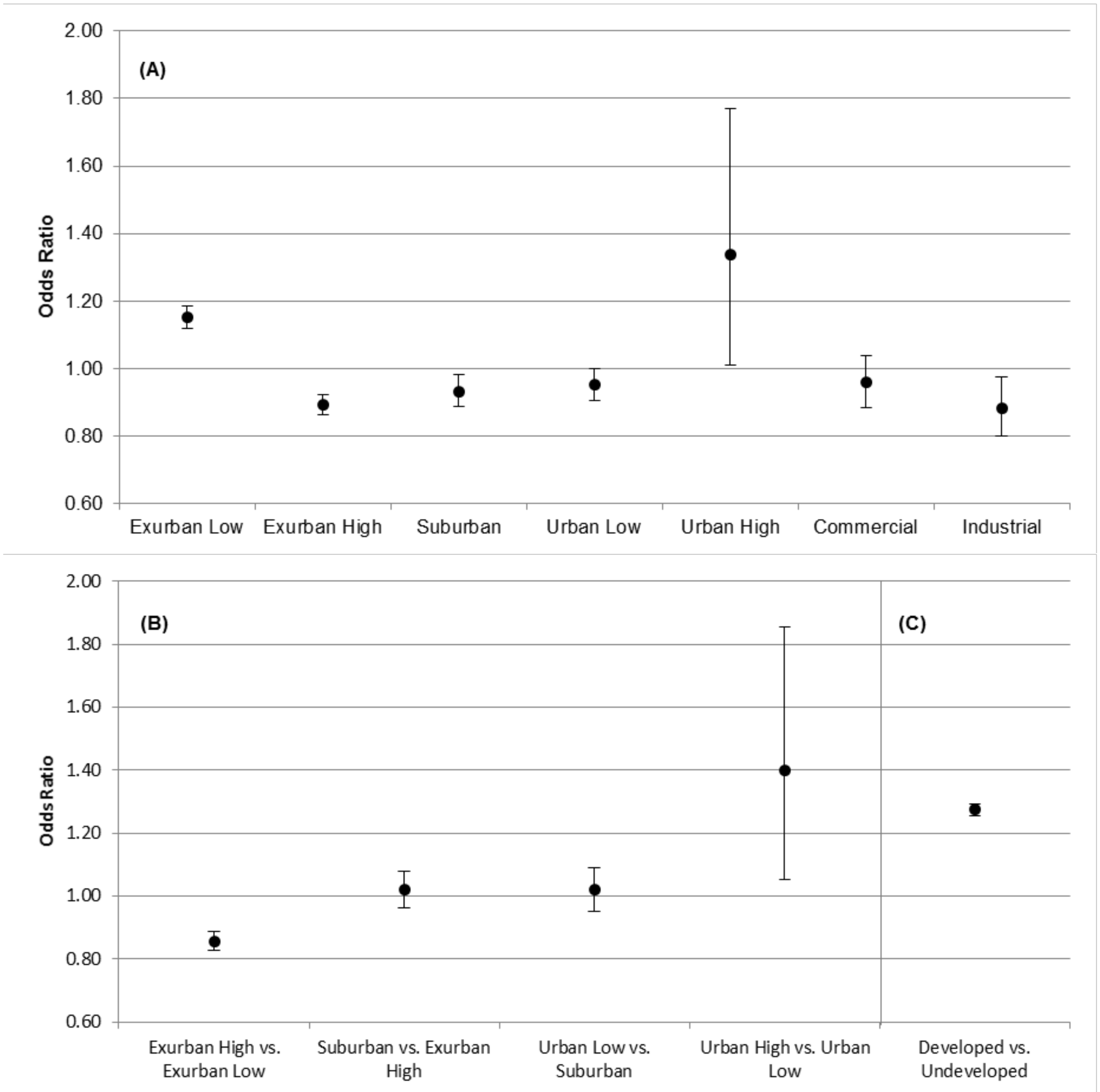


Figure A-3. Land use comparisons between 2000 and 2010 in ICLUS Region 3 (North Central). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.4. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 4 (SOUTH CENTRAL) LAND USE CHANGES

In the South Central region (ICLUS Region 4), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-4, A, Figure A-4, C). Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed (see Table A-4, B). In this particular region, the amount of developed land allocated to the exurban low and exurban high LUCs was lower in 2000 than expected (see Table A-4, B), and a large number of grazing land use pixels transitioned into these LUCs in 2010. However, values for the exurban low and exurban high LUCs were comparable to other regions in 2010, which suggests the model had difficulty distinguishing between exurban and agricultural classes in 2000. As a result, comparisons among the LUCs below are not particularly meaningful, but are presented for completeness. Among the developed classes, the proportion of developed land in the exurban high, suburban, urban low, urban high, commercial, and industrial LUCs decreased, while the proportion of developed land in the exurban low LUC increased between 2000 and 2010 (see Figure A-4, A). Relative growth in the exurban high LUC was less than the exurban low LUC, relative growth in the suburban LUC was less than the exurban high LUC, and relative growth in the urban low LUC was less than the suburban LUC (see Figure A-4, B). The relative amount of growth in the urban high LUC was not significantly different than the urban low LUC.

Table A-4. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 4 (South Central). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	3.90%	11.52%
Undeveloped	96.10%	88.48%
χ^2**:** 41,129.98	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	19.28%	54.43%
Exurban high	31.26%	25.62%
Suburban	16.43%	8.07%
Urban low	19.47%	7.19%
Urban high	0.95%	0.34%
Commercial	8.04%	2.78%
Industrial	4.56%	1.57%
χ^2**:** 17,949.23	**DF:** 8	***p*-value:** <0.0001

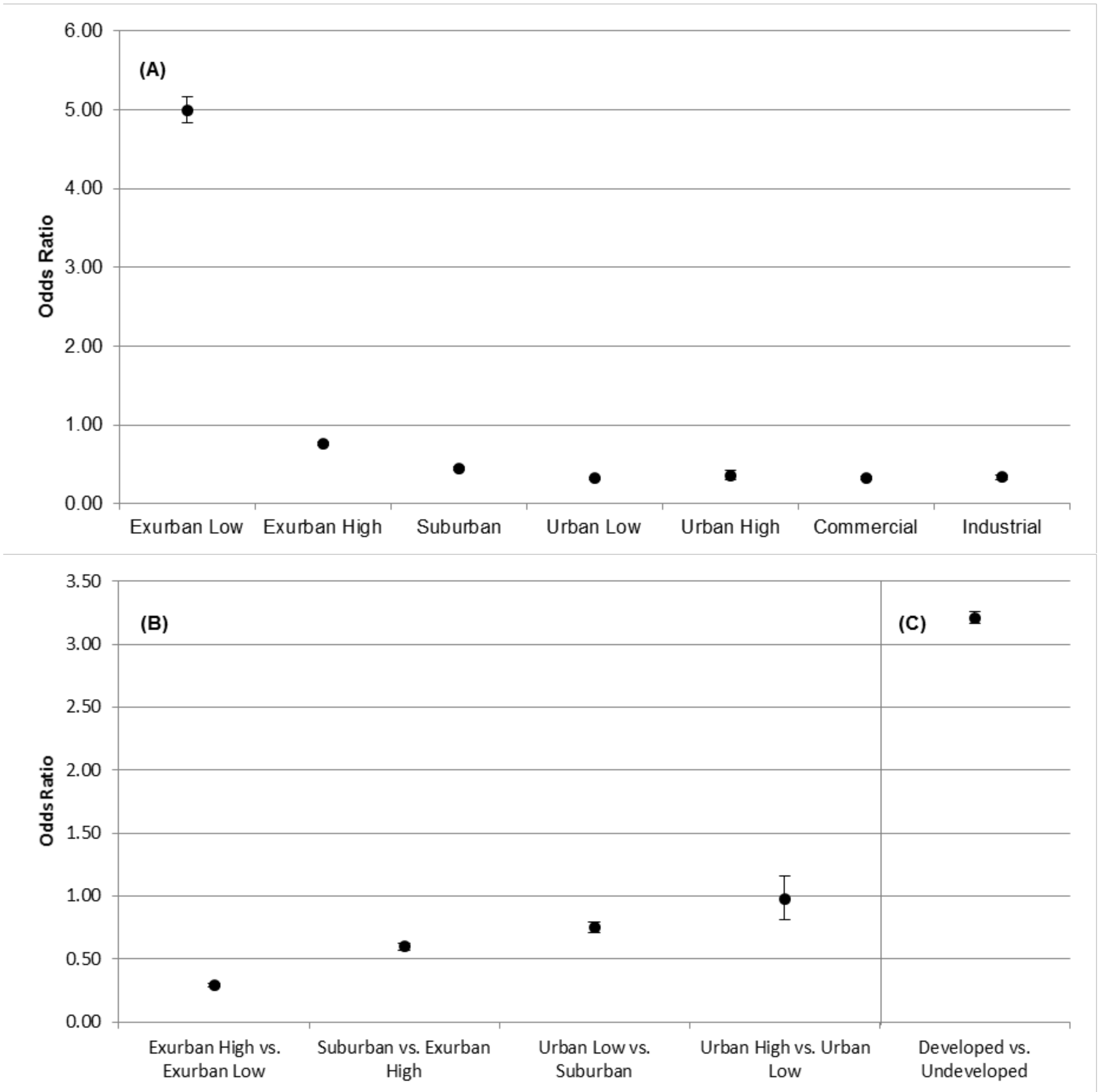


Figure A-4. Land use comparisons between 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 4 (South Central).
(A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.5. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 5 (GREAT LAKES) LAND USE CHANGES

In the Great Lakes region (ICLUS Region 5), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-5, A, Figure A-5, C).

Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed (see Table A-5, B). Among the developed classes, the proportion of developed land in the exurban high and urban high LUCs increased, while the proportion of developed land in the exurban low LUC decreased between 2000 and 2010 (see Figure A-5, A). The relative amount of developed land in the suburban, urban low, commercial, and industrial LUCs did not change significantly. Relative growth in the exurban high LUC was larger than in the exurban low LUC, and relative growth in the urban high LUC was larger than the urban low LUC (see Figure A-5, B). The relative amount of growth in the suburban LUC was not significantly different than the exurban high LUC, and the relative amount of growth in the urban low LUC was not significantly different than the suburban LUC.

Table A-5. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 5 (Great Lakes). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	20.12%	23.99%
Undeveloped	79.88%	76.01%
χ^2**:** 2,329.40	**DF:** 1	***p*-value:**<0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	53.02%	52.07%
Exurban high	25.52%	26.40%
Suburban	8.30%	8.31%
Urban low	9.04%	9.02%
Urban high	0.35%	0.47%
Commercial	2.22%	2.28%
Industrial	1.55%	1.44%
χ^2**:** 55.17	**DF:** 8	***p*-value:** <0.0001

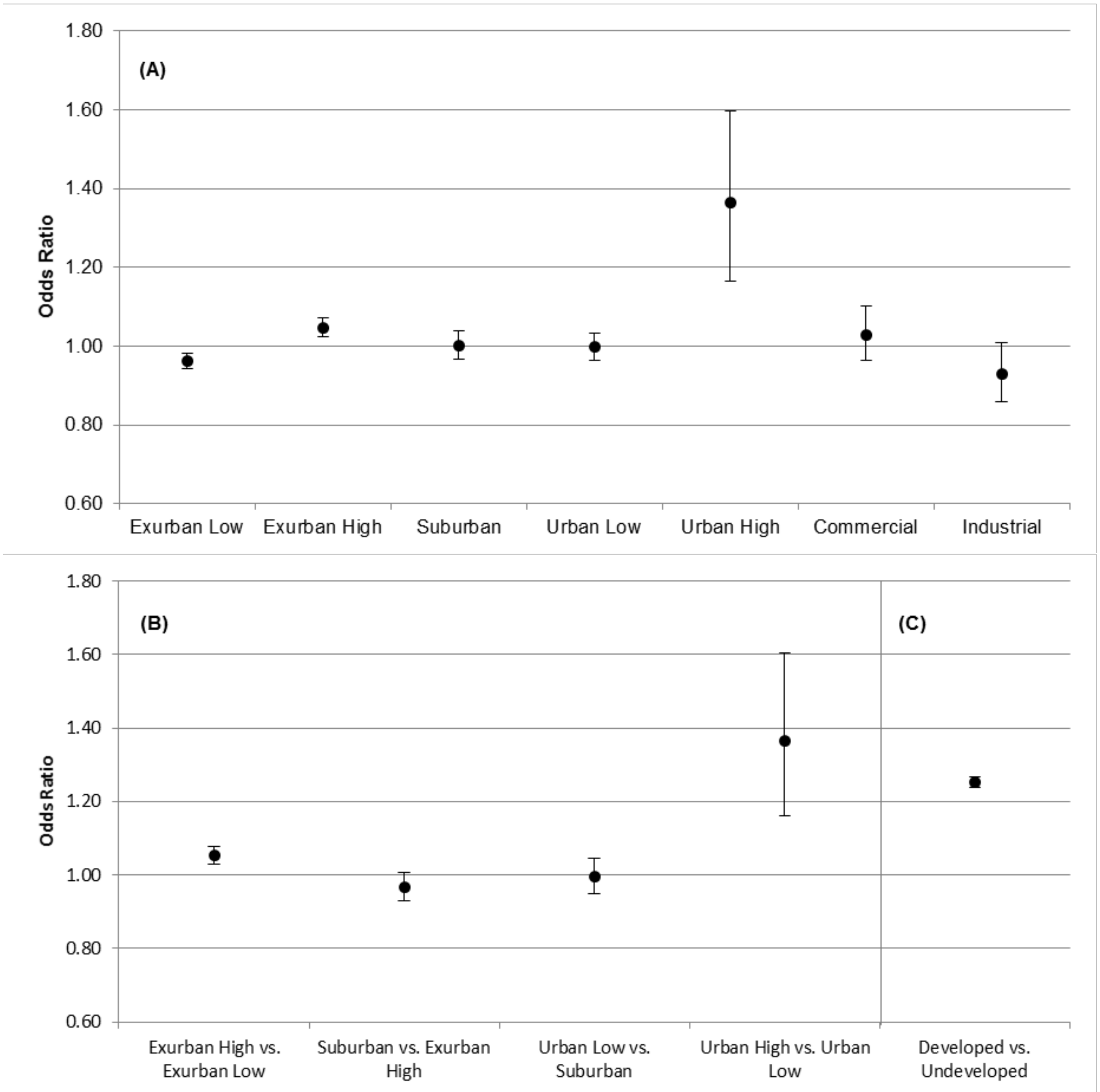


Figure A-5. Land use comparisons between 2000 and 2010 in ICLUS Region 5 (Great Lakes). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.6. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 6 (SOUTHEAST) LAND USE CHANGES

In the Southeast region (ICLUS Region 6), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-6, A, Figure A-6, C). Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed (see Table A-6, B). Among the developed classes, the proportion of developed land in the exurban low LUC decreased, while the proportion of developed land in the exurban high, suburban and urban low, urban high and commercial LUCs increased between 2000 and 2010 (see Figure A-6, A). The relative amount of developed land in the industrial LUC did not change significantly. Relative growth in all of the LUC comparisons were greater in 2010 than in 2000 (see Figure A-6, B).

Table A-6. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 6 (Southeast). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	27.38%	34.17%
Undeveloped	72.62%	65.83%
χ^2**:** 10,532.23	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	61.97%	57.74%
Exurban high	24.18%	25.28%
Suburban	7.55%	9.22%
Urban low	3.87%	5.04%
Urban high	0.17%	0.28%
Commercial	1.47%	1.64%
Industrial	0.79%	0.81%
χ^2**:** 1,562.88	**DF:** 8	***p*-value:** <0.0001

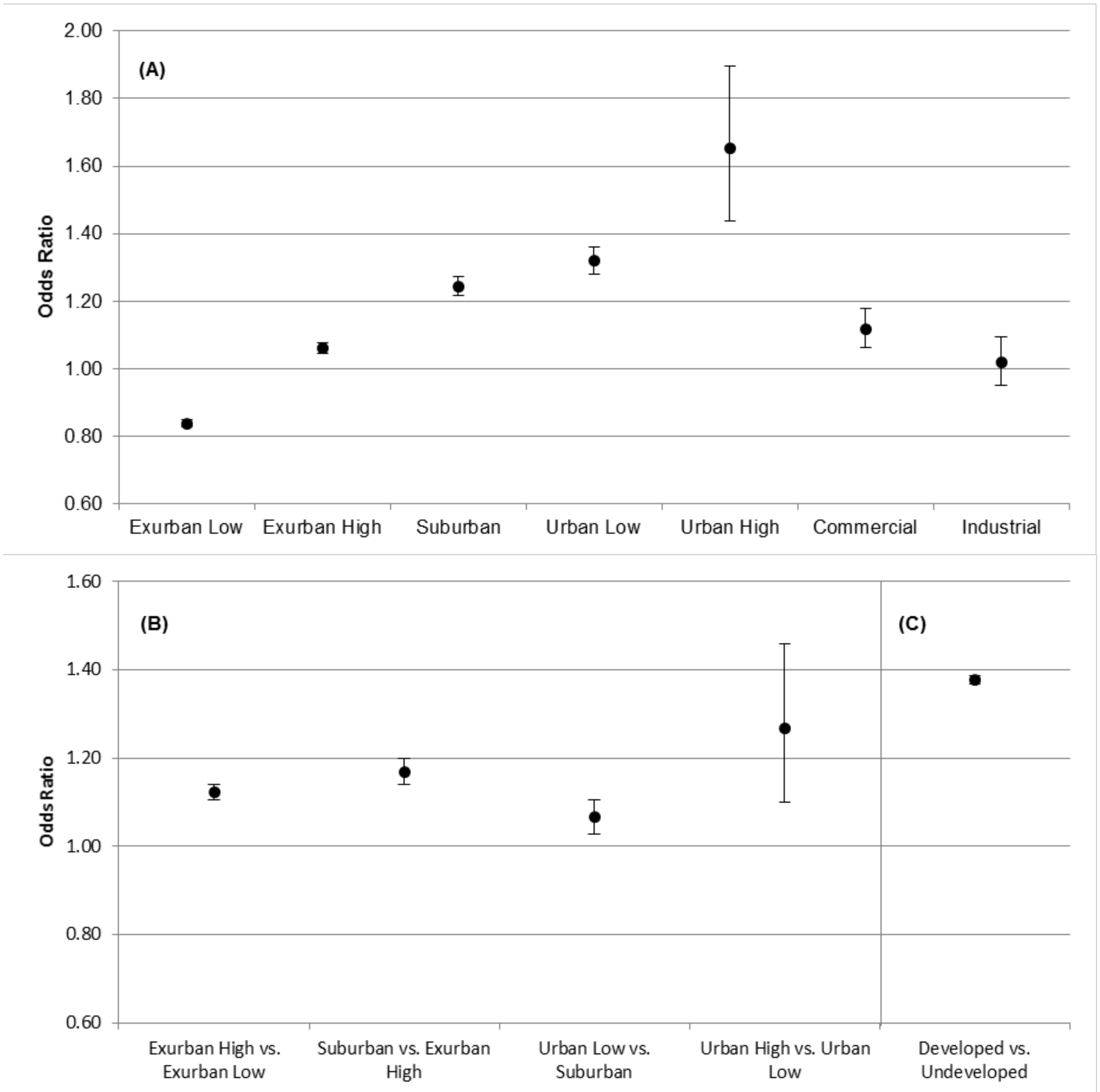


Figure A-6. Land use comparisons between 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 6 (Southeast). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

A.7. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 7 (NORTHEAST) LAND USE CHANGES

In the Northeast region (ICLUS Region 7), the percentage of land assigned to developed use classes increased between 2000 and 2010 (see Table A-7, A, Figure A-7, C). Over the same period, the relative amount of land assigned to each of the seven developed LUCs also changed (see Table A-7, B). Among the developed classes, the proportion of developed land in the exurban low LUC decreased, while the proportion of developed land in the exurban high, suburban, urban low, urban high, and commercial LUCs increased (see Figure 13, A). The relative amount of developed land in the industrial LUC did not change significantly between 2000 and 2010 (see Figure A-7, A). Relative growth in all of the LUC comparisons was greater in 2010 than in 2000, except for the urban low LUC, which was not significantly different from the suburban LUC (see Figure A-7, B).

Table A-7. Goodness-of-fit test results comparing LUCs in 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 7 (Northeast). Values are limited to developable area and LUCs that transition in the model. (A) Land assigned to developed and undeveloped LUCs. (B) Percentage developed land assigned to the seven developed LUCs.

(A) Land Use Type	**2000**	**2010**
Developed	41.02%	46.97%
Undeveloped	58.98%	53.03%
χ^2**:** 2,248.51	**DF:** 1	***p*-value:** <0.0001
(B) Developed LUC	**2000**	**2010**
Exurban low	56.44%	54.21%
Exurban high	27.18%	27.90%
Suburban	8.33%	9.16%
Urban low	5.54%	5.89%
Urban high	0.66%	0.81%
Commercial	1.22%	1.37%
Industrial	0.64%	0.65%
χ^2**:** 178.10	**DF:** 8	***p*-value:** <0.0001

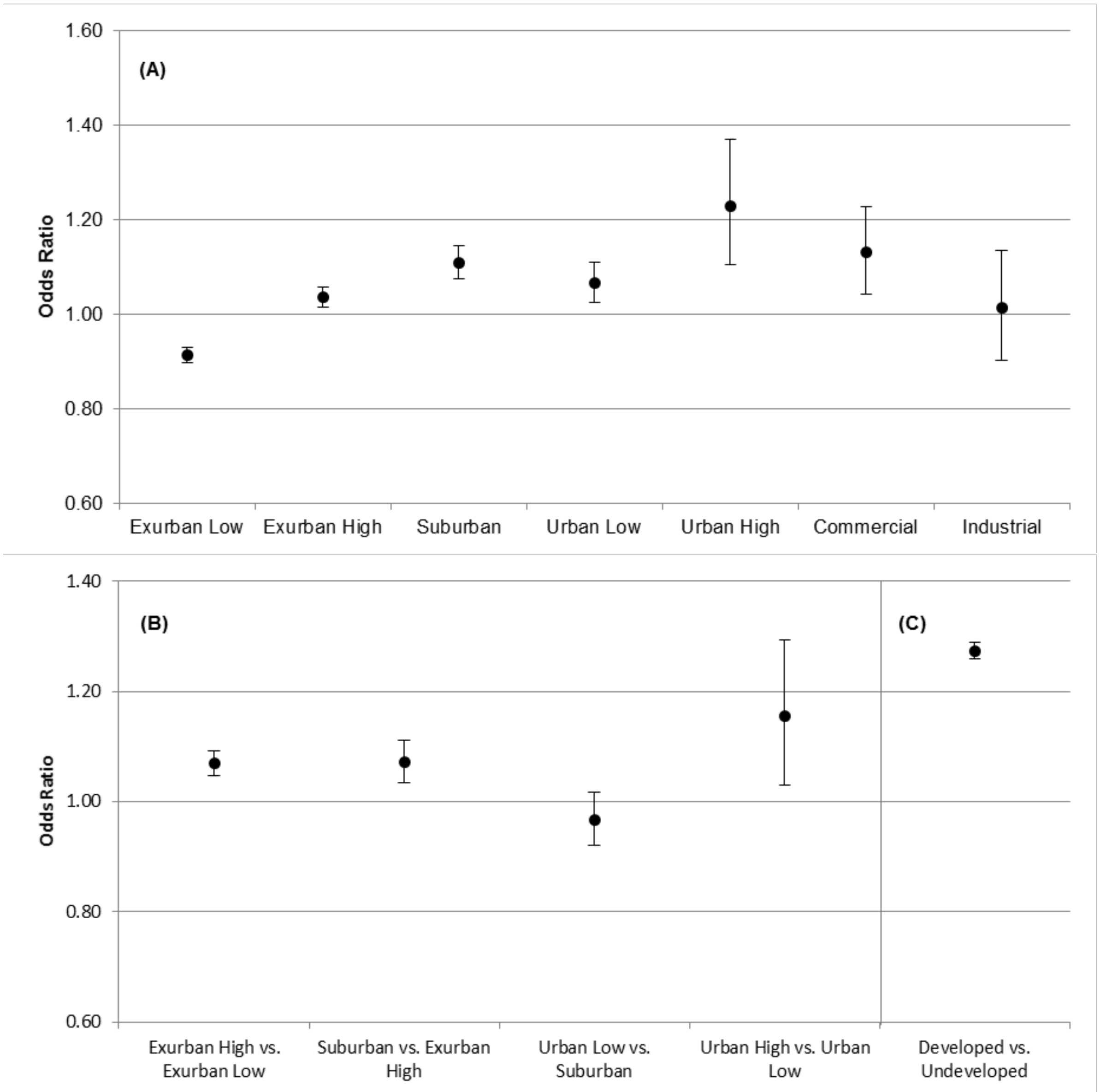


Figure A-7. Land use comparisons between 2000 and 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 7 (Northeast). (A) Odds ratios (ORs) and confidence intervals comparing allocations among the seven developed LUCs; (B) ORs and confidence intervals comparing adjacent residential LUCs (high density versus low density); and (C) OR comparing developed and undeveloped LUCs.

APPENDIX B. REGIONAL TRANSITION PROBABILITY MODELS

B.1. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 1 (PACIFIC) TRANSITION PROBABILITY MODELS

Table B-1. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial Generalized Additive Models (GAMs). The top marginal model predicts the probability of transitioning into each land use class $(LUC)_j$ in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC_i in 2000 given that they transitioned into a particular LUC_j in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

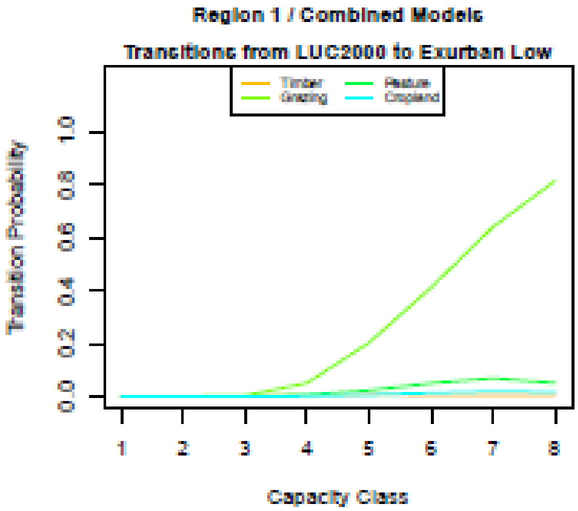
Smoothing Terms	edf	χ^2	*p*
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.87	10,633.33	<0.0001
Capacity class (suburban)	1.73	5,543.97	<0.0001
Capacity class (urban low)	1.66	9,450.96	<0.0001
Capacity class (urban high)	1.48	855.19	<0.0001
Capacity class (commercial)	1.83	29,894.84	<0.0001
Capacity class (industrial)	1.97	604.42	<0.0001
Global test	16.55	1,463,202	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.03	411.02	<0.0001
Capacity class (pasture)	2.01	2,039.43	<0.0001
Capacity class (cropland)	2.02	510.69	<0.0001
Global test	9.07	9,242.02	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.00	221.42	<0.0001
Capacity class (grazing)	1.98	10,906.72	<0.0001
Capacity class (pasture)	2.03	215.47	<0.0001
Capacity class (cropland)	2.08	93.19	<0.0001
Global test	12.09	17,273.73	<0.0001

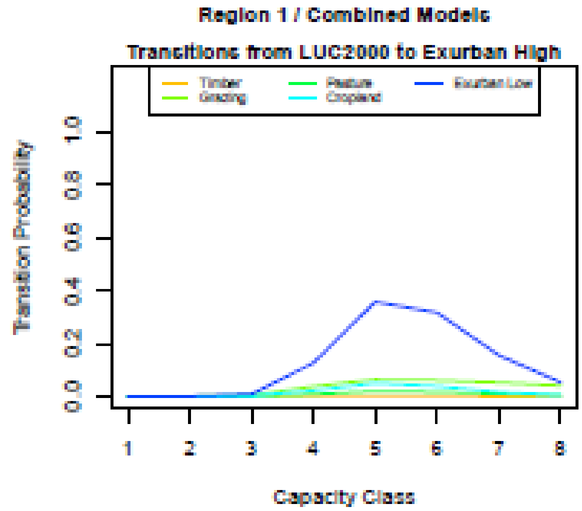
Table B-1. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC_j in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC_i in 2000 given that they transitioned into a particular LUC_j in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

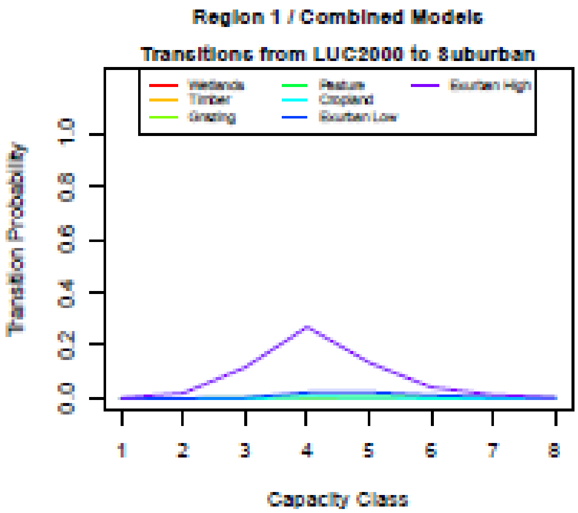
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.94	11.08	0.0036
Capacity class (timber)	2.19	76.11	<0.0001
Capacity class (grazing)	2.12	85.46	<0.0001
Capacity class (pasture)	2.23	85.63	<0.0001
Capacity class (cropland)	2.37	363.75	<0.0001
Capacity class (exurban low)	2.07	594.51	<0.0001
Global test	18.91	15,207.84	<0.0001
From LUC2000 for transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.74	5.59	0.0469
Capacity class (timber)	2.24	86.71	<0.0001
Capacity class (grazing)	2.05	221.43	<0.0001
Capacity class (pasture)	2.39	44.67	<0.0001
Capacity class (cropland)	2.46	278.04	<0.0001
Capacity class (exurban low)	2.18	490.91	<0.0001
Capacity class (exurban high)	1.98	1,315.07	<0.0001
Global test	22.03	10,766.11	<0.0001

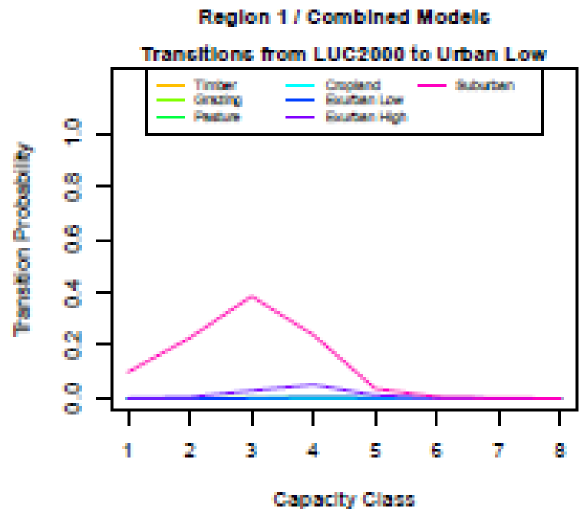
Table B-1. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC_j in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC_i in 2000 given that they transitioned into a particular LUC_j in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

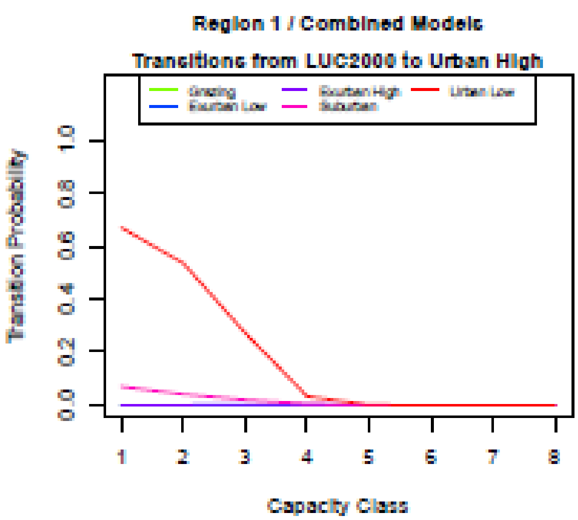
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.42	2.36	0.1966
Capacity class (timber)	1.81	5.66	0.0486
Capacity class (grazing)	1.78	11.73	0.0021
Capacity class (pasture)	1.1	4.43	0.0409
Capacity class (cropland)	1.95	8.8	0.0115
Capacity class (exurban low)	1.98	25.38	<0.0001
Capacity class (exurban high)	1.83	103.49	<0.0001
Capacity class (suburban)	2.00	119.96	<0.0001
Global test	21.84	2,022.44	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.07	270.23	<0.0001
Capacity class (suburban)	1.74	272.1	<0.0001
Capacity class (urban low)	1.73	378.23	<0.0001
Capacity class (urban high)	1.61	6.07	0.0317
Global test	11.14	20,068.51	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (grazing)	0.72	5.79	0.0096
Capacity class (exurban low)	2.06	16.7	3.00×10^{-4}
Global test	4.79	1,078.55	<0.0001

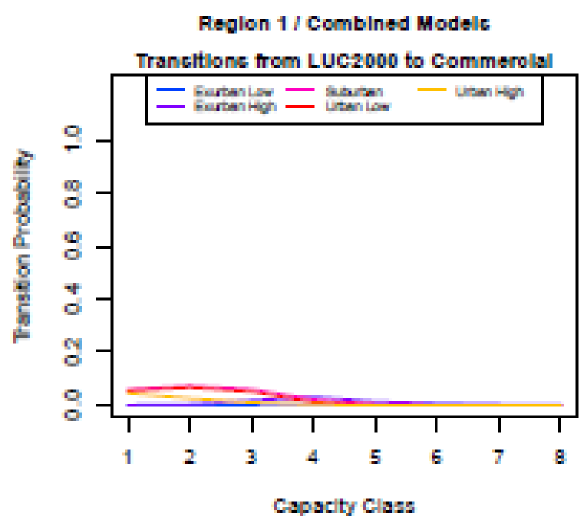

Region 1 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Grazing
Pasture
Cropland
Transition Probability
Capacity Class


Region 1 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Grazing
Pasture
Cropland
Exurban Low
Transition Probability
Capacity Class


Region 1 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Transition Probability
Capacity Class


Region 1 / Combined Models
Transitions from LUC2000 to Urban Low
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Suburban
Transition Probability
Capacity Class


Region 1 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban Low
Exurban High
Suburban
Urban Low
Transition Probability
Capacity Class


Region 1 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Exurban High
Suburban
Urban Low
Urban High
Transition Probability
Capacity Class

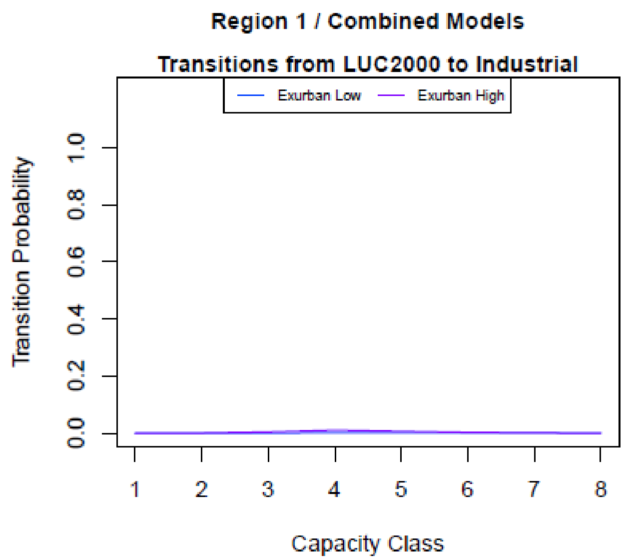


Figure B-1. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 1 (Pacific). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models (i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.2. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 2 (INTERMOUNTAIN WEST) TRANSITION PROBABILITY MODELS

Table B-2. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

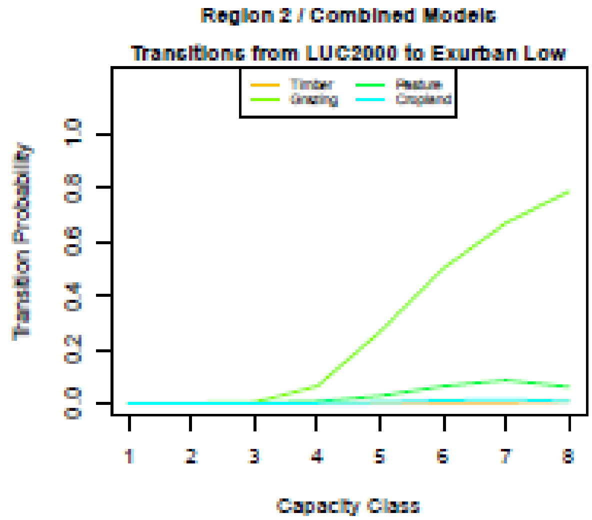
Smoothing Terms	edf	χ^2	*p*
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.89	3,226.33	<0.0001
Capacity class (suburban)	1.8	11,531.99	<0.0001
Capacity class (urban low)	1.7	14,389.11	<0.0001
Capacity class (urban high)	1.78	3,477.46	<0.0001
Capacity class (commercial)	1.9	35,289.11	<0.0001
Capacity class (industrial)	1.91	1,313.18	<0.0001
Global test	16.98	1,050,212	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	1.94	1,030.15	<0.0001
Capacity class (pasture)	2	2,895.73	<0.0001
Capacity class (cropland)	2.01	1,152.97	<0.0001
Global test	8.95	5,582.88	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.13	492.9	<0.0001
Capacity class (grazing)	1.96	3,483.53	<0.0001
Capacity class (pasture)	2	94.44	<0.0001
Capacity class (cropland)	2.04	180.76	<0.0001
Global test	12.13	21,938.08	<0.0001

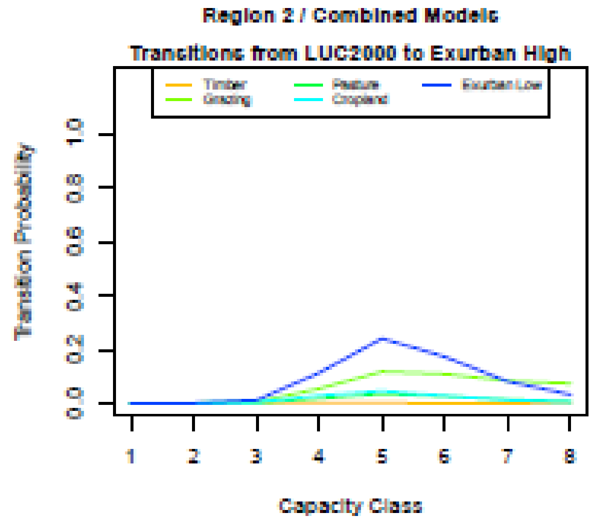
Table B-2. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

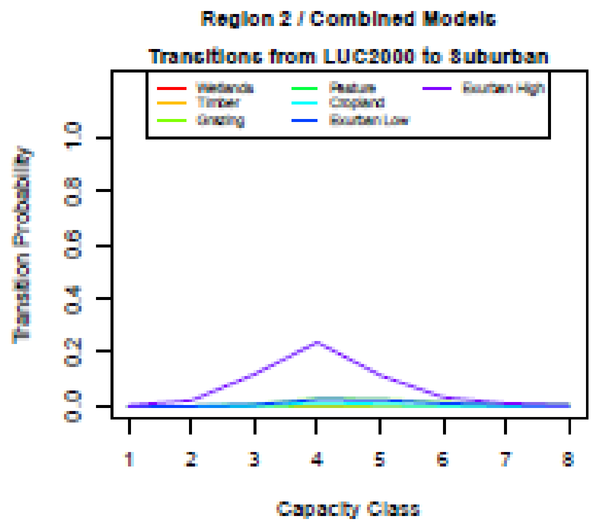
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.91	12.11	0.0021
Capacity class (timber)	2.29	139.88	<0.0001
Capacity class (grazing)	2.02	39.53	<0.0001
Capacity class (pasture)	2.24	55.39	<0.0001
Capacity class (cropland)	2.33	168.36	<0.0001
Capacity class (exurban low)	2.02	481.68	<0.0001
Global test	18.81	16,786.93	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.85	11.91	0.0021
Capacity class (timber)	2.22	46.77	<0.0001
Capacity class (grazing)	2.12	912.79	<0.0001
Capacity class (pasture)	2.27	87.06	<0.0001
Capacity class (cropland)	2.29	454.97	<0.0001
Capacity class (exurban low)	2.21	619.65	<0.0001
Capacity class (exurban high)	1.99	1,638.98	<0.0001
Global test	21.96	12,595.07	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.05	3.04	0.0874
Capacity class (timber)	1.26	6.91	0.0109
Capacity class (grazing)	2.07	219.32	<0.0001
Capacity class (pasture)	2.05	9.09	0.0113
Capacity class (cropland)	1.51	11.57	0.0016
Capacity class (exurban low)	2.23	56.06	<0.0001

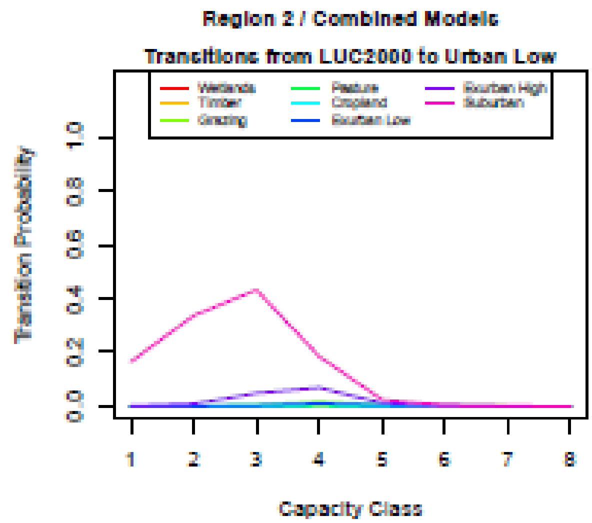
Table B-2. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

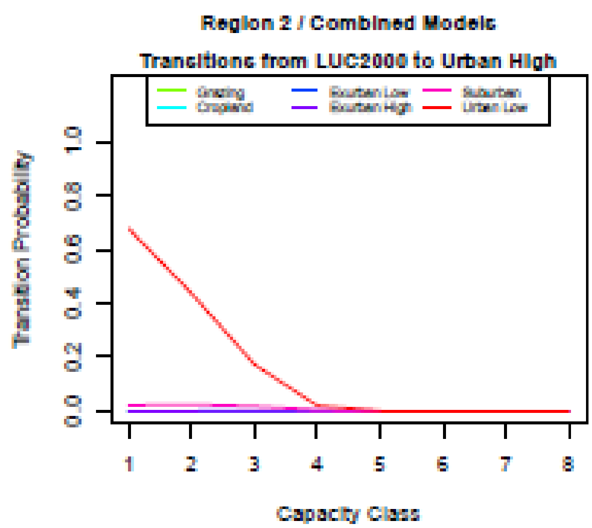
Smoothing Terms	edf	χ^2	*p*
Capacity class (exurban high)	2.04	200.89	<0.0001
Capacity class (suburban)	1.88	83.19	<0.0001
Global test	22.09	1,850.01	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.01	195.61	<0.0001
Capacity class (suburban)	1.95	521.53	<0.0001
Capacity class (urban low)	1.96	272.46	<0.0001
Capacity class (urban high)	1.70	5.78	0.013
Global test	11.62	11,500.45	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.15	24.53	<0.0001
Capacity class (grazing)	1.48	20.35	<0.0001
Capacity class (pasture)	0.64	1.39	0.143
Capacity class (exurban low)	2.08	36.75	<0.0001
Global test	9.36	993.61	<0.0001

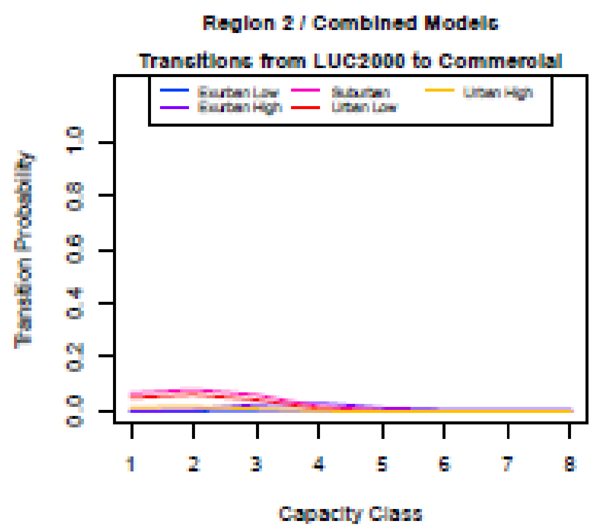

Region 2 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Grazing
Pasture
Cropland
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 2 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Grazing
Pasture
Cropland
Exurban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 2 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 2 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Suburban
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 2 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Cropland
Exurban Low
Exurban High
Suburban
Urban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 2 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Exurban High
Suburban
Urban Low
Urban High
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class

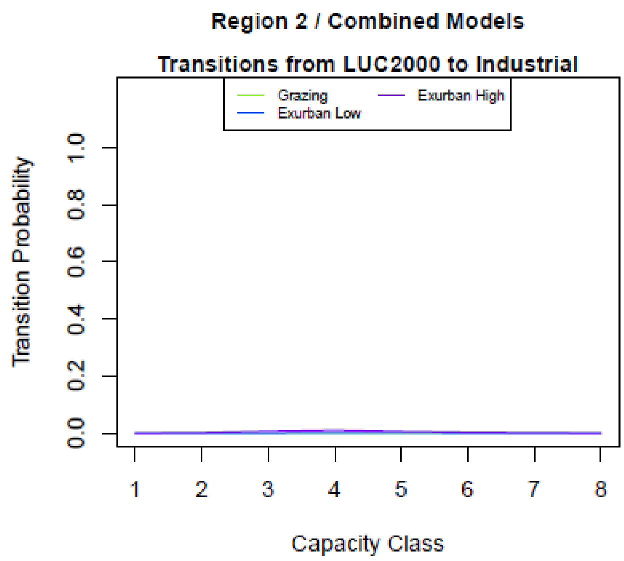


Figure B-2. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 2 (Intermountain West). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.3. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 3 (NORTH CENTRAL) TRANSITION PROBABILITY MODELS

Table B-3. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

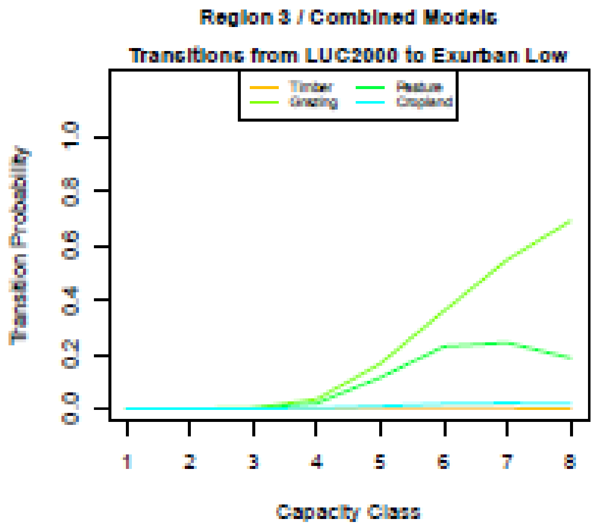
Smoothing Terms	edf	χ^2	*p*
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.86	4,754.47	<0.0001
Capacity class (suburban)	1.8	16,711.47	<0.0001
Capacity class (urban low)	1.74	13,319.25	<0.0001
Capacity class (urban high)	2.18	22,346.04	<0.0001
Capacity class (commercial)	1.85	9,804.43	<0.0001
Capacity class (industrial)	1.94	1,802.87	<0.0001
Global test	17.37	1,058,696	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.02	22.43	<0.0001
Capacity class (pasture)	2.01	3,718.37	<0.0001
Capacity class (cropland)	2.01	237.31	<0.0001
Global test	9.04	24,725.45	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.08	157.92	<0.0001
Capacity class (grazing)	1.96	4,738.75	<0.0001
Capacity class (pasture)	1.99	225.36	<0.0001
Capacity class (cropland)	1.99	801.72	<0.0001
Global test	12.02	9,249.58	<0.0001

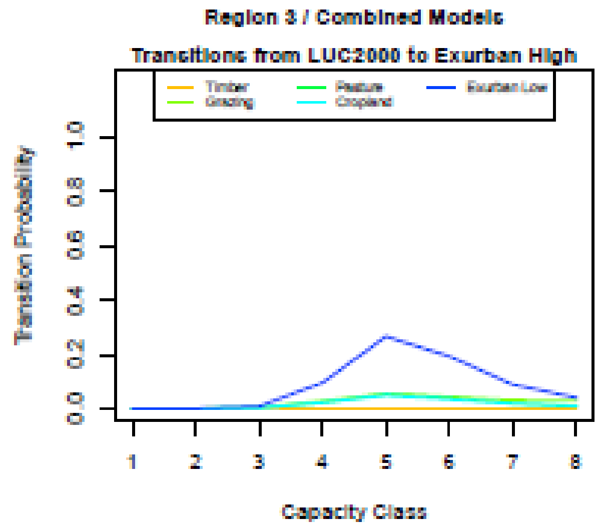
Table B-3. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

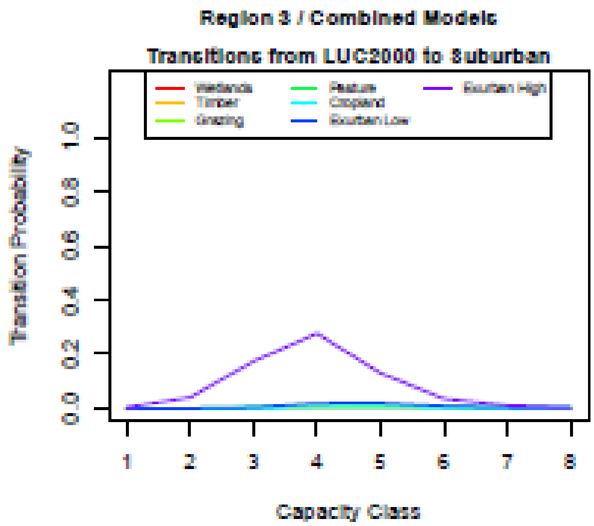
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.97	123.14	<0.0001
Capacity class (timber)	2.05	14.99	0.0006
Capacity class (grazing)	2.04	101.77	<0.0001
Capacity class (pasture)	2.11	216.86	<0.0001
Capacity class (cropland)	2.16	262	<0.0001
Capacity class (exurban low)	2.1	495.46	<0.0001
Global test	18.43	19,567.29	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.74	22.39	<0.0001
Capacity class (timber)	1.87	3	0.2027
Capacity class (grazing)	2.07	214.66	<0.0001
Capacity class (pasture)	2.07	160.27	<0.0001
Capacity class (cropland)	2.2	36.16	<0.0001
Capacity class (exurban low)	2.2	282.27	<0.0001
Capacity class (exurban high)	2.03	955.3	<0.0001
Global test	21.17	8,447.26	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.15	4.86	0.0343
Capacity class (grazing)	2.29	40.23	<0.0001
Capacity class (pasture)	1.74	11.91	0.0018
Capacity class (cropland)	0.97	5.85	0.0149
Capacity class (exurban low)	2.02	39.67	<0.0001
Capacity class (exurban high)	2.03	139.47	<0.0001

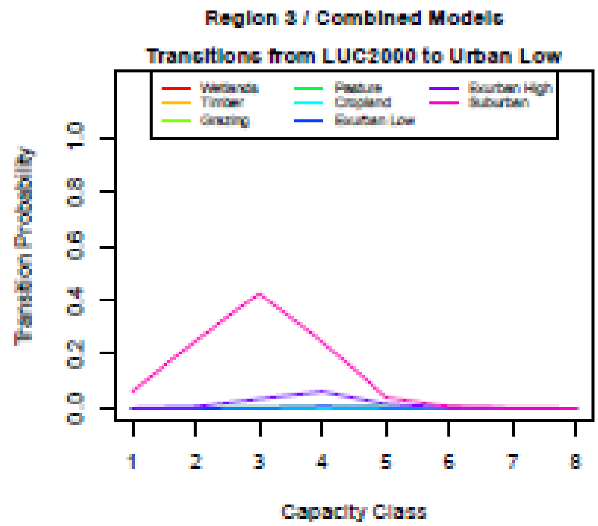
Table B-3. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

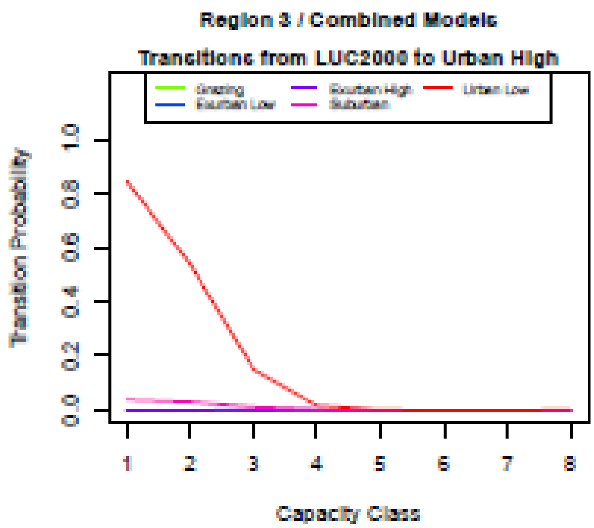
Smoothing Terms	edf	χ^2	*p*
Capacity class (suburban)	1.85	163.45	<0.0001
Global test	19.05	541.05	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	1.91	319.34	<0.0001
Capacity class (suburban)	1.91	1,006.82	<0.0001
Capacity class (urban low)	2.12	1,607.49	<0.0001
Capacity class (urban high)	2.19	674.84	<0.0001
Global test	12.13	9,102.24	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.21	31.74	<0.0001
Global test	3.21	37.65	<0.0001

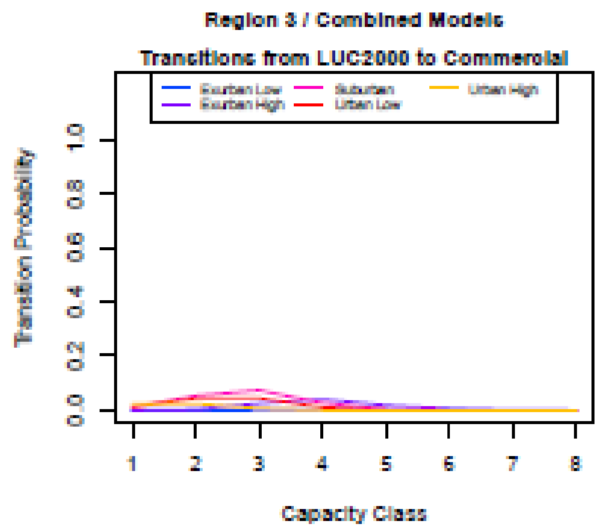

Region 3 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Pasture
Grazing
Cropland
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 3 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Pasture
Exurban Low
Grazing
Cropland
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 3 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Pasture
Exurban High
Timber
Cropland
Grazing
Exurban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 3 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Pasture
Exurban High
Timber
Cropland
Suburban
Grazing
Exurban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 3 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban High
Urban Low
Exurban Low
Suburban
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class


Region 3 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Suburban
Urban High
Exurban High
Urban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1 2 3 4 5 6 7 8
Capacity Class

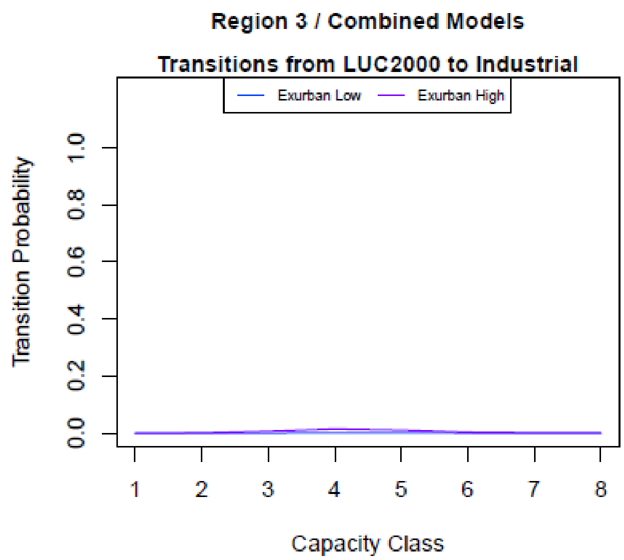


Figure B-3. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 3 (North Central). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.4. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 4 (SOUTH CENTRAL) TRANSITION PROBABILITY MODELS

Table B-4. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

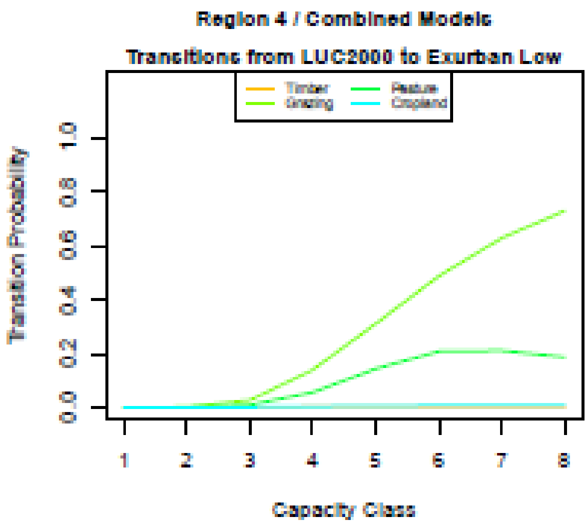
Smoothing Terms	**edf**	χ^2	***p***
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.93	1,729.42	<0.0001
Capacity class (suburban)	1.95	12,232.72	<0.0001
Capacity class (urban low)	1.89	7,131.93	<0.0001
Capacity class (urban high)	2.06	498.58	<0.0001
Capacity class (commercial)	1.90	3,650.58	<0.0001
Capacity class (industrial)	1.87	543.53	<0.0001
Global test	17.60	1,912,574	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	1.99	341.64	<0.0001
Capacity class (pasture)	2.01	6,979.23	<0.0001
Capacity class (cropland)	2.00	277.28	<0.0001
Global test	9.00	50,282.78	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.03	499.96	<0.0001
Capacity class (pasture)	2	1,659.84	<0.0001
Capacity class (cropland)	2	261.75	<0.0001
Capacity class (exurban low)	1.99	806.3	<0.0001
Global test	12.03	19,077.08	<0.0001

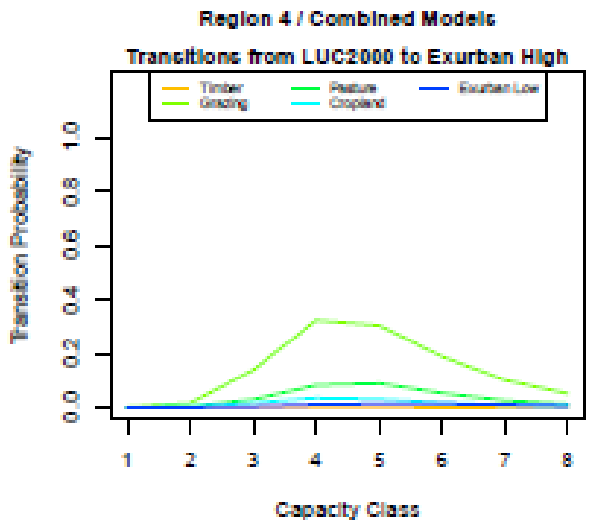
Table B-4. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

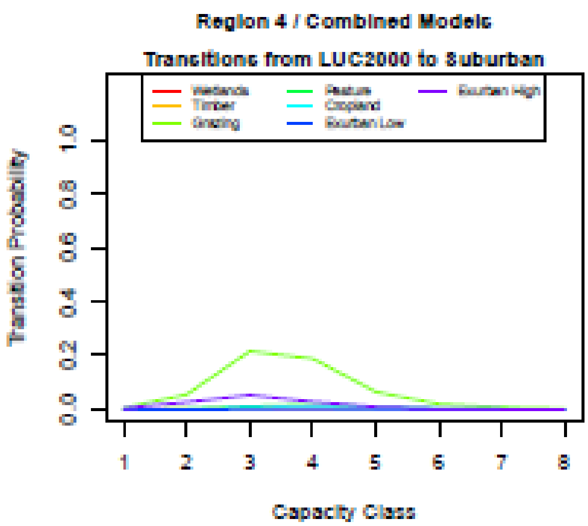
Smoothing Terms	edf	χ^2	***p***
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Grazing)			
Capacity class (wetlands)	2.07	190.8	<0.0001
Capacity class (timber)	2.2	236.43	<0.0001
Capacity class (pasture)	2.07	462.93	<0.0001
Capacity class (cropland)	2.1	224.46	<0.0001
Capacity class (exurban low)	2.04	22.22	<0.0001
Capacity class (exurban high)	1.91	302.98	<0.0001
Global test	18.39	5,044.57	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (wetlands)	1.91	3.03	0.2059
Capacity class (timber)	2.15	20.35	<0.0001
Capacity class (pasture)	2.18	20.45	<0.0001
Capacity class (cropland)	2.28	21.35	<0.0001
Capacity class (exurban low)	2.1	5.58	0.0676
Capacity class (exurban high)	1.94	19.43	0.0001
Capacity class (suburban)	1.95	545.75	<0.0001
Global test	21.51	5,170.4	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.09	1.23	0.2935
Capacity class (timber)	1.98	1.1	0.572
Capacity class (grazing)	1.85	26.12	<0.0001
Capacity class (pasture)	2.37	5.1	0.107
Capacity class (cropland)	2.04	6.98	0.0317
Capacity class (exurban low)	1.68	2.26	0.2599

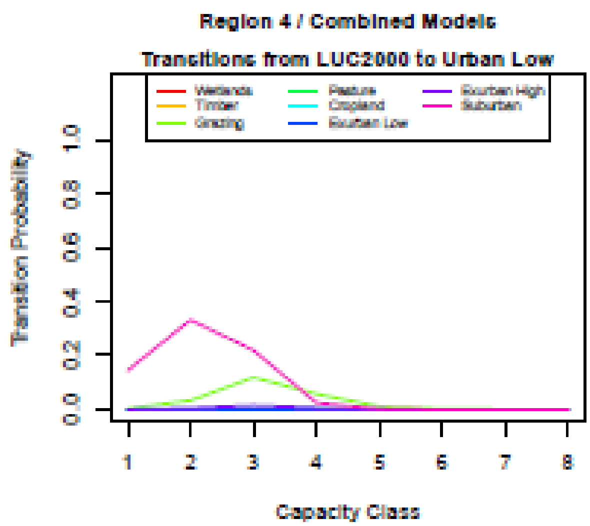
Table B-4. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

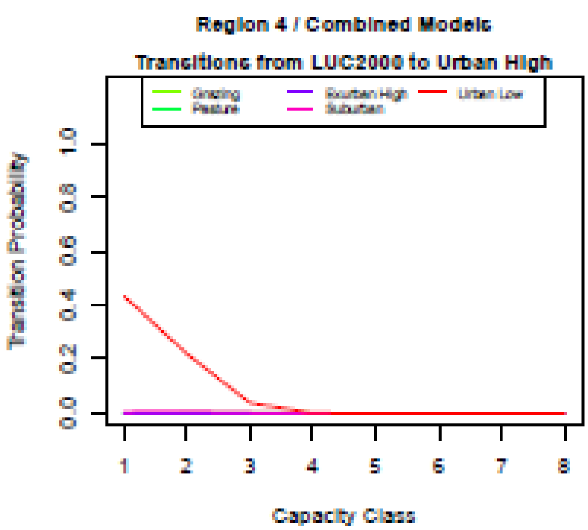
Smoothing Terms	edf	χ^2	*p*
Capacity class (exurban high)	1.84	3.09	0.1888
Capacity class (suburban)	1.85	1.45	0.4467
Global test	22.7	352.8	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.15	32.86	<0.0001
Capacity class (suburban)	1.99	147.97	<0.0001
Capacity class (urban low)	2.06	60.21	<0.0001
Capacity class (urban high)	0.68	2.48	0.0706
Global test	10.88	1,823.53	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	1.99	25.82	<0.0001
Global test	2.99	185.08	<0.0001

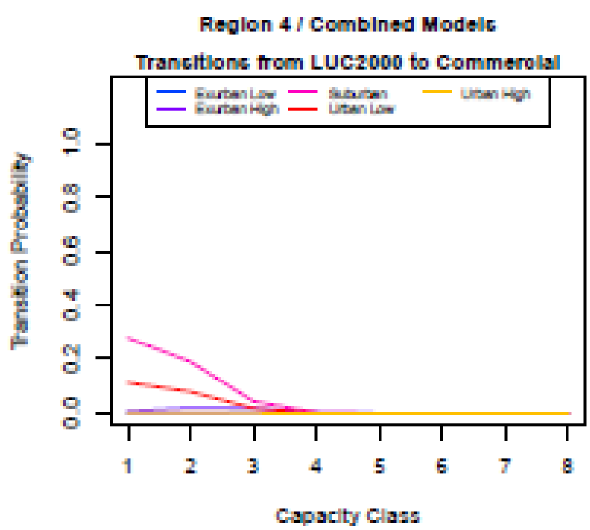

Region 4 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Pasture
Grazing
Cropland
Transition Probability
Capacity Class


Region 4 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Pasture
Exurban Low
Grazing
Cropland
Transition Probability
Capacity Class


Region 4 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Pasture
Exurban High
Timber
Cropland
Grazing
Exurban Low
Transition Probability
Capacity Class


Region 4 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Pasture
Exurban High
Timber
Cropland
Suburban
Grazing
Exurban Low
Transition Probability
Capacity Class


Region 4 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban High
Urban Low
Pasture
Suburban
Transition Probability
Capacity Class


Region 4 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Suburban
Urban High
Exurban High
Urban Low
Transition Probability
Capacity Class

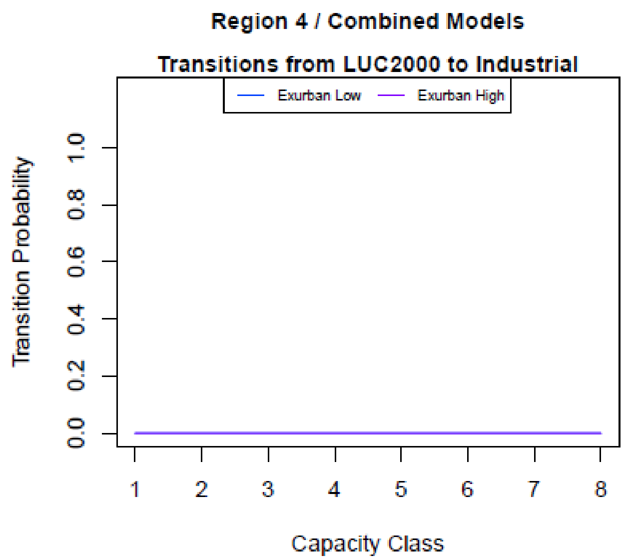


Figure B-4. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 4 (South Central). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.5. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 5 (GREAT LAKES) TRANSITION PROBABILITY MODELS

Table B-5. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

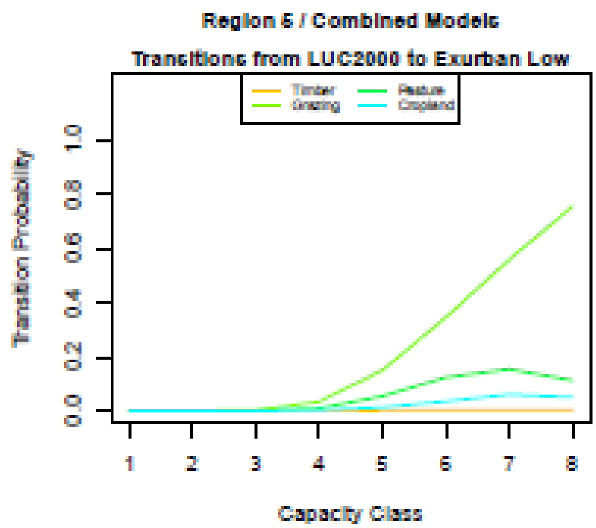
Smoothing Terms	edf	χ^2	*p*
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.82	5,643.06	<0.0001
Capacity class (suburban)	1.74	3,016.31	<0.0001
Capacity class (urban low)	1.71	3,105.97	<0.0001
Capacity class (urban high)	1.72	568.65	<0.0001
Capacity class (commercial)	1.77	6,819.62	<0.0001
Capacity class (industrial)	1.98	125.28	<0.0001
Global test	16.74	1,646,923	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.01	110.82	<0.0001
Capacity class (pasture)	2.02	5,294.72	<0.0001
Capacity class (cropland)	2.02	2,428.31	<0.0001
Global test	9.05	16,604.58	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.22	909.1	<0.0001
Capacity class (grazing)	1.96	4,938	<0.0001
Capacity class (pasture)	2.03	99.87	<0.0001
Capacity class (cropland)	2.04	195.63	<0.0001
Global test	12.24	7,392.31	<0.0001

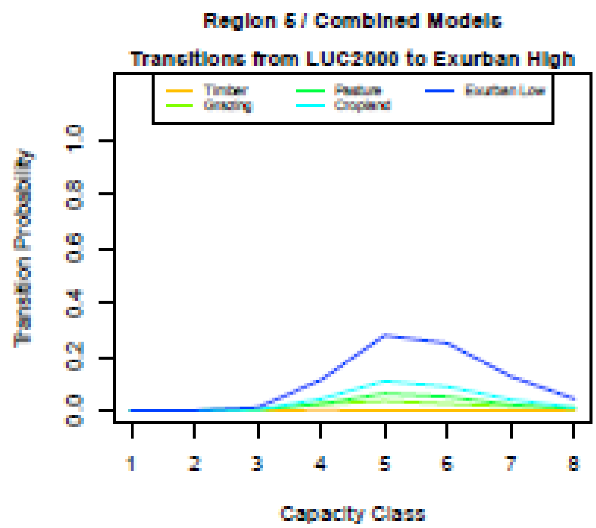
Table B-5. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

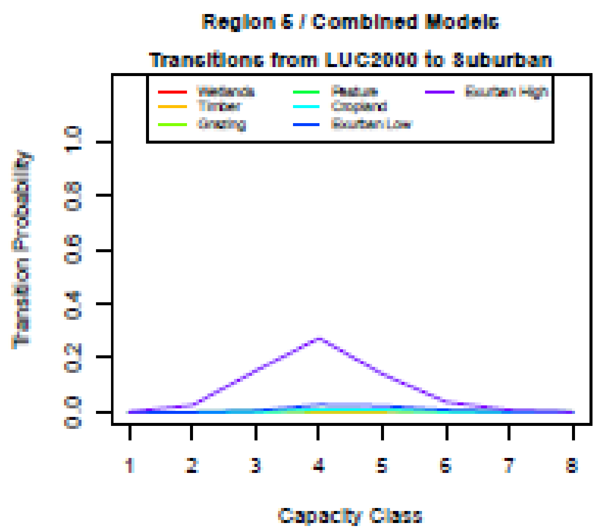
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.93	168.63	<0.0001
Capacity class (timber)	2.21	126.68	<0.0001
Capacity class (grazing)	1.98	112.65	<0.0001
Capacity class (pasture)	2.14	136.16	<0.0001
Capacity class (cropland)	2.3	299.09	<0.0001
Capacity class (exurban low)	2.14	324.83	<0.0001
Global test	18.7	14,336.52	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.88	47.52	<0.0001
Capacity class (timber)	1.97	36.46	<0.0001
Capacity class (grazing)	1.95	108.77	<0.0001
Capacity class (pasture)	2.21	75.13	<0.0001
Capacity class (cropland)	2.29	77.92	<0.0001
Capacity class (exurban low)	2.1	348.34	<0.0001
Capacity class (exurban high)	1.99	741.13	<0.0001
Global test	21.4	8,664.14	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.95	0	1
Capacity class (grazing)	2.15	8.44	0.0172
Capacity class (pasture)	1.50	3.13	0.1373
Capacity class (cropland)	1.79	5.13	0.0629
Capacity class (exurban low)	2.00	16.35	0.0003
Capacity class (exurban high)	2.05	20.07	<0.0001

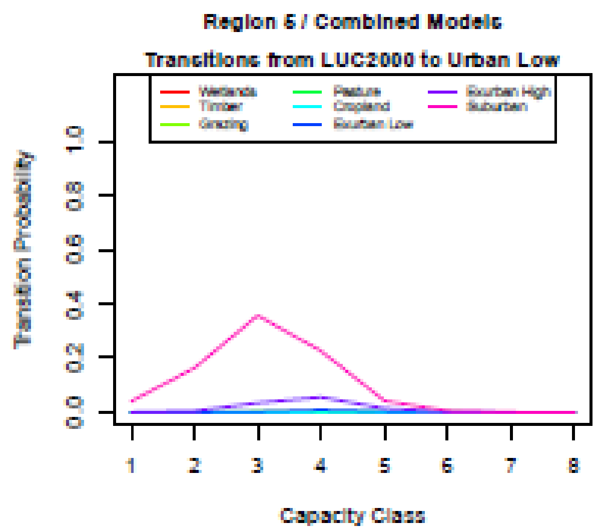
Table B-5. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

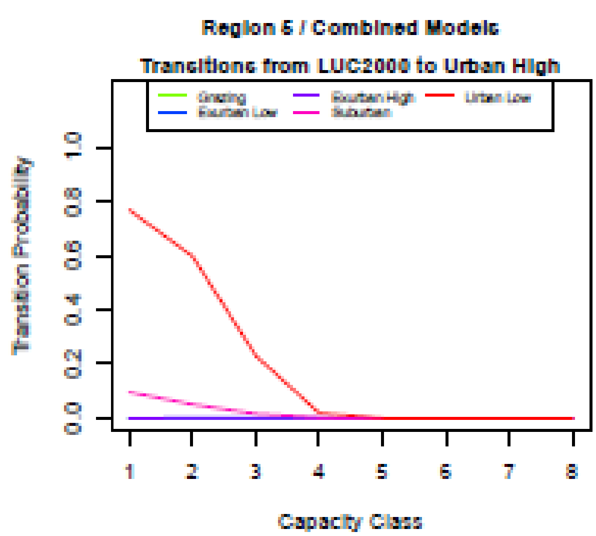
Smoothing Terms	edf	χ^2	*p*
Capacity class (suburban)	1.94	104.79	<0.0001
Global test	20.37	1,324.68	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.06	90.98	<0.0001
Capacity class (suburban)	1.76	36.55	<0.0001
Capacity class (urban low)	1.73	12.29	0.0015
Capacity class (urban high)	1.46	2.26	0.2156
Global test	11.01	12,256.77	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.01	5.08	0.0799
Global test	3.01	278.67	<0.0001

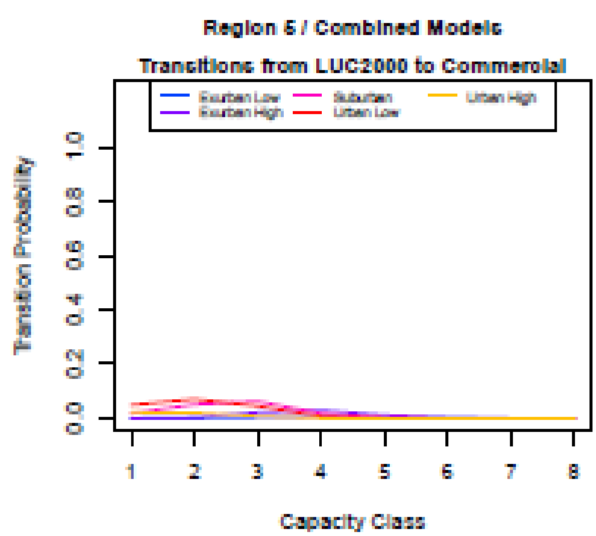

Region 5 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Grazing
Pasture
Cropland
Transition Probability
Capacity Class


Region 5 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Grazing
Pasture
Cropland
Exurban Low
Transition Probability
Capacity Class


Region 5 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Transition Probability
Capacity Class


Region 5 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Suburban
Transition Probability
Capacity Class


Region 5 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban Low
Exurban High
Suburban
Urban Low
Transition Probability
Capacity Class


Region 5 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Exurban High
Suburban
Urban Low
Urban High
Transition Probability
Capacity Class

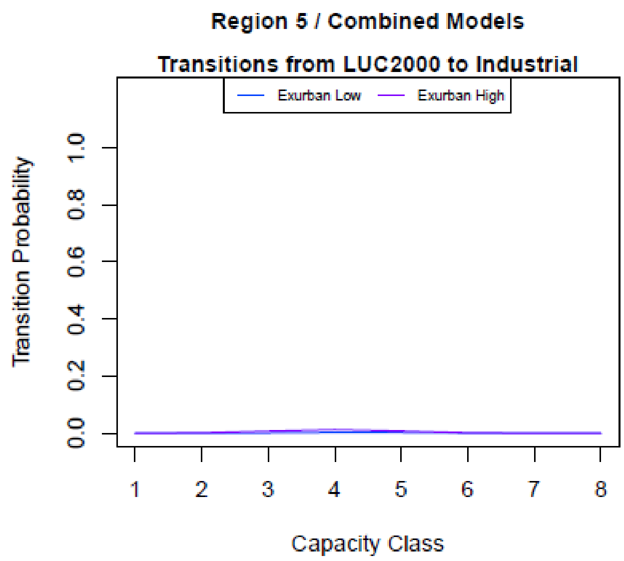


Figure B-5. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 5 (Great Lakes). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.6. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 6 (SOUTHEAST) TRANSITION PROBABILITY MODELS

Table B-6. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated.

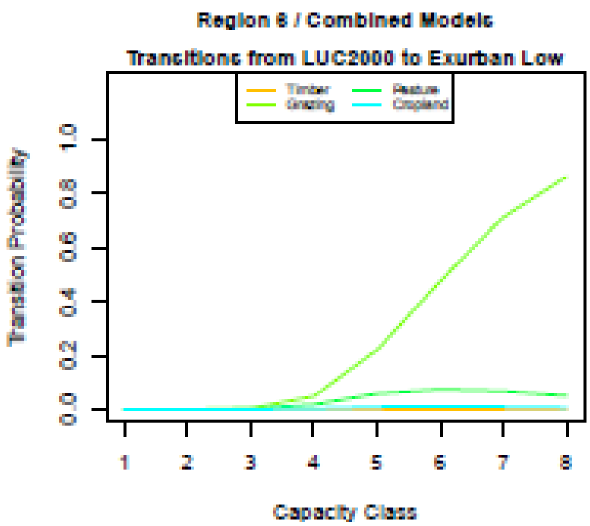
Smoothing Terms	edf	χ^2	*p*
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.8	19,946.39	<0.0001
Capacity class (suburban)	1.63	40,462.82	<0.0001
Capacity class (urban low)	1.64	64,034.18	<0.0001
Capacity class (urban high)	1.78	27,887.66	<0.0001
Capacity class (commercial)	1.83	61,257.16	<0.0001
Capacity class (industrial)	1.93	11,358.44	<0.0001
Global test	16.62	8,232,880	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.01	102.93	<0.0001
Capacity class (pasture)	2.02	2,185.1	<0.0001
Capacity class (cropland)	2.03	995.05	<0.0001
Global test	9.06	183,239.3	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.02	325.96	<0.0001
Capacity class (grazing)	1.95	35,257.99	<0.0001
Capacity class (pasture)	2.04	676.23	<0.0001
Capacity class (cropland)	2.05	1,016.18	<0.0001
Global test	12.06	51,509.93	<0.0001

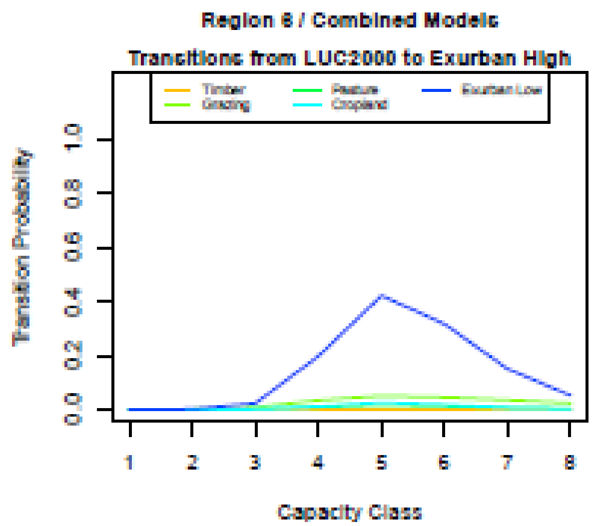
Table B-6. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

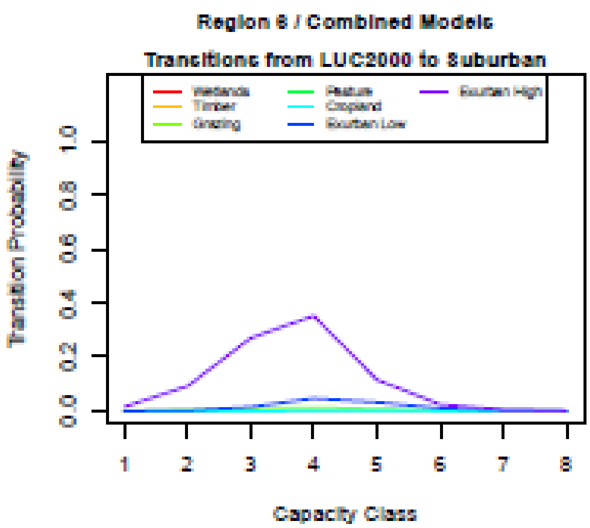
Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.99	105.92	<0.0001
Capacity class (timber)	2.1	118.7	<0.0001
Capacity class (grazing)	1.96	3,812.02	<0.0001
Capacity class (pasture)	2.11	821.79	<0.0001
Capacity class (cropland)	2.17	931.83	<0.0001
Capacity class (exurban low)	1.99	4,745.53	<0.0001
Global test	18.32	94,724.94	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.97	151.68	<0.0001
Capacity class (timber)	1.99	202.48	<0.0001
Capacity class (grazing)	2.00	1,279.8	<0.0001
Capacity class (pasture)	2.13	1,002.82	<0.0001
Capacity class (cropland)	2.21	756.81	<0.0001
Capacity class (exurban low)	2.07	6,374.45	<0.0001
Capacity class (exurban high)	1.97	7,737.2	<0.0001
Global test	21.34	56,526.73	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	1.58	14.89	0.0003
Capacity class (timber)	1.29	8.3	0.0064
Capacity class (grazing)	2.01	219.79	<0.0001
Capacity class (pasture)	2.06	37.33	<0.0001
Capacity class (cropland)	1.87	36.2	<0.0001
Capacity class (exurban low)	1.99	342.86	<0.0001

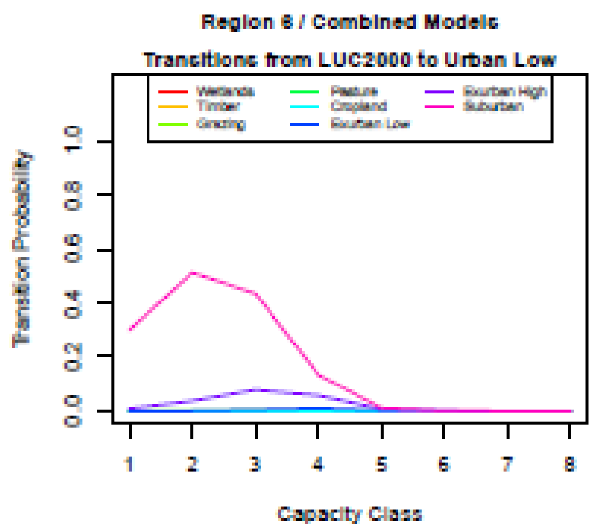
Table B-6. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. RefLevel is the reference level land use from which transitions are calculated. (continued)

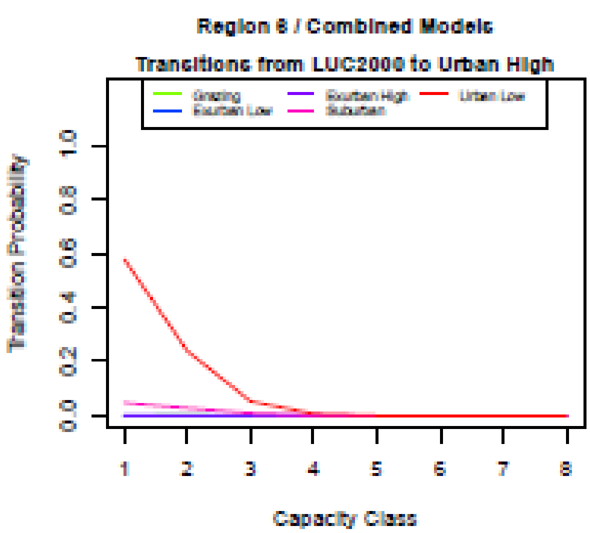
Smoothing Terms	edf	χ^2	*p*
Capacity class (exurban high)	2.01	692.26	<0.0001
Capacity class (suburban)	2.00	357.40	<0.0001
Global test	22.81	3,211.57	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	1.98	241.71	<0.0001
Capacity class (suburban)	1.90	2,772.21	<0.0001
Capacity class (urban low)	1.95	2,106.21	<0.0001
Capacity class (urban high)	1.85	257.98	<0.0001
Global test	11.68	34,302	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	0.78	8.62	0.0022
Capacity class (grazing)	2.39	252.5	<0.0001
Capacity class (pasture)	1.89	59.64	<0.0001
Capacity class (cropland)	1.44	12.58	0.0008
Capacity class (exurban low)	2.11	129.01	<0.0001
Global test	13.61	2,721.24	<0.0001

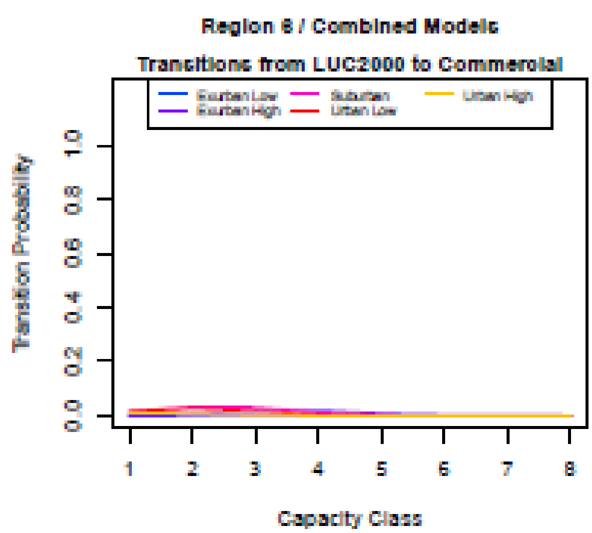

Region 6 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Grazing
Pasture
Cropland
Transition Probability
Capacity Class


Region 6 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Grazing
Pasture
Cropland
Exurban Low
Transition Probability
Capacity Class


Region 6 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Transition Probability
Capacity Class


Region 6 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Suburban
Transition Probability
Capacity Class


Region 6 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban Low
Exurban High
Suburban
Urban Low
Transition Probability
Capacity Class


Region 6 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Exurban High
Suburban
Urban Low
Urban High
Transition Probability
Capacity Class

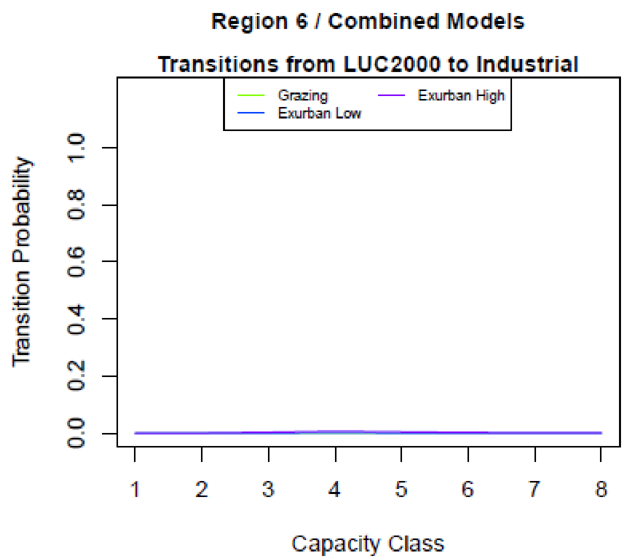


Figure B-6. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 6 (Southeast). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

B.7. INTEGRATED CLIMATE AND LAND USE SCENARIOS (ICLUS) REGION 7 (NORTHEAST) TRANSITION PROBABILITY MODELS

Table B-7. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class.

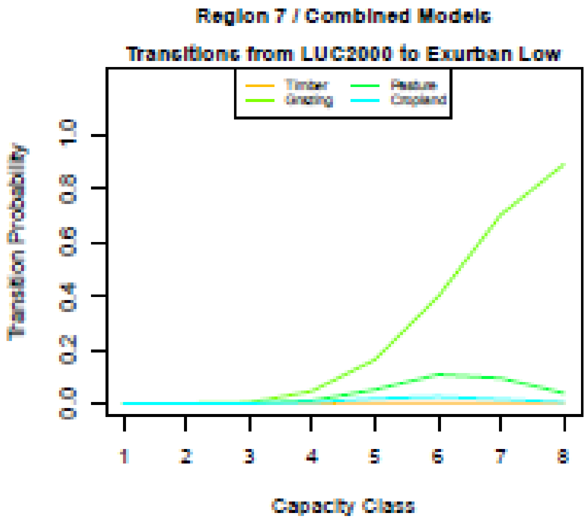
Smoothing Terms	edf	χ^2	***p***
For Transitions into LUC2010 by Capacity Class (RefLevel: Exurban Low)			
Capacity class (exurban high)	1.72	22,867.66	<0.0001
Capacity class (suburban)	1.61	5,812.7	<0.0001
Capacity class (urban low)	1.62	5,180.12	<0.0001
Capacity class (urban high)	1.63	1,221.28	<0.0001
Capacity class (commercial)	1.88	12,214.7	<0.0001
Capacity class (industrial)	1.93	1,653.35	<0.0001
Global test	16.39	2,190,093	<0.0001
From LUC2000 for Transitions into Exurban Low by Capacity Class (RefLevel: Grazing)			
Capacity class (timber)	2.1	68.99	<0.0001
Capacity class (pasture)	2.01	13,104.18	<0.0001
Capacity class (cropland)	2.07	4,203.43	<0.0001
Global test	9.17	72,913.49	<0.0001
From LUC2000 for Transitions into Exurban High by Capacity Class (RefLevel: Exurban Low)			
Capacity class (timber)	2.01	327.83	<0.0001
Capacity class (grazing)	1.99	16,657.91	<0.0001
Capacity class (pasture)	2.04	263.96	<0.0001
Capacity class (cropland)	2.16	1,047.29	<0.0001
Global test	12.2	31,983.46	<0.0001

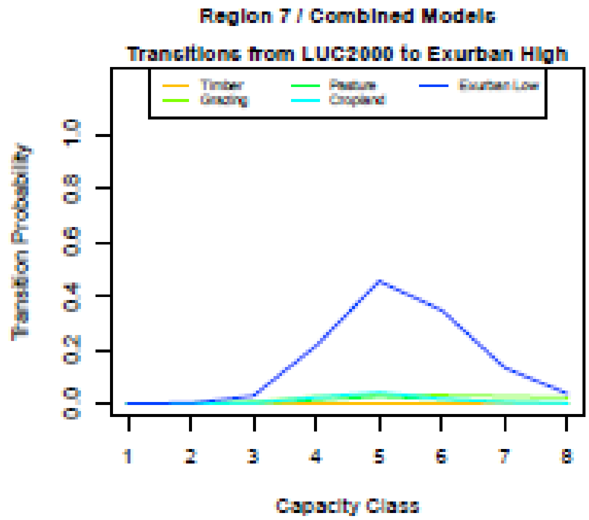
Table B-7. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(\mathrm{LUC}_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(\mathrm{LUC}_{i|j})$, by capacity class. (continued)

Smoothing Terms	edf	χ^2	*p*
From LUC2000 for Transitions into Suburban by Capacity Class (RefLevel: Exurban High)			
Capacity class (wetlands)	1.98	600.77	<0.0001
Capacity class (timber)	1.95	51.98	<0.0001
Capacity class (grazing)	1.94	604.6	<0.0001
Capacity class (pasture)	2.07	32.79	1.00×10^{-4}
Capacity class (cropland)	2.2	225.2	<0.0001
Capacity class (exurban low)	2	205.86	<0.0001
Global test	18.14	18,896.3	<0.0001
From LUC2000 for Transitions into Urban Low by Capacity Class (RefLevel: Suburban)			
Capacity class (wetlands)	1.83	14.17	0.0007
Capacity class (timber)	1.76	8.68	0.0099
Capacity class (grazing)	1.93	103.01	<0.0001
Capacity class (pasture)	2.19	47.36	<0.0001
Capacity class (cropland)	2.15	115.43	<0.0001
Capacity class (exurban low)	2.04	173.29	<0.0001
Capacity class (exurban high)	1.97	713.07	<0.0001
Global test	20.88	9,717.48	<0.0001
From LUC2000 for Transitions into Urban High by Capacity Class (RefLevel: Urban Low)			
Capacity class (wetlands)	0.97	3.08	0.0757
Capacity class (timber)	1.2	1.35	0.3004
Capacity class (grazing)	1.88	32.85	<0.0001
Capacity class (pasture)	1.55	3.21	0.1377
Capacity class (cropland)	1.21	16.2	0.0001
Capacity class (exurban low)	1.9	33.15	<0.0001

Table B-7. Estimated nonlinear degrees of freedom (edf) and significance of the smoothing terms for the multinomial GAMs. The top marginal model predicts the probability of transitioning into each LUC in 2010, $p(LUC_j)$, by capacity class, while the bottom conditional models predict the probability of transitioning from each LUC in 2000 given that they transitioned into a particular LUC in 2010, $p(LUC_{i|j})$, by capacity class. (continued)

Smoothing Terms	**edf**	χ^2	***p***
Capacity class (exurban high)	2.05	44.44	<0.0001
Capacity class (suburban)	1.98	73.51	<0.0001
Global test	20.74	1,673.8	<0.0001
From LUC2000 for Transitions into Commercial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	1.97	576.07	<0.0001
Capacity class (suburban)	1.82	80.49	<0.0001
Capacity class (urban low)	1.78	15.94	0.0003
Capacity class (urban high)	1.68	9.73	0.0052
Global test	11.25	11,010.72	<0.0001
From LUC2000 for Transitions into Industrial by Capacity Class (RefLevel: Exurban High)			
Capacity class (exurban low)	2.13	330.36	<0.0001
Global test	3.13	469.32	<0.0001


Region 7 / Combined Models
Transitions from LUC2000 to Exurban Low
Timber
Grazing
Pasture
Cropland
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
Capacity Class


Region 7 / Combined Models
Transitions from LUC2000 to Exurban High
Timber
Grazing
Pasture
Cropland
Exurban Low
Transition Probability
0.0
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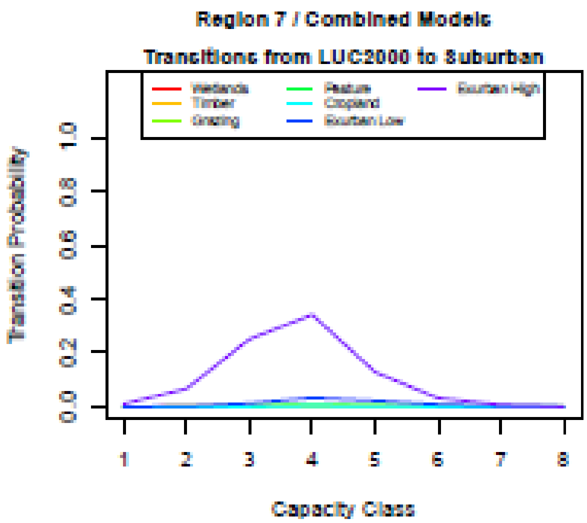
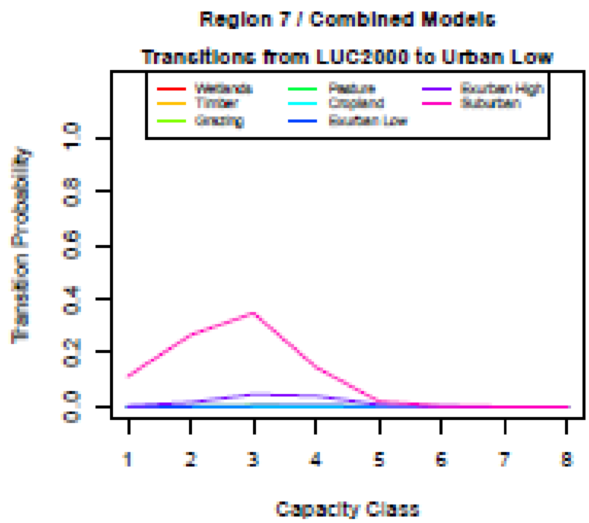
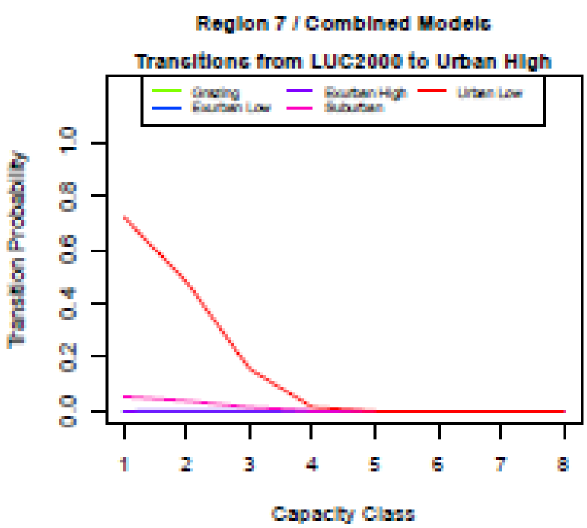
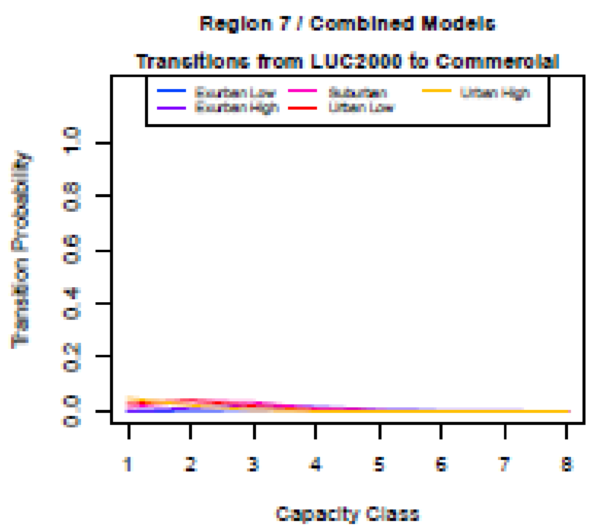
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
Capacity Class


Region 7 / Combined Models
Transitions from LUC2000 to Suburban
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
Capacity Class


Region 7 / Combined Models
Transitions from LUC2000 to Urban Low
Wetlands
Timber
Grazing
Pasture
Cropland
Exurban Low
Exurban High
Suburban
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
Capacity Class


Region 7 / Combined Models
Transitions from LUC2000 to Urban High
Grazing
Exurban Low
Exurban High
Suburban
Urban Low
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
Capacity Class


Region 7 / Combined Models
Transitions from LUC2000 to Commercial
Exurban Low
Exurban High
Suburban
Urban Low
Urban High
Transition Probability
0.0
0.2
0.4
0.6
0.8
1.0
1
2
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Capacity Class

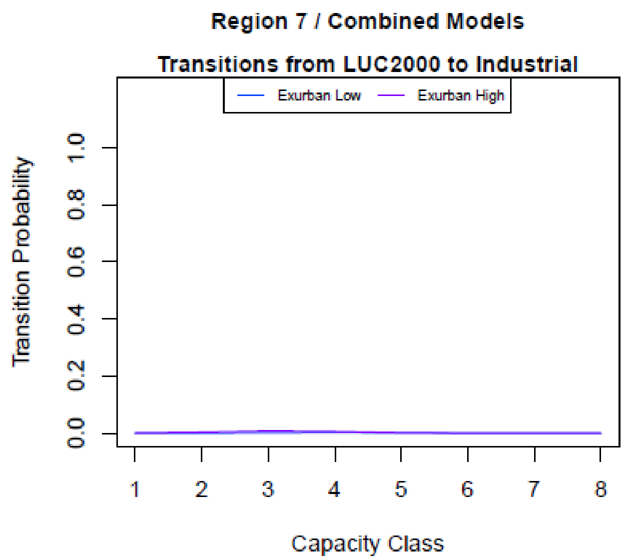

Figure B-7. Predicted transition probabilities by capacity class from LUCs in 2000 to LUCs in 2010 in Integrated Climate and Land Use Scenarios (ICLUS) Region 7 (Northeast). Each panel shows transitions into a particular LUC in 2010. These combined probabilities are the product of corresponding marginal and conditional models, i.e., for a given capacity class the probability of transitioning from LUC_i into LUC_j is $P(LUC_{ij}) = P(LUC_j) \times P(LUC_{i|j})$.

APPENDIX C. LAND USE CLASS (LUC) AND CAPACITY DEMAND MODELS

Table C-1. Generalized additive model (GAM) model output relating natural log (ln) transformed LUC density and capacity to ln transformed population density. Output includes an estimate of the intercept, estimated degrees of freedom (edf) for the smoothing term, the adjusted R^2 associated with the model, the standard error (*SE*) associated with the estimate of the intercept and *T* and *F* statistics associated with the significance of the intercept and smoothing terms, respectively.

GAM Relating ln(Exurban Low Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	0.744	0.027	22.77	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	5.899	773.2	<0.0001	
Adjusted R^2	0.550			
GAM Relating ln(Exurban High Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	0.455	0.011	41.63	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	8.177	2,214	<0.0001	
Adjusted R^2	0.812			
GAM Relating ln(Suburban Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	−0.745	0.007	−100.1	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	7.021	4,453	<0.0001	
Adjusted R^2	0.889			
GAM Relating ln(Urban Low Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	−1.365	0.010	−132.1	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	7.005	2,218	<0.0001	
Adjusted R^2	0.800			

Table C-1. Generalized additive model (GAM) model output relating natural log (ln) transformed LUC density and capacity to ln transformed population density. Output includes an estimate of the intercept, estimated degrees of freedom (edf) for the smoothing term, the adjusted R2 associated with the model, the standard error (SE) associated with the estimate of the intercept and T and F statistics associated with the significance of the intercept and smoothing terms, respectively. (continued)

GAM Relating ln(Urban High Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	−5.559	0.013	−413.4	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	6.730	1,819	<0.0001	
Adjusted R^2	0.761			
GAM Relating ln(Commercial Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	−2.540	0.015	−175.1	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	5.479	1,675	<0.0001	
Adjusted R^2	0.713			
GAM Relating ln(Industrial Pixel Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	−23.182	0.018	−177.0	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	6.056	1,051	<0.0001	
Adjusted R^2	0.629			
GAM Relating ln(Capacity Density) to ln(Population Density)				
Parametric Terms	**Estimate**	***SE***	***T***	***p***
Intercept	9.505	0.004	2,292	<0.0001
Smoothing Terms	**edf**	***F***	***p***	
Population density	7.939	1,109	<0.0001	
Adjusted R^2	0.682			

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