

November 2017

Understanding the Linkages between Urban Transportation Design and Population Exposure to Traffic-Related Air Pollution: Application of an Integrated Transportation and Air Pollution Modeling Framework to Tampa, FL

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Understanding the Linkages between Urban Transportation Design and Population Exposure to Traffic-
Related Air Pollution: Application of an Integrated Transportation and Air Pollution Modeling
Framework to Tampa, FL

by

Sashikanth Gurram

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Civil Engineering
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College of Engineering
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Date of Approval:
November 14, 2017

Keywords: urban sustainability, smart growth, environmental justice, population health, activity and
travel patterns

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DEDICATION

This dissertation is dedicated to my mother Seshu Kumari Gurram, my father Appa Rao Gurram, and my wife Swetha Gurram for their support, sacrifices, and unconditional love.

ACKNOWLEDGMENTS

I sincerely thank my “gurus” (co-advisers) Dr. Amy Stuart and Dr. Abdul Pinjari for their constant support and encouragement throughout this journey. Over the past seven years, I have grown both professionally and personally due to their efforts and inquiry. I would not have succeeded if not for their infectious passion towards science and their push towards quality work. I am a better person as a result of each and every meeting with them and am truly fortunate to have worked with two brilliant and passionate minds. I would also like to acknowledge all the financial support they have provided to me over the years.

I thank the members of my dissertation committee, Dr. James Mihelcic, Dr. Delcie Durham, and Dr. Elizabeth Strom, for the valuable feedback they provided—their critiques greatly improved this work. Special thanks to Dr. Fenda Akiwumi who agreed to be the external chair for my defense committee on very short notice.

This work would not have come to fruition if not for the kind help from several organizations and individuals. I would like to thank Elaine Martino with the Florida Department of Transportation (FDOT), who provided me access to the Tampa Bay Activity-Based Travel Demand Model; Dr. John Gliebe (RSG Inc.), who patiently went over the details of the activity-based model (ABM); Chunyu Lu (Gannett Fleming), Yifan Zhang and Han (BCC Engineering), who helped me with several operational details of the ABM; the MATSim developer and user group, with thanks to Dr. Kai Nagel and Dr. Amit Agarwal, who patiently addressed my queries on the MATSim model runs; Dr. Marcel Rieser, who provided me with a free license for SENOZON Via; Michael Kay of Saxonica, who provided me with a free enterprise license for Saxon XSLT, given my unfunded project; my very good friend Chetan Pinumalla for helping me with Java programming in the course of working with MATSim; and, finally, the user group of Stackoverflow, which helped with several of my queries in R programming.

I have been funded through a variety of sources over the course of my dissertation. I would like to acknowledge the financial support provided by the National Science Foundation (NSF); this material is based upon work supported by NSF under Grant No. 0846342, and any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the NSF. I sincerely thank the USF Department of Civil and Environmental Engineering, which retained me as a teaching assistant for several semesters and provided me with financial stability; the Writing Studio at USF for retaining me as a writing consultant, a position I truly enjoyed, since August 2013; Writing Studio coordinators Karen Langbehn, Megan McIntyre, and Danielle Farrar for retaining my services on a continuous basis; my co-advisers Dr. Stuart and Dr. Pinjari, who believed in my ability to perform the writing consultant duties, and Dr. Sarina Ergas for backing up my application; the USF Graduate School financially supporting me with a University Graduate Fellowship in the first year of my Ph.D.; a grant from the Center for Transportation, Environment, and Community Health (CTECH), which provided me with the necessary funding; and Dr. Stuart for putting me on this grant; Patricia Ball, who provide editorial help for this dissertation; and Barbara Johnson and Shivali Vyas of the USF Department of Civil and Environmental Engineering and Nolan Kimball and Cathy Silva of the USF Department of Environmental and Occupational Health for their help with the tons of paperwork I had to deal with.

I was fortunate enough to make several lasting friendships over the course of my graduate career. I thank Dr. Ryan Michael, a truly great friend, with whom I enjoyed several productive sessions of R programming over food and fun talk—without his encouragement and guidance, I would still be stuck with SPSS; my good friend Haofei Yu, who, despite being busy, was always available to answer my questions on air quality modeling; Dr. Sujan Sikder for his friendship and guidance during the initial years of my Ph.D.; and Dr. Vijay Sivaraman and Aayush Thakur for their help at various stages of my career, especially with the ArcGIS package. I want to acknowledge the influence of some of my best friends from Virginia Tech, Dr. Aly Tawfik, Dr. Hao Chen, and Dr. Charan Tej Tanneru, on my decision to pursue a Ph.D., along with all of the fun times we spent together that made my graduate journey more

enjoyable. I would like to specially acknowledge my friend Jennifer Icton for all her support and advice that turned me into a better person; I sometimes feel that she believes more in me than I believe in myself. Special thanks to Rema Ramakrishnan for inspiring me through her work and for the feedback she provided to improve my defense presentation. Finally, I want to thank my graduate friends Surya Balusu, Divyakant Tahlyan, Talha Kocak, Mokaddesul Hoque (MD), Lukai Guo, Farshad Ebrahimi, Kaleb Marroquin, Steven Slinn, Trang Luong, Manvitha Rajalingola, Akbar Bakshi, Mohammadreza (Maz) Kamali, Bertho Augustin, Jill Sears, and Sarah Burns—know that you are a very special group of people from whom I learned a lot, and I earnestly thank you all for your friendship.

A person may be nothing without his/her family. None of this would have been possible without the great care, affection, and love that my mother Seshu Kumari Gurram has displayed over the past 32 years. I feel that this tribute pales in comparison to the towering selfless love that she has for me. My father Appa Rao Gurram has been my bedrock of support throughout my life, but especially in the last seven years when I needed it the most. He genuinely inspires me through his dedication and honesty towards work. I will succeed if I can put in half the effort he puts into anything he does. My sister Sirisha Gurram is one of the best persons I know and I thank her for the constant support, trust, and love for me. Over the last couple of years, my son Arihant Gurram has brought a lot of joy into our lives and made this journey very memorable. I thank him for all the cuteness and silliness he brought into my life. Finally, I cannot thank my wife Swetha Gurram enough for all her support and love over past seven years. The word “support” does not properly characterize all she has done for me. I truly appreciate her runs to grocery stores so I could focus on my work, all the teas and coffees at midnight, the wonderful and delicious food, and the living within means despite several financial tribulations and instabilities. I would not have been able to cope with such a lifestyle if I were in her place; she is a much better person than I can ever be. For this, I am indebted to her forever, which I can only hope to repay with everlasting love.

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ABSTRACT

Rapid and unplanned urbanization has ushered in a variety of public health challenges, including exposure to traffic pollution and greater dependence on automobiles. Moreover, vulnerable population groups often bear the brunt of negative outcomes and are subject to disproportionate exposure and health effects. This makes it imperative for urban transportation engineers, land use planners, and public health professionals to work synergistically to understand both the relationship between urban design and population exposure to traffic pollution, and its social distribution. Researchers have started to pay close attention to this connection, mainly by conducting observational studies on the relationship between transportation, urban form, and air quality. However, research on this topic is still nascent. Further, most studies do not predict exposures under alternative urban design scenarios. Hence, to understand the relationship between urban design and population exposures, there is a need to build and apply integrated modeling tools that can predict exposures under alternative urban design scenarios.

Within this context, the overarching goal of this dissertation is to understand how the transportation infrastructure of cities can be designed for improved urban air quality and mitigation of population exposure to traffic pollution. The study area is Hillsborough County, Florida, a sprawling region with limited transit availability and a diverse population along with a mix of urban, suburban, and rural areas. The rank of the county for sprawl and congestion metrics (i.e., yearly delay and travel time index) fall in the mid-range in comparison with other US urban regions. Thus, the study area may be representative of other US urban regions with medium sprawl and above-average congestion levels. Oxides of nitrogen (NO_x), a surrogate for traffic pollution, is the focus pollutant. The Health Effects Institute's report on traffic-related air pollution identifies NO_x as a potential surrogate due to its relative ease of measurement and the abundance of epidemiologic studies that characterize exposures to NO_x .

Because exposures are dependent on the spatial and temporal distributions of both people and pollution, this study first sought to understand the importance of activity and travel patterns of individuals for exposure estimation. To estimate exposures, the 2009 National Household Travel Survey (NHTS) data containing daily individual activity records, ArcGIS-estimated shortest-time travel route profiles, and the annual-average diurnal cycle of NO_x derived from hourly CALPUFF dispersion model results from 2002, were combined. Two exposure measures were estimated: activity-based exposure that considers the daily activity and travel patterns of individuals, and residence-based exposure that considers only the pollutant concentrations at the residences. Exposure estimation without inclusion of activity and travel patterns was found to slightly underestimate activity-based exposures on average. Additionally, disproportionately-high exposures were found for blacks, Hispanics, below poverty groups, urban residents, and people whose daily travel time is greater than one hour. Finally, urbanicity and travel time variables were found to be the strongest predictors of daily exposure.

Following this, a modeling framework was developed to predict population exposure by integrating activity-based travel demand modeling (DaySim), dynamic traffic assignment simulation (MATSim), mobile-source emission estimation (EPA MOVES), and pollutant dispersion modeling (R-LINE). This modeling framework was used to predict daily population and subgroup exposures by estimating the high-resolution spatial and temporal distributions of both pollution and individual activities for the year 2010. Persistent exposure inequalities were found at the population-level; blacks, Hispanics, active age groups (19-65 years), below-poverty and middle-income groups, urban residents, and individuals with daily travel times above one hour had higher estimated exposures than the population mean. These inequalities for blacks, Hispanics, and below-poverty non-white groups worsened at higher exposure levels. Use of low-resolution activity and pollution data as opposed to high-resolution data led to underestimation of exposures (by 10% on average).

Finally, the integrated modeling framework was employed to understand the relationship between urban transportation and land use design, air quality, and population exposure. Three scenarios that are based on a combination of diesel-bus transit services and residential distribution were simulated.

Specifically, the low-transit scenario used the 2040 base residential distribution and the 2010 bus services. The enhanced-transit scenario applied the 2040 bus services proposed for the county instead. The compact-growth scenario added an increase of residential density to this latter scenario. Specifically, about 37% of total households were redistributed from locations with low accessibility to jobs and transit to locations near employment and bus stops. Results indicate slight higher non-car travel mode shares in the enhanced-transit and compact-growth scenarios compared to the low-transit scenario (with a 7.1% increase for walking, 0.2% for bicycle, and 1.8% for transit for the compact-growth scenario versus the low-transit scenario). The enhanced-transit scenario resulted in slightly lower daily total travel distances and times compared with the low-transit scenario, but daily total emissions and winter mean concentration of NO_x were higher, i.e., the increase in bus transit services did not induce sufficient shifts in travel mode to overcome the concomitant increase in diesel-bus emissions. The compact-growth scenario resulted in lower daily total travel distance (9%) and travel time (2.1%) and daily total emissions of NO_x (11%) and its winter mean concentration (9%), compared with both the low-transit and enhanced-transit scenarios. Although the compact-growth scenario improved the air quality of the region on average, daily population mean exposure was higher compared with both the low-transit (29%) and enhanced-transit scenarios (25%). This is largely due to the redistribution of population to urban core locations that had higher pollutant levels. Overall, neither the bus-transit improvements nor residential compaction strategies alone were sufficient to mitigate population exposures. Combining them with transit that services both origins and destinations, uses clean fuel technologies, and separates major roadways from dense residential pockets may be needed for greater exposure reductions.

Overall, this dissertation has implications for population exposure to traffic pollution and public health through transportation and land use interventions. Results presented here may be applicable to other study regions that have similar composite sprawl scores as the Tampa Bay area. Future studies should exploit spatially-and temporally-resolved data on human activities and travel, vehicular activities, and air quality for better characterization of population exposure. Engineers and planners should pay greater attention to integrated land use and transport planning; lone, disjointed, and ill-planned design

interventions may exacerbate population exposure to air pollution. The integrated modeling framework presented here may be applied in a wide variety of urban contexts to further explore the nexus between travel demand, air quality, and exposures. However, before such an exercise is undertaken, a preliminary analysis should be conducted to assess the transferability of the framework. Policies that could be studied include mixed land use design, urban compaction with controlled sociodemographic distributions (to assess exposure inequality), and inclusion of additional types of transit and fuel technologies.

CHAPTER 1: INTRODUCTION

1.1 Background

Urbanization refers to the increase in size, density, and heterogeneity of cities and is frequently associated with factors including population mobility, segregation, and industrialization (Vlahov & Galea, 2002). Rapid urbanization is a common feature across the globe today (Alig et al., 2004; Soubotina, 2004). The global urban population has been on the rise since 1950; it exceeded the global rural population for the first time in 2007, and the world population has predominantly remained urban since then. Additionally, it is projected that two-thirds (approximately 66%) of the world population will be urban by 2050 (United Nations et al., 2015). This level of rapid urbanization poses a serious challenge for sustainable development (Cohen, 2006).

Although urbanization is associated with several positive outcomes, including economic growth, poverty reduction, and improved access to infrastructure and services, it also has ushered in an array of concerns. Evidence from around the world suggests that changes in land use and urbanization adversely impact human lifestyle and health (Galea & Vlahov, 2005; Moore et al., 2003; Popkin, 1999), environment (Burak et al., 2004; Seto et al., 2010), and climate (Kalnay & Cai, 2003). It could be argued that the impact of urbanization on human health assumes special significance due to the complex linkages between them. Rapid and unplanned urbanization is associated with several health concerns, including cardiovascular diseases (Yusuf et al., 2001), diabetes (Hu, 2011), and cancer (World Cancer Research Fund & American Institute for Cancer Research, 2007). It should not be surprising that these health outcomes culminate from multiple pathways associated with urbanization, including air pollution, physical inactivity, access to transport and healthy food, and non-communicable diseases (Giles-Corti et al., 2016; World Health Organization, 2010).

One of the major problems of rapid and inadequately planned urbanization is ambient urban air pollution. The World Health Organization (WHO) has estimated that ambient air pollution (in both urban and rural areas) is linked to 3.7 million deaths globally, making it the largest environmental health risk (World Health Organization, 2014). Within the context of the United States, combustion-related emissions were linked to approximately 200,000 premature deaths (Caiazzo et al., 2013). Urban air pollution also has been associated with a variety of environmental and health concerns, including but not limited to acid deposition, asthma, and cardiovascular and cardiopulmonary diseases (Gauderman et al., 2000; HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). In addition to its impact on health, urban air pollution also has significant economic costs, at 2–5% of a nation's gross domestic product (United Nations Environment Programme, 2003). In the US, urban air pollution is responsible for nearly three-quarters of the gross annual damages resulting from air pollution (Muller & Mendelsohn, 2007). Finally, on a positive note, even modest decreases in air pollution levels were associated with significant cost savings (Deschenes et al., 2012; Grabow et al., 2012). Recognizing these complex linkages between air pollution and urbanization, a few studies argue that urban development policies that seek to abate urban air pollution levels hold the key for mitigating the associated human health, environmental, and economic costs.

Whereas urban air pollution is an amalgamation from various sources, pollution from the transportation sector contributes significantly towards it (US Environmental Protection Agency, 1994). The US Environmental Protection Agency (US EPA) estimated that the transportation sector accounted for about 26% of total US greenhouse gas (GHG) emissions for 2014 (US Environmental Protection Agency, 2016). Several studies linked exposure to traffic-related pollution with exacerbation of asthma, onset of childhood asthma, non-asthma respiratory symptoms, impaired lung function, total and cardiovascular mortality, and cardiovascular morbidity (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Further, inequalities in exposure to traffic-related pollution also were documented (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010; Yu & Stuart, 2013).

Considering the broader health- and equity-related impacts, it is necessary to investigate the factors that are linked with transport emissions.

Urban form is suspected to be a factor that determines the air quality of a region. The low-density urban form, pursued during the early and mid-20th century, resulted in increased spatial segregation between communities, increased automobile dependence, sedentary lifestyle, incompetent public transit, and negative health impacts (Camagni et al., 2002; Frank & Engelke, 2001; Frank & Engelke, 2005). Additionally, the prevalence of health and environmental inequalities associated with air pollution has been well documented across the world (Deguen & Zmirou-Navier, 2010; Samet & White, 2004; Stuart & Zeager, 2011). Although past research efforts identified correlations between factors including race, socioeconomic status, and urbanicity and health-related inequalities, the pathways through which these inequalities manifest are not very clear. To this end, researchers proposed a few strategies, including restriction of the outward expansion of cities, increase of residential density, development of mixed-use neighborhoods, and investment in transit services to curb the use of personal vehicles, as a way to design cities that improve public health and reduce environmental concerns; these strategies are collectively referred to as “smart growth” (Burchell et al., 2000; Downs, 2005).

The impact of the aforementioned smart growth approaches on curbing air pollution, population exposure, and inequalities are unclear. A few researchers studied the effects of compact urban forms on traffic-related emissions and found that emissions were generally lower in compact urban forms compared to sprawling forms (Hankey & Marshall, 2010; Makido et al., 2012; Stone et al., 2007). Other studies found a lower number of ozone exceedances (Stone, 2008), lower PM_{2.5} levels across most of the urban region except for urban centers (Hixson et al., 2009) and lower particulate and ozone levels (De Ridder et al., 2008b) in compact urban forms. Despite these improvements in the air quality, several studies observed an increase in population-weighted exposures to traffic-related pollution in compact and high-density urban forms (Clark et al., 2011; Hixson et al., 2009). Thus, it is entirely reasonable to ask, what makes growth strategies “smart” and how can we design cities to simultaneously improve the air quality while reducing the population exposure and the inequalities?

No investigation of the impact of smart growth policies (as currently defined) on air quality would be complete without considering the transportation and land use piece of the smart growth puzzle. Transportation infrastructure plays a crucial role in shaping the urban form of a region and constitutes one of the vital design concepts for sustainable urban forms (Jabareen, 2006). Previous literature clearly identifies the connection between land use and transportation (Cervero & Gorham, 1995), albeit there is some disagreement with regard to the strength and direction of this connection (Crane, 2000; Giuliano, 1995; Handy, 2005). Preliminary investigations show that use of alternate fuels, advanced vehicle technologies, and promotion of public transit systems could lead to the realization of sustainable urban forms (Chen & Whalley, 2012; Harford, 2006). However, a comprehensive understanding of the attributes of transportation infrastructure that advance urban sustainability has not yet been attained. Thus, it is extremely important to investigate the linkages between urban form, transportation infrastructure and land use, air pollution, and the social distribution of exposures. This study attempts to add to the body of literature on sustainable urban design policies that may help achieve health and environmental equity through exploring alternate urban transportation infrastructure and land use design scenarios.

1.2 Research Goal, Specific Aims, and Scientific Questions

The overarching goal of this research was to understand and predict the impact of urban transportation infrastructure and land use design on human exposure to traffic-related pollutants with a focus on impacts on social inequality. To this end, the specific aims addressed here are outlined and discussed below.

Aim 1 of this dissertation was to understand the impacts of spatiotemporally-resolved activity and travel patterns on estimated exposures to traffic-related air pollution in the Tampa area. The specific science questions that were addressed include:

- How are population activities distributed spatiotemporally in the study domain?
- How are exposures distributed among population groups in the study domain?
- What is the strength and direction of disparities between groups?

- Does urban form influence the strength of exposures and their social distribution?
- How much does the representation of spatiotemporal activity locations impact exposure estimates?
- Are the errors associated with exposure estimation different for different population subgroups?

I hypothesize that consideration of activity and travel patterns leads to significantly different exposure estimates, as opposed to residence-based exposure estimates.

Aim 2 of this dissertation was to develop a modeling system that integrates activity-based travel-demand simulation, mobile source emissions estimation, and pollutant dispersion simulation for the study of impacts of urban transportation infrastructure on human exposures to air pollution. A few science questions that were addressed during this model development include:

- How does the spatiotemporal distribution of activities, emissions, and exposures change when the sample is scaled to the full population using the modeling framework?
- Are the results from the modeling framework and the earlier sample-based analysis consistent with one another?
- How much do the exposures and their social distribution vary between sample-based and full population studies?
- Does the use of a highly spatiotemporally-resolved framework as opposed to the low resolution frameworks used in earlier studies warrant improved population and group-wise exposure estimates?

I hypothesize that a population-level analysis will reveal distinct exposure patterns that are not apparent in a sample-based analysis.

Aim 3 of this study was to understand and predict impacts of transit-oriented compact-growth design scenarios on patterns of exposure to select traffic-related air pollutants in the Tampa area. The modeling framework developed under Aim 2 was used to investigate the following science questions:

- How may population activities, traffic-related pollution, and population exposure be distributed spatiotemporally in the study domain under different urban transportation and land use design scenarios?
- What may be the individual contribution of urban transportation and land use design on urban air quality and population exposure?

I hypothesize that transit-oriented compact urban forms will lower population exposure compared to a sprawling urban form with limited transit services.

Thus, this work seeks to improve the current understanding on the nexus between transportation infrastructure and land use design, emissions, air quality, and exposures to urban air pollution.

1.3 Organization of this Dissertation

This dissertation is organized as follows. Chapter 2 presents the current state of science on the impact of smart growth policies on air quality and exposures to traffic-pollution, specifically focusing on studies that investigate the impact of transit-oriented compact-growth scenarios on air quality and exposures. Additionally, air pollution exposure methodologies are reviewed, as are tools that can forecast air quality under alternate urban growth scenarios.

Chapter 3 focuses on the impact of activities and travel on exposures to traffic-related pollution and their social distribution. Data from the 2009 National Household Travel Survey (NHTS) were used to generate activity and travel patterns of individuals, which were used in conjunction with spatiotemporal estimates of 2002 NO_x concentrations to characterize the population and group-wise exposures and their social distribution in the Tampa region.

Chapter 4 focuses on the development of the modeling framework that combines activity-based travel demand simulation, dynamic traffic assignment, mobile source emission estimation, and dispersion simulation to estimate the spatiotemporal distributions of the human activities, regional air quality, and exposures to traffic-pollution. This system was applied to Tampa to estimate the full population and group-wise exposures. Additionally, the system also was used to understand the need for high-resolution population activity and air pollution data for exposure estimation.

Chapter 5 presents the application of the modeling framework developed under Chapter 4 to estimate the spatiotemporal distributions of the regional air quality and exposures to traffic-pollution under alternate urban design scenarios. Three scenarios—low-transit, enhanced-transit, and compact-growth—were simulated for 2040 to predict the impact of compaction strategies and additional bus transit on activity and travel patterns of individuals, urban air quality, and population exposure.

Finally, Chapter 6 provides a synthesis of this research and recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Anthropogenic air pollution is predominantly driven by the combustion process, which generates a variety of pollutants (World Health Organization, 2004) and significantly impacts human health and the environment. The 2014 World Health Organization factsheet on household and ambient air pollution estimates that seven million worldwide premature deaths are attributable to air pollution, making it the largest environmental health risk (World Health Organization, 2014). Thus, in the short term, combustion emissions may pose a great risk to the human health and well-being; even in the longer term, combustion-related emissions are forecast to greatly affect sea-level rise, thus significantly altering current world geography and displacing wide sections of civilization (Winkelmann et al., 2015). In view of these current estimates and long-term forecasts, mitigation of combustion-related emissions assumes great importance.

Energy use in the commercial, industrial, residential, and transportation sectors accounts for a majority of anthropogenic emissions. Within these sectors, transportation often accounts for a substantive portion of the emissions, as shown in Figure 2.1. The primary emissions from motor vehicles are collectively termed “traffic-related air pollution” (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Exposure to traffic-related air pollution has been associated with a wide spectrum of negative health outcomes and health inequalities (Apelberg et al., 2005; HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). As such, accurate characterizations of exposure to traffic-related pollution are needed to understand its impact on human health and the corresponding social inequalities.

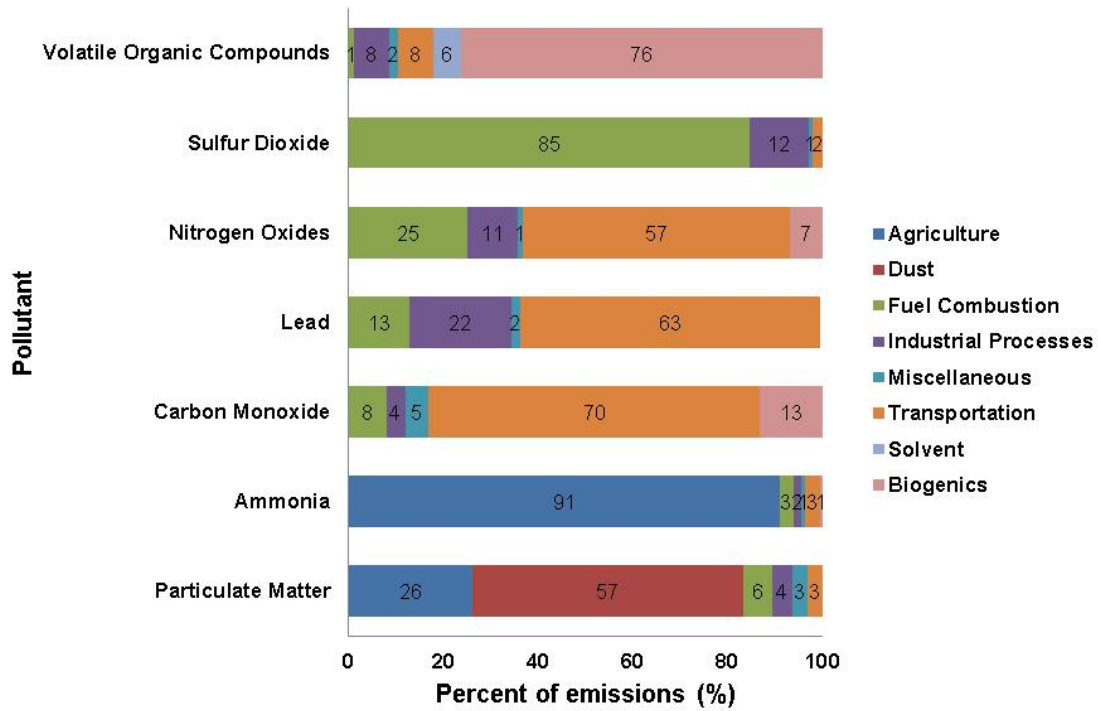


Figure 2.1 Pollutant emissions by source category. (Source: US Environmental Protection Agency, 2016)

Whereas accurately estimating exposures to traffic-related pollution is important, it is also equally important to identify and understand the factors that are linked with this pollution. An emerging area of research suggests that urban form including the transportation infrastructure within it, may perhaps be one of the important factors that influence the air quality, personal exposure levels, and population health (Giles-Corti et al., 2016; Hankey & Marshall, 2010; Stevenson et al., 2016; Stone et al., 2007). However, there is a considerable debate on the effectiveness of urban forms that encapsulate “smart growth” features in realizing sustainability goals (Dieleman et al., 1999; Echenique et al., 2012; Gordon & Richardson, 1997; Neuman, 2005). Thus, there is a need to gather further evidence in this area using tools that can robustly forecast the impact of alternate urban design scenarios on human activity and travel patterns, pollutant emissions, concentrations, and personal exposure to them.

The remainder of this chapter reviews the current state of literature on linkages between urban transportation and land use design, air quality, and exposure to traffic-related pollution and its social distribution. The health impacts of exposure to traffic-related pollution are reviewed first. The literature pertaining to the social distribution of the exposures and the resulting inequalities is reviewed next,

followed by a review of the literature that seeks to understand the relationship between urban design, air quality, and population exposure. Finally, the methodological aspects pertaining to the estimation of population exposure to traffic-related pollution is presented with a focus on choosing the appropriate tools for this research.

2.2 Health Impacts of Exposure to Traffic-Related Air Pollution

Exposure to combustion-related air pollution is associated with mortality and a host of negative health outcomes. Specifically, the Harvard Six Cities study showed that high levels of fine and sulfate particles were strongly associated with mortality (Dockery et al., 1993). Following this, Pope III et al. (2002) found associations between particulate and sulfate pollution and all-cause, lung cancer, and cardiopulmonary mortality. More recently, combustion emissions of PM_{2.5} and ozone were estimated to be associated with about 210,000 premature deaths per year in the US (Caiazzo et al., 2013); of these, transportation-related PM_{2.5} and ozone emissions were estimated to account for approximately 53,000 and 5,000 premature deaths, respectively.

Recognizing the significant contribution of transport emissions toward air pollution, the Health Effects Institute (HEI) commissioned a special panel to review the literature and understand the associations between traffic-related air pollution and negative health outcomes. Traffic-related air pollution comprises a complex mix of primary pollutants emitted from motor vehicles. It should be noted that secondary pollutants such as ozone that originate from the primary pollutants are not considered traffic-related pollutants. Some important traffic-related pollutants include carbon dioxide (CO₂), carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), particulate matter (PM), and mobile source air toxics (MSATs) including benzene, formaldehyde, acetaldehyde, 1,3-butadiene, and lead (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Since it is extremely difficult to measure all the components of this traffic-pollutant mix, surrogate pollutants are usually selected to approximate the impact of exposure to traffic pollutants (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010; Oglesby et al., 2000). The HEI report identifies pollutants including CO, nitrogen dioxide (NO₂), and benzene as potential surrogates for exposure to traffic-related air pollution, although

they caution that none of these pollutants meet the criteria for an ideal surrogate. In this study, NO_x was chosen as the surrogate for traffic-related exposure for a few reasons. First, NO_x consists of both directly emitted NO and secondary nitrogen dioxide, a criteria pollutant regulated by the US EPA. NO₂ is also measured by the US EPA near-road monitoring network due to the influence of traffic-related air pollution. Additionally, ambient NO₂ concentrations, in conjunction with surrogates of traffic (i.e., traffic volumes or distance to roadways), provide a good characterization of traffic-related pollution at the local scale. Finally, several previous studies focusing on exposure to traffic-related pollution used NO_x as a surrogate pollutant (Beevers et al., 2013; Gurram et al., 2015; Kim et al., 2004; Raaschou-Nielsen et al., 1997; Yu & Stuart, 2013), providing for good comparisons for this study.

The HEI panel concluded that individuals living within a range of 300–500 meters from a major roadway are the most affected due to traffic emissions. Given the substantial proportion of population that live near roadways in the United States, exposure to traffic-related pollution is a likely public health concern and deserves attention (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). The panel also concluded that sufficient evidence exists to infer a causal association between exposure to traffic-related pollution and exacerbation of asthma. Additionally, they found suggestive evidence to infer causal association between exposure to traffic-related pollution and onset of asthma, non-asthma respiratory symptoms, reduced lung function, total and cardiovascular mortality, and cardiovascular morbidity (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Thus, exposure to traffic-related air pollution can be categorized as a public health concern, and further studies are needed to characterize the disaggregate, group-wise, and population-level exposures to traffic-pollution.

2.3 Exposure Inequalities

Several studies suggested that exposure levels for different types of pollutants may vary depending on the socio-economic makeup of the population subgroups (Chakraborty, 2009; Marshall, 2008; Samet & White, 2004; Stuart & Zeager, 2011; Yu & Stuart, 2013). For example, Marshall (2008) suggested that certain sections of population residing near an industry might get exposed to higher levels of primary pollutants emitted from the industry when compared to the subgroups residing farther away.

Alternatively, the groups living farther away from the industry might get exposed to higher levels of secondary pollutants, formed due to the chemical reactions between primary pollutants from the industrial source and pollutants from other sources, when compared to the groups residing near the industrial source. These differences in exposure to air pollutants within different population demographics is called environmental inequality (Anderton et al., 1994) and lack of environmental justice (US EPA Office of Minority Health, 2003). Environmental justice has been defined by the US EPA as the fair treatment and meaningful involvement of all people regardless of race, color, national origin, culture, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies (US EPA Office of Minority Health, 2003).

Past studies tried to identify and understand the underlying patterns corresponding to the social distribution of exposures and inequalities (Deguen & Zmirou-Navier, 2010; Marshall, 2008). Deguen and Zmirou-Navier (2010) conducted a literature review on studies pertaining to social inequalities in health risks related to ambient air quality in Europe and concluded that subgroups that belong to lower socio-economic status were subject to greater harmful health effects despite not always being exposed to higher pollutant levels. This could mainly be attributed to inferior medical treatment, limited access to good food, micronutrient deficiencies, and concurrent illnesses (Deguen & Zmirou-Navier, 2010; Romieu et al., 2004). Marshall (2008) used spatially- and temporally-resolved and microenvironment-adjusted ambient air pollutant concentrations to study the pollutant exposure patterns among different population subgroups in California's south coast air basin. The study concluded that non-white and low-income groups were subject to high primary pollutant exposures when compared to white and high-income groups. Conversely, for ozone, white and high-income groups were exposed to higher concentrations when compared to non-white and low-income groups. Similarly, people living in high-density regions were subject to high primary pollutant and low secondary pollutant exposures, whereas people living in low-density regions were exposed to low primary pollutant and high secondary pollutant concentrations. Hajat et al. (2015) conducted a global review of literature on socioeconomic disparities in exposure to air pollution that specifically synthesized 22 North American studies and found a broadly consistent pattern

of higher concentrations of criteria pollutants in lower-socioeconomic status (SES) individuals and communities; a few exceptions in which higher-SES communities were exposed to higher concentrations were observed in New York City, Toronto, and Montreal (Hajat et al., 2015).

A few exposure-related socio-demographic inequality studies were conducted in the Tampa Bay region (Chakraborty, 2009; Stuart et al., 2009; Stuart & Zeager, 2011; Yu & Stuart, 2013). Chakraborty (2009) investigated the environmental inequalities in the region for socio-economically and transportation-disadvantaged groups and concluded that minority groups such as African Americans, Hispanics, and those living below poverty levels were subject to disproportionate cancer risks and respiratory hazards. Further, the study identified that the individuals from households with no vehicles were subject to disproportionately higher health risks. Stuart et al. (2009) studied the social distribution of neighborhood-scale air pollution and identified that blacks, Hispanics, and people living in poverty were disproportionately closer to sources of air pollution yet farther from air quality monitoring sites than whites and non-poverty groups, respectively. For the same study region, Stuart and Zeager (2011) studied ambient NO₂ levels and traffic levels near elementary schools and found higher NO₂ and traffic levels near schools with predominant enrollments of black, Hispanic, and economically-disadvantaged children compared to schools with predominant enrollments of white, Asian, or Pacific Islander children. Yu and Stuart (2013) conducted a modeling study in the Tampa Bay area to characterize the spatiotemporal distributions of NO_x and the exposure inequalities and found that blacks, Hispanics, and lower-income subgroups were subject to greater exposures than the county average. Additionally, they found that this disproportionality of exposures increased with increasing levels of annual average exposures, i.e., the proportion of minorities and low-income groups at greater annual average exposures were higher compared to their proportion at a lower annual average exposure. Finally, Yu and Stuart (2016) expanded their earlier study by considering additional primary and secondary pollutants and found that exposure inequalities and inequality indices (for blacks, Hispanics, and low-income subgroups) were persistent when considering primary pollutants. However, the inequality indices for exposure to secondary

pollutants displayed complex trends and exhibited reverse disproportionality (i.e., minorities and lower-income subgroups) at the highest concentration levels.

A limitation for most of the studies in the Tampa region and the US in general was the non-inclusion of the activity and travel patterns of individuals for exposure estimation. Setton et al. (2011) suggested that non-inclusion of individual activity and travel patterns for exposure estimation results in biased exposure estimates. Thus, studies that explicitly consider individual spatiotemporal locations are warranted to understand the true strength and direction of exposure inequalities. Further, many studies focused explicitly on the associations between inequalities and sociodemographic variables including socioeconomic status, race, and income. However, it is also important to understand how inequalities are related with social identity variables including age, urban/rural status (Miao et al., 2015), and time spent in travel and out-of-home activities. Finally, it would be of interest to understand the social distribution of exposures to traffic-related pollution, in addition to including pollution from point and area sources, given the public health concerns of traffic-related pollution (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Within this context, the current study explores the social distribution of exposures to traffic-related pollution by focusing on demographic, urbanicity, and travel-related variables including race/ethnicity, income, age, residential status (urban/rural), and daily travel time. Thus, this study can add to the body of literature on environmental inequalities by focusing specifically on exposure to traffic-related pollution.

2.4 Interactions of Urban Form and Air Pollution Exposures

“Urban form is defined as a composite of characteristics related to land use patterns, transportation system, and urban design” (Handy, 1996; Jabareen, 2006). Over the past few decades, much focus has been placed on identifying and defining sustainable urban forms due to the potential impact of urban design on human physical and mental well-being (Jackson, 2003). Jabareen (2006) identified seven significant and recurring themes for sustainable urban form—compactness, sustainable transport, density, mixed land uses, diversity, passive solar design, and greening. Transport is inextricably linked with the urban morphology of a region and plays a crucial role in shaping the urban

form; at the same time, transport is also presented as one of the most important issues that connect environmental debates and urban form (Burton et al., 2003). The following sections provide an overview of the interactions between urban form, transport, air quality, exposures, and human health.

2.4.1 Interactions between Urban Form and Transport

Urban form and transport characteristics are invariably linked with one another. However, these linkages appear to propagate through various features of the urban form and built environment. Cervero and Kockelman (1997) found that built environment influences the travel demand along three dimensions i.e., “three Ds”—density, diversity, and design. Specifically, using a variety of data sources including travel surveys, the US Census, land use records, and field surveys, they found that urban forms that are dense, diverse, and pedestrian-oriented would reduce trip rates and encourage non-auto travel. However, they also concluded that the effect of built environment dimensions on transport is marginal, although not inconsequential (Cervero & Kockelman, 1997). Similarly, a review of the interactions between built environment and travel by Ewing and Cervero (2001) found that vehicle miles traveled (VMT) or vehicle hours traveled were a function of regional accessibility more than local accessibility; thus, dense and mixed-use developments that are not well connected to other dense and mixed-use neighborhoods may offer only modest regional travel benefits (Ewing & Cervero, 2001). They also found that land use patterns may have a greater impact on mode choice, and, hence, transit usage is dependent on local densities and mixed-land use. However, a more recent and updated systematic meta-analysis by the same authors showed that the relationships between built environment and travel variables are inelastic; however, interestingly, they proposed that the effect of a combination of built environment variables on travel could be significant (Ewing & Cervero, 2010). Further, they expanded the “three Ds” originally coined by Cervero and Kockelman (1997) to “six Ds” by proposing that destination accessibility, distance to transit, and demand management may be used as measures of built environment.

In a study that seeks to understand the impact of urban expansion patterns on social and environmental costs, Camagni et al. (2002) used the disaggregated travel time and mode information for commuters from 1991 census data for Milan, Italy, and socio-economic variables including population

density, ratio of jobs to resident population, and four types of urban morphology variables to categorize urban form. They used regression modeling to find associations between measures of transit efficiency including competitiveness of transit (ratio of average travel time by private transport and average travel time by public transport) and transit mode shares, and urban form and built environment variables. Using this analysis, they found that urban settlements of compact structure lead to greater competitiveness and use of public transport and lower demand for mobility. In a similar type of study, that tried to understand the impact of built environment on non-work travel, Rajamani et al. (2003) combined travel survey data for the Portland (Oregon) metro area with mode-specific travel cost and travel time data to create an accessibility index. They combined all these data sources with the urban land use data for the study region to create urban form measures. Using a multinomial logit model, they found that mixed-use urban forms promote walking behavior for non-work activities.

Stone et al. (2007) used a population reassignment technique, that resulted in higher share of urban and suburban population as opposed to rural population, to simulate the impact of compact growth on travel and transport emissions. They found that an average increase in population density by 14% results in 6% lower median VMT. More recently, Hankey and Marshall (2010) used the Monte Carlo approach to simulate the impact of six different low- and high-sprawl scenarios along with three different vehicle and fuel technology scenarios, ranging from business-as-usual to a “green fleet” comprising both fuel-efficient and electric vehicles, on the vehicle-kilometers traveled for the urban regions in the US. They reported that greenhouse gas (GHG) mitigation strategies that do not consider urban form will not be effective, as they lead to increase in VMT; on a related note, they also state that focusing purely on compact urban forms without consideration to fuel technology improvements may lead to higher emissions. Thus, overall, a few elements of built environment and urban form impact the transport choices and travel characteristics of urban residents.

2.4.2 Interactions between Urban Form and Air Quality

Since urban form impacts travel characteristics, it also could potentially influence transport-related emissions and concentrations. Specifically, Lyons et al. (2003) used the vehicle kilometers

traveled (VKT) from a few urban centers across the world as a surrogate for vehicular emissions and found that cities that restricted outward growth/sprawl have lower transport emissions, including CO and NO_x. In a study investigating the interactions between land use and health, Frank et al. (2006b) reported that an increase in walkability index, which incorporated land use mix, street connectivity, net residential density, and retail floor area ratios, reduced the VMT and emissions of NO_x and volatile organic compounds (VOCs). Following this, using a population reassignment technique, Stone et al. (2007) simulated emissions in compact urban forms and found higher elasticities between population density and vehicular emissions. Specifically, they found that median drop in pollutant emissions for the compact scenario as opposed to the business-as-usual scenario is 6%, 5.6%, 5.6%, 5.2% for PM_{2.5}, NO_x, CO, and VOCs, respectively.

Following this, Stone (2008) attempted to quantify the associations between urban form measures and air quality by studying the urban form and air quality characteristics of 45 large US metropolitan regions; urban form measures that were considered include centeredness, connectivity, population density, land use, and sprawl index. The study found that, of all the urban form measures of interest, population density is the only measure strongly correlated with the emissions of ozone precursors i.e., NO_x and VOCs; however, the study also reported a much stronger correlation between most urban form measures and annual ozone exceedances. Specifically, centeredness, connectivity, population density, and sprawl index were found to be significantly associated with annual ozone exceedances (Stone, 2008). Marshall et al. (2009) investigated the association between walkability, which provides a measure of mixed-use neighborhood and the connectivity between destinations, and estimated concentrations of ozone and nitric oxide for 49,702 postal codes in Vancouver, British Columbia, and found that urban centers were generally representative of high walkability and high nitric oxide concentrations but low ozone concentrations. Additionally, they found that locations near the urban centers (but not at the urban centers) had reasonably high walkability but lower pollutant levels. In a similar multi-location study, Schweitzer and Zhou (2010) used air quality monitoring data from 80 metropolitan regions to understand the relation between ozone concentrations and urban form. Using the Smart Growth America (SGA)

index scores developed by Ewing et al. (2002) to characterize the urban form, they found evidence for significantly lower ozone concentrations in compact regions but could not find associations between regional compactness and fine particulate concentrations.

Bereitschaft and Debbage (2013) used the urban sprawl indices developed by El-Nasser and Overberg (2001), Ewing et al. (2002), Lopez and Hynes (2003), and Sutton (2003), along with urban form variables and meteorological variables to measure the degree of association between urban form/sprawl and ambient non-point source emissions or/and concentrations of O₃, VOCs, NO_x, PM_{2.5}, and CO₂. The two most important composite measures of urban form are urban continuity and shape complexity. Urban continuity refers to the physical continuity and connectedness of land patches across the urban form or landscape (Bereitschaft & Debbage, 2013; McGarigal et al., 2002), and shape complexity describes the shape and provides a measure of the irregularity or “raggedness” of the land patches (Bereitschaft & Debbage, 2013; Huang et al., 2007). They found that a 1 standard deviation increase in urban continuity led to a 9% reduction in annual VOC emissions; conversely, a 1 standard deviation increase in shape complexity led to 8.7% and 12.4% increases in NO_x and PM_{2.5} emissions, respectively. The study also found that higher urban sprawl levels were significantly associated with high concentrations of O₃ and PM_{2.5}; additionally, residential density was found to be a good predictor of O₃ and PM_{2.5} concentrations (Bereitschaft & Debbage, 2013).

Recently, Yu and Stuart (2017) investigated the impact of compact growth and electric vehicles on future air quality and exposure levels for a seven-county region including the Tampa Bay area. They found that the regional emissions under a compact growth scenario were lower compared to a sprawl growth scenario, although this effect was more pronounced for NO_x as opposed to benzene and butadiene. Additionally, they found that the spatial distribution of the difference in concentrations between the compact and sprawl growth scenarios varied by pollutant type. NO_x concentrations (both annual average and maximum one-hour concentration) in the compact scenario were lower than that of the sprawl scenario. However, benzene and butadiene concentrations under the compact growth scenario were

higher than those of the sprawl growth scenario for a substantial portion of Hillsborough County; this is due to the increase in the population and land development density under the compact scenario.

2.4.3 Interactions between Urban Form, Exposures, and Human Health

Patterns of urban forms that increase dependence on motorized travel may have a direct negative implication on human health through increased pollutant exposures (Frank & Engelke, 2001; Frumkin, 2002). Within the context of Europe, De Ridder et al. (2008b) simulated the impacts of sprawl on air quality and found that sprawl leads to higher concentrations of traffic pollutants and exposures. They allocated 12% of their urban population to the green periphery and found that this population reallocation resulted in a higher traffic volume (17% increase), higher concentrations of ozone and particulate matter (approximately 4% increase), and a 0.5% increase in domain-average exposure (De Ridder et al., 2008b).

In the US, Clark et al. (2011) used a linear regression approach to identify the relationship between urban form and population-weighted pollutant concentrations for ozone, PM_{2.5}, and other criteria pollutants. The urban form variables in the study included population centrality, road density, jobs-housing imbalance, and city shape (a measure of circularity). They found that urban form was associated with air quality to the same degree as climatic factors and that population centrality was associated with lower population-weighted ozone, PM_{2.5}, and aggregate pollutant levels; transit supply was associated with lower population-weighted PM_{2.5} concentrations. This establishes the importance of urban form for air quality considerations. In contrast, they found that population density is associated with higher population-weighted PM_{2.5} concentrations and aggregate pollutant levels (Clark et al., 2011). Similar to this study, Hixson et al. (2009) simulated population-weighted PM_{2.5} concentrations for the San Joaquin Valley under sprawl and compact urban forms and found that exposures to primary PM components including elemental carbon and organic carbon was increased by 10–15% and reduced by 11–19% for the high-density and low-density scenarios, respectively. Additionally, they reported a reverse in trend (low exposures in high-density development and high exposures in low-density development) for secondary PM components including nitrate and ammonium ion. In Tampa Bay, Yu and Stuart (2017) found that compact growth results in lower population-weighted NO_x exposure concentration than the sprawl

scenario; however, exposure concentrations for benzene and butadiene under a compact scenario were found to be higher compared to a sprawl scenario.

Previously, Woodcock et al. (2009) compared the projections of health benefits for the business-as-usual scenario for 2030 with four alternate urban transport scenarios based on both the individual and combined effects of lower-carbon-emission vehicles and increased active travel for London, UK, and Delhi, India. They found that the scenario that used a combination of low-emission vehicles and increased active travel led to the highest health benefits despite an increase in the disease burden from road traffic injuries as a result of more active travel. It should be noted that the benefits from the increased active-travel-only scenario significantly outweigh those of the low-carbon-emission-vehicles-only scenario. Continuing a similar line of inquiry, Stevenson et al. (2016) used a health impact assessment framework to investigate the impact of mode change due to alternate land use policies on population health, using six different cities that fall on the spectrum of upper-income to lower-middle-income and highly-motorized to rapidly-motorizing as their testbeds. A compact cities model was applied to each of the six cities by increasing the residential density, reducing the distance to transit, and increasing the land use diversity. They found that the compact scenario resulted in overall health gains (420–826 disability-adjusted life-years) by shifting individuals to active modes of travel and reducing transport-related particulate matter emissions for all the cities despite a small increase in road trauma incidents for pedestrians and bicyclists.

In summary, most of the literature focusing on the relationship between urban form and transport suggested that compact urban forms led to a reduction in VMT and an increase in active and non-auto mode of travel. Additionally, studies found evidence for lower traffic-related emissions and concentrations in compact urban forms. Despite these improvements in air quality, several studies found that population exposure to traffic-related air pollution increased in compact urban forms. However, a recent macro-level study by Stevenson et al. (2016) found overall health gains due to compact and transit-oriented urban forms. Although these studies provide valuable information toward understanding the relationship between urban form, travel, air quality, and exposures, further studies on this topic are

necessary. First, the research trying to understand the relationship between urban form and population exposure is still budding; as a result, further research efforts are needed on this topic. Second, many studies on this topic used observed data from air quality monitors and existing urban morphologies to understand the linkages between urban design and population exposure. These studies generally may be incapable of answering what-if urban-policy questions; hence, there is a need for studies that use modeling techniques to simulate alternate urban morphologies and estimate their impact on population exposure. Finally, although a few studies used modeling techniques to understand the relationship between urban form and population exposure, they are either macroscopic in nature or used non-behavioral and coarser modeling techniques. Given this, my dissertation focused on using a highly-spatiotemporally-resolved modeling framework to estimate population exposure under alternate urban forms.

2.5 Characterization of Individual Exposure to Traffic-Related Pollution

The characterization of individual exposure to traffic-related pollution has two essential components—the characterization of the spatiotemporal distributions of pollutant concentrations and activity and travel patterns of individuals. In this section, the methodological aspects of characterizing pollutant concentrations is presented, followed by discussion on the current state of knowledge on the characterization of activity and travel patterns. Finally, combining the information provided in the first two sections, methodological details of exposure characterization are addressed.

2.5.1 Characterization of Spatiotemporal Distributions of Pollutant Concentrations

2.5.1.1 Ambient Air Sampling

Direct sampling or measurement of pollutants is perhaps the “gold standard” in accurately characterizing the spatiotemporal distributions of pollutant concentrations. The samplers that are used for direct measurement can be broadly categorized as active and passive samplers (International Agency for Research on Cancer, 2016), and the choice of measurement or sampling device would normally depend on the type of the pollutant and the parameters of the research study.

Previously, studies conducted a wide variety of sampling campaigns to obtain the spatiotemporal distributions pollutant concentrations. For example, Stuart and Zeager (2011) used Ogawa passive samplers to measure ambient NO₂ concentrations near 75 randomly-selected elementary schools in Tampa. Similarly, to estimate human exposures, other studies measured the micro-environmental concentrations, i.e., concentrations within a small area such as a bedroom, a kitchen, or an office using a variety of active and Palmes passive sampler tubes (Kornartit et al., 2010; Lai et al., 2004; Rotko et al., 2001).

Although direct measurement results in highly-accurate characterization of spatiotemporal distributions of concentration, the measurement campaigns entail higher costs. Additionally, notwithstanding the high temporal resolution, the spatial resolution of the measured concentrations can be limited owing to the discrete placement of the samplers. Finally, although these approaches help in understanding the existing air quality trends within an urban area, they are rather limited in addressing the implications of new regulatory policies or pollution sources on air quality (Vallero, 2008). Thus, these methods are ill-equipped to answer the implications of “what-if” scenarios on air quality. As a result, instead of direct measurement, several studies have taken the alternate route of modeling pollutant concentrations.

2.5.1.2 Ambient Air Modeling

A wide variety of models were employed in the past to estimate the spatiotemporal distributions of pollutant concentrations (Brugge et al., 2007; Burke et al., 2001; Jerrett et al., 2005). Air pollution models can be broadly categorized into two types—models that try to characterize atmospheric concentrations by performing statistical analysis of data or by simulating the fundamental physical and chemical interactions within a system (Seinfeld & Pandis, 1998). Since this study aimed to understand and predict the impact of urban form on transportation emissions and exposures, it focused on models that simulate the dispersion and transport of pollutants.

Atmospheric chemical transport models estimate pollutant concentrations at particular times and locations (receptors) using pollutant emission inventories and meteorological data. As mentioned, these

models simulate pollutant concentrations by explicitly accounting for the physical and chemical interactions within the system. Although different solution approaches are used, these models are generally based on the fundamental principle of conservation of the mass of species in a control volume of solution and are generally represented by equation 2.1.

$$\left[\begin{array}{c} \text{rate of accumulation} \\ \text{of mass of A} \end{array} \right] + \left[\begin{array}{c} \text{net rate of outflow of} \\ \text{mass of A from volume} \end{array} \right] = \left[\begin{array}{c} \text{rate of generation of} \\ \text{mass of A by reaction} \end{array} \right] \quad 2.1$$

A common expression of this balance at an infinitesimal point is given by the advective-dispersion expression shown in equation 2.2 (Ramaswami et al., 2005).

$$\frac{\partial C}{\partial t}(\vec{x}, t) + \underbrace{\vec{u} \cdot \nabla C}_{\text{advection}} = \underbrace{\nabla \cdot D \nabla C}_{\text{dispersion}} + \underbrace{R}_{\text{reaction}} + \underbrace{S}_{\text{source}} \quad 2.2$$

Many models, using a variety of approaches, were developed to operationalize the solution of this mass balance. Some commonly-used models in the US include CMAQ, CAMx, and HySplit.

2.5.1.3 Gaussian Formulation

One category of solution approach with a long history of being used for pollutant concentration estimation is the Gaussian approach. Gaussian models assume that the pollutant mass spreads in the horizontal and vertical directions following a Gaussian or normal distribution. Additionally, many of these models, called Gaussian plume models, are based on analytical solution of the steady-state advective-dispersion equation. The plume equation estimates the mean concentration from a continuous point source of pollution (assuming reflection at surface) as shown in equation 2.3.

$$C(x, y, z) = \frac{q}{2\pi u \sigma_y \sigma_z} \exp \left[-\frac{y^2}{2\sigma_y^2} \right] \left[\exp \left[-\frac{(z-h)^2}{2\sigma_z^2} \right] + \exp \left[-\frac{(z+h)^2}{2\sigma_z^2} \right] \right] \quad 2.3$$

where,

C is the pollutant concentration (μ/L^3)

x, y, and z represent the downwind, crosswind, and vertical position, respectively, of the receptor away from the source base location

q is the emission rate of the pollutant (M/t)

u is the horizontal wind speed in the downwind direction (L/t)

σ_y describes the cross wind dispersion in length (L)

σ_z describes the vertical dispersion in length (L)

h is the effective height of release (L)

Changes in concentration in time (e.g., each hour) are estimated from this equation due to changes in the parameters (q , u , σ_y , σ_z , h) with time. Examples of Gaussian plume models include AERMOD, CALINE, and R-LINE. R-LINE is used for air pollution modeling in most of this dissertation. A related approach that relaxes the steady-state assumption and accounts better for rapidly-varying changes in parameters uses a Gaussian puff solution; CALPUFF (California Puff) is an example. Results from air pollution modeling using CALPUFF are used for the analysis in Chapter 3.

2.5.2 Characterization of Spatiotemporal Distributions of Individual Activity and Travel Patterns

Human activity patterns (or activity and travel patterns) refer to the activity distributions of individuals within a certain period of time. Activity and travel patterns describe the movement of individuals in a geographic area by predominantly collecting information related to the activity locations, time and duration of activities, travel mode, travel times and distances, and travel routes between the fixed-activity locations. Characterization of activity and travel patterns is important from an exposure estimation perspective because the physical location of the activity, the time and duration of the activity, and the travel path between activity locations influence the personal exposure to pollutants. A variety of sample-based approaches use computer-assisted telephone interview, travel surveys or diaries, Global Positioning System (GPS) loggers, and home sensors to collect the spatiotemporal distributions of activity and travel patterns of individuals.

2.5.2.1 Sample-Based Activity and Travel Surveys

Several studies used a travel survey or diary format to obtain the spatiotemporal distributions of individual activity and travel patterns. Axhausen et al. (2002) conducted a six-week travel diary-based survey to observe the daily activity and travel routines of individuals in two German cities. The survey collected trip-level information including day of trip, start and arrival times, trip purpose, travel modes, trip destination, and activity and travel costs for 319 individuals from 139 households. To characterize

the daily personal travel patterns of individuals across the nation, the 2009 national household travel survey (NHTS) was conducted using a computer-assisted telephone interview instrument (Santos et al., 2011). The 2009 NHTS collected household and person-level demographic information and trip-level information including origin and destination location and time, length, mode of travel, and purpose for approximately 125,000 households.

Recent studies used advances in sensor-based technologies to record the activity and travel patterns of individuals. Specifically, in a study aimed at testing the feasibility of GPS technology to track individuals, Wiehe et al. (2008) used GPS-enabled cell phones to collect the activity and travel patterns of 15 adolescent women for one week. Although they found that user error and technical issues could affect the reliability of the activity and travel data, the authors argue that GPS technology provides a feasible way for collecting activity and travel data that can be used to identify health-risk behaviors (Wiehe et al., 2008). Similarly, Abdulazim et al. (2013) developed an Android application to collect the location data for individuals and land use data to estimate the travel mode based on the motion pattern as indicated by the cell phone's sensors. Such advanced applications can assist in collecting activity and travel information for a large section of the population in an economically feasible way.

Some of the advantages of using travel diary information are availability of larger sample sizes, detailed representation of spatial and temporal locations of individuals, and wide availability of such data resources including the NHTS, Consolidated Human Activity Database, and California Activity Pattern Surveys. Although the sample sizes from the travel diaries are considered to be fairly large, they typically are not more than 1% of the population. However, larger samples may be required to capture the intra-urban spatial variations in the activity patterns necessary for the estimation of population exposures. As mentioned, the sensor-based technologies could potentially solve the issue of low sample sizes owing to their ability to collect large samples at relatively low expense; however, these technologies are still budding and the gathered sensor data is primitive and heterogeneous, leading to difficulty in assimilating activity data from various sources (Chen et al., 2012). In addition, survey or sensor-based data cannot be used directly to forecast the activity and travel patterns under alternative policy scenarios. For example,

the raw survey data collected in a specific year may not give an indication of the activity and travel patterns of individuals in a future year where a transit-oriented compact growth policy may be implemented. In such alternate policy scenarios, predictive models can be used to simulate the activity and travel patterns of the population. It should be noted that survey data are still invaluable because the predictive models will be built based on the survey data.

2.5.2.2 Modeling the Activity and Travel Patterns of Individuals

In the transportation field, travel demand models were used for several decades by the research community, metropolitan planning agencies, and consulting firms to forecast the aggregate travel patterns of metropolitan residents under alternative policy and investment scenarios. Traditionally, the travel demand of an urban area has been modeled using a four-step or trip-based travel demand model. The fundamental unit of analysis in the trip-based travel models is an individual person trip (Castiglione et al., 2015). The modeling paradigm of a trip-based model consists of four steps—trip generation, trip distribution, mode choice, and network assignment. Trip generation estimates the number of trips produced from and attracted to each zone in an urban context. Trip productions and attractions are generally modeled using a linear regression approach and can be modeled at a disaggregate level for every household and usually are a function of the characteristics of the households, land use, and transportation system. Trip attractions are modeled at the zonal-level and are normally a function of the zonal characteristics. The general formulations for the trip production for a household h in zone i (P_{hi}) and all the households in zone i (P_i) are presented in equations 2.4 and 2.5, respectively.

$$P_{hi} = \beta_0 + \sum_{i=1}^k \beta_i x_i \quad 2.4$$

Here, x_1, x_2, \dots, x_k are the factors affecting trip generation, and $\beta_0, \beta_1, \dots, \beta_k$ are the estimated parameters that capture the effect of an independent variable on the trip production rate. To obtain the trip productions at the zonal level, the disaggregate trip productions for all the households in the zone need to be summed up.

$$P_i = \sum_{h=1}^N P_{hi} \quad 2.5$$

Here, N is the total number of households in the zone i . The trip attractions for the zone i (A_i) are estimated using an equation similar to 2.4, the only difference being the use of zonal-level characteristics including retail employment, commercial employment, gross floor area of retail activity.

Following the estimation of number of trip productions and attractions for each zone, the trips are allocated between the origin and destination zones using a gravity model shown in equation 2.6.

$$T_{ij} = P_i \left[\frac{A_j F_{ij}}{\sum_k A_k F_{ik}} \right] \quad 2.6$$

Here, T_{ij} is the total number of trips between production zone i and attraction zone j . P_i is total number of trips produced in zone i . A_j is the total number of trips attracted to zone j . F_{ij} is called the friction factor and captures the travel impedance, generally in the form of travel time or cost, between zones i and j .

Following the trip distribution, trips between different zones are allocated to one of the available travel modes in the mode choice step. Mode choice typically relies on the use of utility functions to estimate the travel mode shares; the utility of a mode alternative is dependent on the characteristics of the travel mode and the individual making the choice. A more detailed discussion of the utility-based models is provided under the activity-based travel demand model section below. Once the utility (U) for a travel mode (k) is calculated, the travel share for that mode (i.e., the proportion of travelers using mode k) is obtained using a multinomial model structure as shown in equation 2.7 where x represents all the available modes.

$$Pr(k) = \frac{e^{U_k}}{\sum_x e^{U_x}} \quad 2.7$$

Finally, the network assignment step allocates the trips to the traffic network and determines their travel path. The traffic assignment step is generally performed in multiple iterations by assigning trips to roadway links that form the shortest time-path and shifting them to non-congested links when the original roadway links to which they are assigned becomes congested. The process is repeated over multiple iterations until equilibrium is achieved between the travel demand and the supply within a tolerance.

Although trip generation models provide valuable information in terms of the current and future travel demand needs of a region, they are rather limited in their sensitivity towards proposed policy changes. This is because trip-based models consider each trip to be independent of the other (Castiglione et al., 2015; Pinjari & Bhat, 2011). However, in reality, many trips are interrelated. For example, in a household with two working adults who work at different locations and only one car, the individuals might have to coordinate their commute; it is easily conceivable that the travel patterns of this household will be different to that of another similar household with two available cars. Thus, clearly, factors including work location choice, mode choice, and mode availability influence the interrelations between trips, but the trip-based models ignore them. Trip-based models also suffer from aggregation bias (Castiglione et al., 2015; Pinjari & Bhat, 2011). These models characterize the travel behavior at an aggregate level by using broad socio-demographic categories and assuming that households belonging to similar categories behave similarly. For example, the trip generation rate for all households with two working adults and one child living in the same zone is considered to be the same. Thus, there is no way to account for the impacts of socio-demographic characteristics of individuals on the travel demand. Finally, trip-based models do not explicitly account for the temporal dimension of activities. Time is simply treated as the “cost” of making the trip without actual consideration for how participation in activities and travel takes away from the daily allocated time budget (Pinjari & Bhat, 2011). Thus, since these models are insensitive to time-of-day and scheduling choices, they are incapable of simulating the impacts of policies with time-of-day attributes.

Considering these limitations in the trip-based models, the travel demand field has moved towards the “behaviorally-oriented activity-based approaches for modeling passenger travel demand” (Pinjari & Bhat, 2011). These new streams of activity-based travel demand models try to characterize the travel using behaviorally-realistic paradigms. Whereas the trip-based models focus on trips without recognizing the need for those trips and travel, the activity-based approach views travel as a derived demand resulting from individual needs to participate in activities (Bowman & Ben-Akiva, 2001; Pinjari & Bhat, 2011). More specifically, instead of estimating independent trips, the activity-based models

focus on individual decisions to participate in activities and the scheduling and location of those activities along with the modeling of travel mode choices (Kitamura et al., 1997). As a result, activity-based models estimate chains of trips, also known as tours, as part of characterizing individual daily activity patterns (Castiglione et al., 2015). Thus, activity-based travel demand models are more sensitive to policy changes that affect the choice behavior of individuals which in turn affects their travel behavior.

Activity-based travel demand models allow for the estimation of activity and travel patterns at a disaggregate level. Specifically, they can be used to simulate the daily activity and travel patterns for each and every representative individual in the population of interest. The estimated individual-level activity and travel patterns include information on the types of daily undertaken activities, the spatial locations and timing of these activities, and the timing, mode, and routes of travel to these activities (Bradley & Bowman, 2006; Pinjari et al., 2006; Pinjari et al., 2008).

Activity-based travel demand approaches can be broadly categorized into two types—utility maximization-based and rule-based computational process systems. Utility maximization-based models operate under the philosophy that individuals choose only those activity and travel choices that maximize their utility. Here, utility can be thought of as a satisfaction derived from participation in activities. These systems use a suite of utility maximization-based discrete choice structures including multinomial logit and nested logit models, as well as other econometric structures including hazard-based duration models and ordered response models, to simulate individual-level activity and travel choices. For example, the travel mode choice module in an activity-based modeling framework may first estimate the utility of the choice alternative and then employ the multinomial logit structure (as shown in equations 2.7 and 2.8) to estimate the mode choice for an individual. Prime examples of utility maximization-based models include the Comprehensive Econometric Microsimulator for Activity-Travel Patterns (CEMDAP) (Pinjari et al., 2008) and DaySim (Bradley et al., 2010). In contrast, the rule-based computational process models use context-dependent and adaptive choice heuristics to estimate the activity and travel choices of individuals (Arentze & Timmermans, 2004; Pinjari & Bhat, 2011). In other words, instead of assuming that individuals always seek to maximize their utility, these models use an exhaustive set of if-then

condition-action rules to build daily activity and travel schedules for individuals. These condition-action rules generally are based on the observed activity and travel behavioral choices from travel surveys. Examples of rule-based computation process models include A Learning-BAsed TRansportation Oriented Simulation System (ALBATROSS) (Arentze & Timmermans, 2004) and Travel Activity Scheduler for Household Agents (TASHA) (Miller & Roorda, 2003). Since this study uses a utility maximization-based travel demand model, further details on these model systems are presented in the next section.

2.5.2.3 Utility Maximization-Based Travel Demand Models

Utility maximization-based travel model systems are based on the economic theories of consumer choice, which suggests that individuals choose the activity and travel choices that maximize their utility. The utility function for each choice alternative is dependent on the characteristics of the individual, choice alternative, and the interaction between them as shown in equation 2.8 (Koppelman & Bhat, 2006).

$$V_{t,i} = V(S_t) + V(X_i) + V(S_t, X_i) \quad 2.8$$

where,

$V_{t,i}$ is the utility of alternative i for individual t

$V(S_t)$ is the portion of utility associated with characteristics of individual t

$V(X_i)$ is the portion of utility of alternative i associated with the attributes of alternative i

$V(S_t, X_i)$ is the portion of the utility which results from interactions between the attributes of alternative i and the characteristics of individual t .

The general form of utility is linear and is represented using equation 2.9, where $S_{t,1}, S_{t,2}, \dots$ are the characteristics of the trip maker and X_1, \dots, X_r are the attributes of the choice alternatives. a_1, a_2, \dots, a_r are the parameters (or weights) defining the utility function.

$$V_{t,i} = a_1 S_{t,1} + a_2 S_{t,2} + \dots + a_r X_r \quad 2.9$$

Thus, according to the theory of utility-maximization an individual t chooses the alternative i over a set of all other alternatives j if $V_{t,i} \geq V_{t,j} \forall j$. This gives rise to a deterministic system of equations that one may solve simultaneously to determine the activity and travel choices of individuals. However, errors pertaining to incomplete or unavailable information may result in individuals choosing an

alternative with lower utility value. These unobserved factors are incorporated into the utility function as an error (or unobserved) term and the utility definition is updated as shown in equation 2.10 (Koppelman & Bhat, 2006). This gives rise to a probabilistic model.

$$U_{it} = V_{it} + \varepsilon_{it} \tag{2.10}$$

where,

U_{it} is the true utility of the alternative i to the decision maker t

V_{it} is the deterministic or observable portion of the utility estimated by the analyst

ε_{it} is the error or the portion of the utility unknown to the analyst.

Assumptions regarding the distribution of the error term results in different types of model structure. Generally, the errors are assumed to be identically and independently distributed, and follow an extreme-value (gumbel) distribution across the choice alternatives and individuals. This results in a multinomial logit model structure where the probability of choosing an alternative i is given as shown in equation 2.11.

$$Pr(i) = \frac{e^{V_i}}{\sum_j e^{V_j}} \tag{2.11}$$

The multinomial logit structure fails when there is a significant correlation among the choice alternatives (since the model assumes that alternatives are independent). In such a case, the alternatives are arranged into nests as shown in Figure 2.2 with similar alternatives placed into one nest. For example, the transit options including bus and light rail may be placed under a single nest since they share the attributes of public transit.

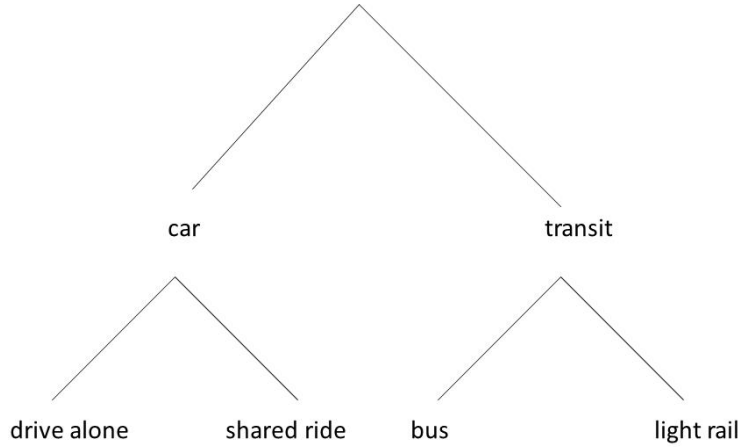


Figure 2.2 Nested mode choice model structure

In the nested logit structure, the probability of choosing an alternative i (under nest n) is conditional upon first choosing the n^{th} nest from a total of m nests and then choosing the i^{th} alternative under the n^{th} nest as given by equations 2.12 and 2.13 (Bowman & Ben-Akiva, 2001; Castiglione et al., 2015; Koppelman & Bhat, 2006). Here θ_n is a dispersion term that accounts for the correlation within a nest.

$$pr(i) = pr(i|n) * pr(n) \quad 2.12$$

$$pr(i) = \frac{\exp(V_{in}/\theta_n)}{\sum_{j \in n} \exp(V_{jn}/\theta_n)} * \frac{\exp\left[V_n + \theta_n \ln\left(\sum_{j \in n} \exp(V_{jn}/\theta_n)\right)\right]}{\sum_{\forall m} \left[\exp\left[V_m + \theta_m \ln\left(\sum_{j \in m} \exp(V_{jm}/\theta_m)\right)\right] \right]} \quad 2.13$$

Although there are certainly other types of econometric modeling structures in use in activity-based travel demand modeling systems, the multinomial logit and nested logit models are perhaps the most widely used. Using these econometric model structures, the activity-based travel demand models estimate the daily activity and travel behavior of individuals given their demographics, urban land use characteristics, and highway and transit characteristics.

2.5.3 Characterization of Individual Exposures to Traffic-Related Pollution

Individual daily exposures to pollutants are dependent on the magnitude of pollutant concentrations, duration of exposure, and the frequency of exposure (Klepeis et al., 2001; Setton et al., 2011); thus, spatiotemporal characterizations of pollutant concentrations and activity and travel patterns

of individuals are important. Epidemiologic studies focusing on exposures to traffic-related pollution used two broad categories of surrogates—measured or modeled concentrations of surrogate pollutant and direct measures of traffic including proximity or distance to the roadway and roadway traffic volumes (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010; Jerrett et al., 2005).

Exposure estimation based on proximity measures, or volumes, are by far the easiest to implement. However, they do not robustly account for factors including fuel type and vehicle mix (Gertler, 2005), and meteorology and terrain (Baklanov et al., 2007; Rijnders et al., 2001) that impact pollutant concentrations and, hence, exposures. As such, studies tried to estimate personal exposures to traffic pollution using a variety of measurement and modeling approaches.

Traditionally, air pollution exposure analysis has been simplistic with regard to the consideration of human activity patterns for exposure estimation. An individual's exposure often is estimated by considering the pollutant concentration at the individual's residential location, also called residence-based exposure, or at a fixed monitoring station (Cortese & Spengler, 1976; Huang & Batterman, 2000). These methods could lead to biased exposure estimates owing to the disregard of spatiotemporal concentrations near the individuals' non-residential activity locations. Realizing this limitation, studies were undertaken to characterize individual daily time use and diurnal activity patterns (Health Canada, 2010; Klepeis et al., 2001; National Exposure Research Laboratory et al., 2000). Among these, the National Human Activity Pattern Survey (NHAPS) (see Klepeis et al. (2001) is a widely-used source of data for pollutant exposure analysis in the US (Burke et al., 2001; Dong et al., 2004). NHAPS used a 24-hour activity diary to collect information pertaining to individual activity participation (type, timing and the duration of activity) and the microenvironment location type (kitchen, bedroom, office, grocery store, etc.) for the activities over one day. Whereas the detailed information collected by NHAPS and similar surveys is of immense value, the small sample size and the lack of detailed geographic coordinates for the activity locations pose an obstacle for exposure characterization. Some additional concerns include issues of representativeness of the activity data for intra-urban exposure applications and temporal validity of activity patterns especially for exposure forecasting purposes.

Recognizing these limitations, a few studies tried to conduct personal monitoring campaigns to accurately estimate exposures to traffic pollution. For example, to characterize individual exposure to NO₂, Kousa et al. (2001) and Kornartit et al. (2010) used Palmes tubes. Similarly, Good et al. (2016) used backpack-based measuring instruments to obtain spatiotemporal distributions of activity and travel patterns of individuals and personal exposures to a variety of pollutants. These personal monitor-based exposure measurement campaigns are, by far, the most accurate methods to estimate the personal exposures; however, large-scale deployment of personal monitors may not be feasible due to the high expenses involved (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010; Jerrett et al., 2005). A few studies also measured the micro-environmental concentrations (for example, bedroom, kitchen, or office) in an effort to characterize personal exposures (Kornartit et al., 2010; Lai et al., 2004; Rotko et al., 2001). In these studies, the microenvironments where individuals typically spend a large portion of their day were chosen for measurement. However, this method offers limited spatial variability and may only be pertinent to the microenvironments under study. Further, this method also can be cost prohibitive similar to the personal-monitoring approach (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010).

To overcome these limitations, a few studies pioneered the use of activity and travel patterns obtained from travel surveys in conjunction with modeled pollutant concentrations to estimate personal exposures (Kornartit et al., 2010; Marshall et al., 2006). Marshall et al. (2006) used an activity and travel survey data of about 25,000 individuals in southern California to compute the pollutant exposures. Although these travel survey-based studies have a fairly large sample size, the spatial variability of the activity and travel patterns of this sample may not be representative of the population. Additionally, this sample-based approach cannot be realistically used to estimate exposures under a hypothetical policy scenario.

Thus, to overcome all of the earlier-mentioned issues, a few recent studies chose the alternate route of modeling both pollutant concentrations and activity and travel patterns of individuals to estimate personal exposures for the entire population. Hatzopoulou and Miller (2010) used an activity-based travel

demand model (TASHA) in conjunction with a mobile source emissions estimation model (MOBILE 6.2C) and dispersion model (CALPUFF) to estimate personal exposures to NO_x for the Greater Toronto area's population. Similarly, Beckx et al. (2009a)), (Beckx et al., 2009c), and Beckx et al. (2009d) used the activity-based model ALBATROSS in combination with the emissions model MIMOSA and pollutant dispersion model AURORA to estimate personal exposures to NO₂ in the Netherlands. Recently, Vallamsundar et al. (2016) used a similar paradigm within the context of the US to estimate the population exposure of Maricopa County, Arizona, to PM_{2.5}. Although these studies certainly laid the groundwork and provided advances for population exposure estimation methodologies using activity-based modeling, their spatial resolution is generally coarse. This is of specific interest when dealing with pollutants such as NO_x that display a high spatial variability at the urban scale. However, more importantly, previous research efforts did not fully exploit the features of activity-based models to simulate the activity and travel patterns and the resulting population exposure under alternate urban design scenarios. Given this, my dissertation focused on creating a modeling framework that combines an activity-based travel demand model with emissions estimation and dispersion models to forecast high resolution activity and travel data and population exposure under alternative urban design scenarios.

2.6 Conclusion

In view of the previous discussion, a clear gap in knowledge exists with regard to the overarching question “how can we design cities so that population exposures and exposure inequalities can be mitigated?” First, although several studies showed the prevalence of exposure inequalities by ethnicity and socioeconomic status, very few studies look at the associations between other social and urbanicity variables of interest. Second, it would be of specific interest to understand if the exposure inequalities would persist when considering only traffic-related pollution. Third, although a few studies investigated the relationships between urban form and air quality, few to none have considered the interactions between them using micro-simulation models that specifically model activity and travel patterns of individuals. This is of particular interest because whereas some studies showed larger influence of urban form on exposures to traffic-pollution, many showed marginal effects. A primary reason for this could be

the non-availability of tools that can realistically predict changes in human activity and travel behavior as a function of changes to the built environment. Fourth, past research efforts that used activity-based travel demand modeling have not fully exploited them to simulate the activity and travel patterns of individuals under different transportation and land use design scenarios. Considering these limitations, this study aimed to understand the relationship between urban design features, human activity and travel patterns, air quality, and population exposure using highly spatiotemporally-resolved activity-based travel demand modeling and air pollution emission and dispersion modeling.

CHAPTER 3: IMPACTS OF TRAVEL ACTIVITY AND URBANICITY ON EXPOSURES TO AMBIENT OXIDES OF NITROGEN AND ON EXPOSURE DISPARITIES

3.1 Note to Reader

This chapter was published in *Air Quality, Atmosphere & Health*. (Gurram, S., Stuart, A.L. & Pinjari, A.R. *Air Qual Atmos Health* (2015) 8: 97. <https://doi.org/10.1007/s11869-014-0275-6>). The article is available online at <http://link.springer.com/article/10.1007/s11869-014-0275-6>. Permission is included in Appendix A.

3.2 Introduction

Estimation of human exposures to air pollution is important to researchers and practitioners in the fields of air quality management, environmental epidemiology, and urban design. Exposure estimation requires characterization of pollutant concentrations when and where a person or group spends time (Ott, 1982). Although personal monitoring has long been used to determine exposures in the field of air pollution epidemiology (Dockery & Spengler, 1981), it is time- and cost-intensive, resulting in small sample sizes that may be limited for representing a general population (Jerrett et al., 2005; Pekkanen & Pearce, 2001). Hence, methods of estimating exposures for a large group of people are needed for population-level risk assessment and policy decisions.

For large-sample studies, exposures to air pollutants often have been estimated using residence address to represent the location of exposure. Concentrations measured at fixed monitoring sites or concentration surrogates (such as nearby traffic counts) are used to derive exposures at the residence locations (Huang & Batterman, 2000; Meng et al., 2007; von Klot et al., 2009). Although this is a relatively simple and generalizable approach that can be applied in the context of available data, it is recognized that human activity patterns may be particularly important for explaining exposure variation (Klepeis et al., 2001; National Center for Environmental Assessment et al., 2011; Ott et al., 1986).

Hence, exposure error and misclassification are concerns, with potential outcomes of inaccurate health and environmental impact assessments and policy interventions (Huang & Batterman, 2000; Krzyzanowski, 1997; Özkaynak, 1986; Sheppard et al., 2012; Thomas et al., 1993; Zeger et al., 2000).

As a result, studies have investigated the use of more refined estimates of population location and concentration to represent personal exposures through methods that characterize or apply patterns of human activity (e.g., from time activity diaries) and microenvironment concentrations (Dons et al., 2011b; Kornartit et al., 2010; Lai et al., 2004). These methods often improve the estimate of group-level and personal exposures, but remain substantially limited in the characterization of spatiotemporal variations in concentrations and activities. A few recent case studies have used detailed activity and travel patterns derived from travel surveys or activity-based models coupled with air pollution modeling to estimate air quality exposures or health impacts (Dons et al., 2014; Gariazzo et al., 2011; Hankey et al., 2012; Hatzopoulou & Miller, 2010), including analysis of exposure error (Dhondt et al., 2012; Setton et al., 2011), exposure inequality (Marshall, 2008; Marshall et al., 2006), impacts of travel (Beckx et al., 2009b; de Nazelle et al., 2013; Zhang & Batterman, 2013), urban form (Stone et al., 2007), and transportation policies (Dhondt et al., 2013). Nonetheless, the literature remains sparse, and additional case studies applying and improving these methods are needed. Additionally, limited literature exists on the social distribution of exposure error.

This study is part of an ongoing project that aims to enhance the current understanding on exposures to traffic-related air pollution, specifically on the social distribution of exposure and impacts of urban design (Evans & Stuart, 2011; Fridh & Stuart, 2014; Stuart et al., 2009; Stuart & Zeager, 2011; Yu & Stuart, 2013). This study investigates impacts of activities and urban design factors on exposures and exposure disparities and estimates the error introduced by use of residence-location-only versus detailed spatiotemporal activity on exposure estimates. Our methods combine information from an available travel survey, estimated travel routes, and concentration data from air pollution modeling results. The following questions were addressed through this work: How are population activities distributed spatiotemporally in the study domain? How are exposures distributed among population groups in the

study domain? What is the strength and direction of disparities between groups? Does urban form influence the strength of exposures and their social distribution? Which factors are most influential? Are findings robust to uncertainties in exposure estimation associated with the representation of exposure location? How much does the representation of spatiotemporal activity location impact exposure estimates? Are the errors associated with exposure estimation different for different population subgroups? Methods and findings on these questions are detailed below.

3.3 Methods

3.3.1 Study Area and Pollutant Focus

Hillsborough County, Florida, shown in Figure 3.1, is the area of study. It contains a diverse mix of air pollutant emission sources, including an extensive highway network. Further, it has undergone considerable urban sprawl during the past few decades; in 2000, Smart Growth America ranked it as the 22nd most sprawled metropolitan area of 83 with populations over a half million (Ewing et al., 2002). In 2012, the Texas Transportation Institute (TTI) ranked Tampa-St. Petersburg as 30th for congestion (yearly delay per commuter) (Schrank et al., 2012), with automobiles as the primary mode of personal transportation. Regarding measured air quality, ozone levels in the area exceed the National Ambient Air Quality Standard (NAAQS) a few times most years, with particle levels close to the 24-hour standard; the American Lung Association grades Hillsborough County's air quality as "F" for ozone and "C" for particulate matter (American Lung Association, 2011). Further, the county is interesting for social equality reasons, as its population is relatively diverse and somewhat residentially-segregated (Stuart et al., 2009).

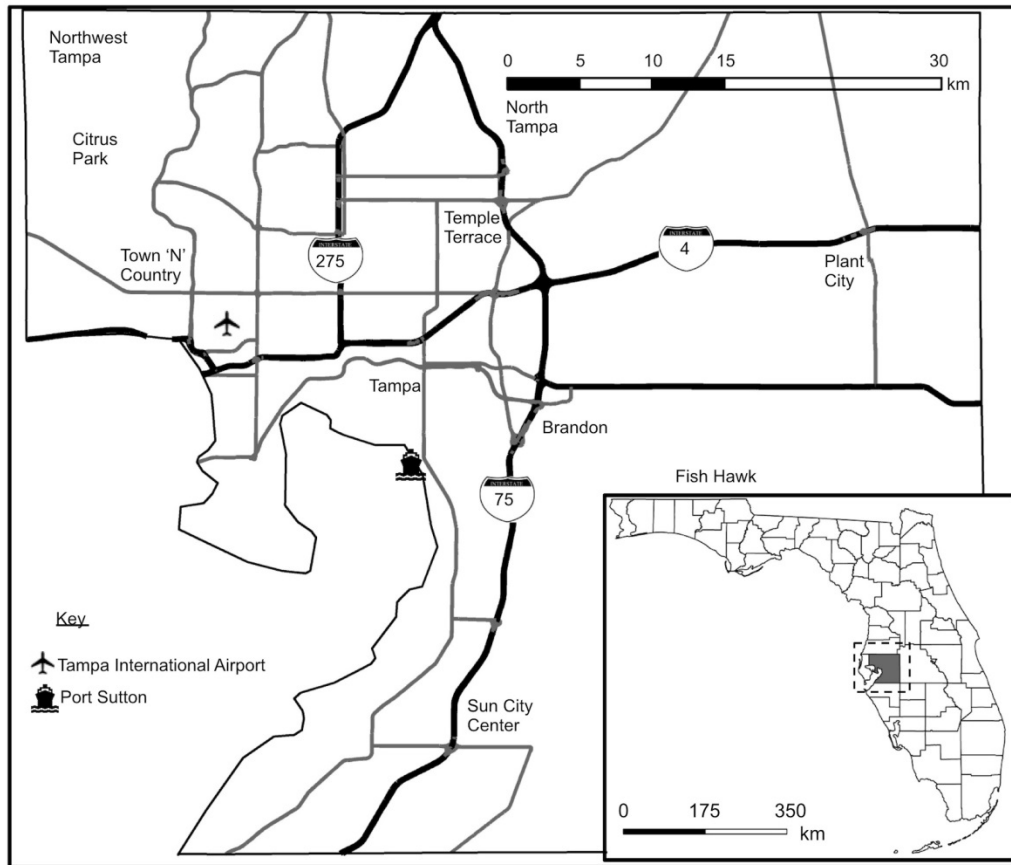


Figure 3.1 Study area of Hillsborough County, Florida. Inset shows location of study area within state of Florida.

The pollutant focus herein is oxides of nitrogen (NO_x), which is the sum of nitrogen monoxide (NO) and nitrogen dioxide (NO_2), a US criteria air pollutant with an established standard level). Although, levels of NO_2 measured by regulatory networks rarely exceed the national standard, NO_x is a precursor to both ozone and fine particles. Further, it is a common urban pollutant that has been associated with respiratory responses for susceptible individuals, particularly children, even at levels below the National Ambient Air Quality Standard (US Environmental Protection Agency, 2008). Studies have linked the exposure to oxides of nitrogen with cardiovascular and respiratory mortality (Faustini et al., 2014), gestational diabetes and preeclampsia (Malmqvist et al., 2013), diabetes mellitus and hypertension (Coogan et al., 2012), and incidence of asthma (Anderson et al., 2013). NO_x is also a recognized surrogate in health outcomes analyses for the complex mix of traffic pollution (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010).

3.3.2 Estimation of Spatiotemporal Human Activity and Travel Patterns

Human activity and travel patterns representing the study area were estimated using data from the National Household Travel Survey (NHTS), a periodic survey that characterizes the daily travel behavior of Americans (Federal Highway Administration, 2009). Data are collected on all out-of-home trips taken over approximately a 24-hour period for individuals sampled by the survey. The data collected include the purpose of each trip (work, shopping, recreation, etc.), trip start and end times, travel times, travel distances for each trip, and the geo-coded locations of activities. Socio-demographic characteristics (including age, race/ethnicity, household income, household size, and neighborhood urbanicity) of those surveyed are also collected. Here, we used data from the 2009 survey to characterize spatiotemporal locations of daily activity and travel in Hillsborough County.

The national household travel survey sample for Hillsborough County includes daily activity records for 1582 persons from 804 households. Prior to use, we filtered the sample to exclude daily activity records that were inconsistent or had missing information. We also excluded records that contained travel outside of the county boundaries (beyond which detailed NO_x concentrations were not available). For a few records, it was necessary to pare the data to exactly 24-hours (beginning at 12:00 am). The resulting sample consisted of 1224 daily activity records, including 239 with no travel away from the residence location on the survey day.

To estimate the locations of daily activities in time and space for the county sample, we first extracted data from each individual 24-hour activity record (a person-day). Specifically, we extracted the geocoded residence location (latitude, longitude), origin and destination locations for each trip, trip start times, and dwell times (time spent at the activity location) using SPSS (version 20.0, IBM Corp. Armonk, NY). Since the national household travel survey does not record information on travel path, we estimated the route of travel for each trip. Specifically, we used the Network Analyst tool in ArcGIS (version 10.0, ESRI, Redlands, CA) to select the shortest time path between each trip's origin and destination, based on roadway link times and a network shape file (NAVTEQ, 2010). Travel times for each link were calculated using link lengths and link free flow speeds provided with the network data. Spatial location

coordinates (latitude, longitude) along each trip path were extracted at a discrete interval of 100 meters of path length using the ET GeoWizards tool (version 10.2, ET Spatial Techniques, Faerie Glen, South Africa). The temporal location coordinate (time of day) for each discrete spatial location was estimated by adjusting the time on each link by the ratio of the total trip time from the survey data to that from the link time estimate. We then combined the trip path location data to create a highly-resolved sequential spatiotemporal record of estimated activity location for each person-day in the filtered county sample.

3.3.3 Estimation of Diurnal Pollutant Concentrations at Activity Locations

To estimate pollutant exposures for the study sample, we used ambient NO_x results from our previous dynamic CALPUFF air pollution dispersion modeling for the study area. Details of the modeling methods, results, and evaluation are provided in Yu and Stuart (2013). In essence, concentrations were estimated using detailed emissions, including link-level roadway emissions, and meteorological data for 8760 hours (all hours of 2002) for the study area. The results provide estimated concentrations on a receptor grid with 1 km spatial resolution for Hillsborough County. For matching with the daily activity and travel records here, we estimated the diurnal cycle of the spatial distribution of NO_x concentration from the model results by averaging the hourly modeled concentration results at each receptor over each hour of the day.

3.3.4 Estimation of Daily Exposure Concentration and Exposure Error

One goal of this work was to investigate the impact of activity and travel patterns on exposure estimates. To do this, we calculated and compared daily exposure concentrations for each person-day using two methods. Both methods estimate the time-weighted exposure concentration, $C = (1/T) \int c dt$, where c is the instantaneous pollutant concentration at an exposure location, dt is the instantaneous time interval of exposure, and T is the total exposure averaging period, which equals $\int dt$ (24 hours for the person-day records here).

The first method uses only the residence location to estimate daily exposure concentration for each person-day. We call this the residence-based exposure concentration (C_R); it represents conventional exposure concentration estimation using only residence address information. Since the spatial location of

exposure does not change with this approach, the discretized exposure concentration during each person-day varies in time only, not in space. Using the ArcGIS intersect tool, we extracted concentrations from the 24 dispersion modeling concentration maps (each representing one hour of the day with 1 km spatial resolution), resulting in ambient concentrations (c_{τ}) for each hour of the day (Δt_{τ} equal to 1 hour) at each residence location. We then numerically integrated these data using time weighting in SPSS to estimate the daily residence-based exposure $C_R = (\sum c_{\tau} \Delta t_{\tau}) / T$ for each person-day in the study sample.

Second, we estimated daily exposure concentrations by matching the spatiotemporal locations in each person-day activity-travel record with modeled concentration at those locations; we call this the activity-based exposure concentration estimate (C_A). Specifically, we extracted concentrations from the modeled data for each discrete location along each person-day activity-travel path. This results in ambient pollutant concentration (c_{σ}) and time spent (Δt_{σ}) for each discretized spatiotemporal activity-travel path location, $\sigma = (\text{latitude, longitude, time})$. Note that concentration for the same hour of day changes due to movement in space. The daily activity-based exposure concentration was then numerically estimated as $C_A = (\sum c_{\sigma} \Delta t_{\sigma}) / T$ for each person-day in the study sample. For explanatory analyses, we also estimated exposures, $E_A = \sum c_{\sigma} \Delta t_{\sigma}$, for sub-daily periods.

To compare the two measures of exposure concentration, we calculated the relative percent difference between the activity-based and residence-based exposure concentration as $(C_A - C_R) / C_A$ for each person-day in the sample. We call this the exposure error, as it estimates the error associated with using residence location only to calculate exposure. Frequency distributions for the study sample of daily exposure concentration (estimated using both methods) and of exposure error were compared to describe differences. A paired-sample t-test was used to quantify the significance of differences in the means for each sample distribution. Finally, we calculated bias factors to quantify the potential bias in relative risk

estimates (based on simple linear models) due to use of the residence-based exposure estimate, following the method outlined by Setton et al. (2011).

3.3.5 Analysis of Exposure Distributions and Inequality

A second goal was to characterize disparities between groups in activity-based exposure concentration and in potential exposure error, including identification of factors impacting both. To do this, we first categorized daily exposure concentrations and exposure errors by population subgroup. We focused on subgroup types representing characteristics that have previously been found to experience exposure disparities or air pollution susceptibility. Specifically, the person-day exposure concentration estimates were categorized by age (5–18, 19–45, 46–65, and older than 65 years), race/ethnicity (Asian, white, Hispanic, black), and household income/poverty (below poverty, above poverty to below \$75,000, above \$75,000). Age less than 5 could not be considered, as no survey data are available for this category. To define the poverty threshold, we used the 2009 federal poverty guidelines that are based on household size (Department of Health and Human Services, 2009). The above \$75,000 threshold was chosen to capture approximately the highest third of the income distribution in the study area. After categorization, group frequency distribution summary statistics (e.g., mean, percentiles) were calculated and compared. To measure the significance of differences between groups of the same type, we used 95% confidence intervals around each mean and performed one-way ANOVA, followed by post-hoc Games-Howell testing (Hayes, 2005). A similar analysis was performed for differences in exposure errors between groups.

To investigate impacts of urban design, travel, and activity factors on exposure and exposure disparities, we performed a few additional analyses. As a proxy for urban design, we first categorized exposure concentrations by the urbanicity of the residence location (urban, suburban, second city, rural), as provided with the survey data (Claritas, Inc. [2004] provides urbanicity category definitions; we use the term rural for the town and country category, to avoid confusion with the proper name – Town ‘N’ Country – of a region in the study area. See Figure 3.1). Next, we categorized exposure concentrations by daily personal travel time. A preliminary analysis of the time spent at different activity location types

shows that mean daily personal travel time is 62 minutes (see Table 3.1); thus, we formulated three daily travel time categories, i.e., no travel, daily travel less than 1 hour, and daily travel greater than 1 hour to understand the distribution of exposures by daily personal travel time. Distributions of activity-based exposure (concentration x time) were also compared between different activity location types to explore the contribution of activity-location type to exposures. Specifically, activity location types were divided into three categories—at-residence, non-residential, and in-travel. Exposures were also compared against daily travel time. Similar analyses were performed for exposure error. Finally, we performed a multivariate linear regression analysis to assess the impact of urban design and activity factors on exposure concentration. Specifically, we used a hierarchical stepwise approach, in which the sociodemographic predictors (gender, age, racioethnicity), followed by the income categories, were introduced first, to control for their impacts on exposure concentration. The urbanicity categories, followed by the activity time variable, were entered subsequently. All predictor variables were introduced into the model as categorical binary variables (e.g., male/female, black/non-black), except the time variable, which was introduced as a continuous variable. A 95% confidence ($p < 0.05$) statistical significance criteria for each predictor variable was used to discard or retain variables at each modeling step. All statistical analyses were performed in SPSS.

3.4 Results and Discussion

3.4.1 Distributions of Human Activity in the Tampa Area

Table 3.1 provides a summary of the average temporal distributions of activity types observed by the 2009 national household travel survey for the filtered study sample in Hillsborough County. Time activity data are also provided from two well-known historical human activity surveys used for exposure analysis, the National Human Activity Pattern Survey (NHAPS) (Klepeis et al., 2001) and the Canadian Human Activity Pattern Survey (CHAPS) (Leech et al., 2002). As in the historical surveys, residents in the study sample spent the majority of their time at home (about 80%), although the percentage of time spent at home is about 13% higher here. The order (from highest to lowest percentage of time spent) of activity location types is also the same here as in the NHAPS and CHAPS. However, the quantitative

distribution of time is somewhat different; the population sampled here spent more time on average at work, and less time travelling, at meals, and at other activities. Some of these differences may be due to differences in spatial scale, geography, and demographics. Specifically, the NHTS results are for Hillsborough County, FL, while the NHAPS and CHAPS results are for the entire US and Canada, respectively. Further, Florida is a state with large older-adult population, which may contribute to more time spent at home. Finally, different definitions of the activity type categories between the surveys could also have led to some differences.

Table 3.1 Average time spent per day by activity location type

Activity Type ⁴	This Work ¹		NHAPS ²	CHAPS ³
	min.	(%)	(%)	(%)
Home	1151	80	67	67
Other	116	8.0	19	20
Work	98	6.8	5.9	6.0
Travel	62	4.3	5.7	5.3
Meals	13	0.9	1.9	1.8

¹Filtered sample from 2009 NHTS for Hillsborough County.

²National Human Activity Pattern Survey (Klepeis et al, 2001).

³Canadian Human Activity Pattern Survey (Leech et al, 2002).

⁴The following specific categories from each study were included under each label. Home – NHTS Home category; NHAPS and CHAPS categories of Indoor at Home and Outdoor at Home. Work – NHTS Work category; NHAPS and CHAPS Office/Factory category. Travel – NHTS categories of Travel and Transport Someone; NHAPS and CHAPS categories of In Vehicles and Near Vehicles - Outside. Meals – NHTS Meals category; NHAPS and CHAPS Bar/Restaurant category. Other – NHTS categories of School/Daycare/Religious Activity, and Medical/Dental Services, Shopping/Errands, Family Personal/Business Obligations, Social/Recreational Activities, and Other categories; NHAPS and CHAPS categories of School/Public Building, Indoors-Other, Outdoors-Other, and Mall/Store.

Figure 3.2 provides the spatial distribution of activity time from the study sample (the percentage of total time spent in each block group area (subplots a–c), along with urbanicity (subplot d) of each block group). To our knowledge, this presentation of a spatially distributed activity time density map applied to exposure analysis is novel. Subplot d indicates that urbanicity generally decreases from central Tampa, surrounded by suburbs (including Citrus Park and Temple Terrace). A few pockets classified as second city areas (Sun City Center, Brandon, Plant City, New Tampa, Town 'N' Country) are farther from central Tampa and are surrounded by areas classified as the rural urbanicity category. The block group areas in the largest time density category (with at least 0.4% of the total time in the sample) are located in areas

that are categorized as rural (e.g., Fish Hawk), suburban, and some second city locations (e.g., in Brandon and Sun City Center) and largely correspond to the areas with the highest percentage of residential activity time (not shown). The block groups with the highest densities of non-residential time are largely special locations (Tampa International Airport, University of South Florida) or, for the second highest category (containing from 0.1% to 0.4% of total time in the sample), in rural, second city, or suburban locations. As a whole, the population of the Hillsborough County sample spent little time in urban block groups, though the time densities are larger for non-residential activities.

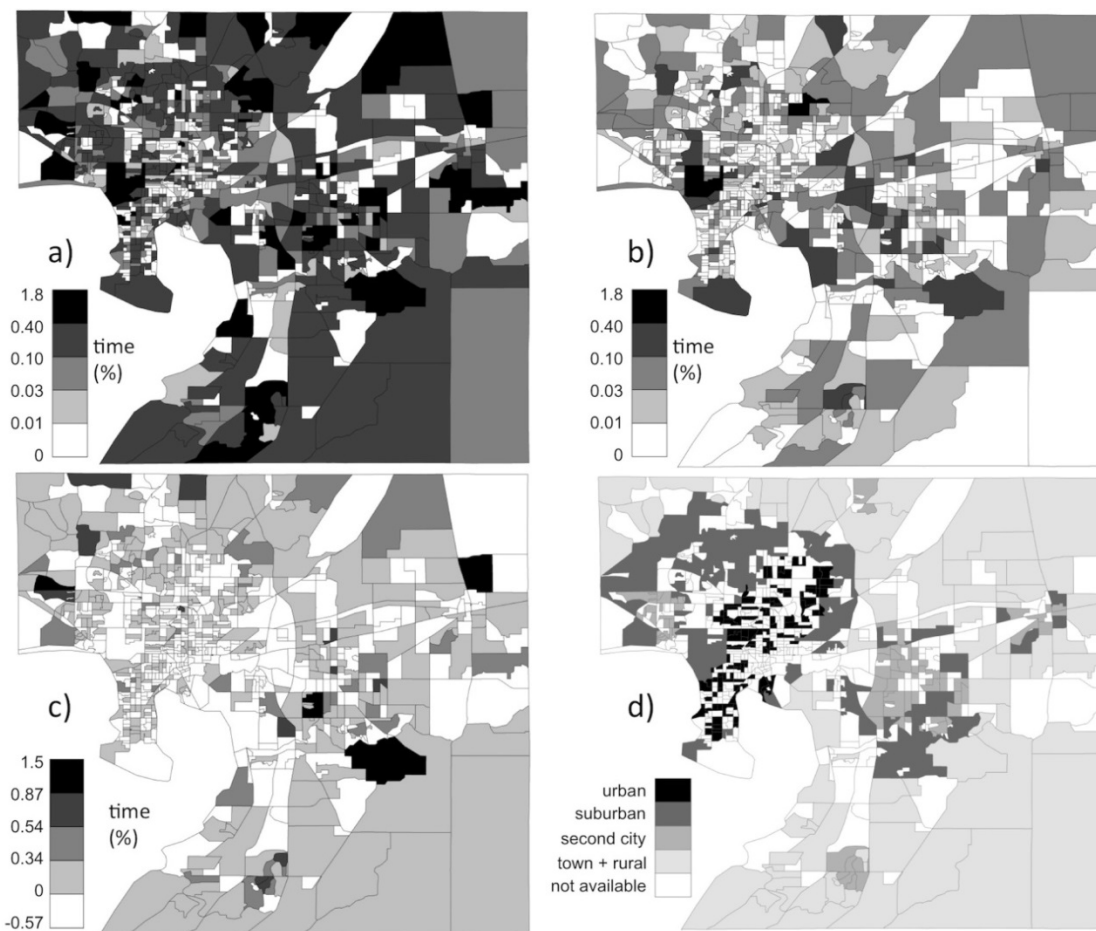


Figure 3.2 Spatial distribution of sample population activity-time (% of time spent) and urbanicity in study area. a) % of total time spent in all activity types within block group, b) % of total time spent in non-residential activities within block group, c) difference (%) between residential (r) and non-residential (nr) activity-times spent in each block group, d) urbanicity category of block group.

3.4.2 Diurnally Varying Spatial Distributions of NO_x Concentration

The average diurnal cycle of modeled NO_x concentration for the study area is shown in Figure 3.3. See Yu and Stuart (2013) for a detailed discussion of the spatial distribution of concentrations in the study area and results from evaluation of model performance. For our purposes here, note that for many hours of the day the concentrations are highest along the major roadways in the area with a broad peak apparent over central Tampa and near Tampa International Airport. A high is also often visible near a major port facility (Port Sutton) to the south of Downtown. Diurnally, concentrations exhibit morning (6:00–8:00 am) and evening (5:00–9:00 pm) peaks, consistent with increased NO_x emissions from traffic during commute hours. The evening peak is more spread out in time than the morning peak, consistent with both a larger meteorological mixing height in the evening and typical commute behaviors; specifically, the morning commute is known to be largely driven by work-related activities, while the evening commute may include maintenance, social, recreational, and other activities (Jou & Mahmassani, 1997; Kim et al., 2008). A detailed evaluation of modeled estimates against measured data is provided in Yu and Stuart (2013).

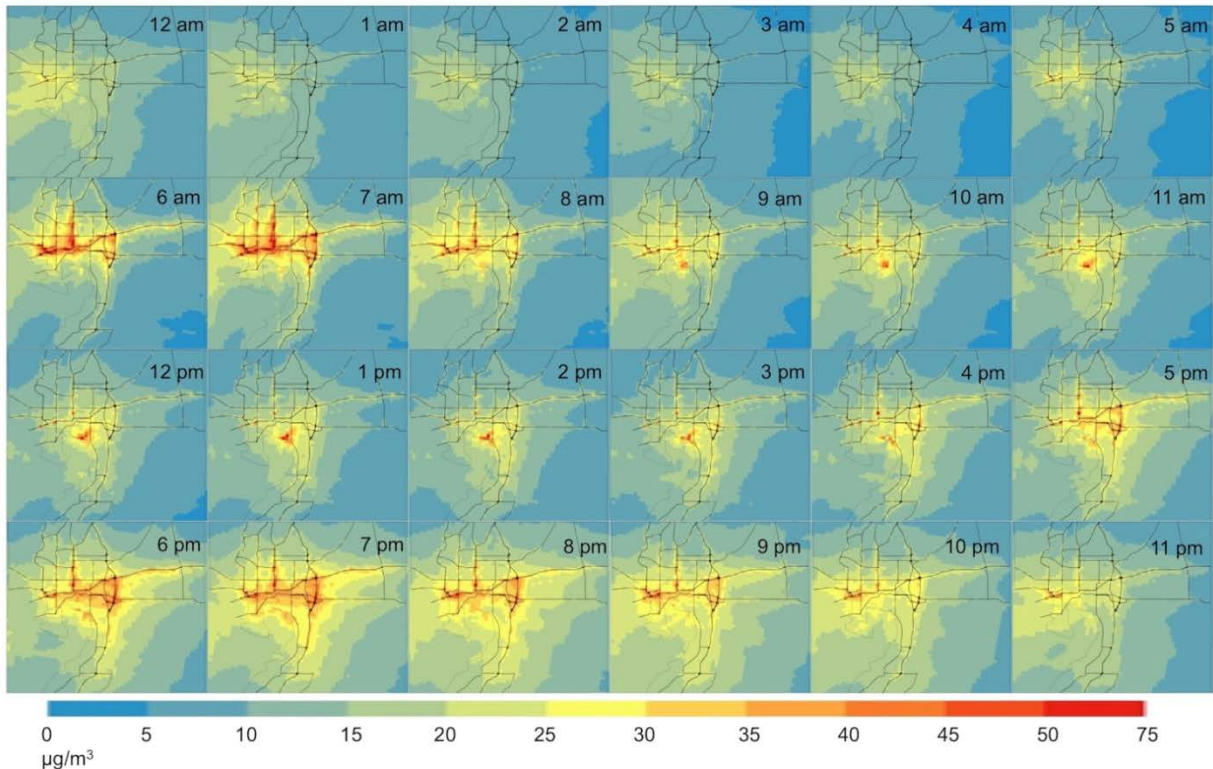


Figure 3.3 Estimated diurnal cycle of hourly average ambient NO_x concentrations (µg/m³) in study area, from dispersion modeling results

3.4.3 Daily Time-weighted Activity-based Exposure Concentrations and their Social Distribution

The cumulative distribution of estimated daily (24-hour) activity-based NO_x exposure concentration is shown in Figure 3.4 (left side). The mean exposure concentration for the study sample is 17 µg/m³, with values for individual person-day records ranging from 7.0 to 43 µg/m³. Using a typical fraction of NO₂ in NO_x estimated for the Tampa area of 0.8 (Poor, 2008), the values found here roughly correspond to daily NO₂ exposure concentrations of 7.4 ppb and 18 ppb for the sample mean and maximum, respectively. Although these values are on the low end of 24-h NO₂ exposure concentrations measured elsewhere (e.g., Delfino et al. (2008); Kim et al. (2006)), they are in the range of 24-hour average NO₂ exposure concentrations that have been found to be associated with a variety of respiratory-related health outcomes (US Environmental Protection Agency, 2008).

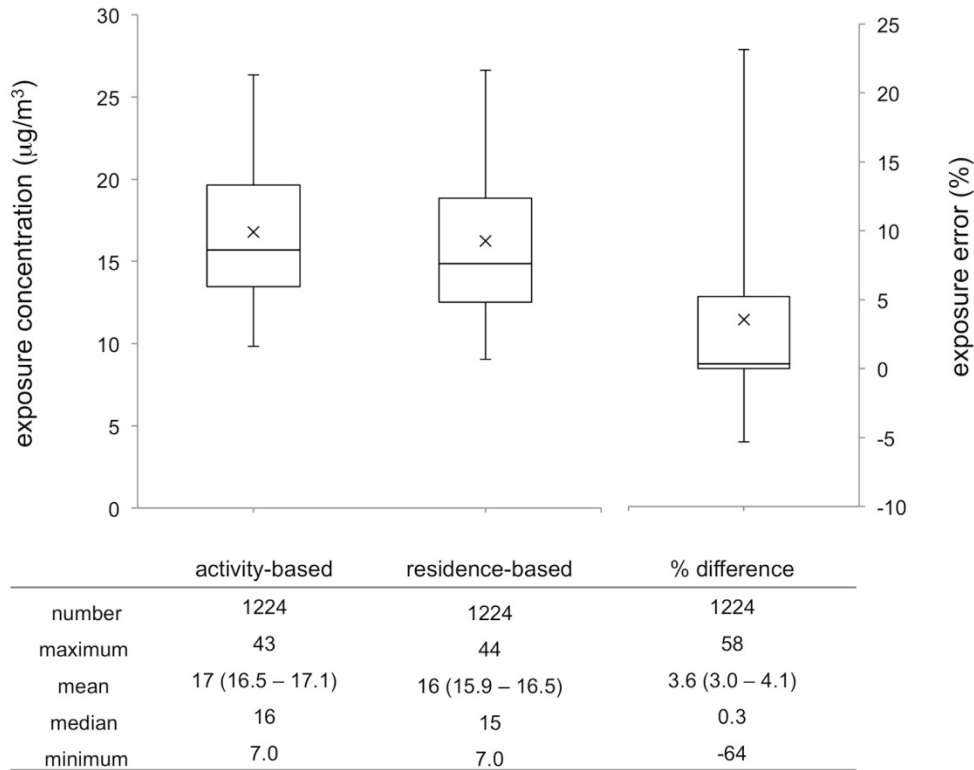


Figure 3.4 Cumulative distributions for daily exposure concentrations. Activity-based daily exposure concentration (left), residence-based daily exposure concentration (middle), and daily exposure error between the two as a percent difference, $(C_A - C_R)/C_A$ (right). Boxplot whiskers indicate 5th and 95th percentile values, (x) indicates mean value. Summary statistics provided below each box plot; 95% confidence intervals around each mean in parentheses.

The distribution statistics of the activity-based daily NO_x exposure concentrations for a few subgroups are provided in Table 3.2. Cumulative distributions are provided in Figure 3.5. Apparent differences in exposure concentrations among subgroups in the racioethnic and income categories are seen. Among the racioethnic groups, estimated mean daily exposure concentration is highest for the black group (20 µg/m³), followed by the Hispanic group; mean exposures were lowest for whites (16 µg/m³). Results for the Asian subgroup are not shown due to the small sample size (14 person-days). Although within-group variations increase with increasing group mean concentrations, the 95% confidence intervals around the means for the black and white categories are far apart, and one-way ANOVA with post-hoc Games Howell testing also indicated high significance for the difference ($p = 6 \times 10^{-8}$). Differences between the other categories were not significant, as the confidence intervals overlap. Among the income categories, the mean daily exposure concentration was highest for the group

characterized by household income below the poverty level ($18 \mu\text{g}/\text{m}^3$). This value is slightly lower than that estimated for the black group. Mean exposure concentration decreases with the income category, to $16 \mu\text{g}/\text{m}^3$ for the group characterized by higher incomes (household annual incomes above \$75,000). The confidence intervals and post-hoc testing indicate statistically significant differences between means for the below poverty versus highest income group, and between the two above poverty groups, but not between the below poverty versus middle income group. Differences in mean exposure among the age-based groups are not apparent.

Table 3.2 Group distribution statistics for daily activity-based exposure concentration and exposure error

Group	N	Exposure Concentration ($\mu\text{g}/\text{m}^3$)				Exposure Error (%)			
		Mean	Confidence Interval	Min	Max	Mean	Confidence Interval	Min	Max
Race/ethnicity ¹	1173								
Black	115	20	(19.0 - 21.5)	8.5	43	1	(-1.1 - 3.3)	-64	34
Hispanic	29	18	(15.9 - 19.2)	11	28	5	(1.3 - 9.6)	-8.9	45
White	1029	16	(16.0 - 16.6)	7.0	41	4	(3.3 - 4.4)	-32	58
Income ²	1131								
Below poverty	137	18	(17.1 - 19.2)	7.4	43	1	(-0.6 - 2.6)	-64	45
Middle income	577	17	(16.8 - 17.6)	7.0	41	3	(1.9 - 3.5)	-52	53
Higher income	417	16	(15.6 - 16.5)	7.4	32	6	(4.6 - 6.5)	-31	58
Age	1224								
5–18	148	17	(16.1 - 17.9)	8.5	29	3	(0.6 - 4.6)	-64	53
19– 65	665	17	(16.6 - 17.4)	7.0	41	5	(4.2 - 6.0)	-48	58
Over 65	411	16	(15.9 - 16.9)	7.4	43	1	(1.0 - 1.8)	-17	23
Urbanicity	1224								
Urban	267	22	(21.2 - 22.4)	12	43	0	(-1.3 - 0.9)	-64	25
Suburban	387	17	(16.3 - 17.2)	10	35	4	(3.3 - 5.2)	-31	42
Second city	287	16	(15.5 - 16.2)	8.8	25	4	(3.1 - 4.9)	-31	38
Town & rural	283	13	(12.6 - 13.6)	7.0	27	6	(4.3 - 7.1)	-17	58
Daily travel time	1224								
More than 60 min	452	17	(17.0 - 17.8)	8.5	41	8	(6.5 - 8.8)	-32	58
Up to 60 min	533	17	(16.2 - 17.1)	7.6	43	2	(1.0 - 2.4)	-64	42
No travel	239	16	(15.3 - 16.7)	7.0	35	0	(0 - 0)	0	0

¹Racioethnic labels used here are shortened forms of Race and Origin category labels used by US Census. Category descriptions are available at www.census.gov. Note that placement in a category is by self-selection, and individuals may be categorized in multiple or no categories.

²Below Poverty, Middle Income, and Higher Income labels refer to households with income below poverty threshold, above poverty threshold but less than \$75,000, and \$75,000 or above.

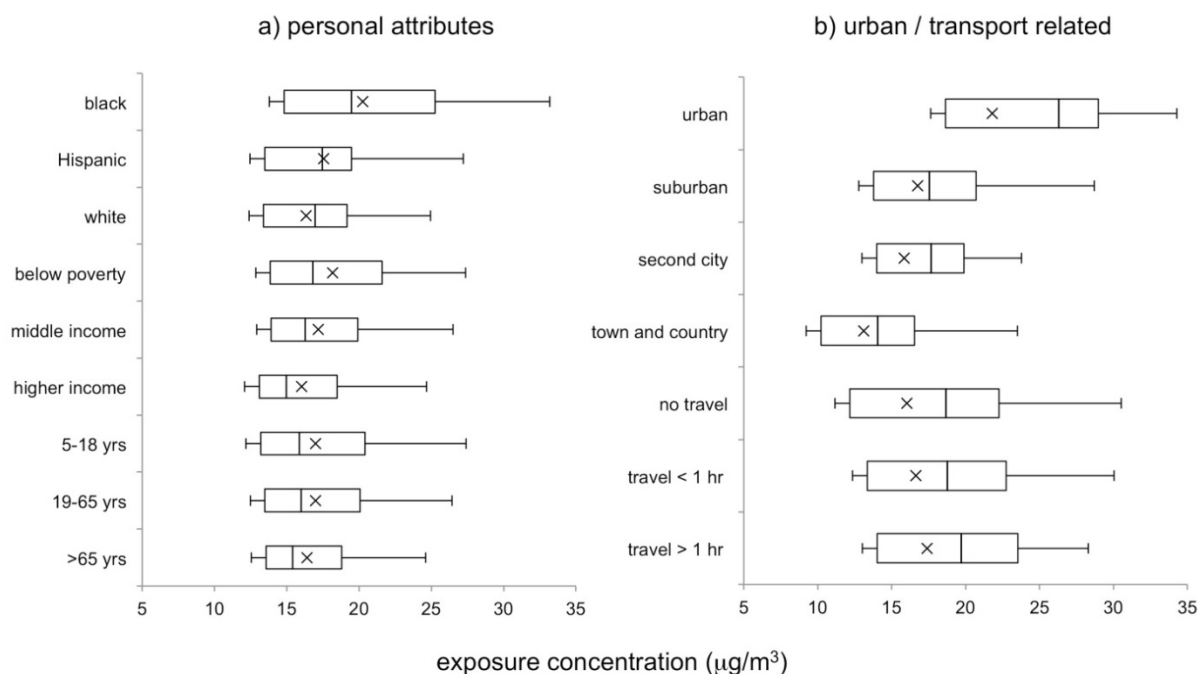


Figure 3.5 Cumulative distributions of daily activity-based exposure concentration for population subgroups. (a) personal attributes and (b) urban characteristics. Category definitions provided in text. Note that racioethnic subgroup populations are not exclusive; populations have overlapping individuals.

Differences in daily activity-based exposure concentrations observed here between the racioethnic groups are consistent with our previous studies that have estimated exposures in the Tampa area using only residence location (Stuart et al., 2009; Yu & Stuart, 2013) or school location (Stuart & Zeager, 2011). Specifically, we found greater exposures for the black, Hispanic, and low-income (below poverty) groups than the white and higher-income groups, respectively. Hence, regardless of the use of individual-level activity information in the exposure estimation, the qualitative direction of the disparities found for the Tampa area appears to be robust.

Furthermore, results are consistent with other findings from the study area and elsewhere. Specifically, in a study of the Tampa area using 1999 National-scale Air Toxics Assessment concentration data and the population distributions from the 2000 US census, Chakraborty (2009) found that the black, Hispanic, and below poverty groups are subject to disproportionate cancer risks and respiratory hazards, while no conclusive inequalities were found for individuals above age 65. Overall, results here contribute to the body of literature across localities in the US and elsewhere (Green et al.,

2004; Houston et al., 2004; Linder et al., 2008; Marshall, 2008; Marshall et al., 2006; Mitchell & Dorling, 2003; O'Neill et al., 2003; Pearce et al., 2006), largely finding typically higher exposures to primary pollutants for socially and economically disadvantaged groups, with some exceptions (Buzzelli & Jerrett, 2007) and reverse finding for secondary pollutants (Marshall, 2008).

It is worthy of mention that the use of spatiotemporal activity information in this study did not change the relative ranking of mean disparities between racioethnic versus income groups. The mean difference between the black and white category was larger than the difference between the below poverty and highest income group; blacks had the highest estimated average exposure of all racioethnic or income groups. However, this result is complicated by the results of regression analysis (discussed below), for which income below poverty was associated with a larger independent increase in exposure concentration ($1.7 \mu\text{g}/\text{m}^3$), than being black (versus non-black, $1.2 \mu\text{g}/\text{m}^3$). However, the comparative difference in group mean disparities found here is consistent with results from other study areas. Specifically, in a study in southern California, Marshall et al. (2006) found that exposure levels differed more among ethnic groups than between high- and low-income households, while Clark et al. (2014) found a similar result through a national level analysis. We note that there are many aspects of social disadvantage that are not captured by race, ethnicity, or income alone. Further, it is well established that there are interactions between factors that affect exposure disparities (e.g., Apelberg et al. (2005); Perlin et al. (2001)) with many studies in the air pollution field now using multi-factor indices that can also include education, occupation, employment status, family size, and home ownership (Forastiere et al., 2007).

Although differences in daily exposure concentrations are evident in our results, their importance to health outcomes is not necessarily clear. To explore the potential importance, we applied literature estimates of increased risk (primarily as reported by US Environmental Protection Agency 2008) to estimate possible health impacts. Neuberger et al. (2007) found a 2.9% increase in risk of total mortality associated with a $10 \mu\text{g}/\text{m}^3$ increase in 24-hour mean NO_2 concentrations. Applying this to the differences in group means found here would suggest an increased risk of 1% for blacks versus whites (on

average), and an increased risk of 0.5% for those living in poverty versus in households with annual incomes over \$75,000 (on average). Even higher differences in health risks may be present between groups, when considering susceptible people, such as children and older adults. Application of the 61.3% increased risk for cough incidence per 20 ppb increase in 24-hour NO₂ concentration found by Schwartz et al. (1994) in a study of children, would result in an approximately 5% excess risk for black compared to white children here, on average. Similarly, applying the ratio of 6.8% increased risk of all respiratory hospitalizations per 20 ppb increase in daily NO₂ concentrations found in a study by Fung et al. (2006) of adults aged 65 and older, suggests a 0.6% higher risk for elderly blacks compared to elderly whites here, on average. Note that for any individual, the comparative risks may be higher or lower due to individual risk factors (smoking, diet, exercise, occupation, access to health care, etc.) (Dockery et al., 1993; Pope III et al., 2002). Additionally, since differences in harmful health effects have been found even when differences in exposures are not clear (Deguen & Zmirou-Navier, 2010), small differences in exposures between groups may be important.

Overall, our results suggest that to attain the policy goal of reducing disparities in health outcomes (Healthy People 2020 & US Department of Health and Human Services, 2010), interventions that reduce existent disparities in exposure between socioeconomic groups may be helpful. Further, the methods used here provide an approach for estimating activity-based exposures specific to individual person-days, but for a large sample. This could be helpful for the study of factors affecting population health outcomes and for estimation of expected risks, without the intractably large costs of personal exposure concentration sampling for a large population.

3.4.4 Urban Form, Activity, and Exposure Relationships

We are interested in understanding how factors related to urban form may impact the magnitude of exposures and their social distribution in the Tampa area. Figure 3.5b provides the distributions of estimated daily activity-based exposure concentrations categorized by the urbanicity of residence location, with statistics provided in Table 3.2. Substantial differences in NO_x exposure concentrations are seen between residence urbanicity types. The highest mean daily exposure concentration (22 µg/m³) was

found for records with urban residence location, while that for records with rural residence location was 40% lower ($13 \mu\text{g}/\text{m}^3$). Mean exposures were intermediate for the suburban and second city categories. The confidence intervals and post-hoc testing indicate that all differences between the category means are significant. The largest difference in means between urban versus rural residence urbanicity categories ($9 \mu\text{g}/\text{m}^3$) is also more than twice as large as the largest difference among the social categories discussed above ($4 \mu\text{g}/\text{m}^3$ for the black versus white subgroup mean difference). Hence, residence urbanicity likely influences exposure and its social distribution among groups. This is broadly consistent with results of previous studies comparing exposures for populations in urban versus rural areas. For example, in the EXPOLIS-Helsinki study, individuals living in Downtown had 23% higher exposures than suburban residents (Rotko et al., 2001). Similarly, in a study of school children, Rijnders et al. (2001) found that both outdoor and personal NO_2 exposures increased with the level of urbanicity (and traffic density), with a mean difference in personal exposures for the highest versus lowest urbanicity category of $14.6 \mu\text{g}/\text{m}^3$.

Results of the multivariate linear regression analysis (Table 3.3) also indicate that urbanicity was the strongest predictor of exposure concentrations (with the highest coefficient value and t-statistic) among the factors studied. A model using only the urbanicity variables as predictors (not shown) captures about 35% of variance in the individual exposures, a substantial portion of the total model variability captured in the more complex model shown. Consideration of interaction terms between the sociodemographic and urbanicity variables provides further insight on the influence of residence urbanicity on the disparities in exposure found above between sociodemographic groups. Specifically, interaction terms urban*black, suburban*black, and suburban*below poverty all had significant t-statistics (significance values of 0.002, 0.005, and 0.004, respectively) and high coefficients (3.2 , 3.1 , and $2.5 \mu\text{g}/\text{m}^3$, respectively) when added to the base model shown. Furthermore, with the interactions terms added, the black explanatory variable (which now represents blacks living in second city and rural regions) was no longer significant, and the below poverty variable had substantially reduced significance (0.04 with a reduced coefficient value of $0.9 \mu\text{g}/\text{m}^3$). Additional comparisons of subgroup exposures (not shown) also indicate that, for those living in second city and rural regions, the difference in the mean

exposure for blacks versus others is not significant. That is, the exposure disparity (higher group mean daily exposure concentration) found here for the black group, on average, above, is due to both higher exposures for the urban and suburban black population, and higher residence urbanicity for the black population in the study area. Residence urbanicity classification also explains some of the disparity between economic groups, but the result is more complicated, as an urban below-poverty interaction term was not found to contribute significantly, but the suburban below-poverty term was.

Table 3.3 Linear regression model for activity-based exposure concentration

Explanatory Variable	Coefficient ¹ (β_i, γ_i)	t statistic	Significance
constant ² (β_0)	11.5	35	3e-180
Black	1.2	2.9	3e-3
Below poverty	1.7	4.3	2e-5
Middle income ³	1.2	4.7	2e-6
Urban	8.3	23	1e-98
Suburban	3.4	11	8e-25
Second city	2.6	7.5	1e-13
Time away from residence	0.2	6.8	1e-11
Goodness of fit			
R ²	0.40		
Adjusted R ²	0.39		
Number of cases	1120		

¹Regression model is $C_A (\mu\text{g}/\text{m}^3) = \beta_0 + \beta_1 X_{c1} + \beta_2 X_{c2} + \dots + \gamma_1 X_{t1} + \gamma_2 X_{t2} + \dots + \varepsilon$, where $X_{ci} \rightarrow (1,0)$ are binary variables, and X_{ti} are continuous variables. Only time variable entered as continuous variable (with units of hours). β_i have units of $\mu\text{g}/\text{m}^3$, γ_i have units of $(\mu\text{g}/\text{m}^3)/\text{hr}$.

²Constant concentration represents exposures for people who are non-black with incomes over \$75,000, who live in town/rural areas and did not travel on sample day.

³Middle income refers to households with income above poverty threshold but less than \$75,000.

Although it is known that residence urbanicity is associated with increased exposure, the reasons for this are not well understood. One contributing reason that has been explored extensively is the presence of higher concentrations of pollutants in urban versus rural areas. We can clearly see in comparing Figure 3.3 and Figure 3.2d that NO_x concentration is generally higher in urban versus rural areas throughout the day. However, we look here at the additional role of activity, with a focus on travel activity. Figure 3.6 provides NO_x concentration and exposure distributions categorized by activity-location types (at-residence, non-residential, and in-travel) for the subsample ($n = 975$) of person-day

records that included some activity in each category on the survey day. The mean (time-weighted) concentration is highest ($19 \mu\text{g}/\text{m}^3$) for the in-travel activity category and lowest ($16 \mu\text{g}/\text{m}^3$) for the at-residence category. That is, ambient concentrations were higher at the locations of non-residential and travel activities (at least during the times when our sample population was located there). However, mean exposures ($\mu\text{g hr}/\text{m}^3$) are lower for travel and non-residential activities, as less time is spent in these activities (see Table 3.1). Overall, the group mean daily exposure concentration increases for those who travel more (Figure 3.5b). Confidence intervals for the categorical means (Table 3.2) indicate significantly different group mean exposure concentrations for daily activity records with more than 60 minutes of travel time versus those with no travel. Our multivariate linear regression (Table 3.3) also indicates a small increase in exposure concentration with increased daily time away from the residence location (travel time plus time at non-residential locations), with concentrations increasing by $0.2 \mu\text{g}/\text{m}^3$ per hour of total daily time. Hence, although residence location remains a better predictor of daily exposure concentration than does time away from the residence (or time travelling), these activity times may play a role.

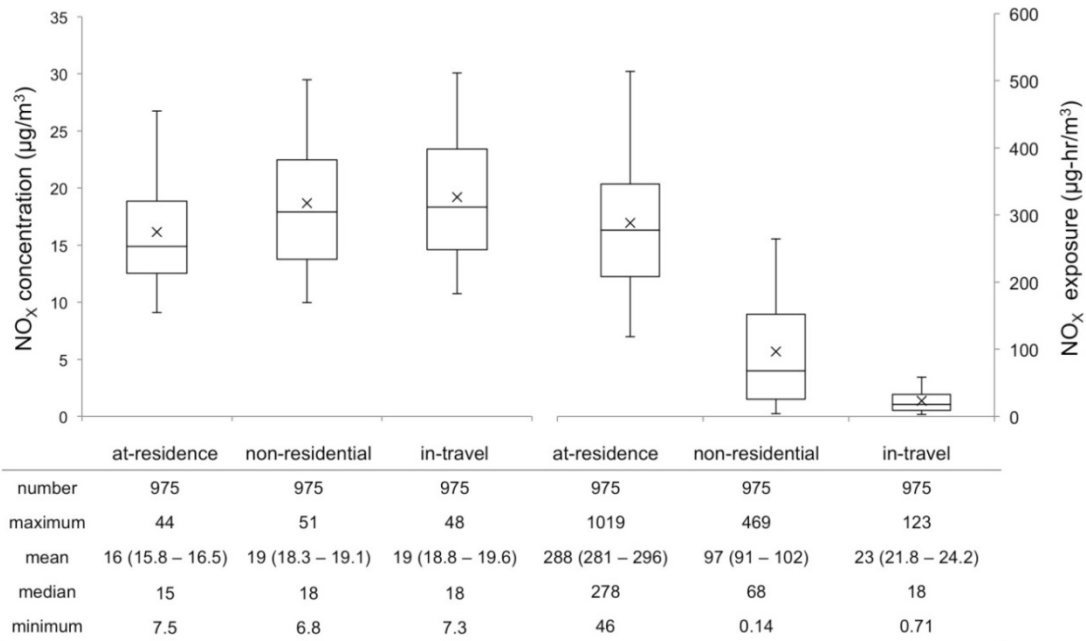


Figure 3.6 Cumulative distributions of time-weighted NO_x concentration ($\mu\text{g}/\text{m}^3$) and NO_x exposure ($\mu\text{g-hr}/\text{m}^3$) by activity type location for all sampled daily records, including some activity away from residence. NO_x concentrations and exposures shown in left and right figures, respectively. Summary statistics provided below each box plot; 95% confidence intervals around each mean are in parentheses.

These results are consistent with those of other recent studies indicating the importance of exposures during travel. de Nazelle et al. (2013) found that travel activities contributed 24% of the total daily intake of NO₂. Dons et al. (2011b) and Dons et al. (2012) found that transport time accounted for 21% of black carbon exposures, and identified transport activity as a primary reason for differences in exposure between family members. Zhang and Batterman (2013) also recently found that increased traffic congestion led to greater population health risks; for the on-road population, this was due in part to increased transport times. We found the contribution of time in travel to be less for our study area, accounting for 6% of the total daily exposure on average, but time at nonresidential locations accounted for 24%.

From an exposure mitigation perspective, it is known that higher concentrations of many pollutants in urban areas are due largely to the proximity and spatial concentration of air pollution sources in urban areas, including car exhaust on congested roadways, combustion emissions from home heating, and nearby industrial emissions. Hence, mitigation policies have focused on reducing emissions from sources (e.g., through engineering control technologies). However, reduction in exposures requires reduction in emissions at a rate outpacing economic and population growth, which has proved difficult to sustain. Another popular strategy has been urban design that displaces sources away from where people live via urban planning and zoning policies (South Coast Air Quality Management District (AQMD), 2005). However, this strategy has resulted in collocation of sources with socially-disadvantaged population groups who cannot afford to live in less polluted areas (Perlin et al., 2001; Pulido, 2000) and with increases in emissions-producing travel necessary for people to access their homes, places of employment, and services.

Hence, “smart growth” urban design strategies are now being promoted as potentially mitigating exposures (Office of Sustainable Communities et al., 2013). Previous work has suggested that high-density urban growth can potentially help in reducing the vehicle miles travelled and the overall emissions (Hankey & Marshall, 2010; Stone et al., 2009). However, simply applying land use intensification (or densification) strategies without making modifications to the existing transportation

infrastructure might increase congestion and lead to higher concentrations in urban areas (Farber et al., 2009). This could also exacerbate social disparities in exposures, as many disadvantaged groups disproportionately live in more dense urban areas (Baum et al., 1999). This underscores the need for caution in implementing high-density developments alone. However, another informative viewpoint may be differences in activity behavior that place people in spatiotemporal locations of high concentrations. Particularly interesting from a policy viewpoint are activity behaviors that are impacted by civic infrastructure. In this study, we found that average concentrations were higher in travel and non-residential activities, and estimated daily exposures were higher for those who travel more. Hence, a focus on civic infrastructure that reduces time travelling (and other non-residential activities) as well as emissions at those locations may be warranted. Implementation of transit infrastructure is one such approach, as it can reduce congestion (with concomitant reductions in emissions) and can reduce the time spent travelling on congested roadways. However, cost-competitive transit infrastructure requires high-density development (Kenworthy & Laube, 1999).

3.4.5 Exposure Error

The cumulative distributions of estimated residence-based daily NO_x exposure concentration and exposure error (due to the use of residence versus activity-based approach) are shown in Figure 3.4. Overall, we found the mean exposure error $[(C_A - C_R) / C_A]$ to be 3.6%, with a range of -64% to 58%. Additionally, for the majority of the sample (56%), the error is positive (the activity-based exposure estimate is larger than the residence-based estimate). There is a small amount of overlap in the confidence intervals around each mean, though a paired samples t-test suggests statistically significant differences ($p = 3e-22$). Additionally, for the subsample of person-day records ($n = 985$) that included at least some travel away from the residence on the survey day, the mean error is slightly increased (4.4%). The calculated bias factors for the full sample and for travelling subsample, were 0.85 and 0.82, respectively, indicating that in a health impact study using residence-based daily exposure estimates, the relative risk may be underestimated by 15%, or 18% for the traveling sample.

Mean exposure bias (or error) values observed in our study are consistent with previously reported results, and suggest the importance of consideration of activity and travel patterns for exposure estimation. For Metro Vancouver, Setton et al. (2011) reported an exposure bias for residence-based versus activity-based exposure estimates of 0.70 to 0.84 for NO₂ (depending on the method used for concentration interpolation). Further, in a study of Flanders and Brussels, Dhondt et al. (2012) found small but significant differences between the mean dynamic (i.e., activity-based) exposures and residential exposures (21.6 versus 20.98 µg/m³), with a resulting exposure error of 2.9%. Similarly, in a Belgian study, Dons et al. (2011b) found that time-activity patterns could account for approximately 30% of weekly personal mean exposure differences between a worker and a homemaker from the same household. While their study does not consider exposure error explicitly, their findings underscore the importance of time-activity patterns and their impact on exposures.

Our results suggest that a residence-based approach likely underestimates exposures for a large proportion of the population, resulting in underestimated risks of health impacts of air pollution. However, for almost half (46%) of the population, exposures and risks may be overestimated using a residence-based approach. Additionally, although the average error was found to be 3.6%, the maximum (absolute) error was 64%. Hence, exposure estimation methods that account for spatiotemporal changes in location and concentration may be needed for more accurate estimation of exposure and better health impact assessments. Nonetheless, this does not discount the importance of exposures at the residence location. Our results above on the large percentage of time spent at the residence location (on average) and on the predictive value of residence urbanicity are consistent with epidemiological studies that continue to suggest the value of exposures at residence location as a predictor for health responses (Brauer et al., 2008; Gan et al., 2011).

3.4.6 Social Distribution of Exposure Error

It is interesting to inquire whether estimated exposure error differs between demographic groups, i.e., whether residence-based estimates may be systematically biased for specific segments of the population; systematic biases could lead to systematic misclassification of exposures by group during

health impact analyses. To address this question, Figure 3.7 provides the cumulative distributions of exposure error for each of the sociodemographic groups studied above, with statistics provided in Table 3.2.

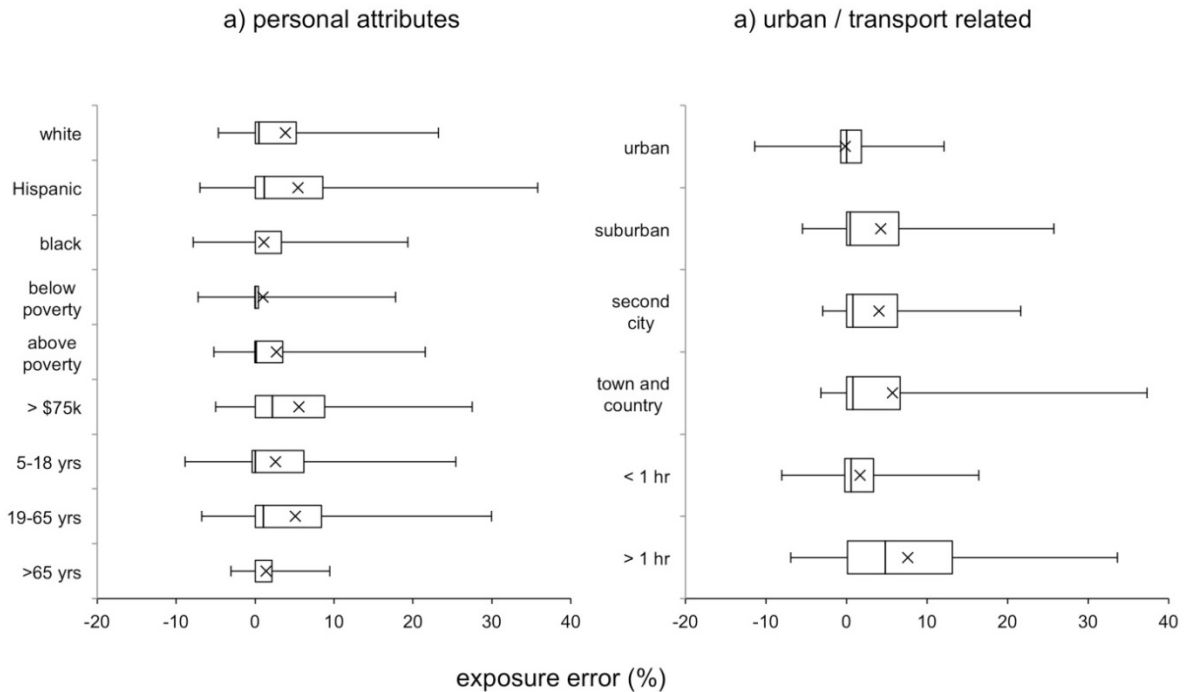


Figure 3.7 Cumulative distributions of exposure error for population subgroups. Exposure errors presented by (a) personal attributes, and (b) urban characteristics. Above-poverty refers to households with income above poverty threshold but with incomes less than \$75,000. Note that racioethnic subgroup populations are not exclusive; populations have overlapping individuals.

Among the racioethnic groups, exposure errors are largely positive (underestimation) for the Hispanic and white subpopulations, with the highest variation seen for the Hispanic group. Results are mixed for the black subgroup, with largely positive errors, but a substantial proportion in the negative (overestimation) range. Mean exposure errors were not found to be significantly different between any of the racioethnic groups considered. With regard to income, exposure errors are largely positive (underestimation) for the higher-income (annual income above \$75,000) and middle-income groups, with some negative (overestimation) errors in the below-poverty group. We found the mean exposure errors between the higher income group significantly different from those for both the below poverty group and the middle income group, but difference between the low and middle income groups was not significant. Mean exposure error is positive for all age groups, but is highest (most underestimation of exposures) for

active adults (ages 19–65), and lowest, with least variation, for older adults (over age 65). Mean errors were significantly different between these two age groups, but not between either of these groups and the child (ages 5–18) group.

Residential location appears to be a major determinant of the direction and the extent of exposure error. As can be observed from the box plots, the residence-based exposure concentrations are almost equal to the activity-based exposure concentrations for a large proportion (50%) of those living in urban areas. This suggests that pollutant concentrations at residential and activity locations may be similar for those living in urban areas. Moreover, with decreasing density, the variability in the exposure error increases. Specifically, there is a greater incidence (and magnitude) of under-estimation of exposures by residence-based estimates in rural regions (and over-estimation in urban regions). Further, the mean exposure error was found to be significantly different for the individuals residing in urban regions and the individuals residing in the suburban, second city and rural regions. These results suggest that using residence-based estimates may lead to underestimation of NO_x exposures (and resulting health effects) for those living in low-density regions, when compared to those in high-density urban areas.

Exposure error also increases, both in magnitude and variability, with an increase in the travel time. Further, an increase in the travel time leads to higher potential for under-estimation of exposures. As such, ignoring activity and travel patterns for individuals who travel for a significant portion of their daily time, could lead to the underestimation of health effect estimates.

In summary, the mean exposure errors are high for age groups 19–65, above-poverty groups, Hispanics, rural residents, and groups with travel time greater than 60 minutes. Specifically, the age-based differences in the exposure error may be a manifestation of the differences in the propensity to travel among the different age groups (children and older adults are likely to travel less). Within the context of income groups and rural residents, their travel patterns may be a contributing factor for the high exposure error (their daily activity patterns may lead them into more polluted areas compared to their residential locations). For the groups with longer travel times, spatial variation in concentrations could be a contributing factor for such large exposure error. These results suggest that residence-based estimates

may underestimate exposures for the advantaged population groups, rather than vulnerable groups (with the exception of Hispanics).

Further, our results suggest that the residence-based approach may not necessarily lead to severely flawed exposure estimates for most vulnerable subgroups of the population. This provides support for previous studies that did not consider activity and travel patterns in exposure analysis. In absence of data on activity and travel patterns, such residence-based approaches may not necessarily lead to significantly biased exposure estimates, at least for a majority of the most vulnerable population segments. However, there are individuals within the susceptible groups who are still prone to either under or over estimation of exposures using the residence-based approach. Additionally, the error may be important for people whose occupations require them to travel or be present for significant portions of time on roadways (e.g., sales personnel, highway workers etc.).

To our knowledge, there is little previous literature on the socioeconomic distributions of exposure error within the US. Limited evidence on this topic is available from Europe (Dhondt et al., 2012). Although it is difficult to compare the social distributions of exposure error between these studies (as groupwise exposure errors are not reported in their study), we are able to observe a few similarities. Specifically, they also report that exposure error in rural locations is significantly higher compared to urban locations. Dhondt et al. (2012) also reported that rural zones had dynamic NO₂ exposure values that could be 15% higher than the static values. Our results above provide differences in the variability of exposure error between urban and rural regions and the distribution of exposure error among population subgroups.

3.5 Limitations

Some limitations affect the robustness of these findings. First, the travel survey data used here may not be representative of the true spatiotemporal distribution of activities. Although the survey sample size is quite large, the county sample may not be large enough to capture the full spatial coverage necessary. Use of activity-based travel demand models for exposure analysis (Beckx et al., 2009b; Dhondt et al., 2013; Dons et al., 2014; Hatzopoulou & Miller, 2010) is one promising approach for

generating the larger sample sizes that are needed. Second, exposures during travel activity were estimated using concentrations along the shortest route, as path data were not available. Although this is a reasonable approach, computed routes may not coincide with the actual travel paths on the particular sampled person-day. Third, due to limitations in the temporal availability of the input data sets, the travel data are from a 2009 survey, but the concentrations are based on 2002 data. Hence, results are not expected to represent exposures for a particular year. Fourth, findings are limited by the use of estimated ambient pollutant concentrations for exposure analysis, rather than indoor, microenvironmental, or personal measurements. In the case of important indoor or personal sources, this could poorly represent exposures. Fifth, we have directly considered only one pollutant (NO_x) in the analysis here. It is well known that spatial and temporal concentration patterns and scales of variability differ by pollutant (Bhugwant & Brémaud, 2001). These differences could result in different distributions of exposure and exposure error. We expect the result here to be somewhat informative to understanding exposures to primary pollutants with substantial traffic emissions, but not to pollutants with substantial secondary formation or important emissions sources that are not collocated with traffic (such as ozone and formaldehyde). Sixth, defining urbanicity based on a single contextual population density measure could limit our findings. Whereas this definition incorporates a few key characteristics of urban form, there is a need to consider additional measures including transportation infrastructure characteristics in defining urbanicity. Seventh, this work has focused on investigating inequality in exposures (and potential health outcomes) between population groups characterized by race, ethnicity, income (and residence urbanicity). However, we note that there are many indices of social disadvantage and inequality that have been used in air pollution exposure and health impact studies; appropriate indicators likely depend on the social and political context. Further, there are many individual and group factors other than differences in exposures that can lead to differences in health outcomes (O'Neill et al., 2003); some of these are access to health care, overall health, smoking, diet, exercise, occupation, and genetics. Finally, it is well established that group averages do not necessarily represent the exposures of individuals in that group. Hence, the social disparity findings and implications can only address group level differences.

3.6 Conclusion

In this study, we estimated ambient NO_x exposures for residents of Hillsborough County, Florida, using activity and travel data (from the national household travel survey) matched to the spatially-resolved diurnal cycle of NO_x concentrations. Travel routes were estimated based on the shortest-time path. We examined the social distribution of these daily activity-based exposures. Finally, we compared our activity-based estimates with those that result from using only residence location.

The findings of this work include the following:

- The Hillsborough County travel survey sample population spent little time in urban block groups. The time densities in urban block groups are larger for non-residential than residential activities.
- The diurnal cycle of NO_x concentration in the study area exhibited typical morning and evening peaks, consistent with increased NO_x emissions from traffic during commute hours. Spatially, concentrations were highest near roadways and in urban areas throughout the day.
- The mean daily activity-based exposure concentration for the study sample was found to be 17 μg/m³, with values for individual person-day records ranging from 7.0 to 43 μg/m³.
- The black, Hispanic, and low-income subgroups had higher mean estimated activity-based exposures than comparison groups. The mean disparity in exposure between the black and white groups is larger (4 μg/m³) than that between the below-poverty and high-income groups (2 μg/m³). However, regression results show that income below poverty is associated with a higher increase in exposure than black heritage alone, whereas Hispanic status was not found to be a significant predictor.
- The highest group mean exposure concentrations (22 μg/m³) were seen for those living in urban regions. Having an urban versus rural residence was also associated with the largest increase in exposure concentration in the regression (8.3 μg/m³). Furthermore, the

residence urbanicity interaction variables largely explained the largest disparities found between sociodemographic groups. Being black while living in urban or suburban areas and living below poverty in suburban locations were each associated with higher exposures.

- Time in travel and other non-residential activities was also associated with higher activity-based exposure concentrations, specifically $0.2 \mu\text{g}/\text{m}^3$ per hour spent away from home. This is due to the higher concentrations at these locations.
- The overall mean exposure error resulting from using residence-based versus activity-based estimation was 3.6% here, with residence-based estimate lower for most of the sample population.
- The mean group exposure errors were highest for person-days with more than an hour of travel, people with higher household income, people living in rural areas, adults aged 19–65, and Hispanics. This suggests that studies that use residence-based exposure estimation may not be severely misclassifying exposures for disadvantaged and susceptible groups including blacks, low-income households, and older adults, at least on average.

In summary, this work demonstrates an approach for using available travel survey data and concentration modeling results for spatiotemporally-resolved estimation of activity-based exposures. Novel contributions include the presentation and use of a spatially distributed activity time density map applied to exposure analysis, and the examination of the social distribution of errors in exposure. Our results suggest that activity-based exposure estimation may be important for assessing exposures of individuals, but a residence-based approach may not necessarily lead to substantially biased exposure estimates for the most vulnerable groups, on average. Within the context of previous work, the results here continue to reveal the presence of social disparities in exposure and, possibly, exposure-related health risks, in the study area, even after accounting for spatiotemporal population movement. Further, they confirm the importance of the urbanicity of residence location (and to a lesser degree, travel time) in

influencing exposures and their social distribution. This supports the need for urban design policies that ensure that densification is accompanied by civil infrastructure (e.g., public transit) that decreases emissions in urban areas as well as time spent traveling, particularly for disadvantaged groups.

**CHAPTER 4: AN INTEGRATED MODELING FRAMEWORK TO ESTIMATE EMISSIONS,
CONCENTRATIONS, AND EXPOSURES UNDER
ALTERNATE TRANSPORTATION DESIGN SCENARIOS IN THE TAMPA AREA**

4.1 Introduction

Human exposure to traffic-related pollution is of specific interest due to its linkages to adverse health impacts (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Past research efforts have focused on accurately estimating exposure to traffic-related pollution using a variety of personal monitoring techniques in which individuals wear exposure measurement devices (Dons et al., 2011b; Kousa et al., 2001); however, personal monitoring campaigns are often limited to small sample sizes due to high costs. Alternatively, studies also used fixed monitoring station measurement data (Sarnat et al., 2010) to estimate individual exposures; however, this approach cannot capture important spatial variations in pollutant concentrations, especially for traffic-related air pollutants (Monn, 2001), potentially leading to exposure misclassification. To address this, locally in Tampa, travel-survey data was used to estimate personal exposures to traffic-related pollution (Gurram et al., 2015). However, these sample-based studies are generally inadequate for exploring impacts of policy scenarios that seek to lower human exposure levels.

Previously, researchers pursued several policy initiatives including pollution control technologies (Kimura et al., 2001), congestion taxation (Johansson et al., 2009), and smart growth approaches such as compact growth urban design and vehicle electrification (Yu & Stuart, 2017) that seek to improve air quality. Within these options, the smart growth approaches are appealing as they seek to improve public health by providing individuals with active forms of transportation while improving air quality (Frank et al., 2006a). However, there is a considerable ambiguity about the utility of smart growth-based urban design policies for alleviating air pollution and reducing population exposure. Specifically, studies

argued that employing a compact growth or high density development would lead to higher primary pollutant exposures for individuals within the high dense zones (Frank & Engelke, 2005; Hixson et al., 2009). Considering this, it is important to gather further evidence by evaluating the impact of alternative urban design policies on air quality and population exposure.

To address these issues, a few recent studies used a variety of transport and land use modeling approaches to estimate exposures to traffic-related pollution and answer policy questions (Beckx et al., 2009a; Hatzopoulou & Miller, 2010; Hixson et al., 2009; Stone et al., 2009). Within these tools, the activity-based travel demand models are equipped to provide high-resolution human activity information both in time and space. This information may be combined with pollutant concentration data to obtain disaggregate exposure measures for a hypothetical population.

A European study led by Beckx et al. (2009c) and a Canadian study led by Hatzopoulou and Miller (2010) produced the seminal work in the area of exploiting activity-based travel demand models to estimate personal exposure to traffic-related pollution. Beckx et al. (2009c) used the activity-based model ALBATROSS in conjunction with the emission model MIMOSA and the dispersion model AURORA to estimate roadway link-specific emissions, ambient concentrations, and personal exposures. Hatzopoulou and Miller (2010) used a similar model setup initially and enhanced this approach later by including an agent-based dynamic traffic assignment model (MATSim) to improve the sensitivity of vehicular emissions to congestion (Hao et al., 2010; Hatzopoulou et al., 2011). Despite the important advances made by these two studies, they have a few limitations. Both studies simulated individual activities at low spatial resolution; Beckx et al. (2009c) used postal codes (with average size of 8.8 km²), and Hatzopoulou and Miller (2010) used traffic analysis zones (TAZ). Typically, the spatial size of a TAZ varies, but it holds under 3000 individuals. Additionally, concentrations were simulated for a short time period in both studies. Moreover, both studies used a receptor grid with low spatial resolution to estimate pollutant concentrations; Beckx et al. (2009c) used a grid size of 9 km², whereas Hatzopoulou and Miller (2010) estimated concentrations at the TAZ centroids. Finally, neither study explicitly modeled individual exposures during travel. The European group tried to address this in a later study by

incorporating domain average near-roadway concentrations (Dhondt et al., 2012). Within the context of the US, a similar framework based on the above two studies was used recently to estimate population exposure to traffic pollution (Vallamsundar et al., 2016). However, the limitations discussed in the earlier studies carry over to this study. For a detailed comparison of the activity-based exposure modeling frameworks, refer to Table 4.1.

The limitations from the earlier studies raise an important point about the spatial resolution that is needed to accurately predict exposure to traffic-related pollution. Since traffic-related pollutant (e.g., NO₂) levels exhibit substantial small-scale spatial variation, use of a high-resolution concentration receptor network in conjunction with high-resolution population activity data may be necessary. Otherwise, the small-scale spatial variations in pollutant concentrations could go undetected, leading to biased exposure estimates. Moreover, exposures during travel have been found to contribute significantly toward overall daily exposures; ignoring them could lead to exposure misclassification (de Nazelle et al., 2013; Dons et al., 2012; Dons et al., 2011b; Gurram et al., 2015).

Table 4.1 Comparison of activity-based exposure modeling frameworks

Study	Spatial Scope	Pollutant(s)	Daily Activity schedules				Traffic Assignment	
			Name and Type	Spatial Resolution	Temporal Resolution	Population Sample Size	Model	Vehicle Population Sample Size
Beckx et al. (2009)	Utrecht, Netherlands (Urban city center with area of 7.8 km ²)	PM ₁₀ and PM _{2.5}	A Learning-Based, Transportation-Oriented Simulation System (ALBATROSS); rule-based computational process model	Postcode area (3987 postcode areas with average size of 8.8 km ²)	1-hour	30% expanded to 100% using extrapolation	All-or-nothing assignment (TRANSCAD)	100%
Beckx et al. (2009b)	Netherlands (Country with area of 42,000 km ²)	NO ₂	A Learning-Based, Transportation-Oriented Simulation System (ALBATROSS); rule-based computational process model	Postcode area (3987 postcode areas with average size of 8.8 km ²)	1-hour	30% expanded to 100% using extrapolation	All-or-nothing assignment (TRANSCAD)	100%
Hatzopoulou and Miller (2010)	Greater Toronto (Metropolitan area that covers 7,200 km ²)	NO _x	Toronto Area Scheduling model for Household Agents (TASHA); rule-based computational process model	Traffic analysis zone (463 TAZs)	5-minutes	5% expanded to 100% using extrapolation	Static traffic assignment (EMME/2)	5%
Hatzopoulou and Miller (2011)	Greater Toronto (Metropolitan area that covers 7,200 km ²)	NO _x	Toronto Area Scheduling model for Household Agents (TASHA); rule-based computational process model	Traffic analysis zone (463 TAZs)	5-minutes	5% expanded to 100% using extrapolation	Dynamic traffic assignment (MATSim)	5%
Dhondt et al. (2012)	Flanders and Brussels, Belgium (Regional cities covering 13,750 km ²)	NO ₂	Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS (FEATHERS); uses the activity-scheduler based on ALBATROSS	Zone-level (1145 zones with average size of 12 km ²)	1-hour	100%	Equilibrium traffic assignment (TRANSCAD)	100%
Vallamsundar et al. (2016)	Maricopa County, AZ (600 km ²)	PM _{2.5}	open-source Activity Mobility Simulator (OpenAMOS); composite of a rule-based computational process and utility-maximization based model	Traffic analysis zone (175 TAZs)	1-minute	5%	Dynamic traffic assignment (DTALite)	5%
This study	Hillsborough County, FL (3280 km ²)	NO _x	The Person Day Activity and Travel Simulator (DaySim); utility-maximization based model	Parcels (1.02 million)	30-minutes (adjusted to 1-minute)	100%	Dynamic traffic assignment (MATSim)	100%

Table 4.1 (continued)

Study	Vehicle Emissions			Pollutant Concentrations			Exposure During Travel
	Model	Spatial Resolution	Temporal Resolution	Model	Spatial Resolution	Temporal Resolution	
Beckx et al. (2009)	MIMOSA	Link-level	1-hour	AURORA	9 km ²	1-hour	Domain-average concentrations measured at traffic-related monitoring stations
Beckx et al. (2009b)	MIMOSA	Link-level	1-hour	AURORA	9 km ²	1-hour	Domain-average concentrations measured at traffic-related monitoring stations
Hatzopoulou and Miller (2010)	Mobile 6.2	Link-level	1-hour	CALPUFF	Traffic analysis zone (463 TAZs)	1-hour	Not modeled
Hatzopoulou and Miller (2011)	Mobile 6.2	Link-level	1-hour	CALPUFF	Traffic analysis zone (463 TAZs)	1-hour	Not modeled
Dhondt et al. (2012)	MIMOSA4	Link-level	1-hour	IFDM	0.02 km ² near roads and 1 km ² elsewhere	1-hour	Averaged the hourly concentrations near the roadway receptors for the entire study area
Vallamsundar et al. (2016)	MOVES	Link-level (only 3 major corridors totaling 55 km was used)	1-hour	AERMOD	0.01 to 0.09 km ² (receptor concentrations are averaged over TAZs)	1-hour	Not modeled
This study	MOVES	Link-level	1-hour	R-LINE	0.25 km ²	1-hour	Estimates intermediate locations along travel routes at every 5-second interval and uses the nearest receptor concentration

In this study, an integrated modeling framework built using an activity-based travel demand model (DaySim), dynamic traffic assignment model (MATSim), mobile source emission model (MOVES), and line-source pollution dispersion model (R-LINE) is presented. This modeling framework may be used to estimate human activity patterns, mobile source emissions, ambient traffic-related pollutant concentrations, and human exposure. Whereas the European and Canadian studies use a similar setup to explore human exposures to traffic pollution, this study is warranted for the following reasons. First, there is a need to gather further evidence on the utility of such frameworks that use the activity-based travel demand, dynamic traffic assignment, and dispersion modeling (ABM-DTA-dispersion) to estimate human exposure to traffic-related pollution. Second, the activity-based models that have been used for exposure estimation in the previous studies are rule-based computational process models that follow a set of if-then condition-action rules to estimate the activity and travel behavior of individuals. Exposure estimation frameworks that use utility maximization-based econometric models are currently non-existent. The utility maximization-based models originate from the economic theories of consumer choice and operate under the philosophy that individuals choose the alternatives that maximize their utility; utility refers to the level of satisfaction that an individual achieves by choosing an alternative. Thus, this study demonstrates the applicability of a utility maximization-based econometric model for exposure estimation. Third, this study simulates the activity and travel patterns of individuals at high spatial resolution. Specifically, activities of individuals are simulated at a parcel level instead of a TAZ level. Here, parcels refer to the detailed coordinates of the centroids of physical structures including office buildings and housing units. Fourth, to my knowledge, no other study that uses an ABM-DTA-dispersion framework explicitly simulates personal exposures during travel. Fifth, unlike previous studies, this study uses the full hypothetical population rather than a sample to simulate detailed spatiotemporal activities of individuals and their exposures. Finally, this study can provide insights on the impact of spatial resolution of modeled activity and pollutant data on individual and population exposures. In essence, this study can add to the current body of work on the utility of transportation

modeling for estimating individual-level population exposure to traffic-related pollutants, using a tool that offers high spatiotemporal resolution.

4.2 Methods

This section provides an overview of the study area and demographics, followed by the integrated modeling framework along with the data sources used.

4.2.1 Study Area, Demographics, and Pollutant Focus

The study area is Hillsborough County, Florida, which is a part of the Tampa Bay region. The geographic context of the county is presented in Figure 4.1 (Google, 2017). Interstate highway 275 acts as a major commuter corridor connecting north of Tampa to the central business district at the south. I-75 and I-4 run along the north-south and east-west directions, respectively, and serve as major highways for intra-city, inter-city, and inter-state travel.

According to the US Census, county population in 2010 was approximately 1.2 million, with 51.2% female. The age categories of under 5 years, 5–19, 20–44, 45–64, and over 65 represented 6.7%, 20.6%, 36.3%, 24.8%, and 11.5% of population, respectively. Within the context of race, the white, black, and Asian categories were the largest, with 74.2%, 16.4%, and 3.4% of the population, respectively. Additionally, 23.9% of individuals identified with Hispanic or Latino origin. Finally, the county household income categories of below \$25,000, \$25,000 to \$75,000, and above \$75,000 correspond to 23.5%, 45.8%, and 30.8% of the population, respectively (US Census Bureau, 2010a).

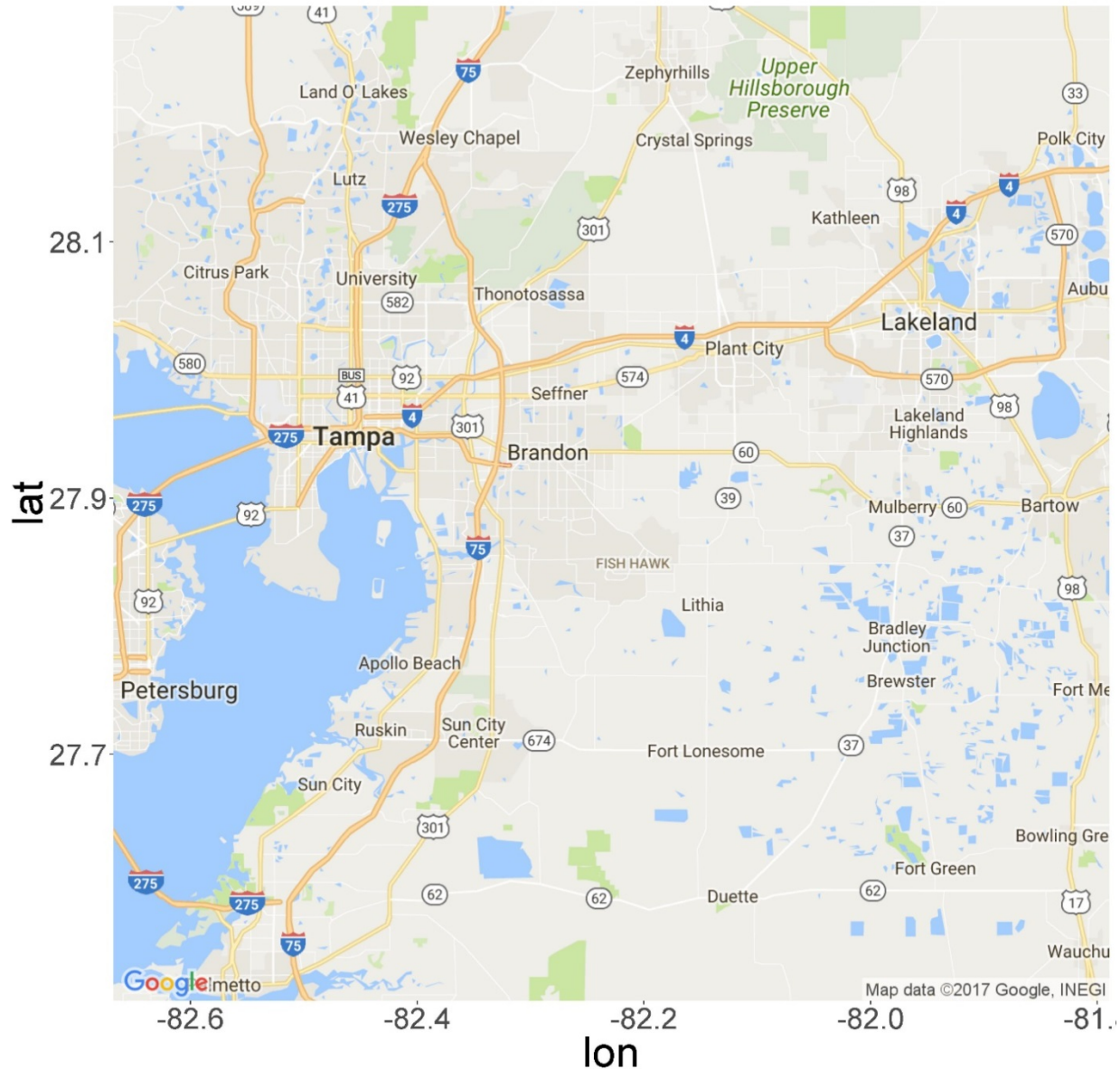


Figure 4.1 Study area of Hillsborough County, Florida (Source: Google 2017)

In addition to a diverse mix of people, the county has few public transportation options, an unsatisfactory air quality record (American Lung Association, 2011), and a sprawling urban form (Smart Growth America, 2014). These attributes make it a good testbed for investigating alternate transportation design scenarios that may improve air quality in the region. The study focused on oxides of nitrogen (NO_x) as a surrogate for traffic-related air pollution (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010).

4.2.2 Transportation and Air Quality Modeling Framework

The integrated transportation and air quality modeling framework used to estimate personal exposures for the entire population in the study region is shown in Figure 4.2.

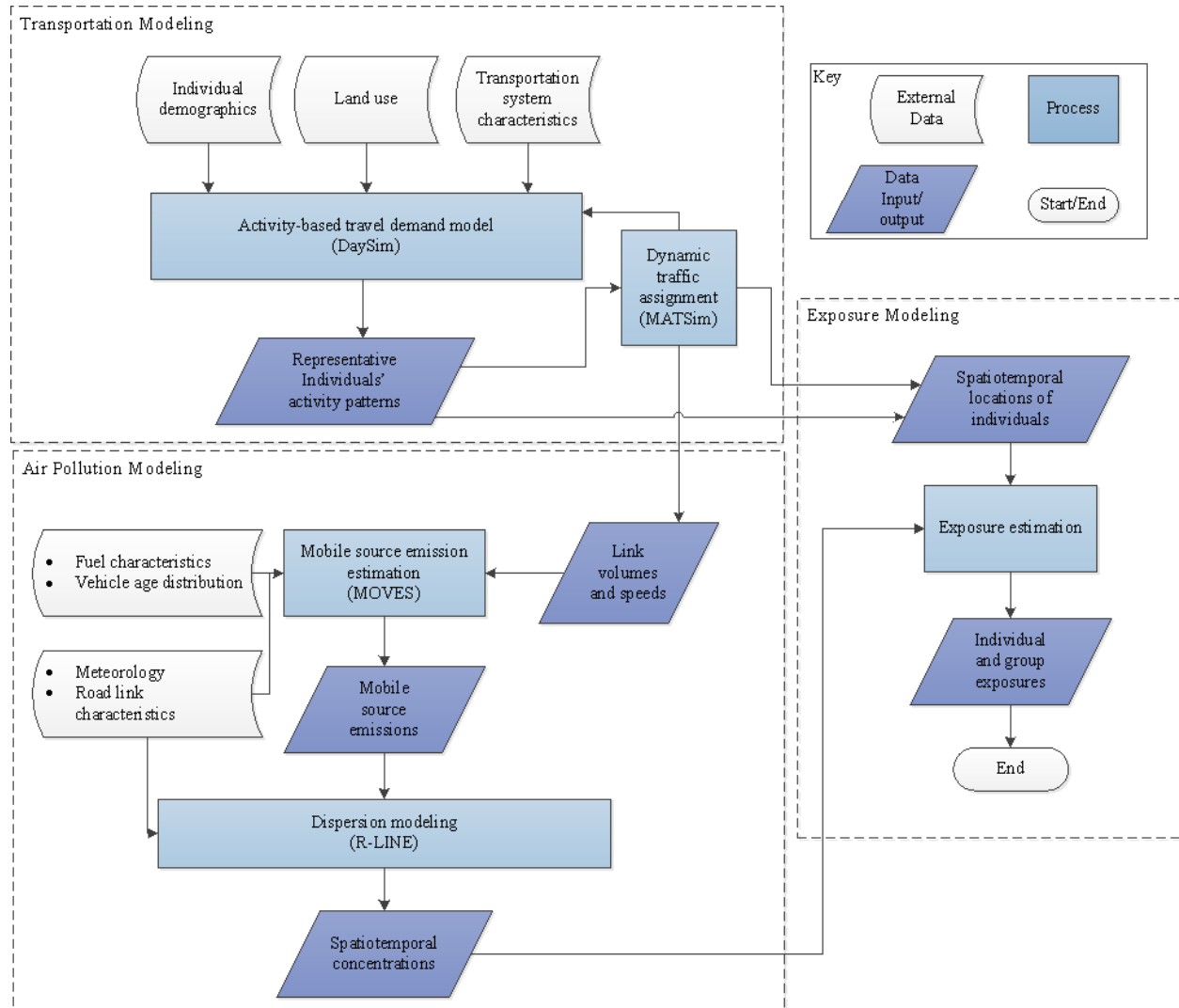


Figure 4.2 Integrated transportation and air quality modeling framework for population exposure estimation

4.2.2.1 Estimation of Travel Demand using DaySim

The Person Day Activity and Travel Simulator (DaySim) shown in Figure 4.2 is an econometric travel-demand model system based on the principle of utility maximization. The theory of utility maximization suggests that individuals choose the activity and travel alternatives that maximize their utility; utility is a representation of the level of satisfaction that individuals achieve by pursuing an

alternative. DaySim predicts the travel demand for a region by estimating the long-term and short-term choices of individuals. Long-term choices include work and school locations for individuals and auto ownership levels for households, and short-term choices include the location and scheduling of daily activities and mode of travel between activities (Bradley et al., 2010).

The DaySim framework requires inputs including synthetic population and parcel information as well as level of service measures including travel time and travel cost for different times-of-day and travel modes to estimate the daily activity and travel behavior of individuals (Bowman & Ben-Akiva, 2001; Bradley et al., 2010). Synthetic population refers to the population records generated from the census data using an Iterative Proportional Fitting approach (Beckman et al., 1996). Specifically, individual records from the Public Use Microdata Area (PUMA) sample are replicated a sufficient number of times so that the resulting aggregate distributions at the level of the census block group match those provided by the census for a few control categories. Similarly, parcel information refers to a high-resolution dataset that provides information including the spatial location, land use, and property value for each land parcel in a region. Using these inputs, DaySim provides the activity and travel information including the location, sequence, and timing of activities and the mode of travel between activity locations, for each and every hypothetical individual in the study area.

For the purpose of this study, the Tampa Bay Activity-based Model (TBABM) was used; TBABM developed for the Tampa Bay area as part of the Federal Highway SHRP2 project, was based on the DaySim modeling framework (Gliebe et al., 2014). The Tampa Bay area consists of five counties—Hillsborough, Pinellas, Pasco, Hernando, and Citrus; thus, the geographic scope of TBABM extends beyond Hillsborough County, which is the primary geographic focus for estimating population exposure. Considering the activity and travel behavior of the adjacent county residents is important to account for the travel related to inter-county activities including work. The demographic inputs based on the 2010 census were developed by using POPGen 1.1 (Ye et al., 2009) for an estimated 3.1 million individuals in the Tampa Bay region, including 1.2 million in Hillsborough County. The parcel-based land use and highway and transit network inputs for the model were created by the staff of the District 7 office of the

Florida Department of Transportation (FDOT District 7). The model structure and parameters initially developed for the Sacramento region were retained in the Tampa Bay ABM, as the consultant team found that local data were insufficient to estimate many key models in the system (Gliebe et al., 2014). Results of a model run of the TBABM provide the daily activity and travel information from 3:00 AM to 2:59 AM on a typical weekday for the entire population in the Tampa Bay region; the activity and travel information include the purpose of each travel trip (work, shopping, recreation, etc.), trip start and end times, travel times and travel distances, and the detailed geo-coded locations of activities.

4.2.2.2 Estimation of Dynamic Traffic Patterns using MATSim

Whereas DaySim provides detailed spatiotemporal information pertaining to the fixed-activity locations of individuals, it is not capable of providing their whereabouts during travel. This knowledge is crucial to accurately estimate exposures because exposures during travel typically were found to be higher compared to other activities (Dons et al., 2011b; Gurram et al., 2015). Therefore, to estimate spatiotemporal locations of individuals for the entire 24 hours, the Multi-Agent Transport Simulation (MATSim) was used, as shown in Figure 4.2. MATSim is an iterative agent-based micro simulation of traffic systems and provides a framework for optimizing the travel demand of each modeled individual or simply an agent (Balmer et al., 2009; Raney & Nagel, 2006). To initiate the optimization process, the program requires the travel plans (i.e., travel-demand) for each agent and the characteristics of the transportation network. Specifically, a plan refers to the activity and travel information including detailed origin-destination location coordinates, activity types, activity start and end times, and travel modes between activities. The network characteristics describe the transportation infrastructure by providing information including geographic coordinates, length, free-flow speed, capacity, number of lanes, and allowed travel modes for each roadway link. Initial plans are the activity and travel patterns obtained from the TBABM. MATSim then simulates the agents' daily schedule (i.e., their initial plan) subject to the network capacity and travel time constraints. Each agent was allowed to store a maximum of three different plans in memory. In every iteration, MATSim selects a plan, executes it, and then calculates a score for the simulated plan based on its utility (Nagel et al., 2016). The utility of a plan S_{plan} with N

activities is obtained by a summation of all utilities from activity participation ($S_{act,q}$) and travel disutilities ($S_{trav,mode(q)}$) and is based on the scoring function developed by Charypar and Nagel (2005) as shown in equation 4.1. Generally, participating in an activity is associated with positive utility while activities like travel are associated with negative utility or disutility.

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad 4.1$$

In this study, the default parameters proposed by Charypar and Nagel (2005) were used for scoring; activity participation, late arrival, and traveling are scored at 6, -18, and -6 utilities/hour, respectively. Thus, plans that maximize activity participation times while minimizing the travel times and avoiding late arrivals have higher scores.

Following the scoring at the end of every iteration, the scores of the executed plan are compared with that of the plans in memory, and the plan with the least score is dropped. Following this, for a fixed percentage of agents, the program replans (i.e., modifies) the activity schedules by either rerouting or adjusting the departing times by 15 minutes. Specifically, in every iteration, 10% of the agents were rerouted, departure times were adjusted for 10% agents, and the rest of the agents stuck to their previous best plans. These percentages were based on computational feasibility and guidance from previous literature (Waraich et al., 2015). Subsequently, the program proceeds to the next iteration. To completely exploit the high computing resources available to us, the simulation was allowed to continue until 300 iterations although only a minimum of 60 iterations is generally needed according to the authors of MATSim (Waraich et al., 2015).

Only those trips that use the automobile mode of travel were simulated in this study as they have the largest mode share (close to 90%) in the study region based on the DaySim modeling results; the total number of automobile trips is approximately 9.7 million. To successfully simulate this large number of trips made by 2.3 million individuals (the rest of the population did not travel), a cluster setup of 48 processors each with 25 GB of RAM was used. The outputs from MATSim include updated activity and travel patterns and travel route information for each and every agent along with roadway link-specific traffic volumes and links-specific average speeds for each hour of a typical weekday.

4.2.2.3 Estimation of Mobile-Source Emissions using MOVES

The roadway-link traffic volumes and speeds simulated using MATSim can be used to generate link-specific mobile source emissions for each hour of the day. To estimate the mobile source emissions of pollutants, the United States Environmental Protection Agency's Motor Vehicle Emission Simulator 2014a (EPA MOVES) model was used (Koupal et al., 2003; US Environmental Protection Agency & Office of Transportation and Air Quality, 2015), as shown under the air pollution modeling component in Figure 4.2. MOVES estimates emission factors (e.g., mass per km per vehicle) or emission totals for both on-road motor vehicles and non-road equipment (Koupal et al., 2003).

Although Hillsborough County, FL, is the area of focus for air quality and exposure estimates in this study, the roadway links that fell within a five-kilometer buffer around Hillsborough County were also included for air quality analysis as impacts of emissions near the county edges on air quality cannot be ignored. The diurnal cycle of hourly emissions was estimated for an average winter day by running MOVES in a batch mode at the project scale for 14,025 roadway links. Specifically, MATSim-generated hourly car volumes and average speeds for each roadway link were input to the MOVES model. MOVES provides default data for the diurnal cycle of hourly temperature and relative humidity for each month of 2010. These observations were aggregated across November through March to generate an average diurnal cycle of hourly temperature and relative humidity for a representative winter day. County-specific default fuel formulation data and the national default vehicle age distribution data for 2010 were also used. The output from MOVES includes roadway link-specific running emissions of NO_x in grams for each hour of a typical winter weekday.

4.2.2.4 Estimation of Pollutant Concentrations using R-LINE

To estimate the pollutant concentrations from mobile sources, R-LINE was used, as shown in Figure 4.2. R-LINE is a line source model based on steady-state Gaussian formulation, which is consistent with current regulatory models including AERMOD and is used to simulate the mobile-source pollutant dispersion of near-surface releases (Snyder et al., 2013). The model includes new treatments for vertical and horizontal plume spread of near-surface releases and incorporates new tracer field and wind

tunnel study data (Snyder et al., 2013). Additionally, it has been formulated to reduce estimation errors under light and variable wind conditions.

As presented by Snyder et al. (2013), R-LINE simulates concentrations from roadway sources by integrating the Gaussian plume formulation as a line segment. Given the coordinates (x_r, y_r, z_r) for the receptor r and a plume with origin at $(0, Y_s)$, the concentration at receptor r due to a line source of length L with origin Y_1 is given by the summation of contribution from a differential element (dC_{pt}) as shown in equation 4.2 (Snyder et al., 2013).

$$C(x_r, y_r, z_r) = \int_{Y_1}^{Y_1+L} dC_{pt} \quad 4.2$$

The element's contribution is further a function of plume (pl) and meander (m) components which are added using a weighting factor f as shown in equation 4.3. Here, f is a function of lateral turbulence and mean wind (Snyder et al., 2013).

$$dC_{pt} = (1 - f) * dC_{pl} + f * dC_m \quad 4.3$$

The plume concentration and the meander component are composed of vertical (VERT) and horizontal (HORZ) dispersion terms, emission rate of q (mass/(time*length)), and effective wind speed of U_e (length/time) and are represented using equations 4.4 and 4.5, respectively (Snyder et al., 2013).

$$dC_{pl} = \frac{qdY_s}{U_e} [VERT * HORZ_{pl}] \quad 4.4$$

$$dC_m = \frac{qdY_s}{U_e} [VERT * HORZ_m] \quad 4.5$$

The vertical component for both plume and meander and the horizontal component for plume, and the horizontal component for meander are shown in equation 4.6, 4.7, and 4.8, respectively. Under low wind speeds, the horizontal plume is assumed to move equally in all directions, thus giving rise to the horizontal meander equation 4.8 (Snyder et al., 2013).

$$VERT = \frac{1}{\sqrt{2\pi}\sigma_z} \left[\exp\left(-\frac{1}{2}\left(\frac{z_s-z_r}{\sigma_z}\right)^2\right) + \exp\left(-\frac{1}{2}\left(\frac{z_s+z_r}{\sigma_z}\right)^2\right) \right] \quad 4.6$$

$$HORZ_{pl} = \frac{1}{\sqrt{2\pi}\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{y_r-y_s}{\sigma_y}\right)^2\right) \quad 4.7$$

$$HORZ_m = \frac{1}{2\pi \sqrt{(x_r - x_s)^2 + (y_r - y_s)^2}} \quad 4.8$$

The diurnal cycle of winter time hourly link-specific emission outputs from MOVES were used as inputs to R-LINE to calculate the diurnal cycle of concentrations throughout the spatial domain, i.e., Hillsborough County, FL. Specifically, link-level emissions were modeled as line sources using the roadway length and width characteristics obtained from the roadway network file provided by FDOT District 7 as part of TBABM. Based on Grimmond and Oke (1999), the ratio of displacement height to roughness length was assumed to be 5. Additionally, the initial dispersion length for the plumes created from the line sources was assumed to be 1.2 m based on an average vehicle height of 1.5 m and in accordance with the US EPA's guidance for hot-spot analysis (US Environmental Protection Agency et al., 2010). Hourly meteorological surface data for November through March 2010 were prepared using the AERMET program by using raw data from the National Climatic Data Center for the Tampa International Airport. A total of 15% of the hours in 2010 had missing meteorological data fields, thus resulting in 3060 hours with valid meteorological data. Concentrations were generated for each hour of this record for a regular grid of receptor locations with 500 m resolution throughout the study area; the number of receptors totaled 13,806. Output values from the simulation were averaged to generate the diurnal cycle of concentrations for each hour of an average winter day.

4.2.2.5 Analysis of Exposure

The exposure modeling step involves combining the spatiotemporal locations of simulated hypothetical individuals with the spatiotemporal distribution of pollutant concentrations to estimate person-level exposures, as shown in Figure 4.2. The outputs from DaySim and MATSim were merged to create a sequential activity-record for each Hillsborough County resident for a 24-hour period. Specifically, the activity records contain the location coordinates, time-of-day, and activity durations both for fixed-location activities and the travel activity, for each individual. This information is combined with the diurnal cycle of winter-average concentrations to generate time-weighted exposure measures for all the representative individuals in the county. The daily activity-based exposure concentration was

numerically estimated as $C_A = (\sum c_\sigma \Delta t_\sigma) / T$ for each person-day in the study sample, with c_σ and Δt_σ representing the ambient concentration and the time spent at each discretized spatiotemporal activity location; σ represents the latitude, longitude, time; and T the total exposure averaging period.

To understand the impact of using high-resolution versus low-resolution data on sub-group and population exposures, two different sets of data were used to model exposures. The high-resolution activity data refers to the activity and travel patterns of individuals at the parcel level for fixed-activity locations and every five seconds during their travel; the low-resolution activity data refers to activity and travel patterns estimated at the block group-level with even assignment of the travel times to the origin and destination block groups. Thus, in the low-resolution scenario, individuals are assumed to stay at the block group centroid instead of the parcel location. Similarly, the high-resolution concentration data were estimated for a 500-meter regularly-spaced receptor network, whereas the low-resolution data were estimated for receptors located at the block group centroids.

4.3 Results

4.3.1 Spatiotemporal Distributions of Activities

Analysis of the time spent by county residents in different locations reveal that they spent little time collectively in the county during active working hours, predominantly from 8:00 AM until 5:00 PM, as shown in Figure 4.3. Conversely, they spent a lot of time collectively in the county during the off-work hours, predominantly from 8:00 PM until 7:00 AM. More specifically, the collective time spent within the county remains highest and fairly constant from 11:00 PM until 6:00 AM, after which it falls steeply until 10:00 AM. It remains fairly constant and at its lowest level from 10:00 AM until 3:00 PM. Finally, the collective time spent in the county increases from 3:00 PM until the end of the day, with a steep rise from 4:00 PM until 8:00 PM.

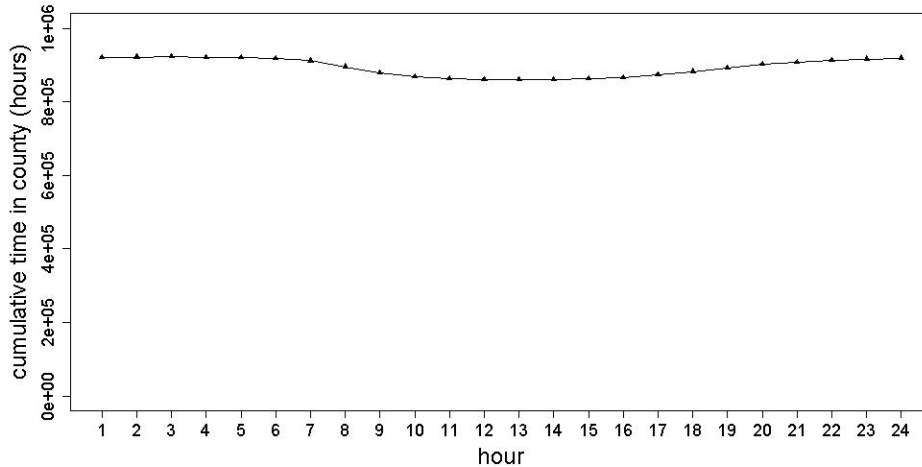


Figure 4.3 Diurnal cycle of daily cumulative duration spent by all county residents

The spatiotemporal distributions of the activity and travel patterns of individuals at block group-resolution are shown in Figure 4.4. Spatially, for much of the day, high activity durations were observed in the residential areas of New Tampa, Westchase, Riverview, Sun City Center, Fish Hawk, Brandon, and Plant City; it should be noted that activity durations at these locations were more pronounced in the off-work hours. As the workday begins, activities spill over into the adjacent block groups and/or block groups that are (often) categorized as employment and business generators. Specifically, starting at 7:00 AM, higher activity durations were observed in the University area, the industrial area behind Tampa International Airport, at the intersection of I-4 and I-75 west of Brandon, MacDill Airforce Base, and the corridor along Dale Mabry Highway. The higher activity durations in most of these employment and business-generator block groups persist until 8:00 PM. Unlike for the high activity durations, the block groups with low activity duration are generally scattered throughout the county. The only exception to this is the set of block groups near Downtown Tampa that appear to have lower activity durations during the off-work hours from 7:00 PM until 7:00 AM.

Although the raw activity durations provide information on the collective locations of individuals, they may overemphasize results toward larger geographies. To account for the impact of block group size on activity duration, the activity durations were normalized by the block group area to create an activity-duration density map, as shown in Figure 4.5. Not surprisingly, high activity-duration densities coincided with smaller block groups concentrated in the urban core of Tampa. High activity-duration densities were

observed throughout the day in smaller block groups that are interspersed near the University area, Westchase, and Egypt Lake. Similarly, high activity duration densities were observed near Downtown from 7:00 AM until 8:00 PM. Conversely, low activity duration densities were predominantly restricted to the larger block groups that form the exoskeleton of Tampa.

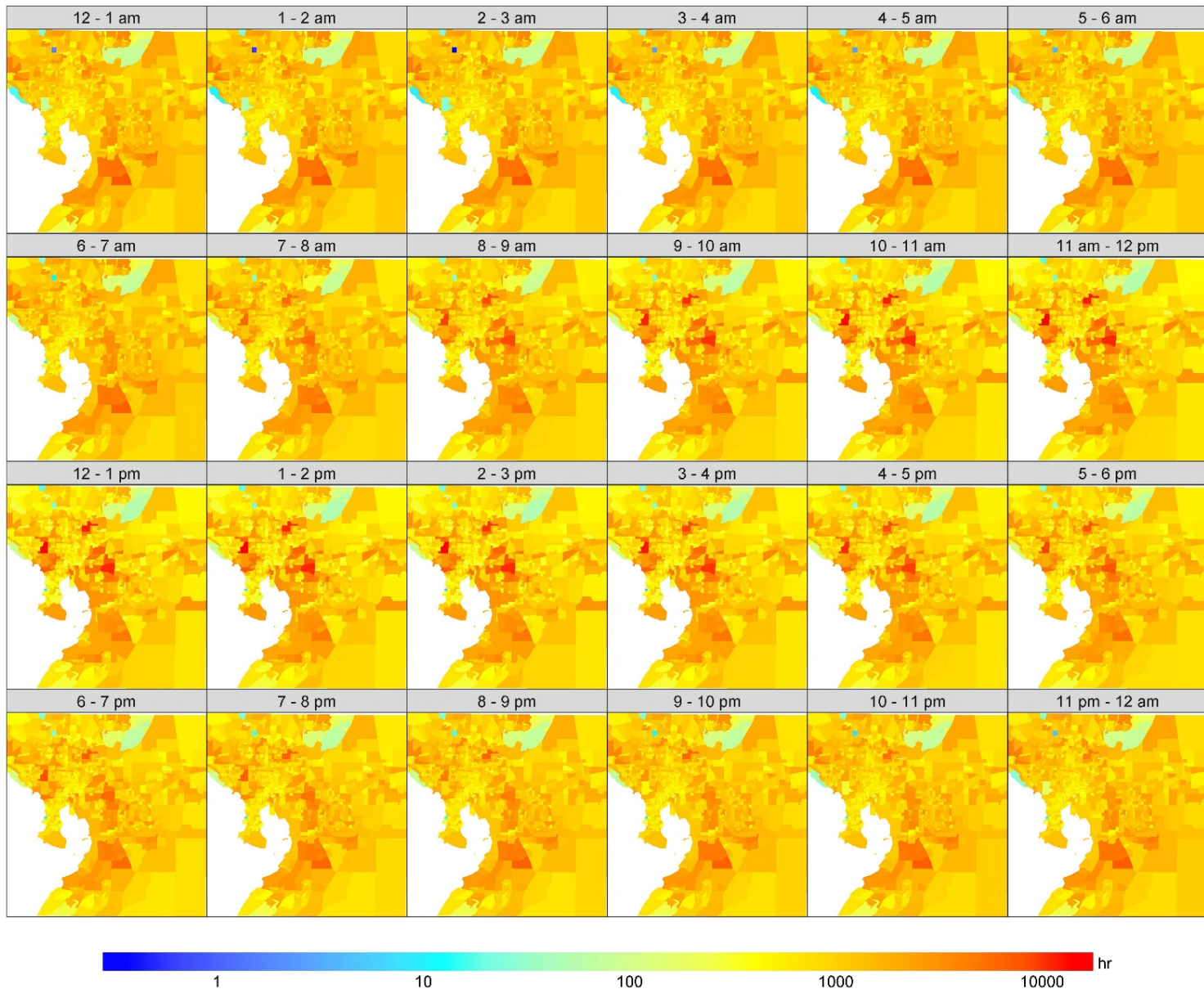


Figure 4.4 Total activity duration (person-hours) by block group and hour of day for all individuals in Hillsborough County

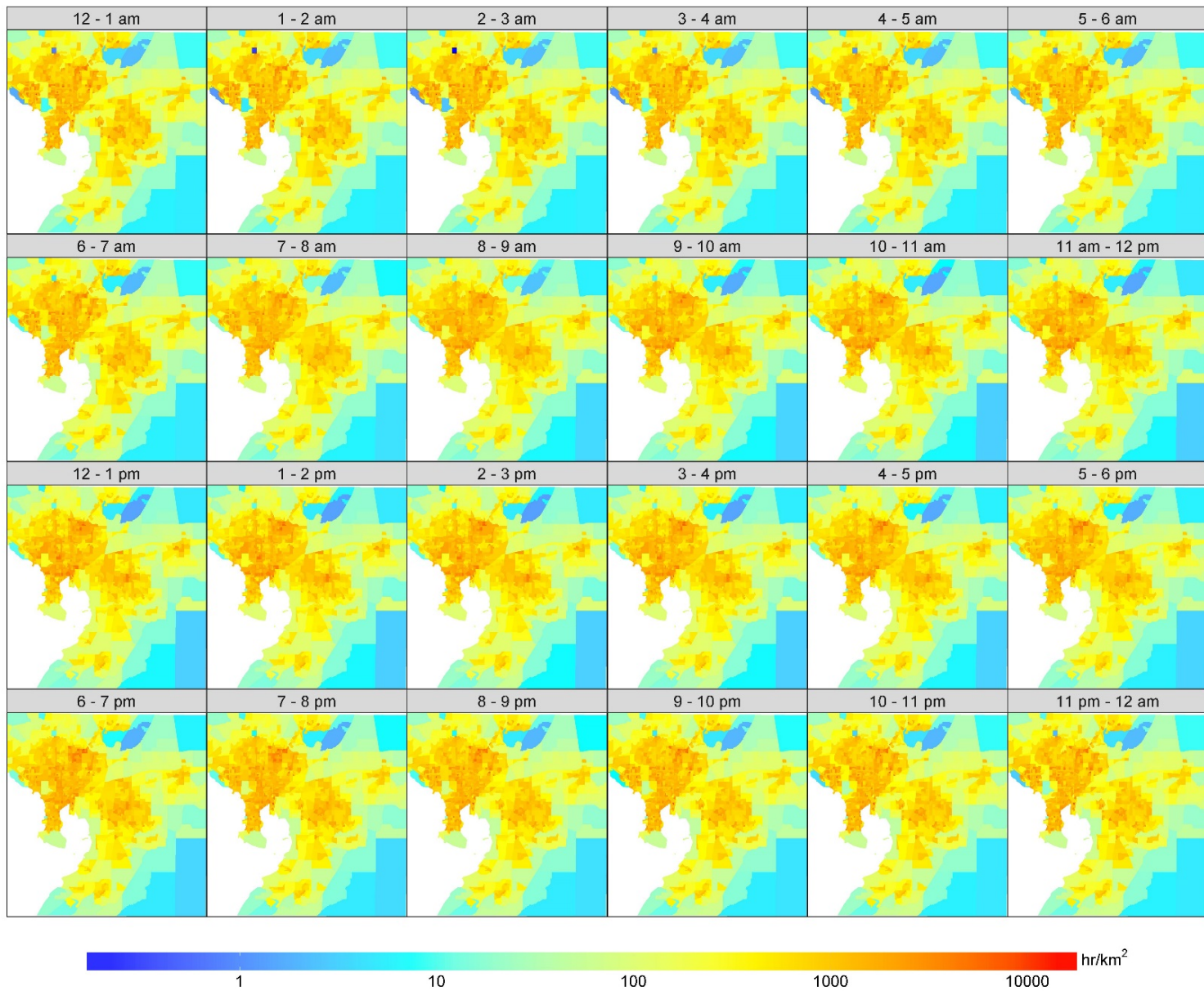


Figure 4.5 Activity-duration densities (person-hours/km²) for Hillsborough resident sample in 2010

Diurnal patterns of link-level passenger car volumes and travel speeds for Hillsborough County are presented in Figure 4.6 (in the form of bi-hourly averages). As expected, traffic volumes, as shown in Figure 4.6a), were higher during the morning (7:00–9:00 AM) and the evening (4:00–7:00 PM) peak hours than the rest of the day. Additionally, traffic volumes during evening peak hours were higher than volumes during morning peak hours. Travel speeds, as shown in Figure 4.6b, correspond to the diurnal pattern of traffic volumes, with lower speeds during the morning and evening peak hours. Spatially, higher volumes were observed along major freeway corridors—I-75, I-275, and I-4. This is expected, as these freeway corridors experience high traffic volumes, which also were observed along the road network near suburban locations including Brandon, Citrus Park, and Town ‘N’ Country. Accordingly, travel speeds were lower in these suburban locations along with the North Tampa area, the University area, and a few sections of the freeway corridors.

Traffic-count data for eight different locations in the Tampa Bay area were available in the transportation network input file of TBABM (Gliebe et al., 2014). Root Mean Squared Error (RMSE) between the estimated daily traffic volumes and observed annual average daily traffic (AADT) volumes, for these eight locations, was found to be 0.41. Further, the error between estimated and observed traffic flows for inter-city roads was higher than those for intra-city roads, presumably because the current model system does not consider long-distance (or inter-city) travel, visitor travel, and freight movement in detail.

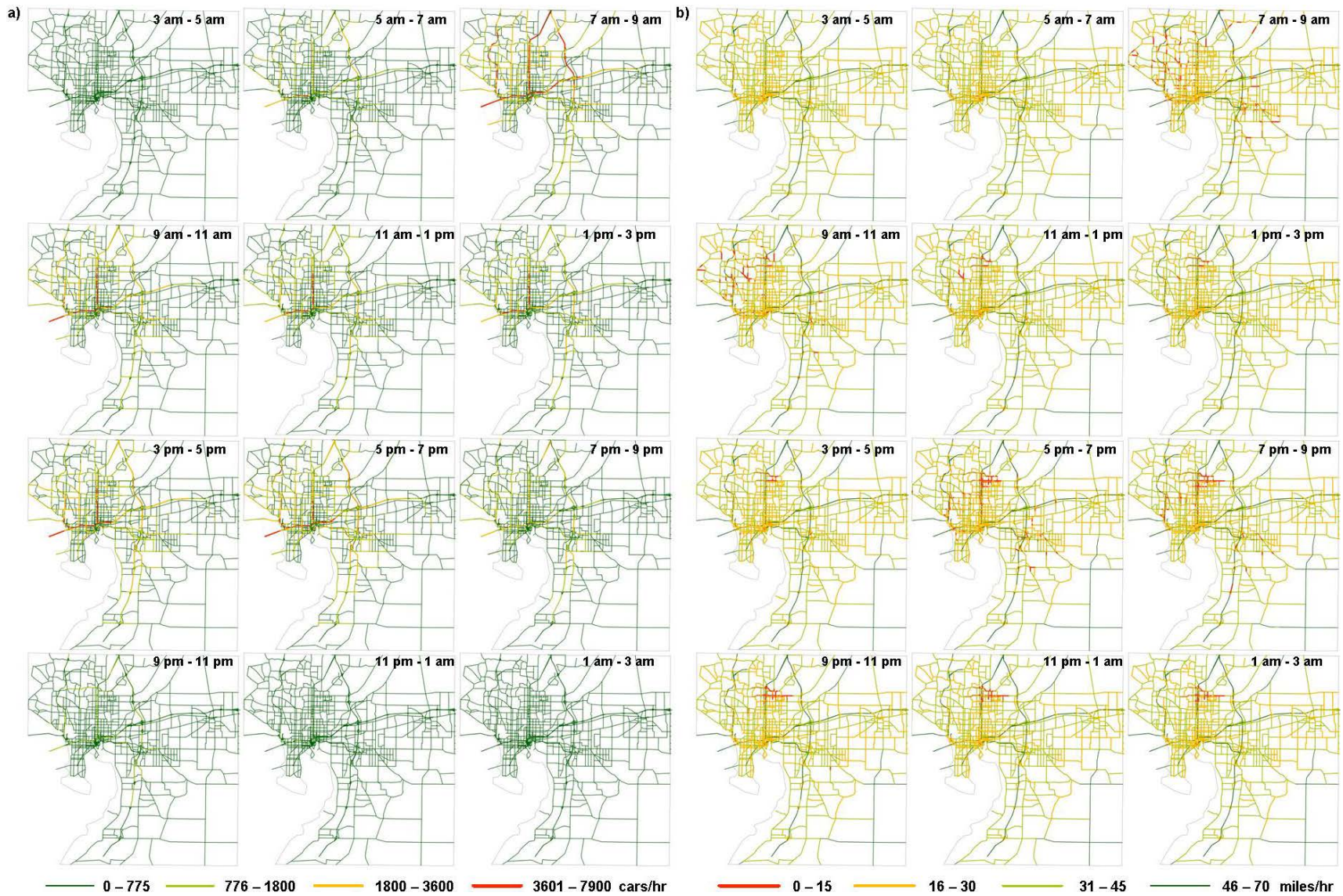


Figure 4.6 Bi-hourly average passenger car volumes (left) and travel speeds (right) for Hillsborough County on typical weekday

4.3.2 Spatiotemporal Distributions of Emissions and Concentrations

The diurnal cycle of spatially-distributed NO_x emissions for a representative winter day (obtained by estimating a mean diurnal cycle of temperature and humidity for November through March) is shown in Figure 4.7. The total emissions resulting from passenger car travel in Hillsborough County was approximately 20.4 tonnes/day. The highest link-specific hourly emission of approximately 9800 grams was observed on the I-275 section in North Tampa from 7:00–8:00 AM. Temporally, emissions were higher during the morning (7:00–10:00 AM) and evening (3:00–7:00 PM) peak hours compared to the rest of the day. Emissions during the morning and evening peak hours make up more than 50% of daily total NO_x emissions. Additionally, emissions during the evening peak hours were higher compared to the emissions during the morning peak hours; specifically, the evening peak hour contributed 30.8% towards daily total emissions, whereas the morning peak contributed 21.8% to total emissions. This could be because the evening commute has a higher propensity for stopping to participate in other activities when compared to the morning commute (Chu, 2003).

Spatially, the highest emissions were observed along the major freeway corridors including I-75, I-275, and I-4; this is expected, as these corridors experience high traffic volumes—specifically, the roadway links on I-275 and I-75 in North Tampa, leading to the I-4 and I-75 intersection point on I-275 to the south of Brandon near Sun City Center, and on I-275 and Courtney Campbell Causeway, which connects Tampa with Clearwater. These roadway sections contributed roughly 7.5% towards daily NO_x emissions. Similarly, high emissions also were observed along the Veterans Expressway and the road network near Brandon and Town ‘N’ Country. Emissions were somewhat low in the Tampa Downtown area.

The diurnal cycle of NO_x concentrations resulting from passenger cars is presented in Figure 4.8. Overall, the predicted winter-average NO_x concentration for Tampa was approximately 4.7 µg/m³. NO_x concentrations have two temporal peaks; one during the morning (5:00–9:00 AM) and the other during the evening (5:00–10:00 PM) peak hours. Note that emission estimates during the evening peak hours were

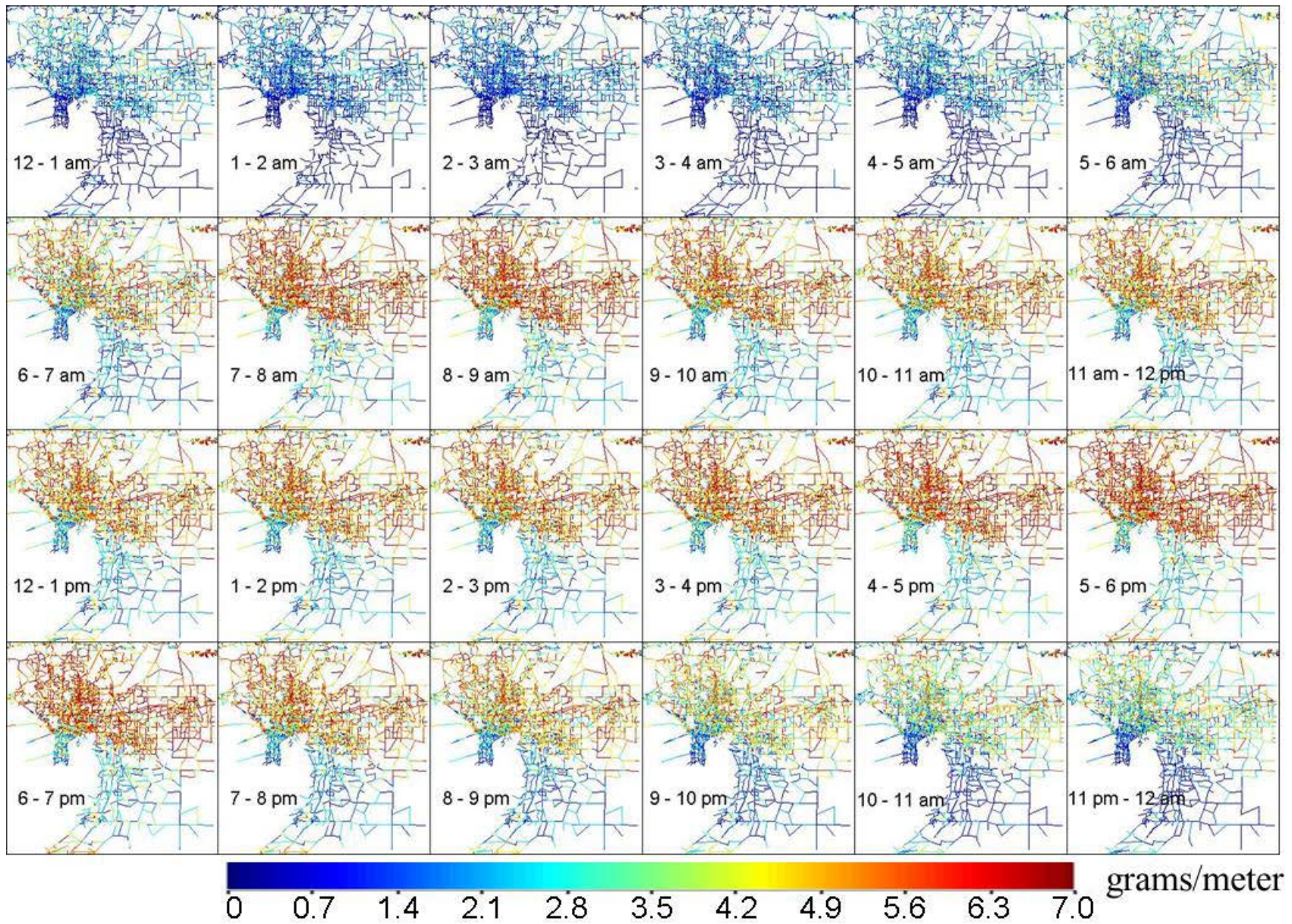


Figure 4.7 NO_x emissions by hour of day from cars for representative winter day in Hillsborough County

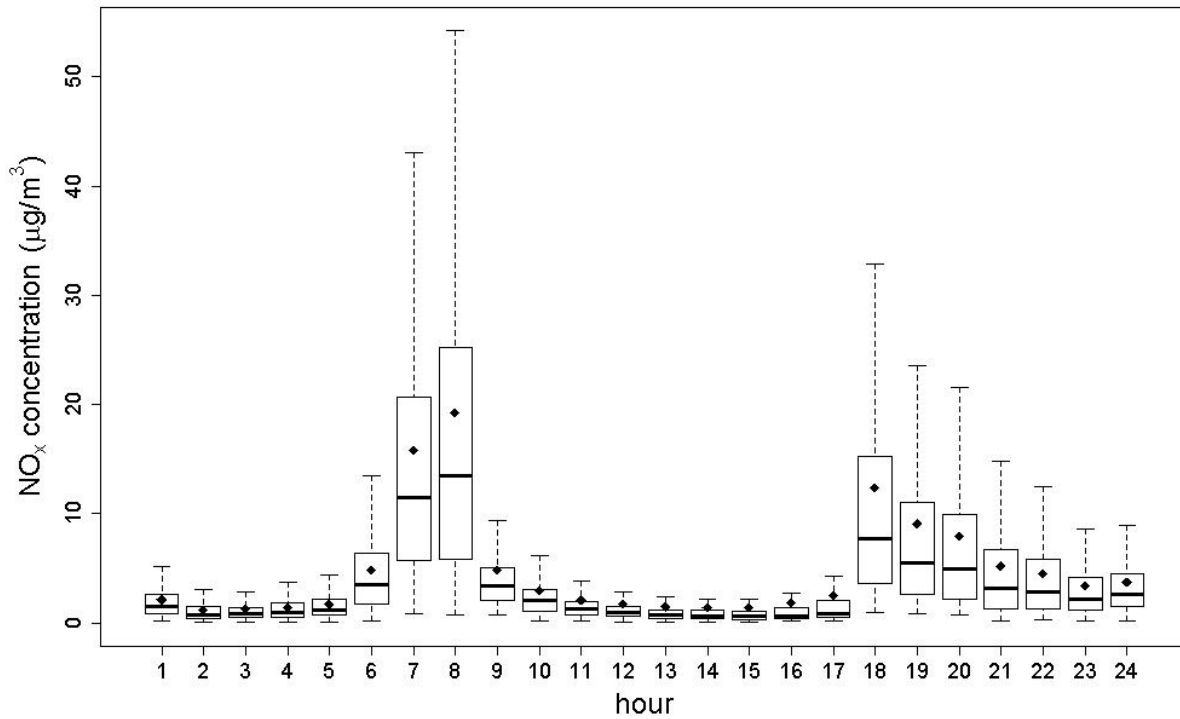


Figure 4.8 Diurnal cycle of NO_x concentrations from on-road passenger cars

found to be higher than emissions during the morning peak hours, which is in contrast to the peak hour concentration estimates. Lower mixing heights could be a reason for the higher morning concentrations.

Similar to the emissions patterns, higher concentrations were observed along the major freeway corridors, including I-75, I-275, and I-4, as shown in Figure 4.9. This is primarily because automobiles were the only pollutant sources modeled here. High concentrations also were observed along the road network near the University area, the Downtown area, and Brandon, a suburban location near Tampa.

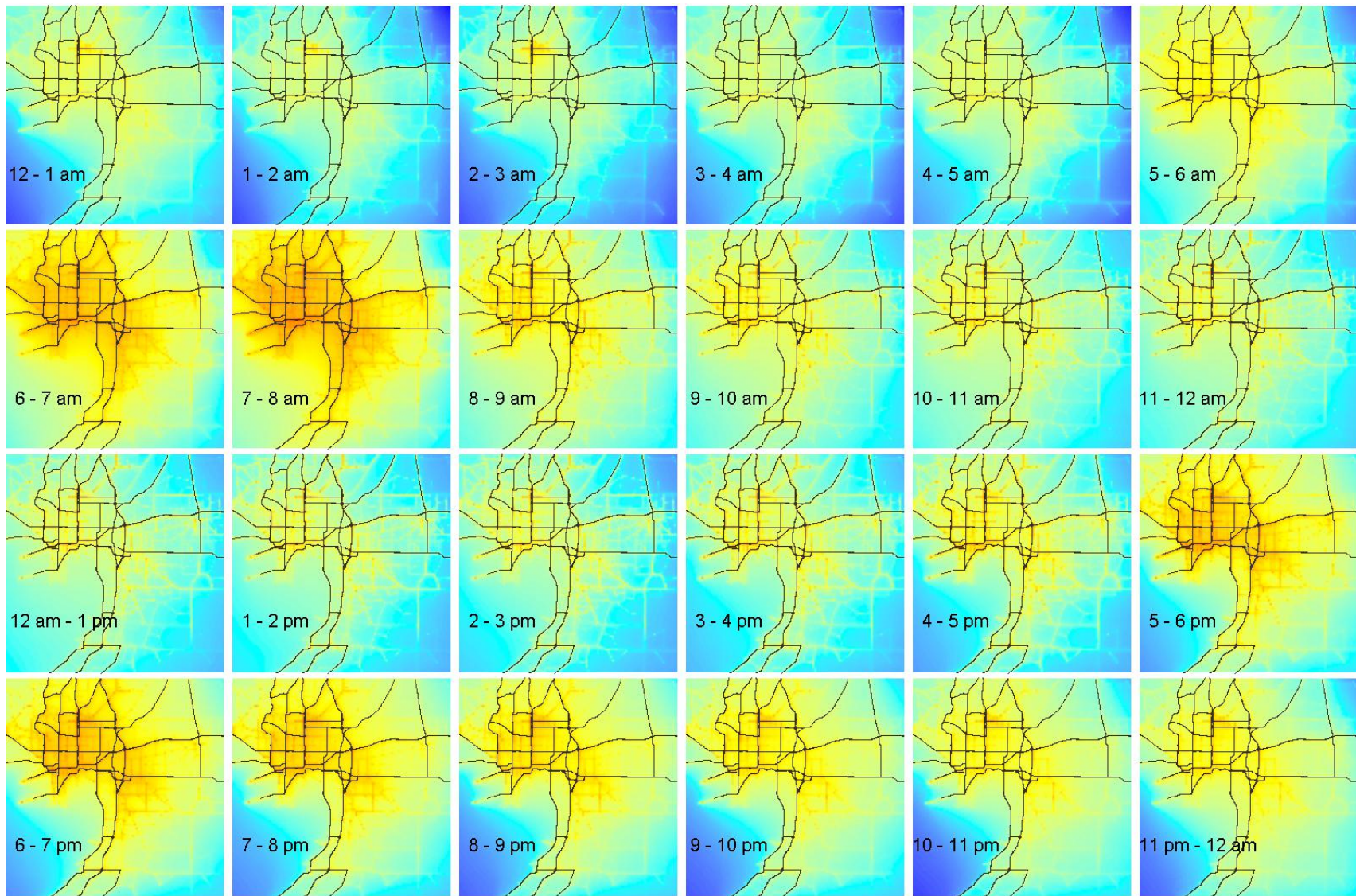


Figure 4.9 NO_x concentration distribution by hour of day due to on-road passenger cars in Hillsborough County for winter months 2010

4.3.3 Distribution of Exposures by Demographics, Urbanicity, and Travel Activity

To understand the potential disparities in exposure to traffic-related pollution, distributions of exposures for a few demographics were obtained; to understand the impact of residence location and transport on exposures, distributions of exposures for urbanicity and travel categories were obtained. The corresponding cumulative distributions of subgroup exposures along with the overall population exposure in Hillsborough County are shown in Figure 4.10. Figure 4.10a shows distributions of NO_x exposures by race, Hispanic origin status, income, and age, and Figure 4.10b shows NO_x exposures by residence location urbanicity and daily travel time in minutes.

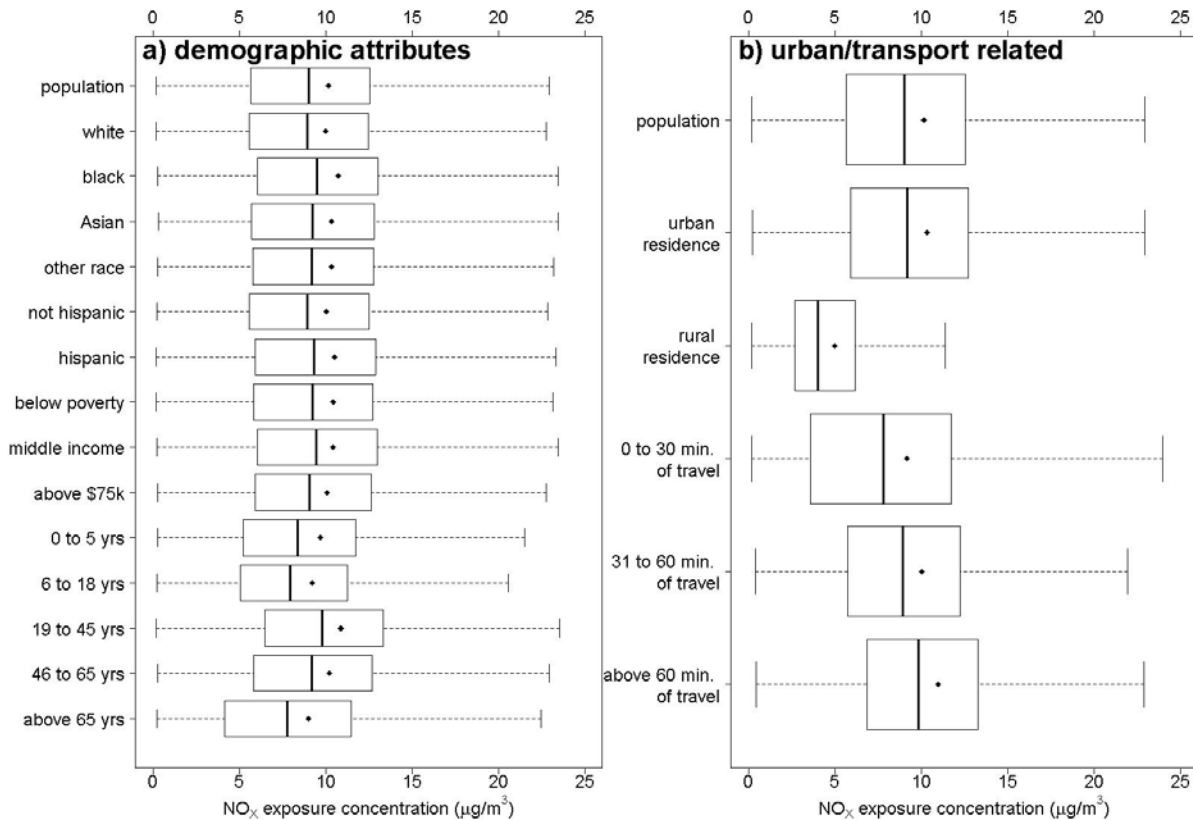


Figure 4.10 Cumulative distributions of personal exposure concentration for NO_x resulting from passenger cars. Exposures are shown by a) demographics and b) urbanicity and travel activity. “Other” racial category includes American Indian or Alaskan Native, Native Hawaiian, multiracial, or other races. Income categories based on the household income. Middle income refers to individuals from households above poverty level but income below \$75,000.

The mean and median daily average population exposure concentration for NO_x resulting from passenger cars was 10.2 and 9 µg/m³, respectively; exposures range from 0.2 to 145 µg/m³. Compared to

the mean population exposure, subgroup mean exposure was lower for whites (lower by 1.4%), non-Hispanics (1%), individuals with household income above \$75,000 (0.6%), children ages 0–5 (4.4%) and 6–8 (9%), and older adults above age 65 (11.2%). Conversely, mean exposure was higher for blacks (higher by 5.9%), Asians (2.1%), other racial subgroups (2.1%), Hispanics (3.7%), individuals from households living below poverty (2.7%) and at middle incomes (2.9%), and adult ages 19–45 (7.2%) and 46–65 (0.5%) compared to the mean population exposure. Similarly, for the urbanicity and travel categories, group mean exposure was lower for individuals living in rural areas (51%) who did not travel (9.7%) and whose daily travel time is less than 60 minutes (1.1%) compared to the mean population exposure; group mean exposure was higher for individuals living in urban areas (1.8%) whose daily travel time is greater than 60 minutes (8.3%) than the mean population exposure. Thus, on average, exposures were higher for the black, Asian, lower-income, middle-income, and active age (19–65) subgroups. Similarly, exposures were higher for individuals residing in urban zones and with higher daily travel times.

Although the distributions of group exposures describe the exposure disparities between groups of interest, they provide few details. To identify the strength of exposure-disproportionality at each exposure level, a subgroup inequality index shown in equation 4.9 was used (Stuart et al., 2009).

$$F_{ij} = \log(Z_{ij}/T_i) \tag{4.9}$$

F_{ij} quantifies the degree to which members of a specific population subgroup i are disproportionately exposed to a particular level of pollutant, j , Z_{ij} is the fraction of the total population with exposures above level that is the specific subgroup, and T_i is the fraction of the total population of Hillsborough County that is the specific subgroup. Thus, positive and negative index values suggest disproportionately high and low representation of that subgroup at any exposure level. Exposure level can be quantified by a number of measures. Here, the percentile values of daily personal exposure concentration were used.

The subgroup inequality indices by race, Hispanic origin, income, and age are shown in Figure 4.11. Blacks, Asians, and other groups have disproportionately high representation at most exposure percentiles. Alarming, this trend accentuates as the exposure levels increases, i.e., minority groups were

more disproportionately affected at higher exposure levels. Conversely, a disproportionately low percentage of the white subgroup was affected at most exposure levels. As the exposure levels increased, the low representation of the white subgroup was further accentuated. Similar trends were observed for the Hispanic and non-Hispanic groups in which Hispanics make up for a disproportionately high percentage of exposed individuals at higher exposure levels. Among the income categories, middle-income group made up for a disproportionately high percentage of exposed individuals at most of the high exposure levels when compared to the below-poverty and above \$75,000 income groups. However, when the below-poverty group was further separated into two groups—i.e., below-poverty white and below-poverty non-white—the below-poverty non-white group had disproportionately high representation at almost all the exposure levels as opposed to the disproportionately low representation of the below-poverty white group at most exposure levels. Further, the inequality index for the below-poverty non-white group increases steeply as the exposure levels rise. Finally, the active age groups—i.e., ages 18–65 years—appear to be disproportionately affected by high exposure levels compared to the relatively inactive age groups.

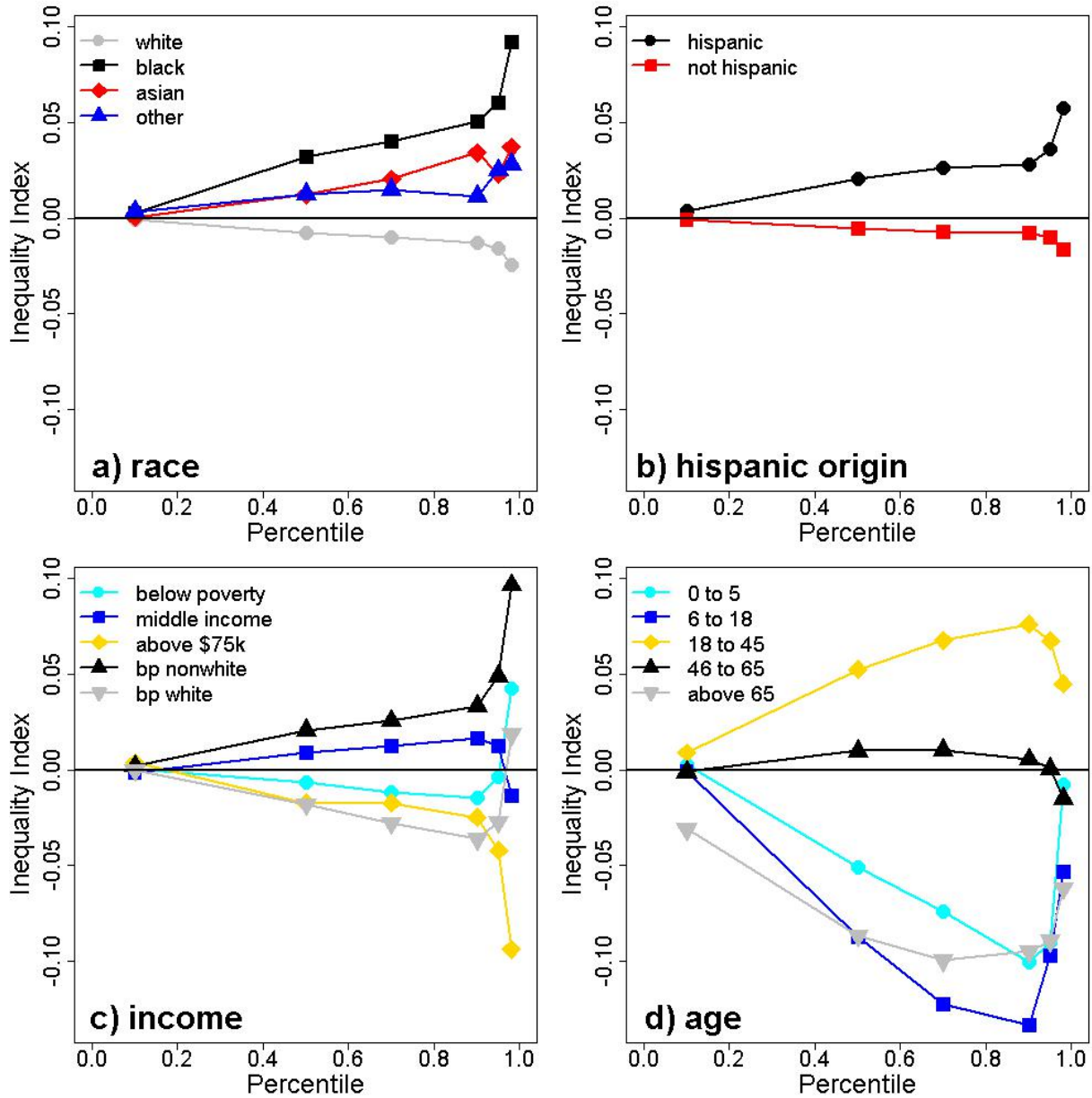


Figure 4.11 Subgroup inequality index by demographics versus percentile of cumulative distribution of individual daily exposure concentrations

4.3.4 Spatiotemporal Distributions of Exposure and Exposure Density

The spatiotemporal distributions of cumulative personal exposure concentration for NO_x aggregated by block groups are shown in Figure 4.12. The diurnal trend of spatially-aggregated exposures aligned very closely with the diurnal trend of estimated NO_x concentrations. The morning (6:00–8:00 AM) and evening (5:00–7:00 PM) commute hours accounted for about 48% of the daily population exposure.

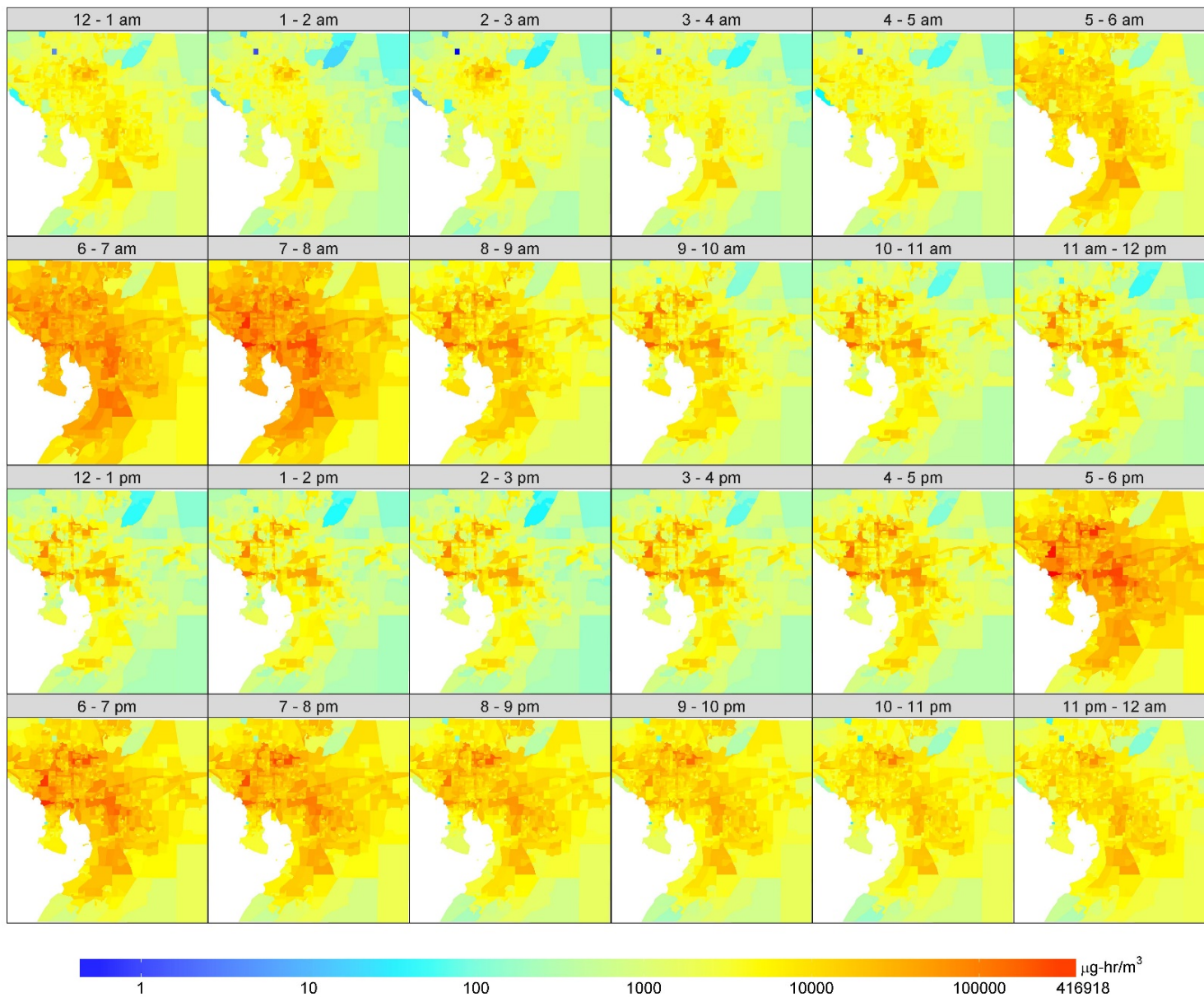


Figure 4.12 Total cumulative exposure ($\mu\text{g}/\text{m}^3$ person-hr) to NO_x by block group and hour for sample of Hillsborough County residents

Spatially, high exposures were observed near the greater Carrollwood area, along the I-275 corridor, Riverview, and Sun City Center during off-work hours. However, during working hours, high exposures were concentrated in those block groups that form the urban core of Tampa; predominantly, Downtown and the corridors along I-275 and Dale Mabry Highway. The University area appears to have high exposures throughout the day. Low exposures were more prominent within the block groups that form the outer skeleton of Tampa, possibly due to the low NO_x concentrations in these areas; interestingly, unlike the activity durations, the Downtown area does not figure in the group of low exposure regions, thus pointing to the impact of ambient concentrations on exposures.

The spatiotemporal distributions of exposure densities (normalized by block group area) are shown in Figure 4.13. Spatially, during off-work hours, high exposure densities were concentrated in the residential pockets between the University area and I-275, along I-275, and near Downtown. During the morning commute from 5:00–8:00 AM, the high-exposure density areas shifted from the residential pockets and spread out across the urban core of Tampa, especially along major highways and suburban areas such as Brandon and Plant City. The spatial distribution of the exposure density remained fairly constant from 8:00 AM until 5:00 PM. During these work hours, the Downtown appeared to have the highest exposure densities. In addition, the University area, areas along I-275, the airport area, and the Carrollwood business area also featured high exposure density pockets; very few pockets in the Brandon and Plant City areas featured high exposure densities. During the evening commute of 5:00–7:00 PM, similar to the morning commute, high exposure densities were spread out across the urban core of Tampa, Brandon, and Plant City. However, it should be noted that the exposure densities during the evening commute appear to be more diffuse compared to that during the morning commute.

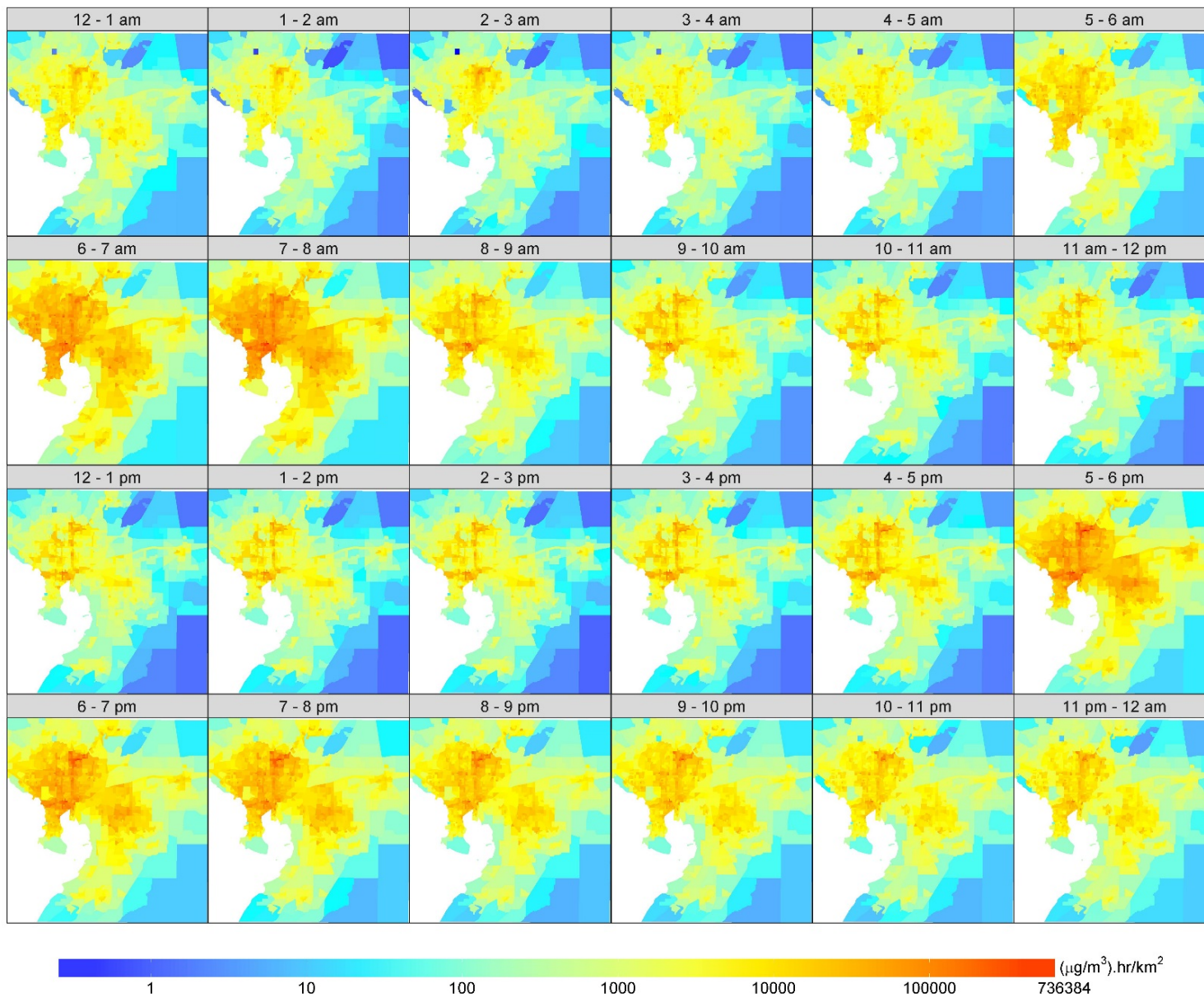


Figure 4.13 Cumulative exposure density ($\mu\text{g}/\text{m}^3 \cdot \text{person hr}/\text{km}^2$) for Hillsborough County resident sample 2010

4.3.5 Impact of Spatiotemporal Resolution of Modeled Data on Human Exposures

The differences in exposures obtained using highly spatiotemporally-resolved activity and concentration data and low-resolution data are shown in Figure 4.14. A positive value in the figure indicates higher estimates for the high-resolution approach compared to the low-resolution approach. A negative value indicates lower estimates of exposures using high-resolution activity and concentration data.

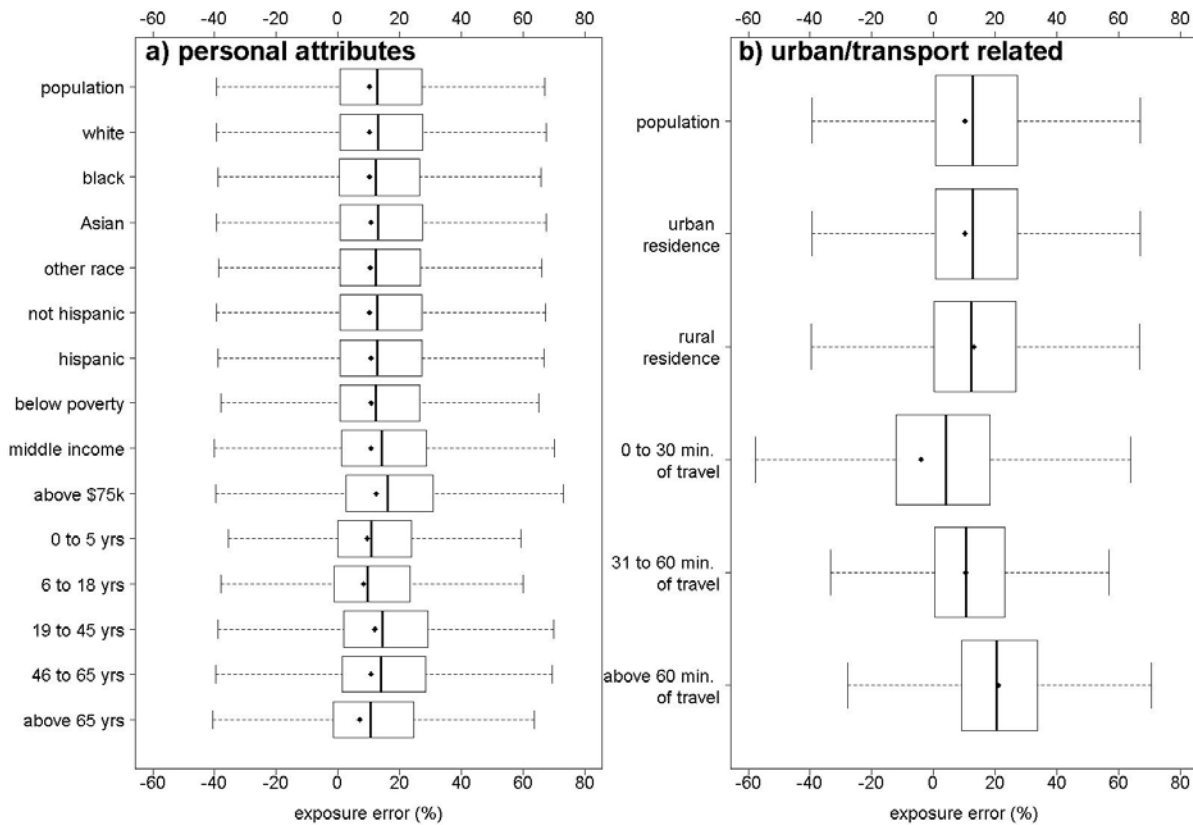


Figure 4.14 Relative percent difference in exposures obtained using highly spatiotemporally-resolved activity and concentration data and low-resolution activity and travel, and concentration data

Overall, the use of low-resolution activity and concentration data over high-resolution data led to 10% lower exposures, on average; the differences range from about -800% to 90%. This difference in exposure resulting from the use of low-resolution activity and concentration data versus high-resolution data can inform our understanding of exposure error resulting from using low-resolution data. On average, use of low-resolution data resulted in underestimation of exposures (positive differences) for all the demographic groups. The distribution of this exposure error among the various racial and ethnic

groups showed little to no variation from the distribution of population-level exposure error. Similarly, the below-poverty income category showed little difference from the population-level exposure errors. However, the exposure errors for the middle income and the above \$75,000 income groups were slightly larger compared to the population-level exposure error. The mean (and median) exposure errors for the middle and above \$75,000 income groups were 0.4% (1.3%) and 2.2% (3.2%) higher compared to the population-level exposure error; this suggests that, on average, these two groups have a greater propensity for underestimation of exposures with the use of low-resolution data, compared to the population.

Comparing age groups, the under 5, 6–18, and over 65 categories had slightly smaller exposure errors compared to the population; the mean (and median) exposure errors for the under 5, 6–18, and over 65 categories were 0.8% (2.1%), 2% (3.2%), and 3.3% (2.3%) lower compared to population exposure errors suggesting a lower propensity for underestimation of exposures on average. In contrast, the more active population groups of age 19–45 and 46–65 had slightly greater propensities for underestimation of exposures compared to the population; the mean (and median) exposure errors for these two groups were 1.6% (1.7%) and 0.4% (1.1%) greater than the population exposure error.

Similar to the demographic groups, the use of low-resolution data resulted in underestimation of exposures for the urbanicity groups on average. Moreover, the exposure error distributions for the urban and rural categories were very similar to the population-level exposure error distribution. The only caveat is the slightly higher (by 2.9%) mean exposure error for the rural category compared to the population suggesting a greater propensity for underestimation on average. In contrast to the demographic and urbanicity categories, the exposure error distributions for the travel categories showed a larger variation compared to the population. On average, use of low-resolution data for the groups traveling up to 30 minutes, 31–60 minutes, and above 60 minutes per day resulted in overestimation by 4% and underestimation by 11% and 21%, respectively. In addition, the mean (and median) exposure error for the group with low travel time was lower by 14.3% (8.8%) compared with population-level error. However, the mean (and median) exposure error for the group with the highest travel time was 11% (7.6%) greater than the population. For the group with travel time between 30 and 60 minutes, the mean

and median errors were respectively greater (0.2%) and lower (2.3%) compared to the population-level exposure error.

The use of low-resolution data also affected the ranking of mean exposures for a few demographic and travel categories. Specifically, use of low-resolution data resulted in a higher rank of mean exposure for medium travelers (31–60 min. per day), whites, other racial subgroups, non-Hispanics, and low-income individuals in their respective subgroups. In contrast, the ranking of mean exposure for heavy travelers (more than 60 minutes per day), medium and high income individuals, and the age group of 45–65 dropped with the use of low-resolution data.

4.4 Discussion

The spatiotemporal distributions of population activities in this study are consistent with observations from other study areas. Specifically, a shift in the activity locations from residential to non-residential (i.e., business, educational, airport, and work) locations between work hours (8:00 AM to 5:00 PM) and non-work hours (9:00 PM to 6:00 AM) was observed. Dhondt et al. (2012) and Vallamsundar et al. (2016) reported similar findings of higher person-hours in industrial or business zones during day and vice versa during nights. Moreover, morning and evening commute from 6:00–8:00 AM and 5:00–7:00 PM, respectively, show slightly different spatial activity patterns compared to the rest of the day predominantly due to individuals' commute.

The spatiotemporal trends of exhaust emissions resulting from passenger car travel in Tampa are comparable to emission estimates from other regions, but the aggregate emissions were slightly lower. Specifically, Hatzopoulou and Miller (2010) found that exhaust NO_x emissions were the highest along the major roads and the emission peaks correspond with the peaks in travel, as in this study. Additionally, they also observed higher emissions during the evening peak. However, this study estimated the daily total NO_x emissions for a typical weekday in 2010 to be 20.4 tonnes, whereas Hao et al. (2010) estimated the daily total NO_x emissions for the Greater Toronto Area in 2001 to be 75.62 tonnes, Beckx et al. (2009d) reported 70,210 tonnes for Netherlands in 2000, Batterman et al. (2014) reported 14,715 tonnes/yr (which roughly translates to a daily total of 40.3 tonnes) for Detroit in 2010, and Yu and Stuart

(2016) reported 44.4 tonnes on-road emissions for the same study region. The lower emissions totals here could be attributed to a variety of factors including the geographic scale, vehicle mix, and emissions processes considered. Specifically, both the Greater Toronto area and Netherlands feature much larger transportation networks compared to Hillsborough County. Further, the Netherlands and Detroit studies estimated emissions from heavy-duty diesel and gasoline vehicles, and the Greater Toronto Area and Netherlands studies estimated NO_x emissions from exhaust, hot, and cold start processes, whereas this study estimated on-road exhaust emissions for passenger cars only; moreover, this study is for 2010 whereas both the Greater Toronto Area and Netherlands studies were conducted for 2000 suggesting a temporal mismatch.

Due to the focus on car emissions only, the predicted NO_x concentrations in this study were also generally lower than the observed concentrations near a roadway monitor, and our research group's previous studies in this region using a more comprehensive emissions inventory (including point and area sources). Specifically, this study found some differences in the diurnal cycles of the estimated and observed hourly concentrations for winter, as shown in Figure 4.15. Generally, estimated NO_x values were lower than the observed values except for the peak hours. Following the peak, modeled concentrations drop rapidly, as opposed to a slow decline in the observed values. This is probably due to the non-inclusion of additional sources of pollution other than passenger cars. The spatially-averaged winter mean NO_x level in this study is 4.7 µg/m³, and Yu and Stuart (2013) reported a domain average annual mean NO_x concentration for 2002 of 12 µg/m³. Using a similar activity-based, emission, and dispersion modeling approach like this study, Beckx et al. (2009c) predicted NO₂ levels of 38 µg/m³ in 2005 for Netherlands.

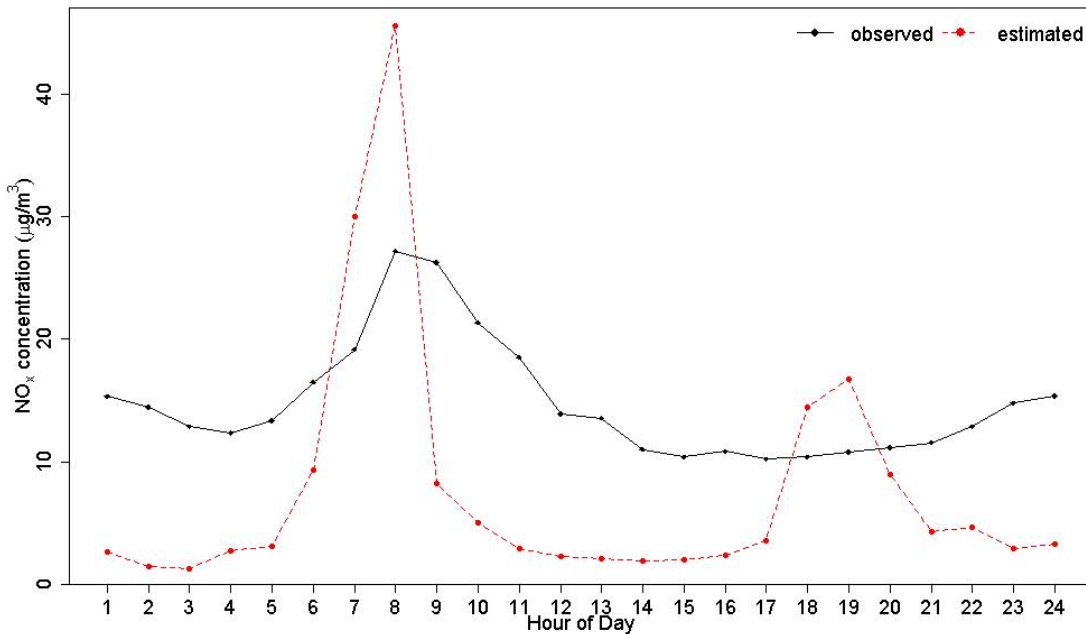


Figure 4.15 Diurnal cycle of hourly observed and estimated concentrations at near-roadway monitor

Although the winter-average NO_x levels in this study appear to be low, the hourly NO_x concentrations at a few locations in Tampa may be high. For example, the NO_x concentration near the intersection of I-275 and I-4 on January 7, 2010 from 5:00–6:00 PM was 4405 µg/m³. Using a NO₂–NO_x ratio of 0.4 for near-roadway locations (Batterman et al., 2014), this translates to 1762 µg/m³ of NO₂. Moreover, the 98th percentile of one-hour daily maximum for 2010 winter measured at the same location was 1642 µg/m³, which is about 9 times higher than the one-hour NO₂ standard (185 µg/m³) set according to the National Ambient Air Quality Standards (NAAQS), defined as the 98th percentile of one-hour daily maximum concentrations averaged over three years. Although this study does not report a three-year average, uses a non-regulatory air quality model, and predicts NO_x instead of NO₂, the high one-hour NO₂ value estimated at this specific location makes a strong case for exploring human exposure to traffic-related pollution.

On average, exposures to NO_x were lower but high-end exposures in this study are greater than maximum exposures from earlier studies. Specifically, mean (and maximum) exposure concentration to NO_x in this study is 10.2 µg/m³ (and 145 µg/m³); a previous study for the same location that included additional sources of emissions reported activity-based NO_x exposure concentration of 17 µg/m³ (and 43

$\mu\text{g}/\text{m}^3$) (Gurram et al., 2015). Similarly, activity-based exposure concentration of NO_2 for Flanders was estimated to be $21.6 \mu\text{g}/\text{m}^3$ (and $44.3 \mu\text{g}/\text{m}^3$) (Dhondt et al., 2012). Finally, Hatzopoulou and Miller (2010) estimated the maximum activity-based NO_x exposure concentration of $81 \mu\text{g}/\text{m}^3$ for the city of Toronto. These findings show that although exposures were low on average in this study, the high-end exposures are either comparable to or greater than the maximum exposures reported in other locations. Additionally, the spatiotemporal exposure plot provides a novel way to interpret population exposures. Specifically, morning and evening commute largely influences the population exposure levels and the highest exposure densities were generally concentrated in the urban core of Tampa. In such a scenario, urban design policies that seek to reduce the travel times and distances, especially during the commute, and encourage non-auto modes of transport may potentially mitigate concentrations and population exposures.

Demographical and urbanicity-related exposure analysis in this study confirms the existence of exposure inequalities at the population-level. Specifically, findings of higher mean exposures for blacks, Hispanics, low-income groups, urban residents, and individuals with higher travel times, in this study, are consistent with previous investigations in the same study area and elsewhere (Gurram et al., 2015; Marshall, 2008; Yu & Stuart, 2013). Although consistent patterns of exposure variations with age were not observed in Chapter 3, this study found that mean and median exposures for active-age groups were higher. This could be of public health significance for working individuals who may be more susceptible (e.g., asthma patients) to the effects of traffic-related pollutants. Additionally, the finding of greater exposure inequalities (shown in Figure 4.11) for the below-poverty non-white group as opposed to the below-poverty white group is consistent with earlier studies (Clark et al., 2014; Gurram et al., 2015; Marshall, 2008). This shows that race may be a stronger predictor of individual exposure inequalities than income in some cases. But more importantly, this confirms that traffic-related exposure inequalities are persistent in Tampa and are propagated by the spatiotemporal distributions of the individuals and pollutants under the existing layout of transportation infrastructure. Thus, it is important to explore urban design policies that not only seek to mitigate exposures but also exposure inequalities.

The spatiotemporal resolution of the modeled activity and travel patterns, and pollutant concentrations has a substantial impact on the accuracy of estimated exposures. This suggests that the disaggregated exposure estimates in previous studies that used low-resolution activity and travel patterns and (or) pollutant concentrations (Beckx et al., 2009a; Beckx et al., 2009c; Dhondt et al., 2012; Hatzopoulou & Miller, 2010; Vallamsundar et al., 2016) and did not explicitly model exposures during travel (Hatzopoulou & Miller, 2010; Vallamsundar et al., 2016) could potentially be underestimated or overestimated in some cases. This also explains the larger disaggregate exposure levels, despite low mean NO_x concentrations, in this study compared to previous studies. Moreover, use of low-resolution data modifies the relative ranking of group-wise mean exposures. It is worthy of mention that earlier studies showed differences in overall (Gurram et al., 2015; Setton et al., 2011) and group-wise mean exposures (Gurram et al., 2015) when activity and travel patterns were included in exposure analysis. This study further demonstrates that the resolution of activity and travel, and pollutant concentration data is important, especially for disaggregated exposure analysis.

4.5 Conclusion

Activity-based travel demand modeling provides a unique opportunity to exploit the rich set of disaggregate spatiotemporal activity and travel data to inform on subgroup and population-level exposures to traffic-related pollution. This study used a framework based on activity-based travel demand modeling (DaySim), dynamic traffic assignment (MATSim), mobile-source emissions estimation (MOVES), and dispersion modeling (R-LINE) to estimate disaggregate and subgroup exposures to NO_x. Passenger-car-related NO_x concentrations at a few near-roadway locations could potentially exceed the one-hour NAAQS standard for NO₂. Additionally, persistent exposure inequalities were observed in the study area. Finally, the spatial resolution of activity and travel, and concentration data was found to influence exposure estimation and use of low-resolution data may lead to both underestimation and overestimation of exposures. Thus, this study adds to the body of literature on exposure modeling frameworks that use ABM-DTA-Dispersion paradigms.

CHAPTER 5: IMPACT OF TRANSIT-ORIENTED COMPACT GROWTH ON AIR QUALITY AND EXPOSURES TO TRAFFIC-RELATED AIR POLLUTION IN TAMPA AREA

5.1 Introduction

Exposure to traffic-related air pollution poses major health risks. A wide spectrum of studies associated exposure to traffic-related air pollution with autism (Volk et al., 2013), negative birth outcomes (Brauer et al., 2008), diminished cognitive development (Sunyer et al., 2015), lung cancer incidence (Beelen et al., 2008b), mortality (Beelen et al., 2008a; Hoek et al., 2002), and respiratory symptoms, atopic diseases, and allergic sensitization in children (Kim et al., 2004; Morgenstern et al., 2008). Understanding the pathways that lead to population exposure to traffic pollution may help in controlling the negative health outcomes.

Urban land use and design and transport planning are considered to be among the important factors that influence population exposure to traffic pollution. Frank et al. (2006b) used a walkability index that characterizes the urban form by quantifying the compactness, connectedness, and diversity of neighborhoods and found that increase in walkability leads to reductions in vehicular travel and emissions. Similarly, (Clark et al., 2011) found from an examination of 111 US urban areas that urban form characteristics such as population density and centrality along with transit supply may influence the urban air quality and corresponding population exposures. Although these studies reported associations between urban form, transport, and air quality, they were mainly observational and did not provide insights on the air quality and exposure effects of pursuing alternate urban forms for future development in a region.

To address this, a few studies modeled the impact of alternate urban forms and/or investment in transit infrastructure on vehicular emissions, concentrations, and population exposure. Stone et al. (2007) simulated vehicular activity in alternate hypothetical urban forms and found that compact urban forms

lead to less vehicular travel and emissions. Hixson et al. (2009) used a GIS-based land use planning tool, a four-step travel demand model, and a source-oriented three-dimensional photochemical air quality grid model to estimate air quality and population-weighted exposure in the San Joaquin Valley. They found that compact growth urban forms, when pursued along with investments in high speed rail and adoption of clean technologies, result in lower emissions of non-methane organic gases, NO_x , and $\text{PM}_{2.5}$ when compared to sprawling or business-as-usual urban forms. Additionally, they showed that compact urban form helps in reducing the $\text{PM}_{2.5}$ concentrations over most of their study region (except for urban centers) but increases the population-weighted exposure by 10–15% when compared with low-density development.

Similarly, De Ridder et al. (2008a) combined spatial land use data obtained from satellite imagery with a four-step travel demand model and an atmospheric chemical transport dispersion model to study the impact of sprawling urban form on regional air quality and population exposure. They found that relocating 12% of the urban population to the greener peripheries results in a 17% increase in traffic volume, approximately 4% increase in ozone and PM_{10} levels, and 13% reduction and 1.2% increase in exposures for the group of individuals who moved out and who stayed, respectively.

More recently, Shekarrizfard et al. (2017) combined a travel demand model with EPA MOVES and the dispersion model CALPUFF to estimate the impact of transit and vehicle technology improvements on air quality and population exposure. Overall, they found that a large portion of reductions in vehicular emissions in the future transit investment scenario is due to improvements in vehicular technology, with transit investment accounting for an additional 3% reduction in the 2031 NO_2 levels; similarly, transit investment resulted in an additional 10% reduction in future-year population exposure to NO_2 (Shekarrizfard et al., 2017).

Locally in Tampa, Yu and Stuart (2017) found that compact urban form development along with vehicle fleet electrification could have varied (in both strength and direction) impacts on air quality and population exposure depending upon the type of primary pollutant being studied. Finally, Stevenson et al. (2016) modeled the health benefits of compact cities and found that such cities can achieve overall

health gains of 420–826 disability-adjusted life-years (DALYs) per 100,000 population. However, they also cautioned that their study quantified the linkages between land use, transport, and population health from a macro-level perspective and argued for the need to look at these linkages using agent-based modeling approaches.

In fact, most of the modeling studies mentioned above use transportation models that rely on aggregated demographic information to estimate travel demand; these models may not be sensitive enough to predict the shifts in the daily activity and travel patterns of individuals, including their travel mode, departure time, and activity-participation preferences. These activity and travel choices may have a significant impact on the distributions of on-road vehicles, emissions from those vehicles, concentrations, and population exposure. Thus, it is important to understand the linkages between urban land use and design, transport, and air quality through the use of highly resolved agent-based modeling approaches.

Previously, studies pioneered this approach by building frameworks that integrate activity-based travel demand models (ABM), dynamic traffic assignment models (DTA), mobile-source emission models, and dispersion models to estimate population-level exposures to traffic pollution (Beckx et al., 2009c; Dhondt et al., 2012; Hatzopoulou & Miller, 2010; Vallamsundar et al., 2016). The activity-based travel demand models, in particular, offer the capability to simulate the daily activity and travel patterns of individuals and their exposures to traffic-related pollution under different policy scenarios. Specifically, using the above ABM-DTA-emissions-dispersion framework, Dons et al. (2011a) studied the impact of altering shopping hours and Dhondt et al. (2013) explored the impact of fuel price increase on population exposures. Whereas these studies provide valuable insights into the effects of local policies on exposures, they did not fully exploit the land use and transportation-related features of this framework to understand the relationship between urban land use, transport design, and population exposure. This is a significant gap, especially considering that such transportation and air pollution frameworks are well-suited for simulating the impacts of alternate land use and transportation infrastructure scenarios on air quality and population exposures. In addition, as discussed in Chapter 4, the integrated transportation and

air pollution modeling framework in this study has more desirable features (over other such modeling frameworks) such as higher spatial and temporal resolution, inclusion of meteorological conditions for an entire season (as opposed to only a few days in a year), and explicit modeling of exposures during travel.

This study—part of an overarching study in Tampa—seeks to use an activity-based travel demand modeling approach to understand the impact of transit-oriented compact-growth strategies on local air quality and exposure levels; the multi-year ongoing project in Tampa is focused on understanding the linkages between urban form, transportation infrastructure design, exposures to traffic-related air pollution, and its social distribution (Evans & Stuart, 2011; Fridh & Stuart, 2014; Gurram et al., 2015; Stuart et al., 2009; Stuart & Zeager, 2011; Yu & Stuart, 2013, 2016, 2017). Specifically, this study uses the ABM-DTA-emissions-dispersion framework to understand the impact of implementing a future-year transit vision in conjunction with population reassignment strategies that reduce the distances between residences and work locations; the daily activity and travel patterns of individuals, vehicular emissions, air quality levels, and population exposure for different urban design scenarios are predicted in this study. Thus, this study will further add to the body of literature on sustainable urban forms that seek to improve public health through policy interventions focusing on land use/urban form and transportation design.

5.2 Methods

5.2.1 Study Area and Pollutant Focus

This study is focused on Hillsborough County, Florida, a county with an estimated population of 1.3 million, and its largest city is Tampa. It is a predominantly urban county, with an estimated 96.5% of the population residing in the urbanized areas (US Census Bureau, 2010b). The county provides an interesting setting to conduct this research due to the limited transit availability, dependence on automobile for travel, and unsatisfactory air quality record (American Lung Association, 2011). Additionally, the metropolitan area of Tampa-St. Petersburg-Clearwater figures in the top 100 sprawling metro areas in the US (Smart Growth America, 2014). More recently, the county is planning to expand the current interstate system by adding express toll lanes (Florida Department of Transportation, 2017).

The impact of these automobile-oriented expansions on the county's air quality and population exposures, especially for the vulnerable population groups, is largely unclear.

HEI identified NO_x as a potential surrogate for traffic-related pollution (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Thus, this study chose NO_x as a surrogate for the more complex mix of traffic-related pollution in the study area. Additionally, NO_x is associated with a variety of adverse health outcomes including reduced lung function, wheezing, and asthma (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010).

5.2.2 Modeling Framework

The integrated modeling framework that comprises activity-based travel demand simulation, dynamic-traffic assignment simulation, emissions estimation model, and pollutant dispersion, and described in Chapter 4, was used to simulate the effect of alternate land use and transportation scenarios on regional travel, air quality, and population exposure. Briefly, the activity-based travel demand model DaySim was used to estimate the initial travel demand of the study region. DaySim employs the principle of utility-maximization and estimates individual daily activity and travel patterns using a suite of econometric models including multinomial and nested logit models. Since this initial travel demand from DaySim does not provide the travel route information for individuals, the dynamic traffic-assignment model MATSim was used to estimate the specific route of travel. In this process, MATSim also provides an updated set of activity and travel information that is consistent with the network travel conditions during the simulation. In contrast to Chapter 4, which focused on simulating car and ride mode trips, this study includes simulation of additional modes of travel such as public transit, walk, and bicycle. Thus, MATSim provides the updated activity and travel information along with the distribution of automobile and public transit vehicular volumes on the roadway network.

Following this, the vehicular volumes on the roadway network were input to MOVES to estimate the hourly roadway link-level emissions. Similar to Chapter 4, the emissions were estimated for an average winter day and the default vehicular distribution on the roadways was used; however, in this study, public transit vehicles were additionally considered for the estimation of emissions. These link-

level emissions were then input to R-LINE to estimate the hourly concentrations for the winter months. Once the hourly concentrations were estimated for the winter months, they were processed to obtain a diurnal average. To estimate the population exposure to NO_x, these diurnal average concentrations were spatially and temporally matched with the locations of individuals. Exposures during travel were explicitly calculated using the travel route information from MATSim. For a more detailed description of the modeling framework, refer to Chapter 4.

5.2.2.1 Specifications for the Transportation Models

To accurately represent the vehicular emissions resulting from daily activity and travel patterns, it is important to consider the inter-regional travel. Thus, this study focused on characterizing the travel within and between Hillsborough County and its surrounding counties using the Tampa Bay activity-based travel demand model (TBABM) developed for the Florida Department of Transportation's (FDOT) District 7 jurisdiction (Gliebe et al., 2014). District 7 includes Hillsborough, Pinellas, Pasco, Hernando, and Citrus counties. Hence, the travel demand was derived for the full projected population in 2040 using TBABM.

Consequently, this initial travel demand was input to MATSim to obtain an updated set of daily activity and travel information along with detailed route information for individuals in the District 7. Due to computational feasibility, MATSim runs were performed using a randomly-chosen 10% population as opposed to the use of full population. Since the simulation used only a sample of the population, the capacities of the highway infrastructure and the transit vehicle sizes were proportionately reduced to simulate real-world conditions (Horni et al., 2016). This was operationalized by setting the flow capacity and storage capacity factors to 0.1 and 0.18, respectively. Similarly, the passenger car equivalent (PCE) value for the transit services was proportionately scaled down using a factor of 0.1.

As mentioned previously, this study includes the simulation of travel modes including car, public transit, shared ride, walk, bicycle, and school bus. To facilitate the simulation of car mode, a hypothetical 2040 transportation roadway network prepared by the FDOT was used (Florida Department of Transportation, 2015). To simulate public transit, MATSim requires an additional set of transit-related

input files that describe the spatial distribution of the stop locations, presence of bus bays, route, schedule, and the physical characteristics of vehicles (e.g., seating and standing capacity, vehicle length) for each transit line. These transit-related input files were created based on the 2040 transit-schedule information provided by FDOT (Florida Department of Transportation, 2015). Further details about the transit inputs are provided in Section 5.2.3.2, as these inputs vary for the low and enhanced-transit infrastructure scenarios. Ride mode users correspond to the individuals who travel via the car mode as passengers. Therefore, ride trips ideally should make route choices similar to that of car trips but without using the roadway capacity. To facilitate the simulation of ride mode trips, the maximum travel speed for the ride mode was set equal to that of the car mode, and the PCE value was set to zero. To accurately simulate the route choices for the bicycle and school bus modes, information on the availability of bicycle paths and school bus routes and schedules is needed. However, this information is not readily available for the FDOT-supplied transportation network. Therefore, bicycle and school bus trips were assumed to use the same roadway network and travel routes as car. The PCE for these two modes was reduced sufficiently so as to not impact roadway capacity. Moreover, travel speed for the bicycle mode was set as 15 km/h, and the travel speed for school bus was set equal to the car mode. Finally, walk mode trips were assumed to travel 1.3 times the beeline-path distance between the origin and destination at a speed of 5 km/h.

MATSim provides a variety of strategies that focus on time, route, and mode innovation to simulate individual daily activity and travel patterns (Horni et al., 2016). This study used the mode innovation, time-allocation-mutator, and reroute strategies. Collectively, these strategies help to optimize individual daily activity and travel patterns by minimizing their daily travel time. More specifically, the travel time reductions are achieved through the substitution of car mode with alternate travel modes such as public transit and bicycle for sub-tours, alteration of trip departure times, and exploration of alternate travel routes. In each iteration, the mode innovation strategy was applied for 20% of the population, the time mutation and reroute strategies were simultaneously applied for 20% of the population, and the remaining 60% of the population stick to their initial (or previously-optimized) activity and travel schedules.

5.2.2.2 Specifications for the Air Pollution Models

The activity-based travel demand outputs from TBABM and MATSim pertain mainly to daily personal travel. Thus, the non-personal or commercial travel including freight was not considered for emissions estimation. To estimate the roadway link-level NO_x emissions, three MOVES onroad source vehicle types, i.e., passenger cars, passenger trucks, and transit buses, were used. Here, passenger cars refer to any coupes, compacts, sedans, or station wagons whose primary purpose is to carry passengers (US Environmental Protection Agency et al., 2015). Passenger trucks refer to light-duty trucks including pickups, sport utility vehicles (SUVs), and vans that are mainly used for the purpose of personal travel (US Environmental Protection Agency et al., 2015). The percentage of transit buses on a roadway link was determined by analyzing the hourly vehicle volumes output from MATSim. However, for car mode trips, separating passenger car volumes from passenger truck volumes is slightly more challenging, because neither TBABM nor MATSim delineate passenger car trips by vehicle type. Therefore, passenger car and passenger truck share for every roadway link was assumed to be 56% and 44% of the automobile volumes on the corresponding link. This share is based on the distributions of VMT by vehicle type in the US for 2010 (Davis et al., 2016).

For the R-LINE dispersion modeling, the surface roughness and displacement height for Tampa were chosen based on guidelines in Grimmond and Oke (1999); specifically, the ratio of displacement height to roughness length is assumed to be 5. Additionally, the initial dispersion for the plumes created from the line sources is assumed to be 1.2 based on an average vehicle height of 1.5 m and in accordance with the US EPA's guidance for hot-spot analysis (US Environmental Protection Agency et al., 2010). Using these parameters, NO_x concentrations were estimated for the winter months, i.e., November through March. The receptor grid is made of 13,806 receptors evenly spaced at 500 meters. Meteorological data for Tampa International Airport for 2010 were obtained from the National Climatic Data Center. Further modeling details pertaining to the specific urban design scenarios are presented below.

5.2.3 Alternate Urban Design Scenarios

Three alternate urban land use, population redistribution, and transportation infrastructure scenarios were used in this study to understand the impact of transit-oriented compact-growth strategies on population exposure to NO_x . All scenarios were implemented for the 2040 model year. The three scenarios include a low-bus service (low-transit) scenario that implements the 2010 bus-transit infrastructure, an enhanced-bus service (enhanced-transit) scenario that uses the planned 2040 bus-transit infrastructure, and a transit-oriented compact (compact-growth) scenario that uses the 2040 bus-transit infrastructure and increases residential density. To control for potential confounding factors that impact vehicular emissions and NO_x concentrations and to systematically identify the impact of urban transportation, population redistribution, and land use characteristics on population exposure, the modeling specifications discussed in sections 5.2.2.1 and 5.2.2.2 were held constant across the three scenarios.

5.2.3.1 Spatial Distribution of Population

Figure 5.1a shows the spatial distribution of the 2040 base residential density (used in both the low-transit and enhanced-transit scenarios); Figure 5.1b shows the spatial distribution of the difference in residential density between the compact-growth scenario and the low-transit/enhanced-transit scenarios. The distribution of population demographics for 2040 is done by the Hillsborough County Planning Commission (Hillsborough Metropolitan Planning Organization, 2014), which used 2010 as the base year and updated the population distribution every five years until 2040. Specifically, the population growth projections made by the Florida Bureau of Economic and Business Research were used as the control totals for the future year. For each TAZ, they developed an attractiveness index based on the vacant developable acres and inverse-weighted it by the square of distance between activity centroids and the vacant developable land. In the compact-growth scenario, the residential distribution is densified. Specifically, an attractiveness index was developed to redistribute the households in the study region. The attractiveness index (AI) for every parcel i in the study region was calculated as shown in equation 5.1.

$$AI_i = \frac{t_i}{\log D_{t_i}} \sum_{k=1}^n \frac{r_k}{\log D_{r_k}} \quad 5.1$$

k represents a parcel within a 0.5-mile buffer around the origin parcel, r_k is the number of retail and service type of jobs in the k^{th} parcel, t_i is 1 if no bus stops are present in a 0.5 mile buffer around the i^{th} parcel and 0 otherwise, D_{r_k} is the distance in feet between the i^{th} parcel and the k^{th} parcel, and D_{t_i} is the distance in feet between the i^{th} parcel and the nearest bus stop. Overall, the attractiveness index assigns weight to a parcel based on the number of service and retail jobs available near it, availability of a walk-accessible bus stop, and the distance to job locations and the nearest bus stop; the parcels that are closest to both locations with a high number of jobs and a bus stop have higher weights. In essence, the attractiveness index developed aims at achieving compaction by directly capturing some of the key D variables including density, diversity, and distance to transit as identified by Ewing and Cervero (2010).

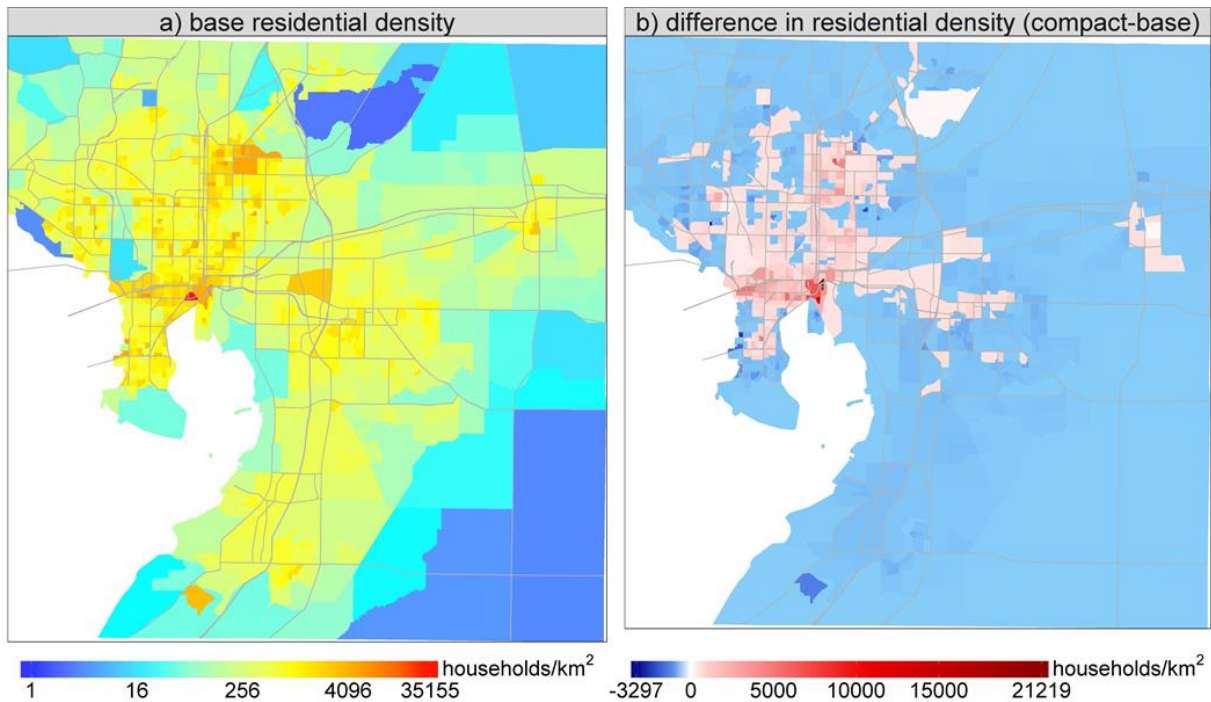


Figure 5.1 Spatial distribution of block group-level residential density in 2040 base and compact-growth scenarios. a) base residential density for 2040, b) difference in residential density between hypothetical compact growth scenario and base scenario. Note that low-transit and enhanced-transit scenarios use base residential density.

Following the development of the attractiveness index, 50% of households that fall in parcels with an attractiveness index below 75th percentile were randomly chosen for reallocation. New parcels were randomly chosen from the set of all parcels with probability (p_i) given in equation 5.2.

$$p_i = \frac{AI_i}{\sum_{i=1}^n AI_i} \quad 5.2$$

Thus, about 37.5% of households in the study region were reallocated from parcels with a low attractiveness index to parcels with a high attractiveness index. As shown in Figure 5.1, residences were more spread out in the 2040 base case compared with the compact-growth scenario. Due to the population reallocation, the residence density of several block groups that form the urban core of Hillsborough County has increased. The mean residential density in the compact-growth scenario is 1199 households/km² and represents an increase of 27% compared to the base residence density in 2040. The highest increase in residence density of 250% is observed for a block group in Downtown near the Selmon Expressway. Conversely, the largest drop in residence density of 49% is observed in the Town ‘N’ Country area.

The high-density block groups resulting from population reallocation fall primarily along I-275, Dale Mabry Highway, Selmon Expressway, near the University area, Downtown Tampa, Brandon, Mango, and Plant City. Particularly, the highest increase in residential density is observed near Downtown Tampa, the University area, and Tampa International Airport. Consequently, the block groups that surround the urban core of Tampa, Brandon, Mango, and Plant City witness a drop in residential density.

5.2.3.2 Bus-Transit Infrastructure

Figures 5.2a and 5.2b show the spatial distribution of 2010 bus service and 2040 bus service, respectively. The 2010 bus service is used in the low-transit scenario, and the 2040 bus service is used in the enhanced-transit and compact-growth scenarios. The county plans to migrate its entire bus-fleet to compressed natural gas (CNG) by 2040. However, to elicit the impact of transportation infrastructure and land use on air quality while controlling for the effect of vehicle and fuel technologies, diesel-powered

buses were simulated in the three alternative urban design scenarios. The bus infrastructure plan for 2010 was created by reducing the frequency of services and removing the additional bus routes from the FDOT-supplied 2040 bus infrastructure plan. Thus, after this adjustment, the newly-created 2010 bus infrastructure plan closely resembles District 7's original transit scheme for 2010. The 2010 bus services comprise 6284 bus stops, 94 routes, and 2811 km of bus-serviced roadways, and 2040 bus services include 8754 bus stops, 195 routes, and 5413 km of bus-serviced roadways.



Figure 5.2 Highway and transit infrastructure in 2040 for low-transit and enhanced-transit scenarios

An overall summary of the scenarios and their urban form and transportation characteristics is provided in Table 5.1. The enhanced-transit scenario captures the impact of additional bus services on the local air quality and population exposure; similarly, the compact-growth scenario captures the impact of both additional bus services and compact urban development on the regional air quality and population exposure.

Table 5.1 Summary of urban land use and transportation infrastructure characteristics for three alternate urban design scenarios

Urban Form and Transportation Characteristics	Scenario		
	Low Transit	Enhanced Transit	Compact Growth
Urban form	2040 base population distribution		Reallocated base population
	Lower residential density		Higher residential density
Transportation	2040 highway		
	2010 bus service		2040 bus service

5.3 Results

5.3.1 Mode Shares and Travel Characteristics for Alternative Urban Design Scenarios

The travel mode shares of daily personal trips for the three urban design scenarios are shown in Figure 5.3. The initial mode shares resulting from the DaySim model and the updated shares following the MATSim model are presented separately. The relative ranking of most of the mode shares was same in both DaySim and MATSim models, with the exception of the bicycle mode, with MATSim comparatively lower than DaySim for the three scenarios.

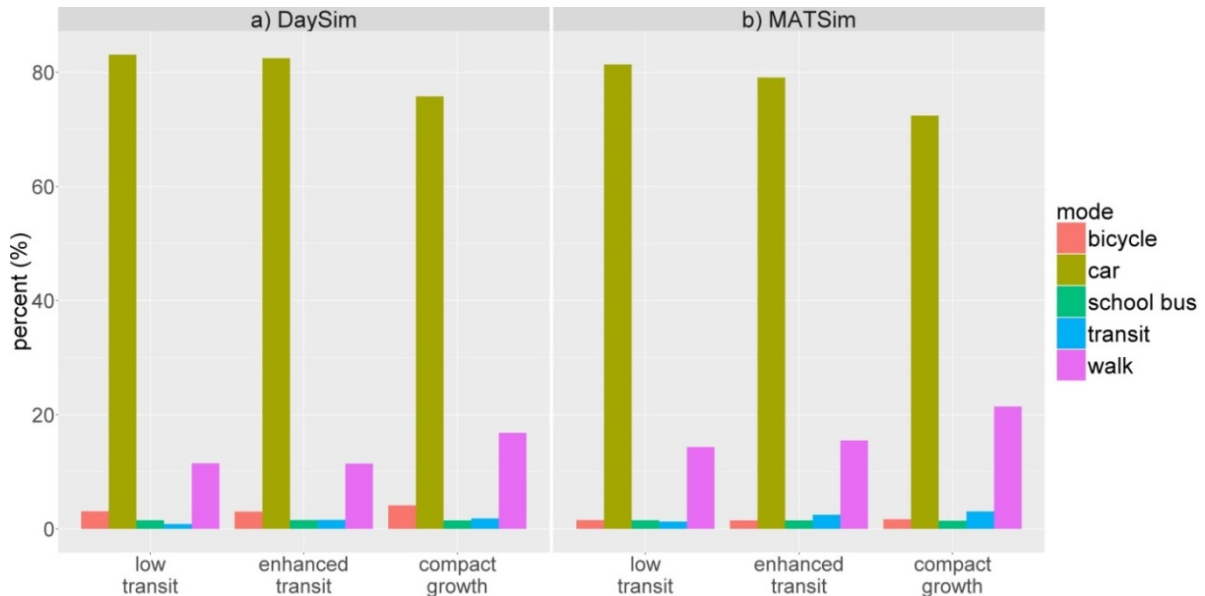


Figure 5.3 Mode shares for low-transit, enhanced-transit, and compact-growth scenarios. Mode shares shown follow simulation in a) DaySim and b) MATSim. Low-transit simulates 2010 transit bus services; enhanced-transit simulates 2040 bus services; compact-growth simulates both 2040 bus services and population compaction.

Overall, in all of the scenarios, the car mode drew the highest share; however, its share dropped from the low-transit scenario to the enhanced-transit scenario and further dropped for the compact-growth scenario. This decline was more discernible in the MATSim model results, with the drop amounting to 2.3% and 9% from low-transit to enhanced-transit and compact-growth, respectively. In contrast to the car mode, both the walk and transit modes experienced a rise in their shares from the low-transit to the compact-growth scenarios; the mode share gain for walk was much higher compared to transit. Specifically, the increase in the share of walk mode from low-transit to enhanced-transit and compact-growth was 1.1% and 7.1%, respectively; the increase in transit share from low-transit to enhanced-transit and compact-growth was 1.2% and 1.8%, respectively. Similar to the walk and transit mode shares, the mode share for bicycle also generally increased from low-transit to compact-growth, although this increase was relatively low. The mode share for the school bus remained relatively constant across all the scenarios.

In addition to shifts in mode shares, the three urban design scenarios led to changes of other travel measures, including travel times and distances. The percent change in the travel measures for the enhanced-transit and compact-growth scenarios when compared with the low-transit scenario are shown in Figure 5.4. The total daily trips predicted in the enhanced-transit scenario was less than that in the low-transit scenario by 0.5%; however, the total daily trips in the compact-growth scenario was very similar to the low-transit scenario. Compared to the low-transit scenario, both the cumulative daily travel time and travel distance for the enhanced-transit and compact-growth scenarios were low, although the reductions in the enhanced-transit scenario were more muted compared to the compact-growth scenario. It should be noted that despite no reduction in the overall number of trips, the compact-growth scenario led to reductions in the travel distances and times.

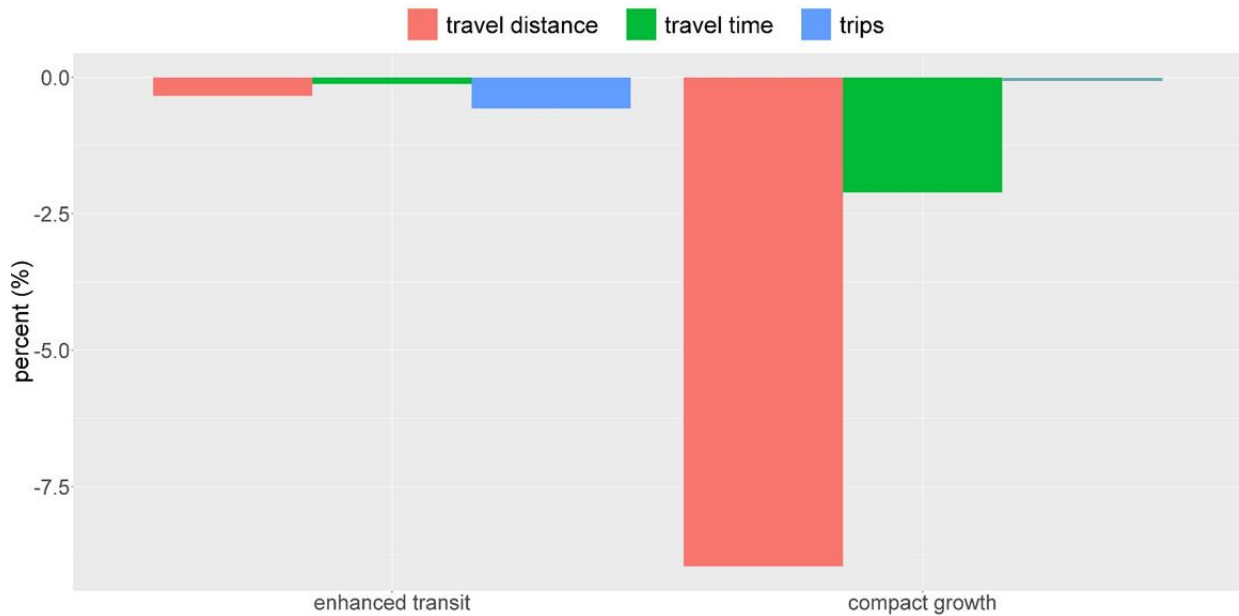


Figure 5.4 Percent change in cumulative travel distance, travel time, and number of trips for enhanced-transit and compact-growth scenarios compared with low-transit scenario. Low-transit simulates 2010 transit bus services; enhanced-transit simulates 2040 bus services; compact-growth simulates both 2040 bus services and population compaction.

5.3.2 Distributions of Emissions and Concentrations of NO_x

Figure 5.5 shows the diurnal emissions for the alternate urban design scenarios. Emissions in all scenarios displayed a similar diurnal trend with a morning peak from 7:00–9:00 AM and an evening peak from 4:00–6:00 PM. The peak emissions in the evening were higher compared to the morning by 15% for the low-transit and enhanced-transit scenarios and 12% for the compact-growth scenario. The daily aggregate emissions in the low-transit, enhanced-transit, and compact-growth scenarios were 47.9, 48.7, and 42.8 tonnes, respectively; thus, the total emissions in the low-transit scenario were 2% less compared to the enhanced-transit scenario and 11% more compared to the compact-growth scenario. The emissions in all scenarios were higher compared to the daily auto-only emissions (20.4 metric tonnes) for 2010 estimated in Chapter 4. The higher emissions in the 2040 scenarios compared to 2010 can predominantly be attributed to an increase in auto-driver trips by 42%, 40%, and 30% for the low-transit, enhanced-transit, and compact-growth scenarios, respectively. Additionally, emissions from bus-transit were also included in the 2040 scenarios.

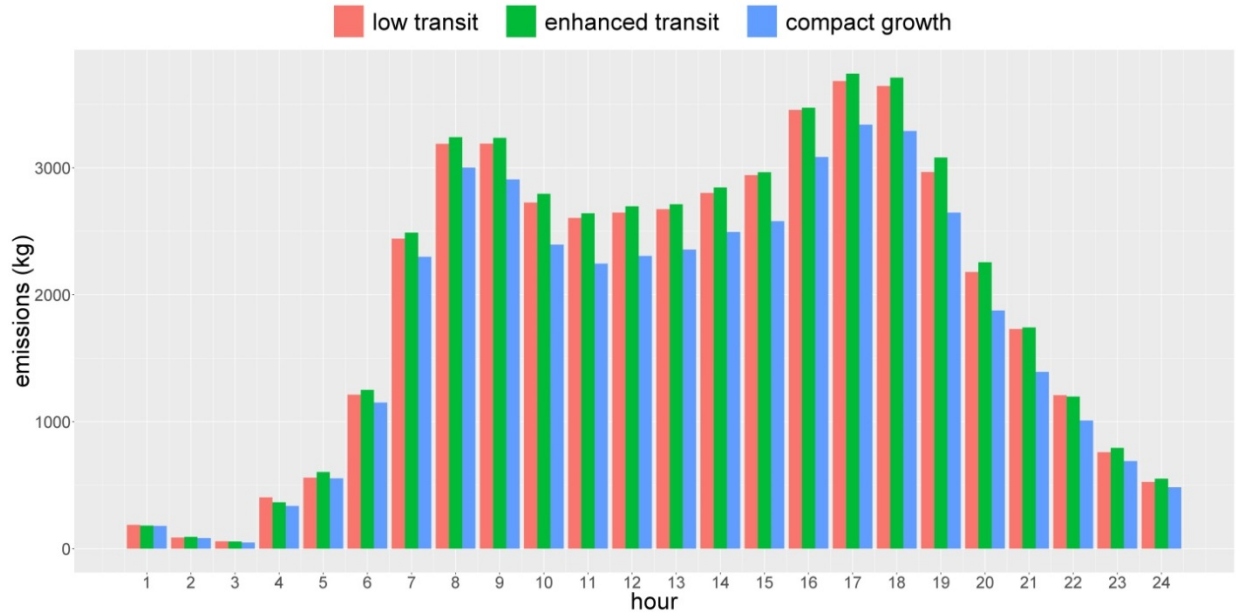


Figure 5.5 Diurnal NO_x emissions for low-transit, enhanced-transit, and compact-growth scenarios. Low-transit simulates 2010 transit bus services; enhanced-transit simulates 2040 bus services; compact-growth simulates both 2040 bus services and population compaction.

Figures 5.6 and 5.7 show the diurnal cycle of the domain-average NO_x concentrations and the distribution of hourly NO_x concentrations for the three urban design scenarios, respectively. The morning peak for the diurnal concentrations led by 1 hour compared to the emissions; thus, the highest mean concentrations were observed from 6:00–8:00 AM. Similarly, the peak hour concentrations in the evening were observed from 5:00–6:00 PM as opposed to 4:00–6:00 PM for the emissions. The peak concentrations in the morning were higher compared to the evening; this trend was in contrast with the diurnal trend for emissions.

The domain-average hourly-mean concentration in the winter season for the low-transit scenario was 10.7 μg/m³. The hourly-mean concentrations in the enhanced-transit and compact-growth scenarios were 2% higher and 9% lower than the low-transit scenario, respectively. The maximum concentrations for the low-transit, enhanced-transit, and compact-growth scenarios were 5072, 5314, and 7321 μg/m³, respectively, and were observed along the interstate corridors of I-275 and I-4 between 5:00–6:00 PM, as shown in Figure 5.8.

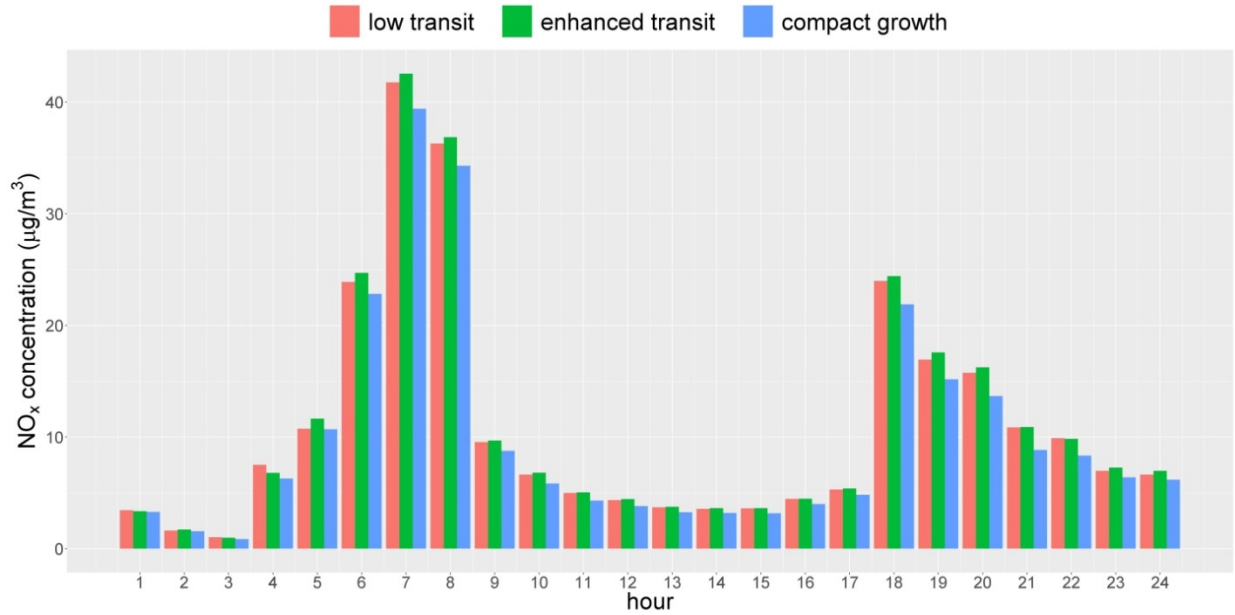


Figure 5.6 Diurnal cycle of domain-average NO_x concentrations for low-transit, enhanced-transit, and compact-growth scenarios. Low-transit simulates 2010 transit bus services; enhanced-transit simulates 2040 bus services; compact-growth simulates both 2040 bus services and population compaction.

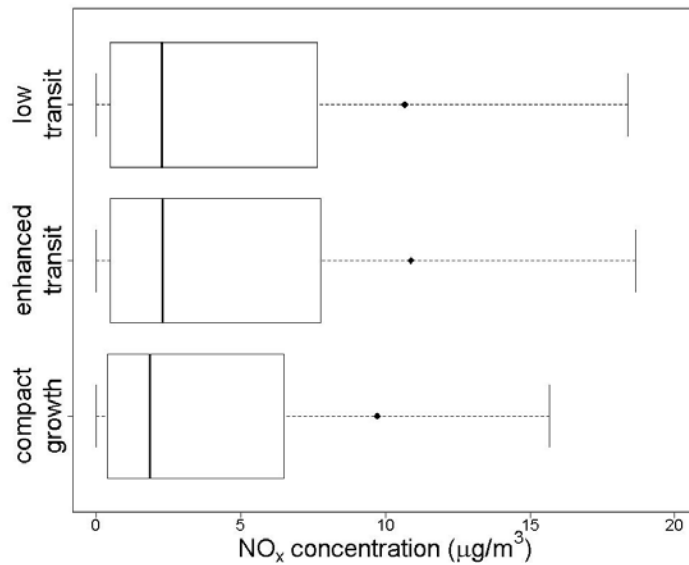


Figure 5.7 Distribution of hourly NO_x concentration for low-transit, enhanced-transit, and compact-growth scenarios. Lower whisker given by $\max(\min(x), Q1 - 1.5 \cdot IQR)$, upper whisker given by $\min(\max(x), Q3 + 1.5 \cdot IQR)$, where x represents vector of concentrations, Q1 is 25th percentile, Q3 is 75th percentile, IQR is Q3-Q1.

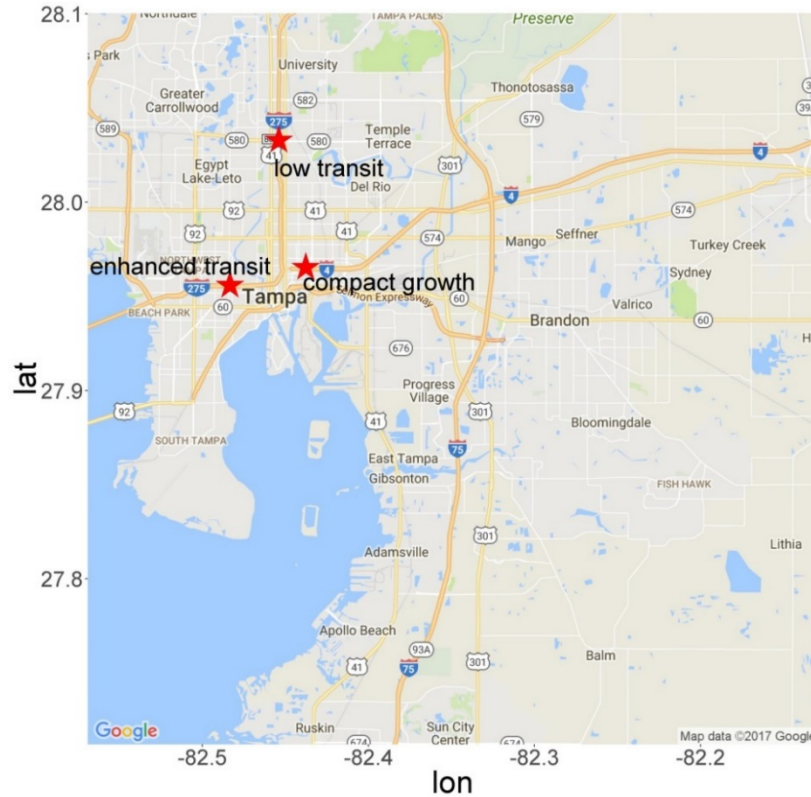


Figure 5.8 Spatial locations of maximum NO_x concentrations for low-transit, enhanced-transit, and compact-growth scenarios

Additionally, Figures 5.9, 5.10, and 5.11 show the spatial distributions of the differences in NO_x concentration between the enhanced-transit and low-transit scenarios, the compact-growth and low-transit scenarios, and compact-growth and enhanced-transit scenarios, respectively. Overall, NO_x concentrations in the low-transit scenario were higher compared to the enhanced-transit scenario in a few outer geography pockets surrounding Tampa's urban core. The concentrations in the enhanced-transit scenario were higher than the low-transit scenario within the urban core of Tampa, especially along the I-275 commute corridor. A similar and more accentuated trend was observed for the concentration differences between the compact-growth and low-transit scenarios. Concentrations in the compact-growth scenario were higher than the low-transit scenario almost entirely within Tampa's urban core along the I-275 starting from the University area, I-4, and Dale Mabry Highway. For the rest of the county, the concentrations in the compact-growth scenario were lower compared with the low-transit scenario. The concentration differences between the compact-growth and enhanced-transit scenarios were very similar

to those between the compact-growth and low-transit scenarios. The only difference was that the urban core, where the concentrations in the compact-growth scenario were higher is spatially smaller when compared with the enhanced-transit scenario (Figure 5.11) instead of the low-transit scenario (Figure 5.10).

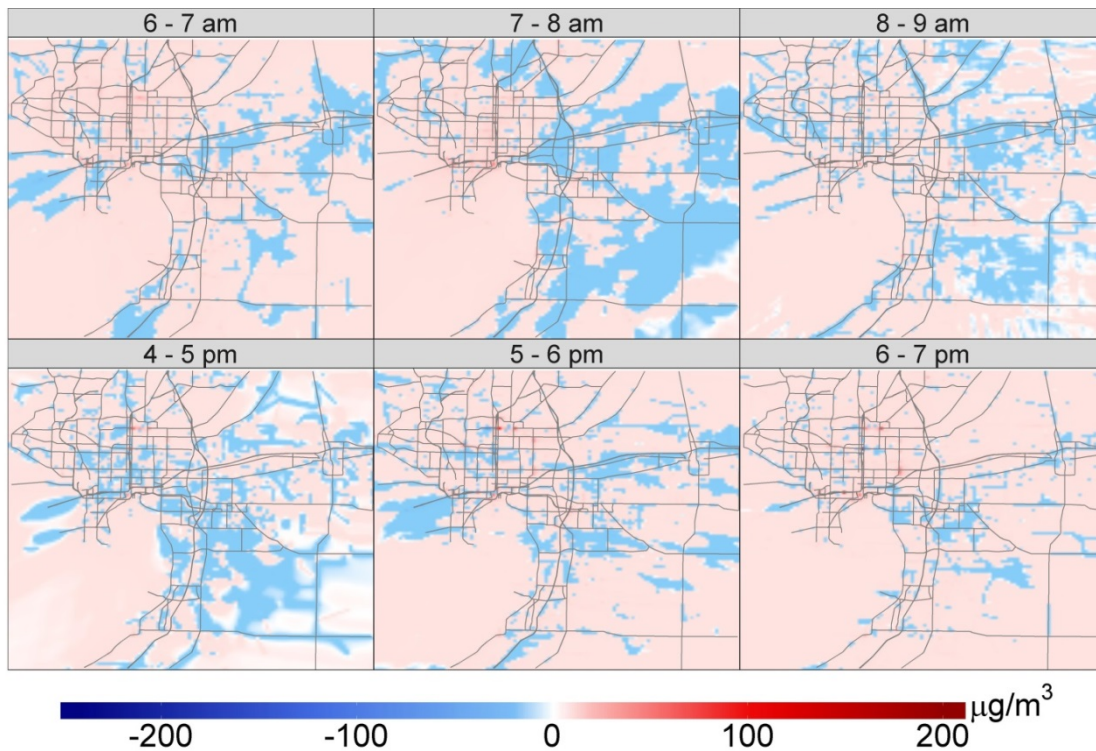


Figure 5.9 Spatial distribution of the difference in NO_x concentrations between enhanced-transit and low-transit scenarios (enhanced transit-low transit) for morning and evening peak hours

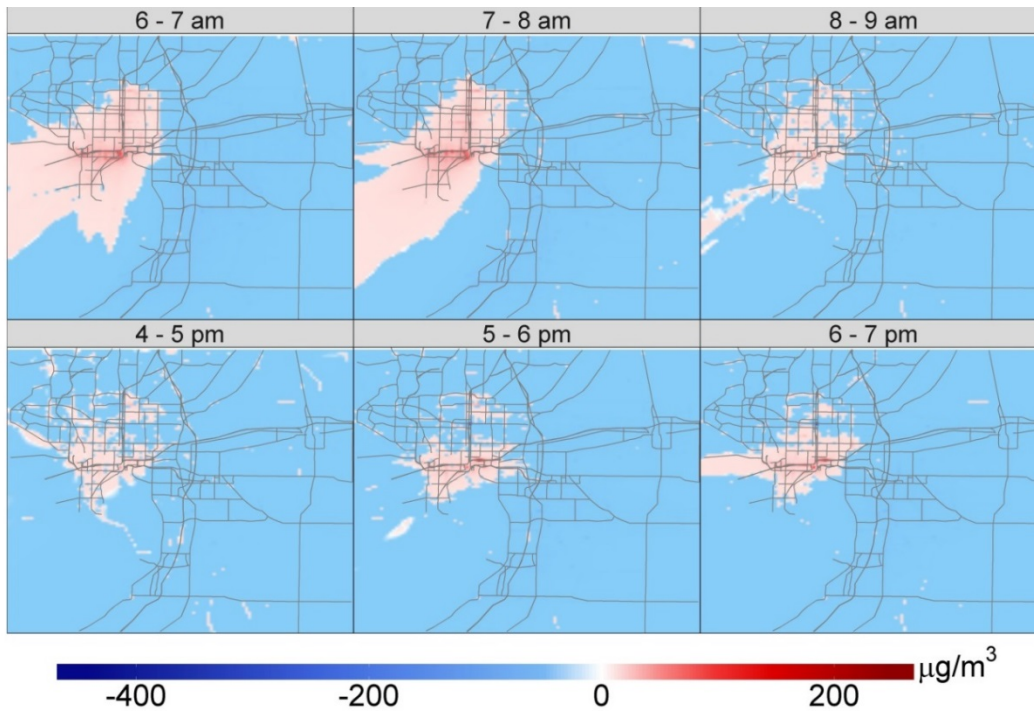


Figure 5.10 Spatial distribution of difference in NO_x concentrations between compact-growth and low-transit scenarios (compact growth-low transit) for morning and evening peaks hours

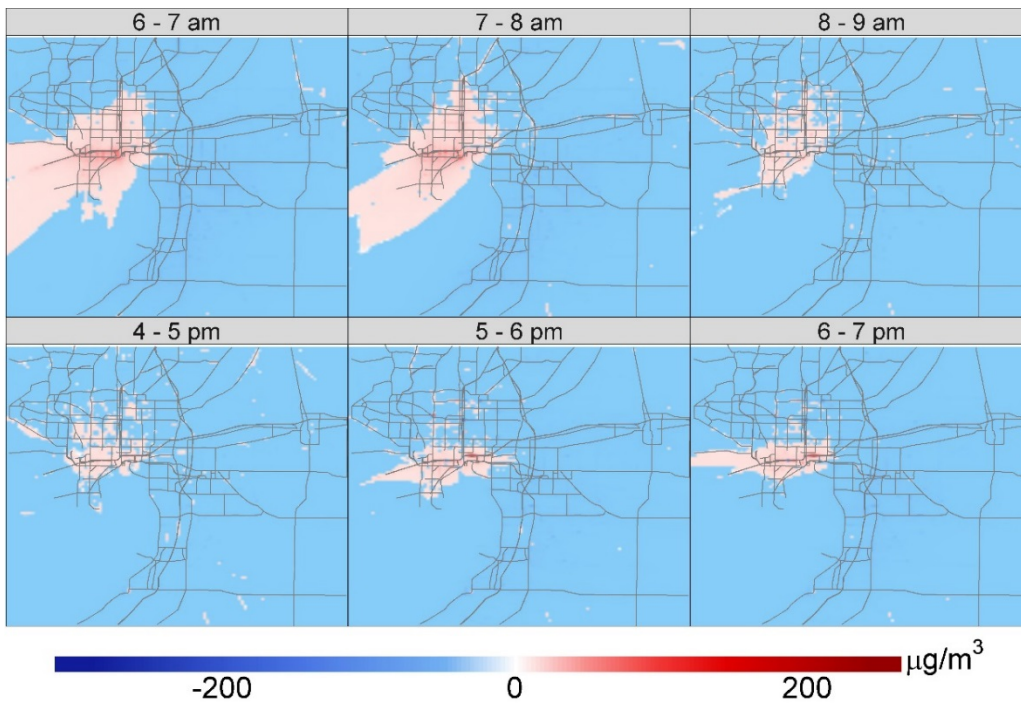


Figure 5.11 Spatial distribution of difference in NO_x concentrations between compact-growth and enhanced-transit scenarios (compact growth-enhanced transit) for morning and evening peaks hours

5.3.3 Population Exposure

Figure 5.12 shows the distribution of the exposures to NO_x for the individuals in the low-transit, enhanced-transit, and compact-growth scenarios. The mean population exposure concentration in the low-transit scenario was $22.7 \mu\text{g}/\text{m}^3$, and the mean exposure concentrations in the enhanced-transit and compact-growth scenarios were higher than the low-transit scenario by 3.3% and 29%, respectively. The spatial distribution of the differences in daily exposure density between the enhanced-transit and low-transit scenarios and compact-growth and low-transit scenarios is shown in Figure 5.13. The mean exposure density for the enhanced-transit and compact-growth scenarios was approximately 3.3% and 33.3% higher than the low-transit scenario, respectively. The block groups with high exposure density in the enhanced-transit scenario compared with the low-transit scenario were interspersed throughout Tampa's urban core and the suburban areas. In contrast, the high exposure density block groups in the compact-growth scenario were concentrated primarily in the urban core of Tampa along I-275, I-4, and Dale Mabry Highway. The highest increase in exposure density in the compact-growth scenario was observed in block groups near the Downtown, especially those between the Selmon Expressway and I-275. High exposure density was also observed in the block group below Tampa International Airport. Low-exposure densities were observed along the I-75 corridor in the southern part of the county.

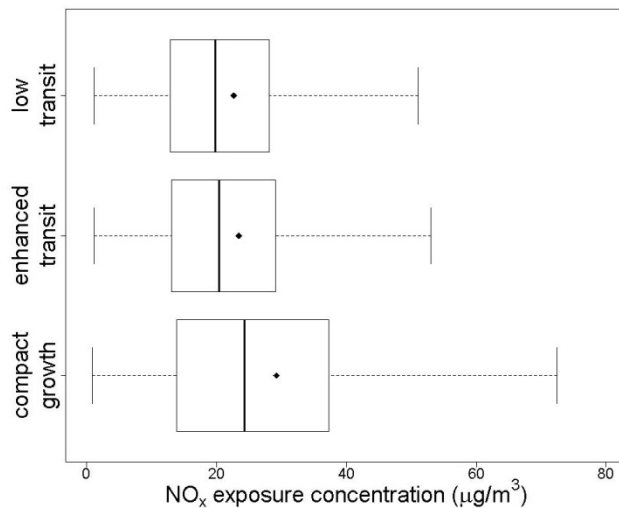


Figure 5.12 Distribution of population exposure for low-transit, enhanced-transit, and compact-growth scenarios. Lower whisker given by $\max(\min(x), Q1-1.5*IQR)$, upper whisker given by $\min(\max(x), Q3+1.5*IQR)$, where x represents vector of concentrations, $Q1$ is 25th percentile, $Q3$ is 75th percentile, and IQR is $Q3-Q1$.

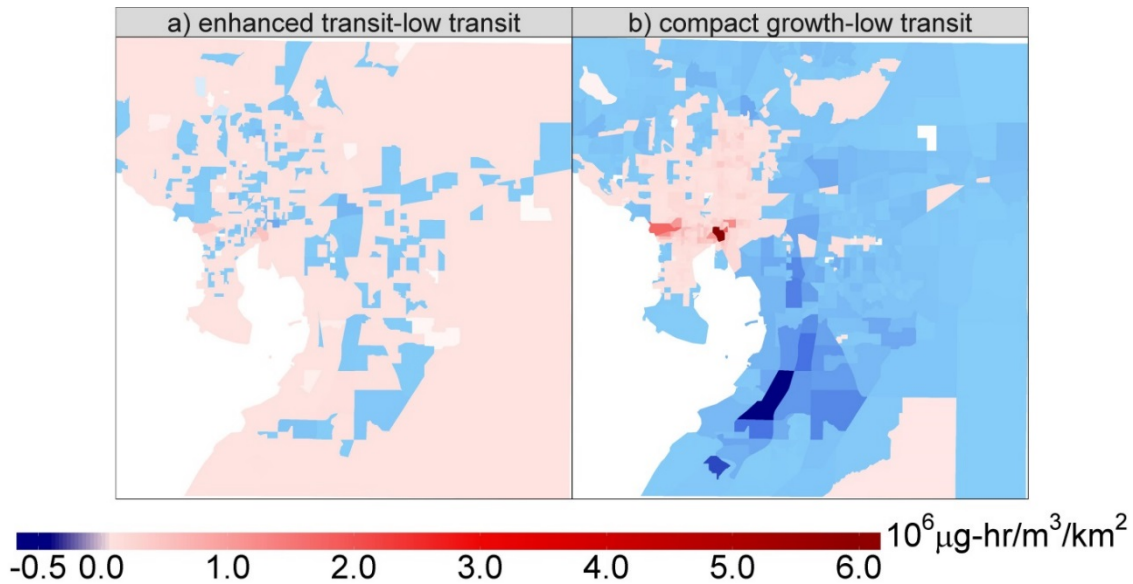


Figure 5.13 Differences in block group-level aggregated exposure densities between different scenarios. Exposure density differences are shown between a) enhanced-transit and low-transit and b) compact-growth and low-transit scenarios.

5.4 Discussion

This study provides complementary evidence on the impact of urban design featuring transit-oriented compact-growth policies on population distribution, traffic emissions, concentrations, and population exposure. Transportation and air pollution models were used to estimate high resolution spatiotemporal distributions of individuals, vehicular activity, and pollutant concentrations. In the study, an increase in household (and population) density was observed in the compact-growth scenario, which employs transit-oriented population compaction policies; the population density in the compact-growth scenario was 7146 people/km², which represents an 8% increase compared to the 2040 base population distribution in the low-transit and enhanced-transit scenarios. This is similar to the findings of Stone et al. (2007), who reported a mean increase in density between 6.6 and 26.8% for different metropolitan statistical areas in their compact growth scenario; similarly, Hixson et al. (2009) created a high-density transit-oriented scenario with an estimated population density of 3935 people/km².

The drop in VMT in this study as a result of simulating transit-oriented compact-growth development is about 10%. This is consistent with the findings of Gim (2012), who performed a meta-analysis on the relationship between density and travel behavior and concluded that higher densities lead

to reduced auto travel in the US (although muted compared to Europe). Additionally, Stone et al. (2007) estimated a median drop in VMT of 6% for a compact-growth scenario when compared to projected business-as-usual growth. Similar reductions in VMT due to increases in residential density were reported by Chattopadhyay and Taylor (2012).

Compact and mixed-use urban forms reduce VMT and boost alternate modes of travel, including walk, transit, and bicycling (National Research Council et al., 2009). In this study, lower share for the auto mode was observed with a concomitant increase in the share for the walk mode in the compact-growth scenario. Only a marginal increase in the share for the transit mode was observed in the compact-growth scenario (3.1% and 2.5% in the compact-growth and enhanced-transit scenarios, respectively, as opposed to 1.3% in the low-transit scenario). Additionally, the shares for the bicycle mode for the three scenarios remained the same. Primarily, two reasons are hypothesized for the lower shares of the transit mode—one, the 2040 hypothetical transit envisioned by the county is simply inadequate for attracting additional transit riders, and two, the attractiveness index developed in this study controls for the presence of transit at individual residences but did not consider the availability of transit at the travel destinations. Previously, it has been shown that transit ridership is primarily dependent on the connectivity between origins and destinations (Arrington & Cervero, 2008). The reason for low bicycle mode shares is unclear.

Overall, air quality in the transit-oriented compact-growth scenario slightly improved. Emissions and concentrations in the compact-growth scenario were lower by 11% and 9%, respectively, compared to the low-transit scenario. This is consistent with the findings of Yu and Stuart (2017), who looked into the effects of compact-growth on the regional emissions, concentration, and population exposure for the Tampa Bay area. They found that regional on-road NO_x emissions in the compact scenario were reduced by 29% compared to the sprawled-growth scenario. However, in their compact-growth scenario, a significant portion of the region-wide future population was reallocated to Hillsborough County; this resulted in 20% higher on-road NO_x emissions for the county in the compact-growth scenario compared to the sprawled-growth scenario. Similarly, Schweitzer and Zhou (2010) studied 80 metropolitan areas and reported lower ozone concentrations in the compact urban forms. Finally, Hixson et al. (2009) also

reported reductions in NO_x emissions when pursuing a compact-growth scenario. However, the emissions and concentrations in the enhanced-transit scenario were higher compared to those in the low-transit scenario. This could be due to the insufficient offset of emissions as a result of lower travel mode shifts from car to bus. In addition to the low mode shift, the increased bus frequencies and the addition of new diesel-powered buses seems to have led to higher emissions. For example, the daily total NO_x emissions for the bus-only roadway links (i.e., only buses travel on these links) is 796 grams/meter for the enhanced-transit scenario as opposed to 73 grams/meter for the low-transit scenario, an increase of almost 1000%. Similarly, the enhanced-transit scenario records daily total emissions of 58,740 grams/meter (an increase of 68% compared to low-transit scenario) for bus links (i.e., other travel modes were allowed on these links apart from bus). However, for non-bus links (i.e., no buses travel on these links), the daily total emissions in the enhanced-transit scenario is 34,018 grams/meter, i.e., 38% lower compared to the low-transit scenario. This suggests that transit intensification strategies, if not targeted precisely, may lead to the deterioration of air quality; hence, transit investment in itself, which several studies use as a predictor for increased share of the transit mode (for example, Hixson et al. (2009)), may not always be a reliable indicator for increased transit use. Additionally, it is not clear if the air quality results in this study will hold with other types of transit, such as CNG-powered buses, light rail, and heavy rail. Nonetheless, compact urban design policies in conjunction with competent transit plans that displace a significant portion of auto drivers to the transit mode may hold the key for improving air quality.

Although the compact-growth scenario marginally improves the urban air quality in the study area, the population exposure is higher compared to the low-transit and enhanced-transit scenarios. This seems to be in contrast with Yu and Stuart (2017), who reported lower population exposure to NO_x in compact scenarios compared to sprawl scenarios for the same study region. However, they also reported higher exposures under compact scenarios for butadiene and benzene, thus arguing that compact forms may have differential effects on population exposure depending on the mix of pollutant sources. Similarly, Schweitzer and Zhou (2010) reported higher neighborhood exposures to ozone and PM_{2.5} in compact regions. Hixson et al. (2009) found 10–15% higher exposure to primary PM_{2.5} components such

as elemental carbon and organic carbon in high-density development scenarios. Thus, compact urban forms by themselves may not always lead to reductions in population exposure. Perhaps they need to be combined with other strategies such as development of public transit infrastructure that improves accessibility between activity locations, urban design that encourages alternate modes of travel including walk and bicycle, fuel and vehicle technologies that lead to lesser life-cycle emissions, and displacing pollutant sources from high-density population zones. A combination of these strategies may lead to lower exposures and better health outcomes especially for the vulnerable population groups.

5.5 Limitations

This study has several limitations, one of which arises from the use of parameters for the activity-based travel demand model from the Sacramento region instead of Tampa. The available sample sizes to estimate the travel demand model parameters for Tampa were insufficient; thus, model parameters were borrowed from the Sacramento region by the developers of the model (Gliebe et al., 2014). Although the model developers concluded that it is preferable to borrow parameters from regions with large sample sizes than estimating parameters with insufficient local data, estimating travel demand based on parameters from a different urban region may introduce some uncertainty and variability.

Although the traffic on the roadways was simulated using MATSim, information on toll roads was not included in the simulation. This could lead to biased estimates of the spatial distribution of traffic in the urban region. The study did not include the emissions from commercial traffic such as freight, shipping, and other on-road sources such as school buses. Further, emissions from point and area sources were not included. Thus, it is not clear if the observed trends in concentrations and population exposure will remain the same even after the inclusion of these additional sources of pollution.

The attractiveness index developed in this study solely considers transit and job accessibility at the residence locations of individuals. However, Arrington and Cervero (2008) argued that transit accessibility between origin and destination is important for improving transit mode share. Additionally, accessibility to other activity locations such as shops, hospitals, and entertainment places was not

considered. Thus, the compact urban form employed in this study may not entirely represent a mixed-use development.

Finally, the transit infrastructure simulated here entirely comprises diesel buses. It is highly unlikely that the county will pursue diesel buses in 2040. Additionally, Hillsborough County's Long Range Transportation Plan includes light rail for 2040 (Tampa Bay Area Regional transportation Authority, 2015). However, the rail mode was not included in the activity-based model by the model developers. As such, the impact of this hypothetical light rail transit on the county's air quality and population exposure was not simulated.

5.6 Conclusion

This study investigated the impact of a transit-oriented compact-growth scenario on population distribution, vehicular travel and emissions, concentrations, and population exposure. Adding more diesel-powered bus routes and improving bus frequencies increased NO_x emissions, leading to higher exposures. Thus, the bus-transit plan adopted for Tampa may not be adequate to cause sufficient travel mode shifts and may, in fact, deteriorate the air quality. Additionally, the compact urban forms co-located individuals near major roadway sources, thus exacerbating their exposures. Hence, there is a need for collaborative solutions from public health and urban design professionals that seek to improve air quality and population health. Future research efforts should consider alternate modes of transit, including light and heavy rail, which improve accessibility between locations and urban design plans that proliferate mixed-use neighborhoods.

CHAPTER 6: SYNTHESIS

6.1 Introduction

Over the past six decades, the world has witnessed continued migration from the rural regions to the urban regions, giving rise to a phenomenon known as urbanization. This urbanization trend is expected to continue at least until 2050 (United Nations et al., 2015). Recognizing the potential impacts of this large-scale population movement on urban regions, the heads of governments across the world have come together to adopt policies consistent with the 2030 agenda for sustainable development (UN General Assembly, 2016). Sustainable development is defined as the type of development that meets the needs of the current generation without taking away from the resources of future generations; thus, sustainable development features elements of intra-generational and inter-generational equity (Brundtland Commission, 1987). The 2030 agenda for sustainable development stipulates targets that include safe and sustainable transport for all, betterment of population health through improvement of air quality, and reduction of inequalities to shift the world onto a more sustainable and resilient path (UN General Assembly, 2015).

Although the 2030 sustainability agenda does not identify curbing air pollution as a standalone goal, it establishes clean air as a desirable target under multiple goals (Lode et al., 2016; UN General Assembly, 2015). This suggests the importance of clean air for improving human health and reducing environmental degradation. Within the urban context, the transportation sector emits a significant proportion of pollutants that are of interest to human health and climate change. Exposure to traffic-related air pollution assumes special interest due to the growing body of evidence on its associations with mortality, morbidity, and environmental justice concerns (Gurram et al., 2015; HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010; Hystad et al., 2015; Marshall, 2008; Schultz et al., 2015; Stuart et al., 2009; Stuart & Zeager, 2011; Yu & Stuart, 2013, 2016). Thus, improving air quality and

mitigating population exposure to traffic-related air pollution and the associated exposure inequalities directly helps to achieve urban sustainability, including the health and inequality-related targets from the 2030 agenda for sustainable development.

Within this context, an emerging field of research suggests that the design of urban form may have an impact on travel demand, regional and local air quality, and population exposure. Moreover, the US EPA's report on the built environment suggests that about two thirds of new development in the next 40–45 years is yet to be built (US Environmental Protection Agency, 2013). This provides the necessary impetus for transportation engineers and urban planners, air quality specialists, and public health policy experts to collaborate in the design of healthy and sustainable cities that improve air quality and population health. However, the underlying mechanisms that govern the relationships between urban transportation infrastructure, land use, air quality, and population exposure are not yet well understood.

To this end, a few major gaps in the literature were identified in this study. First, the importance of consideration of detailed spatiotemporal activity and travel patterns of individuals for the estimation of exposure to traffic-related air pollution is not extensively investigated in the current literature. Also, previous literature did not extensively study the distributions of exposure to traffic-related air pollution for different socioeconomic and urbanicity-related subgroups of the population. Moreover, several previous studies used human activity and travel patterns derived from travel surveys for exposure estimation. Given the limited intra-urban spatial representation of the activity and travel patterns of individuals in survey samples, it is not entirely clear if the exposure results from a survey-based sample analysis are robust compared to a population analysis. Similarly, the importance of using high-resolution activity and travel, and pollutant concentration data in modeling frameworks that estimate exposures has received little to no attention. Finally, previous studies that developed transportation and air pollution modeling frameworks for exposure estimation have not extensively used such frameworks to simulate air quality levels and personal exposures under alternate transportation and land use design scenarios. In view of this discussion, the overarching goal of this dissertation was to understand the linkages between urban transportation infrastructure and land use design, and population exposure to traffic-related air

pollution using a transportation and air pollution modeling framework. Understanding these linkages may aid the design of healthy and sustainable cities and communities.

Section 6.2 provides a summary of each of the aims and their corresponding results in this research. Section 6.3 discusses the policy implications of these findings, and Section 6.4 discusses the limitations of this work along with the directions for future research.

6.2 Summary of Results

6.2.1 Impact of Activity and Travel Patterns, and Urbanicity on Exposures to NO_x

In the study presented in Chapter 3, the activity and travel patterns of individuals generated using the 2009 National Household Travel Survey (NHTS) were combined with CALPUFF-modeled NO_x concentrations for 2002 to estimate the exposures and their social distribution for the residents of Hillsborough County, FL. To understand the importance of human activity and travel patterns for estimation of personal exposures, two exposure measures were estimated—activity-based exposure and residence-based exposure. The activity-based approach considered the movements of individuals in time and space along with time-dependent NO_x concentrations at those locations, whereas the residence-based approach estimated the exposures based on the concentrations at individuals' residences. Finally, to understand the important predictors of exposure, a multivariate regression model was estimated.

It was found that the population from the county's travel survey sample spent more time in suburban and rural areas compared to urban areas. However, time densities for nonresidential activities in urban areas were higher than those of residential activities. Although exposures in this study were found to be generally lower than the National Ambient Air Quality Standards (NAAQS), a large range of exposures was found, from 7.0 to 43 μg/m³. Additionally, disproportionately high mean exposures were found for blacks, Hispanics, low-income households or individuals, urban residents, and individuals with daily travel time above one hour.

On average, exclusion of the activity and travel patterns of individuals (i.e., use of a residence-based exposure measure) led to an underestimation of exposure by 3.6%. However, exposure errors were found to be lower for vulnerable population subgroups including blacks, Hispanics, low-income

individuals, and urban residents. NO_x concentrations during travel and at nonresidential locations were generally high compared to the concentrations at residential locations. However, on average, the concentrations at nonresidential locations made up a small portion of daily total personal exposure. Finally, urban form variables, time spent away from home, income, and race (Black category) were found to be significant predictors of exposure.

Overall, the results suggest the importance of considering the activity and travel patterns of individuals for exposure estimation. Additionally, the study found associations between urban form, activity and travel variables, and exposures. Thus, the study has implications for improving air quality and population health through urban design interventions.

6.2.2 Integration of Models for Travel Demand and Air Pollution to Predict Population Exposures

In the study presented in Chapter 4, an activity-based travel demand model (DaySim) was combined with a dynamic traffic assignment simulator (MATSim), mobile-source emissions estimator (MOVES), and a dispersion model (R-LINE) to estimate population exposure to traffic-related air pollution and its social distribution for the Tampa area. This modeling framework was developed to improve tools for understanding of the relationships between urban transportation and land use design, air quality, and population exposure. Whereas Chapter 3 focused on the estimation of the exposures for a population sample based on a travel survey, Chapter 4 refined the exposure estimation methodology (by computing travel paths of individuals that take congestion effects into consideration) and expanded the exposure analysis to the full population. This modeling framework was used for Hillsborough County for a typical winter day and was applied to explore the impact of using high-resolution data on population and subgroup exposures by computing exposure measures using high-resolution and low-resolution data.

Higher activity durations and densities (normalized by block group area) were found in the urban core of Tampa as opposed to the outer areas. By 7:00 AM, activities began spilling over into the University area, intersections near I-4 and I-75, and locations that generate employment and business in the urban core of Tampa; the high activity durations in these locations persisted until 8:00 PM. A morning peak (7:00–9:00 AM) and an evening peak (4:00–7:00 PM) were observed in the traffic volumes and NO_x

emissions that largely coincided with the commute patterns. The peak-hour emissions contributed more than 50% towards the daily total passenger car emissions in the county. Emissions and the resulting concentrations were high along the major freeway corridors, especially near the zones including Downtown, the airport, and University.

Although concentrations in this study were generally lower than other studies, evidence was found for high NO₂ concentrations (obtained using a NO₂/NO_x ratio) that potentially may be greater than the one-hour National Ambient Air Quality Standard (NAAQS) for NO₂ in some areas. Regarding demographics, higher mean exposures were observed for blacks, Asians, and other racial subgroups compared to whites and Hispanics compared to non-Hispanics, below-poverty and middle-income groups compared to the high-income group, and the active age groups (19–65 years old) compared to the rest of the age categories. Disproportionately higher mean exposures also were found for individuals residing in the urban regions compared with those living in rural areas and those whose daily total travel time exceeded one hour as opposed to individuals whose daily travel time was less than one hour. Moreover, it was found that exposure disparities increased as the levels of exposure to NO_x rose for blacks, Asians, other racial minorities, Hispanics, and below-poverty non-whites.

On average, use of low-resolution activity and travel, and concentration data appears to have resulted in the underestimation of exposures for the population and most of the studied subgroups. The mean underestimation of exposure due to the use of low-resolution data was about 10% for the population; the population subgroup that traveled for more than one hour per day had the greatest underestimation.

Overall, this study suggests the possible harmful impact of traffic-related air pollution on population health due to the current urban transportation infrastructure design, thus providing an impetus for further work on the complex linkages between urban design, air quality, and population health.

6.2.3 Impact of Transit-Oriented Compact-Growth Policies on Population Exposure

In Chapter 5, three alternate urban design scenarios were simulated for 2040 using an integrated modeling framework to understand the relationship between urban transportation infrastructure and land

use design, air quality, and population exposure. Specifically, a low-transit scenario was simulated with the 2010 diesel bus infrastructure and the 2040 default household distribution. The enhanced-transit scenario improved upon this by simulating the 2040 diesel bus infrastructure while maintaining the 2040 default household distribution. The compact-growth scenario used the same bus infrastructure as the enhanced-transit scenario but compactly redistributed the 2040 households to reduce the spatial distance between households, and jobs and transit stops. All the scenarios used the same 2040 highway network.

Compared to the low-transit scenario, a slight drop was observed in the share of auto mode in the enhanced-transit scenario, with a concomitant increase in the shares of walk and transit modes. The highest drop in the share of auto mode was observed in the compact-growth scenario. Most of this reduction in the share of auto mode was reallocated to the walk mode, with a small portion allocated to transit. Thus, the share of transit was rather low in both the enhanced-transit and compact-growth scenarios. Additionally, the enhanced-transit scenario had slightly decreased aggregate travel distances and travel times and total daily trips compared to the low-transit scenario. In contrast, the compact-growth scenario had lower aggregate travel distances and times, despite no apparent change in the daily total number of trips, compared to the low-transit scenario.

The NO_x emissions in 2040 for all the scenarios were higher than the emissions in 2010 (from Chapter 4). Additionally, the lowest and highest total emissions were observed in the compact-growth and enhanced-transit scenarios, respectively. Similarly, the lowest and highest domain-average hourly-mean NO_x concentration was recorded for the compact-growth and enhanced-transit scenarios, respectively. Although the domain-average concentration for the compact-growth scenario was lower than the low-transit scenario (and the enhanced-transit scenario), spatial distribution of the differences in concentrations between the two scenarios revealed that concentrations were higher in the urban core of Tampa for the compact-growth scenario. Conversely, concentrations in the compact-growth scenario were lower compared to both the low-transit and enhanced-transit scenarios for a majority of the outer Tampa area surrounding the urban core. This is likely due to relocation of mobile-pollutant sources from outer/isolated peripheries to inner areas. Mean population exposure in the compact-growth scenario was

higher compared to the enhanced-transit and low-transit scenarios. This is likely due to high exposure densities in the urban core.

Results suggest that compact urban forms potentially may lead to improved air quality; however, to realize similar exposure-related benefits, they may need to be implemented with transportation infrastructure designs that encourage transit-use and active modes of transport including walk and bicycle.

6.3 Implications

Overall, this dissertation seeks to add to the body of knowledge on the relationships between urban transportation infrastructure and land use design, air quality, and population exposure. Specific answers to the science questions determined through this dissertation along with a discussion of their potential science and policy implications are provided below.

6.3.1 Impacts of Activity and Travel Patterns on Exposure Estimates

Through a travel survey-based analysis, it was found that exclusion of activity and travel patterns for exposure estimation significantly underestimated individual exposures by about 3.6%. This is consistent with the findings of Setton et al. (2011). Although this exposure error may appear to be low, it potentially could result in inaccurate/biased health outcome assessments, especially at the high end of exposures. Additionally, this finding may have implications for developing nations where pollutant concentrations are orders of magnitude higher compared to those in developed nations. Thus, assessment of exposures using detailed activity and travel patterns of individuals may be important.

Exposure errors were found to be generally lower for vulnerable population groups, including blacks and below-poverty and middle-income groups. With regard to urban characteristics, high exposure errors were found for suburban and rural residents and individuals whose daily travel time is greater than one hour. Thus, using coarser approaches may particularly affect the health outcome assessments for individuals who travel for a significant portion of the day or whose activity radius is large.

6.3.2 Exposure Disparities

Statistically significant exposure disparities were found for minorities and low-income subgroups in the Hillsborough County. Higher exposures were found for urban residents and individuals whose

daily travel time is greater than one hour. Although NO_x levels observed in this study were somewhat low, a recent analysis on a cohort of about 61 million Medicare beneficiaries suggested that exposure to pollutant levels lower than the current NAAQS may still have an adverse impact on the overall population health, with pronounced effects on racial minorities and lower economic groups (Di et al., 2017); it should be noted that this study focused on exposures to $\text{PM}_{2.5}$ and ozone, although similar observations were made for exposures to NO_2 previously (Young et al., 2014). This challenges policy-makers to take a lead on intervention strategies that seek to reduce exposure disparities along with the overall exposure levels.

6.3.3 Robustness of Exposure Estimates using a Sample-Based and Population-Level Analysis

Distributions of exposure by sociodemographic and urbanicity characteristics had similar exposure disparity trends for the sample-based analysis (using travel survey data) and a population-level analysis. However, there was a substantive difference in the maximum personal exposure levels ($43 \mu\text{g}/\text{m}^3$ for sample vs $145 \mu\text{g}/\text{m}^3$ for population). This is important considering that NO_x concentrations in the population analysis were estimated based only on passenger car emissions, whereas the sample analysis used additional emissions from other point and area sources to estimate NO_x levels. Thus, conducting a population-level analysis may be of help in identifying the high percentile exposures in both developed countries and the highly-polluted regions in developing countries where exposures generally exceed American and European standards.

6.3.4 Impacts of using Low-Resolution Data Versus High-Resolution Data on Exposure Estimates

The integrated transportation and air pollution modeling framework that was adopted in this study to estimate population exposure is computationally more intensive than similar frameworks from other studies (Beckx et al., 2009a; Hatzopoulou & Miller, 2010; Vallamsundar et al., 2016). Specifically, the framework used in this study estimated fixed-activity locations at a high spatial resolution of parcels and the locations of individuals during travel at every five seconds along the roadways; hence, the framework in this study is of higher spatial resolution compared to those in other studies. Therefore, one might naturally ask what are the benefits of such a computationally-intensive, high spatial resolution approach

used in this study? However, it was found in this dissertation research that use of low-resolution modeled data resulted in the underestimation of exposures on average, with a large range of error in exposures. This finding is consistent with previous studies that found that exposures during travel are of high importance to daily total exposure (de Nazelle et al., 2013; Dons et al., 2012; Gurram et al., 2015). Therefore, exposure modeling frameworks that do not incorporate highly resolved fixed-activity locations and travel path information may substantially underestimate exposures, thus potentially leading to inaccurate health assessments.

6.3.5 Impact of Transit-Oriented Compact-Growth on Air Quality and Population Exposure

Neither bus-transit intensification nor compact development, independently or collectively, were found to shift individuals to the transit mode beyond a very small increase in transit share. However, similar to previous studies that investigated the relationships between urban form and transport, it was found that compact-growth increased the travel share for the walk mode. Thus, compact-growth strategies may improve population health by inducing individuals to choose active modes of travel.

Air quality generally improved for the compact-growth scenario, except in the urban core areas, compared to the remaining two scenarios. This could be due to a combination of lower travel distances and travel times and a shift to active modes of travel that resulted in lower daily total NO_x emissions and diurnal concentrations. Thus, compact-growth scenarios may help to improve urban air quality levels.

Although air quality improved in the compact-growth scenario, on average, the mean population exposure was highest in the compact-growth scenario due to the relocation of households into the urban core of the study region. Thus, compact growth may exacerbate population exposure. However, de Hartog et al. (2010) suggest that shifting to active modes of transport such as bicycling could potentially offset health risks due to exposure to air pollution. Thus, although compact-growth policies by themselves may not be a panacea for the negative outcomes due to exposure to traffic-related pollution, they may be combined with other policy initiatives such as active campaigning for bicycle and walk modes, incentivizing the use of active travel modes, and clean-fuel technologies to mitigate emissions and, therefore, population exposure.

Overall, bus-transit intensification did not result in substantial shifts to transit mode in the study area. The low shares for the transit mode in all scenarios suggest that transit planning may need to be rethought for the area. Moreover, several previous studies used transit investment as a surrogate for higher transit shares. However, as demonstrated in this study, that may not always be the case. This is not to say that transit investment is not important; in fact, transit investment plays a very significant role in expanding transit services and improving the mobility of individuals. But equal consideration must be given to transit planning such that both trip origins and destinations are equally serviced. Moreover, the increase of diesel bus services in the scenarios led to higher NO_x emissions and concentrations and a general deterioration of air quality. Thus, transit agencies may also need to give appropriate consideration to the type of fuel used in their services. For example, using compressed natural gas (CNG) powered buses in a compact-growth scenario may lead to the reduction of emissions from transit vehicles and improve the air quality.

6.4 Limitations and Future Research

This research has several limitations. A few important limitations along with the directions for future research are discussed below.

6.4.1 Travel-Survey Samples

Chapter 3 used a travel-survey sample to estimate the activity and travel patterns of individuals, which were then combined with NO_x concentrations to estimate exposures. Although the survey sample is fairly large, it may be limited in capturing the true spatiotemporal distributions of human activities. Additionally, simulating the vehicles from the travel survey on roadways would generally result in uncongested conditions, since the simulated volumes substantially underestimate the actual volumes on the roadways. Thus, estimating routes based on uncongested conditions may result in poor/biased travel path estimates. Overall, the use of travel surveys may result in spatially non-representative and inaccurate activity and travel patterns of individuals. Despite these limitations, it was found that the trends of social distribution of exposures for survey-based analysis was robust compared to a population analysis.

6.4.2 Single Pollutant Analysis

Throughout this dissertation, NO_x was the pollutant of interest. NO_x is an appropriate choice to represent the traffic-related air pollution, as the HEI panel identified it as a potential surrogate for exposures to traffic-related pollution (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Moreover, NO_2 is a component of NO_x and a criteria pollutant regulated by the US EPA and has known health effects. However, the HEI panel also recognized that there is no ideal surrogate that accurately represents the complex mix of traffic-related air pollution. Thus, analysis based on a single pollutant may not fully represent the type of pollution in question. Considering this, future studies that use this framework may consider additional primary traffic-related pollutants including fine particulate matter, benzene, and carbon monoxide. Moreover, to understand the relationships between urban transportation and land use design and population exposure to secondary formations, pollutants including ozone and formaldehyde may be considered (Yu & Stuart, 2016).

6.4.3 Microenvironmental Exposure Factors

In this study, the effect of exposure adjustment factors such as indoor infiltration fractions or inhalation rates on human exposure to traffic-related air pollution were not considered. Furthermore, additive exposure to pollutants due to sources in particular microenvironments including the kitchen or car and exposure to other sources including smoking were excluded in this analysis. Only exposures to ambient NO_x concentrations from traffic were estimated. This may result in overestimation or underestimation of exposures. Since this study focused on exposure to ambient traffic pollution, the microenvironmental sources of pollution were ignored. However, future studies may address this issue by including microenvironmental adjustment factors along with inhalation intakes.

6.4.4 Data Requirements for the Integrated Modeling Framework

The integrated modeling framework used in this study needs significantly large computational resources and detailed data inputs. Given that many local planning agencies may not have such resources, application of this framework for smaller planning agencies may be a challenge. Thus, it is of interest to look further into the question of appropriate spatial and temporal resolution of the activity and travel and

air quality data that may be needed for the estimation of population exposure. On a related note, it is of interest to understand how exposure estimates vary as the sample size increases from one percent to the full population. Such an exercise may give an understanding of the appropriate sample size needed to accurately predict population exposure while meeting the resource constraints.

6.4.5 Health Impact Assessments

Although the modeling framework used in this study integrated several models that use highly spatially- and temporally-resolved data to estimate agent-based exposures, it was not extended to estimate the health outcomes of these exposures. Moreover, the additional health benefits resulting from pursuing active modes of travel were not simulated. Thus, coupling the framework presented herein with health impact assessment tools such as US EPA's Benefits Mapping and Analysis Program (BenMAP) may provide further insights into the potential health impacts of the simulated alternate urban design scenarios.

6.4.6 Model Uncertainty

The integrated modeling framework used in this study comprises a variety of transportation and air pollution models. Each model comes with its own set of uncertainties. Perhaps the greatest uncertainty in the framework comes from the activity-based travel demand model (ABM) due to the use of modeling parameters from the Sacramento region instead of those from the Tampa Bay area. It was found that Tampa had a higher proportion of retirees and non-work-trips compared to Sacramento, which may add uncertainty to the model predictions. Additionally, since the activity-based models were estimated using observed data and since it is difficult to accurately collect all the information pertinent for model estimations, this may add further uncertainty.

Following this, MATSim simulation results in further uncertainties, as evidenced by the differences in the observed and estimated volumes at count stations. Roadway link-specific volumes were used to estimate the link-specific NO_x emissions. Since an average speed method was used instead of the second-by-second vehicle specific power data, emission estimates may be prone to uncertainty. Additional uncertainty may result due to the use of national default vehicle age distributions instead of the local data for the county. Finally, all passenger cars were assumed to be of the same type in the MOVES

analysis, which is unrealistic and may result in uncertainties. Finally, uncertainties in exposure estimates from R-LINE may be due to the use of meteorological data from a single location, uniform values of surface roughness and displacement height for all of Tampa, and an assumed value for the initial dispersion of plumes.

Although the above-mentioned modeling parameters may result in uncertainties, they may be controlled by implementing the same parameters across multiple scenarios. Thus, the relative differences in travel, air quality, and exposure outcomes between the scenarios may be attributed to the differences in the transportation and land use design. Additionally, in future studies, the biggest source of uncertainty for the travel demand models may be addressed by re-estimating the model components using local data for Tampa. Finally, characterization and quantification of uncertainty in exposure estimates of such integrated models is an important avenue for future research.

6.5 Conclusion

This study investigated the relationship between urban transportation and land use design, air quality, and population exposure and its social distribution. Use of highly spatially- and temporally-resolved activity and travel, and pollution data led to more accurate exposure estimates. It was found that lower socioeconomic subgroups, minorities, urban residents, and individuals whose daily travel was greater than one hour were subject to disproportionately high NO_x exposures. Using an integrated modeling framework, it was found that compact development led to improved air quality for a substantial area of the urban region. However, mean population exposure increased under the compact development scenario compared to a scenario with lower population density. Similarly, intensification of diesel bus services led to higher emissions, concentrations, and population exposure, suggesting that the type of fuel used in transit may influence air quality levels. Overall, this study found associations between urban design, air quality, and exposures. Thus, urban design interventions may potentially improve air quality and population health.

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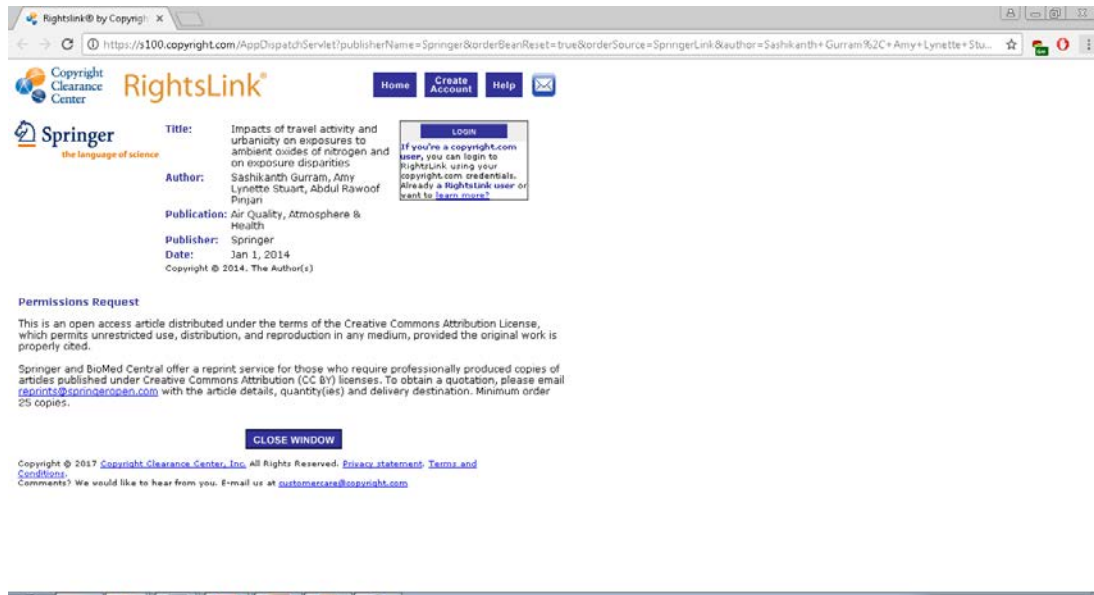
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Title: Impacts of travel activity and urbanicity on exposures to ambient oxides of nitrogen and on exposure disparities

Author: Sashikanth Gurram, Amy Lynette Stuart, Abdul Rawoof Pinyan

Publication: Air Quality, Atmosphere & Health

Publisher: Springer

Date: Jan 1, 2014

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