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Estimating exposure to fine particulate matter emissions from vehicle traffic: Exposure misclassification and daily activity patterns in a large, sprawling region

Mohammad Tayarani[a], Gregory Rowangould[b,*]

[a] School of Civil & Environmental Engineering, Cornell University, Ithaca, NY, USA
[b] University of Vermont, Department of Civil and Environmental Engineering, Votey Hall, 33 Colchester Ave., Burlington, VT, 05405, USA

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1. ABSTRACT

Vehicle traffic is responsible for a significant portion of toxic air pollution in urban areas that has been linked to a wide range of adverse health outcomes. Most vehicle air quality analyses used for transportation planning and health effect studies estimate exposure from the measured or modeled concentration of an air pollutant at a person's home. This study evaluates exposure to fine particulate matter from vehicle traffic and the magnitude and cause of exposure misclassification that result from not accounting for population mobility during the day in a large, sprawling region. We develop a dynamic exposure model by integrating activity-based travel demand, vehicle emission, and air dispersion models to evaluate the magnitude, components and spatial patterns of vehicle exposure misclassification in the Atlanta, Georgia metropolitan area. Overall, we find that population exposure estimates increase by 51% when population mobility is accounted for. Errors are much larger in suburban and rural areas where exposure is underestimated while exposure may be overestimated near high volume roadways and in the urban core. Exposure while at work and traveling account for much of the error. We find much larger errors than prior studies, all of which have focused on more compact urban regions. Since many people spend a large part of their day away from their homes and vehicle emissions are known to create "hotspots" along roadways, home-based exposure is unlikely to be a robust estimator of a person's actual exposure. Accounting for population mobility in vehicle emission exposure studies may reveal more effective mitigation strategies, important differences in exposure between population groups with different travel patterns, and reduce exposure misclassification in health studies.

1. Introduction

Vehicle traffic is known to cause air pollutant emission hotspots along high volume roads (Karner et al., 2010; Matte et al., 2013; Zhou and Levy, 2007). Exposure to these hotspots or simply being located near a high volume road is associated with a wide range of adverse health outcomes including heart disease, respiratory illness, and cancer (Barone-Adesi et al., 2015; Chen et al., 2015; Foraster et al., 2014; Gan et al., 2010; Hart et al., 2014; McConnell et al., 2016; Pennington et al., 2018; Samoli et al., 2016; Mette et al., 2017; Jennifer et al., 2016). Many studies also find that disadvantaged populations are more likely to live closer to higher volume roadways where the concentration of vehicle emissions is expected to be higher (Cesaroni et al., 2010; Gunier et al., 2003; Houston et al., 2004; Rowangould, 2013; Tian et al., 2013) or where emissions have been shown to be greater (Apelberg et al., 2005; Buzzelli and Jerrett, 2007; Chakraborty, 2009; Havard et al., 2009; Kingham et al., 2007), raising environmental justice concerns. This has led to the development of methods for generating high resolution maps of vehicle emission concentrations across urban areas for use in exposure, health impact, and regional transportation planning studies (Beckx et al., 2009a; Cook et al., 2008; Hatzopoulou and Miller, 2010; Lefebvre et al., 2011; Poorfakhraei et al., 2017; Tayarani et al., 2016; Vallamsundar et al., 2016). However, even in studies where vehicle emissions are mapped at high spatial and temporal resolution, exposure is often estimated based on the residential address of individuals rather than where they spend time (Nyhan et al., 2016). When considering exposure to vehicle emission hotspots, failing to account for the daily mobility patterns of a population is likely to result in significant exposure estimation errors.

Several recent studies using cell phone location data (Dewulf et al., 2016; Nyhan et al., 2016; Picornell et al., 2019; Yu et al., 2018) or data from surveys (Park and Kwan, 2017; Shafran-Nathan et al., 2017) have

* Corresponding author.
E-mail address: gregory.rowangould@uvm.edu (G. Rowangould).

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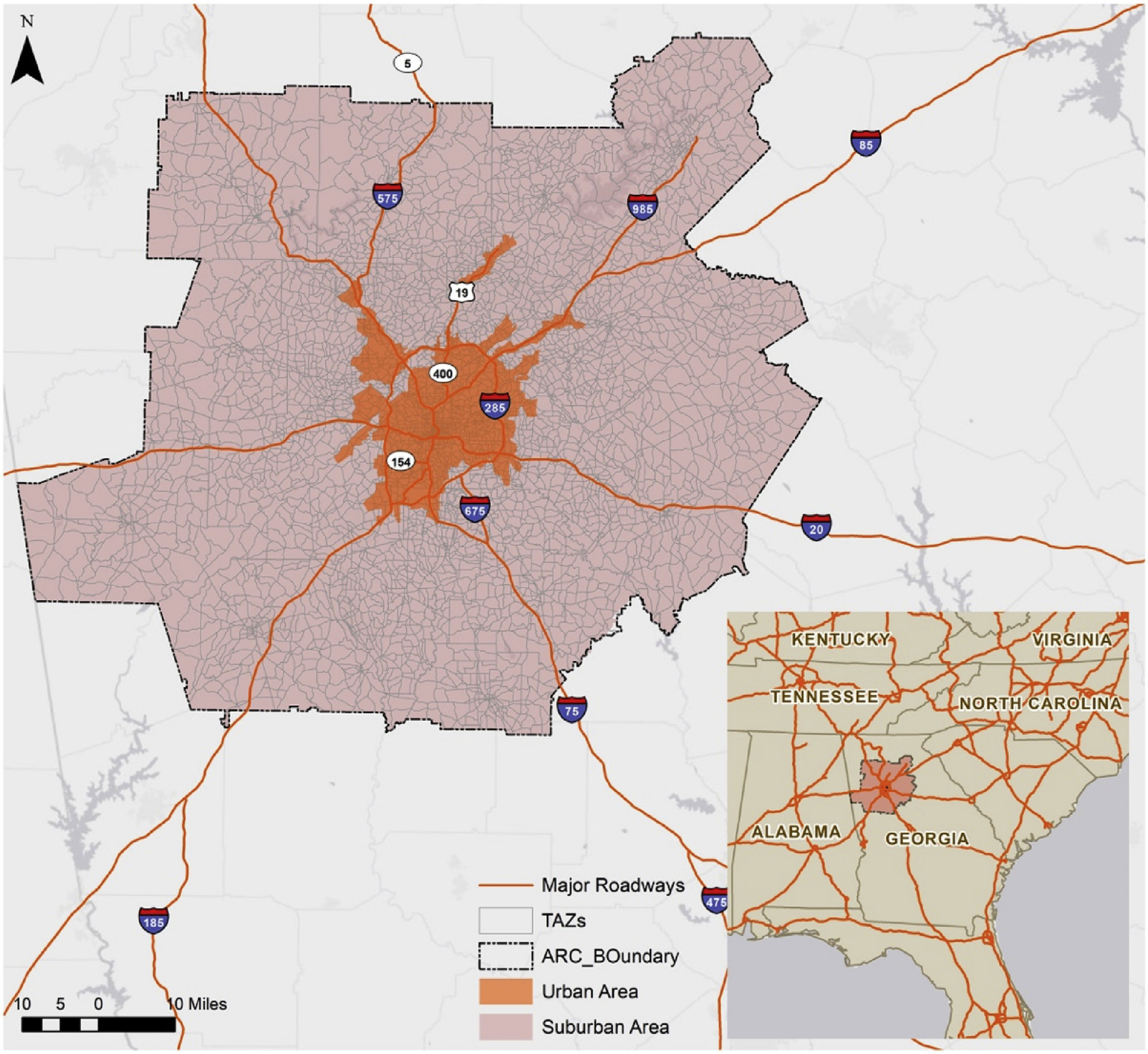

Fig. 1. Study area.

evaluated errors caused by failing to account for population mobility in air pollution exposure studies. These studies consider different air pollutants from mobile and stationary sources and use various methods for estimating air pollutant concentrations (e.g., dispersion modeling, land-use regression, or monitoring), but they all produce spatially detailed concentration maps. Each of these prior studies then compared exposure estimated at the residential location of the population with estimates that consider exposure that occurs while spending time in other places throughout the day. Little to no error is generally found between the two approaches when results are aggregated to the regional scale; however, large errors are found in more disaggregate results. Many studies find that exposure is underestimated in areas located outside of the urban core while exposure within the core may be overestimated when population mobility is not considered (Dewulf et al., 2016; Picornell et al., 2019; Yu et al., 2018). Studies using personal exposure monitors have similar findings to modeling studies (de Nazelle et al., 2013; Nieuwenhuijsen et al., 2015; Ouidir et al., 2015). These errors appear to be caused by those living outside of urban cores where air pollutant concentrations are lower, working in more urbanized areas where air pollution concentrations are higher.

Only a few studies have focused on similar errors in exposure estimates to vehicle emissions specifically, which have used similar study methods (Beckx et al., 2009b; Dhondt et al., 2012; Hatzopoulou and Miller, 2010; Shekarrizfard et al., 2016). Integrated modeling chains are used where an activity-based travel demand model provides mobility data to vehicle emission models to estimate emission rates along roadway networks that are then fed into air quality models to estimate ambient pollution concentration maps. Mobility data from the activity-based travel demand model is then combined with the pollution concentration maps to estimate exposure to vehicle emissions, accounting for population mobility. Dhondt et al. (2012) found that exposure to elemental carbon, which is primarily associated with vehicle emissions, was underestimated by about seven percent on average in Belgium when population mobility was not considered. Larger errors were noted in disaggregate results, particularly in the population living outside of more urbanized areas. Hatzopoulou and Miller (2010) and Shekarrizfard et al. (2016) found almost no difference in average exposure differences to NO_x in Toronto, Canada and NO_2 in Montreal, Canada, respectively, from vehicle emissions when population mobility was considered (although Shekarrizfard et al. (2016) did find larger differences for those who commute using transit or active travel modes); however, exposure errors were larger when evaluating disaggregated results.

Existing studies demonstrate that failing to account for population mobility results in exposure estimation errors that in aggregate are relatively minor and may be either positive or negative. Disaggregate analysis generally find larger errors and that exposure is underestimated in populations living in areas that are more residential or further from the urban core. Most prior studies have been conducted in Europe and Canada and have considered relatively compact cities or regions. Few studies have evaluated larger, more sprawling, urban areas in the United States where one might expect to find larger differences between exposure estimates made at residential locations and those accounting for population mobility. Longer commutes on more congested highways and greater distance separating residential and urban centers are two factors that are likely to result in larger errors in sprawling regions. Greater levels of sprawl have been associated with more vehicle use and worse air quality (Ewing et al., 2007; Schweitzer and Zhou, 2010; Stone et al., 2007; TRB, 2009).

Our study evaluates the magnitude and spatial patterns of errors caused by estimating exposure to vehicle emissions at residential locations in the Atlanta, Georgia metropolitan area which has been ranked as the most sprawling large metropolitan area (and second most sprawling area of any size) in the United States (Ewing and Hamid, 2014). We evaluate exposure to primary $PM_{2.5}$ emissions from vehicle exhaust, tire and brake wear at residential locations and activity locations across the entire 8376 square mile Atlanta, Georgia metropolitan area which is home to over 4.6 million people. We obtain mobility data from an activity based travel demand model and estimate ambient concentrations of $PM_{2.5}$ from vehicle traffic using an integrated modeling chain. We also evaluate how different activities for people living in different parts of the metropolitan area contribute to daily exposure levels, revealing how factors affecting exposure vary spatially within a region. Overall, our study demonstrates that exposure estimation errors are likely to be larger in more sprawling regions, which are very common in the United States (Ewing and Hamid, 2014).

2. Methods

We evaluated exposure estimation errors for the population residing in the Atlanta, Georgia metropolitan area (Fig. 1) using an integrated chain of travel demand, vehicle emission and air quality models. The Atlanta metropolitan area is a large and sprawling region located in the southeastern United States covering 8376 mi^2 with a 2017 population of 5.9 million people making it the 9 most populated metropolitan area in the United States. An important factor in choosing the Atlanta metropolitan area for our study in addition to its sprawling land-use pattern is the availability of population mobility data from the Atlanta Regional Commission's (ARC) activity-based travel demand model (ABM). The ABM provided us with the estimated positions and movements for each individual residing in the Atlanta region for a typical mid-week day during 2017. We used these mobility data to estimate the rate of $PM_{2.5}$ emissions from vehicle trips, the ambient concentration of $PM_{2.5}$ from these vehicle trips, and individual $PM_{2.5}$ exposures at household locations and other places visited during the day. We then compared exposure estimates from household locations with those that integrate exposure over the course of the day as individuals move from location to location.

2.1. Activity based travel demand modeling

Population mobility and traffic data were modeled using two models maintained by the ARC. The Coordinated Travel-Regional Activity Modeling Platform (CT-RAMP) was used to estimate the number and types of trips made by individuals and households while a user equilibrium traffic assignment modeled implemented in Citilabs' Cube Voyager software was used to assign these trips to the transportation network.

For this study, we obtained disaggregate CT-RAMP model outputs from modeling completed by ARC as part of its regional transportation planning process. The modeling output we received was generated from a model scenario designed by ARC to represent baseline conditions for the year 2017. The CT-RAMP output contained records for each trip made by each person (modeling agent) for a typical mid-week day. The output included 19.8 million trip records that contained information about each trip's origin and destination, purpose, departure time and travel mode along with socioeconomic information about the trip maker and their household. We used these data with ARC's traffic assignment model to determine the path and duration of each trip over the transportation network.

The CT-RAMP model is one of several ABM frameworks that are currently used by MPOs in the United States (Vovsha et al., 2011). ABMs differ from traditional aggregate "4-step" travel demand models in three important ways. First, tours are modeled rather than trips. A tour is a series of linked trips that begin and eventually end at a person's residence. Modeling tours ensures consistency in space and time. For example, an individual cannot start the next trip until they have completed the first trip, and they must start each trip form the destination of the previous trip. Second, ABMs derive travel demand from each individual's needs and desires to participate in various activities that are spatially distributed. In an ABM each individual is assigned a daily activity schedule and must seek out a way to complete each activity under a time constraint. ABMs may also consider household vehicle availability and joint tours (e.g., two or more family members sharing a ride to reach similar destinations). In a 4-step model, household trip generation rates and distribution patterns are estimated using aggregate functions fitted to regional observations. Lastly, ABMs are typically designed as agent-based microsimulation models. Each individual and household is represented by an individual agent that makes a series of discrete choices. Information about each agent and their household is retained throughout the modeling process, making it possible to track each agent as they move from place to place in the model. A 4-step model contains a series of aggregate functions that operate at a zonal level rather than at the individual or household level, which means that the zonal household attributes that were used to determine travel demand in earlier stages of the model are not retained in later stages when traffic patterns are determined. While ABMs are developed primarily to understand travel demand and traffic patterns, the disaggregate population mobility estimates that are produced by these models can be used for many other purposes, including modeling exposure to air pollution.

ARC's implementation of CT-RAMP simulates the travel decisions of each person in the Atlanta metropolitan area for a typical weekday (Parsons Brinckerhoff, 2015). The population within the model is divided into 5873 traffic analysis zones (TAZs) which are similar in size and geography to U.S. census block groups (Table A.1). The TAZs are used to identify the location of households and activities. The first step in the modeling process is creating a synthetic population for the study area by expanding the 2007–2011 5-Year Public Use Microdata Sample (PUMS) data from the U.S. Census Bureau. The sample data are expanded so that the distribution of households and population attributes in the synthetic population align with control totals. An overall population control is set for the region. At the household level, controls include the number of households in each TAZ by income, size and number of workers. At the individual level, controls include persons by age (by county) and occupation (by TAZ).

ARC's CT-RAMP model considers three general types of activities: mandatory, maintenance, and discretionary. Mandatory activities, such as work and school, must be made and generally have tight time constraints while other activities have greater flexibility as to when and where they may occur. The synthetic population is classified into eight person-type groups, including full-time worker, part-time worker, college student, non-working adult, non-working senior, driving age student, non-driving student, and pre-school, that can participate in ten types of activities, including work, grade school, high school, university, escorting, shopping, eat out, other maintenance, social, and other discretionary activities. Decisions about mandatory activities are modeled first which then constrain later decisions about maintenance and discretionary activities. The model also considers household

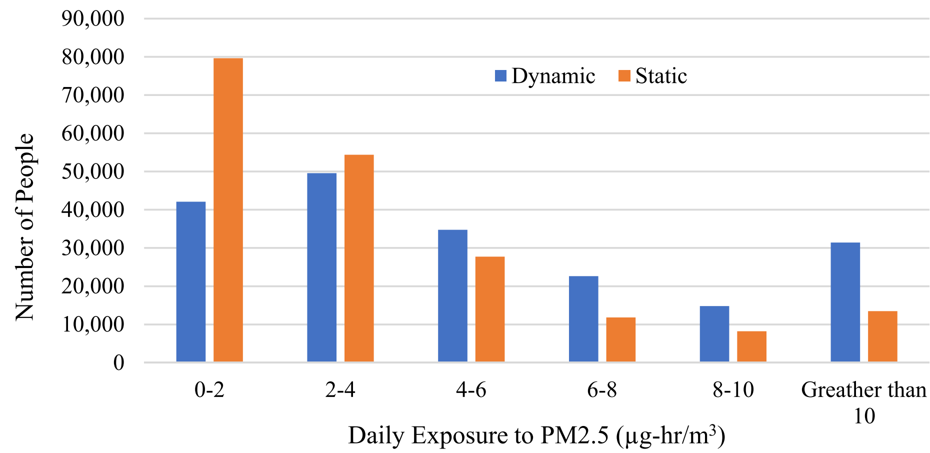

Fig. 2. Comparison of static and dynamic annual 24-h mean $PM_{2.5}$ exposure estimates.

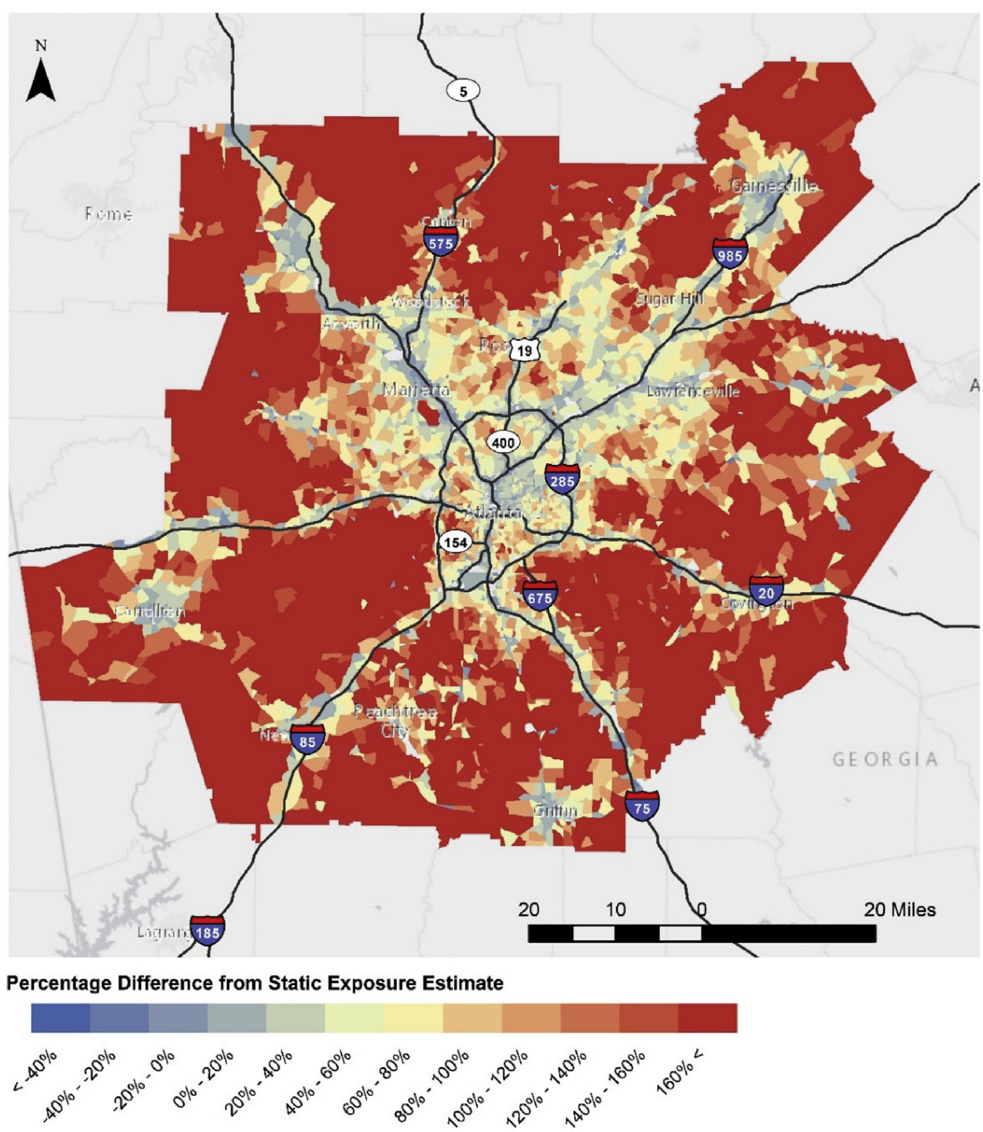

Fig. 3. Estimated error in annual 24-h mean static exposure estimates at individual TAZs.

interactions that may lead to joint tours such as when household members must share a vehicle. The model operates at a half hour time step, estimating the location (TAZ) of each individual and the activity they are engaging in at each time period. Trips are assigned to the transportation network with a user equilibrium traffic assignment model.

ARC's CT-RAMP and traffic assignment models were calibrated with data from ARC's 2011 Regional Travel Survey (WSP and Atkins, 2017;

Table 1
Annual 24-h mean PM2.5 concentrations and activity durations.

	Place	Type of Activity				
		Home	Work	Travel	Education	Other
Annual 24-h Mean Concentration (μg/m^3)	Urban	0.39	0.57	0.85	0.40	0.54
	Suburban	0.11	0.30	0.43	0.20	0.23
Time (Hours)	Urban	15.72	4.43	1.42	0.78	1.67
	Suburban	15.35	4.38	1.55	1.04	1.69

NuStats, 2011). The survey employed a geographically and demographically stratified sampling scheme to ensure that data was collected from a diverse range of households within each of the 20 counties that make up the Atlanta metropolitan region. Each survey respondent was asked to complete a 24-h travel diary and provide a range of socioeconomic information about themselves and their household. The survey had a 6% response rate which compares to similar travel diary surveys conducted in other regions. Data was collected on 26,203 individual tours and 1199 joint tours made by 10,278 households and 25,810 individuals. Additional data from the 2010 U.S. Census and a 2011 on-board transit survey were also used to calibrate the model.

The model was validated against a combination of the survey data and traffic observations. The modeling framework, calibration and validation procedures were also peer reviewed by a panel of modeling experts organized by the U.S. Department of Transportation Federal Highway Administration (Lemp, 2017). The model calibration report indicates that the model can replicate base year county to county trip frequencies and trip distances by trip purpose, traffic volumes, and regional vehicle miles traveled (VMT) estimates reasonably well (WSP and Atkins, 2017). A comparison of modeled work trip flows between counties with survey data shows less than a 1% difference for most county pairs and an overall 0.996 correlation coefficient. Estimated traffic flows deviated less than 5% from the observed traffic flows across 20 screens lines. Modeled VMT for the study area was 17% less than the regional estimate but only 5% less if local roads are excluded from the comparison (WSP and Atkins, 2017).

We use a 5% random sample of the population from each TAZ in our study. Using a sample from the full model output decreases the computational burden of assigning and retaining information from all 19.8 million trips that occurred in the region. The 5% sample includes information on 887,508 trips made by 195,284 individuals in 188,000 households. The difference between the characteristics of individuals, households and their trip attributes in the 5% sample and full synthetic population are not statistically significant (Table A.2). The error introduced by sampling a portion of the trips made by households in each TAZ may introduce some bias when evaluating mobility patterns from individual TAZs, particularly those with very small populations; however, we find clear and consistent spatial patterns in our results that suggest any bias at the TAZ level is likely very small. Since our analysis includes a large population of TAZs we do not expect any significant bias when evaluating regional trends and patters, which is the focus of our study. Note, that the full model output is still used to estimate aggregate traffic volumes and average speeds on the network for our air quality analysis but this process does not require retaining information on individual trips and is therefore less computationally taxing.

We also estimated the duration that individuals spend at different locations engaging in various activities since these data are not included in the CT-RAMP output. The CT-RAMP output contains information about the origin, destination, and departure time of each trip. The duration of each activity was estimated by first calculating the difference between the departure time of the prior trip and the proceeding trip and then subtracting the travel time. We also exclude from our analysis individuals who make transit trips because we did not have access to individual level transit trip routing data.

2.2. Air quality modeling

In this study, we estimate exposure to directly emitted, primary, $PM_{2.5}$ emissions from vehicle exhaust, tire and brake wear. We use the U.S. EPA's Motor Vehicle Emissions Simulator (MOVES2014a) model to estimate vehicle emission rates for each roadway segment. MOVES is tailored with a regional vehicle fleet, travel activity data, fuel, meteorology, and inspection/maintenance program information. We use MOVES to create an emission factor lookup table that tabulates emission rates in 5 mi/h increments for urban restricted access, urban unrestricted access, rural restricted access, and rural unrestricted access roadway types. The lookup table is then used to assign emission factors to each roadway segment and calculate emission rates.

We use U.S. EPA's AERMOD dispersion model to estimate the ambient concentration of $PM_{2.5}$ from each roadway source. Each roadway segment is modeled as an area source with length and width corresponding to the roadway segment, and with other dispersion parameters set following U.S. EPA particulate matter hotspot modeling guidance for transportation projects (U.S. Environmental Protection Agency, 2015). Prior studies have shown that AERMOD is able to predict the concentration of vehicle emissions along roadways (Heist et al., 2013), including $PM_{2.5}$ emissions (Chen et al., 2009), reasonably well. We use 2 days of hourly meteorological observations from each month of a five year meteorology data set recorded at 7 monitoring location(s) to estimate annual average hourly concentrations of $PM_{2.5}$ from vehicle emissions during 2017. Concentrations are modeled for a regular grid of point receptors with 100 m spacing covering the entire Atlanta metropolitan area. We apply AERMOD using a unique rastering

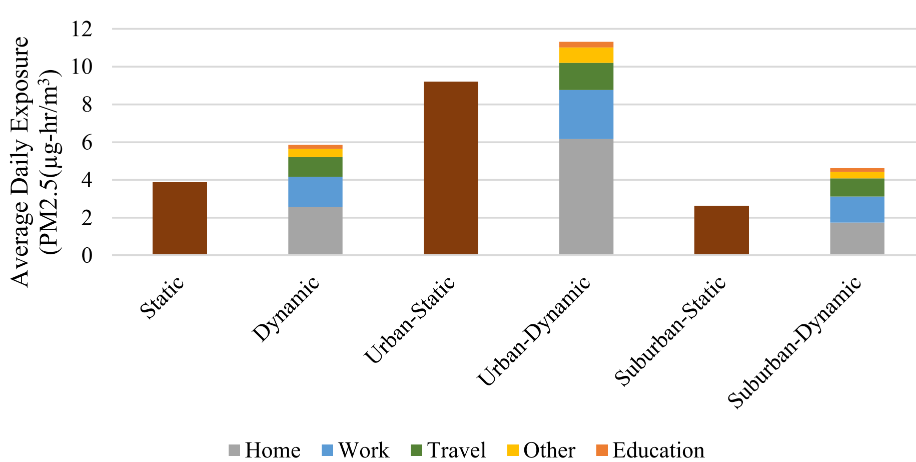

Fig. 4. Annual 24-h mean exposure to $PM_{2.5}$ for different activities.

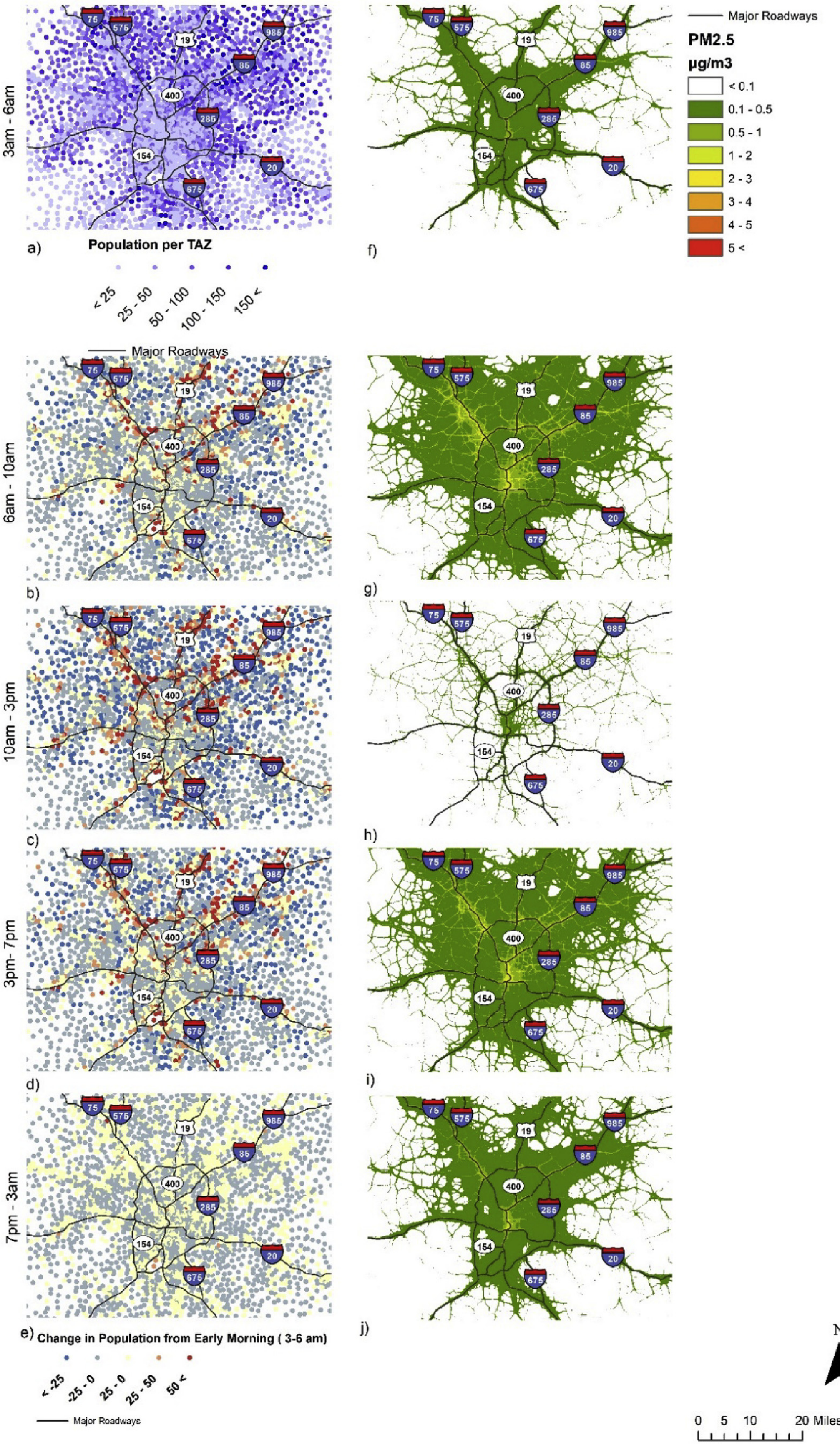

Fig. 5. Population Distribution (a); Population Change from Early Morning (b–e) at TAZ Level; average $PM_{2.5}$ concentration (f–j) at Different Time of Day.

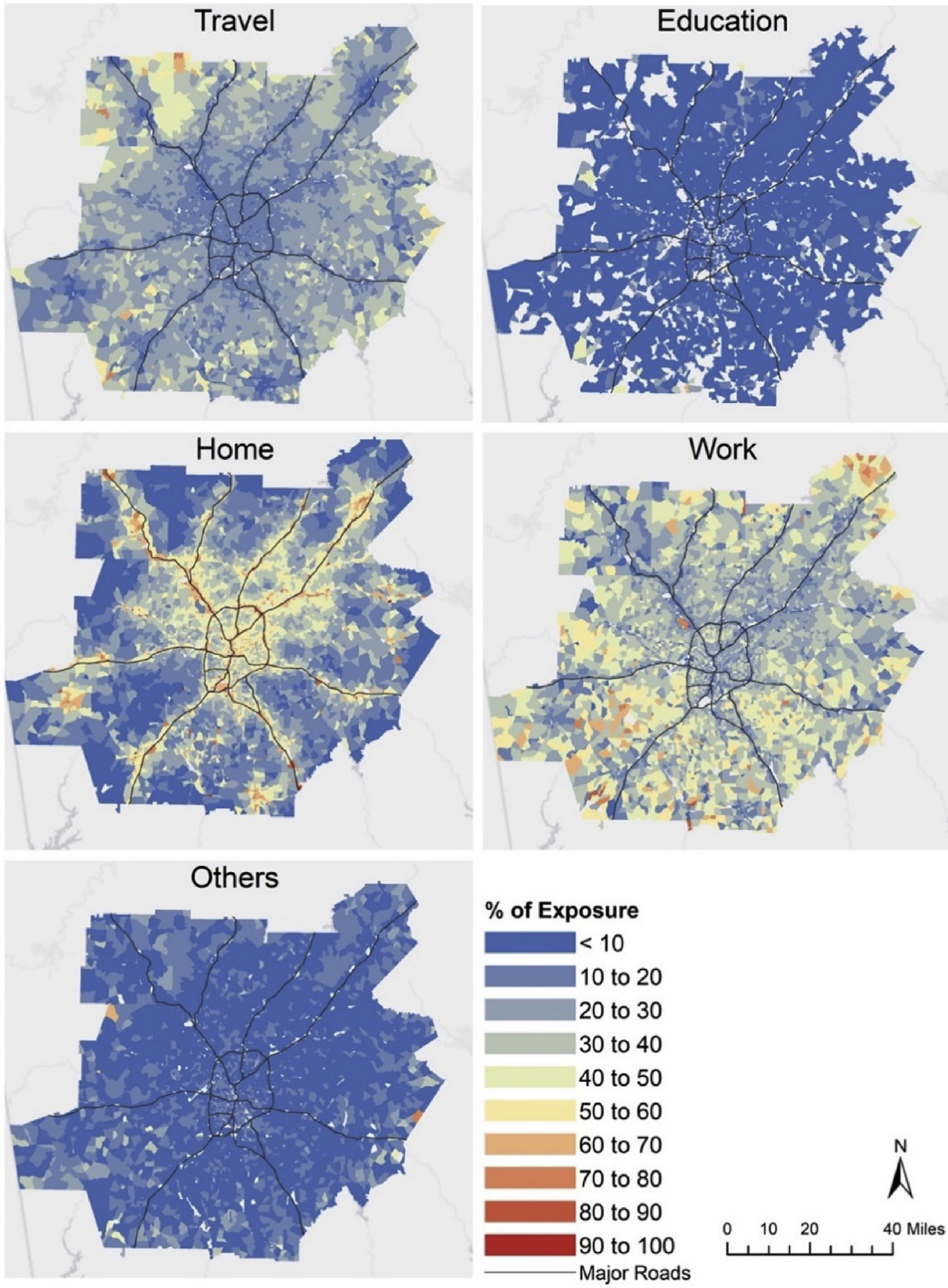

Fig. 6. Share of daily exposure to vehicle emissions from different activities at the TAZ level.

approach that breaks up the modeling domain into small pieces that can be modeled in parallel, significantly reducing modeling run time (Rowangould, 2015). We then create a 20 m resolution raster from the point concentration estimates using empirical Bayesian kriging for each of the 5 time periods considered by the ARC-ABM (Figure A1).

2.3. Static exposure method

We estimate each individual's static exposure based on the daily average $PM_{2.5}$ concentration at their home. The ARC-ABM trip diary provides the TAZ where each individual's home is located. We then calculate the annual average area weighted daily $PM_{2.5}$ concentration within each TAZ from our concentration rasters.

2.4. Dynamic exposure method

We estimate each individual's dynamic exposure by accumulating their exposure over the course of the day as they move through the transportation network and spend time in various places. Annual average area weighted concentrations of $PM_{2.5}$ are estimated for each TAZ for each of the 5 time periods considered by the ARC-ABM. We then estimate each individual's exposure by tracking the amount of time and the time of day that they spend in each TAZ engaging in various activities. We also track exposure that occurs while traveling on the transportation network between TAZs. We estimate the average $PM_{2.5}$ concertation for travel on each network link as the average concentration of the $PM_{2.5}$ raster cells that the link passes through. We then estimate each individual's exposure during travel between each activity using the travel time weighted average concentration of the links that make up the route. Each individual's annual average 24-h exposure is then calculated following Equation (1).

$$E_i = \sum_{t=1}^{5} \left[\sum_{j=1}^{J} (C_{jt} * T_{jt}) + \sum_{k=1}^{K} (C_{kt} * TT_{kt}) \right] \tag{1}$$

where;

E_i is the annual average 24-h exposure to $PM_{2.5}$ for individual i in units of μg-hr/m^3, J is the set of TAZs where individual, i, engaged in activities during time period t, K is the set of network links that individual, i, traveled on to reach each TAZ in J during time period t,

C_{jt} is the annual average area weighted $PM_{2.5}$ concentration in TAZ j for time period t.

T_{jt} is the time in hours that an individual spends in TAZ j during time period t.

C_{kt} is the annual average $PM_{2.5}$ concentration on link k during time period t.

TT_{kt} is travel time on link k during time period t.

Individual exposure estimates were then used to estimate the annual average 24-h mean exposure for the population residing in each TAZ. We also estimated the portion of daily exposure occurring from each activity type and travel for populations living in different locations throughout the study area. Results are also aggregated for urban and suburban residents to understand how exposure misclassification varies between these general populations in addition to our more disaggregate results. Urban areas are defined as the regional core, regional employment corridors, and maturing neighborhoods. Suburban areas include established suburbs, developing suburbs, developing rural areas, and rural areas.

2.5. Results

We find large differences in vehicle emission exposure estimates calculated using dynamic and static exposure methods. The Atlanta metropolitan area annual 24-h population weighted mean dynamic exposure is 1.99 μg-hr/m^3 higher (51% higher) than the static exposure estimate (5.86 μg-hr/m^3 vs 3.87 μg-hr/m^3). The dynamic exposure method estimates nearly 50% fewer people in the lowest exposure category (0-2 μg-hr/m^3) and almost two times the number of people in the highest exposure category (> 10 μg-hr/m^3) shown in Fig. 2.

The size and direction of errors vary extensively across the Atlanta metropolitan area (Fig. 3). The annual average 24-h exposure for populations living near major highways and in the core urban area is overestimated by up to 40% by the static exposure method while exposure is underestimated by up to 160% for populations living in rural areas away from highways. In most suburban areas not directly adjacent to highways, exposure is underestimated by 20%–80% by the static method, while exposure in urban areas away from major roadways is typically overestimated by a smaller amount.

The differences in dynamic and static exposure estimates are caused by people spending some amount of time out of their home in places with different $PM_{2.5}$ concentrations. The average person in the Atlanta metropolitan region spends 38% of the day outside of their home where $PM_{2.5}$ concentrations are on average higher (Table 1). For urban residents, 19% of the population, concentrations are on average 2.5%–118% higher at work, school, while driving and in other outside of home locations. Suburban residents, 81% of population, experience average concentrations that are 82%–290% higher when away from their homes. The highest exposures occur while traveling followed by work for both urban and suburban residents (Table 1).

While concentrations at home are on average lower than elsewhere, home is still the place that accounts for the greatest amount of daily exposure to vehicle emissions because of the relatively long amount of time spent at home (Fig. 4). On average, exposure at home accounts for 43% of daily exposure. Work and travel contribute to most of the remaining daily exposure, accounting for 27% and 18% of daily exposure, respectively.

The absolute difference in the annual average 24-h exposure estimated using the dynamic and static methods are similar for urban and suburban residents (2.1 μg-hr/m^3 and. 2.0 μg-hr/m^3, respectively); however, the relative error is much higher for suburban areas (19% for urban residents and 43% for suburban residents) (Fig. 4). Urban residents also receive a larger portion of their daily exposure at home than suburban residents do (54% vs. 39%). Suburban resident's exposure while at work and at home is somewhat similar, contributing to 31% and 39% of daily exposure, respectively. Exposure while traveling is a more significant contributor to daily exposure for suburban residents than urban residents (20% vs. 12%).

The spatial analysis in Fig. 5 shows how the location of the population and the concentrations of $PM_{2.5}$ change over the course of an average weekday in the Atlanta metropolitan area. The concentration maps (Fig. 5 f-j) show relatively high concentrations of $PM_{2.5}$ along the region's major roadways and urban core during the morning and evening commute periods. The population maps show how people in the region generally move from areas away from roadways where they live to activity centers along the region's major highways during the day (red dots in Fig. 5 b-e) and then back home again in the evening. The patterns shown in Fig. 5 reveal how a large portion of the region's population moves into the highest concentration areas during the day for work, school and other activities. An interesting observation is that the suburban and rural population residing in communities north of the urban core, appear to accumulate a significant amount of exposure by spending time during the day away from the urban core but adjacent to some of the region's largest highways.

Within both urban and suburban areas there is significant variation in exposure and the activities contributing to it (Fig. 6). For people who live near major roads, exposure at their home can account for most of their daily vehicle emissions exposure. In the Atlanta metropolitan area 35% of the population lives within 500 m of high-volume roadways (> 25,000 AADT) where exposure at home on average accounts for 56% of daily exposure. In rural, outlying areas, such as the far northwest suburbs, traveling can be the largest source of daily exposure. For 4.4% of the population in the Atlanta region traveling accounts for more than 50% of their daily exposure. In many suburban areas, time spent at work is the largest contributor to daily exposure. For 25.7% of the region's population work is the largest component of daily exposure, on average accounting for 58.1% of daily exposure. While not apparent in the maps shown in Fig. 6, exposure while at school can also be significant. Time spent at school accounts for 32.4% of daily exposure for those who attend school.

2.6. Discussion

We find that a static analysis of exposure to primary $PM_{2.5}$ from vehicle exhaust, tire and brake wear, where all exposure is assumed to occur at home, in the Atlanta metropolitan area is likely to result in large exposure estimation errors. Using data from the Atlanta Regional

Commission's activity-based travel demand model, we demonstrate that accounting for the daily movement of the population and the location of various activities generally results in higher exposure estimates for both urban and suburban residents. We also demonstrate that exposure patterns and errors in exposure estimates vary significantly across the region. A static exposure method overestimates vehicle emissions exposure for populations residing in Atlanta's urban core and along high-volume roads by up to 40% while underestimating exposure in suburban and rural areas by up to 150%. Exposures at home, work or while traveling can account for most of a person's daily exposure depending on where they live and work. The exposure errors we find are generally larger than those reported in prior studies (Beckx et al., 2009b; Dhondt et al., 2012; Hatzopoulou and Miller, 2010; Shekarrizfard et al., 2016) using similar methods in other cities, which is expected given the more sprawling development pattern and greater car dependence of the Atlanta metropolitan area.

The differences in the two exposure estimation methods may have important planning and policy implications. Since a static exposure estimation method generally underestimates exposure, the benefits of a mitigation strategy or study of exposure burden using this approach would underestimate potential benefits or exposure risks. A more accurate estimate of exposure could help justify additional mitigation efforts. Furthermore, with more knowledge of where exposure occurs, mitigation measures can be more targeted. Most exposure occurs at home and at work. While much of the population lives outside of the urban core in our study area, most of the region's population would benefit from vehicle emission reductions in the urban core because many of the region's jobs are there. For example, policies or projects that reduce vehicle use in the urban core such as a congestion charging scheme or improved public transit would reduce exposure for both urban and suburban residents. A static exposure estimation method would not account for the potentially substantial benefits to people living outside the urban core.

Exposure estimates that account for travel and the location of exposure throughout the day can also improve epidemiological studies of vehicle emissions exposure. Most epidemiology studies have based their exposure estimates on exposure occurring at a person's residence (Setton et al., 2011). A few studies have tracked individuals using personal monitors, but these are the exception and often have small sample sizes (Spira-Cohen et al., 2011; Steinle et al., 2013). Modeled or observed activity patterns that allow for a more accurate exposure estimate may reveal new or stronger (or possibly weaker) associations between various health outcomes and vehicle emissions exposure. Since different population groups are also likely to have different housing, employment and travel patterns, a dynamic exposure method could also provide a more accurate means for evaluating disparities in health effects and exposure across race, income and age groups.

There are also limitations to our study that should be understood. Our analysis focuses on primary $PM_{2.5}$ emissions from vehicle exhaust, tire and brake wear. Other pollutants from vehicle traffic may result in different exposure patterns and errors. We did not model transit trips. We model exposure for typical weekday travel patterns, we do not consider weekends and holidays. Exposure along transit routes is likely less than that on highways and those using transit may also have different travel patterns. Since transit mode share in the study area is relatively low (1.7%) we do not expect this exclusion to have a significant effect on our findings. Our static and dynamic exposure estimates are based on ambient $PM_{2.5}$ concentration estimates. We do not account for differences between ambient and indoor or in vehicle concentrations. All else being equal, we assume that places with higher ambient concentrations also have higher indoor or in vehicle concentrations; however, we acknowledge that regional differences in building stock or the vehicle fleet could challenge this assumption. We do not have comprehensive information about vehicle and building characteristics or how much time people spend inside and outside of vehicles and buildings that would allow us to accurately calculate these differences. We know this causes some amount of error based on a limited number of prior studies (Baek et al., 1997; Marshall et al., 2003). However, presently there is no practical method for addressing these limitations in a spatially detailed analysis of an entire metropolitan region. Future research could combine population mobility with infiltration impacts (Chang et al., 2015) to further enhance the study of exposure misclassification. Although the data we use represent individual agents and households, location data are aggregated to TAZs. As a result, we estimate exposure based on the average concentration of $PM_{2.5}$ within each TAZ, introducing some error to our exposure estimates. The most likely error is the overestimation of exposure in larger and more rural TAZs where much of the population lives away from heavily trafficked roadways. If this is true, then exposure misclassification would be even greater than we have estimated in our study for rural and suburban residents. Finally, we use a complex system of models that each produce point estimates. Uncertainties and errors exist but they are not quantified or propagated through this modeling system which are two widely acknowledged limitations in the transportation system modeling field and one that has yet to be resolved (Rodier and Johnston, 2002).

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2019.108999.

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