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Achieving Public Health and Climate Change Goals: What do we Need to Know about the Transportation System?

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DEDICATION

This dissertation is dedicated to my wife, Mahnaz, my parents and my brothers. And to the loving memory of my auntie, Fariba, who is not here to see my graduation.

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ABSTRACT

Vehicle traffic is responsible for a large portion of toxic air pollutant and greenhouse gas emissions in urban areas. A large body of literature has linked exposure to variety of vehicle emissions with a wide range of adverse health outcomes. Furthermore, it is estimated that a 40%-70% reduction in GHG emissions is required to avoid the most severe climate change impacts. Reducing these emissions should therefore be an important goal in transportation planning.

The United States Department of Transportation requires that MPOs create long range regional transportation plans for urban areas with 50,000 or more residents to address mobility needs for the next twenty to thirty years. Long range regional transportation plans are typically evaluated toward achieving their goals such as transportation emission reduction. However, the current air quality analysis methods used by most MPOs in the United States have several limitations.

First, the land use and transportation strategies that are designed by MPOs to promote smart-growth may increase exposure to toxic vehicle emissions. Smart growth

strategies such as infill and transit-oriented development are being pursued by transportation planning organizations because of their potential to increase sustainability and improve public health by reducing vehicle travel and increasing the share of trips made by transit, walking and bicycling. Fewer vehicle trips results in fewer greenhouse gas and toxic vehicle emissions. Existing studies, however, largely overlook the potential for unexpected public health costs and environmental justice concerns that may result from changes in land use and transportation occurring from these plans.

Second, long range regional transportation plans are typically evaluated with performance measures calculated for the first and final years of the planning period. Planning periods span 20 to 30 or more years, and therefore this approach can overlook important changes that occur during in the interim years. This is important when evaluating air quality because many factors affect vehicle emission rates and exposure over time that may result in complex, non-linear trends. Evaluating cumulative effects of transportation plans such as greenhouse gas emissions that remain in the atmosphere for 1,000s of years and toxic air pollutants that cause chronic or deadly disease is also important.

Third, the most common methods of air quality analysis performed by MPOs provides little information about exposure to air pollutants in vehicle exhaust. Several methods have been used to estimate the concentration of vehicle emissions in urban areas and their impacts on population exposure and health outcomes. Estimating the population exposure to vehicle emissions is not an easy task due to the complex temporal and spatial pattern of vehicle travel and movement of the population throughout the day. Conventional exposure methods assume all exposure occurs near a person's home. There is, therefore, a practical need for more refined exposure modeling methods for transportation planning to understand who is exposed and what policies or plans will be most effective at reducing exposures; and for health studies that aim to understand health outcomes from exposure to vehicle emissions.

Fourth, it is important to investigate what strategies could also help meet the deep GHG emission reduction goals set by the IPCC to avoid the most severe climate change impacts. Prior studies find that improvements in vehicle energy efficiency or decarbonization of the transportation fuel supply would be required for the transportation sector to achieve deep GHG emission reductions but these strategies generally rely on supportive federal policy that may not materialize or technologies that are not yet widely used or fully developed. Strategies that could be employed by regional transportation planning organizations are generally found to provide a relatively small portion of the needed reductions in GHG emissions. The in effectiveness of regional strategies seem to be caused in part by considering the GHG emission reduction potential of strategies that generally easy to implement or politically feasible rather than considering strategies that could actually achieve needed emissions reductions.

The overall aim of this dissertation is evaluating what new knowledge can be gained about the environmental and public health outcomes of regional transportation planning strategies by implementing a suite of more spatially and temporally detailed transportation and air quality models. This new knowledge can be used to better understand the potential health effects of emissions exposure while also guiding the development of new transportation and land-use plans, and related policies that have the potential to achieve large reductions in pollution exposure and GHG emissions at local and regional level.

My research indicates that a set of regional plans designed by a transportation planning agency to promote smart-growth will result in less vehicle use and fewer vehicle emissions than a more typical set of plans but will also increase population exposure to toxic vehicle emissions. The smart-growth plans I evaluated also result in greater income-exposure inequality, raising environmental justice concerns. I conclude that a more spatially detailed regional scale air quality analysis can inform the creation of smarter smart-growth plans.

Furthermore, my research reveals that evaluating long range plans at their endpoints may not be a robust method for identifying the best performing plans. Modeling on an annual basis, rather than the more typical case of just the first and final year of a planning period, results in different estimates of annual emission rates, pollution exposure and other performance measure values.

The results indicate that accounting for the daily travel patterns of individuals produces higher regional population exposure estimates compared to a method that assumes all exposure occurs near a person's home address, which is a common modeling assumption. Results also indicate that traveling is responsible for a sizable portion of a person's total daily vehicle emission exposure. The conventional static method may produce errors in exposure estimates that then may cause bias in both health and environmental justice analysis.

Finally, it is possible to achieve deep GHG emissions reductions from the transportation sector that may be able to achieve reduction targets outlined by the IPCC. Achieving deep reductions requires changes in transportation policy and land-use planning that go far beyond what is currently planned anywhere in the United States. Metropolitan areas would need to grow much more compactly than anything that is currently under consideration, would need to impose a very high VMT tax, and go much further to increase bicycling or other non-motorized modes of transportation.

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CHAPTER 1

INTRODUCTION

Vehicle traffic is responsible for a large portion of toxic air pollutant and greenhouse gas (GHG) emissions in urban areas. The United States Environmental Protection Agency (US EPA) estimates that during 2015 the transportation sector contributed to 26% of U.S. GHG emissions, with a large share of the transportation sector's emissions produced from highway vehicle traffic (US EPA 2017). The fifth assessment report by the Intergovernmental Panel on Climate Change (IPCC) estimates that a 40%-70% reduction in GHG emissions is required to avoid the most severe climate change impacts (IPCC 2014). There is a large body of evidence that exposure to a variety of vehicle emissions is linked with a wide range of adverse health outcomes such as cardiovascular diseases, Chronic Obstructive Pulmonary Disease (COPD), asthma, lung cancer, and negative birth outcomes (Allen et al. 2009; Brugge, John L. Durant, and Rioux 2007; Gan et al. 2010; Garshick et al. 2003; Gauderman et al. 2007; HEI 2010; McConnell et al. 2006; Peters et al. 2004; Franco Suglia et al. 2008; Wilhelm and Ritz 2003). Reducing toxic air pollutant and GHG emissions from vehicle traffic is therefore an important public policy goal aimed at protecting public health and avoiding potentially disastrous climate change impacts.

The overall goal of this dissertation is to develop new knowledge that increases our understanding of how changes in transportation infrastructure and urban development patterns affect exposure to toxic vehicle emissions and GHG emissions. This new knowledge can be used to better understand the potential health effects and environmental justice concerns related to current exposures while also guiding the development of new transportation and land-use plans, and related policies, that have the potential to achieve large reductions in pollution exposure and GHG emissions. Specifically, I address two research questions:

1.1 What level of spatial and temporal detail is required to understand exposure to vehicle emissions for creating more health protective and equitable transportation and land-use plans?

Federal requirements for evaluating how Long Range Regional Transportation Plans (LRTPs) may affect air quality are very limited. The United States Department of Transportation (US DOT) requires that Metropolitan Planning Organizations (MPOs) create long range regional transportation plans for urban areas with 50,000 or more residents. Plans typically focus on the performance of the transportation system. Air quality analysis is only required in areas that the US EPA designates as being in violation of the National Ambient Air Quality Standards (i.e., non-attainment areas). The Clean Air Act requires that transportation plans and projects in non-attainment areas conform to air quality improvement plans approved by the US EPA (i.e., state implementation plans). The Clean Air Act's conformity requirements were primarily designed to address regional air quality problems, including ozone and particulate matter – much of which is formed from vehicle emissions in a series of additional physical and chemical reactions (Finlayson-Pitts and Pitts 1997; Seinfeld 1989). Regional emission inventories, the most common form of air quality analysis performed by MPOs in the United States and their international equivalents, provide very little information regarding exposure to directly emitted, primary, air pollutants in vehicle exhaust.

Many urban areas are perusing smart-growth strategies. Denser and more mixed use urban development may reduce vehicle travel by increasing the share of trips made by transit, walking and bicycling. Fewer vehicle trips results in fewer greenhouse gas and toxic vehicle emissions. Prior research has largely focused on modeling and estimating the smart growth benefits. A largely overlooked area is the potential for unexpected public health costs and environmental justice concerns that may result from increasing density. I evaluate regional land-use and transportation planning scenarios with regard to air quality, exposure to vehicle emissions, and environmental justice and public health concerns with a newly developed regional air quality modeling framework (i.e. this part of the dissertation has been published at Tayarani et al., 2016)

In addition, even if a detailed air quality analysis is conducted, the approach used by most MPOs considers how changes in land-use and the transportation system will affect air pollutant emissions from vehicle traffic and exposure to those pollutants from a single base year to just one or two future years (typically 25 to 35 years into the future). This approach, however, provides no information about the impacts that occur between the present and the future. This is important when evaluating air quality because many factors affect vehicle emission rates and exposure over time causing complex, non-linear trends. Evaluating the cumulative effects of transportation planning outcomes such as greenhouse gas emissions that remain in the atmosphere for 1,000s of years and toxic air pollutants that cause chronic or deadly disease is also important. These negative outcomes cannot be reversed by plans that only perform well in the distant future. In this dissertation, I simulate land-use, travel demand, vehicle emissions, and exposure to vehicle emissions on an annual basis for a transportation plan and compare the results to the more common approach that only considers the present and one or two future years.

The current trend in the academic literature, but not in planning practice, is to use more and more spatially and temporarily detailed traffic, land-use and exposure models. While these models may produce more accurate and spatially precise exposure estimates, they can be extremely complex and data hungry which might increase the risk of unseen modeling errors and adds to the costs of transportation planning. Accurately estimating population exposure to vehicle emissions is a very difficult task because the temporal and spatial patterns of vehicle travel and the movement of the population that will be exposed need to be considered along with factors that affect the dispersion of emissions from roadways. More accurately estimating population exposure to vehicle emissions requires coupling highly spatially and temporally resolved air pollution concentration estimates with detailed estimate of population movements provided by an activity based travel demand model. The research presented in this dissertation develops a novel exposure model to evaluate if a more refined integrated land use-transportation-air quality-exposure modeling framework for evaluating population exposure to vehicle emissions could provide new information that could be used to minimize the air quality and public health impacts of LRTPs.

1.2 What magnitude of change is required to make necessary reductions in GHG emissions from the transportation sector?

We have reasonably well defined global GHG emission reduction targets established by the IPCC. However, typical transportation planning practice in the U.S., and most other places around the globe, is incremental. The common practice is to evaluate what can be done (e.g., politically or within current budgets) rather than what must be done. In this part of my dissertation I evaluate the size of the gap between our current transportation and land-use plans and what must be done to achieve GHG reduction targets suggested by the IPCC. Currently, there is little evidence that our transportation and land-use plans, policies, and regulations are producing the types of changes that seem necessary to protect public health and the climate (Barbour and Deakin 2012; Brisson, Sall, and Ang-Olson 2012; Ewing et al. 2007; TRB 2009).

I evaluate the GHG reductions that a metropolitan area may be able to achieve using an extremely aggressive portfolio of strategies that are generally available to state and local governments. These strategies include increasing the amount of compact and mixed-use development, reducing highway capacity, increasing transit capacity and performance while reducing transit costs, implementing a per-mile tax on driving, and increasing the share of trips made by bicycle. While there are certainly other strategies available to local and state governments, I believe that these span the range of the available options and are among those that are likely to be the most effective.

I exclude strategies that aim to increase the energy efficiency of vehicles or increase the use of lower carbon fuels beyond what is expected to occur under currently adopted federal policy. The potential of these technological solutions has been widely reported elsewhere (Greene and Plotkin 2011; Kay, Noland, and Rodier 2014; McCollum and Yang 2009; Leighty, Ogden, and Yang 2012). Policies such as fuel economy and GHG emissions standards, low carbon fuel standards, and subsidies to encourage the development and adoption of new technologies would be most effective at the federal level. States and local governments with the exception of California are also preempted by federal law from adopting their own fuel economy and vehicle emission standards. Therefore, if the federal government fails to act these technological solutions could be much more difficult to implement in a timely manner.

CHAPTER 2

BACKGROUND

Efforts at the national and local level have been made to reduce vehicle emissions considering both the negative health outcomes of vehicle emissions and their climate change impacts. Evaluating emission and exposure reduction measures has therefore become an important research topic in the field of transportation planning and engineering.

2.1 Evaluating Exposure to Vehicle Emissions

The study of population exposure to vehicle emissions is an ongoing effort by both transportation planners, who want to understand the air-quality impacts of transportation policies, and epidemiologists, who want to understand the effects of air quality on public health. Although each field has taken its own direction, there is a close relationship between their methods and findings.

[redacted] Evaluating Air Quality Impacts of LRTPs: Current State of Practice

LRTPs define long term transportation goals and objectives for each region, a series of performance measures to track progress towards achieving those goals and provide fiscally constrained lists of transportation projects to be completed during the planning period. These plans are typically evaluated using regional travel demand models that forecast how a plan will affect traffic and travel behavior such as traffic volume, mode share, travel speed, and congestion. Travel demand modeling output may also be used with vehicle emission models such as the US EPA Motor Vehicle Emission Simulator (MOVES) program or the California Air Resources Board's EMFAC model to estimate how much plans will contribute to regional greenhouse gas and criteria air pollutant emission inventories. Although it is not common in practice, it is also possible to evaluate how a long range plan affects population exposure to vehicle emissions using an air quality model such as US EPA's AERMOD model.

It has become common to include smart growth strategies in regional transportation planning. While smart-growth strategies are pursued for many reasons, reducing private automobile use and GHG emissions are among the most frequently cited reasons. Smart-growth strategies generally include increasing the density and land-use mix of urban development. In many cases, growth is planned around activity centers and high quality mass transit stations or corridors. These strategies are also expected to increase the use of transit and non-motorized modes of transportation and reduce vehicle use (TRB 2009; Ewing et al. 2007; Ewing and Cervero 2010; Stone et al. 2007). For example, California's Sustainable Communities and Climate Protection Act of 2008 (SB375) requires that MPOs develop land-use plans that will reduce per capita GHG emissions by reducing vehicle use. Reducing GHG emissions and vehicle use may often be equated with achieving other regional goals as well. Specifically, improving air quality and reducing exposure to toxic vehicle emissions. However, these additional benefits may not occur. In fact, smart-growth strategies may increase exposure to toxic vehicle emissions. This can occur when population density increases in areas with relatively high emissions concentrations or when polluting activity (i.e., vehicle traffic) becomes more concentrated in more densely populated areas, or a combination of both. Where reductions in GHG emissions occur is irrelevant to a transportation or land-use policy's effectiveness in mitigating climate change concerns. Where reductions in toxic air pollutants occur, however, is critical to the effectiveness of policies that aim to reduce exposure and improve public health.

Cumulative Air Quality Impacts of LRTPS

The typical approach for evaluating a LRTP is to measure the plan's performance against a baseline year and a business-as-usual or trend scenario. The plan is therefore evaluated at two points in time, the baseline year and a planning horizon year that is at least 20 years into the future. However, changes in performance measures are likely to be non-linear over the planning period given the complexity of the transportation system. This is especially true when considering vehicle emissions and exposure. Not only do factors that affect emission rates and exposure such as traffic volume, speed, mode share, and the location of the population change overtime but so does vehicle technology and emission standards that also affect vehicle emission rates. It is therefore possible that a plan that performs relatively poorly at the end of the planning period may have performed relatively well during the interim years and vice versa. If maximizing welfare is the main goal of regional transportation planning, then evaluating a performance measure throughout the planning period of an LRTP should provide a more robust and accurate evaluation metric.

Measuring air pollutant emissions and changes in air quality over the term of a LRTP is important because impacts on the environment and public health are often long lasting and irreversible. Toxic vehicle emissions present an, at least partially, irreversible impact. For example, exposure to particulate matter from vehicle emissions has been associated with a wide range of negative health outcomes (e.g., see reviews by the Health Effects Institute (2010) and Brugge et al. (2007)). The impacts of these negative health outcomes on people's lives is, for the most part, not undone if air quality is improved in the future. On the other hand, other common transportation planning goals, such as reducing traffic congestion and providing greater mobility, do not necessarily impose long term damage and are relatively reversible.

[redacted] Methods of Evaluating Exposure to Vehicle Emissions

Early efforts of estimating pollution from highway vehicles started with a top-down approach, where the amount of purchased fuel was used to estimate vehicle emission inventories in a region. This type of top-down approach was adequate for evaluating transportation policies and plans that focused on regional air quality concerns such as smog and acid rain. Such an aggregate analysis, however, was not adequate for evaluating how a specific project, such as a highway, might affect air quality. The first bottom-up methods, which allowed for greater spatial detail, began in 1970 with the use of US EPA's MOBILE model (US EPA 2016). MOBILE could estimate vehicle emission inventories for a specific project using input data such as vehicle emission standards, vehicle populations and activities, and local conditions such as the temperature, humidity, and fuel quality. Exposure methods have continued to evolve over time with the advancement in computer technology and as researchers and policymakers have focused on different aspects of mobile source air-quality challenges. Gradually, the focus has turned from estimating emission inventories to estimating exposure to localized emission hotspots. Emission inventories are unable to capture the steep gradient in air pollutant concentrations near roadways that are important for evaluating exposure and public health (Smith 1993). Evaluating the proximity of homes to the edge of major roads therefore became a common alternative to regional emission inventories (Batterman et al. 2014; HEI 2010; Hitchins et al. 2000) that was easy to apply and generally thought to be a good surrogate for exposure to vehicle emissions. With the advent of advanced mapping applications such as the geographic information system (GIS) additional exposure surrogates were developed. The outputs of travel demand models were used to create traffic exposure surrogates such as the traffic volume or traffic density in proximity to a household. These types of emission exposure surrogates were commonly used because of their ease of calculation with modern GIS software, few data requirements, and low implementation cost. Despite the widespread use of these location and traffic base emission exposure surrogates (Lena et al. 2002), there is growing evidence that they fail to accurately estimate exposure vehicle emissions such to nitrous oxide (Roosbroeck et al. 2008) and may bias exposure estimates in health studies in a way that may result is underestimating health impacts (Setton et al. 2011).

The exposure misclassification problem has led researchers to develop more detailed emission models. Next-generation models combine traffic volume and land use with air quality measurements to predict vehicle emission concentrations (Su et al. 2009). The main input to these land use regression (LUR) models are air-quality measurements from central site monitors or a set of portable monitors placed in a region. These air-quality measurements are then used to create a regression equation for predicting concentrations elsewhere using independent variables such as traffic volume and land use data.

More sophisticated mathematical models have also been developed that consider meteorological conditions and dispersion characteristics of pollutants. In this type of modeling approach travel demand models are used to estimate vehicle traffic volume and speed on each roadway segment in a region, which are then used to compute the vehicle emission rates with a vehicle emission factor model such as US EPA's MOVES model. This modeling method then implements an air dispersion model to estimate pollution concentrations across the region. Different methods can then be used to calculate emission concentrations at residential locations and population exposure. For instance, Cook et al. (2008) used the AERMOD atmospheric dispersion modeling system to model benzene and carbon monoxide concentrations at census block group centroids in New Haven, CT, USA.

The above approach is referred to as "static" since it ignores the mobility of the population during daily activities (Chen, Namdeo, and Bell 2008). In other words, the static approach ignores the fact that activities like driving, shopping, and working happen at non-residential areas that may have higher air pollution concentrations. For example, traveling time may not account for a large fraction of a person's day; however, a person may experience their highest exposure during the average 1.3 hours they spend traveling (Beckx et al. 2009). One prior study measured the personal exposure of 16 participants and found that exposure to particulate matter and black carbon inside their vehicles could be 420% higher than exposure at their residential location (Dons et al. 2011).

To address these limitations, recent studies have developed dynamic exposure methods by integrating an activity-based travel demand model with an air-quality model to estimate population exposure (De Ridder et al. 2008). Beckx et al. (2009) introduced a modeling framework, which is based on the ALBATROSS activity-based model in combination with the emission model MIMOSA. They compared their results with the exposure estimated by the static method and found that the static method underestimated the hours people spend in areas with higher than 20 $\mu g/m^3$ of $PM_{2.5}$ concentration by 20%. Another study compared the static and dynamic modeling approaches for estimating exposure to NO_2 (Dhondt et al. 2012). The authors used an activity-based travel demand model to predict individual trajectories throughout the day. This model also estimates the traffic volume and average traffic speed on network links, which are then used to estimate emission rates. The air dispersion model estimates NO_2 concentrations from road networks at a 1-km×1-km resolution, with higher resolution near the roads. The LUR model then estimates the background NO_2 concentration at a 3-km×3-km resolution, which is then coupled with the concentration from the roads. Dynamic exposures are then calculated using the output from the activity-based model at the zonal level plus the exposure during travel. The authors assumed that exposure during travel time was equal to the average road network concentration. They found that the dynamic exposure to NO_2 was 1.2% higher than that found by the traditional static method.

Using cell phone data is another method to track individual trajectories and develop a dynamic population exposure model. Dewulf et al. (2016) used the same coupled air-quality model for the entire Belgium region considered in the prior study. They used cell phone data to track each individual's trajectory. A cell phone location is detected if it is active by a 2-km gridded network of antenna at 15-min time intervals. An individual is assumed to stay at her previous location if no activity is detected at the next time interval. The authors found that people experienced 4.3% higher exposure during their daily activities on weekdays compared to their exposure at home since they mostly work in dense urban areas. The National Household Travel Survey (NHTS) is another data source that can be used to predict daily trajectories for a dynamic exposure model. Gurram et al. (2014) used NHTS data for 1,224 daily activity records for the year 2009 to estimate the locations of daily activities in Hillsborough County, FL. To estimate exposure during travel time, they selected the shortest paths between each origin (O)-destination (D) pair. The CALPUFF model was used to estimate NOx concentrations from vehicle traffic on the assigned routes. The results found a 3.6% difference between the daily exposure estimated by the static and dynamic exposure methods.

The dynamic modeling studies that have focused on traffic-related air pollution rather than ambient air pollution from all sources are limited. Hatzopouluo and Miller (2010) aimed to find more sustainable transportation development patterns by providing a more accurate exposure method. They integrated an activity-based model (TASHA) with an air dispersion model, CALPUFF, to estimate exposure to vehicle nitrous oxide emissions at the census block level in Toronto, Canada. They found that the cumulative daily exposure could be 10% higher than the concentration at any location, which could only be captured using a dynamic model. Shekarizfard et al. (2016) developed a dynamic exposure model using the same integrated emission-dispersion model by Hatzopouluo and Miller (2010). The model estimates traffic volume and speed using the O-D matrix from a household travel survey. Outputs from the traffic assignment model are combined with emission factors and then used in CALPUFF to estimate the NO_2 concentration over the Montreal area at a 1-km×1-km resolution. To predict daily travel trajectories, the model matches the trips from the O-D matrix with the travel paths between each O-D pair modeled from a separate traffic assignment model. Since there are several paths between each O-D, the path with the closest travel time is chosen. The authors reported that the exposure estimated by the dynamic method was 1-2% higher than that estimated by the static method.

[redacted] Health Impacts of Exposure to Vehicle Emissions

The first efforts to understand the health effects of exposure to vehicle emissions started in the early 1950s after residents of Los Angeles, CA, USA, experienced a white haze that caused them irritation, and they called it "smog." Early studies either related urbanization indices such as fuel consumption with the rate of mortality (Prindle 1959) or used emission inventories to measure how vehicle emissions affected public health. Exposure models have been used more recently to find the association between exposure to vehicle emissions and negative health outcomes. Existing studies mostly focus on overall mortality.

A variety of exposure models have been used in epidemiology studies owing to the fact that different air pollutants do not have the same chemical behavior. Residential proximity to major roadways is one of the most common vehicle emission surrogates used in epidemiology studies. For instance, a greater risk of asthma and lung function deterioration is reported in children who live close to major roads (Brugge, John L Durant, and Rioux 2007). People who live within 150 meters of a highway have a 29% higher risk of death due to coronary heart disease (Gan et al. 2010). Central site monitoring is another common method for measuring exposure to traffic related air pollutants in epidemiology studies. For instance, Ghosh et al. (2012) used central site monitoring and found an insignificant association between exposure to NO_2 and negative health outcomes. Beelen et al. (2009) studied the association between mortality due to cerebrovascular disease and $PM_{2.5}$ concentration measured by central site monitors. LUR models have also been widely used in more recent epidemiology studies. Yourifuji et al. (2013) used an LUR model and found a 29% higher risk of death because of ischemic heart disease due to exposure to NO_2. LUR models have also been used to estimate exposure to other pollutants such as PM_{10}. For instance, a study found that PM_{10} is associated with a 12% higher risk of death because of acute coronary events (Cesaroni et al. 2014).

Although, as discussed earlier, simple exposure models and surrogates may cause exposure bias and misclassification, the complexities and costs related to using integrated travel demand-emission-air quality models or personal exposure measurement make these methods less common among epidemiology studies. There are a few epidemiology studies that use air quality modeling with a focus on particulate matter and nitrogen dioxides. For instance, McConnell et al., (McConnell et al. 2010) found a 45% higher risk of asthma incidence in children with higher exposure to NO_2 estimated by a dispersion model. Dispersion modeling is also used to study several other health outcomes such as lung cancer (Raaschou-Nielsen et al. 2011), and mortality (Rosenlund et al. 2009). The personal monitoring method is rarely used despite being able to provide the most accurate exposure estimates. The high cost or personal exposure measurement results in small sample sizes and therefore less statistical power in epidemiology studies. For example, Spiral-Cohen et al. (2011) used personal monitoring system to collect exposure to $PM_{2.5}$ and found that the risk of respiratory diseases increases by 30% with an increase in exposure to vehicle emissions. Despite the known benefits of more accurate exposure models, to our knowledge, no epidemiology study has used a dynamic exposure air pollution model to investigate the negative impacts of traffic-related air pollution on public health.

[redacted] Environmental Justice Impacts of Exposure to Vehicle Emissions

The uneven distribution of vehicle emission concentrations across urban areas also raises environmental justice concerns. Minority and low-income populations in most communities live closer to roads with the highest traffic volumes, placing them at a disproportionately higher risk of suffering from negative health outcomes related to vehicle emissions exposure. MPO's that do consider environmental justice concerns in their regional plans often rely on some type of buffer analysis. A common approach based on our experience is to draw spatial buffers around high volume roadways (where high concentrations of air pollutants can be expected) and compare the socioeconomic characteristics of populations within these buffers to the regional population. For instance, Rowangould (2013) spatially analyzes population at census block level to investigate race and income disparities in near roadway population. He found that being African-American, Hispanic, or low income is associated with higher traffic volume and traffic density compared to White or high-income people; which are similar to findings by Tian et al. (2013) for road density.

However, this approach requires defining critical distance and traffic volume thresholds. This can be problematic for several reasons. Choosing different thresholds may result in different conclusions depending on the spatial distribution of minority and low-income communities with respect to major roadways. For example, a slightly larger buffer or lower traffic volume threshold may include a large minority community that would not be captured in a more narrowly defined analysis. Whether or not there is an environmental justice concern then becomes subject to the choice of these thresholds which could be difficult to defend. For example, prior studies have considered a wide range of traffic volume and distance thresholds (Rowangould 2013); however, MPOs would likely benefit from a more conclusive analysis to aid in decision making. Furthermore, vehicle emission rates and concentrations vary across regions due not only to traffic volume but also congestion levels, the density of roadways, the type of vehicles using roadways (e.g., amount of diesel truck traffic), topography, and varying climate and weather patterns. Most buffer approaches also fail to consider how vehicle emission rates change over time though the planning horizon. As time goes on and vehicle emission rates decline the correlation between traffic volume and near roadway emission concentrations will change significantly, making it difficult to estimate how environmental justice concerns change over time.

To fill the gap, recent studies use air quality modeling at high spatial resolution to investigate environmental justice concerns in transportation. For instance, Kingham, et al. (2007) use an atmospheric air dispersion model for Christchurch, New Zealand to estimate vehicle PM_{10} concentrations. They find that low income populations on average experience 122% higher levels of vehicle emission concentration compared to high-income populations. Similarly, Fan et al. (Fan, Lam, and Yu 2012) use an air dispersion model for Hong Kong and find that low-income populations are exposed to 125% higher vehicle NO_x concentrations compared to high-income populations. Carrier et al. (2016) evaluate disparities in exposure to vehicle emissions between low and high-income populations in Montreal, Canada using a Land Use Regression model to create a NO_2 concentration surface for vehicle emissions. The results show NO_2 concentrations in areas where low-income population live are 30% higher than where high-income people live. They also find more highways, 124%, were built in areas where low-income population live compared to more affluent areas. Racial inequalities were also observed. Non-white populations were exposed to 11% higher NO_2 concentrations and 228% more highways were built near their residences.

2.2 GHG Emissions Mitigation Strategies

Prior research generally finds that improving vehicle energy efficiency and widespread adoption of low carbon fuels are the strategies with the greatest potential for achieving deep GHG reductions in the transportation sector (Kay, Noland, and Rodier 2014; Leighty, Ogden, and Yang 2012; Lutsey and Sperling 2009; McCollum and Yang 2009; Melaina and Webster 2011; Olabisi et al. 2009; Greene and Plotkin 2011; Williams et al. 2012; Yang et al. 2009; Yuksel et al. 2016) and perhaps the only feasible route to achieving cuts that are congruent with IPCC targets. Most studies also acknowledge that no single strategy, alone, can achieve the deep GHG reductions required to meet the IPCC targets. Strategies that encourage more compact and mixed-use development, increase the cost of driving, and shift vehicle trips to lower emitting modes of transportation are also important for achieving deep reductions (Greene and Plotkin 2011; Kay, Noland, and Rodier 2014b; Mashayekh et al. 2012; McCollum and Yang 2009; Melaina and Webster 2011; Yang et al. 2009); however, without substantial increases in vehicle energy efficiency and fuel de-carbonization, prior studies suggest that even aggressive combinations of these non-technology based strategies will only provide a relatively small portion of the needed reductions (Cambridge Systematics 2009; Ewing et al. 2007; Greene and Plotkin 2011; TRB 2009).

There is some evidence on the potential of MPOs to reduce transportation GHG emissions. For instance, the Metropolitan Washington Council of Governments evaluated forty aggressive strategies for their ability to reduce GHG reductions to 2005 levels by 2012, 20% below 2005 levels by 2020, and 80% below 2005 levels by 2050. They found that vehicle and fuel technologies are essential to meet these reduction targets since all other strategies including transit improvement, increasing bike and pedestrian mode share, and pricing would only reduce GHG emission by 1% (Batac, Schattanek, and Meyer 2012). The New York Greenhouse Gas Task Force (Winkelman and Dierkers 2003) concludes "A targeted package of policies can slow the growth rate of VMT" but does not provide what an MPO would have to do to meet the GHG reduction targets. Excluding vehicle technology and fuels strategies, their approach reduces VMT by 5.1%by 2010 and 8.5% by 2020. A review of international planning experience also reveals that transportation demand strategies such as transit improvement, land use policies, and pricing (e.g., fuel pricing, VMT pricing, and parking pricing) are only able to reduce the VMT by up to six percent (Rodier 2009).

CHAPTER 3

STUDY AREAS

This dissertation completed modeling and analysis in two distinct study areas: Albuquerque, NM and Atlanta, GA. The two areas were selected based on the willingness of MPO staff to share data and modeling methods and to provide diversity in urban form and socioeconomics to the analysis.

3.1 Albuquerque, New Mexico

We use the mid region council of governments (MRCOG) most recent long range transportation plan "Futures 2040 Metropolitan Transportation Plan" to demonstrate our analysis approach in chapters 4,5, and 6 with a 2012 population of 890,593 and a total land area of 24,080 km^2, the study area is the most populous and the largest metropolitan area in the state of New Mexico. MRCOG used a scenario planning process that considered changes in both land-use and the transportation system to guide the development of its long range plan. The scenario planning process was also part of a US Department of Transportation sponsored climate change scenario planning project (Lee et al. 2015). A significant effort was made to identify scenarios that would reduce GHG emissions and mitigate potential climate change impacts. A wide range of performance measures were also developed to evaluate other aspects of each scenario including traffic congestion, accessibility, mode share, land development, water use, and economic growth. Therefore, the area was suitable case to study how transportation plans affect vehicle emission and population exposure.

The scenario planning process ended with three final scenarios: the 2040 Trend scenario, 2040 Preferred scenario and 2040 Preferred Constrained scenario. The Trend scenario, representing business as usual, assumes no change in current land-use policies, and transportation investments focus on increasing roadway capacity. The Preferred scenario contains land-use policies and incentives aimed at encouraging infill, mixed use, and transit oriented development near existing activity centers and urban centers. The Preferred scenario also doubles transit level of service over the Trend scenario and adds several new bus rapid transit lines. Highway investments remain the same as in the Trend. The Preferred Constrained scenario is similar to the Preferred scenario in terms of land-use, but assumes a slower pace of transit and highway investment (Lee et al. 2015).

Figure 3-1 Albuquerque Metropolitan Area

3.2 Atlanta, Georgia

In chapter 7 we evaluate dynamic exposure using the 2017 regional transportation plan created by the Atlanta Regional Commission (ARC's). ARC has developed an Activity Based Travel Demand Model (ABM) for the Atlanta metropolitan area which covers 8,376 square miles and had a 2017 population of 4.6 million. The model has 5,873 Traffic Analysis Zones (TAZ). The Atlanta metropolitan area is the most populous metro in the state of Georgia and the ninth most populous in the United States, according to the U.S. Census Bureau. The most recent estimates of income and poverty, published by the US Census Bureau, reports a median household income of $55,733 for the Metro Area in 2013. The Atlanta Regional Commission provided us with output from their 2017 ARC-ABM model which consists of 19.8 million daily trips including origin, destination, mode, and time for each trip. ARC also provided the transportation network, O-D trip matrices, and assignment module to be run in CUBE Voyager software.

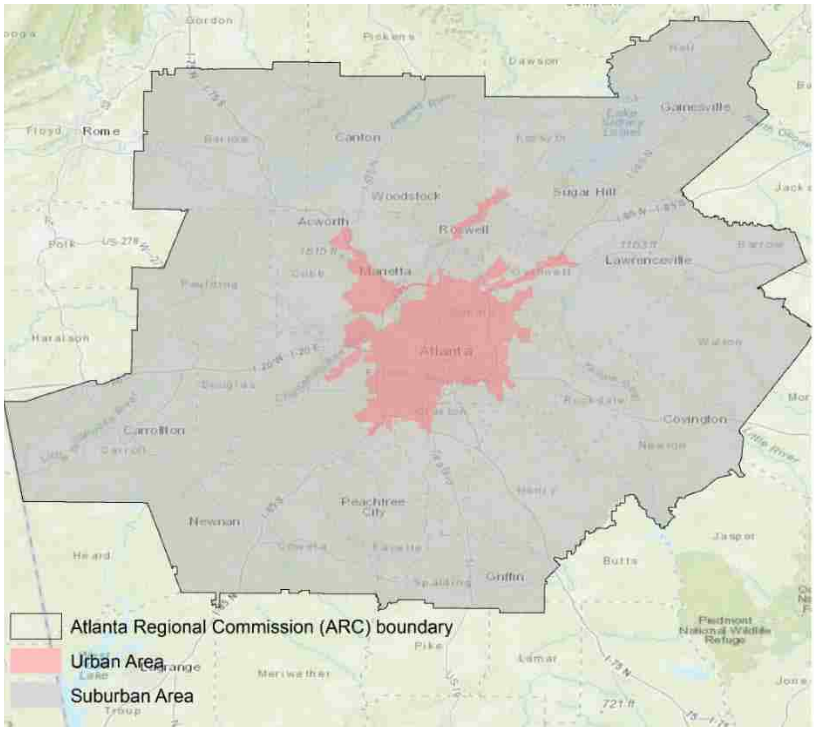

Figure 3-2 Study areas: Atlanta Regional Commission (ARC) boundary

CHAPTER 4

EVALUATING UNINTENDED OUTCOMES OF REGIONAL SMART GROWTH STRATEGIES: ENVIRONMENTAL JUSTICE AND PUBLIC HEALTH CONCERNS

4.1 Introduction

Air pollutant dispersion modeling is a relatively simple method for modeling how air pollutants in vehicle exhaust disperse over the surrounding terrain. Unlike photochemical models such as CMAQ that also model chemical reactions leading to secondary air pollutants such as ozone, most air dispersion models only consider the transport and dilution of primary air pollutants. This limitation comes with the advantage of being able to model primary air pollutant concentrations at a much higher spatial resolution with far fewer data and computational requirements. One of the best examples of using a photochemical model to evaluate regional exposure to air pollutants from vehicle exhaust achieves a resolution of 3 km^2 (Beckx et al. 2009). However, this resolution is still too low to evaluate variation in near roadway exposures that can reach background levels within several hundred meters (Karner, Eisinger, and Niemeier 2010). While an air dispersion model would not be appropriate for evaluating exposure to regional air pollutants such as ozone or secondary particle pollution, they are very useful for evaluating localized exposures near pollution sources such as highways where the concern is exposure to directly emitted primary air pollutants.

Several studies have previously demonstrated the use of air dispersion modeling for evaluating regional exposure to vehicle emissions. Each study begins by estimating vehicle traffic volumes and speed on each roadway segment with a regional travel demand model and then link level vehicle emissions using a vehicle emission rate model. Various approaches are then used to estimate emission concentrations. Hatzopoulou and Miller (2010) use the CALPUFF model to model vehicle nitrous oxide emission concentrations at census block centroids in Toronto, Canada; Cook et al. (2008) use AERMOD to model benzene and carbon monoxide vehicle emissions concentrations at census block group centroids in New Haven, Connecticut; Lefebvre et al. (2013) model nitrogen dioxide and course particulate matter vehicle emissions concentrations using the IFDM model in buffers along major roadways in the Flanders and Brussels region of Belgium; and Houston et al. (2014) model fine particulate matter concentrations at the parcel level for the region surrounding the Ports of Los Angeles and Long Beach in California using CALINE4. These studies have focused on modeling current conditions and have not evaluated different land-use and transportation planning scenarios.

De Ridder et al. (2008) combine travel demand, emission and air quality modeling to evaluate how a more sprawling land-use development pattern may affect air quality and emissions exposure. They create a land-use scenario that moves 12% of the Ruhr region of Germany's population to the urban periphery, and then model the resulting change in travel patterns, emission rates, and air quality. The change in ozone and PM_{10} concentrations are modeled using the AURORA chemical-transport model at a 2 km^2 resolution. They find that exposure declines by 13% for the population moved to the periphery, while exposure increases by 1.2% for those who do not move. Overall, the sprawl scenario results in a small net increase in exposure of 0.35% and 0.55% for PM_{10} and ozone, respectively.

Our study builds on the work of De Ridder et al. (2008) by evaluating a set of actual land-use policy and transportation investment scenarios and evaluates them at a higher spatial resolution to capture near roadway air quality impacts. We use a novel dispersion modeling method that provides an efficient method for obtaining results at high spatial resolution for large urban areas (Rowangould 2015). The efficiency of this method allows us to evaluate several regional transportation planning scenarios generated from a coupled travel demand and land-use simulation model to understand how changes in land-use policies and transportation system investments can affect exposure levels and exposure equity. Our analysis framework provides a unique quantitative method for evaluating the potential exposure impacts of smart-growth policies. In addition, the framework enables us to evaluate how smart growth strategies affect environmental justice issues in transportation.

4.2 Methodology

MRCOG used an integrated land-use and travel demand model to evaluate a 2012 baseline scenario and the three future scenarios described above. UrbanSim, an agent based land-use microsimulation model, was used to model parcel level land-use change, including changes in the distribution of employment and housing across the study area. A traditional trip based 4-step model was used to forecast travel demand for three different time periods: AM peak, PM peak, and the remaining off-peak hours. The models were integrated in the sense that UrbanSim provided employment and population forecasts to the travel demand model and the travel demand model provided origin-destination travel costs to UrbanSim. We then use the output of these models to estimate vehicle emission rates, fine particulate matter concentrations ($PM_{2.5}$), and population exposure to $PM_{2.5}$. Our methodology quantifies concentrations and exposure to primary, directly emitted, $PM_{2.5}$ pollution from vehicle exhaust. It does not account for $PM_{2.5}$ pollution that results from additional, secondary, reaction of vehicle related and other air pollutants that represent a more regional air quality concern. Details of the air quality modeling are discussed below.

[redacted] Emission Modeling

We use US EPA's MOVES model, tailored with regional vehicle fleet and travel activity data, to create a $PM_{2.5}$ emission rate lookup table tabulating emission rates in five miles per hour increments for urban restricted access, urban unrestricted access, rural restricted access, and rural unrestricted access roadway types. The lookup table is used to assign appropriate emission rates to each roadway segment with greater than one vehicle trip per minute. Lower volume links are assumed to contribute an insignificant amount of pollution. Each segment's total emission rate is then calculated by multiplying by each segment's traffic volume and length. Gram per meter squared per second emission rates for each segment (the input needed for the air dispersion modeling step) are then calculated by dividing by each roadway's estimated area (each roadway was assumed to be 15 m wide, except for limited access highways which were assumed to be 15 m wide in each direction) and the time period corresponding to the vehicle traffic volume estimates.

[redacted] Dispersion Modeling

US EPA's AERMOD dispersion model is used to estimate the concentration of traffic related $PM_{2.5}$ over the study area. In a conventional analysis, AERMOD models the concentration contribution of each source at a receptor independently. In a large transportation network, such as Albuquerque's that consists of around 9093 roadway segments (emission sources) and a dense network of 172,700 receptors to capture near roadway concentration gradients, the result is more than 1.5 billion source-receptor pairs. Allowing AERMOD to model each source-receptor pair exceeds feasible computational times (months to years). To overcome this limitation, we use a novel rastering approach previously developed and demonstrated for Los Angeles County, California (Rowangould 2015).This method breaks the modeling domain down into a large set of small 1 km^2 emission source grid cells. A 3 km grid of receptors with 100 m spacing (fine receptor network) is centered over each grid cell and buffered by a 11 km grid of receptors with 500 m spacing (course receptor network). This method divides the large modeling domain into hundreds of smaller modeling sub-domains. Each sub-domain is designed to be large enough to capture the expected extent of pollution dispersion from roadway sources within the sub-domain. The result is a significantly lower number of source-receptor pairs, increasing computational efficiently.

Additionally, each of the sub-domains can be modeled in parallel, further increasing computational efficiency.

We setup AERMOD to model each roadway segment as an area source following US EPA $PM_{2.5}$ hotspot modeling guidance (US EPA 2010). Digital elevation model (DEM) data is obtained from the U.S. Geological Survey (USGS) and meteorological data is obtained from New Mexico Environment Department, Air Quality Bureau. The meteorological data represent hourly surface and upper air data for the years 2001 through 2004. Deviating from US EPA guidance, we only model the first and fifteenth day of each month in the meteorological data to further reduce computational times, an approach previously found to produce accurate annually averaged concentration estimates (Rowangould 2015). We also estimated concentrations with the reduced number of meteorological records and the full records for five individual grid cells in different locations in the MRCOG region and found no significant difference in annual average concentrations.

The individual modeling results for each sub-domain are combined into two geo-spatial point data sets, one for the fine and one for the course receptor networks. The point concentration estimates are then transformed into raster data sets with a 20 m resolution using a spline interpolation procedure in ESRI ArcMap version 10.1. The two raster data sets are then summed to create a single regional $PM_{2.5}$ concentration raster.

[redacted] Exposure Analysis

Population exposure is estimated by assuming an individual's average daily exposure is equal to the estimated concentration outside their home. This commonly used assumption neglects the fact that people spend time at work, school, and social activities. Thus, our method is not completely accurate and may be biased. However, since people spend a significant portion of their time at or near their homes this approach provides a reasonable metric for investigating environmental justice and public health concerns related to vehicle emission exposure (Leech et al. 2002).

$PM_{2.5}$ exposure is calculated by first estimating the area weighted average $PM_{2.5}$ concentration in each US Census block. We then calculate the population of each US Census block by adding up the parcel level population estimates made by UrbanSim for each planning scenario. The parcel data from UrbanSim, however, does not include socioeconomic data necessary for our environmental justice analysis. Therefore, we obtain the racial makeup of each US Census block group from the 2012 American Community Survey. We also obtain median household income estimates for each travel analysis zone (TAZ), roughly the same as a US Census tract, for each scenario from MRCOG. We assign each census block containing our population and $PM_{2.5}$ concentration estimates the same racial and income attributes as the larger census units that they fall within. The racial composition of each census block is assumed to remain constant since we do not have a method for forecasting changes in population growth by race.

4.3 Results

Primary $PM_{2.5}$ emissions from vehicle exhaust generally contribute very little to the average concentration of $PM_{2.5}$ across the Albuquerque metropolitan area but they can be a significant source of $PM_{2.5}$ pollution near high volume roadways. The annual average concentration of primary $PM_{2.5}$ from vehicle emissions was generally less than 1 $\mu g/m^3$ (Figure 4-1). During this same time period, annual 24-h average ambient $PM_{2.5}$ concentrations measured by the two federal reference monitors in the Albuquerque metropolitan area were 7.4 $\mu g/m^3$ (2012 data for US EPA monitor site: 35-001-0023) and 8.7 $\mu g/m^3$ (2013 data for US EPA monitor site: 35-001-0029). These monitors are located near arterial roadways but away from the region's two interstate highways and provide a rough estimate of the region's background $PM_{2.5}$ concentration. Considering these data as the background concentration, concentrations near high volume roadways are estimated to be up to 11–14% higher than the 2012 background. While higher concentrations near roadways pose relatively greater health risks they are unlikely to exceed the annual $PM_{2.5}$ National Ambient Air Quality standard of 12 $\mu g/m^3$.

The results also show significant spatial variation. Concentrations of primary $PM_{2.5}$ are highest along the region's highways and major arterials which is expected given their high traffic volumes (Figure 4-1). The highest concentrations occur along interstates 25 and 40, the two roadways running north-south and east-west through the middle of the maps in Figure 4-1. The maps in Figure 4-1 also indicate that $PM_{2.5}$ concentrations are expected to decline significantly across the entire region by 2040 in both planning scenarios. The large reduction is mostly due to reductions in per mile vehicle emission rates, rather than less driving. The MOVES model used to generate future year emission factors for our analysis projects large reductions in vehicle fleet average emission rates based on the scheduled phase in of approved, stronger, federal vehicle emission standards and the gradual replacement of older, more polluting vehicles, with new vehicles that achieve stronger emission standards. Total vehicle miles traveled (VMT) increases by 48% in the Trend scenario, and 40% in the Preferred scenario, over the 2012 Baseline scenario. The large increase in driving is the result of an expected 52% increase in the region's population by 2040. VMT per capita declines by 2% in the Trend scenario and 7% in the Preferred scenario. There is no apparent change in the relative spatial distribution of $PM_{2.5}$ across the three scenarios.

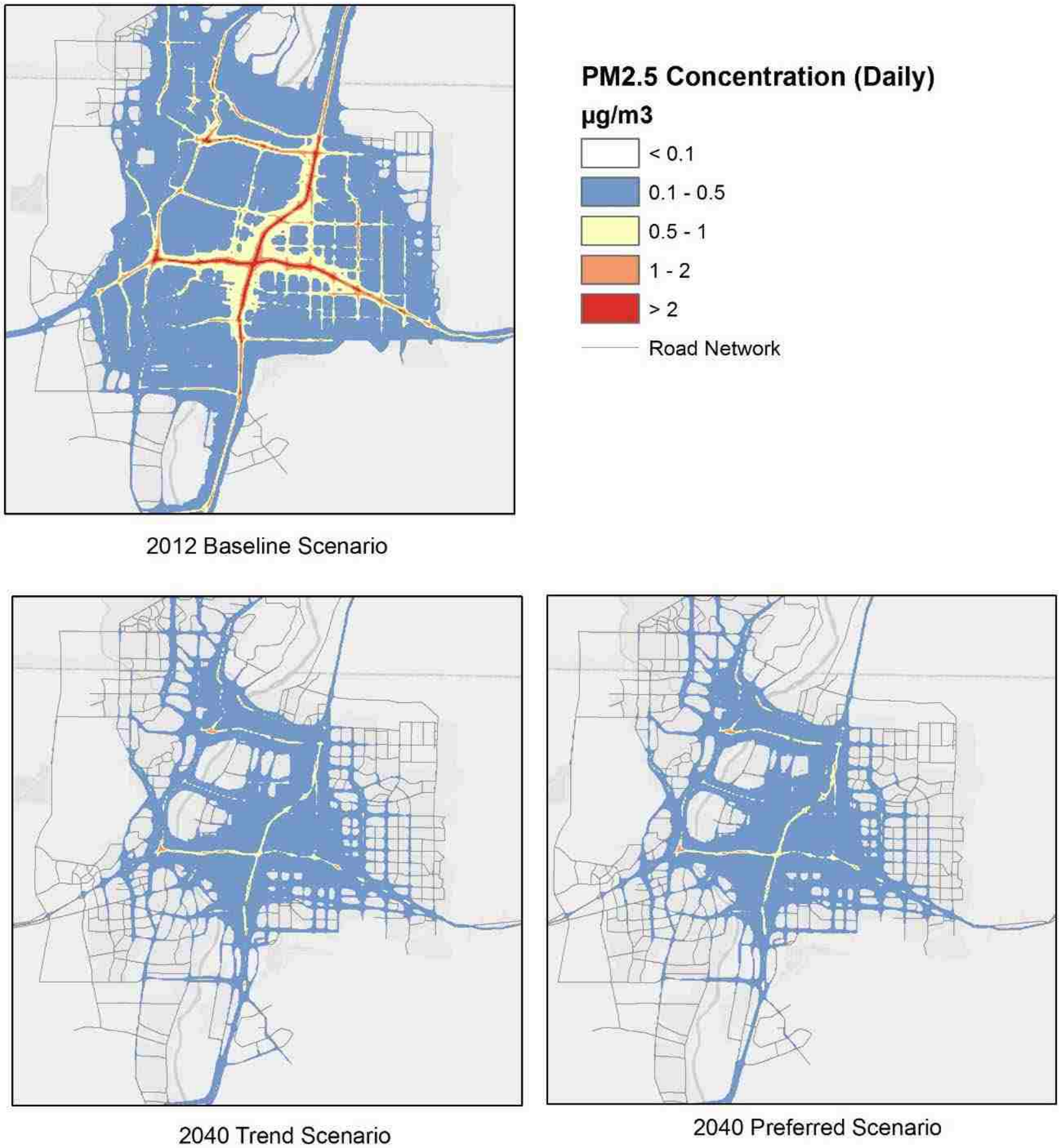

Figure 4-1 Maps of Daily Average $PM_{2.5}$ Concentrations for Each Scenario

The large reduction in $PM_{2.5}$ concentrations also results in large reductions in population exposure (Figure 4-2). The cumulative population exposure curves in Figure 4-2 indicates most of the population is presently exposed to relatively low concentrations of directly emitted $PM_{2.5}$ from vehicle exhaust, and that exposure declines by a large amount in the Trend and Preferred scenarios (i.e., the space between the baseline and 2040 scenario curves).

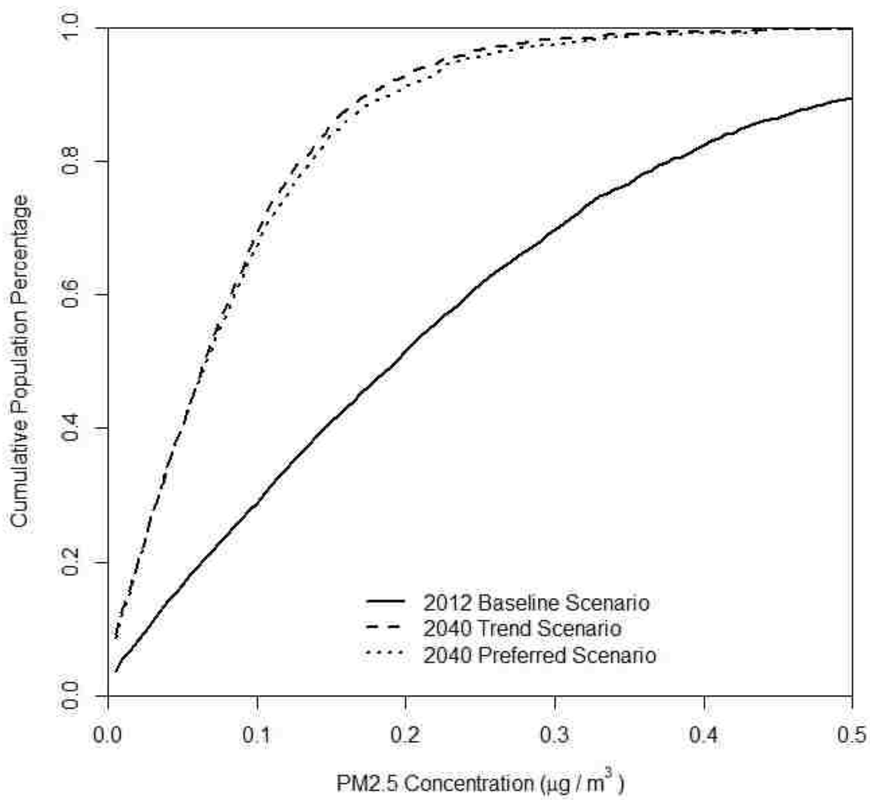

Figure 4-2 Cumulative Average Daily $PM_{2.5}$ Exposure Distribution for Each Scenario

Table 4-1 compares aggregate regional emission, concentration and exposure results. These results are among the most interesting. $PM_{2.5}$ emissions fall by 66.2% in the Trend scenario and 68.8% in the Preferred scenario as do average concentrations. The lower emissions and concentrations are expected from the Preferred scenario as it achieves the largest reduction in VMT and least amount of congestion (average network speed is 6 MPH higher than the Trend scenario and there are fewer hours of delay and congested network links). However, the Trend scenario achieves a 5% lower population weighted $PM_{2.5}$ concentration (i.e., exposure) than the Preferred scenario.

Table 4-1 Average Daily $PM_{2.5}$ Emissions, Concentrations, and Exposures

Scenario	Emission Inventory (kg)	Mean Concentration (μg/m³)	Population Weighted Mean Concentration (μg/m³)					
			Total	White	Hispanic/ Latino	Other Non-White	Low Income	High Income
Baseline	1034.7	20.0x10-3	0.243	0.233	0.251	0.253	0.287	0.209
Trend	349.6	6.3x10-3	0.081	0.076	0.085	0.086	0.096	0.065
Preferred	322.8	5.9x10-3	0.085	0.080	0.089	0.085	0.103	0.063

The higher exposure level in the Preferred scenario, which achieves the lowest emission rates, is the result of two spatial processes. First, as seen in Figure 4-3, the Preferred scenario results in slightly higher concentrations than the Trend scenario does along several portions of highways and arterials in the central part of Albuquerque. The Preferred scenario, which differs from the Trend primarily by incentivizing higher levels of infill, transit oriented, and mixed use development in existing activity centers also results in higher population densities. The preferred scenario's average population density is 7% higher than the Trend's. The combination of increasing population density and $PM_{2.5}$ concentrations in central Albuquerque results in higher average exposure levels. This result indicates that changing population patterns were the main driver of changes in exposure levels between the Trend and Preferred scenarios.

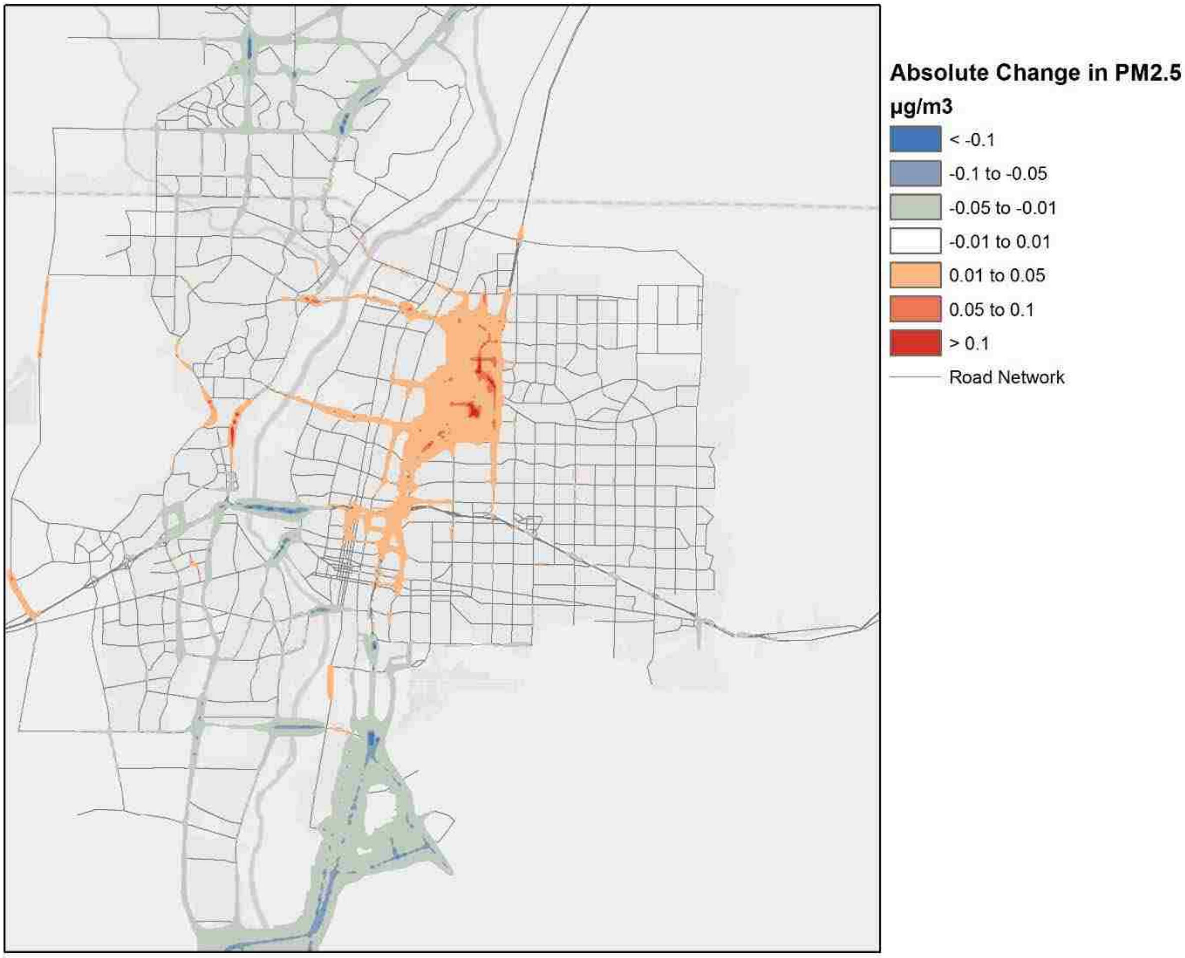

Figure 4-3 Change in Average Daily PM2.5 Concentration between Year 2040 Preferred and 2040 Trend Scenarios

The results in Table 4-1 also indicate that on average minority populations face somewhat higher exposure levels, though the differences are relatively small. The relative difference in exposure faced by minorities also remains constant across the three scenarios. Disaggregate exposure results lead to similar conclusions. Figure 4-4 shows plots of cumulative exposure by race, again indicating that minorities face slightly higher exposure levels and that the relative exposure differences are similar across the scenarios.

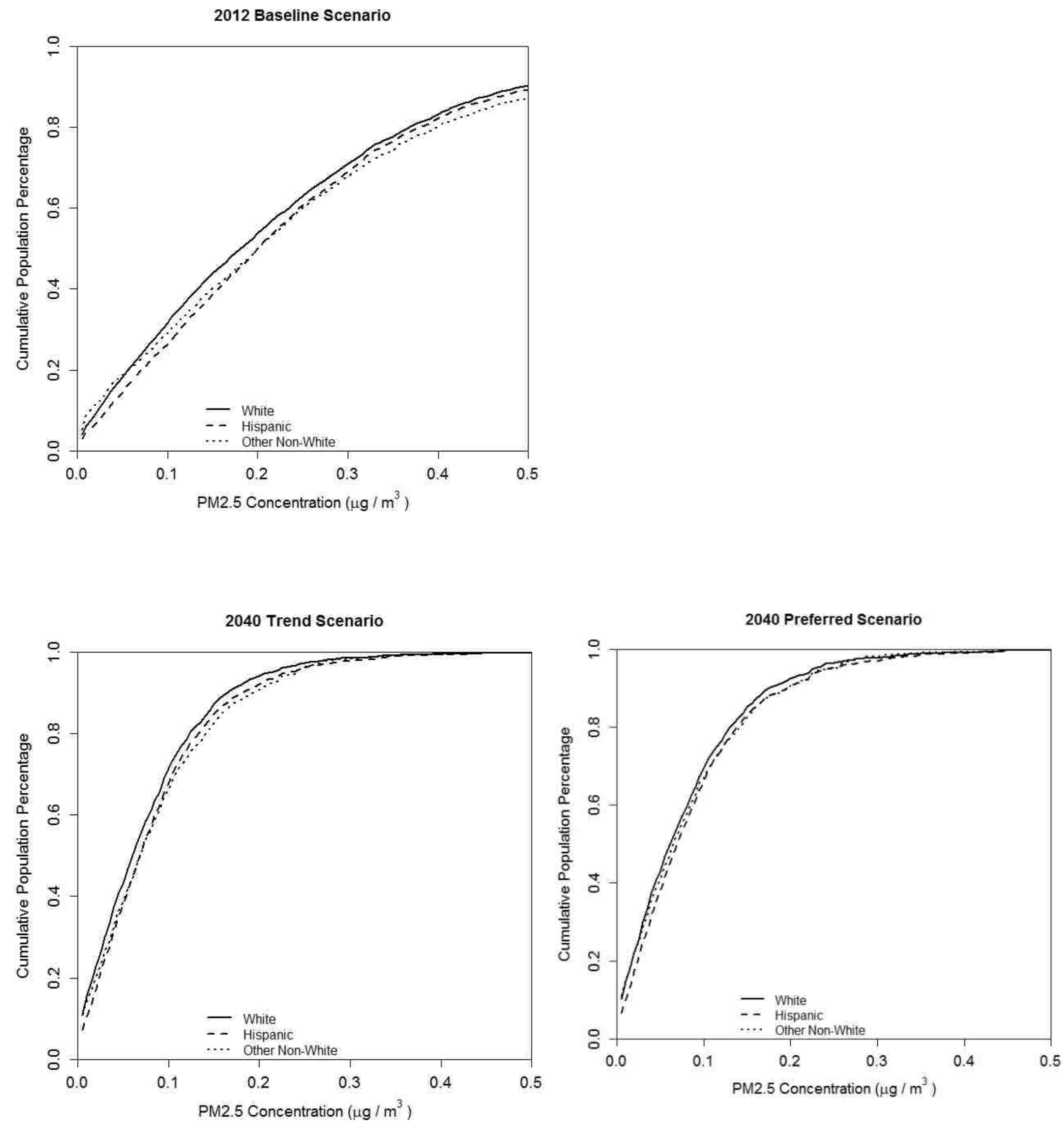

Figure 4-4 Cumulative Average Daily $PM_{2.5}$ Exposure Distributions by Race/Ethnicity Group

While we do not find significant differences in exposure by minority status, we do find significant differences in exposure by income level. We define high income areas as those census blocks that have a higher average household income than the Albuquerque average, and low income areas as those which have an average household income that is lower than the Albuquerque average. Table 4-1 shows that low income households in the Baseline scenario have on average 37% higher exposure than high income households. The exposure disparity by income group grows to 47% in the Trend scenario and 63% in the Preferred scenario. While the relative exposure disparity grows in the future year scenarios, the absolute size of the average disparity measured in µm/m3 declines by a small amount and each income group experiences large reductions in average exposure. Furthermore, these results also indicate that low income households are exposed to nearly 7% higher concentrations under the Preferred scenario when compared to the Trend scenario while exposure for high income households remains constant. Figure 4-5 shows the cumulative exposure distribution for each scenario and income group, indicating again that low income households are burdened with a disproportionately high level of exposure that changes little over time.

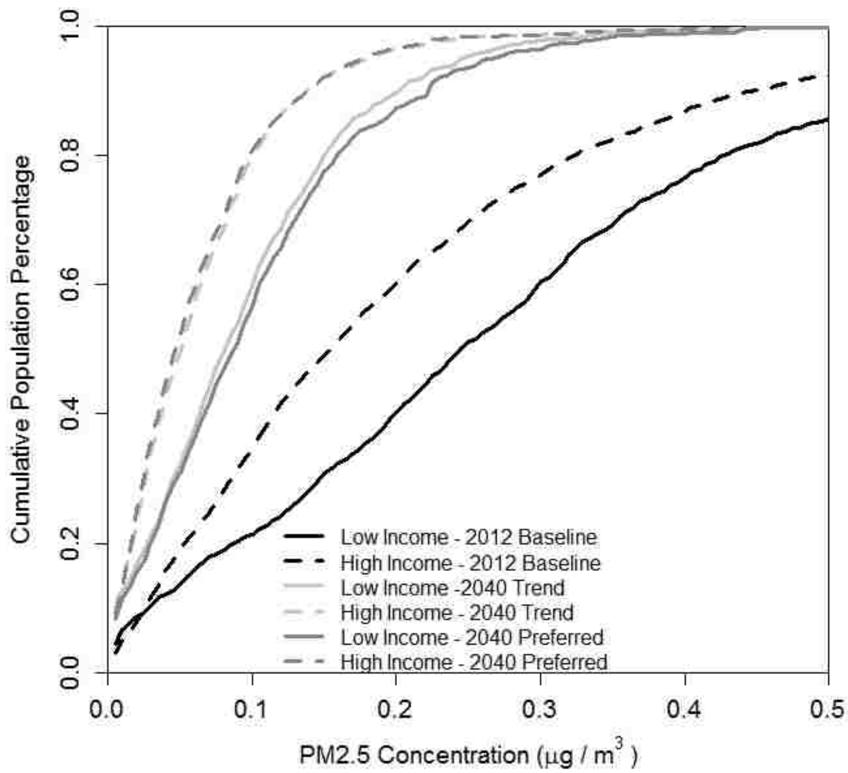

Figure 4-5 Cumulative Average Daily PM2.5 Exposure Distributions by Income Group

4.4 Discussion

Our analysis of the Albuquerque region's land-use and transportation planning process demonstrates the limitation of conventional regional air quality analysis that rely on aggregate emission inventories; the approach used by most MPOs in the United States and which is required by US EPA's transportation conformity process in air quality non-attainment areas. In the Albuquerque metropolitan area, we find that changes in aggregate emission inventories and average emission concentrations for primary $PM_{2.5}$ do not correspond to changes in emissions exposure. A planning scenario with greater vehicle emissions (and higher concentrations) results in less exposure than a scenario with fewer emissions. Differences in land-use and, to a lesser extent, travel behavior account for the misalignment. These results indicate that current regional air quality analysis procedures and performance measures are potentially misleading and not well suited for evaluating the air quality and public health impacts of contemporary transportation and land-use strategies including infill and smart-growth development.

As many metropolitan areas peruse infill and smart-growth strategies aimed at increasing the density and mixture of land-use in urban areas, it is increasingly important to understand how these plans affect public health through exposure to air pollution in addition to their main objectives such as economic development, less car dependence, and GHG emissions reduction. The social welfare gains of smart-growth plans may be at least partially offset by an increase in negative health outcomes from exposure to toxic vehicle emissions. The increase in negative health outcomes will likely fade over time as the vehicle fleet becomes increasingly less polluting, but changes in mid to near term exposures could be significant (especially in regions with high growth rates or poor air quality) and therefore we believe that they should be considered in the regional planning process. We are not suggesting that smart-growth strategies be abandoned all-together but that they be planned more carefully. A more spatially refined analysis framework such as the one we have demonstrated in this paper can help planners identify plans that may increase exposures and make refinements to avoid or minimize them.

As the maps in Figure 4-1 demonstrate, avoiding the highest exposures may only require small changes to land-use plans. At least in Albuquerque's case, elevated concentrations of vehicle emissions are confined to a relatively small area of the metropolitan region, mostly along interstate highways. Zoning changes that prohibit or discourage new development in these areas would significantly reduce exposure and still leave many opportunities for infill and new mixed use development. However, to reduce exposure to the relatively higher concentrations of vehicle emissions in urban centers as compared to suburban and rural areas, more significant changes in plans would likely be required. For example, strategies to reduce congestion levels, promote the use of cleaner fuels or electric vehicles, or increase the share of trips made by transit, walking and biking in urban centers may need to be implemented before significant population growth in these areas occurs.

Our spatially detailed air quality analysis framework also allows for a more robust evaluation of environmental justice concerns while creating regional land-use and transportation plans. In Albuquerque, we find significant exposure disparities between high and low income households, with lower income households experiencing higher exposure levels in all scenarios. We do not find significant disparities across race and ethnicity groups, a result that differs from many prior studies that have been conducted in other regions (Apelberg, Buckley, and White 2005; Chakraborty 2009; Gunier et al. 2003; Houston, Li, and Wu 2014; Jephcote and Chen 2012; Kingham, Pearce, and Zawar-Reza 2007; Rowangould 2015). This finding further demonstrates the importance of conducting a spatially detailed environmental justice analysis, as the different spatial arrangements of each region's disadvantaged populations and vehicle emissions may present unique equity outcomes and challenges.

A more spatially detailed regional scale air quality analysis can help municipalities and state departments of transportation avoid unexpected, and potentially expensive, project level air quality concerns. There are many more possibilities for mitigating unacceptable health risks from air pollution exposure at the regional transportation planning stage then there are at the project implementation stage where traditional environmental review and environmental justice analysis are performed. For example, a new transit system, incentives for cleaner vehicles and active transportation, or changes in land-use policy can be considered as potential mitigation measures for reducing exposure to vehicle emissions at the regional transportation planning stage. However, if air quality concerns are uncovered while implementing a specific highway project the available mitigation measures are usually more limited; for example, scaling back the size of the project, realignment, or expensive exposure abatement measures (e.g., air filtration). Litigation can often stall a controversial project indefinitely. Engaging stakeholders and community groups about their air quality concerns early on in the planning process would provide greater opportunity for considering additional project alternatives as well as regional scale strategies. Early engagement in the planning process may also provide more time for discussion and compromise without delaying project implementation.

Finally, while our spatially detailed air quality analysis framework overcomes many limitations of prior methods and current practice, several limitations exist. The MPO in Albuquerque uses a standard 4-step trip based travel demand model. This model allows us to estimate spatially detailed maps of vehicle emissions concentrations across the region based on the projected movement and volume of vehicle traffic. The travel demand model, however, does not provide detailed information about the movement of individuals and where they spend their time. Our analysis estimated, as most prior studies have, exposure based on the concentration of vehicle emissions at each person's home location. While this is a limitation, we argue that it still provides a reasonable estimate of exposure. A recent study by Shekarrizfard et al. (2016) compares home based and dynamic exposure to nitrogen dioxide (NO2) from vehicle emissions in Montreal, Canada and finds that home based exposure estimates on average underestimate daily exposure by a small amount. Larger errors are found for specific individuals and trip types. Prior studies have also shown that concentrations of vehicle emissions are highest in the evening and early morning hours (Hu et al. 2009; Rowangould 2015; Zhu et al. 2006) which is also when most people are at home. Furthermore, most people spend the majority of their time in and around their home. In regions that use activity based travel demand models, it would be possible to account for the daily movements of the population and estimate a more refined exposure estimate (Dhondt et al. 2012; Shekarrizfard, Faghih-Imani, and Hatzopoulou 2016).

A second limitation is that exposure is based on the estimated ambient concentration of air pollutants, and not the concentration within buildings and vehicles, places where people spend a significant amount of time. Prior studies that measured air pollutants in various microenvironments find that concentrations in buildings and vehicles often exceed outdoor concentrations, though in some buildings they may be lower (Baek, Kim, and Perry 1997; Kim, Harrad, and Harrison 2001a; Marshall et al.

2003). Accounting for how much outdoor concentrations affect indoor and in-vehicle concentrations in a modeling study would generally require the use of indoor/outdoor concentration ratios along with the above mentioned activity data. Ideally, such ratios would be based on measurements made in the specific study area as they will vary with regional differences in building types and climate.

Finally, while we were able to use UrbanSim to forecast the future spatial distribution of the region's population and their income, we were not able to identify a method to forecast the change in the racial makeup of future populations or their spatial distribution. Therefore, the share of the population by race and ethnicity in each area of the region was held constant. Based on a comparison of census tract-level demographic data from the 2000 and 2010 decennial census, we know that the relative size of the non-white population is growing in the Albuquerque metropolitan area and that most areas have become less racially segregated. Had we been able to model potential changes in the relative share and spatial distribution of minority populations we may have uncovered even smaller race-exposure disparities than what are presented in this paper. However, the results are still informative for identifying future air quality impacts for areas that currently have large minority populations – information that should still be relevant to current planning and policy decisions aimed at reducing exposure disparities.

It should also be understood that exposure to primary $PM_{2.5}$ pollution from vehicle emissions is only one source of the population's total $PM_{2.5}$ exposure. Total exposure would have been higher if we included exposure to $PM_{2.5}$ formed from additional reactions between vehicle exhaust emissions and other pollutants in the atmosphere. This requires different modeling methods that have less spatial resolution as explained above. However, we expect that the relative differences in exposure would remain similar since secondary $PM_{2.5}$ pollution exhibits less spatial variation and represents a regional rather than near-roadway air quality challenge. Furthermore, we have not accounted for $PM_{2.5}$ pollution originating from non-highway sources.

There are also several possibilities for expanding upon the framework discussed in this paper. We have estimated the concentration of fine particulate matter to demonstrate our approach; however, the same approach could also be used to evaluate exposure to other directly emitted criteria air pollutants such as carbon monoxide and nitrogen dioxide as well as a wide variety of mobile source air toxics such as benzene and formaldehyde (US EPA 2006). Health impacts functions also exist for many mobile source air pollutants (e.g., see US EPA's BenMAP program), and they could be used with exposure estimated using our framework to evaluate changes in health risk.

CHAPTER 5

EVALUATING THE CUMULATIVE IMPACTS OF A LONG RANGE REGIONAL TRANSPORTATION PLAN: PARTICULATE MATTER EXPOSURE, GREENHOUSE GAS EMISSIONS, AND TRANSPORTATION SYSTEM PERFORMANCE

5.1 Introduction

Instead of evaluating LRTPs one time at the planning horizon, annual average and cumulative performance measures may be a more robust way to evaluate the overall performance of LRTPs and they can be calculated using models and analytical methods currently available to most transportation planning agencies. A travel demand and land-use model for the region of interest are required. Vehicle emission and air quality models are also required, and they are freely available from the U.S. EPA. In this chapter we demonstrate how these models can be used to evaluate the annual and cumulative impacts of an LRTP and discuss how this information can be used to perform a more robust analysis of LRTPs.

An important component of our modeling approach is the use of an integrated travel demand and land-use model. This model integration is critical for understanding how changes to travel demand and land-use co-evolve over time as population grows and new transportation infrastructure investments are made (Iacono, Levinson, and El-Geneidy 2008). For example, while it is well established that highway and transit capacity expansion and congestion relief projects can spur induced demand by lowering travel costs (Cervero 2003; Duranton and Turner 2011; Noland 2001), traditional travel demand models only capture induced demand from traffic re-routing and mode shifts (Kitamura 2009). An integrated transportation and land-use model can capture how a highway capacity project that reduces congestion will increase the likelihood that land along the highway is developed, leading to induced demand and increasing congestion in the future, all else equal. Modeling the evolution of travel demand and land-use also allows us to track year-by-year changes in transportation system performance measures. Furthermore, combining the integrated travel demand and land-use modeling results with vehicle emission and an air dispersion modeling allows us to track the changing concentrations of air pollutants across the planning area and the location of the population exposed to these emissions.

While prior studies have used integrated travel demand and land-use models to evaluate a range of transportation planning and policy questions (Abraham and Hunt 1999; Kakaraparthi Siva Karthik and Kockelman Kara M. 2011; Kitchen et al. 2011; Waddell et al. 2007), these analysis, like current LRTP practice, have used an “endpoint” perspective. While it is common to model some intermediate years en route to the final year in the planning period, the purpose in most studies is primarily for updating the land-use model with revised accessibility data. In most modeling systems, the land-use model requires travel costs (i.e., logsums) from an external travel demand model

(Iacono, Levinson, and El-Geneidy 2008). This requires the land-use and travel demand models to be iterated periodically, where the travel demand model is updated with revised population and employment data from the land-use model and then run to provide the land-use model with revised travel cost data. While interim year iterations create output that could be used to evaluate changes in the transportation system overtime, this is usually not done. For example, Kitchen et al. (2011) use an integrated land-use and travel demand modeling system to evaluate several regional transportation planning scenarios in the Seattle, WA metropolitan area over the period 2010 to 2040. They iterate the region's travel demand model with the UrbanSim land-use model every 5 to 10 years. Each planning scenario is then evaluated based on year 2040 performance metrics; interim year outputs are not discussed.

Many recent studies demonstrate the value of integrating vehicle emission, air dispersion and travel demand modeling for better understanding the air quality and public health impacts of vehicle traffic and transportation planning strategies and policies (Beckx et al. 2009; Dhondt et al. 2012; Dons et al. 2011; Hatzopoulou, Hao, and Miller 2011; Lefebvre et al. 2013; Poorfakhraei, Tayarani, and Rowangould 2017; Rowangould 2015; Shekarrizfard et al. 2017; Tayarani et al. 2016; Woodcock et al. 2009). However, very few of these evaluate how plans or policies affect air quality over time (Hatzopoulou, Hao, and Miller 2011; Poorfakhraei, Tayarani, and Rowangould 2017; Tayarani et al. 2016), and those that do have not considered annual changes or cumulative impacts. Most studies have focused on developing and validating integrated transportation and air quality modeling systems.

The remainder of this chapter discusses our methodology for combining land-use, travel demand, vehicle emission, and air dispersion modeling to evaluate annual and cumulative changes in common transportation system performance measures, GHG emissions, and fine particulate matter ($PM_{2.5}$) exposure for the Albuquerque, New Mexico metropolitan area. A LRTP scenario developed by the regional planning agency with a 2012 base year and year 2040 planning horizon is evaluated. We evaluate exposure to $PM_{2.5}$ from vehicle emissions because exposure to $PM_{2.5}$ from vehicle traffic is associated with many negative health outcomes (Brugge, John L. Durant, and Rioux 2007; HEI 2010) and because the research discussed in this paper is part of a larger and ongoing US EPA sponsored project focused on understanding the challenges of reducing exposure to both $PM_{2.5}$ and GHG emissions from transportation. Other vehicle emissions can be considered using a similar framework. We also compare year 2040 performance measures, GHG emissions, and $PM_{2.5}$ exposure estimated by iterating the land-use and travel demand models annually to when they are estimated using a typical endpoint approach (i.e., no interim year land-use and travel demand model iterations). Our study is the first that we are aware of that evaluates how travel behavior, land-use, and the air quality impacts of vehicle traffic evolve overtime in a metropolitan area. We argue that evaluating year-by-year changes and cumulative impacts can aid in the selection of higher performing LRTPs by considering impacts that occur between the beginning and end of long planning periods. This approach to modeling also allows planners and researchers the opportunity to better understand land-use and travel behavior dynamics, providing new opportunities for reducing traffic congestion, improving accessibility and mitigating air quality and climate change impacts by considering the timing of infrastructure, land-use, and policy implementation.

5.2 Methodology

We use the "trend" scenario from the Mid Region Council of Government's (MRCOG) LRTP "*Futures 2040 Metropolitan Transportation Plan"* as a case study for evaluating the annual change in common LRTP performance measures and cumulative air quality impacts.

[redacted] Integrated Modeling Framework

We use an integrated land-use, travel demand, vehicle emission, and exposure modeling framework to calculate transportation system and air quality performance measures (Figure 5-1). This integrated modeling framework can evaluate a wide range of planning and policy scenarios. The land-use model can consider different regional population growth and employment forecasts as well as changes to land-use zoning such as allowable densities, building heights, and land-uses. The travel demand model can forecast how travel behavior responds to changes in the transportation network and its capacity, new transit routes, and changes in the costs of travel, for example, from travel demand management policies. The vehicle emission model can evaluate changes in the composition of the vehicle fleet (age and vehicle type), fuel properties, and vehicle emission standards.

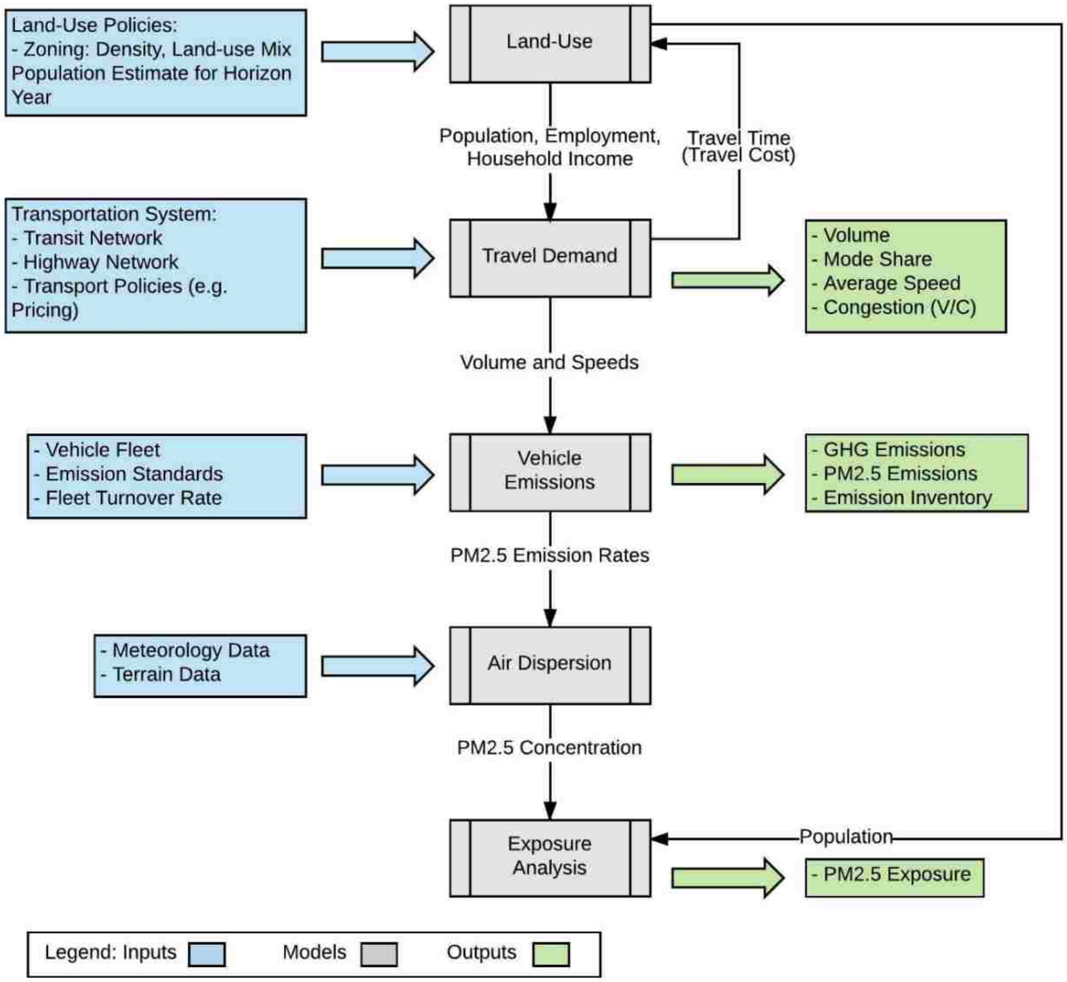

Figure 5-1 Integrated Modeling Framework

[redacted] Travel Demand and Land-Use Modeling

Congested network travel times estimated by a travel demand model are used as input by the land-use model to forecast changes in real estate prices and building locations and the corresponding changes in population, household income, and employment across the region (Table 5-1). Population, household income and employment forecasts from the land-use model are then used as input into future year travel demand modeling where they are inputs to functions used for estimating trip generation rates, origin-destination matrixes, and mode choice.

Table 5-1 Accessibility Variables Used in MRCOG's Parcel Based UrbanSim Land-use Model

Variable/Model	Residential Price	Residential Building Location Choice	Non-residential Price	Non-residential Building Location Choice	Employment Location Choice
Activity centers within 1/2 and 1 mile	E		E	E	E
Open space attractions within 1 mile		E			
Bus within 1/8 and 1/2 mile and	E		E	E	E
Interchange within 1/4 and 1 mile	E	E	E	E	
Major arterials within 1/2 mile					E
Park within 1/2 and 1/4 mile			E	E	E
Number of jobs within 10, 15, 30 and 35 minutes		T		T	T
Number of households within 10 minutes		T			
Occupancy rate within 10 minutes	T				
Population within 20 and 30 minutes	T			T	T
Travel time to CBD					T

E: variables that are not updated by the travel demand model (exogenous)
T: variables that are updated by the travel demand model

In our study we use MRCOG's 4-step, trip based, travel demand model for the Albuquerque metropolitan region. The model is a typical trip based model. The model includes the region's major highway and street networks (highways, arterials and collectors) and transit networks (bus, bus rapid transit, and regional commuter rail routes). The model estimates trip generation rates and origin-destination matrixes for 914 travel analysis zones (TAZs) that generally represent U.S. census tracks and includes a mode choice model that estimates single occupancy, carpool, transit, and non-motorized mode shares. Traffic is assigned to individual network links using a static user equilibrium method for the morning and afternoon peak commuting periods and the remaining off-peak times. The model is implemented in Citilab's CUBE modeling software and was calibrated and validated by MRCOG. The model's calibration and validation report available from MRCOG provides additional details about the model's structure and calibration (Systra Mobility 2010). In addition to supplying travel time data to the land-use model, traffic data from the travel demand model are also used to estimate common transportation system performance measures including, vehicle miles traveled (VMT), peak hour average speed, and transit, non-motorized, and vehicle mode shares.

MRCOG also developed and calibrated a parcel based version of the UrbanSim land-use model (Waddell et al. 2010). MRCOG's implementation of UrbanSim includes current zoning regulations and land-uses for each parcel in the Albuquerque metropolitan area. The model is connected to the travel demand model through its use of congested network travel times in many of its regression and choice functions (Table 5-1) and by supplying population, household income, and employment forecasts for each TAZ to the travel demand model. Longer travel times depress real estate prices and reduce the utility of developing real estate in a particular zone and less development results in less travel demand to and from a zone, all else being equal. This integration captures some of the ways in which land-use and transportation system changes affect each other.

[redacted] Air Quality Modeling

Traffic volume and average speed outputs from the travel demand model for each roadway segment are used with the U.S. EPA's MOVES model to estimate the total quantity of GHG and $PM_{2.5}$ emissions from vehicles traveling along each roadway in the region during each time period. The $PM_{2.5}$ emissions include primary $PM_{2.5}$ from vehicle exhaust, tire wear, and brake wear but does not include secondary $PM_{2.5}$ formed in the atmosphere from other components of vehicle exhaust. The MOVES model includes regional inputs describing the Albuquerque metropolitan area's vehicle fleet and vehicle inspection and maintenance program. We construct a vehicle emission rate lookup table by roadway type and average travel speed using MOVES, allowing us to more quickly calculate emission rates for each roadway segment. The emissions for each roadway segment are aggregated over all roadways in the Albuquerque metropolitan area, for all time periods, to estimate regional GHG and $PM_{2.5}$ emission inventories.

$PM_{2.5}$ emission rates for each roadway segment are also used as input to an air pollutant dispersion model to estimate the annual average ambient concentration of $PM_{2.5}$ attributable to vehicle traffic across the region. We use U.S. EPA's AERMOD dispersion model, which is a static gaussian plume model that can represent emissions from vehicle traffic as a series of area or volume sources. In our study we use the area source method, representing each roadway segment as a rectangular source with its width and length equal to that of the roadway segment. We place receptors every 100m over a regular grid. In our analysis, there are 9,093 roadway sources and 172,700 receptors, which adds up to over 1.5 billion source-receptor pairs. Since U.S. EPA AERMOD models each source-receptor pair individually, the large number of source-receptor pairs would ordinarily take an exceptionally long time to model (several months for each analysis year, over several years for the entire planning horizon). To overcome this limitation, we use a novel rastering approach that significantly reduces modeling times while closely following US EPA regulatory modeling guidance (Rowangould 2015). Point concentration estimates are interpolated from the 100m grid to a 20m resolution raster using empirical Bayesian kriging in ArcGIS. The interpolated raster aids in visualizing the results and for calculating the average $PM_{2.5}$ concentrations for each parcel in the region.

[redacted] Exposure Analysis

The final step in the modeling framework is determining $PM_{2.5}$ exposure. This involves co-determining the location of people and the concentration of $PM_{2.5}$. The population for each parcel is obtain from the output of the UrbanSim model. We use ArcGIS to estimate the average $PM_{2.5}$ concentration within each parcel by intersecting parcel boundaries with the interpolated $PM_{2.5}$ concentration raster. We also calculate the population weighted regional average exposure by summing the product of each parcel's estimated population and its average $PM_{2.5}$ concentration and dividing this sum by the region's total population.

[redacted] Comparing Endpoint and Annual Modeling Approaches

We model a single LRTP scenario for the Albuquerque metropolitan planning area that represents a business-as-usual strategy for the region, one that focuses largely on expanding highway capacity, includes a new bus rapid transit route, and leaves land-use zoning and other policies as they exist today. The scenario was developed by MRCOG as part of its 2040 Metropolitan Transportation Plan (Mid-Region Council of Governments 2015). We model this planning scenario using two different approaches: a typical “endpoint” approach and what we refer to as an “annual” approach. The purpose is twofold. First, we evaluate how each approach affects transportation and air quality performance measures calculated in the final year of the planning period. Additionally, we investigate the robustness of measuring a plan’s performance during the final year of the planning period. The annual modeling approach allows us to evaluate the performance of a plan throughout the planning period by modeling annual changes in performance measures, making it possible to estimate annual average and cumulative performance measures. We compare how the performance of a plan in its final year compares to its overall performance throughout the planning period.

For the endpoint modeling approach, we use the integrated modeling framework discuss in section 5.2.1 above; however, we only perform one iteration between the travel demand model and the land-use model. The modeling begins with the development of a base year travel demand modeling run for the year 2012. This model run includes the region’s existing transportation network, policies, household characteristics, and population and employment distribution. Travel time outputs from the 2012 travel demand modeling run are then input into UrbanSim which simulates residential and commercial building location choice and prices, and associated changes in population and employment at the parcel level on an annual basis from 2013 to 2040. The 2040 parcel level output from UrbanSim are aggregated to TAZs and used as input to a 2040 run of the travel demand model. The 2040 travel demand model run also includes an updated transportation network that reflects any new projects built between 2012 and 2040 and any new transportation policies.

The annual modeling approach described above is representative of typical transportation planning practice in many regions, including those that do not use land-use models to generate future year socioeconomic inputs for their travel demand models. Like the process used in many regions, the travel demand model is only run twice for a given scenario – it is run for the base year and the final year of the planning period. All projects and policy changes are modeled together in the final year of the plan, even though they are implemented incrementally overtime, thus ignoring interim year outcomes and the dynamic relationship between land-use and transportation. Some regions do model interim years; however, the main purpose is usually for updating a land-use model rather than evaluating interim year performance. In these cases, its common to iterate travel demand and land-use models every five years, with the range in the studies we evaluated being between three to ten years (Abraham and Hunt 1999; Kakaraparthi Siva Karthik and Kockelman Kara M. 2011; Kitchen et al. 2011; Troy et al. 2012; Waddell et al. 2010; Waddell et al. 2007; Zondag and de Jong 2011).

The annual approach uses the same integrated modeling approach as the endpoint approach, however, the travel demand and land-use models are iterated annually from 2012 until 2040. In each iteration, the travel demand model is updated with population and employment data from a new run of the land-use model and the transportation network is updated with projects expected to be built during that year. The travel demand modeling outputs for each year are then used to estimate performance measures for that year and provide travel cost data for the next run of the land-use model. This modeling approach is shown along with the endpoint approach in Figure 5-2.

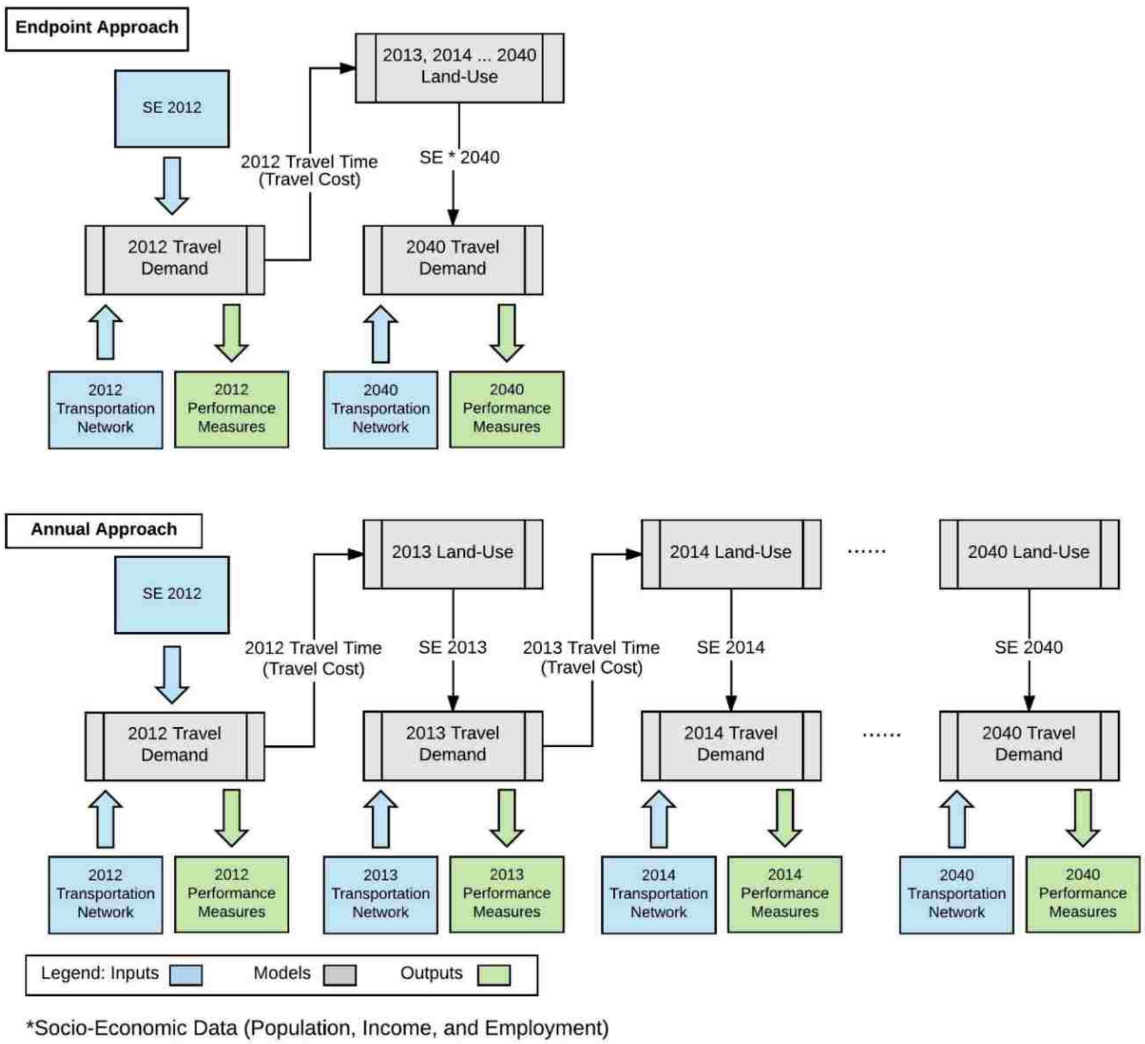

Figure 5-2 Overview of Endpoint and Annual Modeling Approaches

In addition to generating data for calculating performance metrics on an annual basis, the greater level of land-use model integration in the annual approach provides a more realistic treatment of the interaction between land-use and travel demand. One outcome of the greater level of integration is that we expect that performance measures calculated for the last year of the planning period to differ between the annual and endpoint approaches. For example, if congestion grows significantly overtime in the annual approach, the parcels in the land-use model that are further away from travel destinations will be relatively less attractive and therefore a greater level of development and population growth should occur closer to major travel destinations such as large employment centers. As a result, the region should grow more compactly which may also result in less travel demand and greater transit and non-motorized mode share.

Scheduling Transportation Projects

The annual modeling approach requires scheduling projects to be built in each year. MRCOG’s 2040 Metropolitan Transportation Plan contains a fiscally constrained list of projects to be completed by the 2040 planning horizon year but not an annual schedule. The plan does organize projects into one of three time periods: “funded” projects that are scheduled to be completed between 2012-2021; “near term” projects that are expected to be completed between 2015-2025; and “late term” projects that are expected to be completed between 2025-2040. Projects are also categorized by one of eight types: highway and bridge preservation, capacity, bicycle and pedestrian, transit, intelligent transportation system, travel demand management, safety, and other projects.

We develop more refined, annual, project schedules for each of the three broad implementation time periods in MRCOG’s plan. MRCOG’s plan provides share of total funding for each of 8 project types (Table 5-2) as well as the total funding available each year. To create our annualized schedule, we assume that the share of funding by project type remains constant each year. For each of the three implementation periods, we then randomly assign projects to each year in the period until the budget for each project type is met. Next, we review the project schedules and adjust for multipart projects that require a specific implementation order.

Table 5-2 Budget Allocation for Transportation Projects in MRCOG's LRTP

Project Type	**Proportion of Total Budget**
Bike/Ped	5.2%
Highway Capacity	20.4%
Highway and Bridge Preservation	32.0%
Intelligent Transportation System (ITS)	3.0%
Safety	1.6%
Travel Demand Management	0.7%
Transit	35.6%
Miscellaneous	1.5%
Total estimated cost for all projects	$5,087,266,371

Using our annual project schedule, we define travel demand modeling runs for each year. For each travel demand modeling run, we include infrastructure projects that make physical changes to the region's transportation system such as highway and bridge projects that add new capacity, changes that affect intersection operations, changes to speed limits, or transit projects. Other projects such as highway maintenance (e.g., paving) and safety projects (e.g., adding street lighting and public education campaigns) are assumed to have minimal, if any impact on travel demand or behavior and therefore are not modeled. However, these projects are still included in our annual project implementation schedule for the purpose of constraining the annual budget.

Overall, we model the addition of 175 lane-miles of new roadways and 108 lanes-miles of capacity expansion to the 4,441 lanes-mile of existing roadways in the region. There are also numerous intersection and highway interchange projects. Also included are 140 miles of new transit routes added to the 600 miles of existing transit routes as well as new park and ride facilities. Transit lines also receive a 10-50 percent improvement in the existing 10-60 minute headways. Intelligent transportation system (ITS) projects such as installing traffic signals are also modeled by updating individual intersection delay functions in the travel demand model.

One limitation we faced in modeling specific infrastructure projects is that MRCOG's travel demand model does not include non-motorized infrastructure (e.g., bicycle lanes and sidewalks) and it is therefore not able to forecast the effects of these investments. It is possible to complete an off-model analysis to estimate the broad effect of these types of investments; however, we have not done that here since we are interested in evaluating the effect of the scheduling of individual projects and policies. There were also several travel demand management and ITS projects that faced similar modeling limitations. For example, the construction of a regional traffic management center.

5.3 Results

The modeling results indicate that changes in vehicle emissions, $PM_{2.5}$ exposure, and common mobility performance metrics exhibit non-linear, and sometimes complex changes, over the course of the planning period.

Figure 5-3 indicates that in the earlier years of the planning period GHG emissions rise before falling and then eventually rise again. In this case, the rising and falling emission rates in the annual approach tend to balance each other out over time, and the result is that the cumulative GHG emissions over the 28 year planning period are only 1.7 percent less than those based on a linear extrapolation of the endpoint analysis. The cumulative GHG emissions would have been significantly different had a different planning horizon year been chosen; for example, the year 2030. The annual approach also ends up estimating a slightly lower GHG emission rate by 2040, though the difference is only about 1 percent.

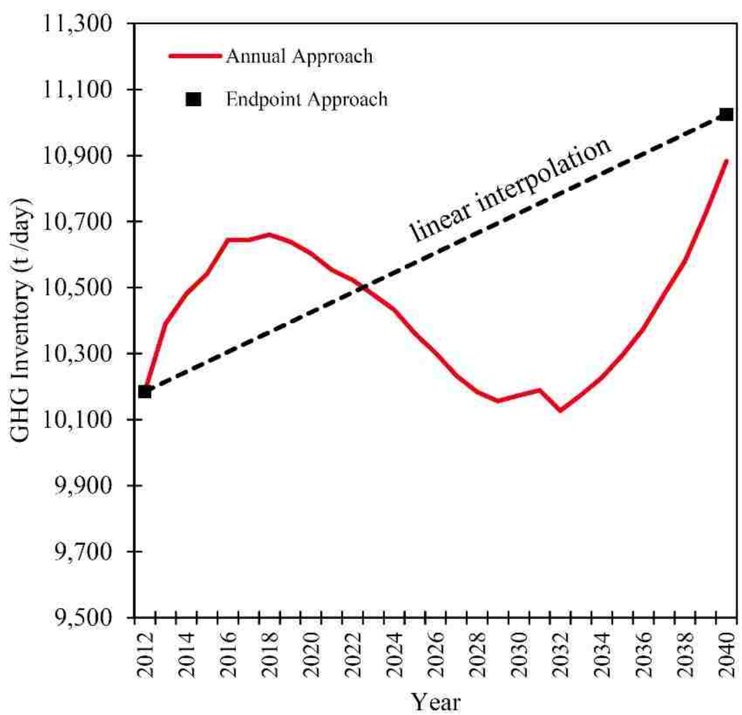

Figure 5-3 Daily GHG Emissions Inventory

Figure 5-4 shows that $PM_{2.5}$ emissions also deviate from a linear trend between 2012 to 2040, displaying exponential decay though about the year 2030. After 2030, emissions begin to slowly increase. In this case, calculating the cumulative $PM_{2.5}$ emissions over the 28 year planning periods based on a linear extrapolation of the endpoint approach would overestimate $PM_{2.5}$ emissions by 1,451 tons or 38 percent. Similar to the GHG emission results, year 2040 $PM_{2.5}$ emissions are about the same under both analysis methods. This result is attributed to the 80 percent reduction in gram per mile $PM_{2.5}$ emission rates that occur over the planning period which overwhelms the more subtle differences in travel demand and congestion produced by the two modeling approaches which also affect $PM_{2.5}$ emissions.

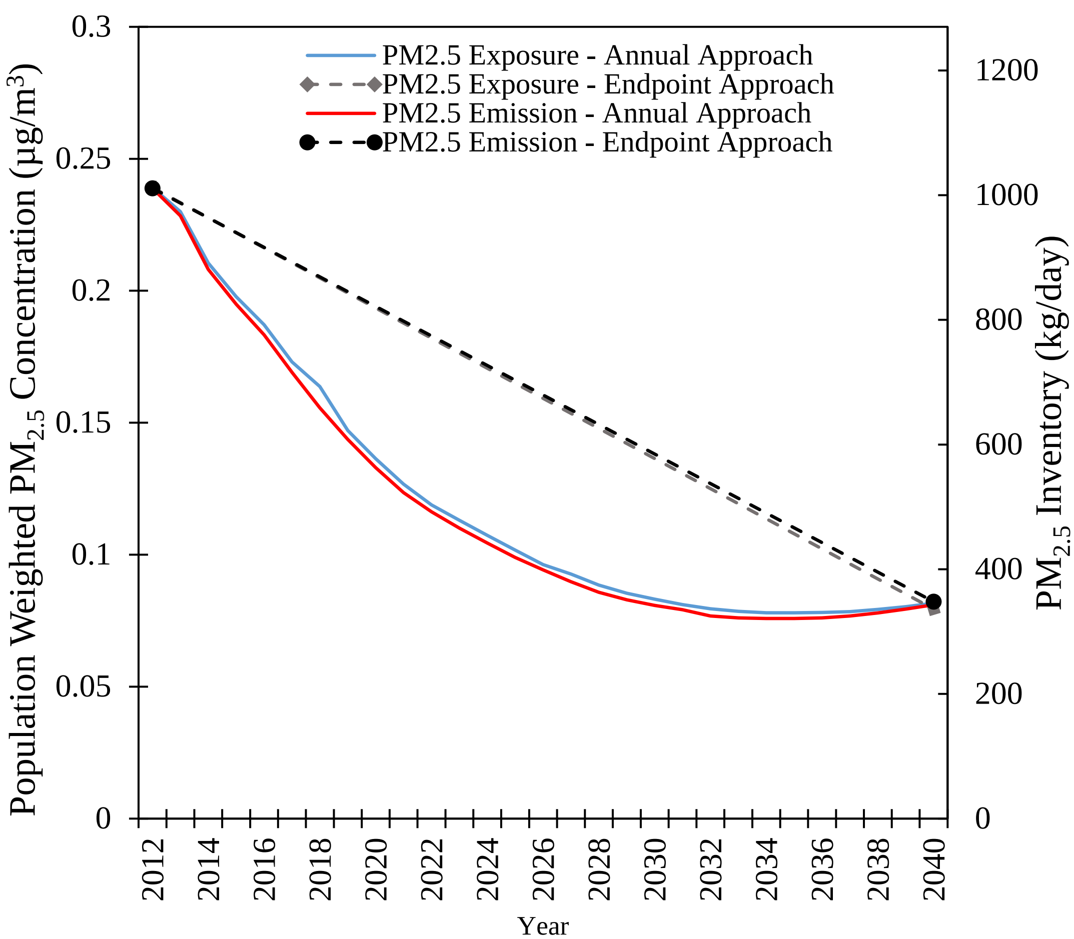

Figure 5-4 Daily $PM_{2.5}$ Inventory and Daily Population Weighed $PM_{2.5}$ Mean Concentration

Figure 5-4 also shows how $PM_{2.5}$ exposure changes over time. The trends over time are generally the same as those for $PM_{2.5}$ emissions. Large exposure reductions occur in the first half of the planning period, and then exposure begins to rise in the final years. A linear extrapolation of the endpoint approach would result in a 47 percent over estimation of population exposure. There are some differences, however, from the $PM_{2.5}$ emissions results. One difference is that the annual approach results in 5.3 percent lower exposure by 2040 than the endpoint approach while the annual approach only produced 1.3 percent fewer $PM_{2.5}$ emissions. This indicates that the annual approach causes changes in either traffic or land-use patterns, or both, that decrease exposure in addition to decreasing the quantity of $PM_{2.5}$ emitted.

Figure 5-5 compares how travel demand modeling outcomes change throughout the planning horizon and vary between the annual and endpoint approaches. Each point corresponds to a performance measure and shows the percentage change from the 2012 baseline value. The results indicate that the change in VMT, vehicle mode share, and average travel speed generally follow a linear pattern which end up being very close to the endpoint approach values by year 2040, which are shown as circles on the right side of the plot. For non-motorized and transit mode share, the annual changes do not follow linear trends and they deviate more significantly from the endpoint values by 2040. Transit mode share generally increases overtime, but there are periods of relatively rapid increases and also periods of slow decline. The complex transit mode share trend is caused by the relatively few, major, transit projects included in the LRTP as compared to the many highway projects. Increases in transit mode share generally follow major transit investments, but then stagnate or decline as investments in highway capacity continue each year. Non-motorized mode share increase by a few percent in the first years of the planning period and then stagnates. This trend may be the result of increasing population density in the initial years of the planning horizon that along with no new transit investments results in non-motorized travel being relatively attractive. Overtime, as population density continues to increase and new transit investments are made, growth in non-motorized mode share may be substituted for growth in transit mode share. Furthermore, the annual approach results in significantly higher transit and non-motorized mode share than the endpoint approach: 7% and 15%, respectively. These differences may be caused by the different treatment of land-use and transportation system evolution that results in the annual approach producing more compact growth, which is more favorable for transit and non-motorized travel.

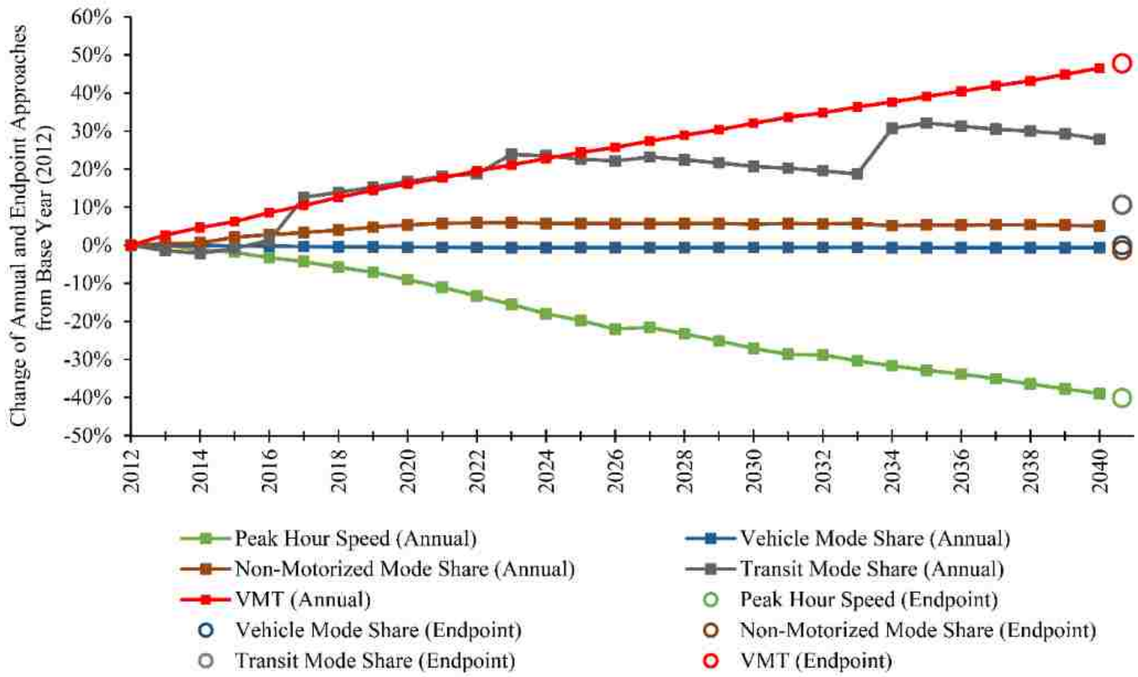

Figure 5-5 Percent Change in Travel Demand Indicators under Annual and Endpoint Approaches

Table 5-3 provides a summary of the regional mobility, emission, and exposure performance metrics produced by the two modeling approaches in the year 2040 as well as annual average performance metrics. The annual average metrics are a simple way to summarize how the plan performs on average throughout the planning period. Differences between the annual average and end of planning period performance metrics indicate instances where the usual endpoint may not be robust. While for some measures the annual average values are close to the year 2040 values, there are relatively large differences for others. For example, annual average $PM_{2.5}$ exposure is 46% higher, average speeds are 32% higher, VMT is 15% lower, and average GHG emissions are 4% lower than year 2040 estimates. The endpoint metrics seem to overstate the improvements in $PM_{2.5}$ exposure, increases in GHG emissions and VMT, and deterioration of travel speeds.

While annual average and the previously discussed cumulative outcomes provide potentially more robust methods for evaluating the performance of an LRTP, and particularly its emission and air quality impacts, they also face limitations. The endpoint and average metrics both fail to provide important trend information that is available from plotting the performance measure overtime. For example, even though $PM_{2.5}$ exposure is much lower than it was in 2012 by 2040 and on average throughout the planning period, it is trending up in the final years of the planning period. In the case of GHG emissions, endpoint and annual average metrics seem to indicate slowly increasing annual emission rates while the time series in Figure 5-3 shows rates rapidly increasing during the final years of the planning period (a 7.5% increase in the final eight years).

Table 5-3 Travel Demand and Emission Indicators under Endpoint and Annual Modeling Scenarios by Year 2040

Indicators	2040 Endpoint	2040 Annual	Annual Average
VMT	28,769,197	28,528,129 (-0.84%)[a]	24,326,361 (-14.7%)[b]
Vehicle Mode Share	93.21%	92.67% (-0.58%)	92.79% (0.13%)
Non-Motorized Mode Share	5.62%	5.99% (6.6%)	5.97% (-0.33%)
Transit Mode Share	1.17%	1.34% (14.5%)	1.24% (-7.5%)
% of Population Living Within 0.5 Mile of Highways	11.90%	12.73% (7.0%)	12.42% (-2.4%)
Peak Hour Speed (MPH)	22.78	23.22 (1.9%)	30.67 (32.1%)
Population Weighted Concentration (μg/m^3)	0.079	0.082 (3.8%)	0.12 (46.3%)
Daily $PM_{2.5}$ (kg/day)	348.00	343.00 (-1.4%)	498.72 (45.4%)
Daily GHG (t/day)	11,025	10,883 (-1.3%)	10,422 (-4.2%)

[a] percentage change from endpoint approach
[b] percentage change from 2040 Annual

We also evaluate spatial changes traffic volume, travel speed, $PM_{2.5}$ concentration, and population density across the region. Figure 5-6 shows the difference in these metrics for the year 2040 between the annual and endpoint modeling approaches. The annual approach results in more congestion (high volumes and slower speeds) in Albuquerque's downtown and along major highway corridors where many of the region's employment and other activity centers are located such as Journal Center. As a result, the annual approach results in higher $PM_{2.5}$ concentrations along major highways and in Downtown areas. Much lower emissions are seen in more outlying areas. This result provides evidence that the annual modeling approach responds to congestion by growing the region more compactly and closer to major activity centers as we expected. This can also be seen from the population density map that displays the change in population between the two modeling approaches. Although the pattern is somewhat difficult to see the change in population density is generally greater in the urban core and along major highway corridors near the region's activity centers.

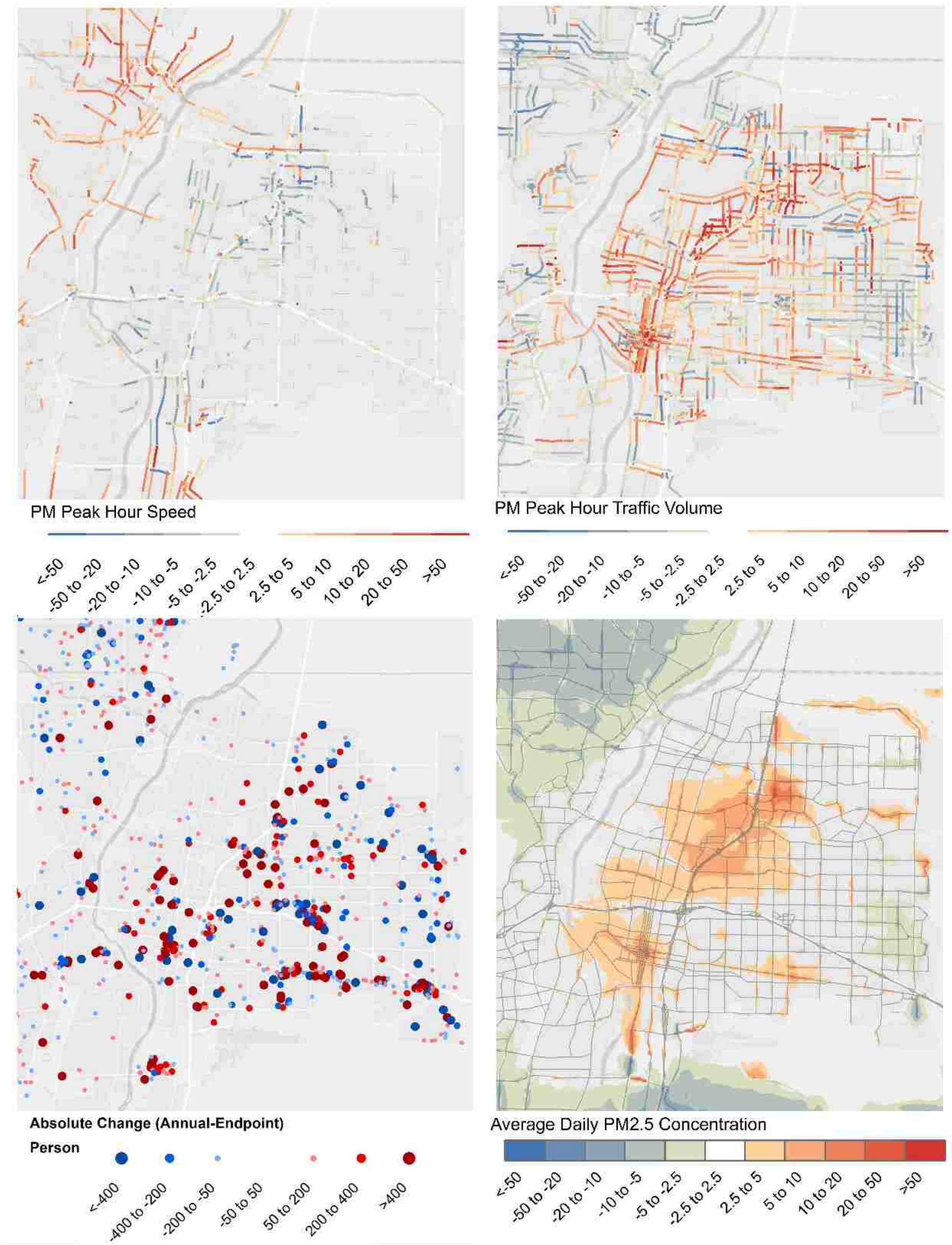

Figure 5-6 Changes in PM Peak Hour Traffic Volume and Speed, Population, and Average Daily $PM_{2.5}$ Concentration by Year 2040 Between the Annual and Endpoint Modeling Approaches

The annual modeling approach also allowed us to view the change in $PM_{2.5}$

concentration over time and space (Figure 5-7). The results show, unsurprisingly, that concentrations are highest along the region's highest volume roadways and lower elsewhere. Over the first 10 years of the planning period, emissions decline rapidly everywhere. After that, concentrations remain about the same with small increases and decreases along individual roadways.

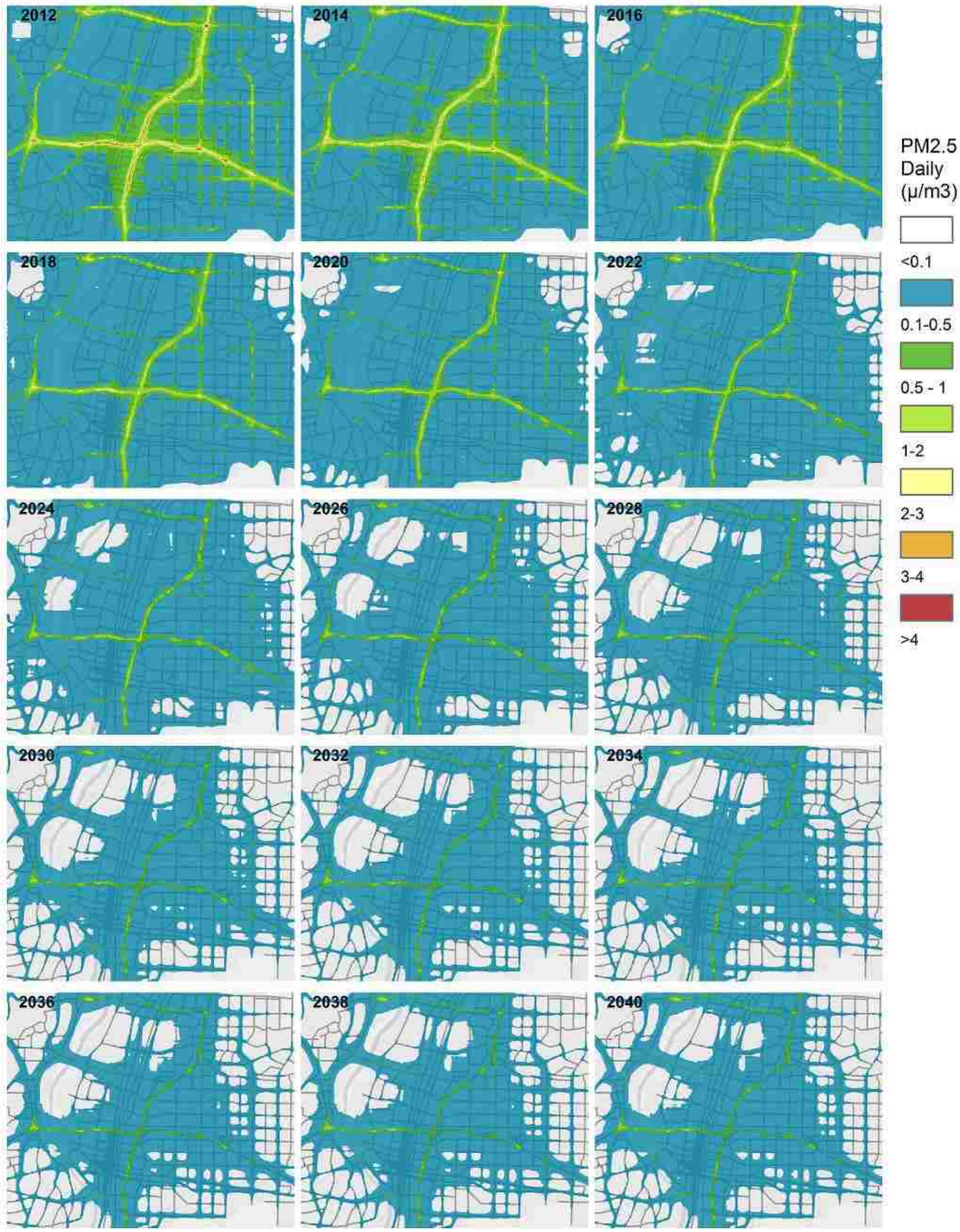

Figure 5-7 Average Daily $PM_{2.5}$ Concentrations Based on the Annual Approach

5.4 Discussion

We evaluate an LRTP using a standard endpoint approach and an annual approach. While for most of the performance measures we evaluated the two methods produce similar results by the final year of the planning period, there are important differences. First, the two modeling approaches imply different pathways through the planning period. The endpoint approach implies a linear trend from the baseline year to the final year of the planning period. Our results demonstrate that trends over time can be highly non-linear and quite complex, particularly for changes in vehicle emissions, exposure, and transit and non-motorized mode shares. The nonlinear change over time means that the value of a performance measure during the planning horizon year may not be a robust or accurate measure of a plan's performance throughout the entire planning horizon. That is, the typical endpoint approach may fail to identify the best plans when multiple plans are being considered – those that result in the greatest annual average or cumulative performance or greatest overall welfare gain. The endpoint approach can also result in over or underestimating the value of common performance measures in the planning horizon year because it also has a less robust treatment of how travel demand and land-use co-evolve over time. In our case, increasing traffic congestion and a limited amount of highway capacity investment results in the annual approach forecasting a more compact region by 2040 than the endpoint approach.

The differences in the two modeling approaches may have important planning and policy implications. The typical endpoint approach is not as well suited for evaluating how LRTPs affect GHG emissions since the accumulation of emissions overtime is not considered. Yet, it is the accumulation of GHG in the atmosphere overtime that results in climate change. Similarly, the endpoint approach fails to consider exposure to toxic vehicle emissions that impacts the population's health throughout the planning horizon. Cleaner air in 2040 does not eliminate negative health outcomes that occurred previously just as fewer GHG emissions in the future will not eliminate GHG emissions already in the atmosphere. The best plans should therefore minimize emissions and exposure throughout the planning period. Identifying the best plan then requires evaluating performance throughout the planning period. Annual average and cumulative performance measures offer a simple way to summarize performance throughout the planning period; however, evaluating time series plots can provide information about problematic interim years and hint at trends that may continue beyond the current planning period.

Besides providing more robust performance measures, the annual modeling approach provides a more realistic treatment of how land-use and travel demand evolve overtime. In our specific case, this difference results in relatively small changes in the value of performance measures from the typical endpoint approach. The differences could be larger under different circumstances; for example, in a region expected to grow more quickly, with much greater traffic congestion, or where more significant infrastructure or policy changes are being implemented. The annual modeling approach did result in a very different distribution of $PM_{2.5}$ concentration and land-use across the region. The annual modeling approach forecasted a more compact region, with greater population density in the urban core and along major roadways where activity centers are located and lower average $PM_{2.5}$ exposure. The annual approach may therefore provide more accurate emission and exposure forecasts. The change in spatial concentration patterns and land-use may also affect the outcome of regional environmental justice and other equity analysis.

CHAPTER 6

DIFFERENCES IN EXPOSURE TO VEHICLE EMISSIONS: COMPARING DYNAMIC ANALYSIS TO CONVENTIONAL STATIC EXPOSURE ANALYSIS AT THE HOME ADDRESS

6.1 Introduction

Several methods have been used to estimate emission concentrations in urban areas and their impacts on population exposure and health outcomes. Estimating population exposure to vehicle emission is not an easy task owing to the complex temporal and spatial pattern of vehicle emissions and the population that is exposed to them. There is substantial evidence that the concentration of vehicle emissions are generally elevated along roadways by up to 50% above background values and sharply decline within 250-500 meters from the edge of the road (Karner, Eisinger, and Niemeier 2010; Zhou and Levy 2007). In addition, the travel patterns of people during their daily activities adds extra complexity to the estimation of population exposure to vehicle emissions. The current trend in the academic literature and professional practice is to use more and more spatially and temporarily detailed traffic, land use, and exposure models to address these complexities. Although these models may produce more accurate and spatially precise exposure estimates, they can be extremely complex and data hungry.

The research presented in this chapter focuses on developing a refined exposure method for investigating the patterns of daily activity with the aim of evaluating the exposure to vehicle emissions more accurately.

The need for more refined exposure methods has been noticed in the literature. Thus, more spatially refined modeling methods such as air dispersion modeling and LUR modeling methods are replacing fixed-monitoring or surrogate methods to provide more accurate exposure estimates. These methods, although costly, better reflect the spatial resolution of air pollution concentration over urban areas.

Although attempts have been made to develop dynamic exposure methods, there is still very little evidence on how the errors that may occur when using static exposure methods to evaluate exposure to air pollutants and health impacts. In addition, prior studies do not always consider exposure during travel time or make simplifying assumptions about it. Modeling exposure during travel can be difficult because travel activity data at the individual level are rarely available (Lefebvre et al. 2013) and modeling exposure during travel time requires calculating pollutant concentrations for tens to hundreds of links for each individual trip, requiring billions of calculations for a mid-size city, and is further complicated if differences in in-vehicle and out-of-vehicle air pollutant concentrations are considered. Prior studies (Gurram, Stuart, and Pinjari 2014; Shekarrizfard, Faghih-Imani, and Hatzopoulou 2016) calculate exposure using routes determined from user equilibrium traffic assignment methods, the shortest path between origins and destinations (Beckx et al. 2009; Gurram, Stuart, and Pinjari 2014; Shekarrizfard, Faghih-Imani, and Hatzopoulou 2016), or the average network concertation (Dhondt et al. 2012). The shortest path may diverge significantly from the actual route used by travelers(Ortúzar and Willumsen 2011).

Some prior studies have evaluated population using variety of dynamic methods such as activity based model, cell phone data, personal monitoring, and surveying. They find few differences between dynamic and static modeling approaches. However, these studies mostly focused on relatively dense and compact urban areas in Europe and Canada, and not the more sprawling urban areas in the US. Furthermore, prior studies have not explored in much detail the various contributing factors to differences between static and dynamic methods.

We develop a dynamic exposure model for the Atlanta metropolitan area using the knowledge on activity patterns and traffic assignment to determine to what extent and for what cases it could improve the estimate of population exposure. Although we model $PM_{2.5}$ because of its significant association with several negative health outcomes, the method could be used for any other nonreactive pollutant in vehicle emissions. We first evaluate how the dynamic and static exposure methods differed in estimating a population's exposure to vehicle emissions and then investigate the details that made the difference. We find that providing a more refined exposure model would affect the evaluation of long range transportation plans and health analysis.

6.2 Methodology

Two exposure modeling approaches, static and dynamic, are developed for the Atlanta metropolitan area for the year 2017 to determine how providing high-resolution activity pattern data affects the estimation of population exposure to vehicle emissions. Both approaches start with estimating traffic volume and speed and vehicle emission rates.

We then model the pollution concentration using a dispersion model. The exposure modeling step is where the two approaches deviate from each other. Whereas the dynamic approach tracks the trajectories of every individual, the static approach only estimates the exposure at home locations.

To develop the dynamic exposure model, we need to identify where people are throughout the day and how they travel. This type of information can be obtained from an activity-based travel demand model (ABMs). ABM are an agent-based models that retain information on each agent's movement throughout the day. The agent-based Atlanta Region Commission (ARC-ABM) was developed using the CT-RAMP platform (Coordinated Travel-Regional Activity Modeling Platform (CT-RAMP)) in a microsimulation framework. The platform is characterized by the ability to fully simulate travel decisions at both the household and the person levels, modeling activities at half-hour time increments and considering intra-household travel interactions. These characteristics make the ARC-ABM a suitable choice for the purpose of our study.

The model first synthesizes the population at both the household and the person levels using data from the US Census and a household travel survey (HTS). The HTS data include the total number of households in four-income quartile groups, the average income in each quartile, and the population in five age categories. These data used to control the synthesized population. The synthesized population is classified into eight person-type groups using the HTS data including: full time worker, part-time worker, college student, non-working adult, non-working senior, driving age student, non-driving student, pre-school. The model then predicts long-term choices including workplace/university/school at the individual level and car ownership at the household level. The HTS data also classify daily activities into 16 groups, which is cumbersome to work with and, therefore, only 10 types of daily activities are used in the model: work, grade school, high school, university, escorting, shopping, eat out, other maintenance, social and other discretionary activities. The model also classifies activities into three groups for defining tours: mandatory, non-mandatory, and home. These classifications help the model understand which type of person conducts what type of activity and the relative importance and flexibility of the activity. The work and school activities are mostly considered mandatory, whereas other activities have higher flexibility in terms of where and when they happen. The model assigns tours to each individual and defines the frequency and time of day for each mandatory tour.

The CT-RAMP platform can link the daily pattern-type choices of household members so that decisions made by one member are reflected in the decisions made by the other members. Thus, the model prioritizes any mandatory tour, either for a person or for other household members, over non-mandatory ones and uses the overlapping individual residual time windows for each household member to assign joint tours. The model then assigns the time of stops for each tour at half-hour time increments, the trip departure time, trip mode (driving alone, HOV2, HOV3, transit, and walk/bike trips), and parking location for auto trips. The assignment sub-model then assigns the trips to highways or transit networks to estimate the traffic volume and speed on each network link for five time periods: early morning (3:00 AM to 5:59 AM), AM (6:00 AM to 9:59

AM), midday (10:00 AM to 2:59 PM), PM (3:00 PM to 6:59 PM), and evening/late night (7:00 PM to 2:59 AM).

Estimating the dynamic exposure for about 5 million individuals is a time-consuming process that could take several months to complete. Thus, we randomly select a sample of 5% of the population from every TAZ. We also exclude individuals who make transit trips during the day since the data on individual's transit trips were not available from ARC. Results from the statistic of comparing the sample and the population means show that the 5% random sample represents the population in terms of both socioeconomic and travel behavior characteristics; since the computed *z* and *t* test variables do not exceed the "test values" obtained from normal and student's-t distribution tables, we could infer that the differences between the mean values of the sample and the population are insignificant (Table 6-1).

Table 6-1 Population and Sample Data Profile

	Complete Data	5% Sample Data	Statistic Test
Household Income			
<$20,000	6.63%	6.65%	0.36[b]
$20,000-$49,999	24.57%	24.76%	1.85[b]
$50,000-$99,999	40.03%	39.90%	1.17[b]
$100,000+	28.77%	28.68%	0.88[b]
Age	39.00	38.98	0.47[c]
Gender (% of Female)	50.91%	51.02%	0.97[b]
Household Size			
1-2	38.58%	38.67%	0.82[b]
3-4	44.07%	43.93%	1.25[b]
5 and more	17.35%	17.40%	0.58[b]
Occupation			
student of driving age	4.19%	4.11%	1.76[b]
student of non-driving age	7.40%	7.31%	1.52[b]
University student	3.89%	3.84%	1.14[b]
Worker (full and prat time)	63.23%	63.39%	1.47[b]
Non-worker	9.40%	9.40%	0[a]
Average Trip Distance (mile)	7.74	7.72	1.31[a]
Trip Purpose			

Home	32.19%	32.19%	0 [b]
Work	20.47%	20.55%	0.88 [b]
Educational	3.13%	3.10%	0.76 [b]
other	44.21%	44.16%	0.45 [b]

[a] t-static value; [b] z-statistic value; z value from standard normal distribution table 1.96; t value from Student's-t Distribution table 2.807

The trip diary contains information about the origin and destination of each trip an individual makes, and departure time of the trip. The data, however, do not contain information about the duration of each activity. To estimate the duration of activities, we first chronologically sort the individual daily trips starting from the first one to the last trip and by chaining the individual trips together, we calculate the duration of activities by subtracting the departure time of the following trip from the departure time of the preceding trip minus the travel time. To estimate the exposure during travel time, we run the assignment step of the travel demand model to obtain the path between each pair of O-D under the user-equilibrium condition, considering the time of day. We use the shortest path for walk/bike trips assuming these trips use the shortest path between O-D pairs. Moreover, for trips that start and end within a TAZ, for which there are no routes from the assignment model, we assume that the concentration during travel times is equal to the average concentration of that TAZ. The assignment step also provides us with the traffic volume and speed on each network link, which are then used to calculate the $PM_{2.5}$ concentration surface.

[redacted] Air Quality Modeling

To estimate population exposure to vehicle emissions, we first need to calculate the concentration of $PM_{2.5}$ from vehicle traffic. We use US EPA’s Motor Vehicle Emission Simulator (MOVES) to estimate the vehicle emission rates for each roadway segment.

MOVES is tailored with a regional vehicle fleet, travel activity data, fuel, meteorology, and inspection/maintenance program information. To create a $PM_{2.5}$ emission rate, we use a lookup table that tabulates emission rates in 5 mi/h increments for urban restricted access, urban unrestricted access, rural restricted access, and rural unrestricted access roadway types. The lookup table allows us to quickly assign the average emission rates to each roadway link, which is required for calculating the link level emission rates for input into US EPA's AERMOD dispersion model, which estimates the concentration of traffic-related $PM_{2.5}$ over the study area. AERMOD models the concentration contribution of each source at a receptor independently. However, modeling each source-receptor pair exceeds feasible computational times (months to years). Our prior work discusses the development and implementation of a novel rastering approach, which tackles the AERMOD computational limitation (Rowangould 2015) and its regional transportation planning applications (Poorfakhraei, Tayarani, and Rowangould 2017; Tayarani et al. 2016). We then create a 20-m resolution $PM_{2.5}$ concentration raster across the entire region. For the Atlanta area, $PM_{2.5}$ concentration surfaces are calculated for the five time-of-day periods that the travel demand model considers. We estimate the average $PM_{2.5}$ concentration, which, unsurprisingly is highest along the region's highest volume roadways and is lower elsewhere. Figure 6-1 shows that the $PM_{2.5}$ concentration is higher in both AM and PM peak hours because of higher traffic volume combined with lower speed during peak hour periods and because of meteorological conditions.

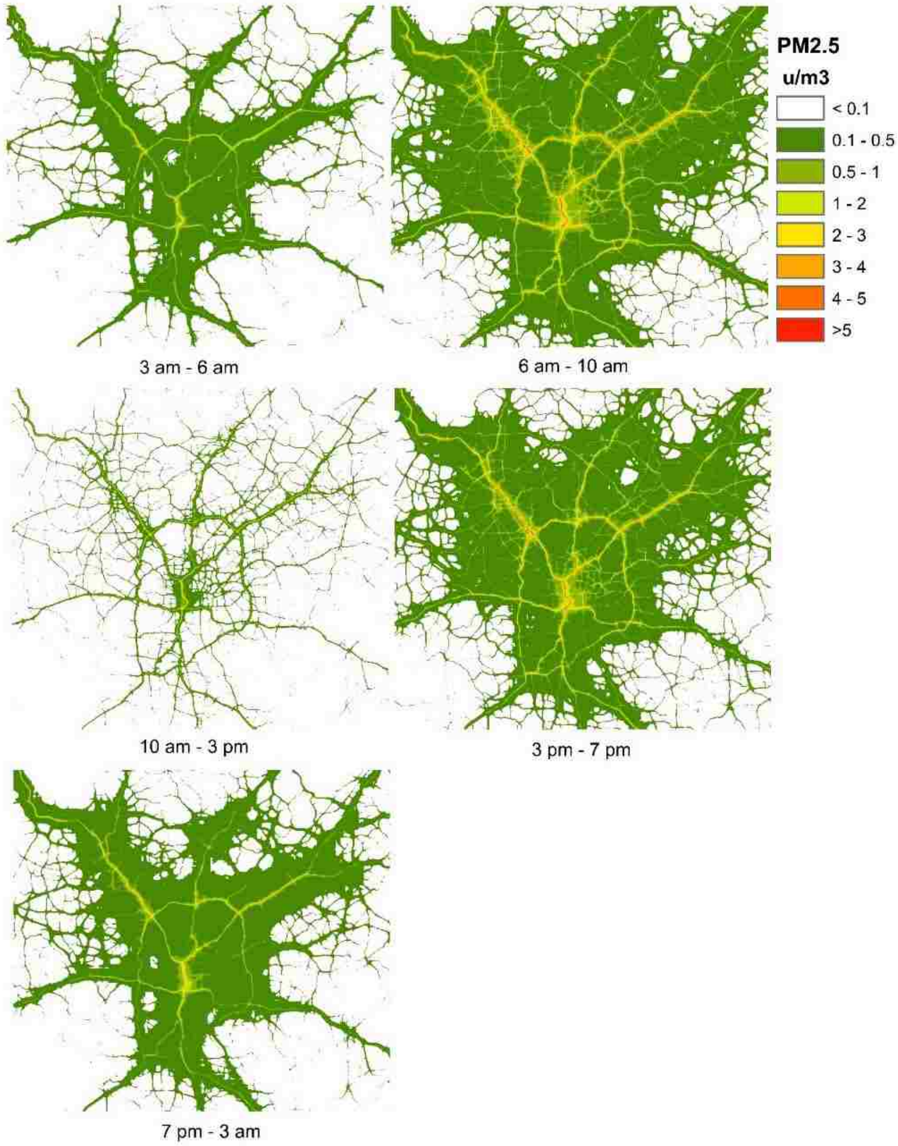

Figure 6-1 $PM_{2.5}$ concentration from motor vehicle exhaust for ARC region in the year 2017 by time of day

We develop static and dynamic exposure methods. We then disaggregate each individual's daily exposure by activity type to evaluate how the two methods differ in estimating the exposure to vehicle emissions.

[redacted] Static Exposure Method

The static method calculates an individual's exposure to vehicle emissions by estimating the average daily $PM_{2.5}$ concentration of a TAZ. We then assume that each person's exposure is equal to the average concentration in the TAZ where they live. To estimate the average daily exposure, we use ArcMap10.3.1 to intersect the TAZ population shapefile with the average daily $PM_{2.5}$ concentration surface raster provided by the air-quality modeling step. The TAZ population is obtained from the trip diary database, which contains the home address for each person. The zonal statistics tool in ArcMap estimates the average $PM_{2.5}$ concentration for each TAZ as the average value of raster cells falling within each TAZ boundary.

[redacted] Dynamic Exposure Method

The dynamic exposure method calculates the exposure for each individual at a TAZ where an individual spends time throughout the day plus the exposure during travel time. We estimate the exposure during activities by summing the average $PM_{2.5}$ concentration at the TAZs where the activities take place at half-hour time increments. We also subtract the travel time from the activity duration since the exposure during travel time is estimated separately. To calculate exposure during travel time, we use trip routes from the assignment step in the travel demand model. The traffic assignment step provides a path between each pair of O-D, considering the time of day. The paths are merged with the individuals' trip diary, which consists of the origins and destinations for trips made by an individual during the day. We then estimate the pollutant concertation at the transportation network links' centerline by intersecting the transportation network shapefile with the $PM_{2.5}$ concentration surface raster and then multiply it by the travel time on the link, considering the travel speed. The total travel exposure is equal to the sum of exposures from all the links on the travel route.

Equation 1 calculates the 24-h exposure based on the concentration of air pollutants in *J* microenvironments for the time that a person spends time there, plus the exposure during *R* travel that each includes while traveling on *K* links.

$$TDE_i = \sum_{j=1}^{J} Concentrtaion_{jt} * Staying\ time_j + \sum_{r=1}^{R} \sum_{k=1}^{K} Link\ Concentration_{rkt} * Travel\ Time_{rkt} \quad \text{(Eq-1)}$$

Where;

TDE_i is the individual i's daily exposure to $PM_{2.5}$ $(\frac{\mu g}{m^3} * hr)$,

$Concetration_{jt}$ is the concentration at microenvironment *j* at time *t*,

$Staying\ time_j$ is the time an individual spent at microenvironment *j*,

$Link\ Concentration_{kt}$ is the concentration of link *k* at time *t* for travel *r*,

$Travel\ Time_{kt}$ is travel time on link *k* at time *t* for travel *r*.

To understand why the static and dynamic methods differ in estimating the population exposure to vehicle emissions, we divide the daily exposure according to the activity type, place of residence, and trip mode. The activity-type data is obtained from the ARC-ABM output, which defines the type of activity for each stop during each tour. The places of residence are grouped into urban and suburban area according to the Atlanta region's plan. Urban areas are defined as region core, regional employment corridors, and maturing neighborhoods. Suburban areas include established suburbs, developing suburbs, developing rural areas, and rural areas. For the trip mode, we are also interested in the differences in exposure between active travelers (pedestrians and cyclists) and vehicle users.

[redacted] Health and Environmental Justice Analysis

We analyze how the static and dynamic methods differ in predicting the negative health outcomes from exposure to vehicle emissions. Three health outcomes are considered: chronic obstructive pulmonary disease (COPD) mortality, ischemic heart disease mortality, and lung cancer mortality. Prior studies show that these health outcomes are significantly associated with exposure to vehicle emissions. To estimate health effects, we relied on our prior work (Poorfakhraei, Tayarani, and Rowangould 2017), which developed a method for evaluating how regional transportation plans affect air quality and public health. Briefly, we use epidemiology studies that use either a cohort or a case-control study design to evaluate the effect of air pollution exposure on the likelihood that a person develops a negative health outcome. Results from these studies can then be used to create concentration-response functions that describe the relationship between air pollutant concentrations and negative health outcomes. The risk of a particular negative health outcome after a change in the concentration of an air pollutant is then estimated by Equation 2.

$y = y_0 e^{\beta \Delta X}$ (Eq-2)

Where,

y_0 is the base risk of negative health outcome,

ΔX is the change in the concentration of the pollutant,

and β is the effect estimate (change in risk per unit change in concentration of pollutant).

The y_0, is obtained from CDC WONDER at the county level. CDC WONDER is an online database that provides access to publicly available Centers for Disease Control and Prevention (CDC) data. The county level is the smallest geographic unit in which these data are publicly available. We obtain the baseline mortality risk in each TAZ based on the risk at the county level. ΔX is the difference in exposure estimated with the static and dynamic methods. We obtain βs for three types of health outcomes from the peer reviewed literature (Krewski et al. 2009). Krewski et al. (2009) derived health impact functions after adjusting for 44 individual specific covariates and based on 18 years of data from approximately 1.2 million adults in about 172 US metropolitan areas. These health impact functions are also in EPA's Environmental Benefits Mapping and Analysis Program (BENMAP).

Table 6-2 Effect Estimate for Health Outcomes Assessed in This Study (Derived from Krewski et al., 2009)

Health outcome	**β (95% CI)**
COPD Mortality	0.012 (0.010–0.015)
Ischemic Heart Disease Mortality	0.022 (0.017–0.025)
Lung Cancer Mortality	0.013 (0.006–0.021)

We then estimate the average daily exposure for different income groups using both the static and dynamic methods to evaluate how the different methods may affect the evaluation of environmental justice concerns. The synthesized population data from the activity based model include household income for each individual. We classified people into five groups based on their household income: less than \$25,000, \$25,000-\$50,000; \$50,000-\$75,000; \$75,000-\$100,000; and more than \$100,000.

6.3 Results

The main result of this study is a comparison between the exposure estimated by the dynamic and static methods. Figure 6-2 shows that the static approach underestimates population exposure (more people are in the lower exposure ranges). The static method neglects the exposure during travel time and that people spend times at places other than their homes. On average, the static method estimates the cumulative population exposure as 3.87 $\mu g/m^3$-hr per day, whereas the dynamic method estimates it as 5.86 $\mu g/m^3$-hr per day. Figure 6-3 shows how the difference between exposure estimated by the two methods change over the study area. Suburban areas experience a positive change in their exposure as estimated by the dynamic method, whereas the urban areas experience a negative change.

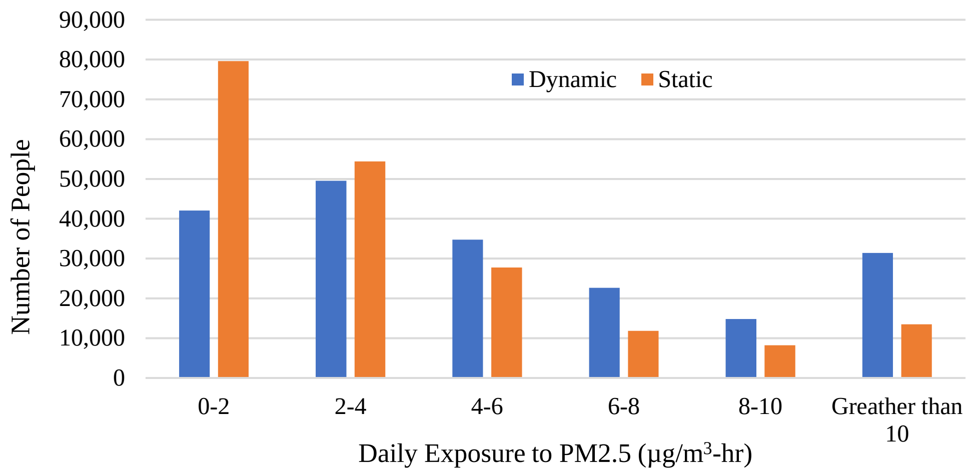

Figure 6-2 Average Daily $PM_{2.5}$ Exposure under Static and Dynamic approaches

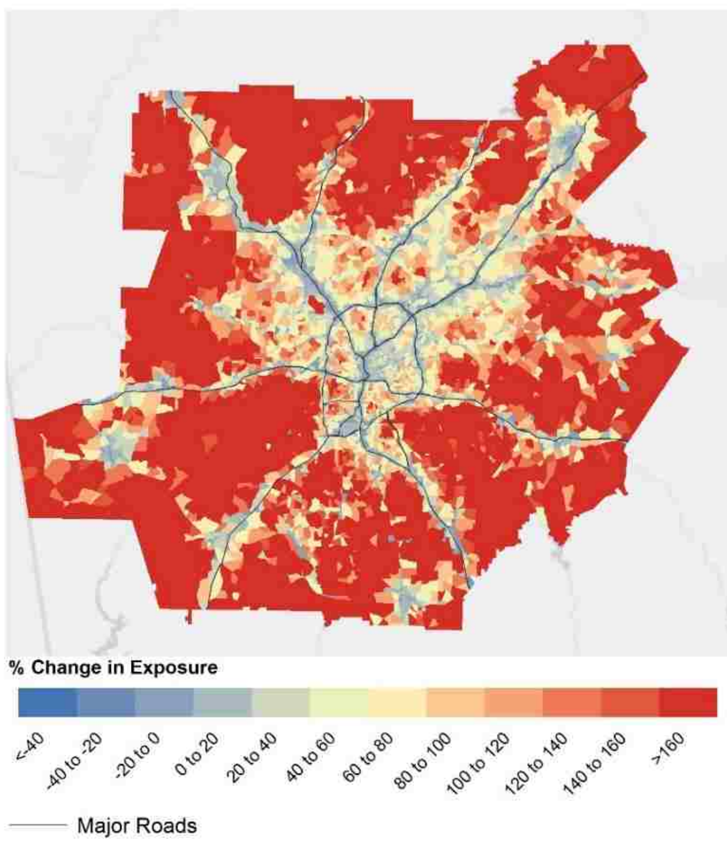

Figure 6-3 Average Percentage of Difference between Daily Exposure estimated by Static and Dynamic methods at TAZ Level

We investigate the reasons why the two methods differ in estimating population exposure by plotting the average daily exposure according to the type of activity. Results from Figure 6-4-a illustrate that many people experience exposure to the highest concentrations of vehicle emissions in places other than their homes. The average $PM_{2.5}$ concentration at home may be lower because many residential areas in the Atlanta metropolitan area are located in suburban locations. In contrast, the places where activities are conducted, such as work and shopping, are located in more urban areas closer to major roadways. However, when we calculate the average daily exposure to vehicle emissions, including the time spent associated with different activities, the home is the place that accounts for the greats amount of exposure to vehicle emissions (Figure 6-4-c). It was expected for people to experience this since they spend most of their time at their home (Figure 6-4-b) even though the pollution concentration there is lower than that in other places. On average, exposure at home accounts for 43% of daily exposure, which increases to 54% for urban residents but falls to 37% for suburban residents. On average, exposure at work accounts for 27% of daily exposure, whereas that during travel time accounts for 18%. The static approach estimates the average exposure of urban residents as 9.22 $\mu g/m^3$-hr and that for suburban residents as 2.64 $\mu g/m^3$-hr. Using the average concentration at home, which is common in epidemiology studies, would underestimate the actual population exposure to vehicle emissions.

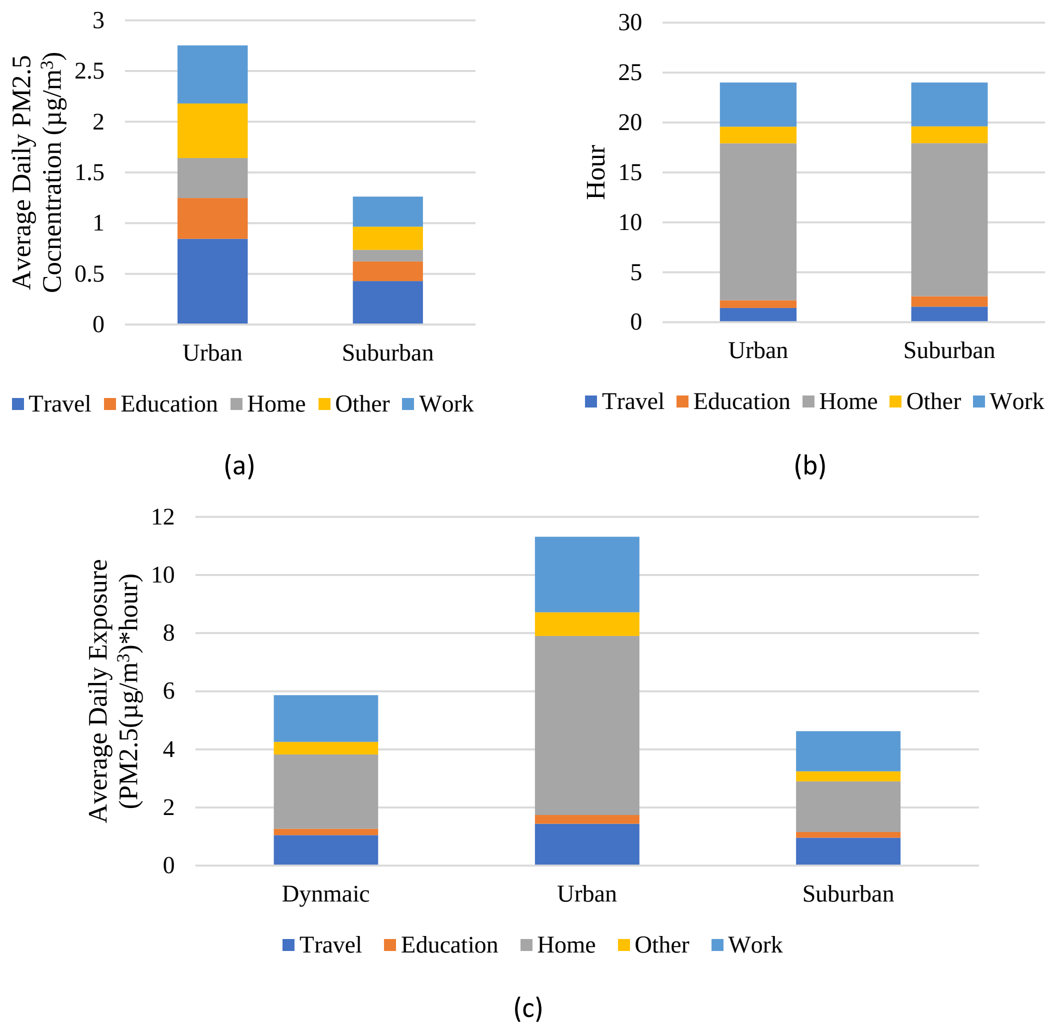

Figure 6-4 a) Average Daily $PM_{2.5}$ Concentration, b) Average Daily Spending Time, c) Average Daily Exposure to $PM_{2.5}$ at different Activities

The gap between exposure estimated by the static and dynamic approaches becomes larger when we separate the exposure for residents of urban areas versus that for residents of suburban areas (Figure 6-5). People who live in suburban areas experience higher exposure at their work place, which is also true for exposure during travel time. We find that, although 80% of the population live in suburban areas with low $PM_{2.5}$ concertation at their home locations, they conduct their activities at other areas with higher concentration. In sprawling areas, this could cause a major difference in exposure estimated by the static and dynamic approaches. For those who live near major roads, exposure at their home would still account as their highest share of exposure even if we use the dynamic approach. Figure 6-5 also shows to what extent each type of activity accounts for the daily exposure for the residents of each TAZ. Although the suburban residents have a higher share of exposure from traveling, education, and work activities, those who live close to roads experience higher shares of exposure at their home.

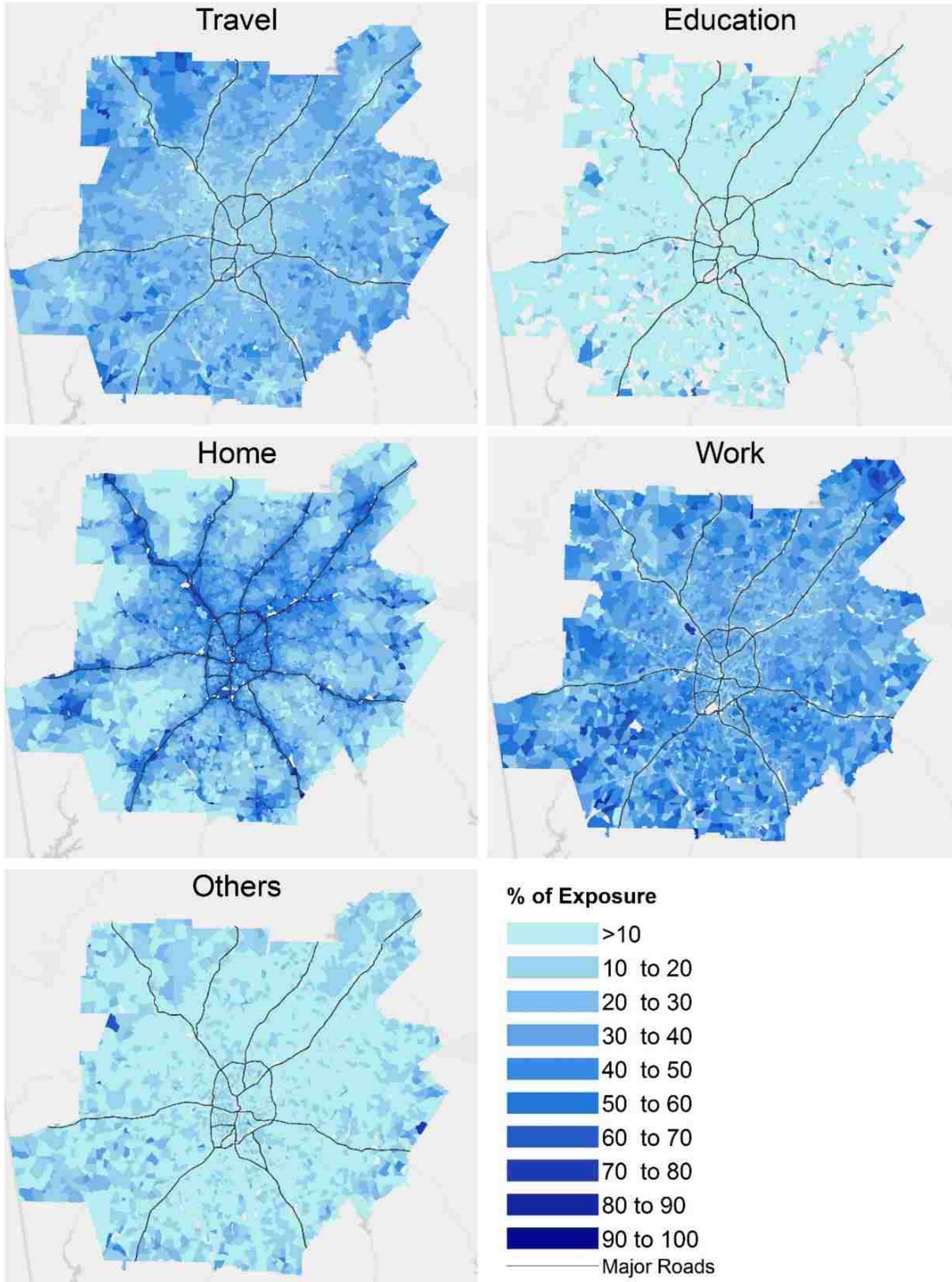

Figure 6-5 Share of Daily Exposure to Vehicle Emissions from Different Activities at TAZ Level

Exposure during travel time contributes to a large portion of daily exposure (Figure 6-6). Exposure during travel time accounts for 17.8% of average daily exposure while people spend only about 6.6% of their day traveling.

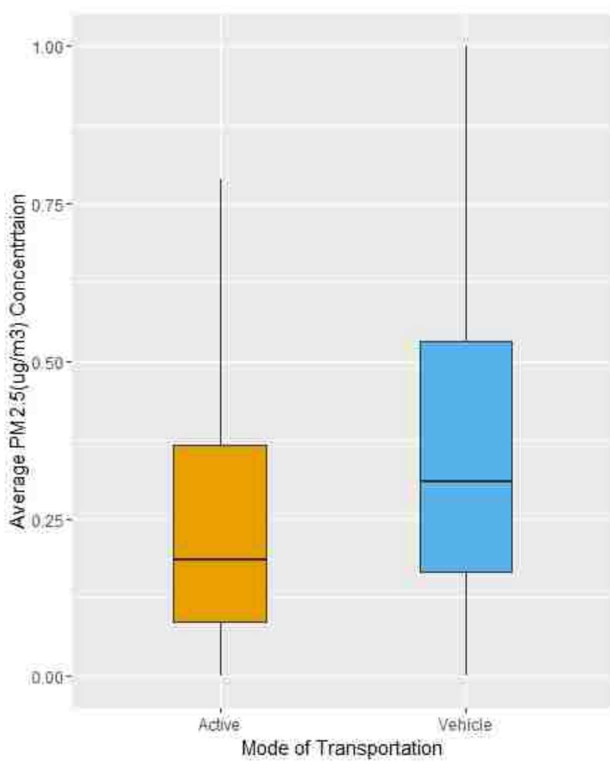

Figure 6-6 Average $PM_{2.5}$ Concentration during Traveling time for Drivers and Active Travelers

We also evaluate how using the dynamic exposure approach could affect evaluation of environmental justice in long range transportation planning (Figure 6-7). The static approach estimates that people with the lowest income have the highest exposure with 5.02 μg/m3- hr. The static method estimates daily exposure of people with the highest income is 27% lower than the lowest income group or people. We then estimate daily exposure to vehicle emissions for different income groups using the dynamic exposure method. On average people are exposed to 5.86 μg/m3-hr $PM_{2.5}$ per day, which is higher for those living in the inner-city areas, 11.31 μg/m3-hr, and lower for the suburban residence, 4.62 µg/m3- hr. On average the highest and lowest-income groups have higher exposure to vehicle emissions, 6.04 µg/m3- hour and 6.06 µg/m3-hr, respectively, compared to middle income groups.

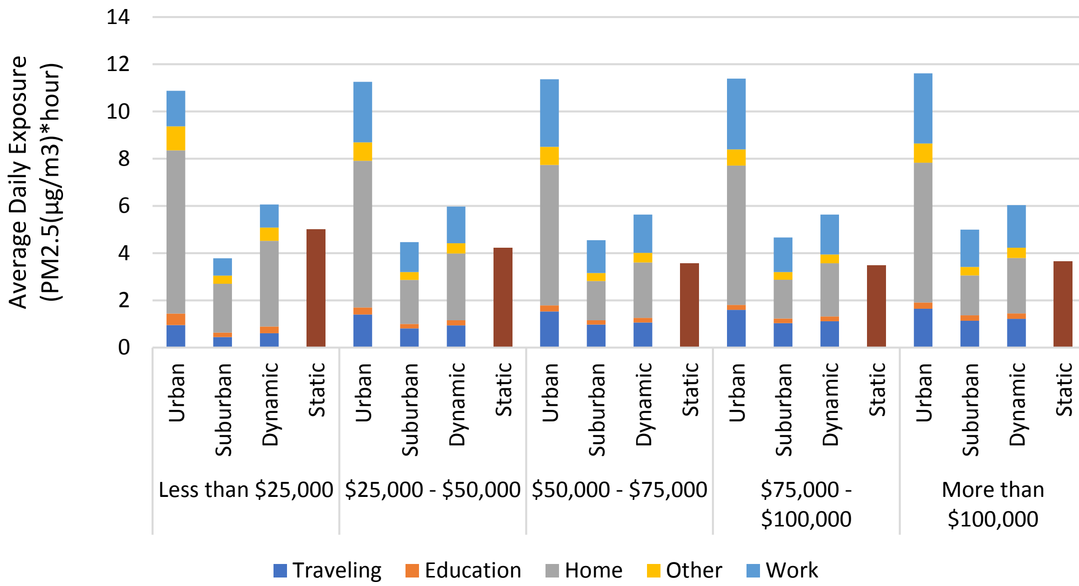

Figure 6-7 Comparing Average Daily Exposure Estimated by Dynamic and Static Approaches for Different Population Groups

Finally, we estimate the change in the number and percentage of deaths in the study area for three different health incidences. The changes resulted from the change in population exposure estimated with the two different approaches. Although the changes may seem small, we should mention that these estimates are only for these three causes of deaths during one single year (Table 6-3).

Table 6-3 Annual Changes in the Health Outcomes Incidences

Cause of Death	Change in the number	Change in the Percentage
Ischemic	9.51 (7.34-10.80)	0.42%
COPD	1.37 (1.14-1.74)	0.21%
Lung Cancer	1.06 (0.49-1.72)	0.23%

6.4 Discussion

In this study, we evaluate the differences between conventional (i.e., static) and dynamic approaches in measuring exposure to vehicle emissions. We find that the static approach underestimates the average daily exposure to vehicle emissions by 33%. The static approach is unable to capture the often higher exposures at work places and during travel time. The difference between static and dynamic exposures are higher for suburban residents who live in relatively unpolluted areas but conduct activities such as work in dense urban areas or spend more time traveling. We also find that the static method causes misclassification in environmental justice analysis.

The differences in the two modeling approaches may have important planning and policy implications. Investigating the exposure to vehicle emissions in more detail could help refine air pollution reduction policies so that more people can benefit from them. This can be used to justify the efforts in terms of time and money to develop dynamic models for other metropolitan areas. For instance, pollution reduction programs such as Low Emission Zones (LEZ) should focus on areas where more people spend their time. The dynamic modeling approach can also be beneficial for epidemiology studies that investigate the link between vehicle emissions negative health outcomes. The more accurate exposure estimates can diminish exposure misclassification and potentially reveal strong associations. Moreover, on average, people are exposed to a higher concentrations of vehicle emissions in schools and universities compared to their home. Although about 24% of people spend time in these locations, exposure in educational places may not be counted as a large portion of population exposure. The results indicate that the average $PM_{2.5}$ concentration for drivers is 57.6% higher than that for active travelers partly because active travelers avoid major highways. We, however, did not consider the change in ventilatory parameters (Int Panis et al. 2010) that could cause higher exposure for active travelers as they inhale more pollution in areas with lower $PM_{2.5}$ concentration.

Our findings show that exposure during travel time may be considered as an important part of daily exposure. This is important since it could boost research on trip assignment models that aim to find routes that minimize exposure to vehicle emissions. Finally, we estimate the change in the number of deaths due to different health outcomes resulting from emission exposure, which is estimated by the static and dynamic approaches. Although the changes may seem small, when the small effects of vehicle emissions on the overall risk of deaths are considered, they may justify the development of dynamic exposure models. The finding shows that policies aimed at improving urban air quality should not ignore the high exposure during short travel times.

There are some limitations to our study. We exclude the transit trips which may introduce bias to our results, as people who use trans it may have different socioeconomic and travel patterns. Exposure calculations should consider indoor concentrations at home and work, and in vehicle concentrations during travel time. Our air-quality model, however, estimates the ambient air pollution concentration. We assume that indoor air pollution is the same as outside air pollution since we did not have information about vehicle and building characteristics that would allow us to calculation these differences. We know that this causes some amount of error based on a limited number of prior studies(Baek, Kim, and Perry 1997; Kim, Harrad, and Harrison 2001b; Marshall et al. 2003). However, presently there is no practical method for addressing these types of errors.

CHAPTER 7

CAN REGIONAL TRANSPORTATION AND LAND-USE PLANNING ACHIEVE DEEP GHG EMISSIONS REDUCTIONS?

7.1 Introduction

While several studies investigate potential GHG emission reductions from different strategies (Boston Region MPO 2016), there is, however, little research indicating the actions an MPO would need to take to achieve GHG emission reduction targets, such as those set by IPCC. As part of the team working with Mid-Region Council of Government (MRCOG) to develop the climate change project (Lee et al. 2015), we were aware of some of the actual barriers in the planning process to achieve the needed GHG reduction in the transportation sector. The mobility and accessibility considerations such as congestion relief are the main performance measures to evaluate the transportation plans while concerns related to sustainability and environmental justice get less weight. Under these plans, GHG emission per capita usually declines while total net emission will still grow higher than today's level due to population growth. It has been shown that among regular GHG abatement strategies with the exception of a very high VMT tax, other strategies are still not able to hold GHG emissions at today's levels.

For instance, a growth boundary requiring all future growth to occur in already developed areas would only reduce GHG emission by 3.8% and planned bicycle infrastructure and traffic signal enhancements would likely only reduce GHG emission by 0.2% (Lee et al. 2015).

This study is similar in its aims and methods to Brisson et al. (2012) study of "what it would take?" to achieve the City of San Francisco, California's GHG emission reduction goal of a 80% reduction below 1990 levels by 2050 using strategies under the municipality's control. In that study, the authors conclude that achieving San Francisco's GHG emission reduction goals is impossible without policies that would have to be adopted at a higher level of government. Like Brisson et al. (2012), this study fills an important gap in the literature by evaluating the potential to achieve deep GHG emission reductions from transportation using policies under the control of local and regional governments, in the setting of an actual urban area. The main difference in this study is that we consider an entire metropolitan region (the Albuquerque, New Mexico metropolitan area), which is a region that is more representative of most urban areas in the United States than San Francisco. The Albuquerque metropolitan area has a relatively low density and sprawling development pattern and as a result over 93% of trips are made using a personal automobile. Transit mode share is only 1%. This study also evaluates even more aggressive implementation of each strategy since prior studies generally find that deep GHG emission reductions are not possible without advanced technology. Other than Brisson et al. (2012), all prior studies that we are aware of have been conducted a much more aggregate, usually national, scale or have not taken a “what would it take” approach, instead constructing scenarios based on what seems relatively feasible to implement.

This study is motivated by two observations that suggest to us that there is a very large gap between the emission reductions expected from current regional LRTPs and those required to achieve deep GHG emission reductions congruent with the IPCC targets. In California, state law (SB 375 – The Sustainable Communities and Climate Protection Act of 2008) requires that MPOs meet per-capita GHG emission reduction targets ranging from 5% to 18% below 2005 levels by 2035 (California Air Resources Board 2017). However, California’s population is expected to grow by 22% between 2010 and 2035, with much higher growth rates in the most urbanized areas (e.g., 33% in Los Angeles and 38% in San Francisco Counties) according to projections from the State of California Department of Finance. This level of population growth exceeds, often by large margins, the per-capita GHG emission reductions expected in each metropolitan area. This means that total GHG emissions are expected to increase, rather than decrease. The MPO per-capita reduction targets and projections in California do not account for potential state-wide policies that may increase vehicle efficiency (something only California is allowed to do under federal law), de-carbonize fuel or enact some form of road user pricing.

In Albuquerque, New Mexico expectations are similar. The Albuquerque metropolitan area was the site of a U.S. Department of Transportation supported climate change scenario planning study that the authors also participated in, the Central New Mexico Climate Change Scenario Planning Project (Lee et al. 2015). The project aimed to demonstrate how scenario planning can be used to develop a long range regional transportation and land-use plan that mitigates GHG emissions and risk from climate change impacts. The scenario planning project led to the adoption of a regional long range transportation and land-use plan by the Albuquerque area MPO that is expected to reduce GHG emissions by 8.4% over a business-as-usual, trend, scenario by 2040. However, total GHG emissions are expected to increase by 30% over those in the 2012 baseline year due to population growth outpacing per-capita GHG emission reductions (MRCOG 2015).

While there is no data on the expected level of GHG mitigation from a large sample of MPOs to understand if the above examples are widely representative of current planning practice, that MPOs in places where mitigating GHG emission is an important goal are expected to achieve so little raises concerns. The situation in California is particularly concerning given the strong government and popular support for the pursuit of deep GHG emissions reductions there (e.g., California Assembly Bill 32 - California Global Warming Solutions Act of 2006, which requires the state to reduce GHG emissions to 1990 levels by 2020, California Executive Order S-3-05 signed by Governor Arnold Schwarzenegger in 2005 setting a target for an 80% reduction below 1990 levels by 2050, and California Executive Order B-30-15 signed by Governor Jerry Brown in 2015 setting a target for a 40% reduction below 1990 levels by 2030). Furthermore, in a study of regional long range transportation and land-use plans developed by over 50 MPOs, Bartholomew (2006) finds that most plans result is very modest changes in travel demand from business-as-usual, trend, scenarios. The median reduction in VMT from a trend scenario after 20 years is only two percent. The failure of most plans to significantly reduce VMT from a trend scenario (where VMT is much higher than it is today) means that they are also unlikely to result in significant GHG emission reductions, if any, from the baseline year.

The overall aim of this study is understanding the maximum GHG mitigation potential at the local and regional level in absence of the political and financial constraints and biases that seem to limit the aggressiveness of plans developed by MPOs (Brömmelstroet and Bertolini 2010; Flyvbjerg, Skamris Holm, and Buhl 2005; Handy 1992; Hatzopoulou and Miller 2009; Wachs 1990; Wachs 1989). Evaluating this question is important because if deep, or at least deeper, reductions are possible than this raises a question about the effectiveness of the current regional long range transportation and land-use planning process. The current process seems to be moving us in the complete opposite direction of where we need to go to avoid the most severe climate change impacts.

7.2 Methodology

Below we begin by describing the region's current long range regional transportation and land-use plans and planning process. We then describe the additional strategies we developed and how we evaluate them using the region's existing modeling capabilities and off model analysis.

[redacted] Integrated Land-Use, Travel Demand and Emission Modeling System

Each of the land-use and transportation planning scenarios developed by MRCOG were evaluated with an integrated land-use/travel demand/emission model. The first step in this analysis uses UrbanSim, an agent based land-use model, to determine the future population, employment, and land-use mix in each transportation analysis zone (TAZ). UrbanSim predictions are driven by estimates of land and housing values that depend on accessibility, land-use regulations (e.g., zoning), land availability, and the expected population and employment growth in the region. For example, parcels with greater accessibility are more attractive but will also tend to be more expensive; UrbanSim considers these types of dynamics in determining the probability of development for each parcel in the region.

Zonal population and employment output from UrbanSim become input for MRCOG's trip based (4-step) travel demand model that is used to forecast traffic volume and average travel speeds on each roadway link as well as mode share. UrbanSim and the travel demand model work together to model the interaction between land-use and the transportation system. UrbanSim requires base year zone to zone travel times that are produced by the travel demand model to initialize its year by year land-use simulation. The travel demand model uses future year population and employment predictions from UrbanSim to forecast future year travel demand. Future zone to zone travel times from the travel demand model are fed back into UrbanSim during an intermediate time period, 2025, so that future land-use decisions respond to changes in travel time.

The US EPA MOVES model is then used to create a GHG emission factor look-up table that provides gram per mile emission rates for a range of speeds for each of four roadway types. These emission factors are matched to each roadway link based on roadway type and the speed estimated for that link by the travel demand model. Each link's forecasted traffic volume is then used with the corresponding GHG emission factor to estimate total GHG emissions for each link, which are then aggregated to produce a regional GHG emission inventory for each scenario.

[redacted] GHG Abatement Strategies

In this study, we developed additional GHG abatement strategies that have the potential to produce significant GHG emission reductions. We used the modeling system described above to investigate what changes to either the transportation system, land-use plans or some combination of both would be required achieve deep GHG emission reductions. The main difference in our analysis approach to that of most existing studies is that we do not constrain our analysis to what is generally considered politically or financially feasible. So, for example, we investigate scenarios with much greater density than what exists today, large reductions in roadway capacity, and significant transit system expansion and level of service improvements. The aim of this analysis is to evaluate the size of the gap between current plans and what would likely be required, information that may then allow for greater budgets and political acceptance.

7.2.2.1 Transit Scenarios

The transit strategies include adding one loop bus line to the existing 2040 adopted transit plan along with significant headway and transit fare reductions. We add only one new transit line since there is currently at least one transit line on every major street in the existing plan (Figure 7-1). We enhance the performance of existing transit lines by reducing their headways by 50% and 90%. Under the 90% reduction scenario, headways range from 5 to 12 minutes. While we modeled a 50% reduction scenario, we have excluded this scenario from the results section since the change in GHG emission and transit mode share were negligible. We also eliminate transit fares. Current average transit fares are 65 cents.

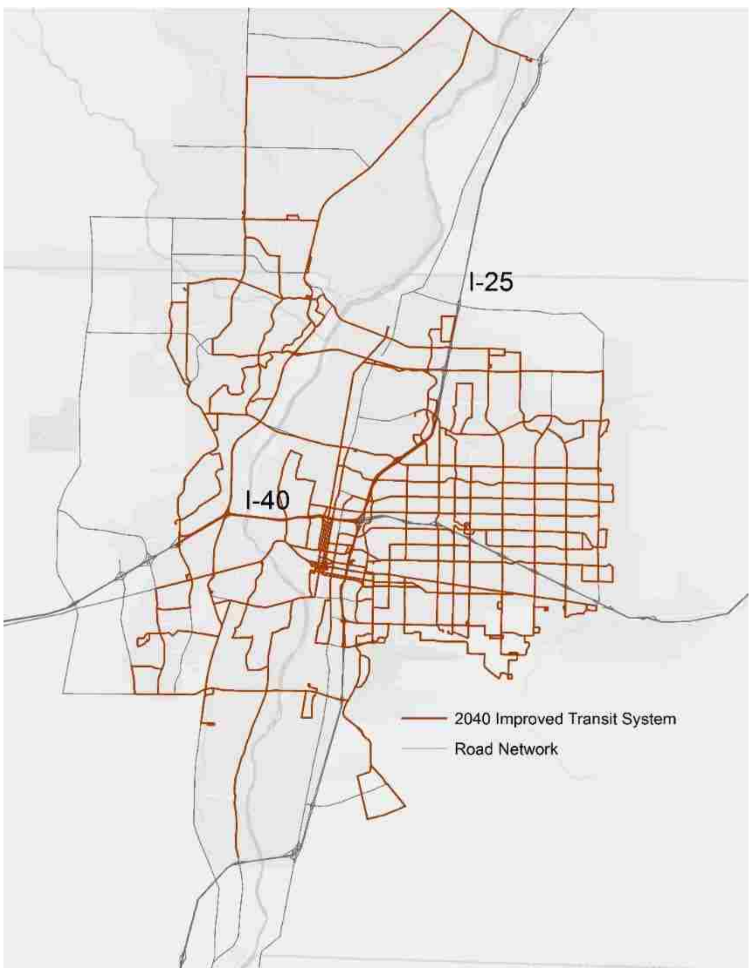

Figure 7-1 Transit Network

7.2.2.2 *Roadway Capacity Reduction Scenario*

We develop a scenario that significantly reduces the capacity of roads with more than one lane in each direction. The aim of this scenario is two-fold. First, we are interested in if roadways actually require this capacity, and if not, we assume the additional roadway space could go towards improving bicycle facilities, the pedestrian environment or BRT bus lanes. The Albuquerque metropolitan area has many four and six lane urban arterials with relatively low traffic volumes. Additionally, we are interested in how the potential increase in congestion levels would affect travel demand and GHG emissions. Greater congestion could result in shorter trips and greater non-motorized and transit mode share. We removed one lane per direction from all links of the transportation network that have more than one lane in each direction (Figure 7-2). This strategy removes lanes from 42 percent of the network in the travel demand model.

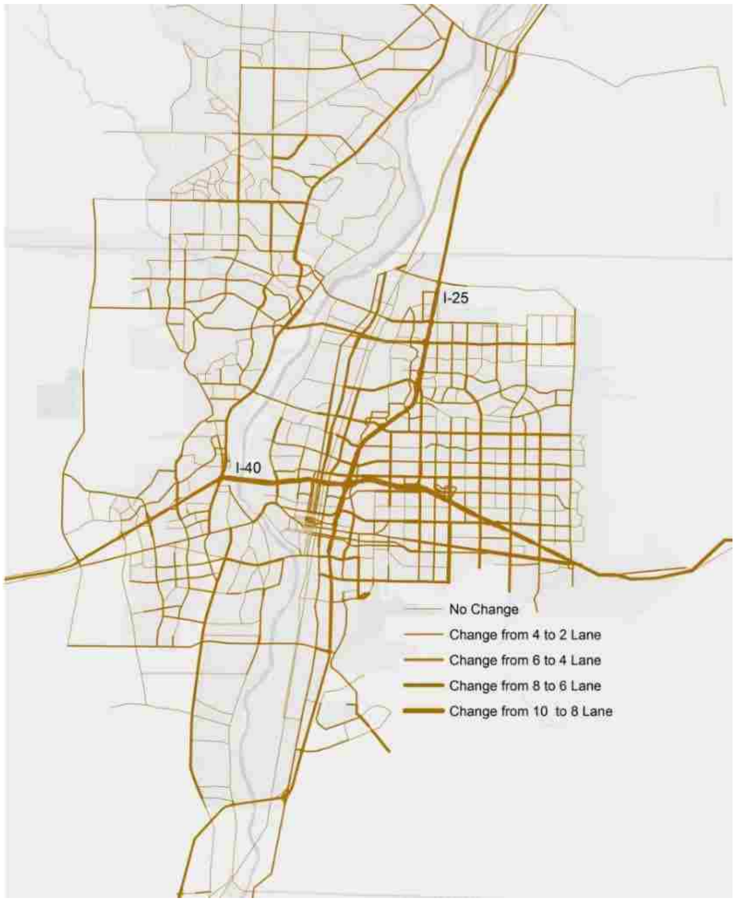

Figure 7-2 Roadway Capacity Reduction

7.2.2.3 Infill and Smart Growth Development Strategies

We developed several infill and smart growth strategies that increase development density near transit stops and activity centers and increase commercial density at existing commercial centers. We create each scenario by concentrating population, housing, and employment growth forecasted to occur by 2040 under MRCOG's adopted plan into smaller, currently developed, areas. To do this, we create four increasingly aggressive growth boundaries that define where all future growth will be occur (Figure 7-3). Growth that was previously forecasted to occur outside of these areas is redistributed to occur within each growth boundary in proportion to the current population density of each TAZ within each boundary. This procedure directs more growth to higher density areas and less growth to lower density areas. The intent is to maintain existing development patterns as much as possible.

The very compact land-use development scenario places all future development into four major existing activity centers which cover just 1.8% of the developed land in the region. These activity centers currently contain the highest concentrations of commercial and retail development in the area, are located along the region's major transportation corridors, and are generally well served by transit. They include downtown Albuquerque, the area around the University of New Mexico, and two areas of mixed retail and office space located outside the downtown area but still located within the City of Albuquerque. The transit oriented land-use development (TOD) scenario places all future development within one mile of Central Avenue, which is Albuquerque's main transit corridor (contains a Bus Rapid Transit line) and passes through many of the region's largest activity centers including downtown and the University of New Mexico. This scenario directs future development to 12.8% of developed land in the region. The compact land-use development scenario is a less aggressive form of the very compact land-use development scenario, directing future growth to activity centers that make up 5.3% of the region's developed land. These areas are generally well served by transit, have high access the major transportation corridors, and are generally more dense and have a greater diversity of land-use than other parts of the region. The moderately compact land-use development scenario is the least aggressive scenario. It directs all future growth to the current boundary of the

City of Albuquerque. This scenario allows development of 47% of currently developed land in the region. We choose Albuquerque (over other cities in the region) because it is the largest city in the region and only out of convenience for modeling a less aggressive land-use scenario. Table 7-1 compares the population density under each land-use scenario.

Table 7-1 Population Density in the Target Areas under the Land-Use Scenarios

	Population Density within Growth Boundary[a]			
Development Scenario	**Very Compact**	**Transit Oriented**	**Compact**	**Moderately Compact**
2012	2,881	3,887	3,104	3,052
2040 adopted	6,303	5,435	6,030	4,319
Compact Development	64,471	12,565	24,021	5,397
% Change (Compact Development – 2040 Adopted)	922%	131%	298%	25%

[a] Population Density = persons per square mile

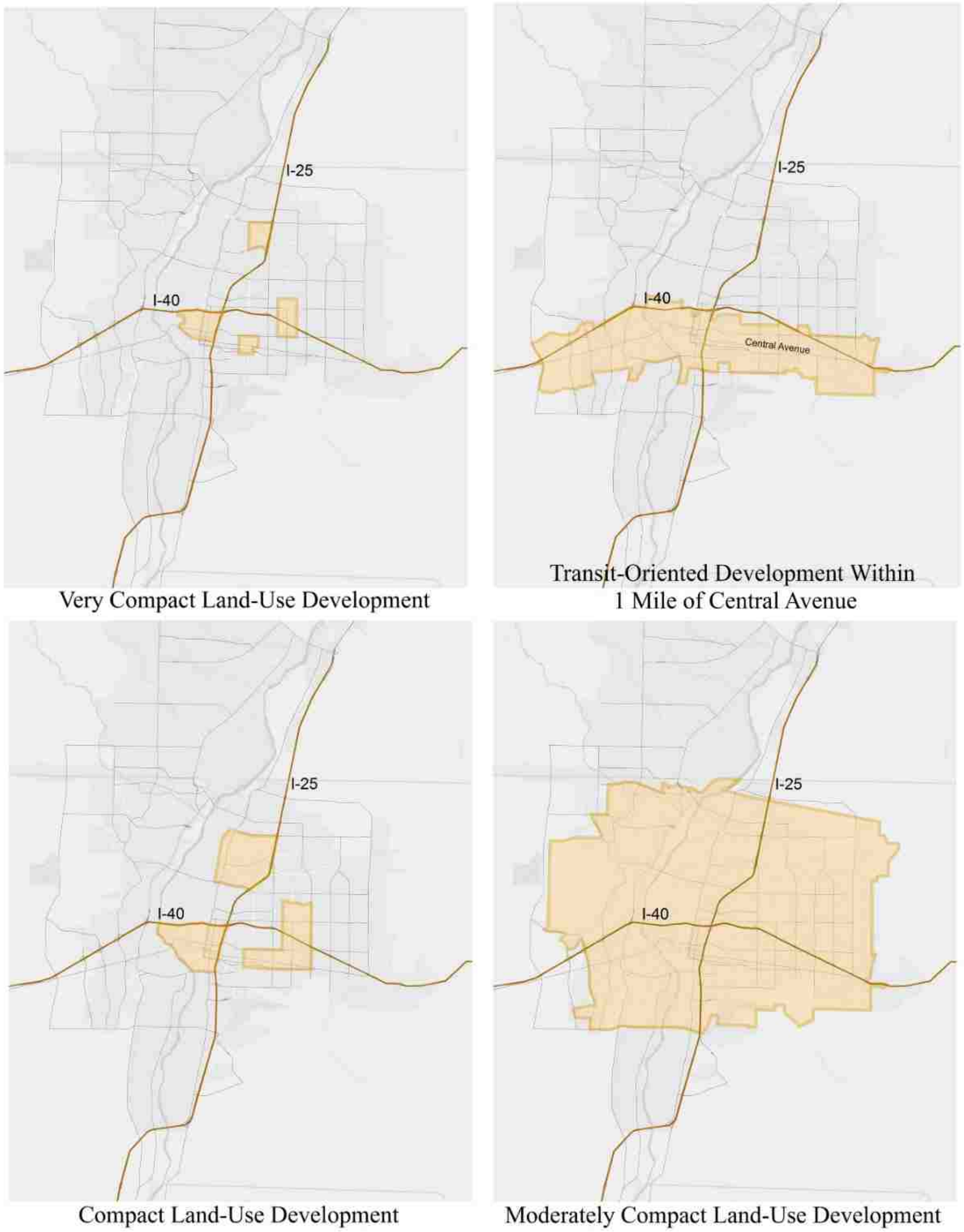

Figure 7-3 Boundaries for Compact Growth Scenarios

The compact development scenarios would be a major change for Albuquerque, but even the most aggressive scenario is not without precedent within the United States. For example, the areas target for growth in the very compact land-use scenario would rank 34th zip code in terms of population density in the U.S. The downtown areas of New

York, Boston, San Francisco, and Los Angles have population densities of 65,753, 28,341, 33,703, and 17,042, respectively. The highest population density zip code, located in New York City, achieves a population density of 227,800.

7.2.2.4 Bicycle Scenarios

MRCOG's four-step travel demand model, like those used by most MPOs, estimates the number of non-motorized trips (walking and cycling), but not bicycle trips specifically. Additionally, these estimates are mostly influenced by household characteristics (income and vehicle availability), transportation costs, and trip distance. The presence of bicycle and pedestrian infrastructures such as bicycle lanes and wide sidewalks are not a factor even though they are likely to be important. Therefore, we develop two bicycle scenarios that assume a particular level of bicycle mode share: 20% which is similar to the mode share in Davis, CA (the highest bicycle mode share of any U.S. city) and 10% which is similar to mode share in other popular bicycling city's such as Boulder, CO (McLeod, Flusche, and Clarke 2013). Both of these bicycle mode shares are still well below what has been achieved in several European countries (Haustein and Nielsen 2016; Heinen, Maat, and Wee 2013). To estimate the effects of increasing bicycle mode share on travel patterns and ultimately the GHG emissions inventory, we first scale down the vehicle O-D trip matrix created by the travel demand model after the mode choice step so that bike mode share can be increased to 10% or 20% while keeping the number and distribution of total trips the same. The adjusted vehicle O-D trip matrix is then used in the assignment step to calculate vehicle traffic volumes and speeds on every transportation link, which are then used with MOVES to estimate a GHG emission inventory.

7.2.2.5 VMT Tax Scenarios

Existing literature provides a wide range of proposed tax rates that aim to reduce VMT and GHG emissions. Taxes rates have been proposed based on the marginal cost of climate damages caused by GHG emissions (Collantes et al. 2007; Metcalf 2008), cost of externalities from traffic including congestion, accidents, and pollution (Parry and Small 2005; Parry, Walls, and Harrington 2007), or as a method to reduce the GHG emission from transportation (Cambridge Cambridge Systematics 2009; Chen et al. 2014; Ross Morrow et al. 2010). These studies have proposed VMT taxes or fuel excise tax equivalents that range between \$0.05 per gallon to \$6 per gallon. We develop four VMT tax scenarios that add a \$0.05, \$0.1, \$0.15, \$0.25 per mile tax to the existing state and federal gasoline excise taxes which are \$0.1888 and \$0.1840, respectively. The tax was modeled by adding the additional per-mile charge to the generalized cost function in the travel demand model. These tax rates are relatively large. Using an average fleet fuel economy of 20.6 miles per gallon (assumption used in the MRCOG travel demand model), the \$0.05, \$0.1, \$0.15, \$0.25 per mile taxes are equivalent to a \$1.03, \$2.06, \$3.09, and \$5.15 per gallon increase in the gasoline excise tax, respectively.

[redacted] Scenarios that Combine Strategies

We evaluate each scenario alone and in combination with the other strategies since it is unlikely that any single strategy would be completely effective or efficient. While we do not evaluate every possible combination, we create a series of scenarios that bundle increasingly aggressive versions of each individual strategy discussed above. For example, we combine the highest VMT tax with the most compact development scenario. Modeling the combination of strategies allows us to evaluate their combined mitigation potential which is likely different than the sum of their individual mitigation potentials. Table 7-2 describes each strategy and strategy bundle that we model.

Table 7-2 GHG Emission Abatement Strategies

Scenario	Scenarios Description[a]
Transit	90% reduction in bus headway + eliminating transit fares (transit improvement)
Roadway Capacity Reduction	One lane reduction from links with 2 or more lanes per direction
VMT Tax	$0.05 per mile VMT Tax $0.10 per mile VMT tax $0.15 per mile VMT tax $0. 25 per mile VMT tax
Bicycle	20% bike mode share 10% bike mode share
Smart Growth	Very compact land-use development Transit oriented development (TOD) Compact land-use development Moderate compact land-use development
Strategies Bundles	Very compact + transit improvement + $0.25 VMT tax Compact + transit improvement + $0.10 VMT tax Moderate compact + $0.05 VMT tax Very compact + transit improvement + $0.25 VMT tax + 20% bike + lane reduction Compact + transit improvement + $0.10 VMT tax + 10% bike mode share

[a] All scenarios are applied to MRCGO's adopted 2040 long range transportation and land-use plan.

7.3 Results

No single strategy is likely to achieve even a 40% reduction in year 2012 GHG emissions by the year 2040, which is the low end of the emission reductions called for by the IPCC (Table 7-3). A high VMT tax would achieve the largest reductions, and taxes higher than what we have modeled would likely achieve more. The potential for compact development is more limited than for VMT taxes. The very compact and compact development scenarios achieve about the same GHG reductions, and just a small amount more than the transit oriented development scenario, even though the very compact development scenario is much more compact. This suggests that the potential for compact development, alone, has its limits. Increasing the share of trips made by bicycle had a relatively large effect on reducing GHG emissions as expected since we forced the model to create the prescribed bicycle mode shares. What is more interesting, however, is that achieving a 20% bicycle mode share would be just as effective in reducing GHG emissions as a relatively high VMT tax ($0.15 per mile) or very compact development. Transit improvements had little effect of GHG emissions. The ineffectiveness of improving transit service may have occurred since the Albuquerque metropolitan area generally has low levels of congestion and a sprawling land-use pattern, two factors that making driving a car relatively attractive. Transit level of service therefore may not be a binding constraint to increasing transit demand in Albuquerque.

Surprisingly, the results indicate that removing roadway capacity would result in a relatively large increase in GHG emissions. This is caused by increasing congestion (see Table 7-3) which results in higher per mile GHG emission rates. Our original hypothesis was that reducing highway capacity would reduce vehicle travel demand due to increasing congestion levels which would then reduce GHG emissions. While this scenario did reduce average trip distance and VMT per capita, the increasing GHG emissions caused by congestion more than outweighed the GHG emission reductions from these.

As expected, combining strategies results in greater GHG emission reductions. Combining the most aggressive form of each strategy would result in at least a 40% reduction in GHG emissions by 2040, but would still leave reductions from the 70% target. Combining the most moderate form of each strategy would not achieve the 40% reduction target; however, it would achieve GHG emission reductions that are equivalent to the most aggressive compact development scenarios, a 20% bicycle mode share or the relatively high $0.15 VMT tax. In each case, the GHG emission reductions from the combined strategies are also less than the sum of the individual strategies. This is most apparent for the most aggressive strategies. A potential explanation for this result is that a large portion of the Albuquerque metropolitan area is already built and much of the area has a low density development pattern. The result is that some portion of the population is locked into a land-use pattern that requires some minimum amount of vehicle travel. The compact development scenarios improve conditions for the population living near the areas covered by these scenarios but do little for those already living elsewhere. Furthermore, the areas targeted for more compact development are areas that are already more densely populated and have a greater mix of land-uses. The population living in these areas are therefore also more likely to reduce their travel or switch modes when taxes are raised. People living elsewhere have fewer options for avoiding higher taxes.

While interpreting the results, it is also important to note that our analysis uses 2012 as base year and 2040 as the planning horizon year. This is planning period aligns with MRCOG's planning process and the models they developed. The IPCC targets are defined as reductions from a base year of 2010 by the year 2050. If we extended our analysis by another 12 years, the impact on our results is unclear. After 2040 further reductions in per mile vehicle GHG emissions are very minor based on results from US EPA's MOVES model, where most of the reductions occur in the first half of the analysis period. With little additional reductions from the vehicle fleet, no new GHG mitigation policies, and an expectation of continued population growth, GHG emissions could begin to increase from their 2040 levels.

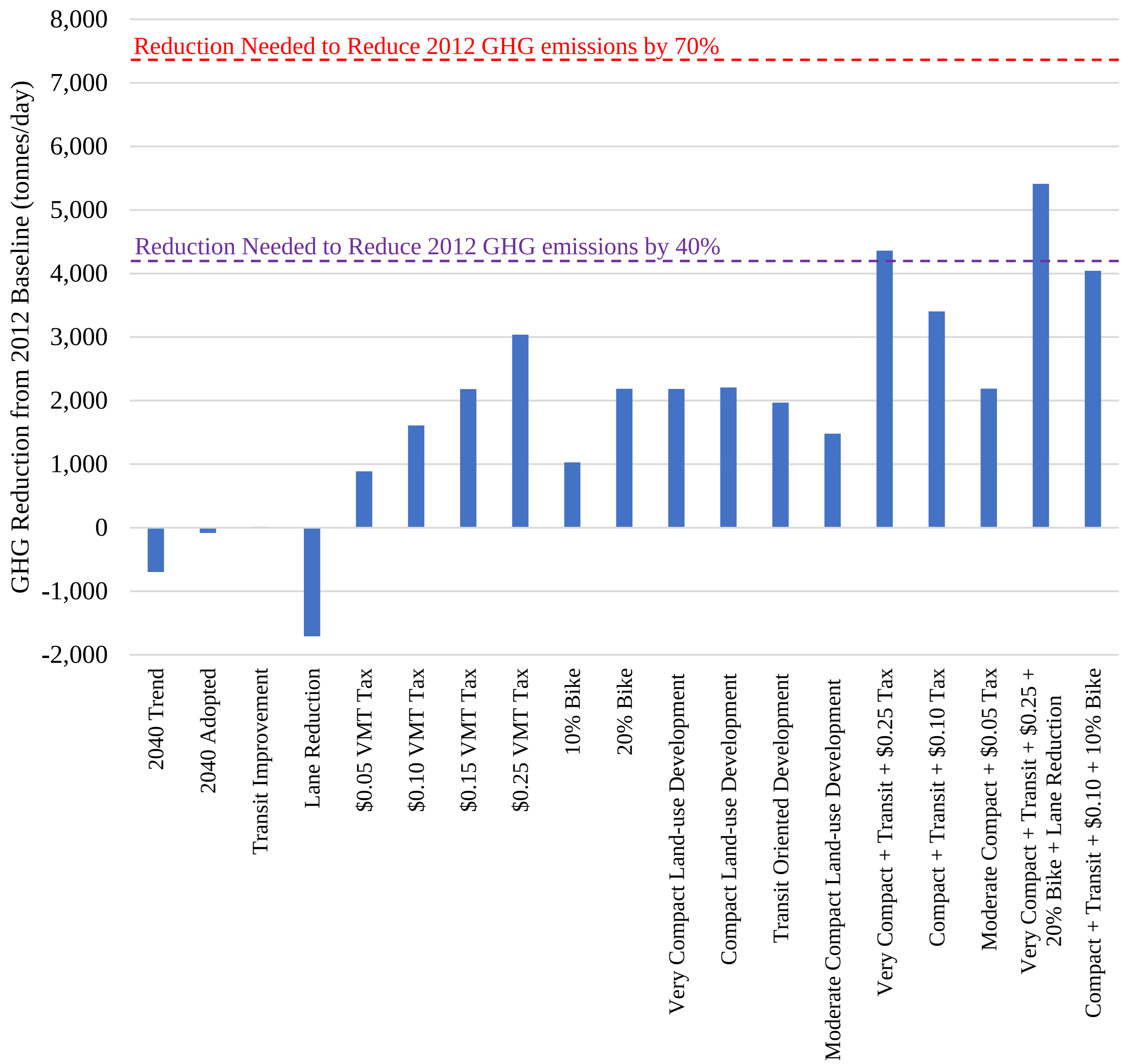

Figure 7-4 GHG Reductions from MRCOG's 2040 Trend Scenario for Single Strategies

In addition to evaluating the GHG mitigation potential of each scenario, we also evaluated their impact on typical long range, regional, transportation planning performance measures (see Table 7-3 and Figure 7-5). With the exception of the land reduction strategy, every strategy performs better at reducing congestion (increasing average speed and reducing roadway segments where demand is forecast to exceed capacity), reducing vehicle travel (VMT and average trip length), and at increasing the use of alternative modes of transportation that MRCOG's adopted plan. Strategies the achieve large GHG emission also achieve significant gains in mobility and accessibility, though in each case congestion is still expected to increase over 2012 levels. The performance measures also reveal differences in how each strategy achieves GHG emission reductions. High VMT taxes and compact development both have similar effects on trip distance and VMT; however, taxes results in less congestion while compact development results in higher non-motorized and transit mode shares. The transit oriented development strategy was also effective at increasing transit mode share and was slightly more effective than increasing transit level of service. These results suggest that without a supportive land-use pattern, higher taxes or better transit service do little to promote the use of alternative modes of transportation.

Table 7-3 Traffic Performance Measures and Their Change From 2012 Base Scenario

Scenarios	Ave. Trip Distance (miles)		Percentage of Links with V/C >1		Daily VMT per Capita		Ave. PM Speed (MPH)	
	Value	change	Value	change	Value	change	Value	change
2040 Trend	7.9	0.8%	7.8%	238.9%	21.9	-2.2%	23.7	-35.8%
2040 Adopted	7.6	-3.9%	7.0%	205.2%	21.0	-5.9%	25.7	-30.4%
Transit Improvement	7.6	-3.7%	6.8%	194.8%	20.9	-6.6%	26.0	-29.5%
Lane Reduction	7.5	-5.1%	26.9%	1072.5%	20.5	-8.5%	12.2	-67.0%
$0.05 VMT Tax	7.1	-9.7%	5.4%	136.7%	19.4	-13.4%	28.4	-22.9%
$0.10 VMT Tax	6.7	-14.5%	4.6%	99.6%	18.1	-19.2%	30.9	-16.2%
$0.15 VMT Tax	6.4	-18.3%	3.7%	59.8%	17.0	-24.1%	32.9	-10.8%
$0.25 VMT Tax	6.0	-23.9%	2.7%	17.5%	15.3	-31.6%	35.9	-2.8%
10% Bike	7.6	-3.4%	5.5%	138.4%	19.2	-14.2%	28.9	-21.7%
20% Bike	7.6	-3.2%	4.1%	77.3%	17.1	-23.4%	33.0	-10.6%
Very compact land-use development	6.1	-21.9%	5.2%	128.8%	17.0	-24.0%	32.8	-11.1%
Transit oriented development	6.1	-22.3%	4.2%	81.7%	17.1	-23.6%	34.3	-7.1%
Compact land-use development	6.3	-19.5%	3.7%	62.9%	17.5	-21.8%	32.9	-10.8%
Moderate compact land-use development	6.5	-17.3%	5.0%	117.0%	18.4	-17.8%	30.4	-17.5%
Very Compact + Transit + $0.25 Tax	5.0	-36.5%	1.8%	-23.6%	12.6	-43.7%	39.8	7.9%

Compact + Transit + $0.10 Tax	5.5	-30.3%	2.3%	-0.4%	14.7	-34.3%	38.2	3.6%
Moderate Compact + $0.05 Tax	6.1	-22.4%	3.8%	64.2%	17.0	-23.8%	32.7	-11.3%
Very Compact + Transit + $0.25 Tax + 20% Bike + Lane Reduction	5.0	-36.5%	4.0%	73.4%	10.2	-54.4%	34.5	-6.6%
Compact + Transit + $0.10 Tax + 10% Bike	5.5	-30.2%	1.6%	-29.3%	13.4	-40.1%	39.7	7.5%

The results depict that to reduce the GHG emission by the required level, an average resident of the Albuquerque metropolitan area needs to drive 12.6 mile per day which is about 42% and 40% less than what is expected under the trend and adopted scenarios. It is also 30% less than what currently people are driving in New York, or 50% less than Boston's residents (Federal Highway Administration 2016).

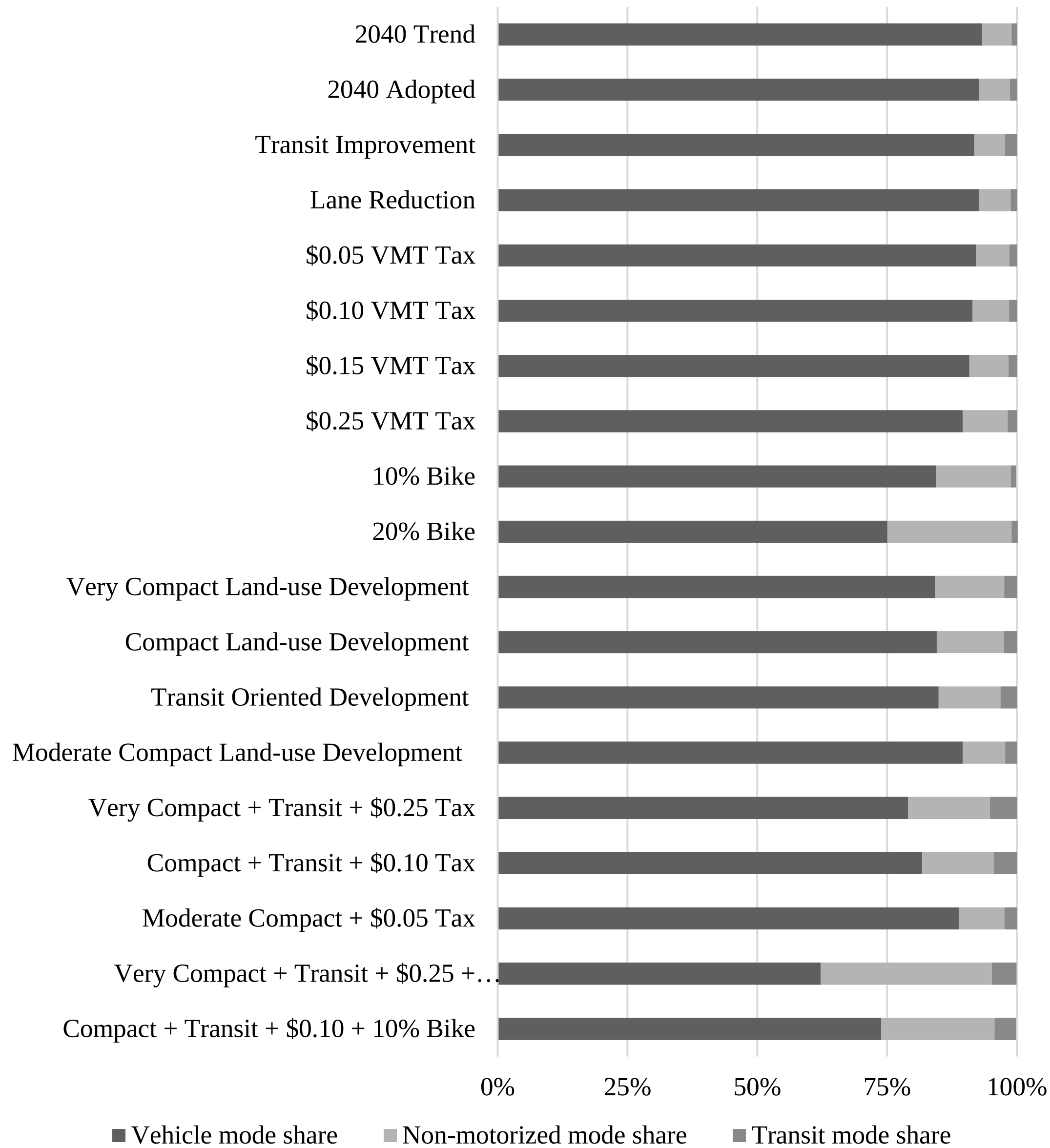

Figure 7-5 Mode Share Change Over Different Scenarios

7.4 Discussion

This study highlights the large changes in the way the Albuquerque metropolitan area must grow and travel in order for its surface transportation sector to make a proportional contribution to the IPCC's GHG emission reduction targets of 40%-70% by 2050 in the absence of greater than currently forecasted changes in transportation technology. The Albuquerque metropolitan area would need to grow much more compactly than anything that is currently under consideration, would need to impose a very high VMT tax, and go much further to increase bicycling. While what is needed is far from what is currently being planned, it is also not outside the realm of what is possible. The compact development scenarios do not require moving the existing population (e.g., abandoning the suburbs that have been built) but rather directs future growth to areas that are relatively dense and have a greater than average diversity of land-uses. In the most extreme case, the very compact development scenario, densities are very high but still less than some areas of New York City today, while the other compact development scenarios produce densities similar to what exists in the central areas of many U.S. cities. The high VMT tax is similar to the equivalent gasoline tax currently imposed in many European countries. Furthermore, a 10% to 20% bicycle mode share, while much greater than Albuquerque's current bicycle mode share of 1.8%, is still below what has been achieved in several European cities and close to current bicycle mode shares in Davis, California and Portland, Oregon, respectively. Combinations of these strategies can also produce significant GHG emission reductions with relatively modest versions of each strategy.

While this study focuses on the Albuquerque metropolitan area, I expect that similar results could be produced in other metropolitan areas in the U.S. No metropolitan area that I am aware of has created a long range regional transportation and land-use plan that is expected to produce GHG emission reductions commensurate with the IPCC targets (this is based on the interim results of a study we are currently conducting). To do so, would likely require large and unprecedented changes to what has been planned. Our scenarios are not very creative and probably not the most efficient; however, they demonstrate what can be achieved by starting with a goal and working backward to identify ways to potentially accomplish it. The largest barrier to creating more effective long range plans appears to be a political or citizen mandate to do so. With commonly used planning tools we were able to identify strategies that are likely to produce large GHG emission reductions and also improve mobility and accessibility.

We argue that the typical planning process, which considers constraints such as funding availability, political feasibility, and the current regulatory environment (e.g., local zoning) in developing scenarios that are then modeled and evaluated is problematic and one cause of incremental plans that are ineffective at significantly reducing GHG emissions and achieving other transportation system goals. The common practice of comparing an adopted plan's performance to strawman business-as-usual or do-nothing trend scenarios is also problematic. These comparisons inevitably find that doing something is better than doing nothing. Understanding how far off we are from meeting important goals, such as achieving deep GHG emission reductions, and the type and scale of changes required to meet goals, may be information that could change the dynamics of the planning process as well as its constraints. While current planning practice may identify the gap between expected GHG reductions and those that would be required to meet targets like the IPCC's, it does not identify the additional policies, plans and infrastructure that would be needed to fill the gap. Citizens, policy makers, and planners therefore may not fully grasp the scale of changes that may be required should technological advances fail to provide significant GHG emission reductions soon enough.

Finally, several limitations to our study should be noted. In this study we use a 4-step travel demand model which has several limitations. First, there is no representation of the bicycle facility network. We assume bicycle mode shares in our analysis which in practice would be produced from improvements to bicycle facilities along with supportive land-use changes. The number of trips is also fixed in the travel demand model as they are determined by the characteristics of households which are held constant. It is likely the large changes we modeled would also affect trip generation rates, with various factors potentially causing increases (e.g., transit improvements and increased density) and decreases (e.g., VMT taxes). The largest potential limitation; however, is that the current travel demand model was built and calibrated with information about the current population and its experience with current and past transportation infrastructure and policies. The large changes I modeled are far from what most people in the region have experienced and such large changes may result in very different behavior than what the model predicts. Finally, this study was conducted using socio-economic, land-use and network data specific to Albuquerque, New Mexico. In addition to strategies having potentially greater or lesser effects in other regions, their relative effectiveness may also vary. For example, increasing transit level of service in a denser urban area that lacks good transit may be more effective than increasing density.

Our analysis focuses on the change in GHG emissions from vehicle traffic attributable to each strategy that we evaluated. Each strategy would provide a range of additional benefits. For example, reductions in VMT would also reduce toxic vehicle emissions and potentially reduce traffic crashes. Increases in active travel such as biking and walking could improve public health. More compact development could also further reduce GHG emissions through the increased thermal efficiency of multiunit buildings. Most of the strategies we evaluated also reduced travel times and congestion. A full benefit cost analysis of these strategies is beyond the scope of our study which is focused on what is possible rather than what is most cost effective. However, consideration of the full range of benefits and costs of the strategies we have evaluated, those considered in prior studies that have focused on vehicle efficiency and fuel decarbonization, and the mitigation potential in other sectors, should be part of any process that aims to implement an aggressive GHG mitigation strategy.

CHAPTER 8

CONCLUSION

In this dissertation, I evaluate different vehicle emission and exposure modeling and find what they can tell us about transportation and land use plans. First, I find that while smart growth strategies such as compact development may reduce GHG emissions and other toxic air pollutants, they may also increase population exposure to vehicle emissions. They may even widen the disparity in emissions exposure between different races and income groups. The findings confirm that a more refined analysis method could be useful for creating transportation plans that reduce GHG emissions, exposure to air pollutants and reduce exposure inequities.

I also evaluate the cumulative impacts of LRTPs and in particular air quality and exposure to vehicle emissions using an innovative annual approach. The annual modeling approach provides new information, which might help planners fine-tune their plans. For example, planners could better understand the potential for a highway-capacity project to induce demand or produce unwanted sprawl and test options to mitigate these undesirable outcomes. The ability to see spikes in vehicle emissions, exposure, or other undesirable outcomes during the interim years also provides an opportunity for planners to test alternative plans or strategies that avoid undesirable outcomes or smooth them over. For example, policies to promote infill development might inadvertently increase exposure to toxic air pollutants if adopted too quickly or in the wrong locations. As vehicle emission rates are expected to decline quickly in the next few years, it might be possible to avoid increasing exposure by delaying certain projects, by delaying the implementation of infill policies, or by implementing additional projects to further reduce travel demand or relieve congestion in areas targeted for infill development.

The annual modeling approach could also be used to better evaluate and monitor the performance of models for regional travel demand, land use, and air quality. Rather than waiting 20 to 30 years to determine how accurate model forecasts would be, model performance could be evaluated each year. Model forecasts that are observed to be trending significantly away from observations each year could signal potentially significant problems with one or more models.

In this dissertation, I also investigate how providing high-resolution activity data could affect the evaluation of a transportation system regarding exposure to vehicle emissions, public health, and environmental justice. The dynamic exposure model was developed using the activity-based travel demand model from Atlanta, GA. The findings provide details that could help planners to understand where and how people are exposed to vehicle emissions. Results show that the common static exposure modeling that estimates exposure only at home locations causes misclassification of exposure for both health outcomes and environmental justice issues. While some people experience their highest exposure at their home, others might experience it at their workplace.

People also experience high exposure during their daily travel time. The results from this study reaffirm the disparity gap in exposure to vehicle emissions found in the literature.

The findings could help to make transportation plans more protective of health and fairer environmentally. This new knowledge could help transportation and land-use planners to fine-tune smart growth and development plans that bring activity centers closer to residences, make active transportation modes more desirable, and concurrently avoid exposure to high pollution concentrations near highways. Transportation funds could be better spent knowing that low-income people are exposed to higher levels of air pollution when they are walking or biking in the downtown areas compared with high-income people.

During the second phase of this study, I addressed what the transportation and land use system should look like to meet the GHG reduction target. I found that no single strategy on its own, no matter how aggressive, could reach the target reduction. The goal of reducing emissions by 70% by 2050 would not be achieved without a combination of all of the following: very compact land-use development, significantly higher active transportation mode, transit improvement, and a high VMT tax.

While this study provides insights on how dynamic exposure modeling could improve the evaluation of transportation plans, further research could use the proposed method to plan a future transportation system that reduces the population's exposure to vehicle emissions. In the second phase, the suggested combination of land-use and transportation strategies achieved the reduction goal, but based on previous experience in Albuquerque, New Mexico, the implementation of these strategies might increase exposure to vehicle emissions. Thus, further research should combine the GHG emission-reduction goal with reducing exposure to vehicle emissions.

CHAPTER 9

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