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EXPOSURE ASSESSMENT OF CITIZENS TO TRAFFIC RELATED AIR POLLUTANTS IN A LONG-RANGE TRANSPORTATION PLAN

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Exposure Assessment of Citizens to Traffic Related Air Pollutants in a Long-Range

Transportation Plan

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Abstract

A large body of evidence links fine particulate matter ($PM_{2.5}$) exposure with a wide range of negative health outcomes. Research finds that about 30% of individuals' exposure to particulate matter in urban areas come from mobiles sources. Evaluating regional transportation plans and estimating how they impact air quality and exposure to $PM_{2.5}$ in the future is thus of major concern.

There are two major concerns about the current practice of evaluating regional transportation plans also known as long-range transportation plans (LRTPs). First, how LRTPs affect future air quality are at best evaluated by estimating the change in regional vehicle emission inventories. These aggregate emission inventories provides no information about localized air quality impacts and provide no way to estimate exposure levels. The lack of spatial detail also limits the consideration of differences in exposure among minority and low-income households – two groups known to suffer from higher exposures in many urban areas. Second, LRTPs are evaluated in terms of how they improve traffic, air quality and other performance metrics between the current time period and the end of the planning period, which is typically 30 years into the future. This

evaluation method does not consider the performance of the plan during the planning period, a 30 year period or almost half a person's lifetime.

The ultimate goal of this study is to create a clearer picture of how LRTPs affect exposure to $PM_{2.5}$ from vehicle traffic and health outcomes, and develop a modeling approach that evaluates the cumulative effects of LTRPs over the entire planning period. Together, the new information that the techniques developed in this dissertation can provide may help MPOs develop more effective and health protective LRTPs.

I develop a dispersion modeling framework to evaluate the current exposure to $PM_{2.5}$ in the Atlanta Metropolitan area and how the region's LRTP will affect this. I show how a more detailed exposure assessment framework provides a more tangible measure of how the LRTP affects health. I also develop an integrated land use, travel demand, emission, and dispersion modeling framework that models the annual outcomes of a LRTP developed by the MPO in Albuquerque, New Mexico and calculate cumulative performance metrics to compare with more typical end of planning period metrics. I then use the annual modeling method to evaluate strategies for improving air quality, reducing exposure, and improving travel conditions in the region. I also perform a willingness to pay study to estimate the welfare change associated with improving bicycling facilities in the region which could be a low cost and practical method to reduce vehicle emissions and congestion.

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Chapter 1. Introduction

The overall goal of this research is to evaluate how long-range transportation plans change exposure to traffic related fine particulate matter ($PM_{2.5}$) and investigate the potential in the planning process for reducing exposure. A long-range transportation plan (LRTP) is a document prepared by a Metropolitan Planning Organization (MPO), which is a federally mandated and funded organization in urban areas with a population of more than 50,000. The plan is a document that lays out a regional vision and goals for transportation in the region and serves as a framework for regional decision making and investment.

I focus on evaluating LRTPs in terms of exposure to $PM_{2.5}$ for two reasons. First, epidemiology literature has linked exposure to $PM_{2.5}$ with many negative health outcomes, most importantly chronic obstructive pulmonary disease (COPD) mortality, ischemic heart disease mortality, and lung cancer mortality. Second, the dispersion of primary $PM_{2.5}$ emissions from vehicle traffic peaks along highways and declines sharply with distance from the road (see Rowangould 2015, Tayarani et al. 2016). This dispersion pattern means that a high level of spatial detail is required to evaluate the air quality impacts of primary $PM_{2.5}$ emissions from vehicle traffic and understand their health effects in a region.

To accomplish the main goal of creating a clearer picture of how transportation plans affect exposure and can be improved to minimize exposure, I divide my research into three parts. Each part tries to answer a separate research question. Answering each of these questions contributes to the overall goal of the research.

In the first part, chapter 2 of this manuscript, I use a spatially detailed dispersion modeling method to estimate exposure to $PM_{2.5}$ in Atlanta, Georgia. Exposure estimates for the years 2010, 2020, and 2040 are then used to estimate the change in health risks due to exposure to $PM_{2.5}$ across the region. I then discuss the results to demonstrate how this modeling approach can be used to improve the regional transportation planning process by identifying you long range plans affect health risks, and how risk is distributed across the region and different socioeconomic groups.

In the second part, Chapter 3, I evaluate how assessment of a long range transportation plan may be affected by the modeling approach. Typically, transportation plans are evaluated by how well they perform in the final year of the planning period – ignoring up to 30 or more interim years. This practice neglects the impacts of the plan during the entire planning period. Note that a plan that leads to a satisfactory condition at some point in the future does not guarantee that the path to the future is also satisfactory. Accounting for interim years is particularly important when evaluating health effects and greenhouse gas (GHG) emissions as these impacts are largely irreversible. In my analysis I evaluate a long range transportation plan in the Albuquerque, New Mexico metropolitan area using the usual approach of just considering the first and final year of the planning period and a new approach that models how the transportation system and travel behavior evolves throughout the planning period – accounting for impacts that occur each year.

In the third part, Chapter 4, I use the annual modeling method developed in Chapter 3 to evaluate two long range planning scenarios that I develop with the aim of reducing exposure to $PM_{2.5}$ while also reducing GHG emissions and improving other performance measures such as congestion. Iknow that some strategies that are used in the planning

process to reduce GHG emissions and improve travel demand measures, such as land use strategies that encourage infill development or greater density, can increase exposure vehicle emissions by encouraging development close to highways and concentrating traffic, and emissions, where we are also encouraging people to live. The annual modeling approach developed in this dissertation can help understand how land-use, travel behavior, and ultimately exposure to vehicle emissions change overtime which can help identify not only cumulative impacts, which are important when considering health impacts and GHG emissions, but also new strategies to mitigate undesirable outcomes in certain years of the planning period.

The final part of this dissertation, Chapter 5, evaluates the demand for improved bicycle facilities. Increasing bicycling can be a cost effective method to reduce vehicle emissions and congestion. Willingness to pay is a measure of economic value and can be used in gauge support for improving bicycling facilities. I use a contingent valuation method to understand the willingness to pay for several improvements to on street bicycle facilities in Albuquerque, New Mexico.

The remainder of this manuscript explains the background, methods and results of each part of the dissertation in greater detail along with a more detailed discussion of the results.

Chapter 2. Evaluating health outcomes from vehicle emissions exposure in the long-range regional transportation planning process

Introduction

A large body of evidence links fine particulate matter ($PM_{2.5}$) exposure with a wide range of negative health outcomes including cardiopulmonary mortality (Boldo et al. 2006; Krewski et al. 2009; Pope et al. 1995), ischemic heart disease mortality (Krewski et al. 2009; Laden et al. 2000; Pope and Dockery, 2006), lung cancer mortality (Krewski et al. 2009; Pope et al. 2002; Pope et al. 2011), and infant mortality (Woodruff et al. 1997). Prior research also finds that the concentrations of many vehicle emissions, including $PM_{2.5}$, are elevated along roadways (Karner et al. 2010; Zhou and Levy, 2007) and that up to 30% of an individual's exposure to particulate matter in urban areas may come from mobile sources (Boudet et al. 2000). Furthermore, exposure to $PM_{2.5}$ from vehicle exhaust has been linked to a broad range of negative health outcomes (Allen et al. 2009; Brugge et al. 2007; Gan et al. 2010; Garshick et al. 2004; Gauderman et al. 2007; Health Effects Institute, 2010; McConnell et al. 2006; Peters et al. 2004; Suglia et al. 2008; Wilhelm and Ritz, 2003). Reducing exposure to $PM_{2.5}$ from vehicle exhaust emissions is therefore an important public health goal.

Identifying populations at risk from exposure to vehicle exhaust and developing effective plans and policies to abate emissions and mitigate exposure, however, is challenging because vehicle exhaust emissions are unevenly distributed across urban areas. Furthermore, the uneven distribution of vehicle exhaust emissions often raises environmental justice concerns. Minority and low income populations are more likely to live near high volume roads where the concentration of vehicle exhaust emissions are

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elevated (Apelberg et al. 2005; Buzzelli and Jerrett, 2007; Chakraborty et al. 1999; Jephcote and Chen, 2012; Kingham et al. 2007; Rowangould, 2013, Rowangould, 2015). Over the past several decades, broad measures have been implemented to reduce health impacts linked to vehicle emissions exposure. The United States Department of Transportation requires Metropolitan Planning Organizations (MPOs) to create long-range regional transportation plans for urban areas with 50,000 or more residents. However, requirements for evaluating how these long-range plans may affect air quality, exposure and public health are very limited. The Clean Air Act requires the US Environmental Protection Agency (US EPA) to set National Ambient Air Quality Standards (NAAQS) for six criteria air pollutants, including $PM_{2.5}$, at levels that will protect public health. US EPA regulations only require those MPOs located in areas violating the NAAQS (i.e., nonattainment areas) to perform an air quality assessment of their transportation plans. Even then, transportation conformity regulations only require that MPOs simply estimate regional emission inventories and ensure that they fall below emission budgets prescribed in an approved State Implementation Plan. There is no spatial detail, no assessment of how exposure to emissions changes, no assessment of the change in health risk and no consideration of environmental justice concerns.

While MPOs, regardless of their NAAQS attainment status, tend to voluntarily incorporate improved air quality and health as specific objectives in their planning processes (Handy, 2008), the measurement of these objectives is typically limited to a qualitative review of the plan. For example, a study by Lyons et al. (2012) evaluated the activities of four MPOs that were considered leaders in integrating health and transportation in to their planning processes (Nashville Area MPO; Puget Sound Region

Council; Sacramento Area Council of Governments; and San Diego Association of Governments). The study indicates none of these MPOs estimated changes in exposure to vehicle emissions and their potential health impacts in the development of their long-range transportation plans. We followed up and reviewed the most recent long-range transportation plans developed by the same four MPOs and find that this is still the case today.

While quantitative exposure and health risk assessments are not being implemented at the regional transportation planning level, they do occur at the individual project level. For example, the change in $PM_{2.5}$ exposure and associated health impacts were evaluated for the proposed development of the MacArthur BART Transit Village Project in Oakland CA (UC Berkeley Health Impact Group, 2007). A line source dispersion model (CAL3QHCR Version 2.0) was used to model how exposure to $PM_{2.5}$ emissions from vehicle traffic would change once the project was developed. The authors found that project related traffic would increase average $PM_{2.5}$ concentrations by 0.30 $\mu g/m^3$. The study then translated this into 2.7 additional deaths in a population of 100,000. Similar, project level, assessments are not uncommon and are often carried out as part of US EPA required hotspot analysis in non-attainment areas or when an Environmental Assessment or Environmental Impact Statement is required under the National Environmental Policy Act (NEPA).

Project level exposure assessments may also be required by policy. For example, in 2008, the City and County of San Francisco adopted an ordinance on roadway proximity health effects that requires modeling the concentration of $PM_{2.5}$ (as a measure of traffic pollutants) when projects are built near busy roadways. If modeled levels of traffic

related PM$_{2.5}$ exceeds 0.2 μg/m^3, then the developers are required to incorporate ventilation systems that remove at least 80 percent of PM$_{2.5}$ from outdoor air. (San Francisco Health Code, Article 38 - Air Quality Assessment and Ventilation Requirement for Urban Infill Residential Development, Ord. 281-08, File No. 080934, December 5, 2008).

Project level exposure and health risk assessments may identify potential health risks, but at this late stage in a project's development if significant risks are identified mitigation measure are relatively limited. For example, San Francisco's air quality ordinance requires filtration of a building's air to remove high pollutant concentrations but does not consider or require abatement of emissions. Evaluating vehicle emissions exposure and health risks during the long-range regional transportation planning process could provide information for creating potentially more effective and efficient emission abatement and exposure mitigation strategies. For example, strategies such as a greater investment in regional transit systems or revising land use policies to incorporate smart growth principles that encourage less vehicle use could be evaluated and their effect on exposure hotspots and disadvantaged communities could be identified. These types of regional strategies, however effective and efficient they may be, are generally not considered within the scope of a project subject to project level environmental analysis, such as that required by the National Environmental Policy Act.

Prior studies demonstrate a variety of methods for integrating regional travel demand, vehicle emission and atmospheric dispersion or chemical transport models to estimate the concentration of vehicle emissions across urban areas and exposure to them. For example, several studies have advanced methods for integrating models to develop more

spatially detailed regional vehicle emission concentration and exposure estimates (Beckx et al. 2009b; Cook et al. 2008; Lefebvre et al. 2011; Rowangould, 2015). Several similar studies evaluate how the movement of a region's population throughout a day affects exposure estimates from these integrated models (Beckx et al. 2009a; Dhondt et al. 2012; Hatzopoulou and Miller, 2010; Shekarrizfard et al. 2016) including time spent in different micro environments (Vallamsundar et al. 2016). Furthermore, Dhondt et al. (2012) use an integrated modeling approach to estimate vehicle emission exposure for each municipality in Flanders, Belgium and then apply health impact functions to estimate health risk from their exposure estimates. The primary aim of the study by Dhondt et al. (2012) is evaluating how risk estimates differ when the movement of the population is accounted for.

While the above cited studies demonstrate the technical capacity to evaluate how regional transportation systems affect local air quality and health risks, these methods have not been applied to the analysis of regional transportation plans. Prior studies have focused on the development, demonstration and evaluation of methods, typically using current or a previous year's travel data. In this study, using an integrated travel demand-vehicle emission-air quality-health risk modeling approach similar to previous studies, we evaluate the long-range transportation plan for Atlanta, Georgia. Our analysis quantifies how vehicle emission exposure and health risks vary across the region at a spatial scale much finer than most prior studies and then how exposure and health risks change over time based on the region's long-range transportation plans. This approach provides a unique look at how regional transportation plans can affect neighborhood level exposure and health risks, and how these health risks can vary across space and over time. Our

analysis also evaluates disparities in exposure and health risks and how these change over time, demonstrating how a spatially refined approach can be used to identify exposure hotspots and environmental justice concerns and then evaluate how a transportation plan may affect these over time.

The ultimate objective of the research described in this study is to provide new methods and information for transportation planning agencies that can help them create more health protective and equitable regional transportation plans, and to accomplish these tasks more efficiently. We argue that identifying exposure and health risk hotspots during the regional planning process provides more opportunity for identifying effective strategies, avoiding unanticipated health risks, and improves efficiency by avoiding delays and expense that may occur when project level analysis identifies unexpected exposure and health risk concerns. Our framework also relies on data that most MPOs routinely generate in the course of the regional transportation planning process and makes use of software that is widely used or freely available and in the public domain. Therefore, most, if not all, MPOs should be able to implement our framework. While we demonstrate our approach by considering $PM_{2.5}$, which is a pollutant of concern in Atlanta, our approach could be used to evaluate other, non-reactive, vehicle emissions such as nitrogen dioxide, carbon monoxide, and a wide range of toxic vehicle emissions.

Methods

Our approach to estimate health effects associated with changes in air pollutant emissions from vehicle traffic, follows three steps: (1) dispersion modeling, (2) exposure analysis, and (3) health impact analysis. The following sections explain how these steps are carried out in this study and describe our study area.

Study area

We demonstrate our proposed method with three regional transportation planning scenarios provided by the Atlanta Regional Commission (ARC's), developed during its 2040 long-range transportation planning process. The scenarios include a 2010 base year, 2020 intermediate year, and 2040 planning horizon year.

Atlanta's diverse population and land use patterns provide an ideal case study location. With a total area of 8376 square miles (21,694 km2) and a 2014 population estimate of 5,614,323, 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. Of 5,614,323 people residing in the region, 3,332,844 (59.4%) are white and 1,729,477 (30.8%) are black. Other races in total, account for about 10 percent of the population (US Census Bureau, 2015). 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 which is a decrease from 2010 when median household income was $56,850. During the same four-year period, the percent of the population below the poverty level increased from 14.8% to 15.9% (US Census Bureau, 2014).

Dispersion modeling

We use dispersion modeling to estimate the concentration of $PM_{2.5}$ from on-road vehicle exhaust emissions. Dispersion models consider how atmospheric, weather and sometimes terrain influence the dispersion of emissions from their source (e.g., roadways) to receptors (e.g., a person's home). Photochemical models such as CAMx and CMAQ perform similar functions; however, they can also model chemical reactions that occur in the air column to account for the depletion and formation of various air pollutants over

time and space while dispersion models typically do not. The main drawback of using a photochemical model for accessing near roadway emissions is that they operate over a relatively course grid, usually greater than 3 km x 3 km (US EPA, 2007). Photochemical models also require information on all sources of air pollutants to accurately model chemical reactions which depend on the concentration of other air pollutants and therefore require more data inputs. Air dispersion models on the other hand offer a simplified approach that generally only consider the dispersion (transport and dilution) of air pollutants. Dispersion models are also advantageous for studying near roadway air quality because they can achieve much higher spatial resolution with relatively less computational burden.

Two air dispersion models are widely used for modeling mobile source air pollutant emissions, CALINE4 and AERMOD. A relatively new model, RLINE, has also been developed by the US EPA, providing a more streamlined method for modeling roadway emissions. RLINE has not been approved for regulatory use by US EPA. These models predict hourly concentrations at user-specified receptor locations and have demonstrated abilities to model the concentration of vehicle emissions along roads. Each model was evaluated in a recent validation study conducted by US EPA by comparing measured concentrations of a tracer gas with modeled concentrations along a roadway (Heist et al. 2013). The tracer gas experiments find that AERMOD and RLINE are similar and somewhat more precise than CALINE. In this study, we use AERMOD primarily because it is US EPA's preferred model for near roadway hotspot analysis and also because it considers topography which is important when considering the dispersion of emissions across large urban areas.

We use a rastering method for applying AERMOD to large transportation networks developed by Rowangould (2015). This method generally follows US EPA's $PM_{2.5}$ hotspot modeling guidance for modeling roadways area sources (US EPA, 2015) but breaks up the modeling domain into a large number of small grid cells that can be modeled individually (Figure 1) and then later combined to produce a region wide concentration raster with a spatially interpolated 20 m resolution. Additionally, since we are only interested in an annual average concentration rather than demonstrating compliance with the National Ambient Air Quality Standards (i.e., the 24 hour $PM_{2.5}$ standard requires estimating the 98th percentile daily concentration), we use a subset of the full meteorological record (the 1st and 15th day of each month for 5 years). These methods and simplifications make it possible to model Atlanta's large transportation system in a relatively short amount of time (days rather than months or years).

0   25   50   100 Kilometers

(a)

0   1   2   4 Kilometers

(b)
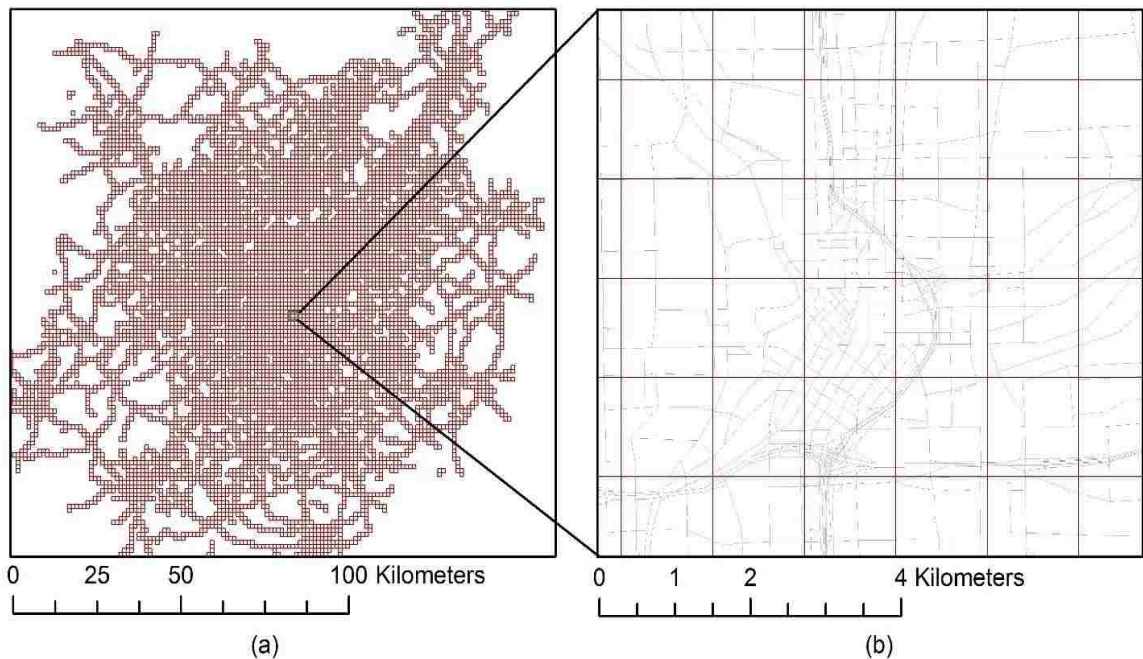
Figure 1. Defining 1km grid and intersecting it with Atlanta Metropolitan Area (a), zoomed-in view showing the roadway network in downtown Atlanta (b).

Data required for setting up the model are obtained from several sources. For each scenario, ARC provided the output of its 4-step travel demand model and hourly, link level, gram per mile vehicle emission rates estimated with the U.S. Environmental Protection Agency's Motor Vehicle Simulator Model (MOVES). Digital Elevation Model (DEM) data defining the terrain are obtained from the U.S. Geological Survey (USGS). Meteorological data are obtained from Georgia Department of Natural Resources, Environmental Protection Division. The meteorological data consists of 7 stations, each reporting hourly surface and upper air data from January 1st, 2007 to December 31st, 2011.

Exposure analysis

We estimate $PM_{2.5}$ exposure by overlaying US Census block level population estimates with the $PM_{2.5}$ concentration rasters we created using AERMOD. We estimate the mean $PM_{2.5}$ concentration for each census block as the average value of raster cells falling within each census block boundary using the zonal statistics tool in ESRI's ArcGIS software. For the year 2010 scenario, we use block level population estimates from the 2010 decennial census. For the year 2020 and 2040 scenarios, we use ARC's population projections available from their open data website (http://www.arcopendata.com). ARC's population projections are available at the census track level and do not include race or ethnicity. Each 2020 and 2040 census block is assigned a population from its corresponding track level population estimate in proportion to its 2010 population. The racial profile of each block is also maintained in proportion to the 2010 population data. We also add median household income estimates from the 2010 American Community Survey to each census block in all three scenarios. Median household income estimates

are only available at the larger census block group level and there are no income forecasts

for the future year scenarios. Each block, in each scenario, is assigned the 2010 median

household income estimate from its corresponding block group.

Our exposure analysis approach has three obvious limitations. First, we assume that the

spatial distribution of race and income remain constant over time. Second, we do not

account for the daily activity patterns of each individual. We assume exposure occurs at

each individual's home. Third, these home based exposure estimates assume exposure to

the estimated outside $PM_{2.5}$ concentrations which likely differs from the concentration

indoors. These are simplifying assumptions that could be resolved with additional data

and research (e.g., the measurement of outdoor air pollutant penetration rates into

buildings and homes of various types in the region and the MPO's use of an activity

based travel model that can track the location of individuals throughout their daily

routine); however, we believe they provide a reasonable estimate of exposure since many

people spend a large amount of time at or near their homes.

Health impact analysis

Epidemiology studies 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 cohort and case control studies can then be used to create

concentration-response functions that describe the relationship between concentration

(exposure) and response (negative health outcome). The majority of epidemiology studies

focusing on air pollution exposure have developed log-linear concentration-response

functions (Post et al. 2012) as shown in Eq. (1). A review by the US EPA for its PM

regulatory impact assessment also suggests that a log-linear model provides the best estimate of long-term mortality associated with exposure to PM (US EPA, 2012).

$$\ln y = \alpha + \beta X \tag{1}$$

Where,

α = constant

y = risk of response (health outcome) in a given year

β = effect estimate (change in risk per unit change in concentration of pollutant)

X = concentration of pollutant

β can be estimated using a linear regression model or a cox proportional hazards model (see for example Pope et al. 2012). An expansion of equation (1) yields the risk of a particular negative health outcome after a change in the concentration of a pollutant (equation 2).

$$y = y_0 e^{\beta \Delta X} \tag{2}$$

Where,

y_0 = base risk of negative health outcome

ΔX = change in the concentration of the pollutant

The change in the risk of a negative health outcome associated with a change in the concentration of an air pollutant (equation 3) is then used along with population data to estimate the change in the annual incidence of health outcomes (equation 4).

$$\Delta y = y - y_0 = y_0 \left(e^{\beta \Delta X} - 1 \right) \tag{3}$$

$$\Delta I = \Delta y \, P = y_0 \left(e^{\beta \Delta X} - 1 \right) P \tag{4}$$

Where,

Δy = change in the risk of health outcome

ΔI = change in the annual incidence of health outcome

P = mid-year population

The effect estimate of PM$_{2.5}$ on different negative health outcomes (β) is commonly reported in the epidemiology literature. We obtain β for three types of health outcomes from the peer reviewed literature, including chronic obstructive pulmonary disease (COPD) mortality, ischemic heart disease (coronary artery disease) mortality, and lung cancer mortality (table 1). While there are many studies estimating the association between the health outcomes and change in PM$_{2.5}$, we select estimates from (Krewski et al. 2009) due to their robustness. Their estimates were derived after adjusting for 44 individual specific covariates and based on 18 years of data from approximately 1.2 million adults (aged > 33 years old) in about 172 US metropolitan areas, making this, one of the most notable studies linking PM$_{2.5}$ and mortality. Estimates by Krewski et al. (2009) are also used in EPA's Environmental Benefits Mapping and Analysis Program (BENMAP). Furthermore, prior work of Krewski et al. (2000) was described by Health Effects Subcommittee of the Advisory Council on Clean Air Compliance Analysis (US EPA 2010) as the most careful work on defining a dose-response function.

There are other health outcomes, such as bronchitis, wheezing, and asthma (see McCubbin 2011 for a comprehensive list of PM$_{2.5}$ dose-response functions for different health outcomes in different studies); but the effect of PM$_{2.5}$ on the risk of such outcomes is either too small to be considered significant or is highly variable among different studies. In this study, we only considered the health outcomes for which the effect of PM$_{2.5}$ on their risk is relatively strong and consistent across studies.

Table 1. Effect estimate for health outcomes assessed in this study (derived from Krewaki 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)

To perform the health impact analysis, we obtain age adjusted, baseline, mortality risks (risks that are standardized to account for variations in age profiles in different areas) for each health outcome in Table 1 at the county level for the 2010 base year (y_0) from CDC WONDER. 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 that these data are publicly available. While baseline mortality risks in each county are expected to vary not only by age, but also across socioeconomic groups, CDC Wonder does provide data broken out socioeconomic attributes of the population at the county level. We use the 2010 county average baseline mortality risks to estimate the 2010 block level mortality risks based on the difference in each block's estimated PM$_{2.5}$ concentration from the estimated average county PM$_{2.5}$ concentration following equation 5, where $\overline{X_c}$ is the county mean concentration, X_b is the mean block concentration, and $\overline{y_c}$ is county baseline mortality risk.

$$y_b = \overline{y_c}e^{\beta(X_b-\overline{X_c})} \tag{5}$$

We also estimate the change in future mortality risk (Δy) and incidence (ΔI) based on the change in block level PM$_{2.5}$ concentration (ΔX) from the 2010 base year, to the year 2020 and year 2040. The change in mortality risks and incidence are estimated by applying equations (3) and (4) to the estimated change in block level PM$_{2.5}$ concentrations.

An alternative to the direct use of health impact functions is to use US EPA's BENMAP software to assess health impacts. BENMAP, takes as inputs, concentration estimates for different scenarios and automates estimation of the change in the risk of health outcomes. BENMAP then uses default baseline incidence risks for different health outcomes and estimates changes in the number of outcomes and the economic benefits/loses associated with those changes in each county. One advantage of our approach is that it allows us to calculate health outcomes using more detailed block level concentration estimates. This level of spatial detail allows us to more precisely estimate the health impacts for those living near roadways where concentrations are elevated but rapidly decay with distance. Our spatially detailed analysis also allows us to investigate the potential relationships between block level socioeconomic attributes (e.g., race and income) and health outcomes. While BENMAP can be altered to also provide block level output, it requires an extensive and complicated manipulation of input data.

Results

The modeling results indicate that concentrations of directly emitted $PM_{2.5}$ emissions from on-road vehicle exhaust, brake and tire wear are highest along major highways throughout the metropolitan area and the urban core (figure 2). The highest concentrations occur along interstate 75 running north-south and interstate 285 circling the city of Atlanta. Concentrations near highways can approach 30 μg/m^3 and decline rapidly from the roadway edge; however, in some areas in the urban core and near major interchanges there are extended areas of relatively high $PM_{2.5}$ concentrations. The maps also show large reductions in $PM_{2.5}$ concentrations between 2010 and 2020 almost everywhere. However, the maps in figure 2 shows that by 2040 concentrations of $PM_{2.5}$

from vehicle traffic begin to increase, especially in more outlying areas. The large

reductions noted in most areas are largely due to reductions in per mile vehicle emission

rates, rather than less driving. While VMT per capita declines 3% by 2020 and 4% by

2040, total vehicle miles traveled (VMT) increases by 19% by the year 2020 and by 52%

by the year 2040, over the base year scenario. The large increase in driving is the result of

an expected 52% increase in the region's population by 2040.
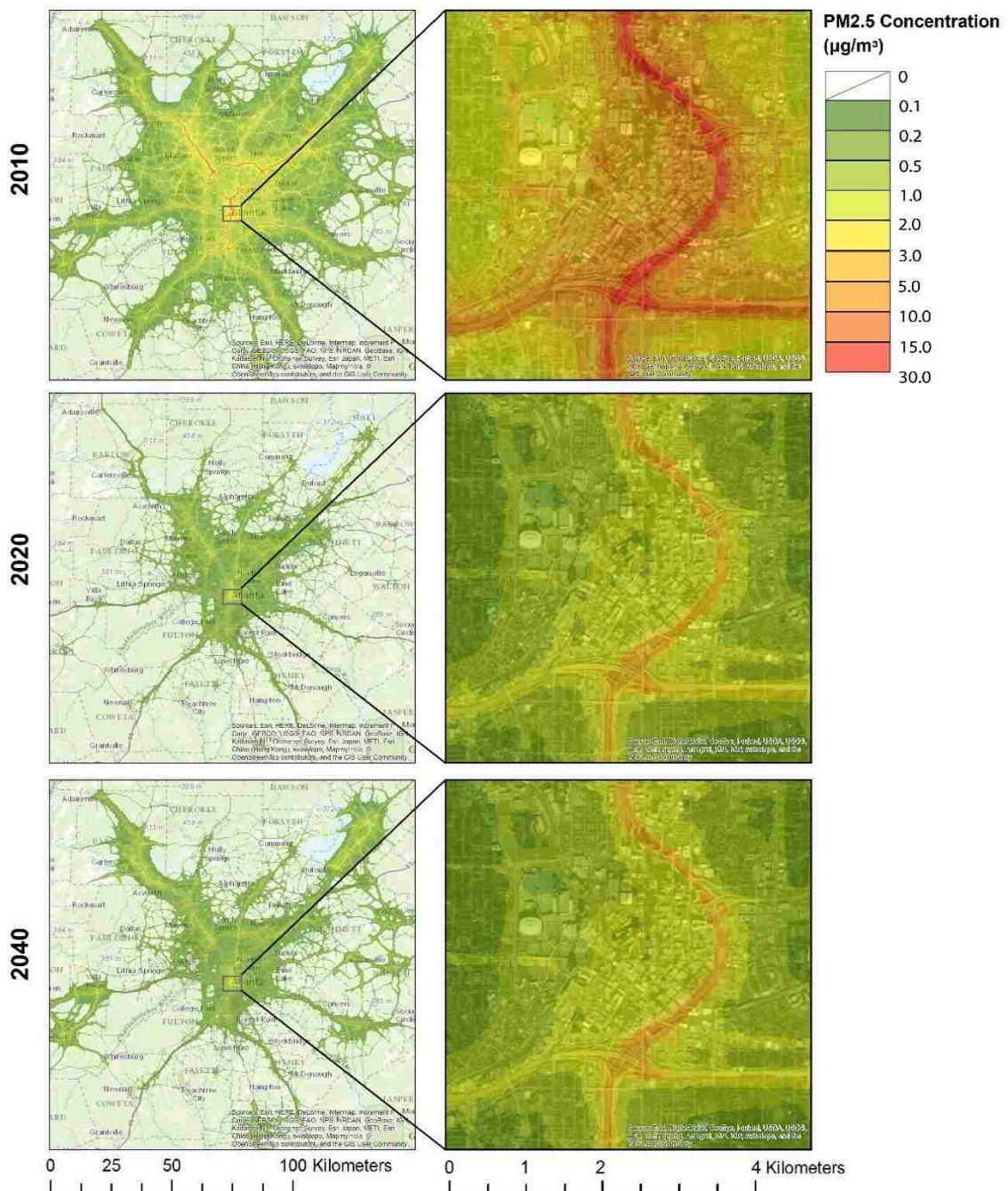
Figure 2. Spatial distribution of PM₂.₅ concentration from vehicle traffic across the Atlanta

The maps in figure 3 compare the scenarios in more detail by computing the absolute and

percentage changes between each scenario. From these maps it is clear that most of the

reduction in the concentration of PM$_{2.5}$ from vehicle traffic occurs in the first 10 years,

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and then begins to gradually increase. The initial reduction is mostly attributed to the penetration of new vehicles meeting recent, more stringent, vehicle emission standards. Overtime, the results suggest that growth in vehicle use eventually overcomes the initial benefits of stronger emission standards. The eventual growth in emission concentrations is largest in outlying areas where in some places the increase is relatively large, ranging from 0.1 $\mu g/m^3$ to about 20 $\mu g/m^3$ in the vicinity of highways. While some areas will experience an increasing trend in future years, almost all areas of the Atlanta metropolitan area will still experience much lower concentrations of $PM_{2.5}$ from vehicle traffic in 2040 than they do now.
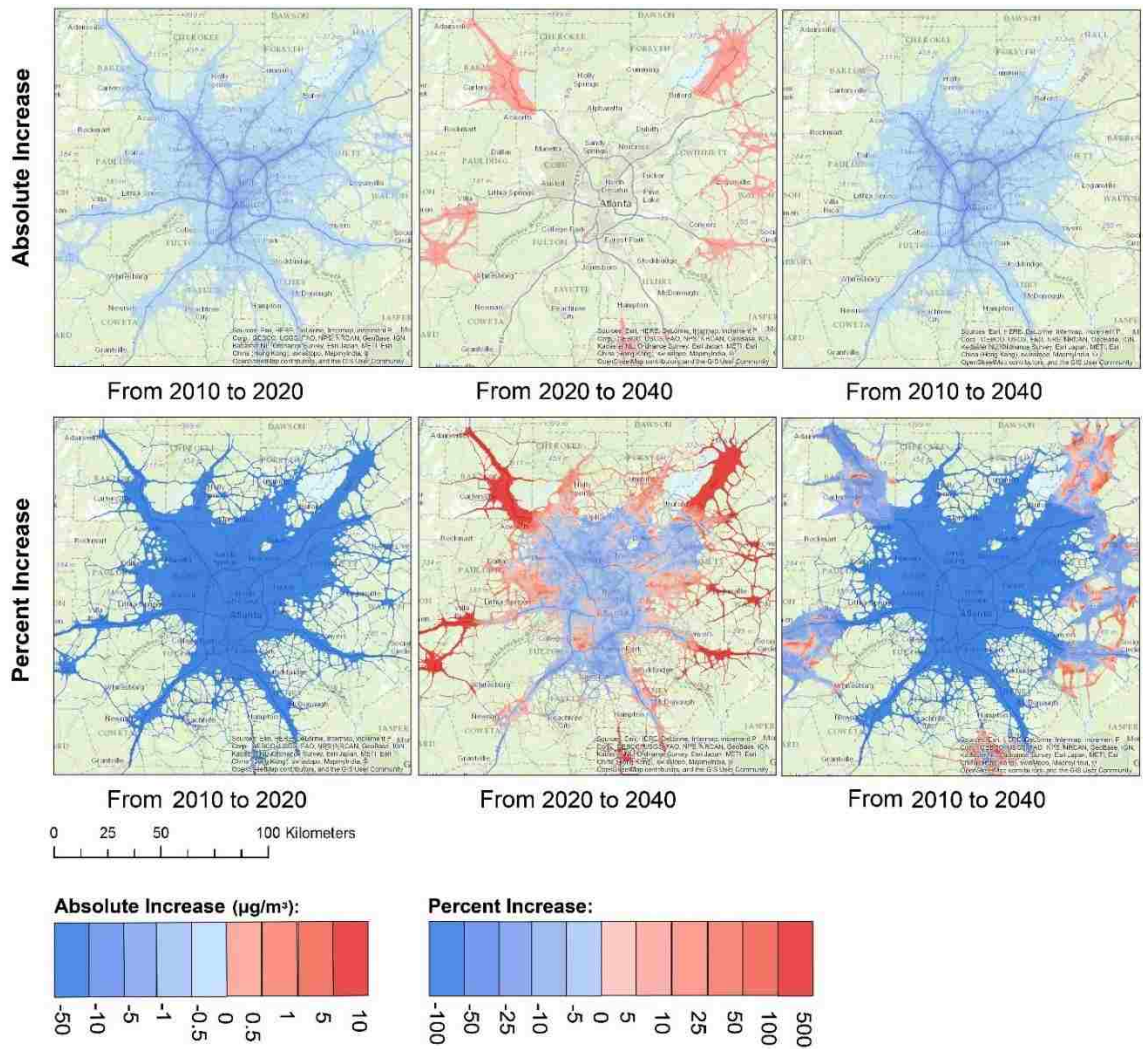
Figure 3. Absolute and percent change in estimated PM$_{2.5}$ concentration

We also calculated aggregate changes in population exposure to PM$_{2.5}$ emissions from vehicle traffic by estimating the change in population weighted PM$_{2.5}$ concentrations. These are shown in Table 2. The population weighted average daily PM$_{2.5}$ concentration declines from 0.58 μg/m^3 in 2010 to 0.16 μg/m^3 in 2040, a decline of almost 75 percent over the 30-year planning horizon. As noted above, the reductions occur in the first 10 years, after which concentrations and exposure begin to rise. The aggregate results also indicate that the non-white population is on average exposed to higher concentrations than the white population. For example, in 2010, blacks were exposed on average to a

daily population weighted PM$_{2.5}$ concentration of 0.66 μg/m^3, and other non-whites to

0.77 μg/m^3 of PM$_{2.5}$, exposures that are 29 and 51 percent higher than that of whites,

respectively. Lower income populations are also exposed on average to much higher

concentrations. In 2010, low income populations, defined as households with an income

less than $33,860 which is 200% of the federal poverty level based on the region's

average household size of 2.6, were exposed on average to a daily population weighted

PM$_{2.5}$ concentration of 0.94 μg/m^3, which is 80 percent higher than that exposure of

higher income households (0.52 μg/m^3). These patterns of exposure inequality extend

into the two future planning scenarios.

Table 2. Estimated daily PM$_{2.5}$ emissions and PM$_{2.5}$ emissions concentrations from vehicle traffic in the Atlanta Metropolitan Area

Year	Emission Inventory[a] (kg)	Mean Concentration[b] (μg/m^3)	Population Weighted Mean Concentration (μg/m^3)					
			Total Population	White	Black	Other non-white	Low Income	High Income
2010	7,606	0.19	0.58	0.51	0.66	0.77	0.94	0.52
2020	3,686	0.05	0.15	0.12	0.17	0.20	0.26	0.13
2040	5,545	0.07	0.16	0.14	0.18	0.21	0.29	0.14

[a] Total daily quantity of PM$_{2.5}$ emissions across the study area.
[b] Mean daily PM$_{2.5}$ concentration across the study area (e.g., includes concentrations in unpopulated areas).

We evaluate exposure inequity by race and income group in more detail with cumulative

population exposure plots (figures 4 and 5). The cumulative exposure plots indicate that

low income and non-white populations are more likely to live in areas with higher

concentrations of PM$_{2.5}$ from vehicle traffic. This inequality exists both in 2010 and

future scenarios. The plots also provide additional information that is not apparent in the

aggregate calculations in Table 2. They show that the population within each race and

income group are exposed to a wide range of emission concentrations.
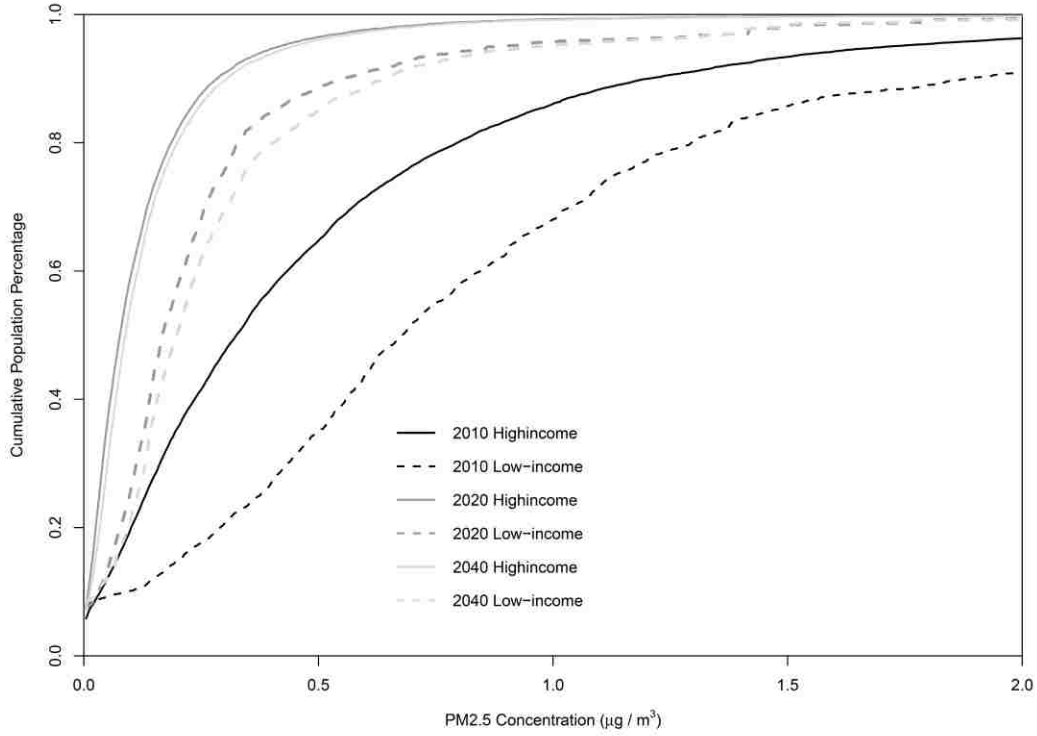
Figure 4. Cumulative exposure distribution by income level
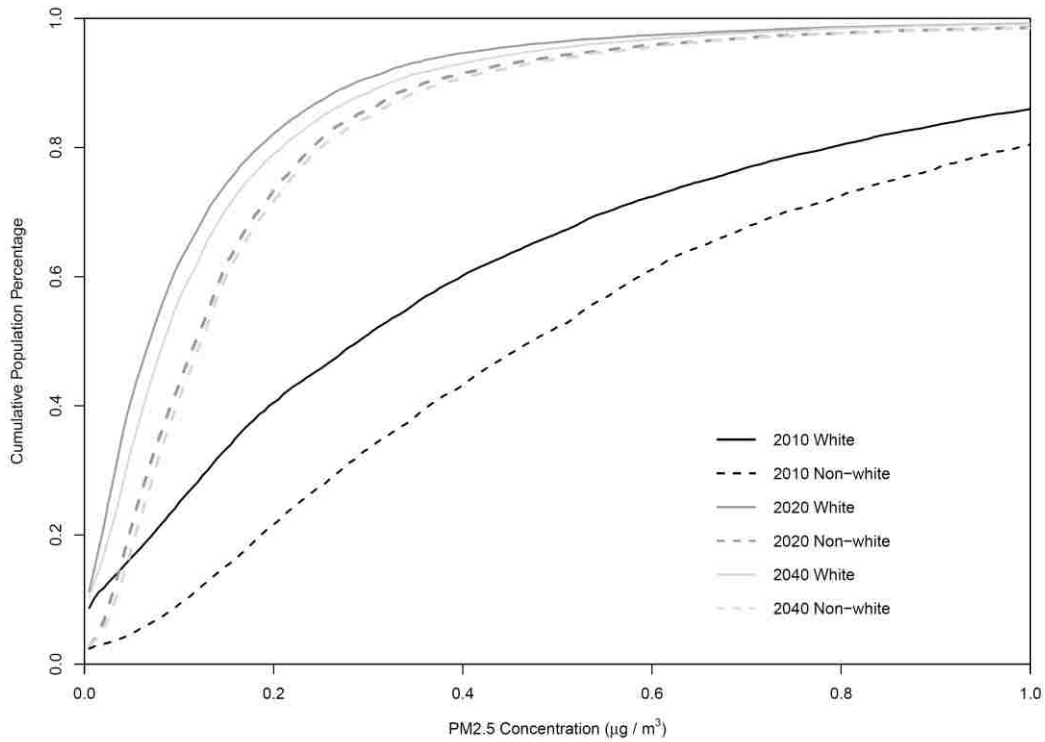
Figure 5. Cumulative exposure distribution by race group

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The large reduction in $PM_{2.5}$ concentrations also results in large reductions in health risks. Figure 6 shows the pattern of mortality risk reduction from 2010 to 2040 as a result of the estimated change in $PM_{2.5}$ emissions from vehicle traffic and the associated change in $PM_{2.5}$ concentrations. The largest risk reductions follow the largest reductions in $PM_{2.5}$ concentrations which occurs in downtown Atlanta and along the region's highways. While not entirely visible on each of the maps in figure 6, a few urban peripheral areas experience a small increase in mortality risk.

We also evaluate the change in risk by race and income. Census blocks were grouped into deciles by income and their proportion outcomes we evaluated for populations in each decile. These results are shown in figures 7 and 8. These results indicate that places with the lowest and highest income populations and those with the largest share of minorities experience the largest risk reductions. By 2020 and 2040, there is relatively little difference in risk across race or income deciles. These risk reduction patterns reflect the demographics of the region. Areas that currently have the highest concentrations of vehicle emissions are located close to the center of Atlanta or along major roadways extending outward from the city center to the suburbs. These are also areas with some of the lowest and highest income communities along with a large minority population. Suburban areas with more modest levels of air pollution also have more modest income levels and a relatively smaller minority population.
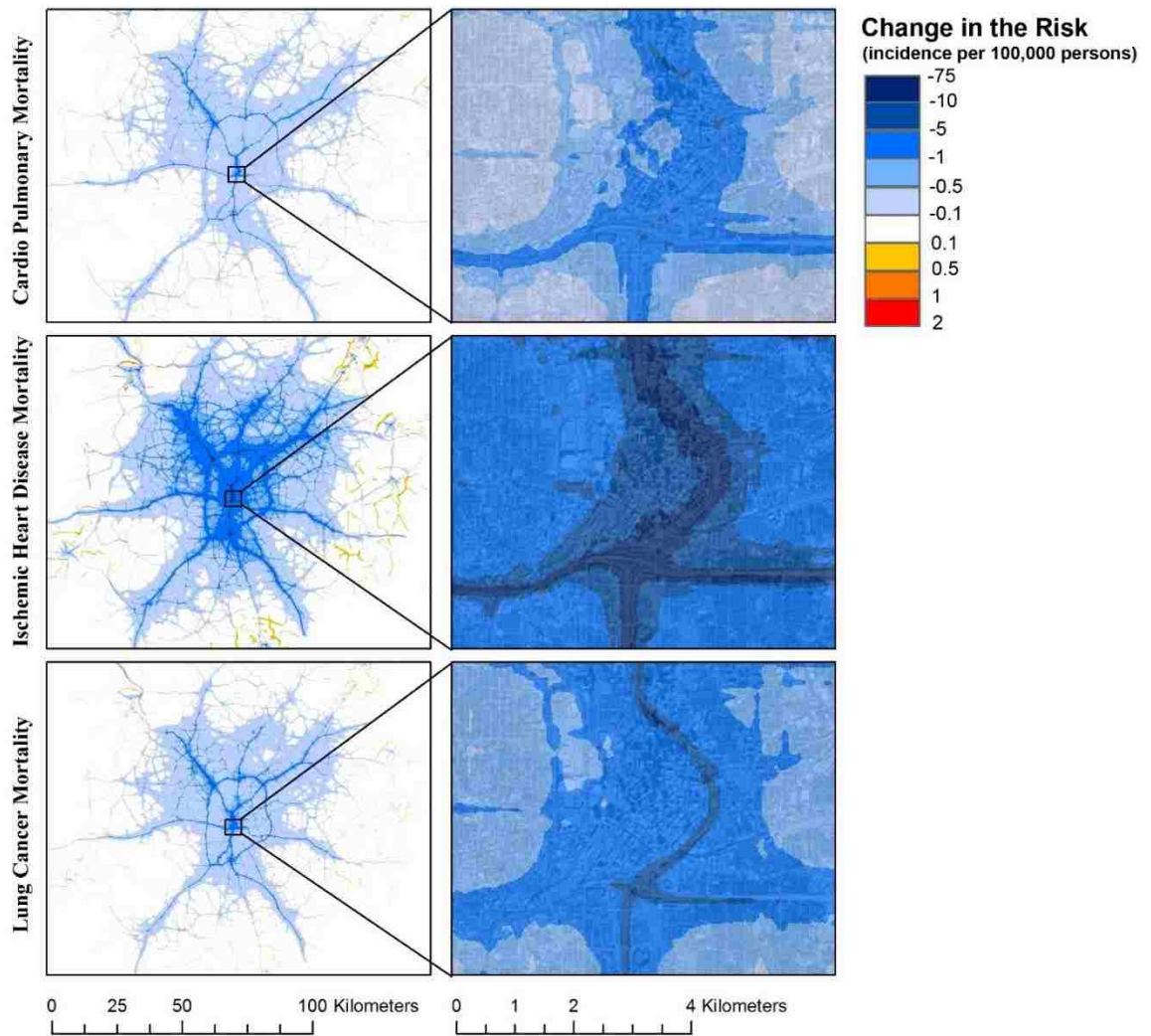
Figure 6. Change in mortality risk from 2010 to 2040 due to change in PM$_{2.5}$ concentration
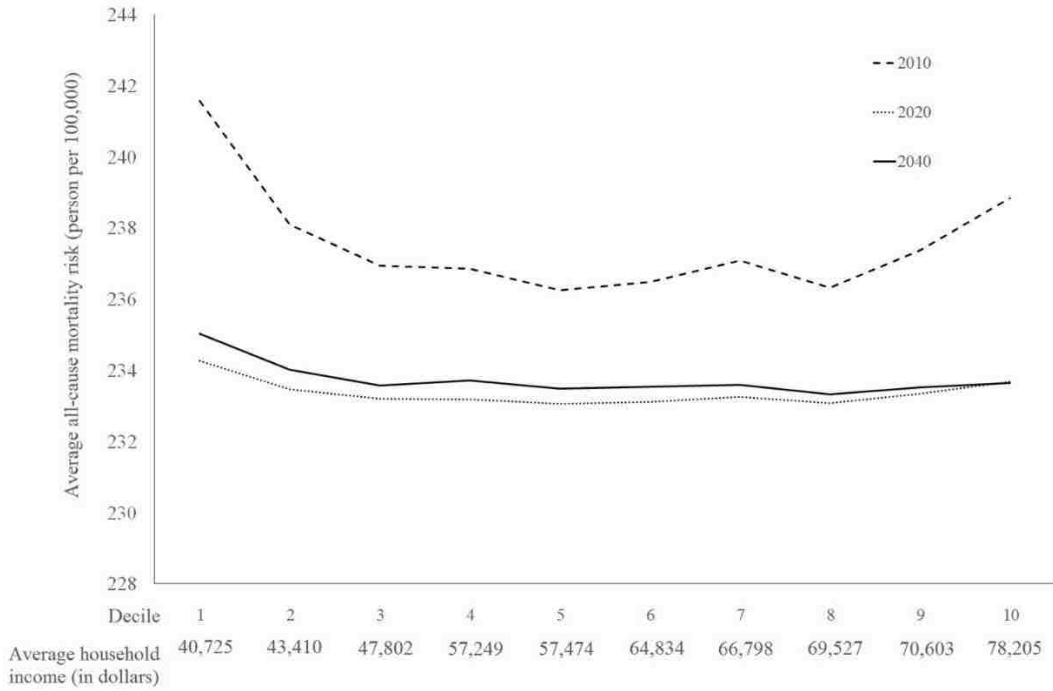
Figure 7. Mortality risk by income decile from 2010 through 2040
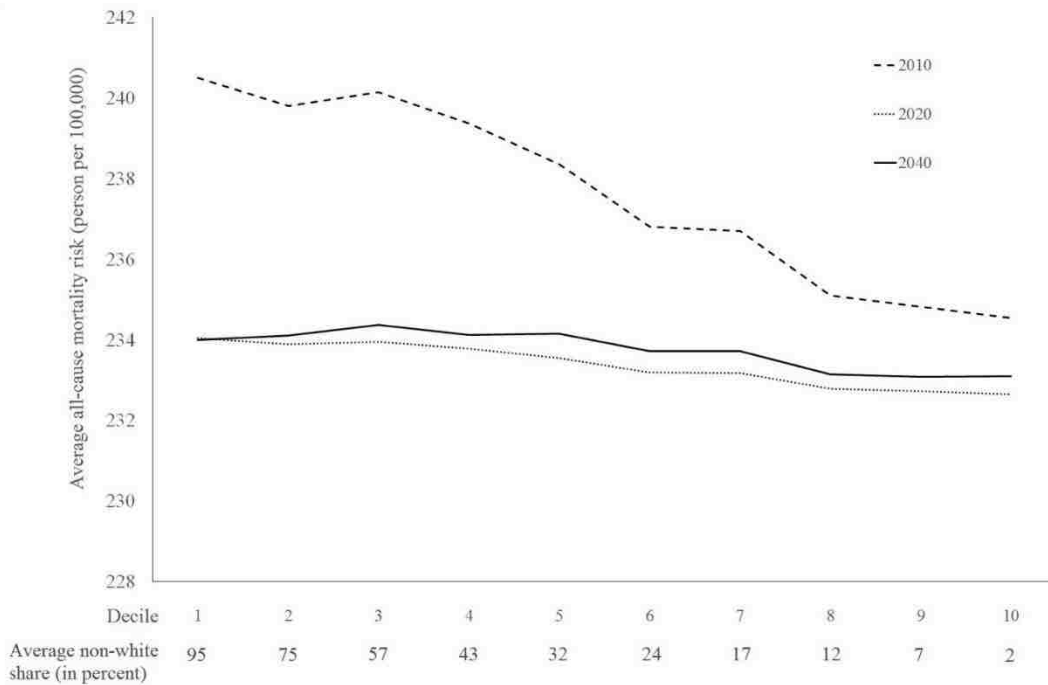
Figure 8. Mortality risk by race decile from 2010 through 2040

Our analysis finds a mean of 125 deaths avoided in 2020 and 142 in 2040 in the Atlanta

Metropolitan Area for three major health outcomes related to $PM_{2.5}$ exposure (figure 9).

These include: 17 avoided COPD deaths in 2020 (1.3% reduction from 2010) and 19 in 2040 (1.5% reduction from 2010); 85 avoided ischemic heart disease deaths in 2020 (3% reduction from 2010) and 96 in 2040 (3.4% reduction from 2010); 23 avoided lung cancer deaths in 2020 (1.2% reduction from 2010) and 27 in 2040 (1.4% reduction from 2010). There is little improvement in lives saved between 2020 and 2040 since the bulk of emissions reductions occur during the first 10-year period. The results also find that non-whites have a higher mortality reduction even though they make up a smaller share of the region's population. Similarly, while low and higher income populations have similar mortality, the low income population is only 16 percent of the total population.
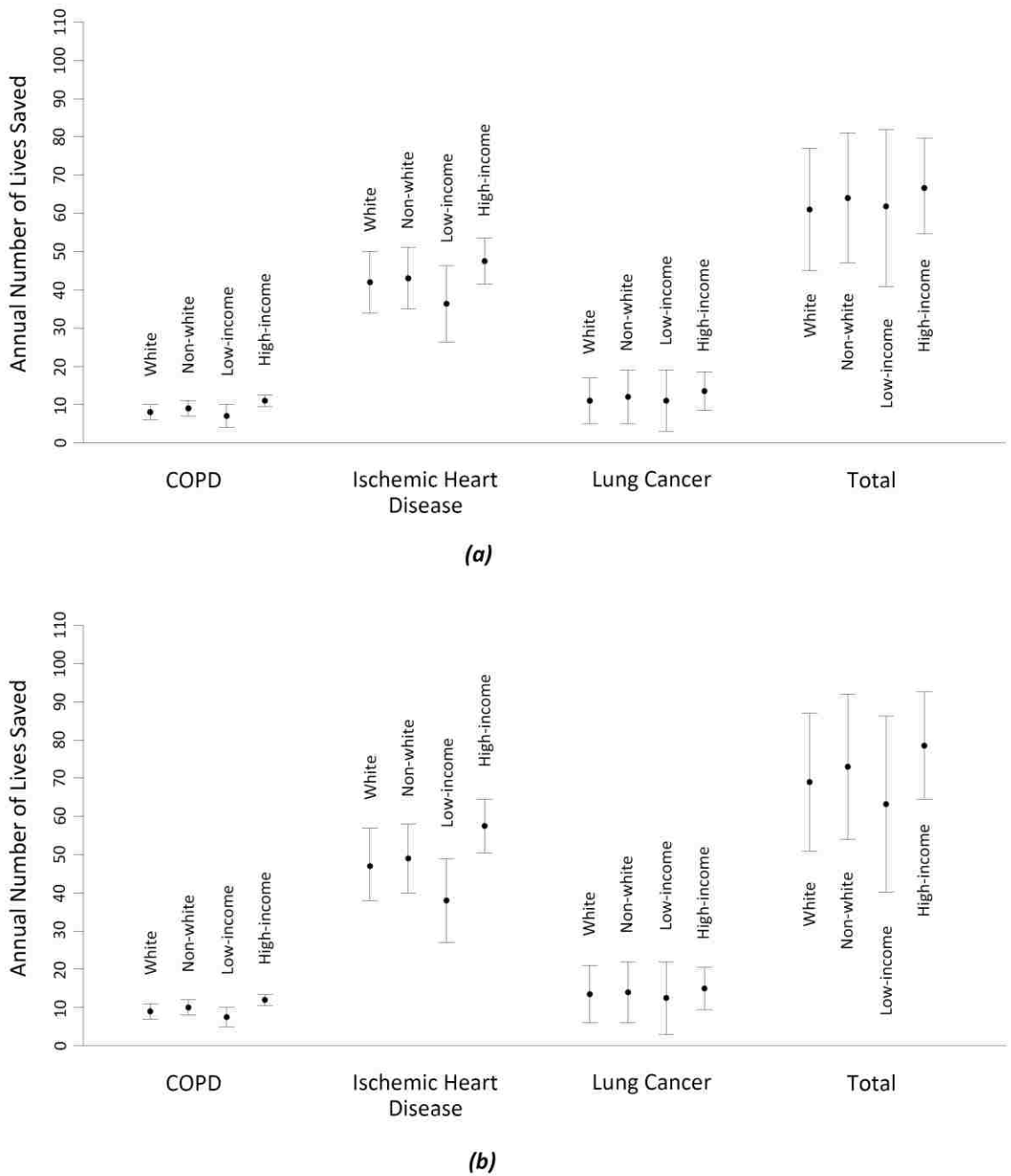
Figure 9. Annual number of lives saved from 2010 to (a) 2020, and (b) 2040. The bars represent the 95% confidence interval with the mean in the center.

Discussion

In this study, we integrated outputs from a travel demand model with vehicle emission,

air quality and health impact models to evaluate the health outcomes associated with

change in exposure to vehicle emissions. Our study is novel in that it estimates the change in vehicle emission concentrations, exposure and associated health risks expected from a metropolitan planning organization's long-range transportation plan. Prior studies and analysis completed by metropolitan planning organizations that have evaluated changes in air quality for various long-range, regional, transportation planning scenarios are limited to estimating the change in regional emission inventories. While there have been academic studies that model exposure to vehicle emissions and estimate their health impacts, they have not investigated changes expected under various planning scenarios, they have focused on current conditions.

Our analysis of the Atlanta Metropolitan Area's long-range transportation plan, finds that $PM_{2.5}$ concentration and population weighted average exposure declines by almost 75 percent over the 30-year planning horizon. Most of reduction occurs in the first 10 years and concentration begins to gradually increase after the year 2020. The initial reduction is mostly due to improvements in vehicle and fuel technology expected from stricter federal vehicle emission standards. Growth in travel demand over time eventually begins to overcome the benefits of stronger emission standards. The eventual growth in concentrations is largest in suburban areas in the vicinity of highways where the increase from year 2010 to 2040 can reach up to 20 $\mu g/m^3$. The large initial decrease in vehicle emissions exposure results in large reductions in mortality risk and incidence. The decrease in risk and incidence remains about constant after the rapid decline observed in the first 10 years. These results demonstrate the benefit of federal vehicle emissions standards. However, the results also suggest that vehicle emission standards will either need to be tightened in the future or more aggressive measures to reduce travel demand

will need to be adopted to prevent the erosion of initial air quality and public health gains.

Our findings also suggest that large inequalities and environmental justice concerns exist in Atlanta, where low income and minority communities experience the highest vehicle emission concentrations and therefore the largest health risks. These findings are similar to what has been found in other regions in prior studies (e.g., Apelberg, 2005; Chakraborty, 2009; Gunier, 2003; Houston, 2004; Rowangould, 2013). The relative size of exposure inequalities were also found to remain about the same overtime. While low income and minority communities experience the greatest health risks, they also experience the greatest reduction in risk over time, which substantially reduces the gap in absolute health risks between low and high income groups as well as white and non-white groups.

While many prior studies find that low income and minority communities are more likely to be exposed to higher concentrations of vehicle emissions, as we found in this study, exposure patterns vary from place to place and are often complex. For example, we also find that high income deciles also face increased $PM_{2.5}$ exposure and associated health risks. A study by Havard et al. (2009) finds that in Strasbourg, France, households falling within the mid-point of a social deprivation index that provides a general measure of socioeconomic status had the highest exposure to traffic emissions. Similarly, Cesaroni et al. (2013) find that in general communities in Rome with medium and high socioeconomic status had the greatest potential traffic emissions exposure based on their proximity to high volume roadways; however, when they evaluated disparities within smaller areas of the city this was not always the case. As our study and these prior studies

demonstrate, vehicle emissions exposure patterns are complex and vary across communities and regions, underscoring the value of conducting spatially detailed exposure and health risk analyses.

The approach we have developed and the quantitative exposure and health impact information it can provide should be useful for identifying more health protective regional transportation plans that limit exposure by decreasing travel demand in pollution hotspots or by limiting development in these areas. Such a proactive approach is also likely to increase efficiency as projects that may pose serious health risk concerns can be identified early on in the regional planning process where there are many more degrees of freedom to explore alternatives than there are during a project level analysis. This information can also be used to evaluate the long term effectiveness of federal vehicle emission standards in major population centers. Furthermore, the capability to estimate spatially resolved health risks and the change in risk under various planning and policy scenarios could be valuable in communication with the public. Changes in emission inventories are largely disconnected from changes in a community's health risks. And, even spatially resolved vehicle emission concentration estimates provide little contextual information to the average person. It is unlikely that most people understand, for example, what a 1 $\mu g/m^3$ change in $PM_{2.5}$ might mean for their health. Communicating changes in risk may therefore result in more effective public participation and provide greater contextual information for evaluating tradeoffs with other regional transportation planning goals such as congestion mitigation, traffic safety, and economic growth.

Our spatially detailed approach to regional air quality analysis also allows for a more robust evaluation of environmental justice concerns. MPO's that do consider

environmental justice concerns related to air quality in their regional plans often rely on some type of spatial 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. 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 there is an environmental justice concern then becomes subject to the choice of these thresholds which could be difficult to defend. Furthermore, vehicle emissions 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.

Our analysis of exposure addresses many limitations in current practice and the latest academic advances but several important limitations persist. First, we did not account for the movement of individuals. We estimate exposure, as most prior studies have done,

based on pollution concentrations at the population's residential location. Clearly, the population's exposure is accumulated throughout the day as people travel to conduct their daily business. While this is a limitation, we also argue that it still provides a significant improvement over current methods used in practice and provides a reasonable estimate of exposure since most people spend the majority of their time in and around their home. Our prior research also finds concentrations are highest in the early mornings and evenings when most people are at home (Rowangould, 2015). Second, exposure is based on the estimated outdoor ambient air pollution concentration and not the concentration within buildings. Prior studies find that concentrations inside and outside of buildings may vary significantly (Baek et al. 1997; Kim et al. 2001; 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 data on individual's movement in the region. Currently, there is insufficient regional data on indoor/outdoor concentration ratios to carry out this refinement. We assume that higher outdoor concentrations are associated with relatively higher indoor concentrations. Third, in analyzing equity concerns, we assumed that block level household incomes and the proportion of each race remained constant over time. The population of blocks could grow or decline, but their socioeconomic profile remained constant. We are unaware of any methods for forecasting these changes at a refined spatial scale. There are also limitations specific to the health impact functions used in our study. First, dose-response functions are obtained from studies that considered exposure to $PM_{2.5}$ from many different sources. Therefore, we cannot be

certain if the change in PM$_{2.5}$ from traffic sources would result in similar, higher or fewer health impacts.

Finally, while the models we use have each been evaluated and validated to some extent by the agencies that created them, the amount of uncertainly in each model's estimates for a particular set of modeled conditions are largely unknown. For example, travel demand models are calibrated and validated against current travel data at a few roadway locations and with aggregate regional statistics. How well these models actually predict future travel conditions or travel conditions on particular links is largely unknown (Zhao and Kockelman, 2002). Dispersion models have occasionally been evaluated with field tests using tracer gases or a set of near roadway monitors (Heist et al. 2013; Wang et al. 2016; Yura et al. 2007) but the very limited conditions of each test; each using different models, experimental designs, and traffic and land use conditions does not provide enough information to estimate uncertainties for particular modeling applications. These dispersion model validation studies each reached very different conclusions. Each travel demand, emission factor, and dispersion model that we use only provide point estimates. This is a well-known limitation in the transportation forecasting and vehicle emission modeling field and one where little progress has been made. By passing point model estimates from one model to another in our modeling chain, we are likely compounding these unknown uncertainties to an unknown extent.

There are 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 wide variety of mobile source air toxics such as benzene and formaldehyde (US EPA, 2006). Health impact functions also exist for many mobile source air pollutants (e.g., see US EPA's BENMAP program), and they could be used with exposure estimates estimated using our framework to estimate changes in health risk. 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). The relative importance of accounting for differences in indoor and outdoor concentrations also warrants further investigation. Finally, research aimed at understanding the uncertainties of individual modeling steps and their propagation though commonly used modeling chains is sorely needed and requires a significant, new, research effort by the transportation and air quality research field and the agencies who develop and use many of these models.

Chapter 3. Evaluating the cumulative impacts of a long-range regional transportation plan: particulate matter exposure, greenhouse gas emissions, and transportation system performance

Introduction

In the United States, Metropolitan Planning Organizations (MPOs) are responsible for developing coordinated, long-range, regional transportation plans (LRTPs) for urban areas with 50,000 or more people. The plans 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 United States Environmental Protection Agency's (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. While not common in practice, it is also possible to evaluate how a long-range plan affects population exposure to vehicle emissions using an air dispersion model such as US EPA's AERMOD model (Poorfakhraei et al. 2017; Tayarani et al. 2016).

The typical approach for evaluating an 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 (i.e., the current year) and a planning

horizon year that is at least 20 years into the future. This approach evaluates the two endpoints of the planning period, which presents an important limitation for evaluating an LRTP's performance, and particularly its air quality impacts. Under the typical "endpoint" approach, it is implicitly implied that changes in performance measures between the beginning and end of the planning period are linear. That is, the plan that achieves the greatest improvement in a performance measure by the end of the planning period is the one that maximizes total welfare gains related to that performance measure. 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 (Poorfakhraei et al. 2017; Tayarani et al. 2016). 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 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 an LRTP is also important because their impacts on the environment and public health are often long lasting and irreversible. First, consider greenhouse gas (GHG) emissions. Most GHGs persist in the atmosphere for a relatively long period of time (e.g., carbon dioxide released today can remain in the atmosphere for thousands of years (Solomon et al.

2009)). Thus, the ability of a plan to reduce the accumulation of GHGs is much more important for mitigating climate change risks than achieving a particular emission rate at a particular point in time. An irreversible and damaging accumulation of GHGs could be released by the time low emission rates are achieved at the end of a planning period. GHG emission rates may also rise in the future beyond the planning period. Toxic vehicle emissions also 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.

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. Environmental Protection Agency. In this paper 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 et al. 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, 2010). 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 et al. 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 also 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 et al. 2011; Lefebvre et al. 2011, 2013; Poorfakhraei et al. 2017; G. 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 et al. 2011; Poorfakhraei et al. 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 our paper 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 exposure for the Albuquerque, New Mexico metropolitan area. An 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 et al. 2007; Health Effects Institute, 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.

Methods

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. MRCOG is the Albuquerque, New Mexico area MPO. With a 2012 population of 890,593 and a total land area of 24,080 km2, it is the largest and most populous urban area in New Mexico.

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 10). 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.
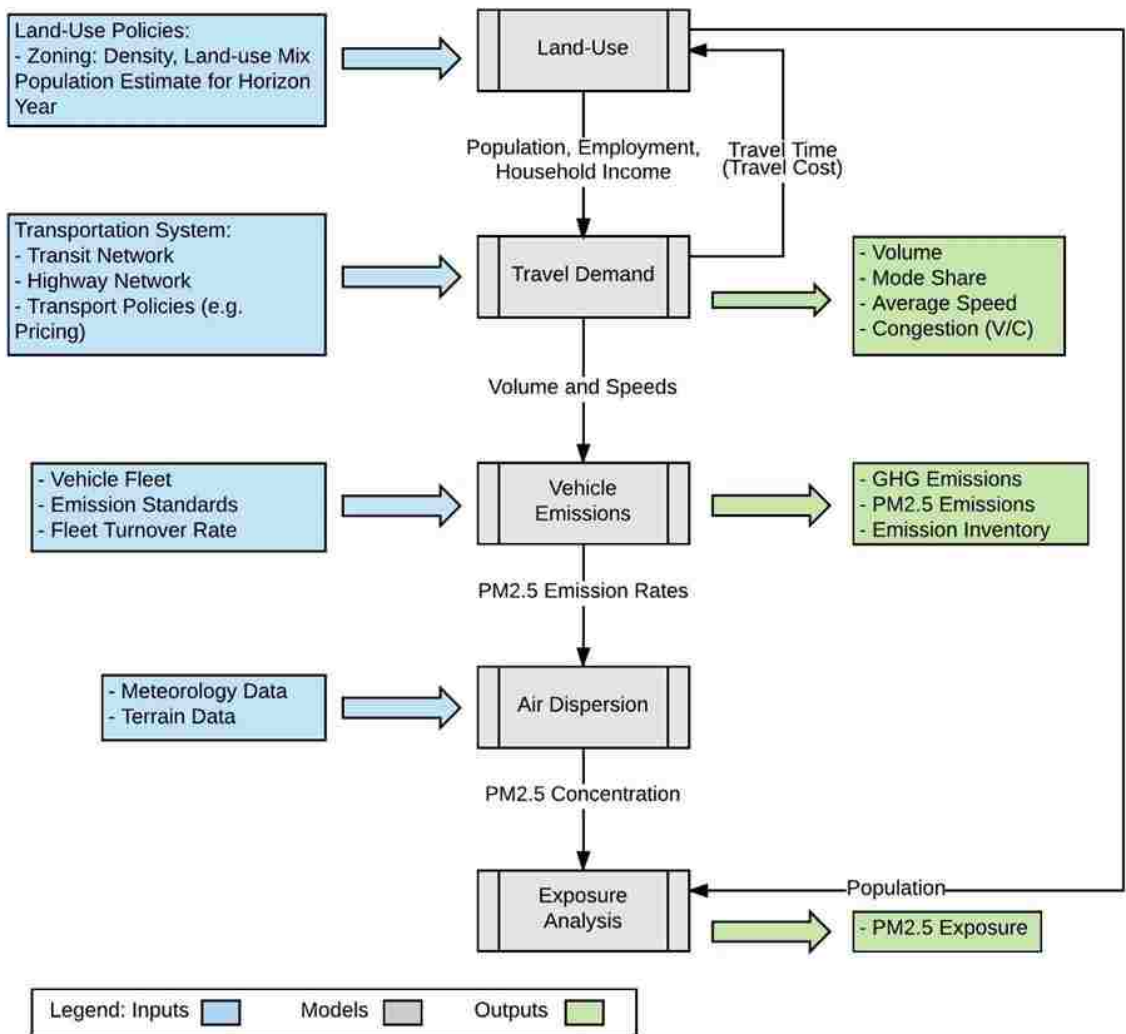
Figure 10. Integrated modeling framework

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 3). 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 matrices,

and mode choice.

Table 3. 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 3) 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.

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 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 (G. M. 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.

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 obtained 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.

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 Metropolitan Planning Organization, 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 discussed 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, 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 Fig 11.

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.
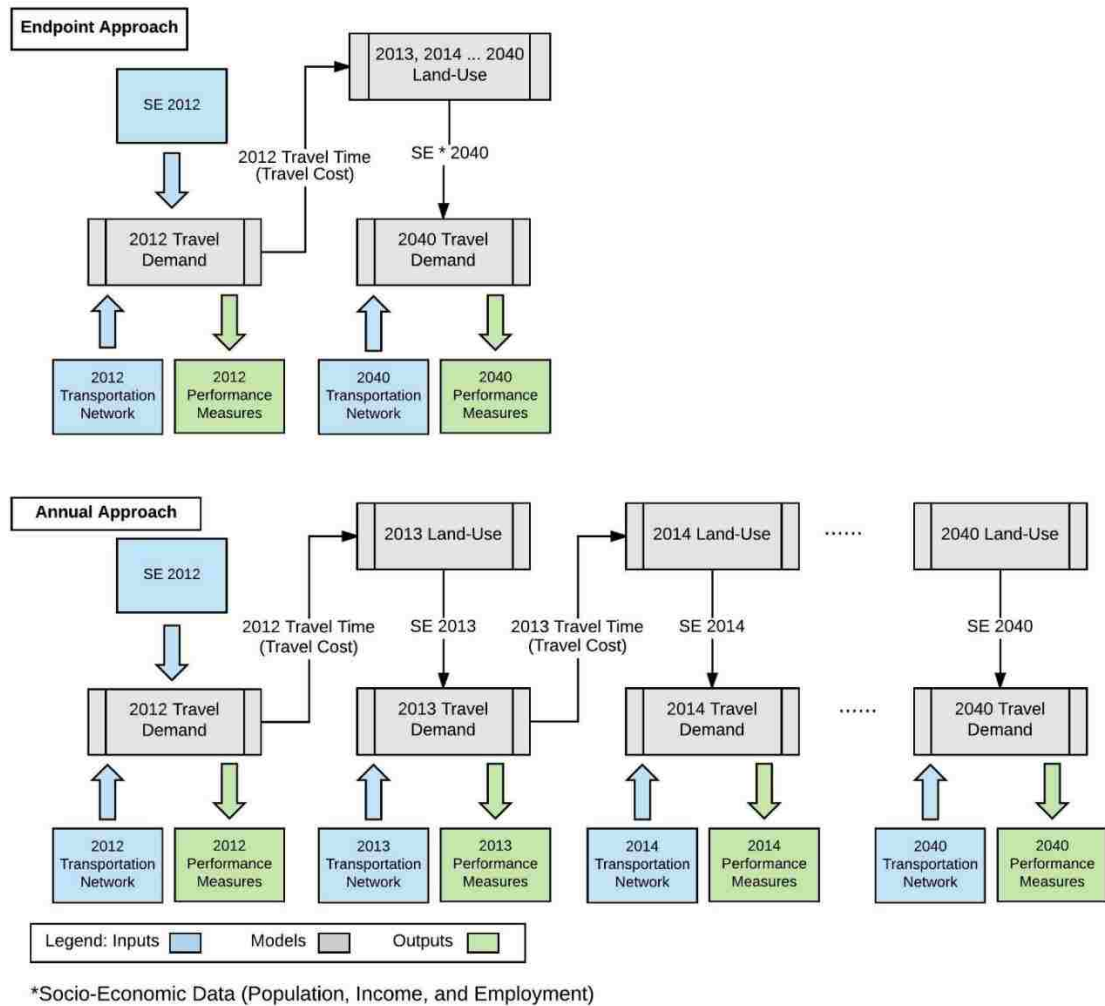
Figure 11. Overview of endpoint and annual modeling approaches

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 4) 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 4. 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.

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 12 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.
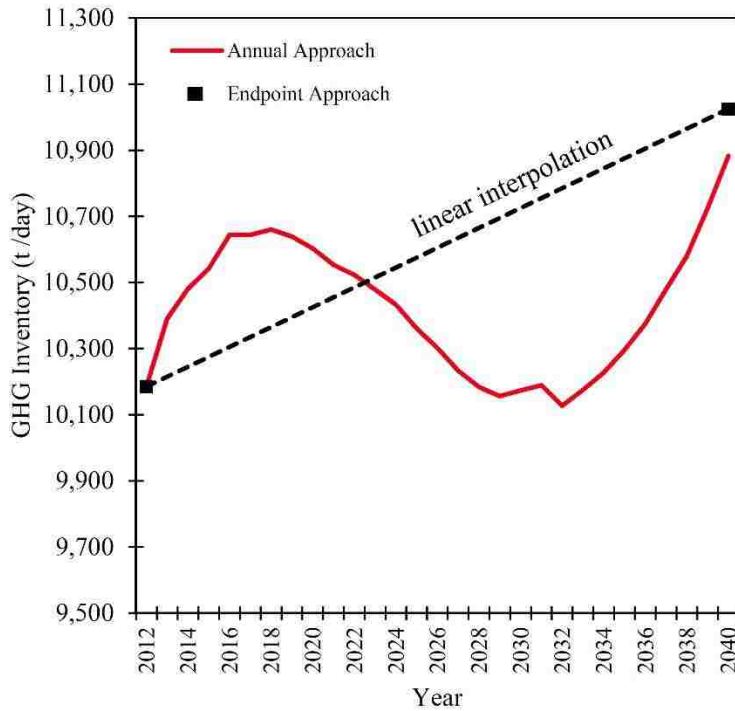
Figure 12. Daily GHG emissions inventory

Figure 13 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.
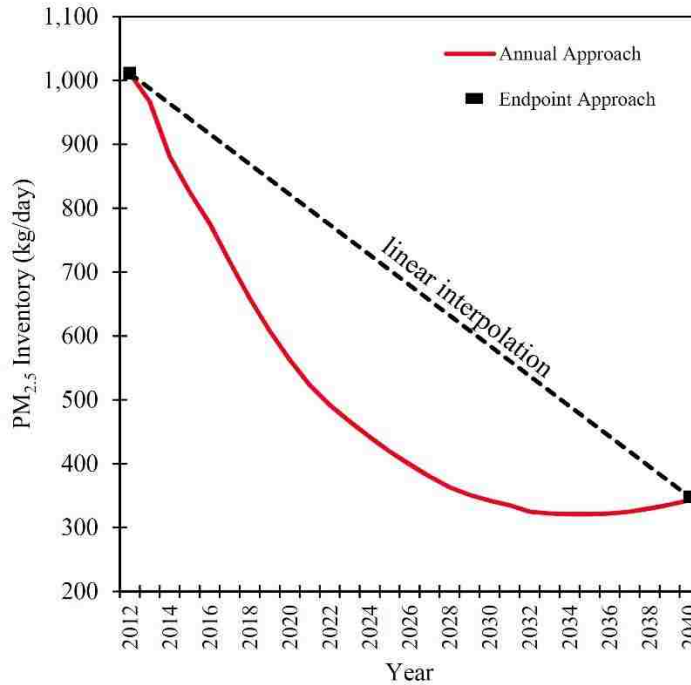
Figure 13. Daily PM$_{2.5}$ inventory

Table 5 provides a summary of cumulative emissions, exposure and vehicle mileage traveled performance metrics produced by the two modeling approaches in the year 2040. The major difference between two approaches happens where the endpoint approach overestimates PM$_{2.5}$ emission and exposure by 37.1% and 31.6%, respectively. The rises and falls of GHG emission during the planning years balances each other out so the cumulative value estimated by the endpoint approach is only 1.4% higher than the annual approach. No major difference observed for VMT since it follows a linear trend in under both modeling approaches.

We also analyze how PM$_{2.5}$ exposure changes over time (figure 14). The trend over time are generally the same as those for PM$_{2.5}$ emissions shown in figure 13. 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.
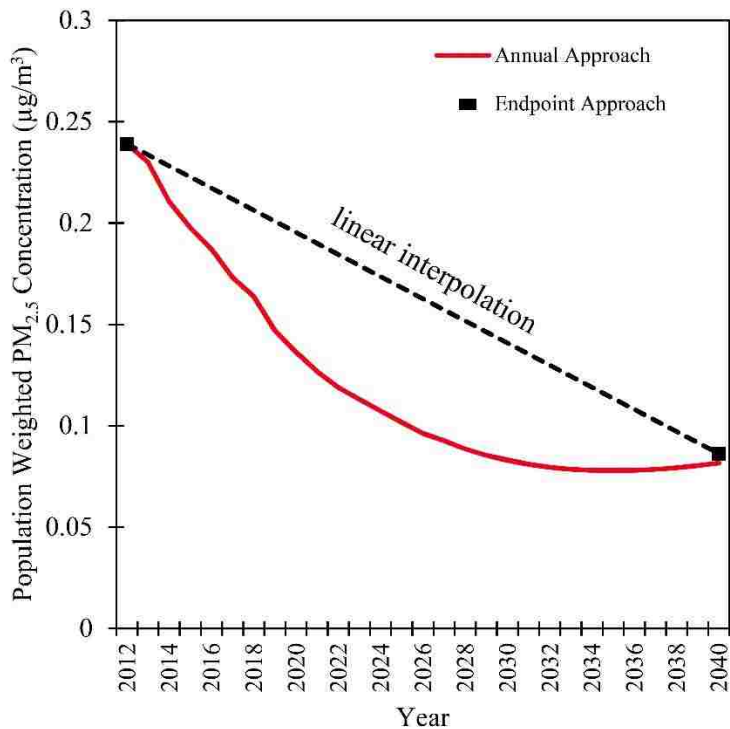
Figure 14. Daily population weighed PM$_{2.5}$ mean concentration

Table 5. Cumulative VMT and emission indicators under endpoint and annual modeling scenarios by year 2040

Indicators	Cumulative 2040 Endpoint	Cumulative 2040 Annual	Percentage Change
VMT (miles)	699,417,491	705,464,476	-0.9%
Daily PM$_{2.5}$ (kg/day)	19,899	14,514	37.1%
Daily GHG (tone /day)	304,848	300,743	1.4%
Population weighted concentration (ug/m3)	5.13	3.90	31.6%

Figure 15 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 base year 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.
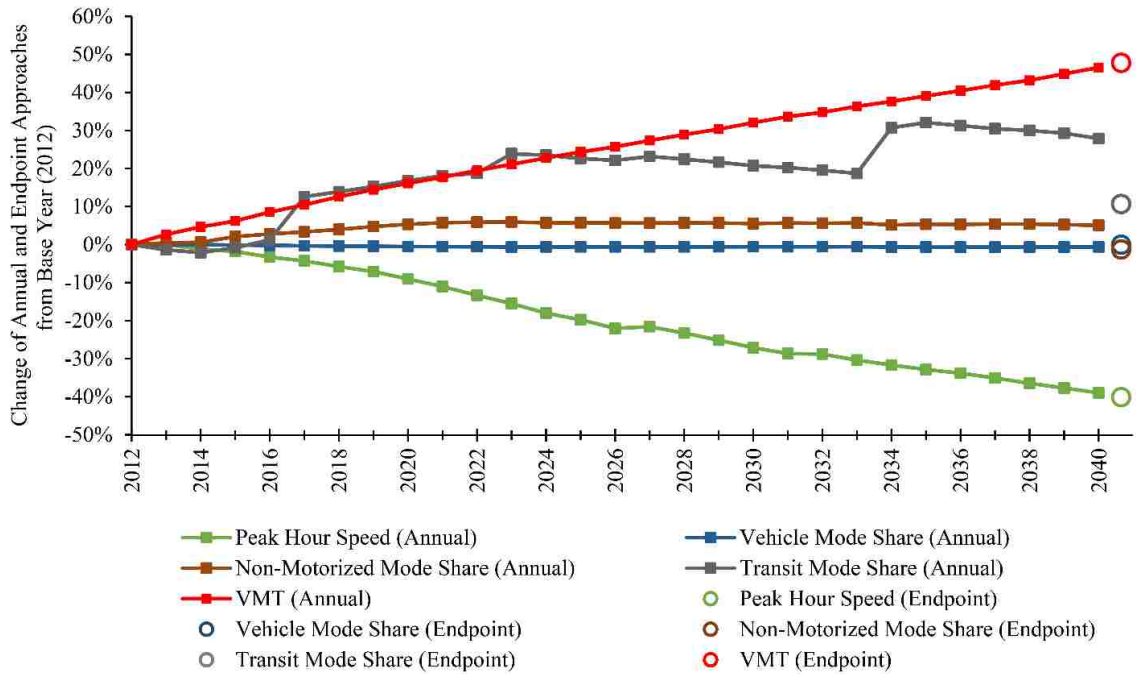
Figure 15. Percent change in travel semand indicators under annual and endpoint approaches

Table 6 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.

Table 6. 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 ($\mu g/m^3$)	0.086	0.082 (-5.3%)	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

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 12 shows rates rapidly increasing

during the final years of the planning period (a 7.5% increase in the final eight years).

We also evaluate the change in the spatial distribution of $PM_{2.5}$ concentration and

population density across the region. Figure 16 shows the difference in year 2040 $PM_{2.5}$

concentrations between the annual and endpoint modeling approaches. The annual

approach results in higher $PM_{2.5}$ concentrations in Albuquerque's downtown and along

major highway corridors where many of the regions employment and other activity

centers are located such as Journal Center. 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 in figure 17 which displays the change in

population density between the two modeling approaches. Although the aggregation to

TAZs makes it somewhat difficult to see the patterns, population density is generally

greater in the urban core and along major highway corridors near the region's activity

centers.
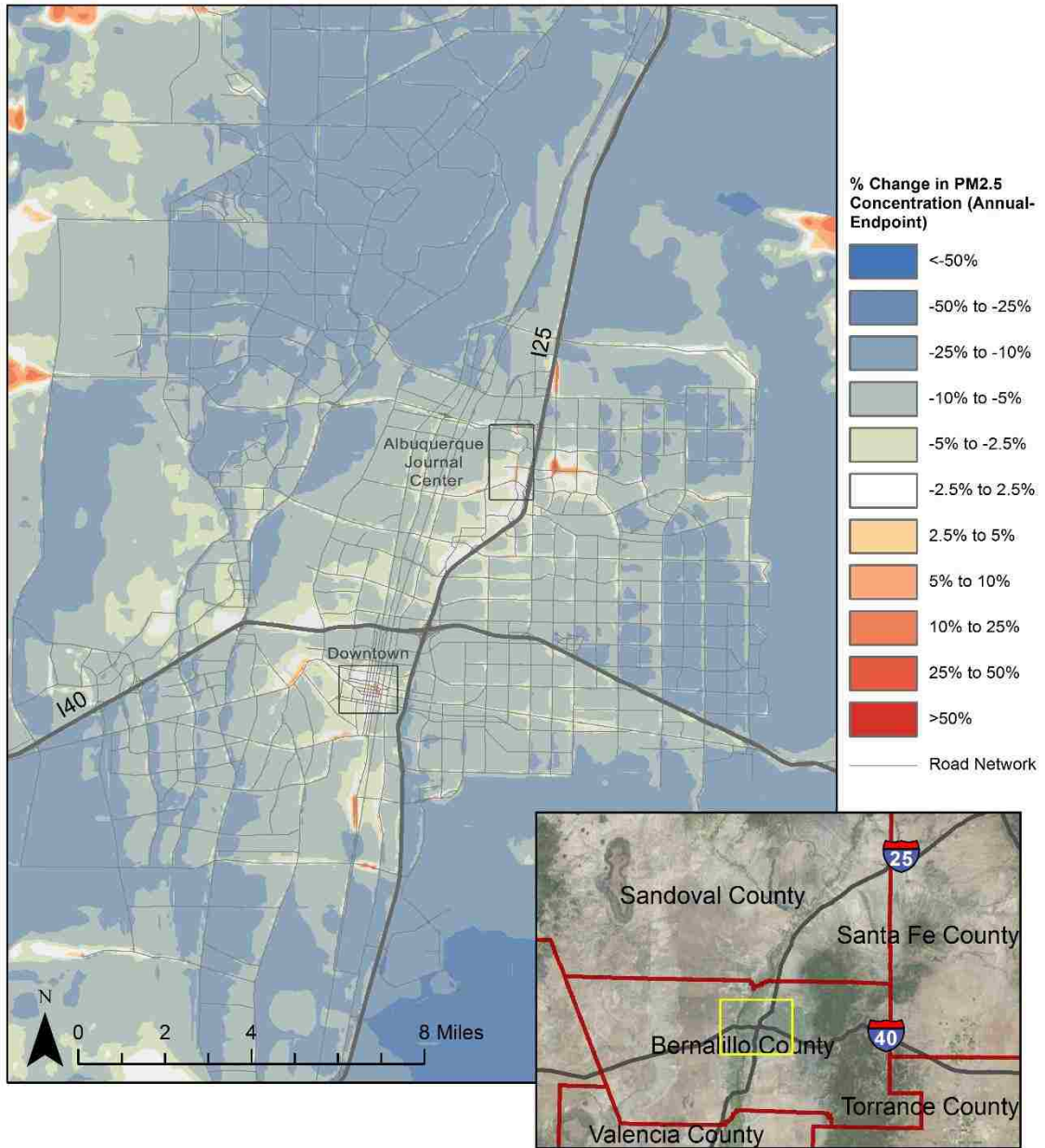
Figure 16. Change in average daily PM₂.₅ concentration by year 2040 between the annual and endpoint modeling approaches
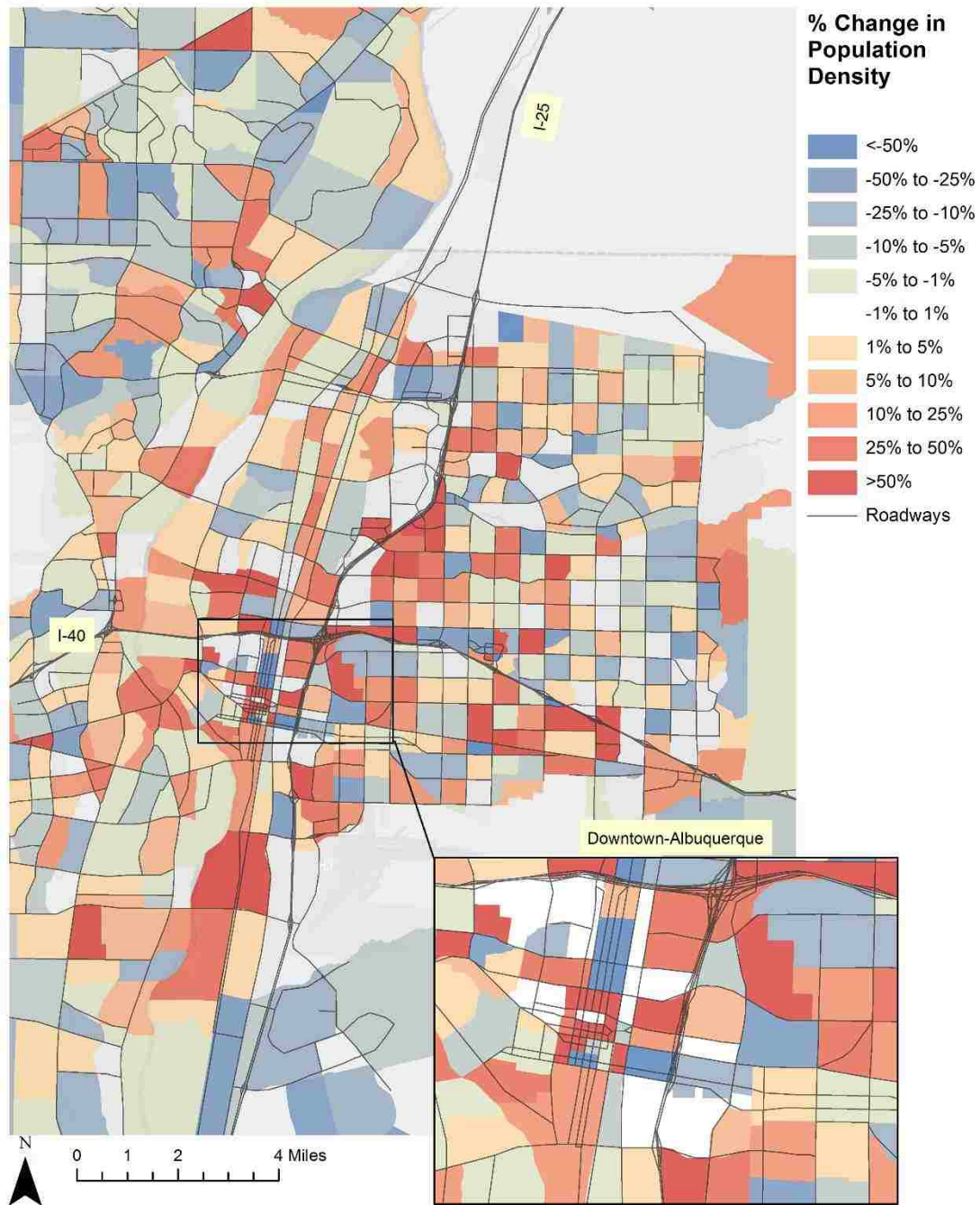
Figure 17. Percentage change in 2040 TAZ population density from the endpoint to the annual approach

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

over time and space. 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.

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. Considering the significant difference between two modeling approach in estimating cumulative impacts of LRTPs, justify the cost of using annual modeling approach. The fact that direction of bias and its significance differ for each performance metrics, require further analysis to define the best planning horizon step to evaluate effects of LRTPs. 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.

The annual modeling approach can also provide new information to help planners fine tune their plans. For example, planers can better understand the potential for a highway capacity project to induce demand or produce unwanted sprawl and test options to mitigate these 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 them or smooth them over. For example, policies to promote infill development may inadvertently increase exposure to toxic air pollutants if adopted too quickly or in the wrong locations (Tayarani et al. 2016). Since vehicle emission rates are expected to decline quickly in the next few years, it may be possible to avoid increasing exposure by delaying certain projects or 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 can also be used to better evaluate and monitor the performance of regional travel demand, land use, and air quality models. Rather than waiting 20 to 30 years to determine how accurate model forecasts were, model

performance can 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.

There are also some limitations to our study. We use a traditional four-step trip based travel demand model, which unlike an activity based model, does not provide information about individual travel patterns. Hence, we assume all $PM_{2.5}$ exposure occurs where each person lives. A recent study in Montreal, Canada suggests that on average this assumption may produce relatively small errors, although they may be larger for specific populations (Shekarrizfard et al. 2016). Regions or studies that use activity-based models can avoid this limitation (Dhondt et al. 2012; Shekarrizfard et al. 2016). We also assume that $PM_{2.5}$ concentrations are the same indoors as they are outdoors. We know this is not true (Baek et al. 1997; Kim et al. 2001; Marshall et al. 2003); however, without more information about air exchanges rates for building in the region, this is a limitation that is difficult to address. In Albuquerque, this particular limitation may be less important since many homes are cooled with evaporative coolers that draw in fresh air during the summer and the winters are relatively mild, minimizing the duration of time when homes are completely sealed. We have also generated a project implementation schedule that may differ from when projects are actually built. We assume an MPO implementing the annual modeling approach would have more complete information about the likely schedule of project implementation.

Chapter 4. Evaluating the impacts of transportation and land use strategies on air quality and travel measures

Introduction

Transportation and land use strategies intended to decrease travel demand and GHG emissions consist of a wide range of policies including fuel taxes, transit improvements, and increasing the density and land-use mix of urban development. These strategies are expected to reduce vehicle miles traveled (VMT) by increasing the use of transit and non-motorized modes of transportation and reducing the length of vehicle trips (Ewing et al. 2007; Ewing and Cervero, 2010; Stone et al. 2007; TRB, 2009). Based on the assessment by the Intergovernmental Panel on Climate Change (IPCC), GHG emissions must be cut 40–70% by 2050 from 2010 levels to keep the increase in the global mean temperature below 2 °Celsius and potentially prevent the most severe climate change impacts from happening (IPCC, 2014). The transportation sector is responsible for 27% of GHG emissions in the United States, a share that is increasing (US EPA, 2017) and if cut, can play important role in achieving high levels of GHG reduction.

A review of the literature finds that even aggressive combinations of land use and transportation pricing strategies that incentivize people to use lower emitting modes of transportation can lead to significant GHG reduction (Greene and Plotkin, 2011; Kay et al. 2014; Mashayekh et al. 2012; McCollum and Yang, 2009; Melaina and Webster, 2011; Yang et al. 2009) but not nearly enough to achieve the IPCC recommendations (Cambridge Systematics, 2009; Ewing et al. 2007; Greene and Plotkin, 2011; TRB, 2009). Several studies suggest that improving vehicle energy efficiency and increasing the adoption of low carbon fuels are the only strategies that can result in GHG reductions

in the transportation sector that can achieve the reductions that the IPCC suggests are

necessary (Greene and Plotkin, 2011; Kay et al. 2014; Leighty et al. 2012; Lutsey and

Sperling, 2009; McCollum and Yang, 2009; Melaina and Webster, 2011; Olabisi et al.

2009; Williams et al. 2012; Yang et al. 2009; Yuksel et al. 2016). Bartholomew (2006)

studied the long-range transportation plans developed by over 50 MPOs and found that

the they are not expected to result in significant reductions in VMT. The failure to reduce

VMT means that the plans are also unlikely to result in significant, if any, GHG

reductions (other than what is expected to occur from improved vehicle fuel efficiency).

In a former study, we showed that in the Albuquerque Metropolitan area, only a

combination of very compact development, large transit improvements, significant gas

tax increases, and increasing bicycling mode share, can achieve GHG reductions beyond

40% in 2040 without any new vehicle technology or low carbon fuels. We also found that

no single strategy is likely to achieve a 40% GHG reduction (Tayarani et al. 2018).

In addition to GHG emissions reductions, transportation and land use strategies can also

help reduce exposure to toxic vehicle emissions such as $PM_{2.5}$. However, strategies that

reduce GHG emissions may not be the best for reducing vehicle emissions exposure. In a

former study, we found that the Albuquerque Metropolitan Area's long-range

transportation plan would reduce GHG emissions more than other long range planning

scenarios that were considered by the MPO but that average exposure to $PM_{2.5}$ emissions

would be higher (Tayarani et al. 2016). The increase in exposure occurs since the land

use strategies in the adopted plan increase population density in areas with relatively high

levels of traffic and therefore concentration of $PM_{2.5}$. As another example, De Ridder et

al. (2008) used travel demand, emission, and air quality modeling to evaluate the effect of

development patterns on exposure to PM10. In a hypothetical land use scenario, they moved 12% of the Ruhr region of Germany's population to the suburbs. The modeling of the scenario showed that PM10 exposure for those who had moved to the suburbs decreased by 13% while the exposure for those who were not moved, increased by 1.2%. The overall aim of this chapter is to investigate if practical transportation and land use strategies can be combined to develop planning scenarios that significantly reduce GHG emissions and at the same time, do not increase exposure to other pollutants. We design two scenarios made up of a series of transportation and land use strategies that are generally available to local and state governments. The strategies include increasing the amount of compact and mixed-use development along transit and highway corridors, improving transit performance and reducing the fare, and implementing a per-mile tax (VMT tax) on driving. In designing our strategies, we do not consider political constraints that may limit the plans developed by MPOs in practice (Brömmelstroet and Bertolini, 2010; Flyvbjerg et al. 2005; Handy, 1992; Hatzopoulou and Miller, 2009; Wachs, 1989, 1990); however, the strategies are designed to be technically and financially reasonable. We do not consider strategies that focus on vehicle and fuel technology, including low-carbon fuels, electric vehicles, and government programs to promote greater vehicle fuel efficiency. These strategies may be highly effective in reducing emissions but most requires implementation at the federal level.

An important part of our study is the use of an integrated land use, travel demand, vehicle emission, and air dispersion framework that helps us understand how travel demand and land use interact with each other over time up to the planning horizon.

Methods

Study area

The geographical context of our study is the Albuquerque metropolitan area in the State

of New Mexico which is portrayed in figure 18. With a 2017 population of 909,906 and a

total land area of 24,080 km^2, our study area is the most populous and the largest

metropolitan area in the state.
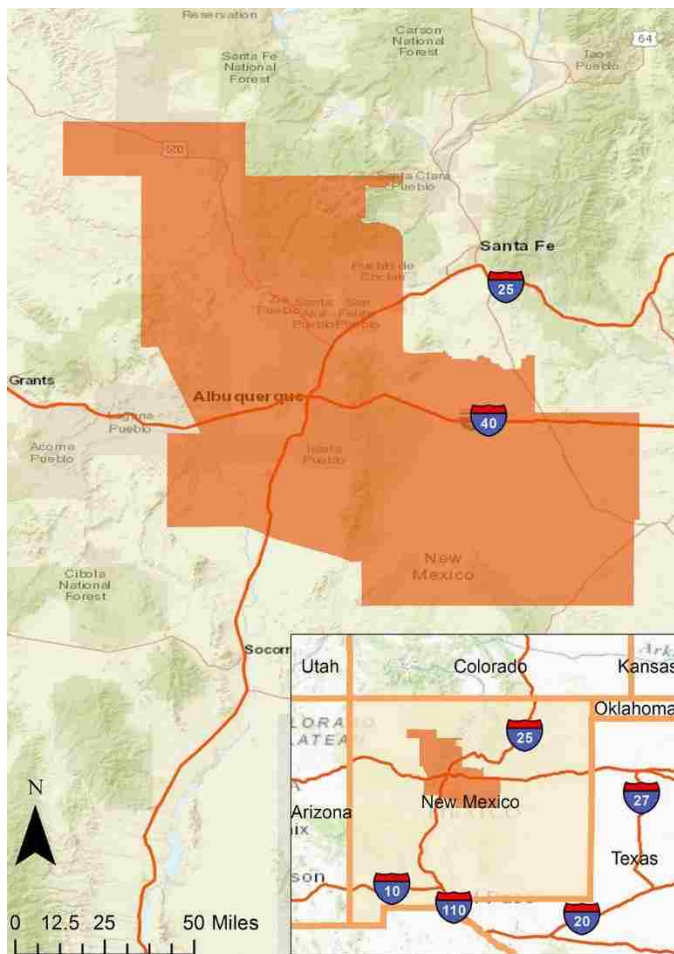
Figure 18. The study area highlighted in orange

Development of scenarios

The Mid Region Council of Governments (MRCOG), the federally designated MPO for the Albuquerque Metropolitan Area developed a several transportation and land-use planning scenarios for the future of the region as part of its long-range transportation planning process. A "Trend scenario" was the was developed and as a reference to compare other scenarios with. The trend scenario –which represents business as usual in the region– assumes that the land use zoning in the region stays unchanged between the 2012 base year and the 2040 planning horizon. The scenario also assumes that the highway projects are limited to those included in the region's prior long range plan, and that there is no change in public transit except for the addition of a planned bus rapid transit line. The MPO projected that the population and employment in the region increases by 52% and 46% respectively, from 2012 to 2040.

In this study I use the "trend scenario" as a baseline for evaluating two additional scenarios that I devise with the aim of further reducing GHG emissions and $PM_{2.5}$ exposure. Table 7 shows how these two strategies differ from the trend scenario.

Table 7. Strategies represented in each of the devised scenarios

Analysis year	Scenario 1 VMT tax (per mile)	Land use	Scenario 2 VMT tax (per mile)	Land use	Transit fare	Transit frequency	Transit lines
2012	0	Relaxing development restrictions within 200 meters of principal arterial and freeways, and in Uptown and Journal Center areas	$0.05	Relaxing development restrictions within 200 meters of principal arterial, freeways, Railrunner, and in Uptown and Journal Center areas	Reduce all transit fares by 25%	Increase all transit frequency by 15%	No change
2013	$0.01	Similar to 2012	$0.05	Similar to 2012	No change	No change	No change
2014	$0.01	Similar to 2012	$0.10	Similar to 2012	No change	No change	No change
2015	$0.01	Similar to 2012	$0.10	Similar to 2012	No change	No change	No change
2016	$0.02	Similar to 2012	$0.12	Similar to 2012 Additionally, relaxing development restrictions west of cottonwood mall	No change	No change	Add Coors Blvd. rapid line
2017	$0.02	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2018	$0.02	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2019	$0.02	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2020	$0.02	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2021	$0.03	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2022	$0.03	Similar to 2012	$0.12	Similar to 2016	No change	Increase transit frequency and speed on Central Ave. and Coors Blvd. by 20%	No change
2023	$0.03	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2024	$0.03	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2025	$0.03	Similar to 2012	$0.12	Similar to 2016	No change	No change	Add Paseo Blvd. and University Blvd. rapid lines
2026	$0.04	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2027	$0.04	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2028	$0.04	Similar to 2012	$0.12	Similar to 2016	No change	Increase frequency and speed of transit on Paseo Blvd. and University Blvd. by 20%	No change
2029	$0.04	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2030	$0.04	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2031	$0.06	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2032	$0.06	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2033	$0.06	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2034	$0.06	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2035	$0.06	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2036	$0.08	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2037	$0.08	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2038	$0.08	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2039	$0.08	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change
2040	$0.08	Similar to 2012	$0.12	Similar to 2016	No change	No change	No change

Evaluation of scenarios

An integrated land use, travel demand, emission, dispersion, and exposure framework is used to estimate the travel and air quality outcomes of each scenario. The integrated framework is represented symbolically in figure 19.
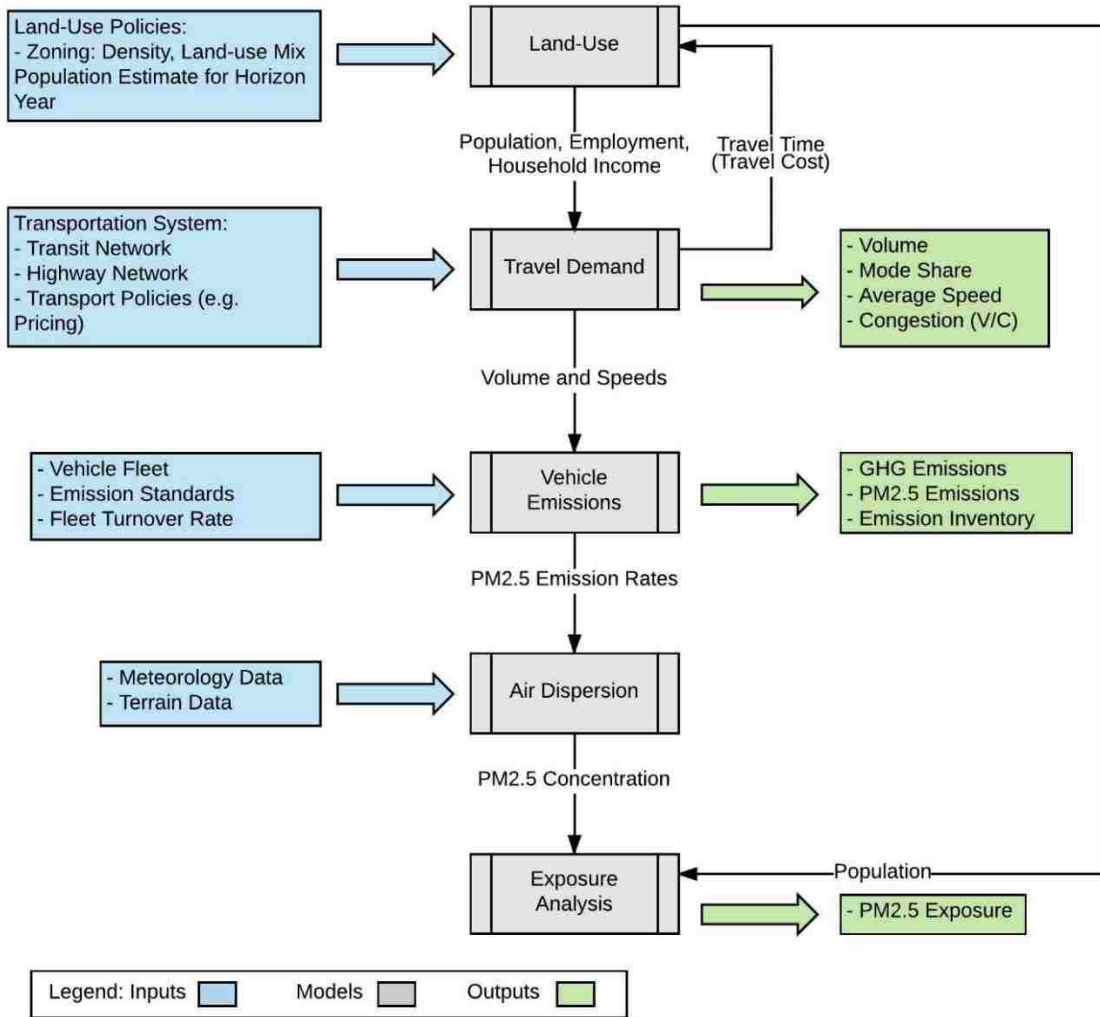

Figure 19. Integrated modeling framework

The first part of the framework is the land use model. We use an agent-based land use model named Urbansim. Urbansim takes as inputs variables such as the estimates of land and housing values, land availability, travel time between the zones, expected total population and employment, and models the future population, employment, and land use

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mix in the region. Urbansim can be used to see how changes in zoning such as allowable densities and building heights affect the distribution of the population and employment. The second part of the framework is the travel demand model. We use a traditional 4-step model developed in Citilabs' Cube platform. The model takes as inputs, the transportation network, transportation policies and land use, and outputs forecasts of traffic volume and travel speed on each roadway link, zone to zone travel times, as well as modal share in the region.

U.S. EPA's MOVES model is used as the vehicle emissions modeling part of the integrated framework. MOVES uses regional information about the vehicle fleet, vehicle inspection and maintenance program, emission standards, and fuel properties to estimate the emission rates for a variety of pollutants. These emission rates are used along with the estimated traffic volume and average speed on each link to calculate GHG and $PM_{2.5}$ emissions on each link and in the region. $PM_{2.5}$ emission rates on each link is then fed into the US EPA's AERMOD model –the dispersion part of the framework. AERMOD estimates the annual average ambient concentration of $PM_{2.5}$ emitted from the traffic across the region. At the final step in the modeling framework, we use ArcGIS to overlay the distribution of the population in the parcels with rasters of $PM_{2.5}$ concentration. In this way, the average daily concentration of $PM_{2.5}$ in each parcel is estimated and is considered the human exposure in the parcel. The population-weighted average exposure to $PM_{2.5}$ is also calculated by summing the product of each parcel's population and its average $PM_{2.5}$ concentration and dividing the sum by the region's population. The framework is explained in more detail in Tayarani et al. (2016) and Tayarani et al. (2018).

The first two parts of the framework are run in an iterative way. In the first iteration, the travel demand model uses the base year (year 2012) land use in the region to estimate the zone to zone travel times in the year 2012. Urbansim then takes zone to zone travel time estimates along with other inputs to estimate the land use in 2013. 2013 estimates are then used to model the travel demand model and estimate zone to zone travel times in 2013. The iteration continues on an annual basis up to the planning horizon which is the year 2040. See Tayarani et al. (2018) for more details on how this novel iterative framework was developed.

Each of the scenarios devised in this study are composed of the strategies represented in table 7. The following sub-sections explain these strategies and how they are evaluated in the modeling framework.

VMT tax strategies

The generalized cost function in the travel demand model can be adjusted to model the effect of VMT taxation. A parameter of the generalized cost function is the out-of-pocket cost of driving which is currently $0.164 per mile in the trend scenario. We will increase the out-of-pocket cost to reflect the VMT taxation.

In scenario 1, we add a VMT tax of 1 cent per mile to the out-of-pocket cost in 2012 that will be gradually increased to 8 cents per mile in 2040. Scenario 2 assumes a more aggressive VMT taxation: 5 cents per mile in 2012 gradually increasing to 12 cents in 2040. Assuming an average fuel economy of 20.6 miles per gallon in the region (an assumption used in the MRCOG travel demand model) a 1-cent per mile VMT tax is equivalent to a $0.206 increase in the price of one gallon of gas; which is a very

significant amount. The VMT tax is in addition to the existing state and federal gasoline taxes which are currently $0.1888 and $0.1840 per gallon, respectively.

Land use strategies

Land use strategies in the framework are modeled by changing the zoning codes in the Urbansim land use model. Each geographic parcel in the land use model has a zoning code that defines (restricts) variables such as floor to area ratio, maximum building height, maximum dwelling units per acre, and allowable uses in the parcel.

In scenario 1, we relax the zoning codes by almost eliminating all development restrictions within 200 meters of the major arterials in the city of Albuquerque, within Journal Center area, and within Uptown. In scenario 2, the zoning code is additionally relaxed along the Rail Runner intercity rail line, and on the west side of Cottonwood Mall. Figure 20 represents these areas on a map of the region. For selected areas, zoning relaxation includes allowing single family, multi family, commercial retail, commercial services, office, and community development; allowing maximum floor to area ratio of 10; allowing maximum building height of 120 feet; and allowing a maximum of 125 dwelling units per acre.
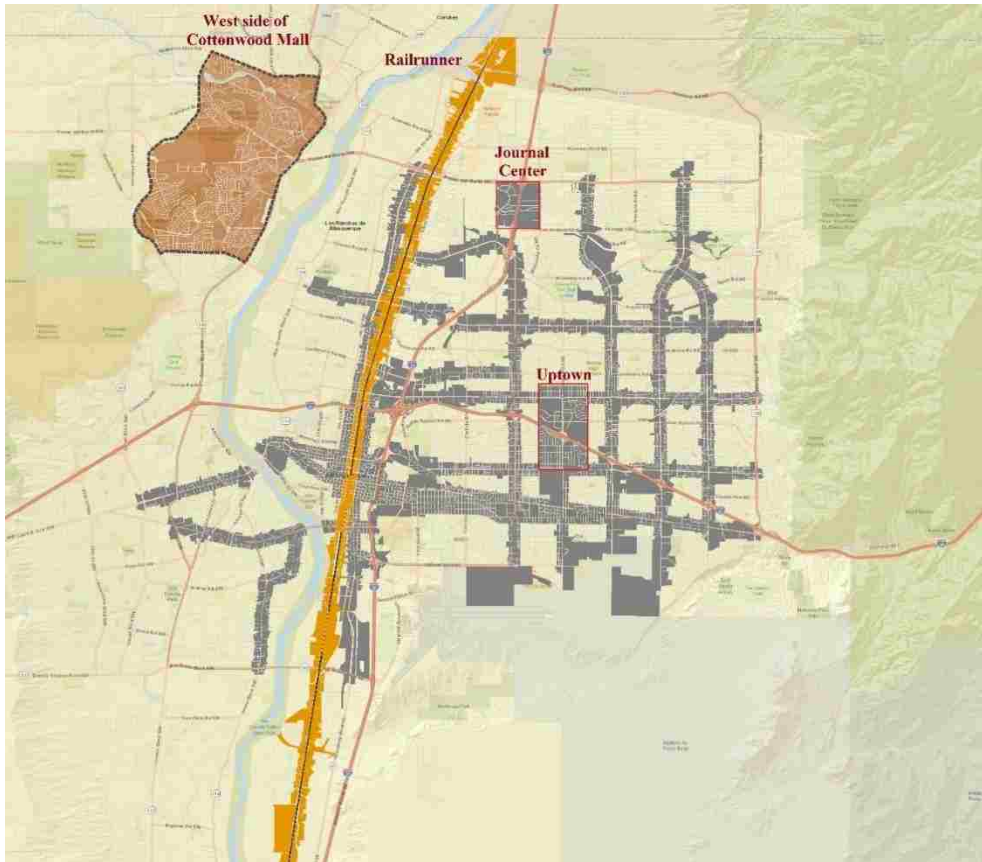
Figure 20. Highlighted areas represent where the zoning restrictions are relaxed

Transit improvements strategies

Transit improvement strategies are implemented in the framework by changing the transit inputs to the travel demand model. These inputs include the geographical representation of the transit lines and text files that contain the schedule, frequency of service, and fares for all the lines.

Figure 21 represents the new transit rapid lines that will be added to the network in the devised scenarios. Note that the University Blvd. rapid line is a planned transit improvement and is included in trend and both additional scenarios. University Blvd., Coors Blvd., and Paseo Blvd., rapid lines are additional lines that will be considered only

in Scenario 2. Reduction in transit fares and frequency increases in scenario 2 are

implemented by changing the text file inputs of the travel demand model.
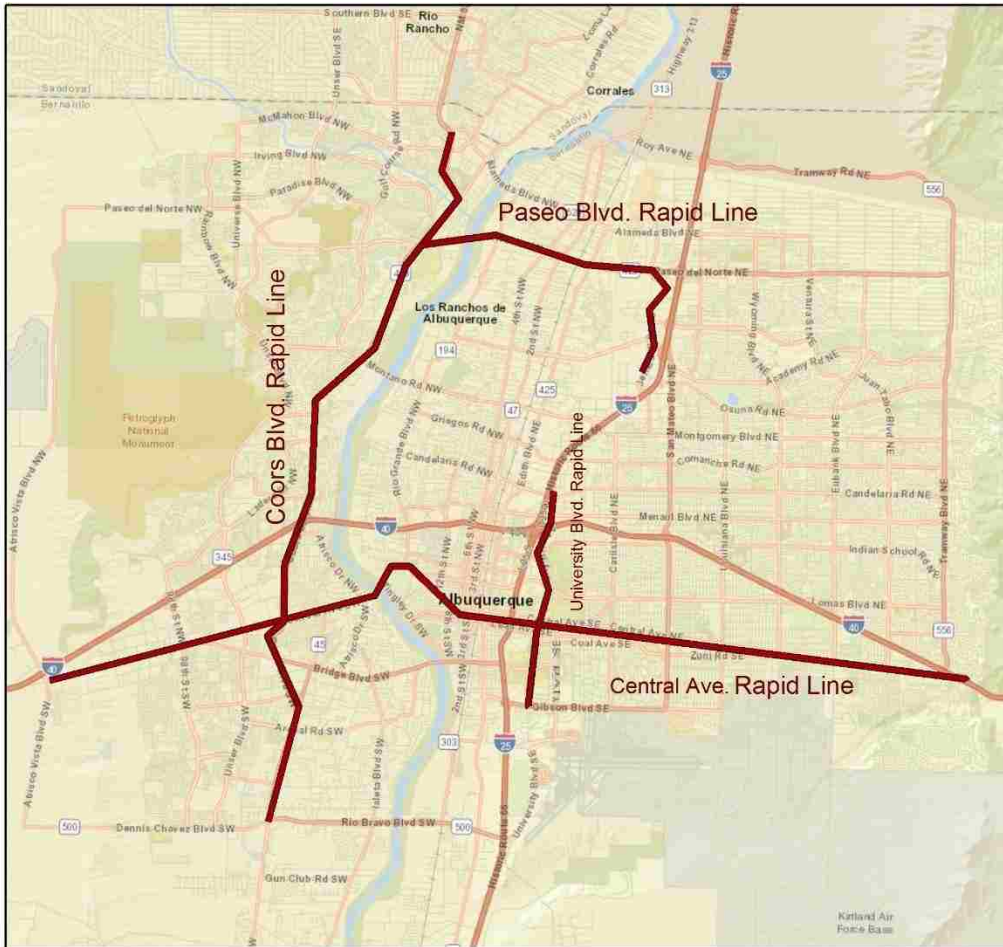
Figure 21. New rapid lines added to the current transit network

Results

Figure 22 represents the air quality measures in the region for each of the analyzed

scenarios. More aggressive strategies in scenario 2 lead to lower emissions and vehicle

exposure in the region. One thing to notice is that while scenario 1 leads to lower $PM_{2.5}$

emission inventory and exposure in 2040 compared to the trend scenario, both emission

inventory and exposure in the near future are higher in this scenario.

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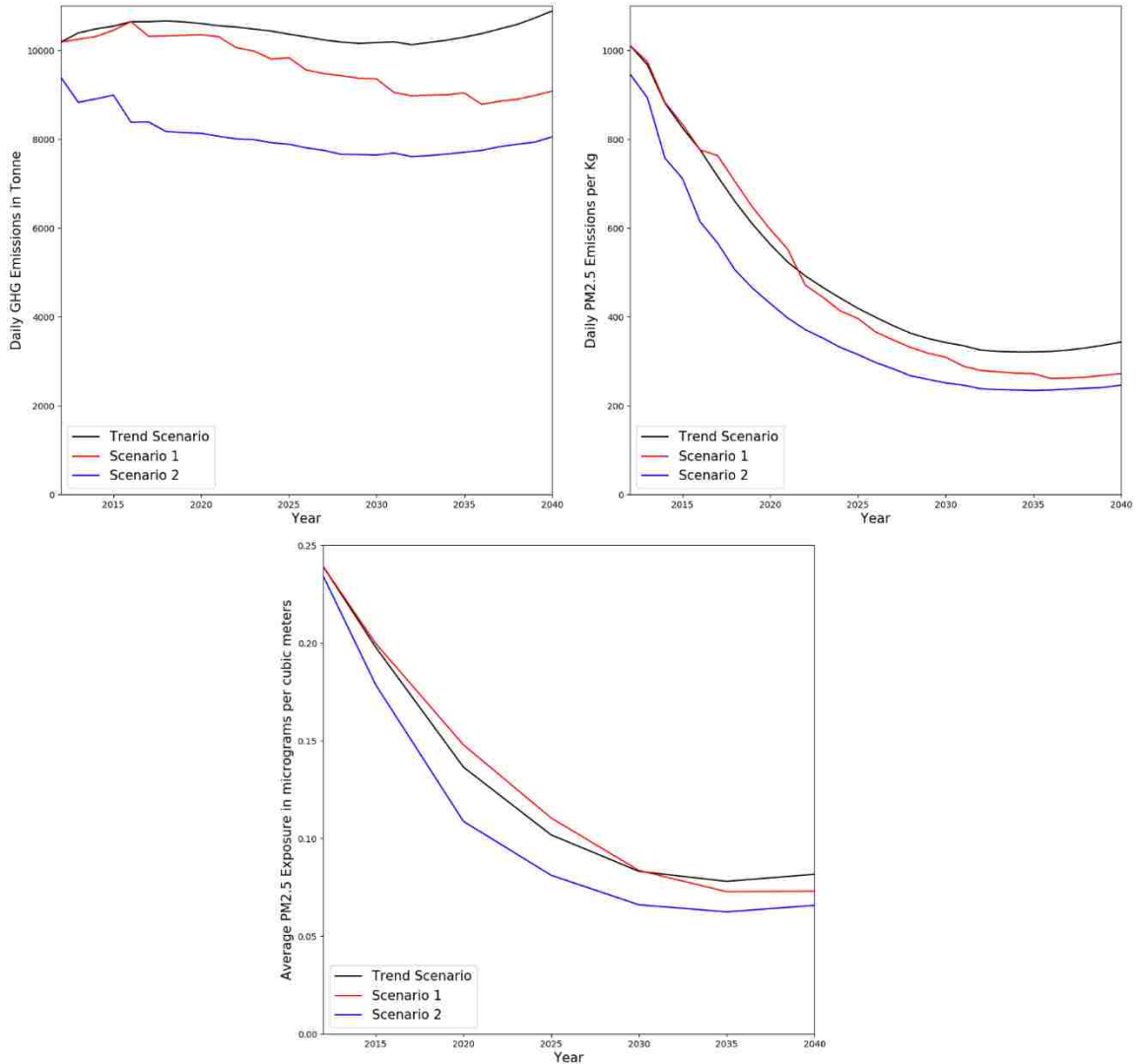
Figure 22. Air quality measures from 2012 to 2040

Figure 23 represents the maps of $PM_{2.5}$ concentration (exposure) in the urban core of the

study area. All scenarios lead to similar patterns of $PM_{2.5}$ concentration in 2040 (figure

23a through 23c). The concentration is highly elevated along the major roadways and

declines sharply with distance from the road. The comparison of the trend and the new

scenarios (figures 23d and 23e) shows that scenarios 1 and 2 reduce average 2040 $PM_{2.5}$

exposure compared to the trend scenario, and that these reductions occur in all locations.

Figure 23. 2040 PM$_{2.5}$ concentration (exposure) in each scenario (a through c), and the decrease in the 2040 PM$_{2.5}$ concentration in scenario 1 and 2 compared to the trend scenario (d and e)

In figure 24, we plot the cumulative distribution of PM$_{2.5}$ exposure in year 2040. A point on each curve in this figure represents the percentage of people whose PM$_{2.5}$ exposure is less (or more) than a certain amount. This figure shows that scenario 1 and scenario 2 reduce PM$_{2.5}$ exposure compared to the trend scenario.
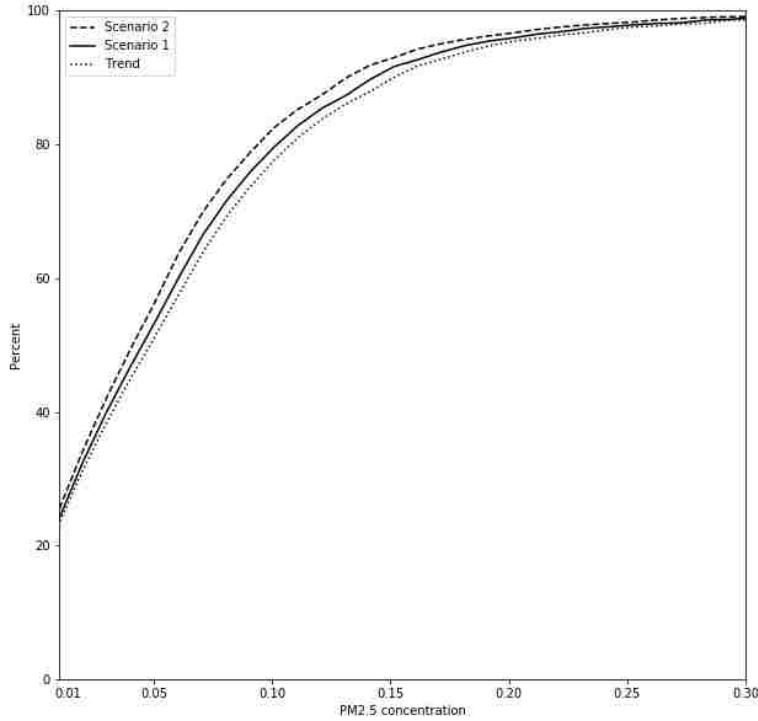
Figure 24. Cumulative distribution of PM$_{2.5}$ exposure in year 2040

Figure 25 represents the change in travel performance measures. VMT is decreased

significantly in both devised scenarios in 2040, compared to the trend scenario. Similarly,

both the devised scenarios represent higher average speed, lower volume to capacity

ratio, and higher non-motorized shares of trips. Scenario 1 and trend scenario represent

similar transit mode shares in 2040 which is due to the fact that Scenario 1 assumes the

same transit network and service as the trend scenario. Notice that VMT is increasing in

all the scenarios in the 2040 relative to 2012 which is due to the increase in population

and employment, subsequently, average speed and volume to capacity ratios also degrade

over time.
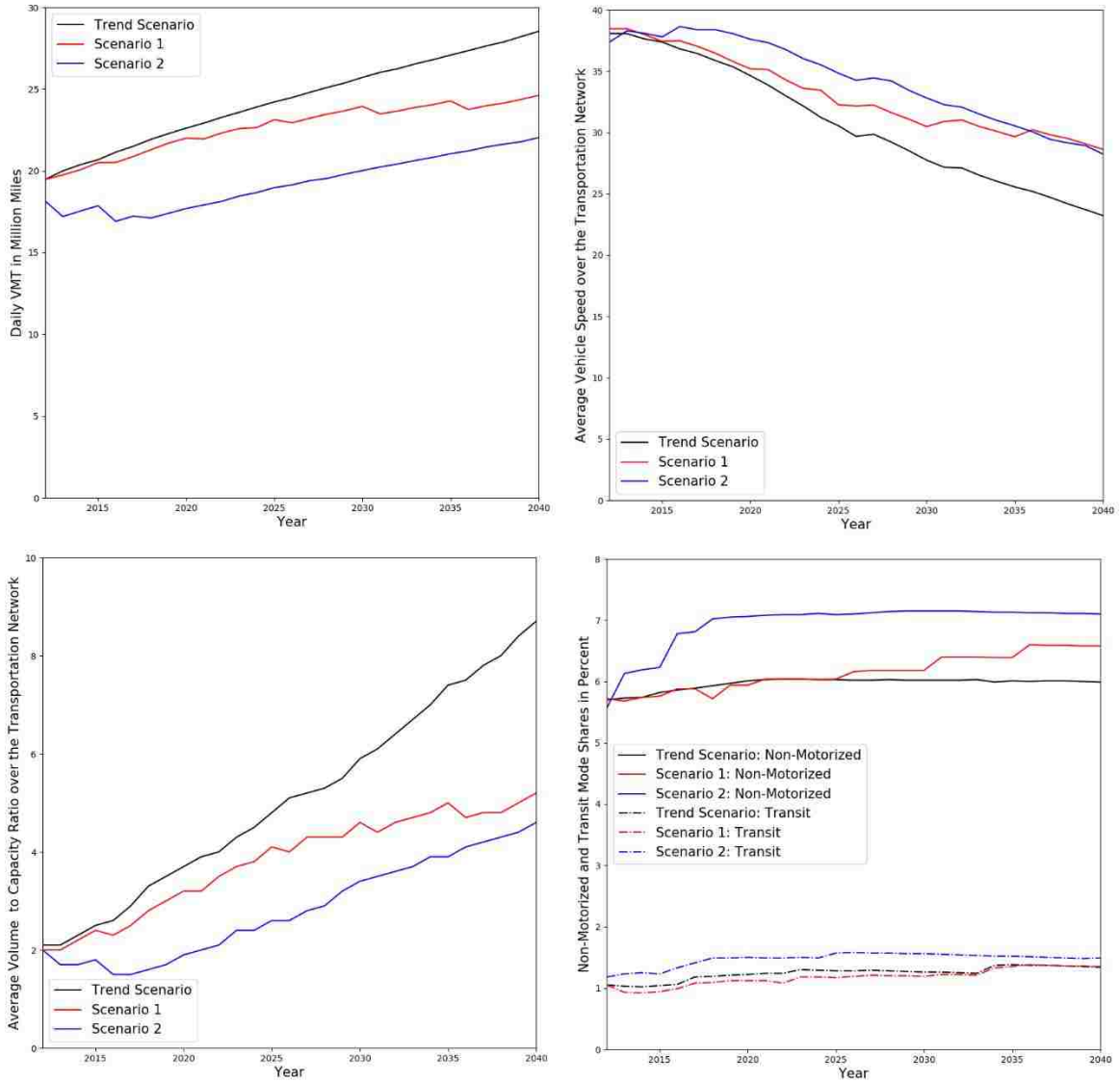
Figure 25. Travel measures from 2012 to 2040

Table 8 represents the change in air quality and travel measures in each scenario. While

the trend scenario leads to a 6.85% increase in GHG emissions in 2040 compared to the

2012 level, both scenario 1 and scenario 2 show significant reductions in GHG emissions.

Additionally, $PM_{2.5}$ emissions, and average $PM_{2.5}$ exposure in scenario 1 and scenario 2

are significantly lower than that of the trend scenario in 2040.

While VMT has increased in all the scenarios, the percent increase in VMT is lower in

devised scenarios. The increase in VMT in scenario 1, is less than half the increase in

VMT in the trend scenario. Other travel measures, including the average speed and the average volume to capacity ratio also improve in the devised scenarios. Average speeds are more than 20% higher, and the average volume to capacity ratios are more than 40 percent lower in the devised scenarios compared to the trend.

Table 8. Changes in air quality and travel measures from 2012 to 2040 in each scenario

Scenario	Measure	Base year (2012) value	Planning horizon (2040) value	Percent change from 2012 to 2040	2040 percent change compared to the trend scenario
Trend	• GHG emissions (tonnes per day)	10,185	10,883	6.85%	-
	• $PM_{2.5}$ emissions (kg per day)	1,011	343	-66.07%	-
	• Average $PM_{2.5}$ exposure (micrograms per cubic meters)	0.239	0.082	-65.69%	-
	• Daily VMT	19,466,492	28,528,129	46.55%	
	• Average speed	38.07	23.22	-39.01%	-
	• Average volume to capacity ratio	2.1	8.7	314.29%	-
	• Transit mode share	0.0105	0.0134	27.62%	-
	• Non-motorized mode share	0.0570	0.0599	5.09%	-
Scenario 1	• GHG emissions (tonnes per day)	10,185	9,080	-10.85%	-16.57%
	• $PM_{2.5}$ emissions (kg per day)	1,011	272	-73.10%	-20.70%
	• Average $PM_{2.5}$ exposure (micrograms per cubic meters)	0.239	0.073	-69.46%	-10.98%
	• Daily VMT	19,466,492	24,606,387	26.40%	-13.75%
	• Average speed	38.46	28.62	-25.59%	23.26%
	• Average volume to capacity ratio	2.0	5.2	160.00%	-40.23%
	• Transit mode share	0.0105	0.0135	28.57%	0.75%
	• Non-motorized mode share	0.0572	0.0658	15.04%	9.85%
Scenario 2	• GHG emissions (tonnes per day)	9,394	8,049	-14.32%	-26.04%
	• $PM_{2.5}$ emissions (kg per day)	947	246	-74.02%	-28.28%
	• Average $PM_{2.5}$ exposure (micrograms per cubic meters)	0.234	0.066	-71.79%	-19.51%
	• Daily VMT	18,149,729	22,030,149	21.38%	-22.78%
	• Average speed	37.36	28.24	-24.41%	21.62%
	• Average volume to capacity ratio	2.0	4.6	130.00%	-47.13%
	• Transit mode share	0.0118	0.0149	26.27%	11.19%
	• Non-motorized mode share	0.0557	0.071	27.47%	18.53%

Interval analysis

In the annual modeling approach, we run the integrated framework with annual iterations between the travel demand and land-use models. Individual model runs for each year are time consuming, and modeling each year in 20 to 30 year long planning period can lead to very long modeling times (weeks to months). A different approach would be to increase the length of the modeling interval; for example, by iterating the land use and

travel demand model every two years, five years, or more. This alternative approach

could significantly reduces the computational burden; however, how reducing the number

of iterations affects the results in unknown and has not been studied previously.

We evaluate scenario 1, with a 2-year, 5-year, 10-year, and 15-year iteration interval. The

goal is to investigate if the length of the modeling interval could be increased without

significantly changing modeling outcomes.

Figures 26 through 28 represent the estimates of GHG inventories, $PM_{2.5}$ emisisons

inventories, and VMT from our modeling system using different iteration frequencies.

With the exception of a 15-year interval, the value of each performance measures in the

planning horizon is not that sensitive to the choice of interval length. However, the

pattern of change in the measures from the base year to the planning horizon is not linear

and by choosing a larger interval, the information about the performance of the long

range plan in the intermediate years is lost.
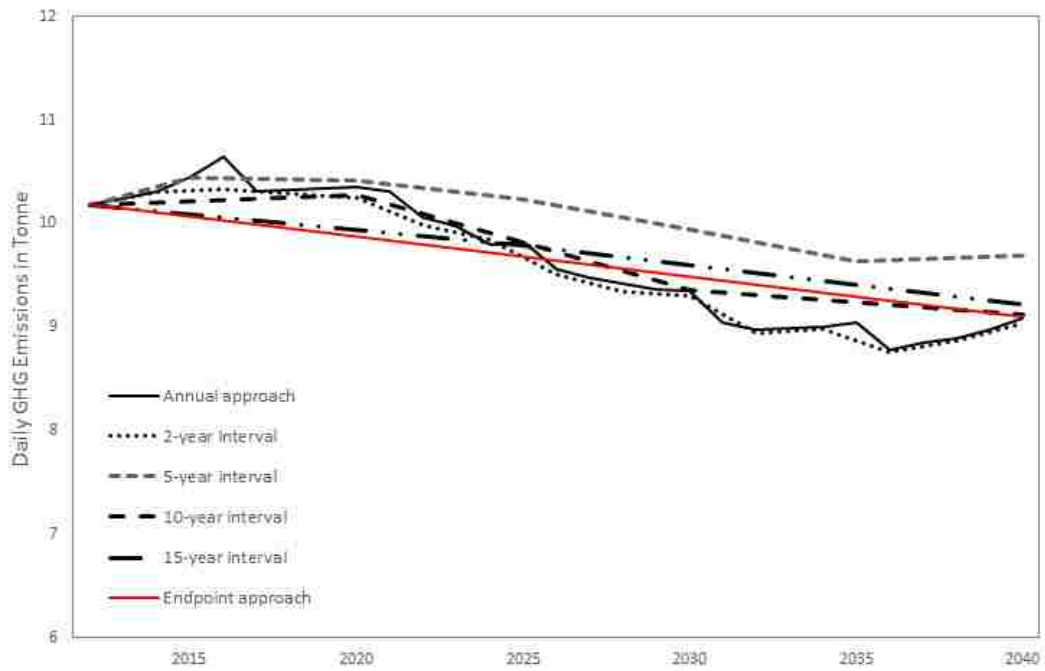
Figure 26. Daily GHG inventory estimates with different analysis approaches
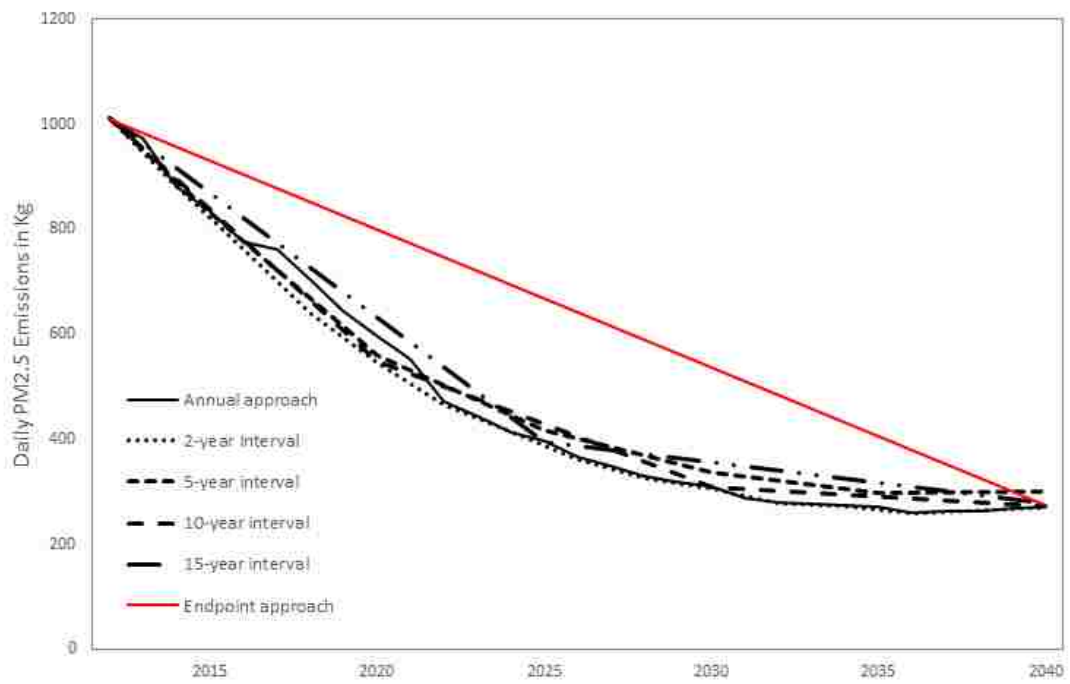
Figure 27. Daily PM₂.₅ inventory estimates with different analysis approaches
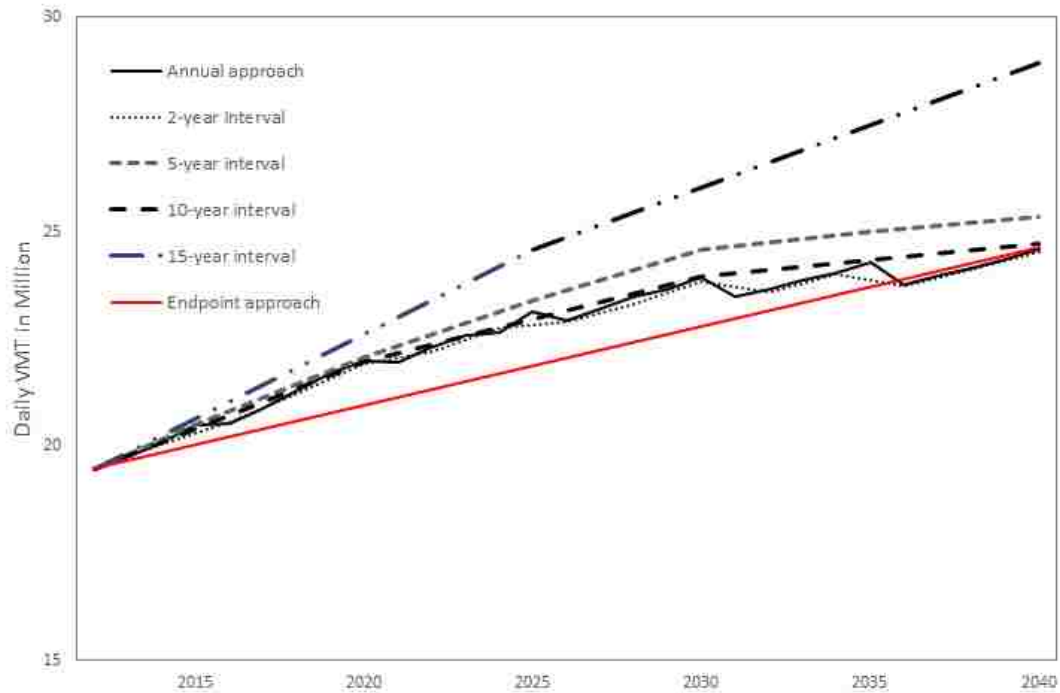
Figure 28. Daily VMT estimates with different analysis approaches

We also estimate the zonal population and employment in 2040 using the annual and

multi-year-interval approach and plot them in figures 29 through 33. Each dot on these

figures represent one zone. These figures depict very erratic and unexpected differences

in 2040 population and employment estimates. We expected the smaller intervals to

result in estimates that are closer to the annual approach but we notice that the endpoint

approach (which has a large interval of 28 years) is producing estimates that are closer to

the annual approach than the 5-year, 10-year, and 15-year interval estimates.

Our interval analysis shows that the estimates of GHG inventory, $PM_{2.5}$ inventory, and

VMT with a 2-year integration interval is not very far from the annual integration

approach. A two-year interval reduces the computation by half, from about one month to

two weeks. However, the two year interval fails to observe the increase in $PM_{2.5}$

emissions in the near future and estimates significantly different population and

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employment patterns in 2040. For intervals larger than two years, the behavior of the

integrated land use and travel demand model becomes very complex and is difficult to

interpret. Our results indicate the iteration frequency is important but more research is

needed to understand how different levels of temporal resolution affect estimates.

Figure 29. Difference in population (left) and employment (right) estimates in 2040: annual vs 2-year interval approach

Figure 30. Difference in population (left) and employment (right) estimates in 2040: annual vs 5-year interval approach

Figure 31. Difference in population (left) and employment (right) estimates in 2040: annual vs 10-year interval approach
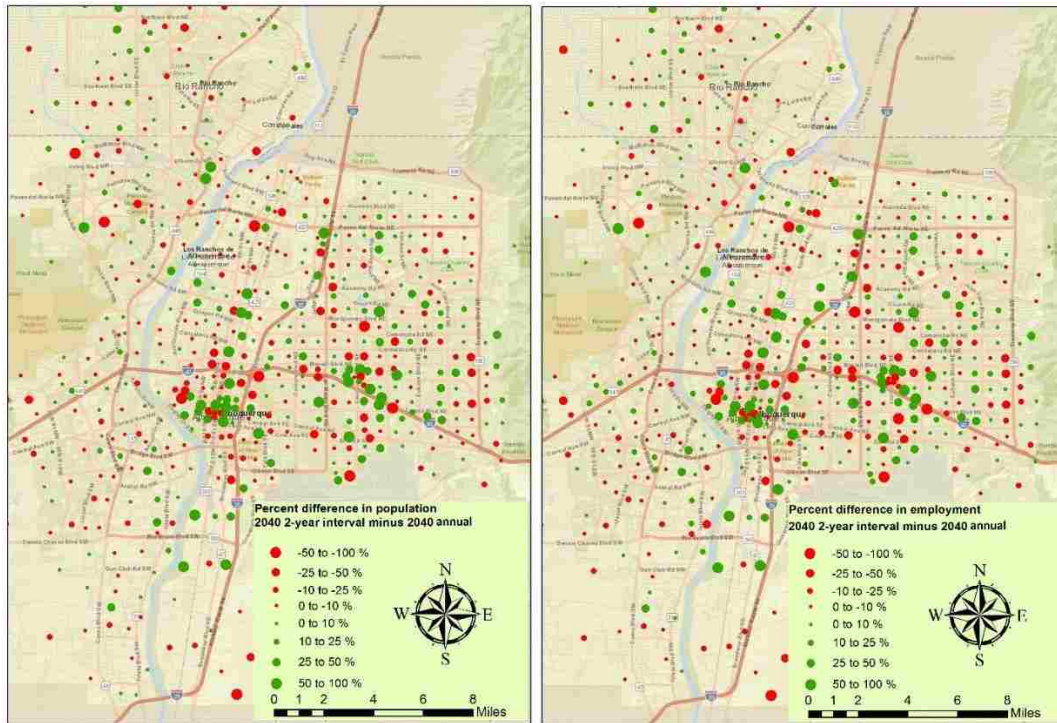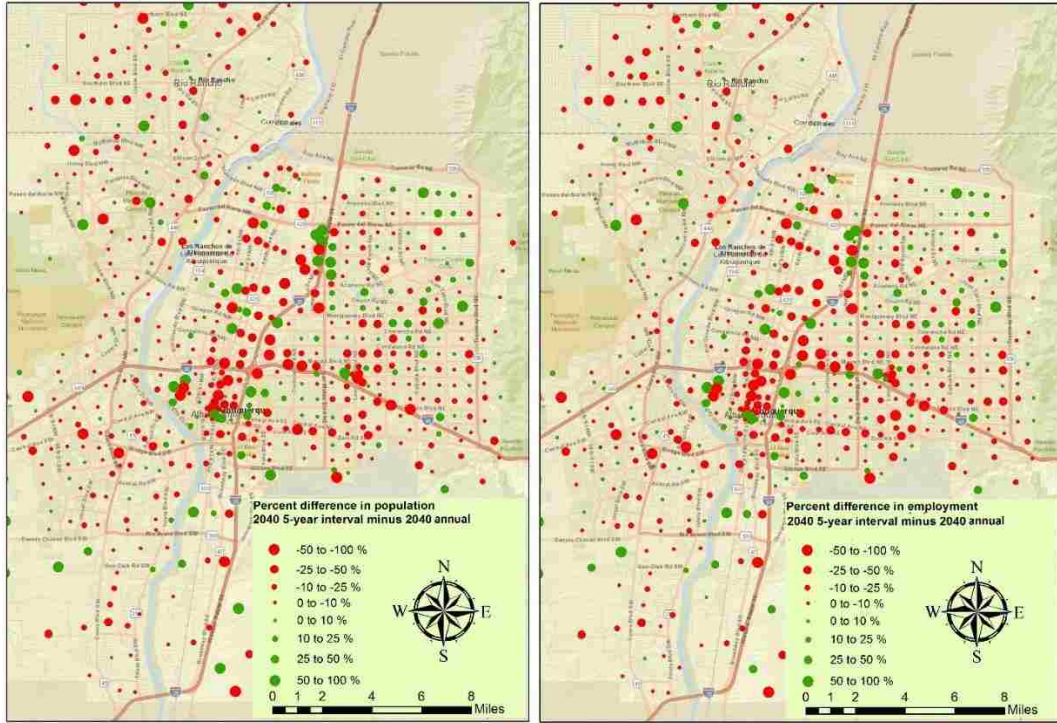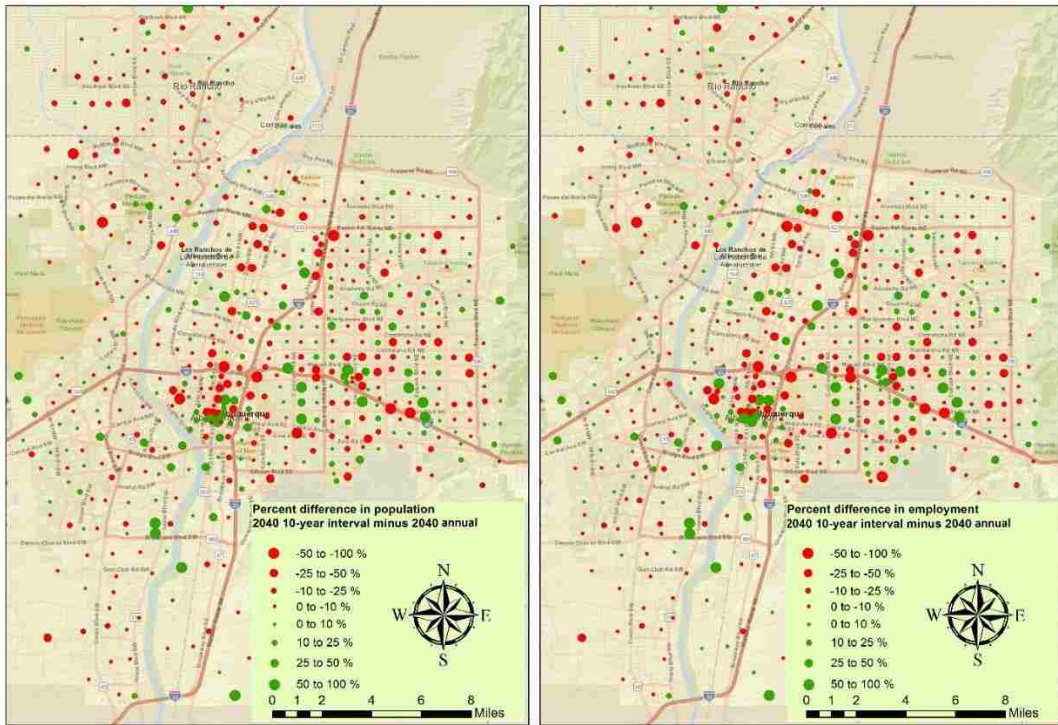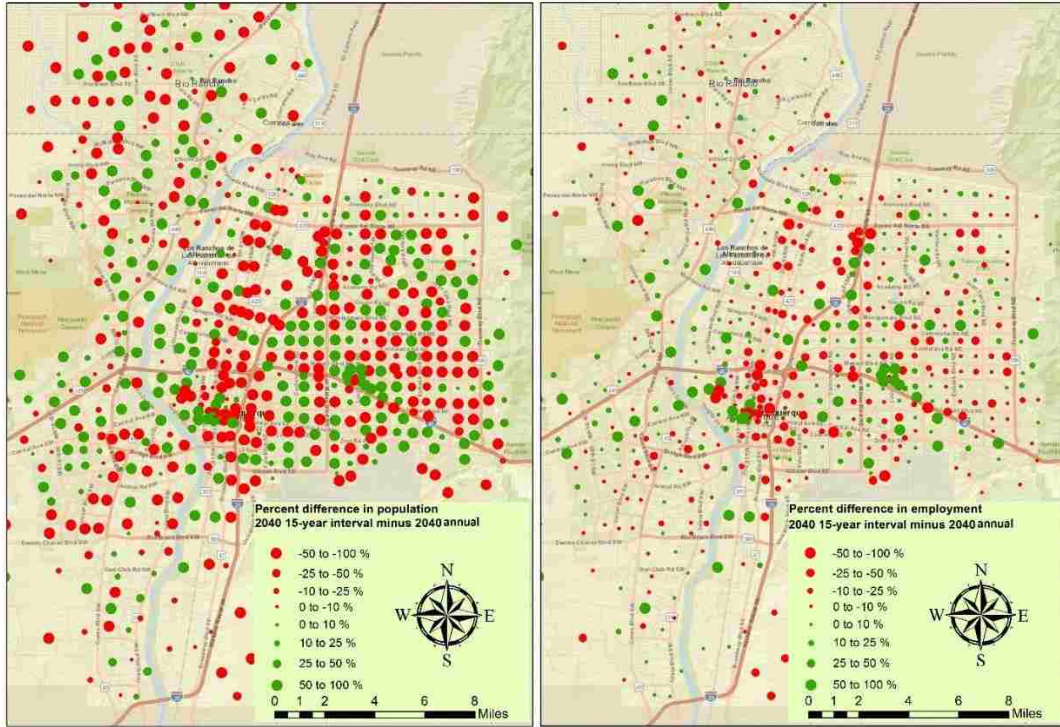
Figure 32. Difference in population (left) and employment (right) estimates in 2040: annual vs 15-year interval approach
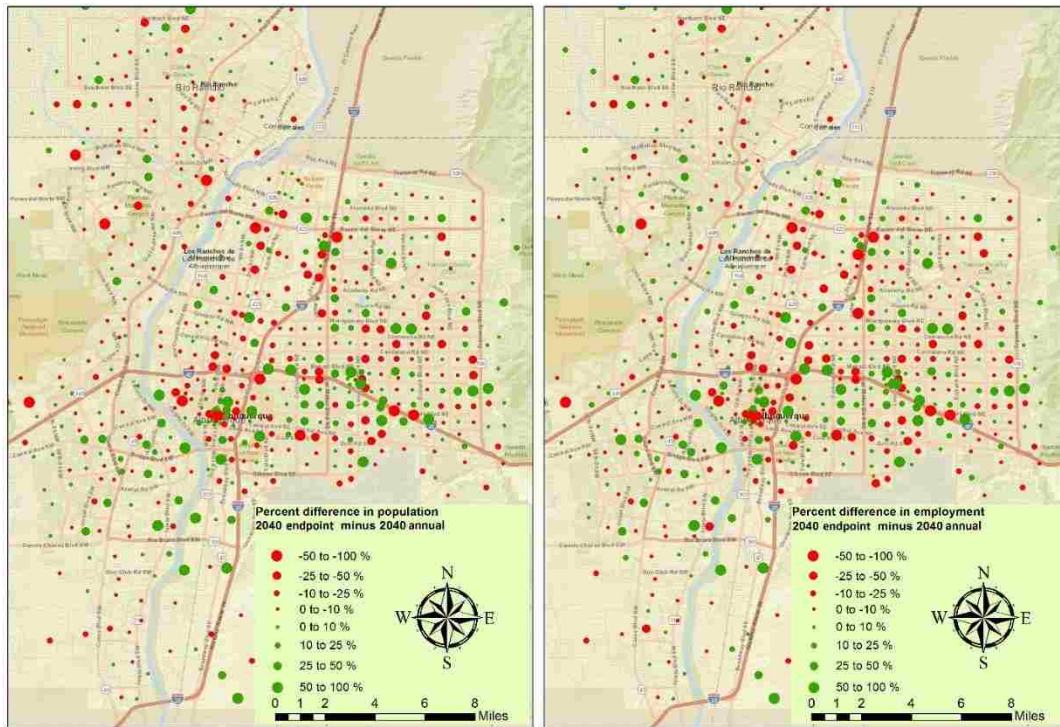
Figure 33. Difference in population (left) and employment (right) estimates in 2040: annual vs endpoint approach

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Discussion

The transportation sector is responsible for more than a quarter of GHG emissions in the United States. Many metropolitan areas use land use strategies in an effort to improve air quality and reduce GHG emissions. Land use strategies however, might increase population exposure to vehicle emissions by increasing residential development close to major roads and increasing travel activity and congestion close to where people live.

The goal of this study is to see if using realistic strategies, we can come up with scenarios that reduce GHG emissions compared to a business as usual scenario while not increasing exposure to $PM_{2.5}$. We devised two long-range transportation planning scenarios for the Albuquerque Metropolitan Area. The scenarios are made up of land use and transportation strategies that are believed to reduce GHG emissions and are available in a local and regional decision making setting. Strategies such as improving vehicle technology that are beyond the control of regional planning agencies or are unrealistic such as very high fuel taxes are not considered.

While a business as usual scenario leads to about a 7 percent increase in GHG emissions, both scenario 1 and scenario 2 reduce GHG emissions in 2040 compared to the 2012 level by 10 to 15 percent. Neither of the two scenarios however seemed to be promising reductions even close to the IPCC suggested level of 40–70% in 2050. What is more concerning is that figure 22 shows GHG emissions start to increase in all the scenarios in near future; this is due to the fact that reductions caused by improved vehicle fuel efficiency is offset by the increase in VMT. This means that not only will the region not be able to meet the IPCC suggested GHG reductions in 2050, but that emissions might begin rising in 2050. These findings confirm a former study of ours that showed in order

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to get close to the IPCC reduction targets, the Albuquerque Metropolitan area needs to adopt very aggressive transportation strategies.

The non-linear temporal change in performance measures, amplify the importance of evaluating transportation plans for each year in the planning period, instead of only the endpoint. The non-linear change in the air quality and travel demand measures means that the value of the measures in the end year do not provide much information about the overall performance of the scenario in the planning period. For example, low $PM_{2.5}$ exposure in scenario 1 in 2040 fails to describe that this scenario imposes the highest exposure among the scenarios earlier in the planning period. Note that the performance of a scenario in terms of the exposure to the pollutants is more important in the near-future than the far-future. As the vehicle fleet becomes increasingly less polluting, the negative health outcomes from exposure to pollutants will likely fade; the most severe health impacts from the exposure to air pollutants will happen in the near-future.

Our study focuses on the Albuquerque metropolitan area, but the same modeling framework can be used to devise and evaluate long-range transportation plans in other metropolitan areas in the U.S. The scenarios that we devised for the study area are probably not the most efficient; however, they demonstrate that even the strategies that can be implemented in a local and regional level have the potential to improve the air quality and travel measures.

Finally, there are some limitations to note about our study. We use a traditional 4-step travel demand model which has several drawbacks. The model calculates the total trips based on the characteristics of the households that are held constant in trend and devised scenarios. More importantly, the model was built and calibrated based on the travel

behavior from the most recent travel survey for the region. The future economy might change the travel behavior and trip generation rates in households. Another limitation of the 4-step travel demand model is that it does not provide detailed information about the movement of individuals. Thus, we are not able to estimate an accurate measure of individuals' exposure as they move around the network during the day and assume their exposure to be equal to the concentration of the pollutant where they live. However, we believe that our assumption still provides a reasonable estimate of exposure as individuals spend a large amount of their time where they reside.

In our study, we only estimated exposure to primary $PM_{2.5}$. Total exposure to $PM_{2.5}$ from the transportation network would be higher if we account for the exposure to secondary $PM_{2.5}$ formed from chemical reactions between vehicle exhaust and other pollutants in the atmosphere.

Our study can be expanded by devising methods to find the most effective combinations of land use and transportation strategies in developing the scenarios. Use of an activity based rather than 4-step travel demand model can also increase the accuracy of the exposure estimates as such models provide detailed information about the movement of the individuals during the day. Additionally, our framework can be used to account for other air pollutants such as carbon monoxide, nitrogen dioxide, and vehicle emissions of air toxics.

Chapter 5. Estimating welfare change associated with improvements in urban bicycling facilities

Introduction

Prior research reveals the health, air quality, and congestion relief benefits of cycling (De Hartog et al. 2010; Frank et al. 2006; Sælensminde 2004) which has led government agencies to increasingly promote cycling as part of a comprehensive regional transportation plan. Investing in new or improved bicycle facilities such as bike lanes and cycle tracks is a common strategy to increase the level of cycling with the aim of realizing these benefits (Buehler and Pucher 2012; Handy et al. 2010). However, commonly estimated bicycle facility benefits such as increased safety, less air pollution and congestion relief, represent only a partial list of potential benefits (Elvik 2000). Amenities such as cycling facilities are considered public goods and have economic value because they contribute positively to peoples' wellbeing by providing them with a safer and more enjoyable cycling experience. For example, in addition to the benefits of fewer accidents, bicyclists also value the feeling of a more protected trip (Ruiz and Bernabé 2014). This value is generally not considered in a traditional analysis since it involves a difficult to estimate non-market value. The economic value of cycling facilities is challenging to determine since, like other public goods, there is no market where money is exchanged for them. On the other hand, it is important to estimate these values because they are required to complete robust cost-benefit assessments of these facilities. The estimates of economic value are also important for considering how much to invest in bicycle facilities given a limited amount of transportation funding and many competing transportation projects.

Calculating a person's willingness to pay (WTP) for the provision of a public good is a common method to estimate the economic value or welfare change expected from their provision (Freeman 2003). Welfare change is represented in money terms, is tangible, and once estimated, can be used in the decision making process along with other costs and benefits. Several methods that use stated preference (SP) and revealed preference (RP) techniques are available to value public goods and services (Bishop and Woodward 1995). These methods indirectly estimate the value people place on public goods using their stated behavior in a hypothetical situation (SP methods) or their observed behavior in a real situation (RP methods).

Prior studies in the field of transportation have used SP and RP methods to estimate the monetary value that people place on transportation improvements including: congestion relief (Brownstone et al. 2003); travel time reliability (Li et al. 2010); travel time (Devarasetty et al. 2012; Jong et al. 2014; Uchida 2014); accident risk (Muller and Reutzel 1984; Rizzi and Ortúzar 2003; Iragüen and Ortúzar 2004; Hensher et al. 2009; Jou et al. 2013); transit improvements (Drevs et al. 2014); and traffic related air pollution (Wardman and Bristow 2014).

Several studies have also valued bicycle infrastructure. In an attitudinal survey of households in the city of San Diego, the majority of respondents expressed their willingness to pay for cycling facility improvements by supporting a $10 annual fee for bicycle registration (Jackson and Ruehr 1998). Krizec (2006) used a SP approach to evaluate preferences for different types of cycling facilities. University of Minnesota staff participated in the survey and were asked how much additional time they were willing to travel if their trip could be made using an improved bicycle facility. The study finds that

bicyclists are willing to spend 16.3 additional minutes to make a trip using a bike lane, 8.9 minutes when parallel parking is prohibited along the road, and 5.2 minutes when a trail is provided. The additional travel time is multiplied by an estimate of the average value of travel time, which is assumed to be $12 per hour based on guidance from the Minnesota Department of Transportation, to estimate WTP for the improved cycling facilities. Other studies have estimated changes in travel time but not WTP. Using the same data set as Krizec (2006), Tilahun et al. (2007) find that University of Minnesota staff who are bicyclists are willing to spend 16.4, 9.3, and 5.1 additional minutes, respectively to make their trips using a bike lane, a facility with prohibited parallel parking, and a trail, respectively. Stinson and Bhat (2003) use a SP approach to determine bicyclists' preferences for a wide range of attributes related to the cycling environment and find that bicyclists are willing to spend 16.9, 14.5 and 12.3 additional minutes, respectively to make their trips using a bike lane, a cycle track and on smooth pavement. While Krizec's study provides the only example of a bicycle facility WTP estimate in the peer reviewed literature, the assumption of a single value of time for all individuals, is a potentially important limitation. Most travel time valuation methods assume that the value of travel time is some proportion of an individual's wage (Cesario 1976). Since cyclists may have a different distribution of wages than the general population, using a population average value of travel time may also bias results upwards or downwards. Additionally, McConnell and Strand (1981) show that the proportion of the wage used to estimate the value of travel time may also vary across population groups.

Our study uses a SP method and estimates WTP for bike lanes, cycle tracks and street lighting; providing an estimate of the change in welfare associated with each. The study

is designed to observe the tradeoffs that bicyclists make between travel time and using an improved cycling facility to estimate WTP. The study also considers several methods for valuing travel time, which is then used in estimating WTP. Each individual's value of time is estimated as a function of their reported wage and as the pay they would accept to work an additional hour. The study also investigates how using the sample average wage rate and the region's average wage rate in estimating value of time lead to differences in WTP estimates. Additionally, the study investigates how cycling experience and cyclist's age affect WTP estimates.

Methods

Survey design

We create a SP survey and use a random utility model to estimate WTP for three facility improvements. While RP data is often preferable, observing the actual choices made by bicyclists is very difficult in most cases; it's impossible in our case, where few alternative facilities exist in the study area. SP surveys overcome this limitation by presenting study participants with any number of alternatives: existing or planned.

The validity of SP methods requires that study participants understand the choices that they are presented with, that the choices are realistic, and that participants have the required information to make an informed decision. Surveys such as ours can threaten the study's validity because respondents are asked to choose between cycling facilities that currently do not exist in the region and that they may have no prior experience using. To minimize this threat, respondents are shown illustrative videos of different types of cycling facilities. Video clips, obtained from YouTube, show the experience of biking on

a road, without a bike lane, with a bike lane and with a cycle track in the city of Montreal,

Canada from the view of a camera mounted on a bicyclist's helmet.

The SP questionnaire is designed to obtain information on bicyclists' preferences about

hypothetical bicycling facilities. The questionnaire presents three bicycle facility

improvements: bike lanes, cycle tracks and street lighting (figure 27).
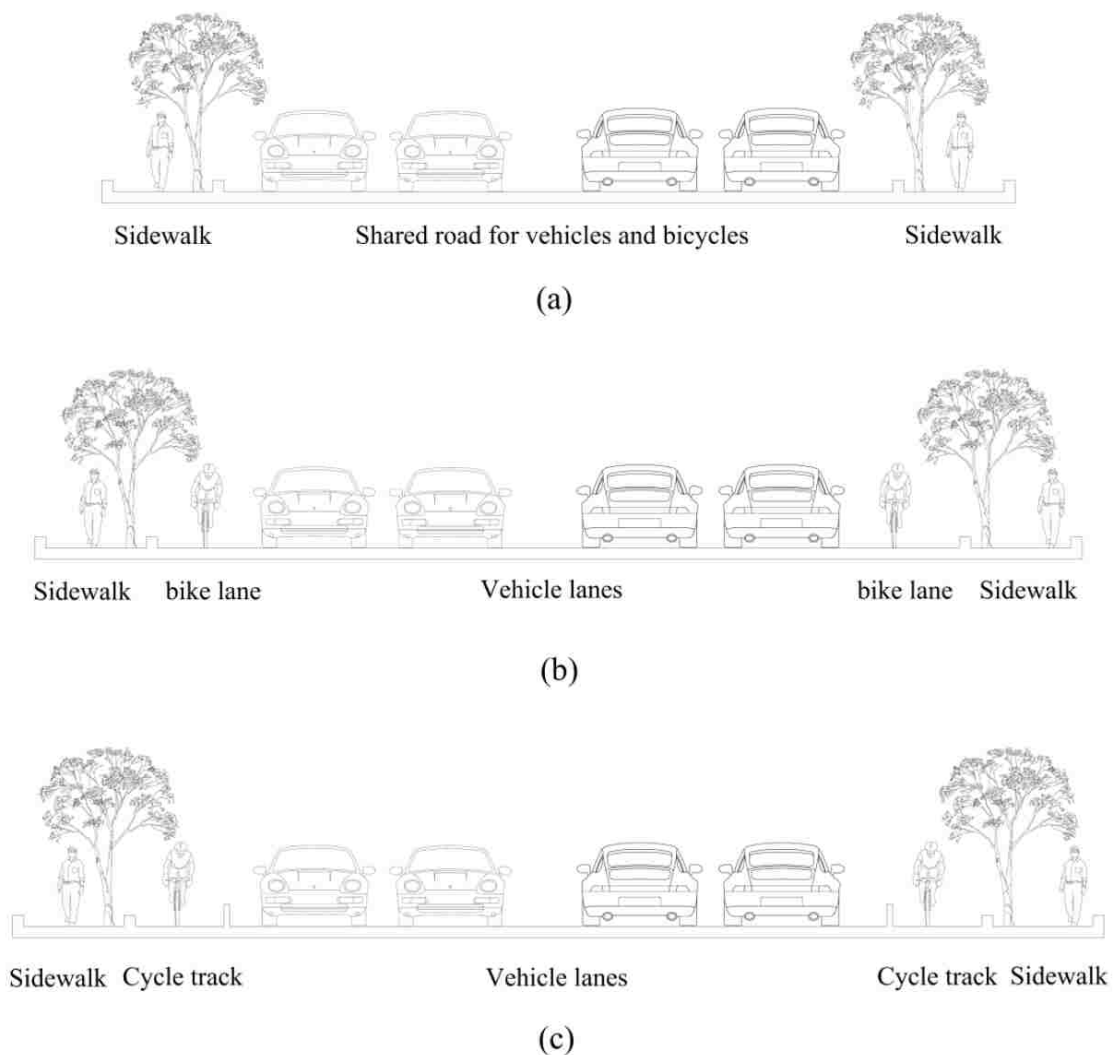

Figure 34. Cycling facilities included in SP questionnaire: shared roadway (a), bike lane (b), and cycle track (c)

Bike lanes and cycle tracks are included because they are thought to have the greatest impact on the level of cycling (Buehler and Pucher 2012). Additionally, evidence in the literature suggests that roadway lighting may also have a significant effect on the level of non-motorized activity that occurs after dark (Cervero and Kockelman 1997). We also consider street lighting because the study area has a general lack of street lighting and prior studies have not evaluated how much bicyclists value street lighting. We do not evaluate improvements including bicycle paths or trails, prohibited parallel parking and pavement smoothness as has been done in prior studies. These improvements are not as applicable to the study area and we aimed to keep the choice experiment as relevant and short as possible to minimize respondent fatigue. The study area is a moderately dense urban area and there is very little right of way where bicycle paths or trails could be placed. Cycle tracks, which are essentially roadside paths, are considered and could be built in existing roadway right of ways. Most of the study area's main streets (arterials and collectors) where bicycle facilities would likely be placed already prohibit on street parking. The study area's streets are also generally in good condition owing to Albuquerque's dry and mild climate.

After watching illustrative videos of each facility type, respondents are given six choice sets (figure 28). In each choice set, the respondents are asked to imagine traveling to school or work by bike and are then asked to choose their preferred facility: the inferior facility with lower travel time, and the improved facility with higher travel time. The preference of the respondents over two facility is recorded in six question. In each question, travel time on the inferior facility (for example no bike lane) remains at 20 minutes while travel time on the improved facility (for example the bike lane) increases

consequently from 20 to 50 minutes (20, 25, 30, 35, 40 and 50 minutes). In this way, we

can capture an estimate of the maximum additional travel time that the respondent is

willing to spend to ride on the improved facility. Respondents are also asked about their

cycling experience, socioeconomic characteristics including sex, age, income, marital

status, and whether they are a parent or not.
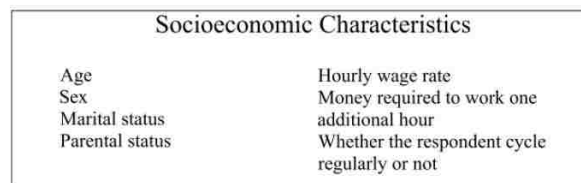
Figure 35. Survey structure

Estimating welfare changes

We use utility theory to estimate the welfare change associated with each bicycle facility

improvement. Individuals gain a certain amount of utility by consuming a good or service

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–this good might be a public good such as a bike lane. The utility individuals gain from consuming a good is a function of several observable and unobservable factors. It is assumed that the utility individuals gain by riding on each cycling facility is a function of travel time, the type of facility and their socioeconomic characteristics. Mathematically, the utility of alternative facility i for individual n can be written as the following:

$$U_i^n = \alpha'\, \mathbf{S}^n + \boldsymbol{\beta}_i' \mathbf{I}_i + \lambda C_i \tag{6}$$

Where,

U_i^n = The utility of alternative i for individual n

$\mathbf{S}^n$ = The vector of socioeconomic attributes for individual n

$\mathbf{I}_i$ = Vector of dichotomous variables representing whether each improvement is provided in alternative i or not

C_i = Travel cost (time) of riding bike in alternative i

α = Vector representing estimated coefficients on socioeconomic characteristics

$\boldsymbol{\beta}_i$ = Vector representing estimated coefficients of bike lane, cycle track, and lighting

λ = Estimated coefficient of travel cost

Willingness to pay is then calculated following the definition of the marginal rate of substitution. The marginal rate of substitution between a pair of goods is the rate at which an individual trades off one good in exchange for another one while maintaining a constant level of utility (Varian 1992). This can be written as follows:

$$MRS_{xy} = \frac{MU_x}{MU_y} \tag{7}$$

Where,

MRS_{xy} = Marginal rate of substitution between good x and good y

MU_x = Marginal utility of good x

MU_y = Marginal utility of good y

Marginal utility is the gain or loss in the utility due to consuming or giving up some quantity of goods and services. Based on the linear formulation of our utility function (equation 6), the marginal utility of a good (facility improvements and travel time) is its estimated coefficient in the model. In equation 7, consider good x as a facility improvement and good y as the monetized value of travel time. The willingness to pay for a facility improvement is the money that a bicyclist is willing to trade off to use the improvement while maintaining a constant level of utility (equation 8).

$$WTP_{improvement} = MRS_{improvement,money} = \frac{MU_{improvement}}{MU_{money}} = \frac{\beta_i}{\lambda} \tag{8}$$

Monetized value of travel time

An accurate estimate of the monetary value of travel time is of great importance in our study since it is the basis for estimating WTP. Prior studies have valued travel time as a function of the hourly wage rate; ranging between 20 to 80 percent of the wage rate (Cesario 1976; U.S. Department of Transportation 2011). The value of time is generally thought to be less than the wage rate because work is generally less enjoyable than travel and that many individuals have little flexibility in the number of hours they can work. McConnell and Strand (1981) argue that the proportion of the wage rate used to estimate the value of travel time should vary based on the socioeconomic characteristics of the population being studied. For example, some people may like their job more than others or dislike travel. Current guidance from the U.S. Department of Transportation, based on a comprehensive survey of existing valuation studies, suggests using 50 percent of total

income or the wage rate as the value of travel time for the average person in the United States (U.S. Department of Transportation 2011).

Our study uses two methods to estimate the monetary value of travel time. The first method uses each respondent's response to the question, "how much money do you request to work one additional hour". This provides a simple method for estimating the marginal value of time for each respondent in our study that does not require choosing a single wage rate proportion, responding to the concerns raised by McConnell and Strand (1981). The second method estimates the value of time at 50 percent of each individual's hourly wage rate based on U.S. Department of Transportation guidance.

We create four logit models to estimate WTP as shown in figure 29. Models one and two convert travel time to travel cost (where cost is the monetized value of time) using each of the two methods described above. Comparing the results from models one and two allows us to investigate how a commonly used fixed wage rate proportion may bias WTP estimates. Models three and four are estimated using travel time. Travel times are then converted to travel cost using 50 percent of the average wage rate from our sample population and the region, respectively. Model 3 allows us to investigate how using a fixed wage rate proportion along with a single average wage rate may bias WTP estimates. Model 4 represents a worst case study design where a single proportion of regional wage rate is used that may not correspond to the wage rage of bicyclists.
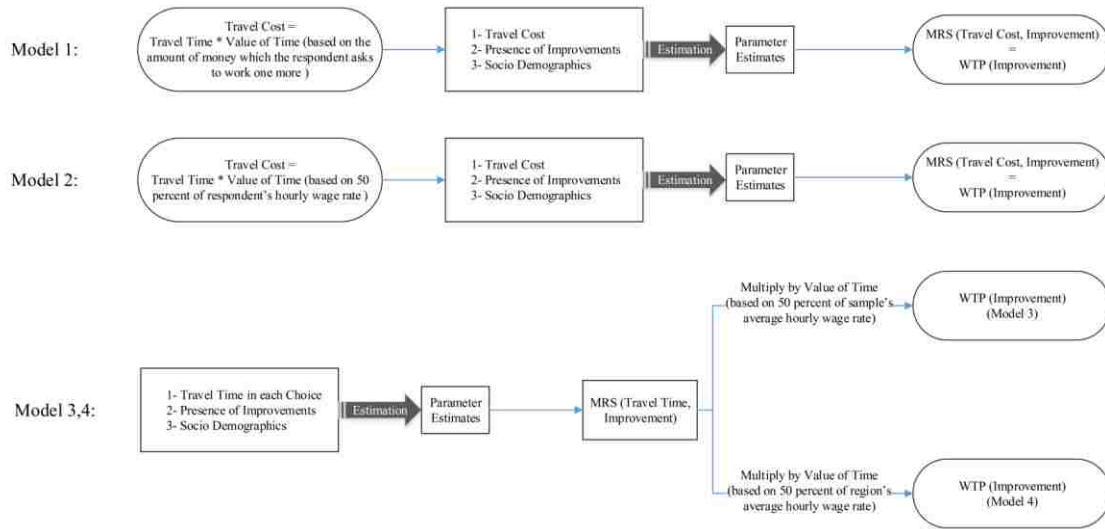
Figure 36. The procedure of estimating WTP in each of the four developed models

Data

The SP survey was administrated during the spring of 2014 to students taking economics courses at the University of New Mexico's main campus in Albuquerque, New Mexico. Of the eight main streets leading to the campus, two have bike lanes with lighting and one without lighting. The four other main streets that define the border of the campus do not have any bicycle facilities. Other routes to campus are on local residential streets that generally lack street lighting.

Questionnaires were completed in classrooms at the end of the class period. The surveys took an average of about 15 minutes to be completed. Most students in each class participated in the surveys. During four weeks, a total of 178 students in 8 classes were surveyed. Data associated with 17 students were removed from the dataset due to incomplete information in the questionnaire, leaving 161 observations. Table 9 provides a summary of the respondent's socioeconomic information. Most students were not

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frequent cyclists, 16 students biked to campus or work at least once a week with 10

biking regularly.

Table 9. Summary of socioeconomic data collected from respondents

Description	Value	Mean (Standard Deviation)
Gender	*Female* (1)	0.337 (0.373)
	Male (0)	
Age	*In years*	24.13 (6.12)
Marital status	*Married* (1)	0.11 (0.31)
	single (0)	
Parental status	*Parent* (1)	0.04 (0.11)
	Non-parent(0)	
At least one bicycle trip per week	*Yes* (1)	0.10 (0.29)
	No (0)	
Regularly travels by bicycle	*Yes*(1)	0.06 (0.01)
	No(0)	
Monthly income	*In dollars*	1,205 (577.87)
Hours worked per week	*In hours*	19.4 (6.34)
Hourly wage rate	*In dollars*	14.79 (3.70)
Money required to work an additional hour	*In dollars*	10.15 (4.14)

Results

The model results are shown in table 10. The statistical significance of the parameters

were estimated using robust standard errors. In a stated preference survey, each

individual responds to several choice situations, thus, several data points in the data

belong to one person. Individual's unobservable characteristics affect these choices and

lead to a systematic correlation between them. Robust standard errors address this

possible systematic correlation among data points (Kezdi 2004).

The model results generally meet our prior expectations. The positive sign on the

coefficient estimates for provision of bicycle lanes, cycle tracks, and street lighting

indicates that respondents are willing to accept a longer travel time to use these improved

facilities. Longer travel times indicate that respondents value these facilities over a

roadway with no bike facilities. Cycle tracks were the most valued improvement

followed closely by street lighting and then bicycle lanes. The importance of street

lighting highlights a potentially overlooked strategy to increase the amount of bicycling.

Street lighting was valued much more than bicycle lanes which are perhaps one of the

most commonly added bicycle facilities. The travel cost and time parameters are negative

as expected, indicating that increasing costs or travel time lowers the desirability of a

particular facility option all else being equal.

Table 10. Logit model results

Variable	Model 1	Model 2	Models 3 and 4
Presence of cycle track	0.559***	0.617***	0.737***
	(0.129)[a]	(0.133)	(0.238)
Presence of bike lane	0.248***	0.340***	0.418***
	(0.080)	(0.096)	(0.172)
Presence of lighting in dark time trips	0.440***	0.501***	0.567***
	(0.146)	(0.182)	(0.212)
Travel cost (model 1)	-0.288***	-	-
	(0.008)		
Travel cost (model 2)	-	-0.350***	-
		(0.010)	
Travel time (model 3 and 4)	-	-	-0.051***
			(0.003)
Age	0.008***	0.006***	-
	(0.002)	(0.003)	
At least one bicycle trip per week	-0.116*	-0.095*	-
	(0.063)	(0.052)	
Regularly travels by bicycle	-0.180***	-0.133***	
	(0.063)	(0.052)	
Constant	1.018***	0. 659***	1.661***
	(0.100)	(0.113)	(0.337)
Number of respondents	161	161	161
Number of choice situations	4830	4830	4830
Pseudo R squared	0.110	0.139	0.089
Chi square	64954	40713	73355

   [a] Standard errors are presented in parenthesis
   *** Coefficient estimate is significant at 0.01 level
   **   Coefficient estimate is significant at 0.05 level
   *   Coefficient estimate is significant at 0.10 level

The results also indicate that age and cycling experience affect facility preferences. The

coefficient on the respondent's age is positive and statistically significant in the first and

second models. The positive sign indicates that the preference for bicycle facilities over an unimproved roadway increases with age. This may be a result of a decline in risk-taking behavior that has been observed in travelers as age increases (Turner and McClure 2003, Lott and Tardiff 1978). Cycling experience had a negative and statistically significant coefficient estimate. The negative sign on the two parameters measuring cycling experience indicates that greater experience reduces the preference for cycling facility improvements. These results seem to make sense, as more experience likely reduces fear or discomfort in sharing roadways with vehicles and therefore reduces the value of facility improvements (Antonakos 1994).

The coefficient estimates in table 10 are used to calculate the average WTP for bicycle facilities (table 11). For models 1 and 2, WTP by bicycling experience was also calculated. The results indicate that WTP for cycle tracks is greatest, followed closely by street lighting, regardless of how we measured the value of travel time. WTP for bicycle lanes is much less, about 45 to 50 percent less than cycle tracks and 30 to 40 percent less than street lighting. The results also indicate that experienced bicyclists have a lower WTP for any facility improvement compared with the sample average. The elasticity of WTP to bicyclists' age is also calculated and shown in table 12. Elasticity estimates provide the percentage change in WTP due to a percentage change in age. The results generally indicate that WTP for improved bicycle facilities increases with age, though the limited range of age in our sample constrains this portion of our analysis.

Table 11. Willingness to pay per trip for different facility improvements

		Improvement		
Model	**Sample Population**	**Cycle track**	**Bike lane**	**Lighting**
	Sample average	$1.94	$0.86	$1.53
Model 1	Bike users	$1.54	$0.46	$1.12
	Bike commuters	$1.32	$0.24	$0.90
	Sample average	$1.76	$0.97	$1.43
Model 2	Bike users	$1.49	$0.63	$1.16
	Bike commuters	$1.38	$0.52	$1.05
Model 3	Sample average	$1.78	$1.01	$1.37
Model 4	Sample average	$2.47	$1.40	$1.90

Table 12. Elasticity estimates of WTP to bicyclists' age in models 1 and 2

	Improvement		
Model	**Cycle track**	**Bike lane**	**Lighting**
1	1.43	3.23	1.82
2	0.97	1.76	1.20

The two methods for valuing travel time (models 1 and 2) produce approximately the same WTP estimates even though the average marginal wage rate required to work an additional hour in model 1 is 37 percent higher than 50 percent of the average wage rate which is used in model 2. In this regard, the US DOT guidance suggesting that travel time should be estimated as 50 percent of the average wage seems reasonable, at least for our small sample. The largest difference in WTP estimates occurs when replacing the sample average wage rate with the much higher (39 percent) regional average wage. There was also little difference in the estimated WTP when each respondent's individual wage was used directly (model 2) or the sample average wage was applied to regression results estimated with travel time (model 3).

Discussion

We estimate WTP for improved bicycle facilities at $1.76 to $2.47 for adding cycle

tracks, $1.37 to $1.90 for adding street lights, and $0.86 to $1.40 for adding bicycle lanes

to a roadway without these improvements. Two different methods of valuing

respondents' time, using their marginal value of time or 50% of wage rate, lead to similar

WTP estimates. While we maintain that estimating the marginal value of a person's time

is theoretically more consistent, simply assuming 50% of the wage rate may be sufficient

and is information that is widely available. Information about wages rates or annual

income is routinely collected in many travel surveys and also available from other data

sources. We urge caution in using the fourth method, the regional wage rate or average

income, since the regional population may value their time differently than the population

of current and potential bicyclists (those willing to bicycle if better infrastructure were

provided), biasing estimates up or down.

We also find that WTP is higher for respondents who do not currently bike and lower for

bicyclists with more experience. The significance of this finding is that the WTP for

improved bicycle facilities will be underestimated if only current bicyclists are surveyed.

Additionally, this result indicates the value of improved bicycle facilities for attracting

new bicyclists and those with less experience.

While WTP for cycle tracks is higher than other improvements, considered alone, this is

not evidence that cycle tracks should be provided over other types of bicycle facility

improvements. The average cost of building cycle tracks is $133,170 per mile, which is

much more than the $25,070 cost of adding bike lanes but less than the $244,000 cost of

adding street lighting (Bushell 2013). The cost of facility improvements must be

compared with the total private and social costs and benefits that these facilities provide in order to make an economically efficient decision. This requires first estimating how each bicycle facility affects bicycle and vehicle mode share. The change in mode share can then be used to estimate the change in the value of external costs and benefits from each mode including, changes in congestion, air quality, greenhouse gas emissions, traffic safety, and health benefits associated from active transportation. These external costs and benefits can then be added to the private WTP estimates to comprehensively evaluate the net benefits of each facility.

It is also important to note that this study is based on a relatively small convenience sample of university students. The WTP estimates are unlikely to represent those obtained from a more representative sample of Albuquerque's population or the population in any other region. Despite this limitation, the results generally agree with those from prior studies, cycle tracks are preferred to bicycle lanes. The results also suggest that street lighting is something that future bicycle facility valuation and preference research should consider.

Chapter 6. Conclusions

Federal surface transportation regulations require that state and metropolitan planning organizations adapt to a performance and outcome based planning process that provides for a greater level of transparency, improved decision-making, and more efficient investment of Federal transportation funds. However, there are no federal guidelines for evaluating the future outcomes of long range transportation plans in terms of exposure, and the only requirements that incorporate air quality in the planning process do not necessarily lead to adaptation of health-protective plans. This dissertation provides planning organizations with a clear methodology to include exposure assessment as part of their outcome based planning process.

I developed a clearer picture of how long-range transportation plans affect exposure to traffic related $PM_{2.5}$. I showed that $PM_{2.5}$ emission from traffic is distributed unevenly in a region and is highest close to the major roads and interchanges, and concluded that future planning scenarios, specifically those that focus on land use change can have strong impacts on the exposure of the population living in a region. I developed and suggested an integrated modeling framework that can be used in planning process to evaluate the plan's performance in terms of air quality and travel measures. This framework improves transportation planning process in many ways. Unlike the current practice that focuses on evaluating the plans in terms of only aggregate measures of air quality such as emission inventory, my suggested framework takes into the account the exposure to the emission as an important measure determining the health-protectiveness of a plan. Additionally, my suggested framework evaluates the plans annually, from the base year up to the planning horizon; the current practice focuses on evaluating the plans

only in one or two future years and neglects the mid-term performance. The annual

evaluation allows planning agencies to obtain information about how the timing of land

use and transportation system changes affects air quality and travel demand measures and

helps them devise more efficient plans.

State and metropolitan planning organizations can implement a similar modeling

framework to obtain clear pictures of their plans' impact on population exposure as well

as on GHG emissions and travel demand measures. The models that I used to create the

framework are available to planning agencies. Most of these agencies have access to

travel demand models and a type of land use model or can dedicate budget to purchase

them. The other models used in the framework including MOVES emission model,

AERMOD model, and GIS (QGIS) are freely available. Automating the framework and

creating a user friendly GUI -which is a suggested area for future research and

development- can simplify the process of setting up and running the modeling

framework.

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