# Influence of human activity patterns, particle composition, and residential air exchange rates on modeled distributions of $PM_{2.5}$ exposure compared to central-site monitoring data

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Abstract

Central-site monitors do not account for factors such as outdoor-to-indoor transport and human activity patterns that influence personal exposures to ambient fine particulate matter ($PM_{2.5}$). We describe and compare different ambient $PM_{2.5}$ exposure estimation approaches that incorporate human activity patterns and time-resolved location-specific particle penetration and persistence indoors.

Four approaches were used to estimate exposures to *ambient* $PM_{2.5}$ for application to the New Jersey Triggering of Myocardial Infarction Study. These include ***Tier 1***: central-site $PM_{2.5}$ mass; ***Tier* 2A**: the Stochastic Human Exposure and Dose Simulation (SHEDS) model using literature-based air exchange rates (AER); ***Tier 2B***: the Lawrence Berkeley National Laboratory (LBNL) Aerosol Penetration and Persistence (APP) and Infiltration models; ***Tier 3***: the SHEDS model where AERs were estimated using the LBNL Infiltration model.

Mean exposure estimates from Tier 2A, 2B, and 3 exposure modeling approaches were lower than Tier 1central-site $PM_{2.5}$ mass . Tier 2A estimates differed by season but not across the 7 monitoring areas. Tier 2B and Tier 3 geographical patterns appeared to be driven by AERs while seasonal patterns appeared to be due to variations in PM composition and time activity patterns. These model results demonstrate heterogeneity in exposures that are not captured by the central-site monitor.

## Introduction

Large air pollution epidemiological studies commonly use ambient measurements from central-site monitors to characterize a population's exposure to ambient air pollutants (Laden, Schwartz et al. 2006; Pope, Ezzati et al. 2009; Zanobetti and Schwartz 2009). However, central-site monitors do not account for several factors that could influence personal exposures to outdoor-generated fine particulate matter ($PM_{2.5}$) such as spatial and temporal variations in residential air exchange rates (AER), particle penetration, particle losses indoors, and human activity patterns (e.g. time spent in different microenvironments).

Recently, there has been interest in using exposure models to better characterize ambient air pollution exposures for epidemiological studies. Examples of these exposure estimation approaches include air quality models (Appel, Bhave et al. 2008; Lobdell, Isakov et al. 2011), geostatistical models (Nuckols, Ward et al. 2004; Beelen, Hoek et al. 2007; Aguilera, Guxens et al. 2009), models incorporating human activity patterns (Burke, Zufall et al. 2001; Blangiardo, Hansell et al. 2011), factor analysis (Strand, Hopke et al. 2007), and a combination of approaches (Georgopoulos, Wang et al. 2005; Jerrett, Arain et al. 2005; Özkaynak, Palma et al. 2007; Isakov, Touma et al. 2009; Mölter, Lindley et al. 2010; Tonne, Beevers et al. 2010) . However, limited work (Strand, Vedal et al. 2005; Strand, Hopke et al. 2007) has been done to compare alternative exposure metrics for PM and gaseous pollutants within a single health study. This paper conducts a comparison of alternative $PM_{2.5}$ exposure metrics that were later applied to an epidemiologic study of myocardial infarctions (MI) conducted in New Jersey (NJ), USA.

Previously, Rich et al (Rich, Kipen et al. 2010) used a time-stratified case-crossover design to study the triggering of MI by ambient $PM_{2.5}$ mass and species in the previous few hours and days. They used hourly concentrations from 7 central-site $PM_{2.5}$ monitors across New Jersey from 2004-2006 to estimate each subject's 24 h average ambient $PM_{2.5}$ exposure. Our objective was to modify the ambient $PM_{2.5}$ concentrations from these same central-site monitors to account for human activity patterns and particle penetration and persistence in homes. A tiered approach to exposure estimation was taken, with increasing tier numbers representing increasing model complexity and/or data requirements. The four different exposure approaches are:

- ***Tier 1***: Central-site $PM_{2.5}$ concentrations from 7 monitor locations across NJ
- ***Tier 2A***: The Stochastic Human Exposure and Dose Simulation (SHEDS) model, a population exposure model that uses a probabilistic approach to estimate personal exposures for simulated individuals of a defined population based on ambient PM concentrations, literature-based distributions of residential AERs and particle infiltration parameters (i.e., penetration factors and deposition rates), and time spent in various microenvironments (e.g. home, office, school, vehicle) from a large database of human activity diaries (Burke, Zufall et al. 2001; Georgopoulos, Wang et al. 2005; Cao and Frey 2011). By setting indoor concentrations to zero, exposures to only *ambient* $PM_{2.5}$ were simulated.
- ***Tier 2B***: The Lawrence Berkeley National Laboratory (LBNL) Aerosol Penetration and Persistence (APP) and Infiltration models are physically based semi-empirical models that estimate residential AER and indoor concentrations of ambient $PM_{2.5}$ based on central site concentrations, meteorology, housing data, and particle size and composition, spatially and temporally resolved residential AERs, and ambient particle penetration and persistence by size and species (Lunden, Thatcher et al. 2003; Hering, Lunden et al. 2007). These models do not account for time in different microenvironments and assume that all time is spent in residence.
- ***Tier 3:*** A hybrid approach of 2A and 2B that incorporates the site-specific and spatially and temporally refined estimates of AERs from 2B into the SHEDS model of 2A.

In this analysis, we describe the four approaches, compare Tier 2 and 3 estimates to the central-site $PM_{2.5}$ concentrations (Tier 1), examine how the treatment of residential AERs, particle losses, and human activity patterns impacts the $PM_{2.5}$ exposure estimates, and evaluate the degree of spatial variability between zip codes within 10 km of a central site monitor.

## Methods

### *Description of Exposure Metrics*

Tier 1 exposure estimates are derived from hourly ambient $PM_{2.5}$ concentrations measured using Tapered Element Oscillating Microbalance at 7 monitoring stations by the New Jersey Department of Environmental Protection that were used in the original epidemiologic study (Rich, Kipen et al. 2010). Patients were assigned $PM_{2.5}$ concentrations from the closest monitor to their residence, regardless of wind direction, which varies considerably over 24 hours. Patients (n = 5864) were adults 45 years and older living with 10 km of a monitoring station (Rich, Kipen et al. 2010). Concentrations were then averaged over the 24 hours immediately prior to emergency department admission for transmural MI. Monitoring stations used were located in the following cities in NJ: Camden, Elizabeth, Flemington, Jersey City, Millville, New Brunswick, and Rahway (Figure S-1).

For Tier 2A estimates, the SHEDS model was used to estimate distributions of personal exposures to ambient $PM_{2.5}$ based on the hourly Tier 1 $PM_{2.5}$ concentrations. Detailed descriptions of SHEDS are available in previous publications (Burke, Zufall et al. 2001). Briefly, SHEDS uses a probabilistic approach to estimate distributions of PM exposures for a population of interest based on ambient PM concentration data, US Census demographic data at the census tract level, time-location diary data from EPA's Consolidated Human Activity Database

(CHAD)(McCurdy, Glen et al. 2000), and distributions of exposure factor inputs. SHEDS generates a simulated population of demographically representative individuals for each census tract selected. A set of diaries of human activity pattern data from CHAD for different seasons and day types (weekday/weekend) are then randomly assigned to each individual matching the demographic characteristics of the simulated individual (gender, age, and employment status). SHEDS stochastically computes a PM concentration in various microenvironments (e.g. outdoors, in-residence, in-office, and in-vehicle) in which the person spent time by randomly sampling from the exposure factor distributions, and estimates the contribution from both PM of ambient origin (in this case central-site monitoring data) and indoor PM sources (set to 0 for this analysis). The hourly time series of total PM exposures for the individual is calculated by weighting the PM concentrations in each microenvironment by the amount of time that the person spent in that microenvironment.

For this analysis SHEDS was applied to simulate ambient $PM_{2.5}$ exposures for 10,000 individuals age 45 years and older (to match the age cohort of original study population) for all census tracts within 10 km of each of the seven monitoring station using the hourly (Tier 1) $PM_{2.5}$ concentrations from that central-site monitoring station as input. $PM_{2.5}$ penetration and decay rate distributions and seasonal distributions of residential AERs representative of the NJ area (Burke, Zufall et al. 2001) were also used as input. Indoor $PM_{2.5}$ sources were set to zero in order to predict exposure to $PM_{2.5}$ of ambient origin alone.

Tier 2B estimates provided daily, location-specific variations in exposure from central-site concentrations (Tier 1) by accounting for 1) variations in AER because of housing stock and meteorology, and 2) variations in particle losses with outdoor-to-indoor transport because of changes in particle size and behavior with changes in daily particle composition as previously described in detail by (Hodas, Lunden et al. 2012). The LBNL-APP mass balance model (Hering, Lunden et al. 2007) was used to capture the transport and fate of aerosols in the indoor environment, while meteorology and census tract-level housing characteristics were used in LBNL Infiltration model (Sherman and Dickerhoff 1994; Chan, Nazaroff et al. 2005) to calculate AERs.

The LBNL Infiltration model calculates AER in two steps. First, the normalized leakage distribution for individual census tracts is calculated using variables describing the housing stock, including floor area, year built, resident poverty status (Chan, Nazaroff et al. 2005) and prevalence of air conditioning derived from US Census and America Housing Survey data (United States Census Bureau 2004; United States Census Bureau 2004). Next, the normalized leakage distributions are used to predict hourly AER using meteorological data and assumptions concerning the local geography (Sherman and Dickerhoff 1994).

The LBNL APP model then predicts indoor concentrations of ambient $PM_{2.5}$ and its chemical components. The model describes the concentration of $PM_{2.5}$ species in indoor air as a function of its outdoor concentration, AER, the efficiency of particle penetration across the building envelope, and the rate of indoor loss by deposition. For nitrate, volatile losses indoors are also considered. Hourly indoor concentrations of ambient $PM_{2.5}$ are therefore calculated from central site Tier 1 $PM_{2.5}$ incorporating the AER (from the LBNL Infiltration model) and size- and chemically-resolved $PM_{2.5}$ penetration, deposition, and loss due to indoor chemical transformation (Hering, Lunden et al. 2007; Hodas, Lunden et al. 2012).

Tier 3 exposure estimates are a hybrid of Tiers 2A and 2B approaches. The SHEDS model from Tier 2A simulated the same individuals and used the same input parameters except that census-tract specific hourly AERs from the LBNL Infiltration model were used instead of the seasonal distributions used in Tier 2A. The input parameters for Tier 2A, 2B, and 3 are shown in Table S-1 through S-3 in supplemental information.

*Data Analysis*

Hourly average Tier 1, 2A, 2B, and 3 exposure estimates were aggregated to 24 hour averages for comparison as follows. To compare the exposure estimates to central monitor data across NJ (i.e. between-monitoring areas), we calculated 24 hour $PM_{2.5}$ exposures averaged across all simulated individuals and all census tracts within 10 km of the nearest central site monitor. We used Tukey's post-hoc tests to compare the seasonal estimates for each tier. For each monitoring area, we calculated Spearman correlation coefficients between monitoring area –specific exposure estimates generated by the different tiers. Ambient exposure/concentration (E/C) ratios, defined as the ratios of Tier 2A, Tier 2B, or Tier 3 over Tier 1, were calculated for each monitoring area. The spatial and temporal variability of residential AERs and the spatial variability of time spent in different microenvironments were also examined to determine their influence on the E/C ratios. All analyses were conducted using SAS 9.2 (SAS Institute Inc. 2011).

To examine spatial and temporal variability within a 10 km monitoring area we generated zip code-specific 24 hour exposure estimates for Elizabeth, NJ, a city with diverse population demographics and housing characteristics. We examined the difference between the zip code-specific Tier 2A, 2B, and 3 daily exposure estimates and the overall mean (across all zip codes) and investigated the influence of AERs and time activity patterns on these values. Figure S-2 presents the locations of these zip codes in Elizabeth, NJ.

## Results

### *Between-monitoring area comparisons*

Exposure estimates are summarized in Table 1. Mean Tier 2A, 2B, and 3 exposure estimates were approximately half of those generated for Tier 1, in other words the exposure-concentration ratios are about 0.5. The tiers follow the same overall geographical pattern, with the highest estimates in Elizabeth and the lowest in Flemington. While the median E/C ratios are similar across tiers the variability in the ratios are different. Tier 2A, 2B, and 3 exposure estimates were also more variable compared to Tier 1 estimates as shown by the larger coefficient of variations (CV). The seasonal summary is provided in Tables S-4 through S-7 in supplemental information. Using Tukey's post-hoc tests we determined that the exposure estimates for all tiers were significantly higher in the summer compared to the other seasons. Exposure estimates were generally lowest in the fall for Tiers 2A (SHEDS) and 3 (Hybrid), and lowest in the winter for Tier 2B (APP).

Daily monitoring area-specific exposure estimates were strongly correlated ($\rho \geq 0.94$) across tiers for any given monitoring area (results not shown). Seasonal distributions of exposure-concentration (E/C) ratios are presented in Figures 1 (Tier 2A), 2 (Tier 2B), and 3 (Tier 3). For Tier 2A (SHEDS) results, E/C ratios were lower, had very low variability within a season, and smaller differences across cities compared to Tiers 2B and 3. However, there was slightly larger variability in Flemington and New Brunswick. E/C ratios and variability were generally larger than for Tiers 2A and 3. Tier 2A and 2B median E/C ratios were highest in the summer. Tier 2A ratios were lowest in the fall, whereas Tier 2B ratios were lowest in the winter. Tier 3 ratios did not appear to follow a consistent seasonal pattern.

Figure 4 presents the seasonal distributions of the AERs used for Tiers 2B and 3 by monitoring area. AERs were highest in Jersey City and lowest in Flemington. Some monitoring areas (i.e. Elizabeth, Jersey City, Millville, and Rahway) had stronger seasonality with higher AERs in the summer with other monitoring areas exhibited only modest seasonal differences. Tier 2A E/C ratios (Figure 1) mirrored the seasonal pattern of the AERs used in the Tier 2A estimates (Table S1). The geographical patterns observed in Tier 2B (APP) and especially 3 (Hybrid) E/C ratios reflected differences in the geographic variability in modeled AER (Figure 4).

Census age distributions and employment status for individuals simulated for Tier 2A and 3 exposure estimates (i.e. SHEDS) are shown in Figure S-3 and Table S-9, respectively. Flemington and New Brunswick have a younger population with a higher proportion of employed residents compared to populations within 10 km of other monitoring areas affecting their activity patterns. Table 2 examines these patterns by summarizing time spent in different microenvironments from SHEDS results for Tiers 2A and 3; seasonal distributions are shown in Table S-8. Individuals in Flemington and New Brunswick spent less time in the home and more time in other indoor microenvironments; time spent in these microenvironments was more variable compared to the other locations. Time spent outdoors was similar across monitoring areas but time spent in vehicle was higher in Flemington than the other monitoring areas. The slightly larger variability in Flemington and New Brunswick observed in Tier 2A exposure estimates is be due to their more variable activity patterns.

Seasonal distributions of time spent in different microenvironments (Table S-8) show that the SHEDS simulated individuals tended to spend less time in the home and more time in other indoor microenvironments during the spring and summer compared to winter and fall. Time spent outdoors and in-vehicle was similar across seasons.

*Variability within 10km of monitoring area: Elizabeth*

As illustrated by the Figures 1-3, a range of exposure estimates across census tracts and 24 hour periods were generated for each monitoring area. To explore this variability further, we examined the geographic variability within 10 km of the Elizabeth monitor using 22 zip codes (Figure S-2). For all tiers and the air exchange rates, the zip code-specific differences follow a geographically similar pattern regardless of season. Generally, the largest range of differences was observed in the summer season. Figures 5 present the summer differences between the 24 hour average zip code-specific exposure estimate and the overall (average across all zip codes) exposure estimates for Tiers 2A, 2B, and 3 as well as the zip code-specific differences in residential air exchange rates. Figures S-4 through S-6 show these differences for the other 3 seasons. Note, if the difference is positive, the exposure estimate for that zip code is greater than the overall average.

For Tier 2A , median differences for all zip codes were generally close to 0 and exhibited a smaller variability compared to the other tiers. This was expected given that AERs did not vary by zip code. We observed higher estimated Tier 2B and 3 exposures for zip codes closest to the center of city (Figure S-2). Differences between zip codes for Tier 2B and 3 followed the same geographical patterns, although the magnitudes of the differences were larger for the Tier 3 estimates (note differences in scale). Similarly, we observed larger within-zip code variability for Tier 3 estimates. The geographic patterns for the air exchange rates corresponded with difference in zip code-specific Tier 2B and 3 exposure estimates.

Results for the zip-code specific time activity patterns are shown in Figure 6. The substantial time-activity variability shown in Figure 6 is the likely driver of the small differences observed in Tier 2A exposure estimates, since the same AER values are used across the study area. Tier 3 differences also appear to be affected by time activity patterns albeit to a lesser extent than from AERsThe amount of time spent per day outdoors (Figure 6c) was similar across zip codes with differences close to 0 for the majority of zip codes. Finally the pattern for time spent in-vehicle (Figure 9d) seemed similar to time spent in other indoor microenvironments.

## Discussion

Since people spend the majority of their time indoors they are only exposed to a fraction (E/C ratio) of ambient $PM_{2.5}$. When central-site monitor concentrations are used as a surrogate for ambient $PM_{2.5}$ exposures, the assumption is that this fraction is the same for all participants. As illustrated by our results this is not necessarily the case. E/C ratios differed seasonally, between monitoring areas, and within a city. Geographic and spatial differences in E/C ratios occur because of variations in AER (which is affected by housing stock, meteorology and poverty status), and time-activity patterns. Assigning exposures based on the central-site monitor data alone could result in non-differential exposure misclassification, potentially biasing the estimates towards the null.

Seasonal variability in E/C ratios was driven by the predetermined seasonal AER distributions and time-activity patterns for Tier 2A, changes in AER and/or $PM_{2.5}$ composition (which affects particle loss indoors) for Tier 2B, and changes in AER and time-activity patterns for Tier 3. The seasonal pattern of Tier 2A E/C ratios mirrored the pattern of the predetermined seasonal AER distributions indicating that the AER parameter choice is a dominant factor. Tier 2B exposure estimates did not exactly follow the seasonal patterns of the estimated AERs. Winter Tier 2B E/C ratios were lower than E/C ratios for other seasons even though AERs were not lowest in the winter. Variation in the PM composition accounted for by the APP model is the likely reason. The APP model accounts for infiltration and physical and chemical removal processes of important $PM_{2.5}$ species. In particular, nitrate concentrations are the highest in the winter, and this $PM_{2.5}$ species tends to evaporate in the indoor environment resulting in lower $PM_{2.5}$ exposure estimates in the winter (Lunden, Revzan et al. 2003). Finally, the seasonal pattern of Tier 3 ratios is similar to the seasonal pattern of AERs with the exception of Flemington. We expect that Flemington deviates from this pattern because of differences in time activity patterns.

Geographical variability in E/C ratios was driven by variations in time activity patterns for Tier 2A, changes in AER and/or $PM_{2.5}$ composition for Tier 2B, and changes in AER and time-activity patterns for Tier 3. For Tier 2A, small differences between monitoring areas was expected, given that all monitoring areas were assigned the same seasonal AER distributions. However Tier 2A E/C ratios were more variable in Flemington and New Brunswick, monitoring areas with larger variations of time activity patterns because they have younger populations. For Tiers 2B and 3, E/C ratios were highest in Jersey City which had the highest estimated AERs, and lowest in Flemington which had the lowest estimated AERs. Tier 2B ratios were the most variable compared to the other Tiers, This was unexpected given the incorporation of spatially and time-resolved (modeled) AERs into SHEDS for Tier 3. In contrast to Tier 3, which only uses the LBNL Infiltration model, Tier 2B also accounts for the effects of particle composition by using the APP model. It also assumes that all time is spent in the home so the estimated AERs are only for the residences. In SHEDS, linear regression algorithms are used for the non-residential microenvironments, as opposed to the mass-balance equation used for residences (Table S-2). Therefore the more spatially and temporally resolved AERs are only applied to the residence and not the other indoor microenvironments.

Similar to between-monitoring area comparisons, the temporal pattern of zip code-specific exposure estimates was driven by the temporal pattern of the AERs (predetermined seasonal distributions and estimated). Only small differences were observed between zip codes for Tier 2A estimates while Tier 2B exposure estimates followed the same spatial patterns as the zip code-specific AERs. Tier 3 exposure estimates seemed to be influenced by AERs and to a lesser extent time-activity patterns.

We also observed higher Tier 2B and 3 exposure estimates in zip codes closest to the city center. For zip code-specific Tier 2B estimates, AER is the only thing that changes across zip codes for the same day because the same PM composition is used throughout Elizabeth at any given time. The meteorology is also the same for all zip codes, therefore variations across zip codes for the estimated AERs (used in Tier 2B and 3) are due to changes is housing stock. It is possible that housing in those zip codes closer to the city center is older.

The SHEDS and LBNL APP and Infiltration models all make certain assumptions in order to generate estimates of exposure. The accuracy of these assumptions has been discussed previously (Sherman and Dickerhoff 1994; Burke, Zufall et al. 2001; Chan, Nazaroff et al. 2005; Hering, Lunden et al. 2007). Briefly, insufficient data is one of the biggest limitations of the SHEDS and the LBNL APP and Infiltration models. SHEDS uses CHAD to simulate time spent in a variety of microenvironments. Uncertainties in subject estimated exposure would be substantially reduced if individual level time-activity data were used. For Tier 2A previously reported regional distributions were used for the air exchange rates (Murray and Burmaster

1995). These may not be the most accurate or representative estimates of air exchange rates. The purpose of the LBNL was to develop a better approach to estimates air exchanges. The disadvantage of this new approach is that is the lack of individual level data on AER or AER model inputs (e.g. housing characteristics and window opening) potentially increasing the uncertainties in Tier 2B and 3 exposure estimates. Additionally, geographic variations in particle composition and size distribution are not well documented, and thus this analysis captures only variability due to temporal (and not spatial) changes in PM composition. However, these exposure estimates were calculated for an epidemiology study making use of a case-crossover design, thus we are only concerned with the temporal variability. Finally, for all tiers ambient concentrations were based on the monitoring station closest to their residence. Individuals may spend a significant amount of time at an alternate location (e.g. work or school) outside the 10 km radius of residence so that only using the monitor closest to the residence may result in further biases (Setton, Marshall et al. 2011).

## Conclusions

More refined estimates of exposure can lead to less exposure error and bias in associated health effect estimates than the traditional use of central site $PM_{2.5}$ data alone. Our main objective was to develop, compare, and contrast innovative approaches for $PM_{2.5}$ exposure prediction. High correlations between exposure surrogates suggest that the temporal variability in $PM_{2.5}$ concentrations were adequately captured by the central-site monitor, suggesting that more complex exposure models may not be necessary for epidemiologic study designs such as a time-series or case-crossover, driven by temporal variability. This may not necessarily be true for other pollutants. However, this work suggests that geographic heterogeneity in housing stock

(AER) and demographics (activity patterns) result in substantial heterogeneity in ambient $PM_{2.5}$ exposure both within and between cities that is not captured by the central-site monitor. This could be important for study designs such as a cohort study where spatial variability is important.

The requirements for more complex modeling approaches are more substantial than for Tier 1 (i.e. central site monitoring data). Tier 2A relies on preexisting databases and literature so while the need for additional data is limited, additional computation time is necessary. There may also still be questions as to accuracy of the time-activity databases and parameter inputs. For Tier 2A and 3, housing stock and meteorological information are needed to estimate AERs, and $PM_{2.5}$ speciation data is an input to the APP model. While these data are publicly available, the effort involved in processing these data should not be discounted. However if adequate data exist to support such estimates, exposure model predictions could result in greater risk estimates with narrower confidence intervals and better model fits.

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Supplemental Information

Supplementary information is available at Journal of Exposure Science and Environmental Epidemiology website.

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Table 1. Summary statistics of the 24 hour exposure estimates (μg/$m^3$) generated by the different tiers for each monitoring area

| | Tier 1 (Central Site) | | | Tier 2A (SHEDS) | | | Tier 2B (APP) | | | Tier 3 (Hybrid) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | CV[a] | $5^{th}$,$95^{th}$ | Mean (SD) | CV | $5^{th}$, $95^{th}$ | Mean (SD) | CV | $5^{th}$, $95^{th}$ | Mean (SD) | CV | $5^{th}$, $95^{th}$ |
| Camden | 12.9 (8.3) | 64.2 | 3.6, 28.9 | 6.5 (4.7) | 71.9 | 1.5, 15.7 | 6.8 (4.5) | 65.6 | 2.0, 15.0 | 6.0 (3.9) | 70.8 | 1.6, 14.3 |
| Elizabeth | 14.5 (9.6) | 66.2 | 2.8, 33.8 | 7.2 (5.35) | 74.6 | 1.0, 18.3 | 7.7 (5.4) | 69.7 | 1.6, 18.4 | 7.0 (5.0) | 74.0 | 1.1, 17.7 |
| Flemington | 9.8 (7.6) | 77.4 | 2.1, 24.3 | 5.4 (4.3) | 80.9 | 1.1, 13.9 | 4.8 (4.0) | 82.9 | 1.2, 12.3 | 4.4 (3.3) | 79.8 | 1.0, 11.5 |
| Jersey City | 13.2 (9.3) | 70.7 | 3.0, 32.1 | 7.0 (5.2) | 74.7 | 1.6, 18.0 | 7.2 (5.5) | 75.6 | 1.7, 18.1 | 7.0 (5.0) | 74.6 | 1.7, 18.5 |
| Millville | 11.7 (7.7) | 66.3 | 3.0, 27.7 | 6.2 (5.0) | 81.4 | 1.4, 16.2 | 6.2 (4.4) | 71.9 | 1.6, 15.5 | 5.5 (4.1) | 78.0 | 1.4, 15.1 |
| New Brunswick | 11.1 (7.4) | 66.8 | 3.0, 25.0 | 5.5 (4.2) | 75.3 | 1.2, 13.7 | 5.7 (4.2) | 74.0 | 1.5, 13.7 | 4.8 (3.4) | 71.2 | 1.2, 12.3 |
| Rahway | 13.7 (7.1) | 52.0 | 6.6, 28.6 | 7.1 (4.2) | 58.7 | 1.2, 13.7 | 7.1 (4.2) | 59.5 | 3.1, 16.3 | 6.8 (3.8) | 57.0 | 3.2, 15.5 |

[a] CV is the coefficient of variation which is the standard deviation divided by the mean

Table 2. Summary statistics for percent of time spent per day[a] in the home, in other indoor microenvironments, outdoor, and in-vehicle used in Tier 2A and 3 exposure estimates by monitoring area

| | In Home | | Other Indoor[b] | | Outdoor | | In-vehicle | |
|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | Range | Mean (SD) | Range | Mean (SD) | Range | Mean (SD) | Range |
| Camden | 74.93 (3.75) | 72.01 – 81.53 | 17.15 (3.96) | 10.76 – 20.21 | 8.89 (1.11) | 7.72 – 11.25 | 8.33 (0.83) | 6.88 – 9.10 |
| Elizabeth | 74.72 (3.75) | 71.81 – 81.53 | 17.15 (3.69) | 10.7 – 20.21 | 9.03 (1.11) | 7.85 – 11.94 | 8.33 (0.83) | 6.74 – 9.17 |
| Flemington | 70.76 (5.56) | 66.60 – 80.28 | 19.93 (5.63) | 11.18 – 24.03 | 8.82 (1.39) | 7.57 – 11.60 | 9.10 (1.11) | 7.22 - 10 |
| Jersey City | 75.21 (3.47) | 72.50 – 81.53 | 16.74 (3.68) | 10.63 – 19.58 | 9.03 (1.11) | 7.99 – 11.46 | 8.26 (0.83) | 6.74 – 9.03 |
| Millville | 75.00 (3.47) | 72.36 – 81.32 | 17.22 (4.03) | 10.69 – 20.28 | 9.10 (1.11) | 8.13 – 11.94 | 7.92 (0.56) | 6.81 – 8.47 |
| New Brunswick | 73.19 (4.44) | 69.86 – 81.11 | 18.47 (4.79) | 10.90 – 22.15 | 8.82 (1.25) | 7.71 – 11.94 | 8.33 (0.76) | 6.74 – 9.03 |
| Rahway | 74.38 (3.89) | 71.39 – 81.25 | 17.43 (4.10) | 10.76 – 20.56 | 8.96 (1.18) | 7.85 – 11.53 | 8.40 (0.83) | 6.94 – 9.24 |

[a] assumes 1440 minutes in a day
[b] refers to other indoor microenvironments such as restaurants, offices, etc

Figure 1. Seasonal distributions of 24 hour Tier 2A (SHEDS) exposure-concentration ratio (ratio of Tier 2A estimates over Tier concentrations) by monitoring area (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)

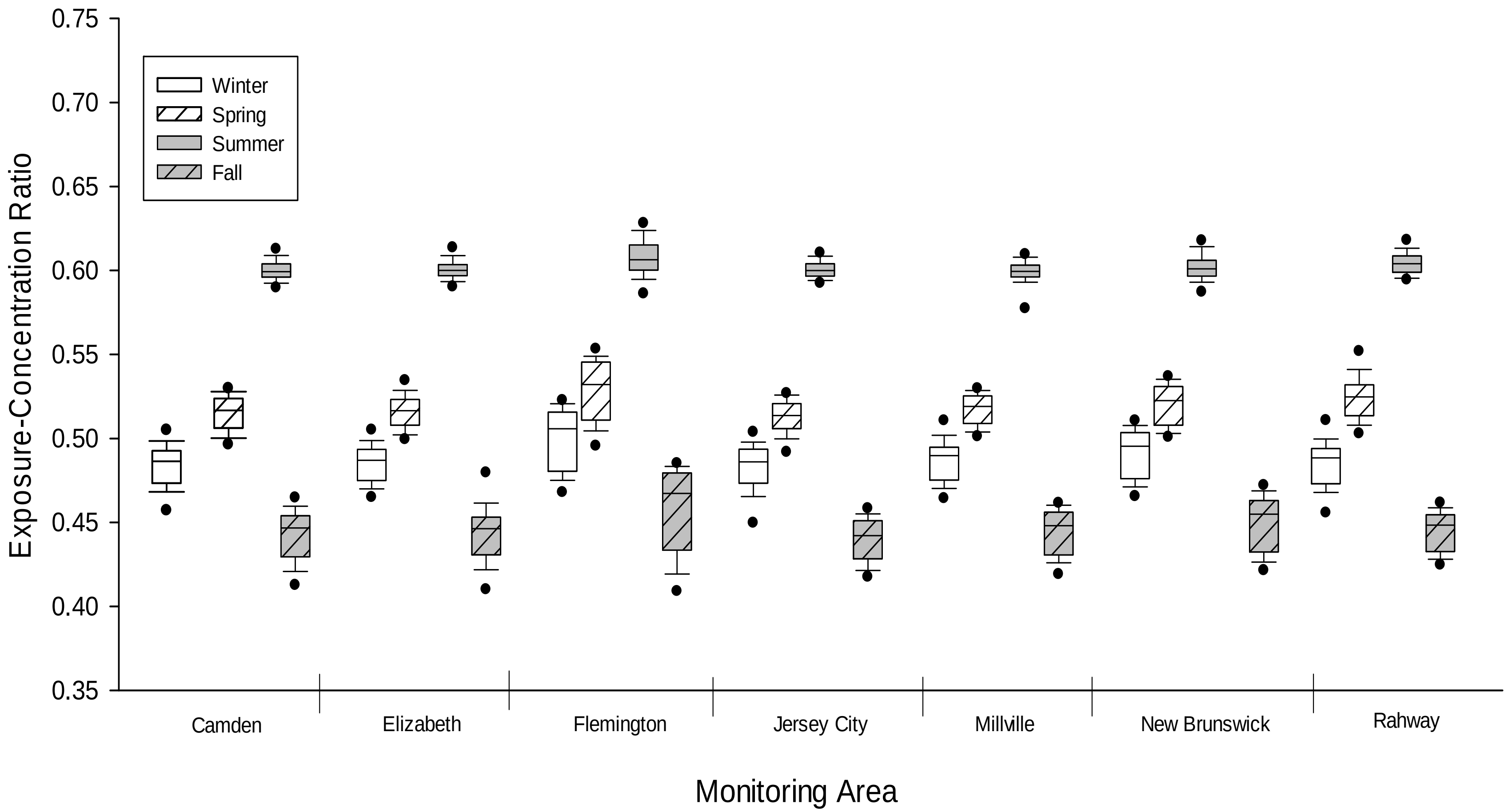
Figure 2. Seasonal distributions of 24 hour Tier 2B (APP) exposure-concentration ratio by monitoring area (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)

Figure 3. Seasonal distributions of 24 hour Tier 3 (Hybrid) exposure-concentration ratio by monitoring area (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)

Figure 4. Seasonal distributions of estimated 24 hour air exchange rates by monitoring area used in Tier 2B (APP) and 3 (Hybrid) exposure estimates (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)

Figure 5. Summer differences between a) Tier 2A (SHEDS model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, b) Tier 2B (LBNL APP and Infiltration model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, c) Tier 3 (Hybrid model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, and d) zip code-specific daily air exchange rates and overall average (all zip codes) air exchange rates used in Tier 2B and 3 exposure estimates in Elizabeth, NJ (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)

Figure 6. Difference between zip code-specific time spend in different microenvironments and overall average (all zip codes) time spent in different microenvironments in Elizabeth, NJ used in Tier 2B and 3 exposure estimates for a) Home, b) Other Indoor, c) Outdoor, and d) In-Vehicle (solid line = median; boxes = $25^{th}$ and $75^{th}$ percentiles; whiskers = $10^{th}$ and $90^{th}$ percentiles; dots = $5^{th}$ and $95^{th}$ percentiles)



0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
Exposure-Concentration Ratio
Winter
Spring
Summer
Fall
Camden
Elizabeth
Flemington
Jersey City
Millville
New Brunswick
Rahway
Monitoring Area


Figure 1.

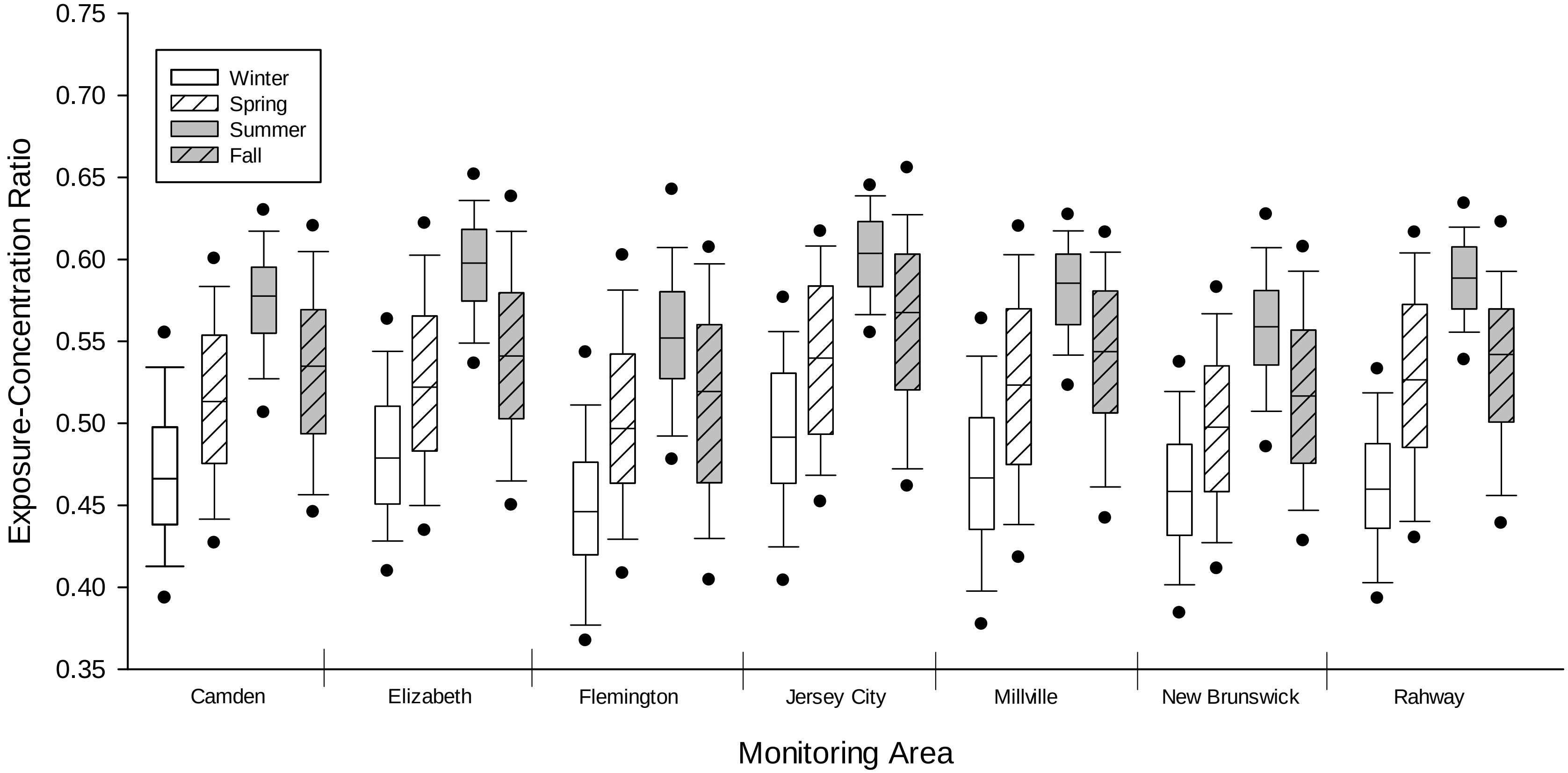

Winter
Spring
Summer
Fall
Exposure-Concentration Ratio
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
Camden
Elizabeth
Flemington
Jersey City
Millville
New Brunswick
Rahway
Monitoring Area

Figure 2.

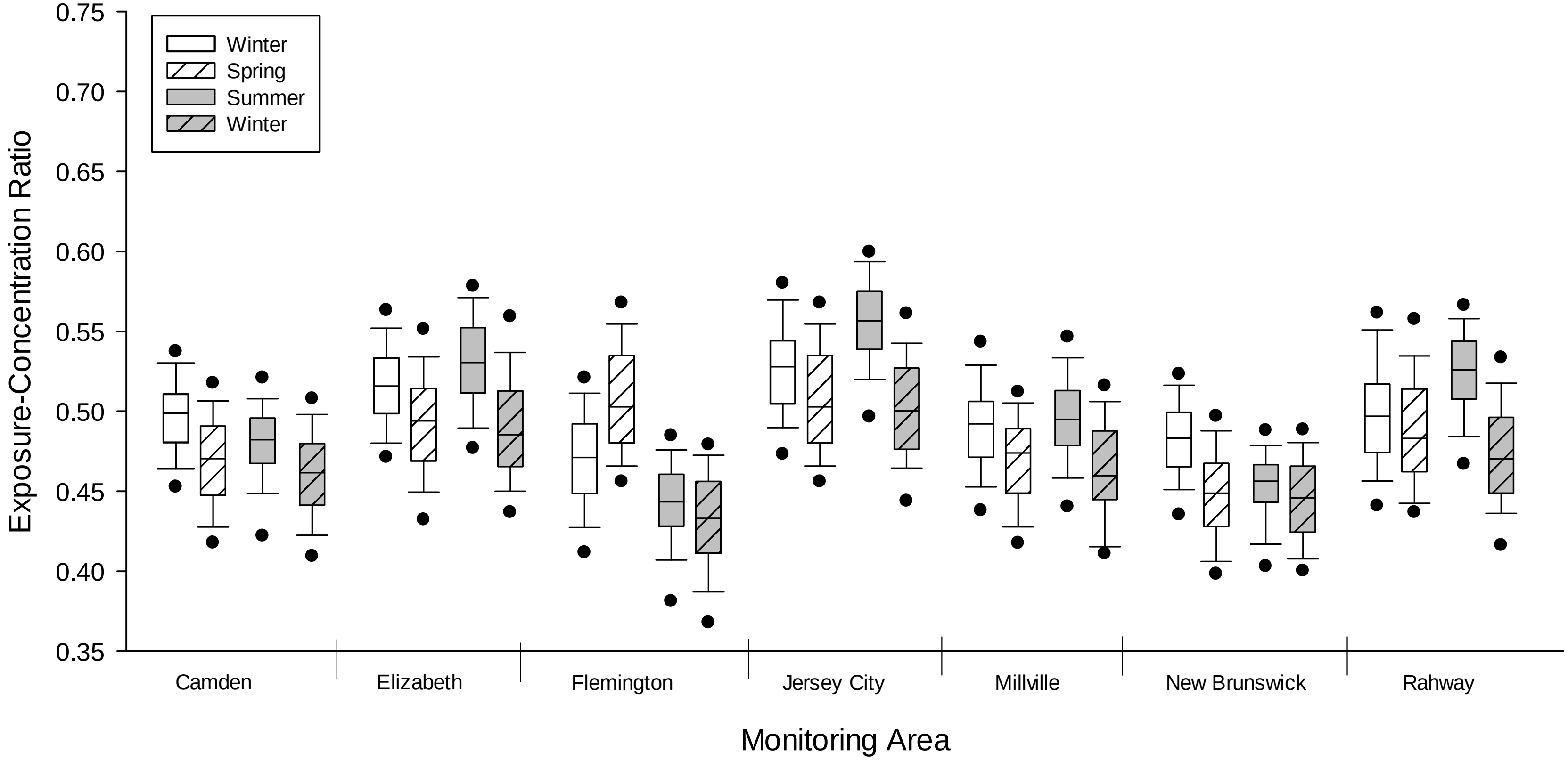

0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
Exposure-Concentration Ratio
Winter
Spring
Summer
Winter
Camden
Elizabeth
Flemington
Jersey City
Millville
New Brunswick
Rahway
Monitoring Area

Figure 3.

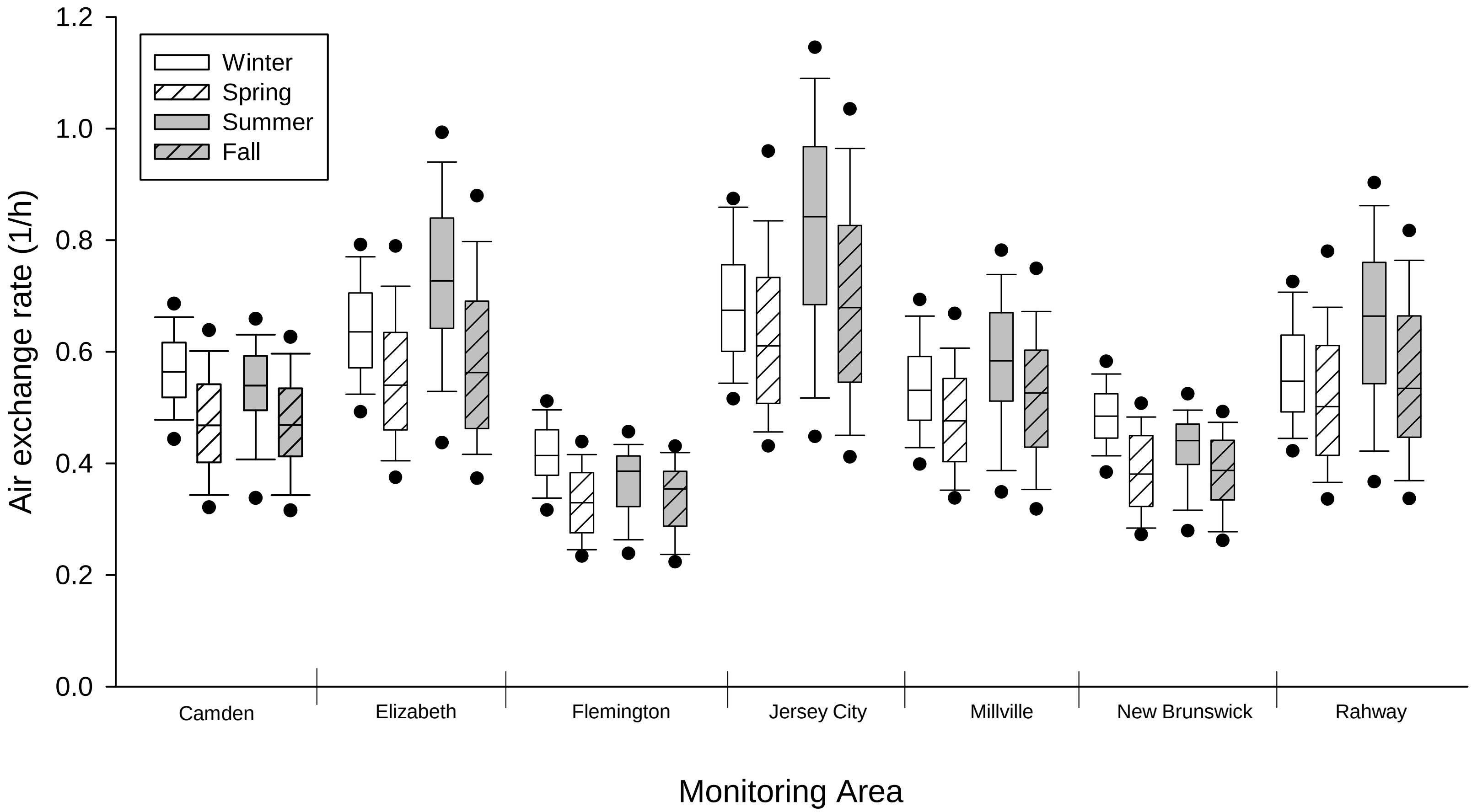
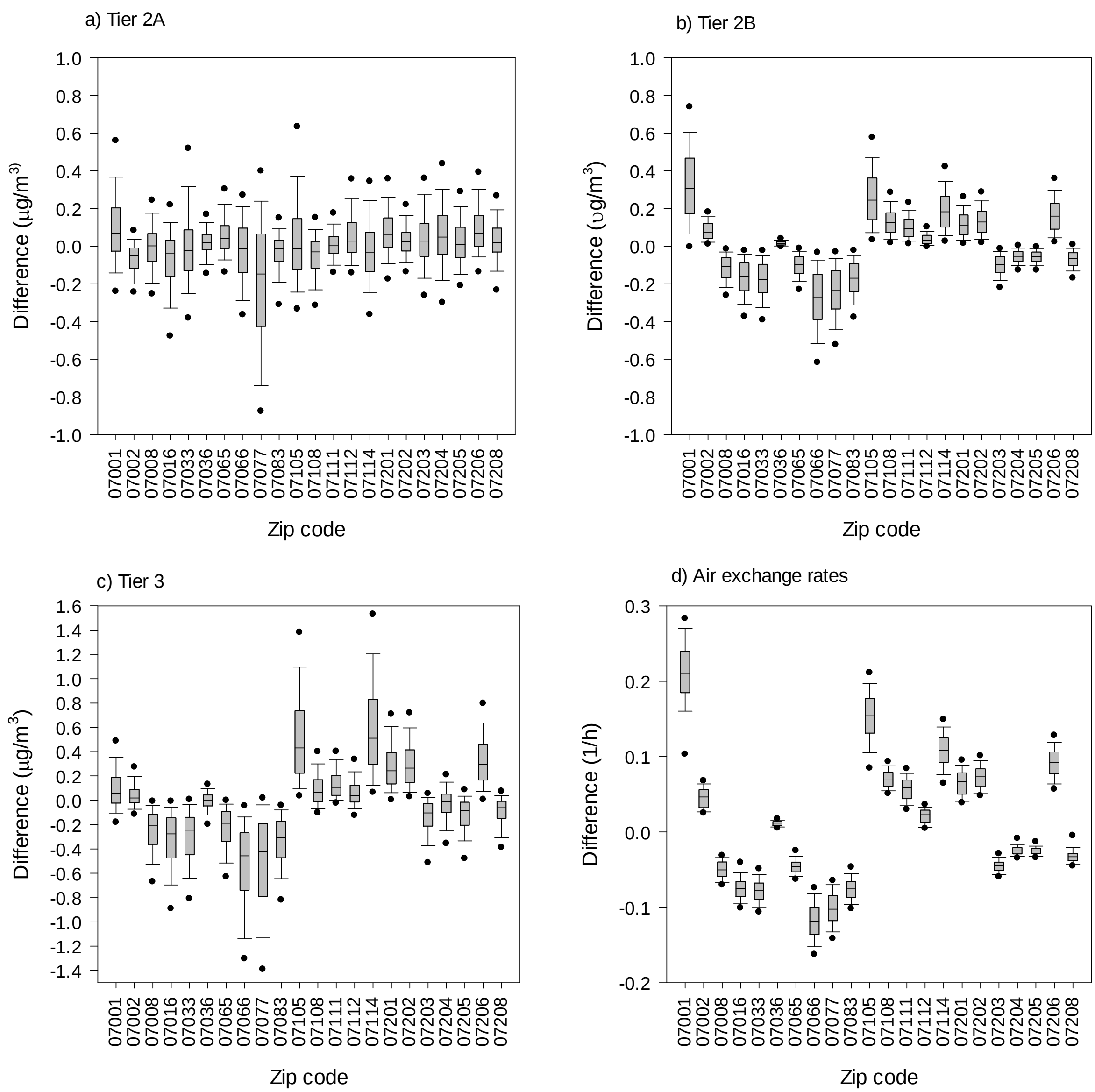
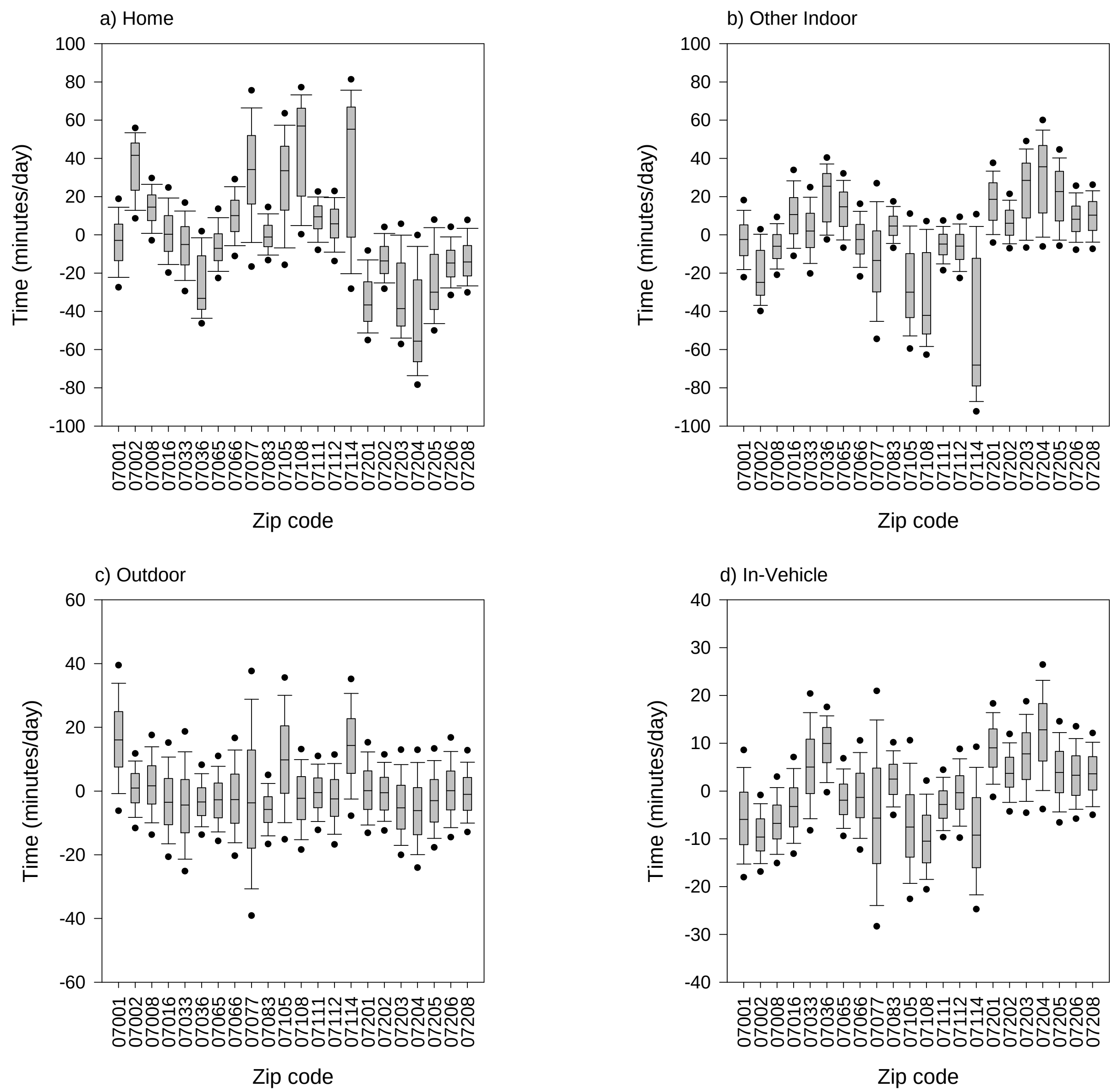

Winter
Spring
Summer
Fall
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Air exchange rate (1/h)
Camden
Elizabeth
Flemington
Jersey City
Millville
New Brunswick
Rahway
Monitoring Area

Figure 4.



a) Tier 2A
b) Tier 2B
c) Tier 3
d) Air exchange rates
Difference (μg/m³)
Difference (υg/m³)
Difference (1/h)
Zip code
07001
07002
07008
07016
07033
07036
07065
07066
07077
07083
07105
07108
07111
07112
07114
07201
07202
07203
07204
07205
07206
07208


Figure 5.



a) Home
b) Other Indoor
c) Outdoor
d) In-Vehicle
Time (minutes/day)
Zip code
07001
07002
07008
07016
07033
07036
07065
07066
07077
07083
07105
07108
07111
07112
07114
07201
07202
07203
07204
07205
07206
07208


Figure 6.

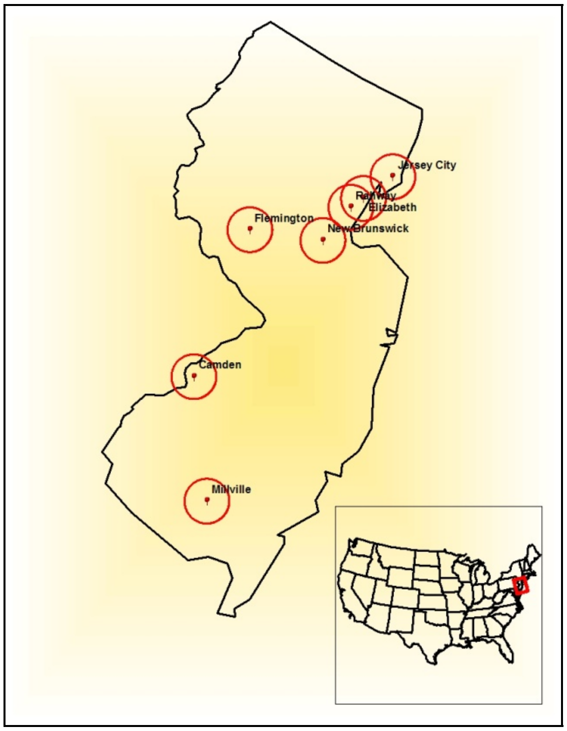



Figure S-1. Map of monitoring stations with 10km buffer

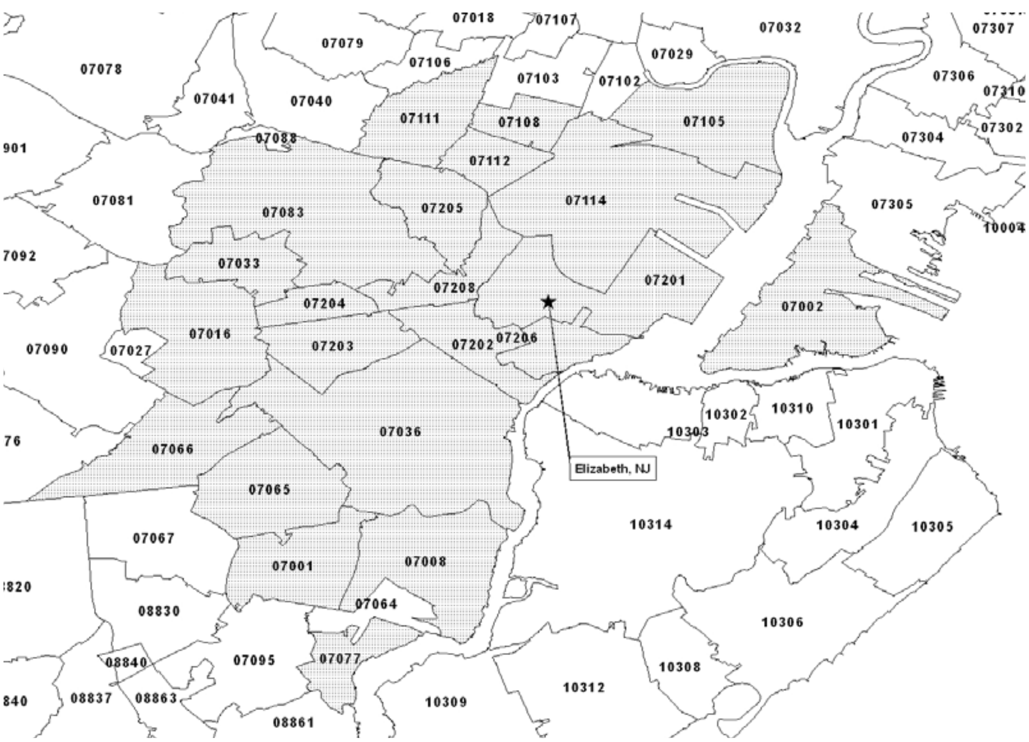



Figure S-2. Map of zip codes in Elizabeth, NJ where exposures were estimated

Table S-1. Input seasonal air exchange (1/h) distributions for the SHEDS model used to generate Tier 2A exposure estimates

| Season | Distribution | GM (GSD) | Min, Max |
|---|---|---|---|
| Winter | lognormal | 0.49 (2.06) | 0.01, 4.8 |
| Spring | lognormal | 0.6 (2.03) | 0.01, 6.6 |
| Summer | lognormal | 1.11 (2.29) | 0.01, 11.8 |
| Fall | lognormal | 0.32 (3.54) | 0.01, 6.4 |

Source: Murray, D. M. and D. E. Burmaster (1995). "Residential air exchange rates in the United States: empirical and estimated parametric distributions by season and climatic region." Risk Analysis 15(4): 459-465.

Table S-2. Input parameters for the SHEDS model used to generate Tier 2A and Tier 3 exposure estimates

| Macroenvironment | Microenvironment | Calculation Method | Parameter Values |
|---|---|---|---|
| Inside-Home[a] | | Mass-Balance | Penetration Factor = N[c][0.91, 0.1], limits [-, 1][d] |
| | | | Decay/Deposition rate ($h^{-1}$) = N[0.79, 0.3], limits [0.1, -] |
| Inside Other[b] | Inside Office (non smoking) | Linear regression | 3.6 + 0.18*Ambient[e] + N[0,2.9], limits [-, -] |
| | Store | | 9 + 0.75*Ambient + N[0,2.1], limits [-, -] |
| | School | | 6.8 * 0.6*Ambient + N[0,5.4], limits [-, -] |
| | Restaurant | | .8 + 1*Ambient + N[0,10], limits [-, -] |
| Outside[b] | | none | Ambient |
| In-vehicle[b] | | Linear regression | 0.7125*Ambient + N[0,6.64], limits [-12, 20] |

[a]Source: Meng, Q. Y., B. J. Turpin, et al. (2005). "Influence of ambient (outdoor) sources on residential indoor and personal $PM_{2.5}$ concentrations: analysis of RIOPA data." Journal of Exposure Analysis and Environmental Epidemiology 15(17-28).

[b]Source: Burke, J.M., and Vendantham (2005).”SHEDS-PM (Stochastic Human Exposure and Dose Simulation for Particulate Matter): User Guide

[c] N indicates a normal distribution

[d] - indicates no limit

[e]units are µg/$m^3$

Table S-3. Mass median diameter and associated deposition ($k_{dep}$) used for particulate sulfate, nitrate, elemental carbon (EC), and organic carbon (OC) used in the LBNL APP model

| Species | Sulfate | Nitrate | EC | | OC | |
|---|---|---|---|---|---|---|
| | | | Mode 1 | Mode 2 | Mode 1 | Mode 2 |
| Mass Median Diameter (µm) | 0.5 | 0.5 | 0.08 | 0.5 | 0.08 | 0.5 |
| $k_{dep}$ ($h^{-1}$) | 0.09 | 0.09 | 0.05 | 0.09 | 0.05 | 0.09 |

Table S-4. Seasonal summary statistics of Tier 1 exposure estimates (μg/m$^3$) by monitoring area

| | Winter | | | Spring | | | Summer | | | Fall | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ |
| Camden | 12.0 (6.4) | 53.3 | 3.9, 25.4 | 11.2 (6.7) | 59.9 | 3.6, 25.6 | 17.3 (10.4) | 59.8 | 4.8, 28.0 | 10.4 (6.8) | 64.9 | 2.5, 24.0 |
| Elizabeth | 13.5 (8.8) | 65.5 | 2.8, 32.5 | 13.2 (8.2) | 62.4 | 3.3, 30.0 | 18.5 (10.8) | 58.3 | 3.8, 38.6 | 12.6 (9.3) | 73.3 | 1.5, 31.4 |
| Flemington | 8.4 (4.9) | 58.0 | 2.2, 16.6 | 7.7 (5.4) | 69.6 | 2.4, 19.8 | 13.7 (9.8) | 71.6 | 2.2, 36.1 | 8.3 (6.2) | 74.9 | 1.7, 21.1 |
| Jersey City | 11.2 (7.6) | 67.5 | 2.5, 26.3 | 11.3 (7.6) | 67.7 | 2.8, 25.9 | 18.1 (11.3) | 62.3 | 5.0, 40.2 | 12.0 (8.5) | 70.6 | 3.1, 30.0 |
| Millville | 9.6 (5.2) | 54.0 | 2.9, 21.1 | 9.8 (6.2) | 63.7 | 3.0. 24.1 | 16.7 (9.8) | 58.4 | 4.9, 32.2 | 10.4 (6.2) | 59.5 | 2.7, 24.6 |
| New Brunswick | 9.7 (5.2) | 53.4 | 2.9, 20.8 | 9.6 (5.6) | 58.4 | 3.2, 21.2 | 15.4 (9.9) | 64.3 | 3.8, 34.8 | 9.4 (6.1) | 64.8 | 2.3, 20.6 |
| Rahway | 11.2 (4.0) | 35.9 | 6.5, 19.4 | 11.6 (5.3) | 45.8 | 6.1, 22.2 | 17.8 (9.0) | 50.8 | 8.2, 36.6 | 13.5 (6.1) | 45.5 | 6.6, 27.1 |

Table S-5. Seasonal summary statistics of Tier 2A exposure estimates (μg/m$^3$) by monitoring area

| | Winter | | | Spring | | | Summer | | | Fall | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ |
| Camden | 5.7 (3.1) | 54.1 | 1.8, 11.9 | 5.6 (3.5) | 63.4 | 1.7, 13.2 | 10.1 (6.1) | 60.6 | 2.6, 22.5 | 4.6 (3.0) | 65.5 | 1.1, 10.8 |
| Elizabeth | 6.5 (4.4) | 68.5 | 1.2, 16.0 | 6.6 (4.4) | 67.1 | 1.5, 16.2 | 10.7 (6.6) | 61.4 | 2.0, 23.4 | 4.9 (3.8) | 76.0 | 0.51, 12.1 |
| Flemington | 4.1 (2.3) | 57.2 | 1.1, 8.4 | 4.0 (2.8) | 70.6 | 1.2, 10.1 | 8.5 (5.8) | 68.6 | 1.5, 20.2 | 4.2 (2.8) | 67.7 | 0.86, 10.0 |
| Jersey City | 5.5 (3.6) | 65.3 | 1.4, 12.7 | 5.8 (3.9) | 67.9 | 1.4, 13.2 | 10.9 (6.7) | 61.9 | 2.8, 23.5 | 5.6 (3.7) | 65.5 | 1.5, 13.3 |
| Millville | 4.7 (2.5) | 53.8 | 1.3, 10.0 | 5.0 (3.2) | 64.3 | 1.5, 12.4 | 10.7 (7.2) | 67.2 | 2.0, 23.3 | 4.4 (2.5) | 57.0 | 1.4, 9.3 |
| New Brunswick | 4.7 (2.6) | 56.4 | 1.2, 10.0 | 4.8 (3.0) | 61.9 | 1.6, 10.9 | 8.8 (5.7) | 65.3 | 1.9, 20.2 | 3.9 (2.6) | 66.0 | 0.92, 8.6 |
| Rahway | 5.3 (1.9) | 35.9 | 2.9, 9.4 | 6.0 (2.8) | 45.6 | 3.2, 11.6 | 10.8 (5.4) | 50.0 | 4.9, 21.3 | 5.8 (2.6) | 45.2 | 2.8, 11.1 |

Table S-6. Seasonal summary statistics of Tier 2B exposure estimates (μg/m$^3$) by monitoring area

| | Winter | | | Spring | | | Summer | | | Fall | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ |
| Camden | 5.7 (2.8) | 48.9 | 2.0, 11.3 | 5.6 (3.4) | 61.8 | 1.9, 12.1 | 10.0 (5.9) | 59.3 | 2.8, 22.4 | 5.9 (3.2) | 53.7 | 1.7, 11.1 |
| Elizabeth | 6.3 (4.0) | 64.0 | 1.6, 15.3 | 6.8 (4.3) | 64.4 | 2.0, 15.7 | 11.1 (6.5) | 58.6 | 2.7, 23.6 | 6.6 (4.7) | 71.1 | 0.95, 15.6 |
| Flemington | 3.6 (2.0) | 57.4 | 1.1, 7.2 | 3.8 (2.7) | 72.5 | 1.1, 10.4 | 7.4 (5.4) | 73.3 | 1.3, 18.4 | 3.9 (2.8) | 70.4 | 1.1, 9.7 |
| Jersey City | 5.3 (3.6) | 67.3 | 1.2, 13.0 | 6.1 (4.4) | 72.5 | 1.5, 16.1 | 11.0 (6.9) | 62.0 | 2.9, 25.2 | 6.4 (4.4) | 67.9 | 1.8, 16.6 |
| Millville | 4.5 (2.4) | 52.9 | 1.4, 9.2 | 5.0 (2.8) | 66.3 | 1.6, 12.5 | 9.9 (5.7) | 57.5 | 2.9, 19.1 | 5.4 (3.2) | 59.8 | 1.6, 12.2 |
| New Brunswick | 4.4 (2.3) | 52.8 | 1.5, 9.2 | 4.6 (2.8) | 60.9 | 1.7, 10.6 | 8.8 (5.8) | 64.8 | 2.1, 20.5 | 4.6 (2.9) | 63.1 | 1.3, 10.4 |
| Rahway | 5.0 (1.9) | 37.9 | 3.0, 8.9 | 5.9 (3.1) | 52.0 | 3.0, 13.4 | 9.8 (5.5) | 55.9 | 4.5, 21.0 | 7.0 (3.1) | 44.6 | 3.7,13.8 |

Table S-7. Seasonal summary statistics of Tier 3 exposure estimates (μg/m$^3$) by monitoring area

| | Winter | | | Spring | | | Summer | | | Fall | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ | Mean (SD) | CV | 5$^{th}$, 95$^{th}$ |
| Camden | 5.9 (3.2) | 56.4 | 1.7, 13.0 | 5.0 (3.1) | 68.2 | 1.6, 12.3 | 8.1 (5.0) | 67.3 | 2.0, 20.0 | 4.9 (3.1) | 66.5 | 1.2, 11.7 |
| Elizabeth | 6.7 (4.4) | 72.9 | 1.3, 17.2 | 6.2 (4.1) | 66.8 | 1.5, 15.7 | 9.6 (6.1) | 64.9 | 1.8, 22.5 | 5.4 (4.0) | 75.3 | 0.64, 13.5 |
| Flemington | 3.8 (2.2) | 56.6 | 1.0, 7.8 | 3.3 (2.4) | 73.1 | 1.0, 9.6 | 6.2 (4.4) | 74.2 | 1.1, 16.3 | 4.0 (2.7) | 67.1 | 0.88, 9.5 |
| Jersey City | 5.8 (3.5) | 69.3 | 1.7, 15.2 | 5.7 (3.9) | 70.2 | 1.5, 13.6 | 10.1 (6.6) | 66.7 | 2.6, 25.2 | 6.5 (4.2) | 65.0 | 1.7, 14.9 |
| Millville | 4.6 (2.4) | 56.2 | 1.3, 10.3 | 4.5 (2.9) | 67.0 | 1.4, 11.5 | 8.8 (6.1) | 70.8 | 2.1, 22.4 | 4.6 (2.6) | 56.9 | 1.6, 10.3 |
| New Brunswick | 4.5 (2.6) | 61.5 | 1.2, 11.6 | 4.1 (2.7) | 66.6 | 1.3, 10.8 | 6.9 (4.6) | 67.8 | 1.4, 16.0 | 3.9 (2.6) | 65.5 | 0.94, 8.7 |
| Rahway | 5.4 (1.8) | 33.5 | 3.1, 9.3 | 5.6 (2.6) | 51.1 | 3.1, 12.3 | 9.5 (5.1) | 53.7 | 4.1, 19.8 | 6.3 (2.9) | 45.4 | 3.2, 12.1 |

Table S-8. Seasonal distributions of time spent per day (minutes) in different microenvironments by monitoring area

| | | Winter | | Spring | | Summer | | Fall | |
|---|---|---|---|---|---|---|---|---|---|
| Monitoring Area | Location | Mean (SD) | Range | Mean (SD) | Range | Mean (SD) | Range | Mean (SD) | Range |
| Camden | Home | 1082 (55) | 1038 – 1174 | 1076 (52) | 1039 – 1164 | 1076 (52) | 1037 – 1164 | 1081 (55) | 1038 – 1175 |
| Elizabeth | | 1080 (56) | 1035 – 1171 | 1073 (52) | 1034 – 1160 | 1073 (52) | 1034 – 1161 | 1078 (55) | 1037 – 1174 |
| Flemington | | 1025 (83) | 962 – 1156 | 1015 (78) | 961 – 1144 | 1014 (78) | 961 – 1143 | 1022 (81) | 957 – 1150 |
| Jersey City | | 1086 (52) | 1045 – 1174 | 1079 (48) | 1044 – 1161 | 1079 (48) | 1044 – 1163 | 1084 (50) | 1045 – 1171 |
| Millville | | 1084 (52) | 1042 – 1169 | 1077 (49) | 1042 – 1159 | 1077 (49) | 1043 – 1159 | 1082 (51) | 1043 – 1171 |
| New Brunswick | | 1058 (67) | 1006 – 1166 | 1050 (63) | 1007 – 1155 | 1050 (63) | 1006 – 1157 | 1056 (65) | 1006 – 1168 |
| Rahway | | 1075 (58) | 1027 – 1168 | 1068 (54) | 1031 – 1158 | 1068 (55) | 1030 – 1159 | 1073 (57) | 1030 – 1169 |
| Camden | Other Indoor | 243 (59) | 155 – 290 | 251 (56) | 156 – 290 | 250 (56) | 157 – 291 | 246 (58) | 155 – 291 |
| Elizabeth | | 243 (59) | 154 – 290 | 250 (56) | 158 – 291 | 250 (55) | 157 – 290 | 245 (58) | 154 – 289 |
| Flemington | | 281 (83) | 161 – 346 | 291 (79) | 162 – 345 | 291 (79) | 162 – 291 | 285 (82) | 162 – 346 |
| Jersey City | | 237 (55) | 154 – 282 | 244 (52) | 158 – 281 | 244 (52) | 157 – 345 | 240 (54) | 153 – 281 |
| Millville | | 243 (59) | 156 – 292 | 251 (56) | 158 – 292 | 250 (56) | 158 – 290 | 245 (58) | 155 – 291 |
| New Brunswick | | 262 (71) | 158 – 319 | 270 (67) | 158 – 318 | 270 (67) | 159 – 319 | 265 (70) | 158 – 316 |
| Rahway | | 247 (61) | 155 – 295 | 254 (58) | 158 – 295 | 254 (58) | 158 – 296 | 249 (60) | 156 – 295 |
| Camden | Outdoors | 129 (16) | 113 – 162 | 127 (16) | 112 – 157 | 127 (16) | 113 – 157 | 128 (16) | 114 – 160 |
| Elizabeth | | 131 (17) | 114 – 172 | 129 (16) | 114 – 160 | 129 (16) | 113 – 161 | 130 (16) | 115 – 160 |
| Flemington | | 129 (20) | 111 – 167 | 126 (21) | 109 – 164 | 126 (21) | 110 – 163 | 127 (20) | 109 – 164 |
| Jersey City | | 131 (16) | 115 – 165 | 130 (16) | 116 – 161 | 130 (16) | 115 – 160 | 131 (16) | 116 – 162 |
| Millville | | 132 (16) | 117 – 172 | 131 (16) | 117 – 161 | 131 (16) | 118 – 160 | 132 (16) | 117 – 161 |
| New Brunswick | | 128 (18) | 112 – 172 | 127 (18) | 111 – 158 | 127 (18) | 111 – 161 | 127 (18) | 111 – 161 |
| Rahway | | 129 (16) | 114 – 166 | 128 (17) | 113 – 158 | 128 (17) | 114 – 161 | 128 (16) | 114 – 158 |
| Camden | In-vehicle | 119 (12) | 99 – 130 | 120 (12) | 99 – 131 | 120 (12) | 99 – 130 | 119 (12) | 99 – 130 |
| Elizabeth | | 119 (12) | 97 – 132 | 121 (12) | 99 – 131 | 120 (12) | 97 – 132 | 119 (12) | 98 – 131 |
| Flemington | | 130 (16) | 104 – 144 | 132 (16) | 105 – 144 | 132 (16) | 104 – 144 | 131 (16) | 104 – 144 |
| Jersey City | | 118 (12) | 99 – 130 | 120 (12) | 99 – 130 | 119 (12) | 98 – 130 | 118 (12) | 97 – 130 |
| Millville | | 114 (8) | 98 – 122 | 115 (8) | 99 – 122 | 115 (8) | 99 – 122 | 114 (8) | 100 – 121 |
| New Brunswick | | 120 (12) | 100 – 130 | 121 (11) | 100 – 130 | 121 (11) | 97 – 130 | 120 (11) | 100 – 130 |
| Rahway | | 121 (13) | 100 - 133 | 122 (12) | 100 – 132 | 122 (12) | 101 – 133 | 121 (13) | 100 – 132 |

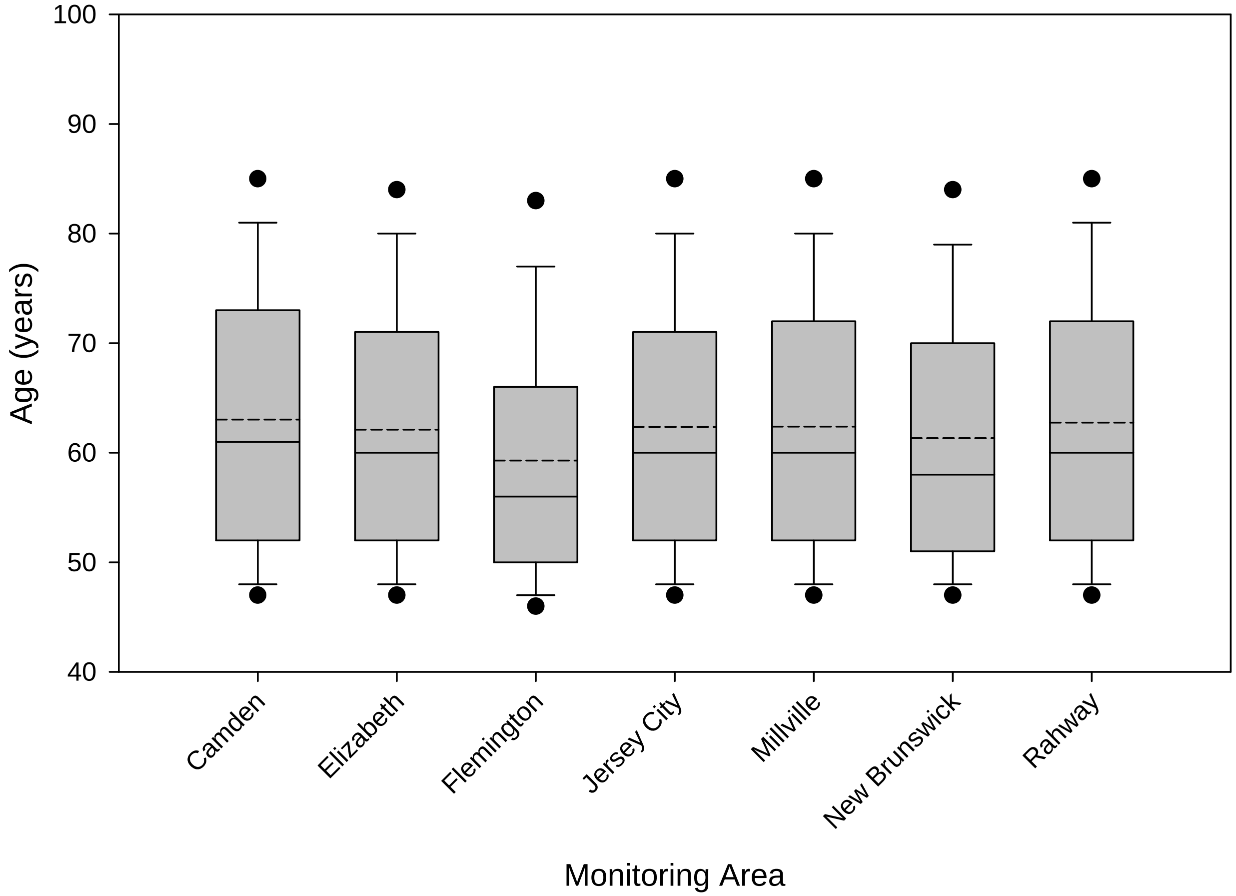



Figure S-3. Distributions of age of simulated individuals used in Tier 2A and 3 exposure estimates by monitoring area (solid line = median; dotted line = mean; boxes = 25$^{th}$ and 75$^{th}$ percentiles whiskers = 10$^{th}$ and 90$^{th}$ percentiles; dots = 5$^{th}$ and 95$^{th}$ percentiles)

Table S-9. Percent (%) of simulated population employed vs. unemployed used in Tier 2A and 3 exposure estimates by monitoring area

| | Employed | Unemployed |
|---|---|---|
| Camden | 39 | 61 |
| Elizabeth | 39 | 61 |
| Flemington | 58 | 42 |
| Jersey City | 37 | 63 |
| Millville | 38 | 62 |
| New Brunswick | 47 | 53 |
| Rahway | 41 | 59 |

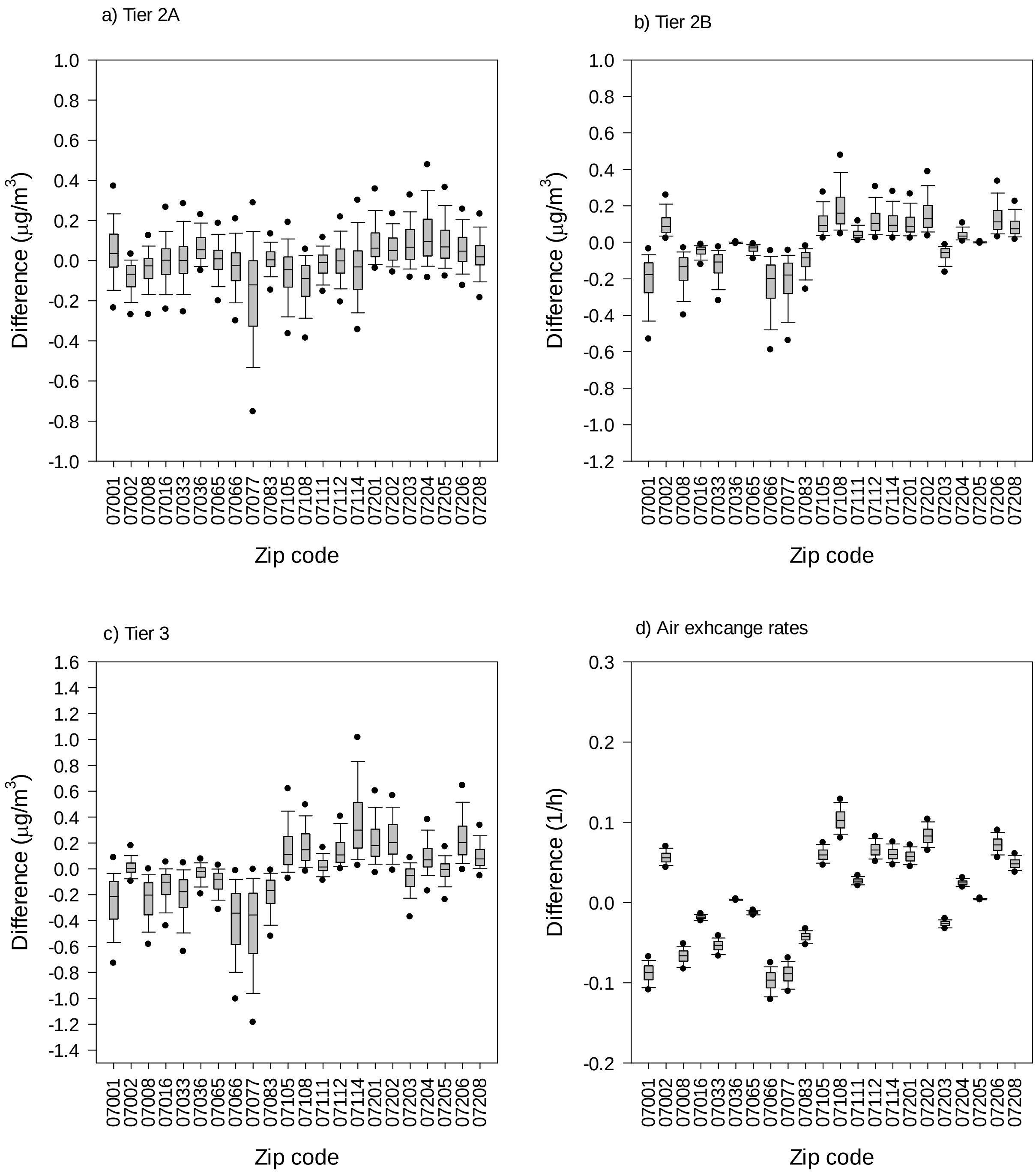



Figure S-4. Winter differences between a) Tier 2A (SHEDS model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, b) Tier 2B (LBNL APP and Infiltration model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, c) Tier 3 (Hybrid model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, and d) zip code-specific daily air exchange rates and overall average (all zip codes) air exchange rates used in Tier 2B and 3 exposure estimates in Elizabeth, NJ for winter (solid line = median; boxes = 25th and 75th percentiles; whiskers = 10th and 90th percentiles; dots = 5th and 95th percentiles)

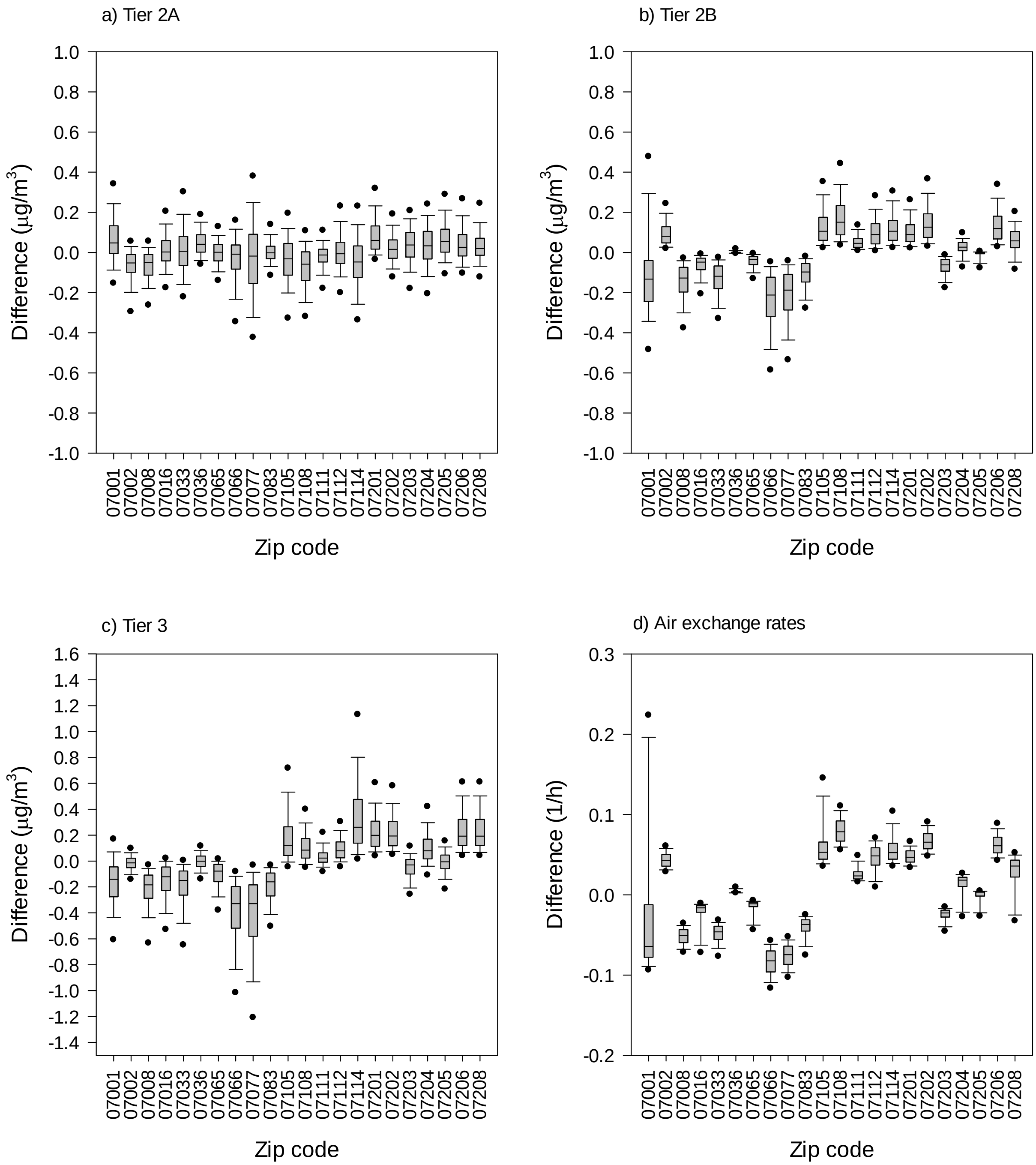



Figure S-5. Spring differences between a) Tier 2A (SHEDS model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, b) Tier 2B (LBNL APP and Infiltration model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, c) Tier 3 (Hybrid model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, and d) zip code-specific daily air exchange rates and overall average (all zip codes) air exchange rates used in Tier 2B and 3 exposure estimates in Elizabeth, NJ (solid line = median; boxes = 25$^{th}$ and 75$^{th}$ percentiles; whiskers = 10$^{th}$ and 90$^{th}$ percentiles; dots = 5$^{th}$ and 95$^{th}$ percentiles)

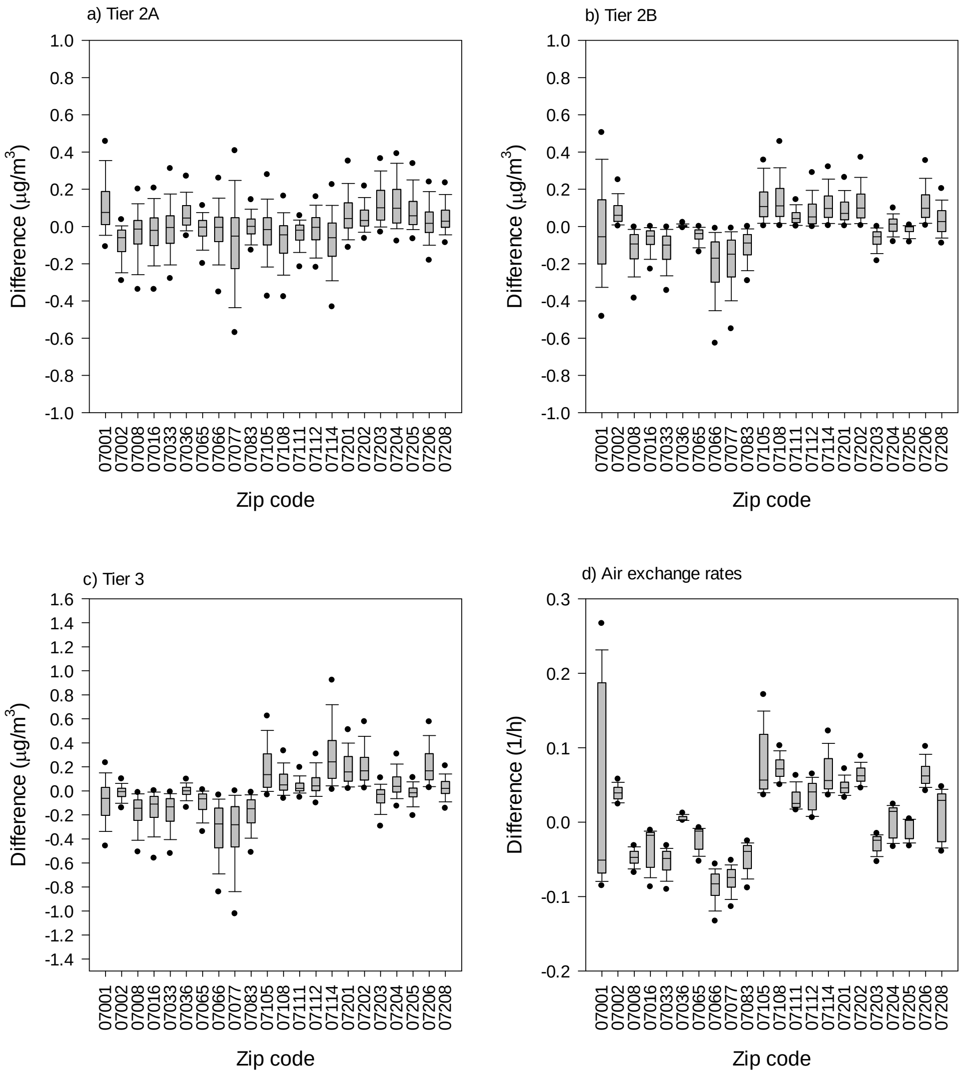



Figure S-6. Fall differences between a) Tier 2A (SHEDS model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, b) Tier 2B (LBNL APP and Infiltration model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, c) Tier 3 (Hybrid model) zip code-specific daily $PM_{2.5}$ exposure estimates and overall average (all zip codes) daily $PM_{2.5}$ exposure estimates, and d) zip code-specific daily air exchange rates and overall average (all zip codes) air exchange rates used in Tier 2B and 3 exposure estimates in Elizabeth, NJ (solid line = median; boxes = 25$^{th}$ and 75$^{th}$ percentiles; whiskers = 10$^{th}$ and 90$^{th}$ percentiles; dots = 5$^{th}$ and 95$^{th}$ percentiles)