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Evaluating unintended outcomes of regional smart-growth strategies: Environmental justice and public health concerns

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ABSTRACT

Many urban areas are perusing infill, transit oriented, and other "smart-growth" strategies to address a range of important regional goals. Denser and more mixed use urban development may increase sustainability and improve public health by reducing vehicle travel and increasing the share of trips made by transit, walking and bicycling. Fewer vehicle trips results in fewer greenhouse gas and toxic vehicle emissions, and more trips made by walking and bicycle increases physical activity. Prior research has largely focused on modeling and estimating the potential size of these and other smart-growth strategy benefits. A largely overlooked area is the potential for unexpected public health costs and environmental justice concerns that may result from increasing density. We evaluate regional land-use and transportation planning scenarios developed for the year 2040 by a metropolitan planning organization with a newly developed regional air quality modeling framework. Our results find that a set of regional plans designed by the MPO to promote smart-growth that are estimated to result in less vehicle use and fewer vehicle emissions than a more typical set of plans results in higher population exposure to toxic vehicle emissions. The smart-growth plans also result in greater income-exposure inequality, raising environmental justice concerns. We conclude that a more spatially detailed regional scale air quality analysis can inform the creation of smarter smart-growth plans.

1. Introduction

Smart-growth strategies generally include increasing the density and land-use mix of urban development. In many cases, growth is planned around activity centers and high quality mass transit stations or corridors. These strategies are expected to increase the use of transit and non-motorized modes of transportation and reduce vehicle use (Ewing et al., 2007; Ewing and Cervero, 2010; Stone et al., 2007; TRB, 2009). While smart-growth strategies are pursued for many reasons, reducing private automobile use and greenhouse gas (GHG) emissions are among the most frequently cited reasons. For example, California's Sustainable Communities and Climate Protection Act of 2008 (SB375) requires that metropolitan planning organizations (MPOs) develop land-use plans that will reduce per capita GHG emissions by reducing vehicle use. Reducing GHG emissions and vehicle use may often be equated with achieving other regional goals as well. Specifically, improving air quality and reducing exposure to toxic vehicle emissions. Unfortunately, as we demonstrate in our study these additional benefits may not occur. In fact, smart-growth strategies may increase exposure to toxic vehicle emissions. This can occur when pop-

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ulation density increases in areas with relatively high emissions concentrations or when polluting activity (i.e., vehicle traffic) becomes more concentrated in more densely populated areas, or a combination of both. Furthermore, we show that the spatial scale of exposure analysis can result in different conclusions.

Where reductions in GHG emissions occur is irrelevant to a transportation or land-use policy's effectiveness in mitigating climate change concerns. Where reductions in toxic air pollutants occur, however, is critical to the effectiveness of policies that aim to reduce exposure and improve public health. There is strong evidence demonstrating that the concentration of many vehicle emissions are elevated along roadways (Karner et al., 2010; Zhou and Levy, 2007) and that exposure to these emissions likely results in a wide 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). The uneven distribution of vehicle emission concentrations across urban areas also raises environmental justice concerns. Minority and low income populations in most communities live closer to roads with the highest traffic volumes, placing them at a disproportionately higher risk of suffering from negative health outcomes related to vehicle emissions exposure (Rowangould, 2013). Smart-growth strategies affect both land-use development patterns and travel behavior, and in doing so change the gradient of vehicle exhaust concentration across an urban area while also changing the paths that people move through it. The complex change in land-use and travel behavior mean that common methods for evaluating how a regional land-use or transportation plan may affect air quality and ultimately public health and environmental justice are inadequate.

Federal requirements for evaluating how long range regional transportation plans may affect air quality are very limited. The United States Department of Transportation requires that MPOs create long range regional transportation plans for urban areas with 50,000 or more residents. Plans typically focus on the performance of the transportation system. Air quality analysis is only required in areas that the United States Environmental Protection Agency (US EPA) designates as being in violation of the national ambient air quality standards (i.e., non-attainment areas). The Clean Air Act requires that transportation plans and projects in these areas conform to air quality improvement plans approved by the US EPA (i.e., state implementation plans). These improvement plans contain emission budgets for important source categories such as transportation. Conformity is demonstrated when a region's vehicle emission inventory falls within the transportation emission budget. It is very common for MPOs outside of non-attainment areas to also estimate regional vehicle emission inventories to gauge their plan's potential impact on air quality.

The Clean Air Act's conformity requirements were primarily designed to address regional air quality problems, including ozone and particulate matter – much of which is formed from vehicle emissions in a series of additional physical and chemical reactions (Finlayson-Pitts, 1997; Seinfeld, 1989). Regional emission inventories, the most common form of air quality analysis performed by MPOs in the United States and their international equivalents, provide very little information regarding exposure to directly emitted, primary, air pollutants in vehicle exhaust. A more spatially detailed approach is required to evaluate exposure to these air pollutants.

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

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

De Ridder et al. (2008) combine travel demand, emission and air quality modeling to evaluate how a more sprawling land-use development pattern may affect air quality and emissions exposure. They create a land-use scenario that moves 12% of the Ruhr region of Germany's population to the urban periphery, and then model the resulting change in travel patterns, emission rates, and air quality. The change in ozone and PM10 concentrations are modeled using the AURORA chemical-transport model at a 2 km^2 resolution. They find that exposure declines by 13% for the population moved to the periphery, while exposure increases by 1.2% for those who do not move. Overall, the sprawl scenario results in a small net increase in exposure of 0.35% and 0.55% for PM10 and ozone, respectively.

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

2. Study area

We use the mid region council of governments (MRCOG) most recent long range transportation plan *Futures 2040 Metropolitan Transportation Plan* to demonstrate our analysis approach. With a 2012 population of 890,593 and a total land area of 24,080 km^2, the study area is the most populous and the largest metropolitan area in the state of New Mexico. MRCOG used a scenario planning process that considered changes in both land-use and the transportation system to guide the development of the long range plan. The scenario planning process was also part of a US Department of Transportation sponsored climate change scenario planning project (Lee et al., 2015). A significant effort was made to identify scenarios that would reduce GHG emissions and mitigate potential climate change impacts. A wide range of performance measures were also developed to evaluate other aspects of each scenario including traffic congestion, accessibility, mode share, land development, water use, and economic growth. Environmental justice and air quality were not evaluated.

The scenario planning process ended with three final scenarios: the 2040 Trend scenario, 2040 Preferred scenario and 2040 Preferred Constrained scenario. The Trend scenario, representing business as usual, assumes no change in current land-use policies, and transportation investments focus on increasing roadway capacity. The Preferred scenario contains land-use policies and incentives aimed at encouraging infill, mixed use, and transit oriented development near existing activity centers and urban centers. The Preferred scenario also doubles transit level of service over the Trend scenario and adds several new bus rapid transit lines. Highway investments remain the same as in the Trend. The Preferred Constrained scenario is similar to the Preferred scenario in terms of land-use, but assumes a slower pace of transit and highway investment (Lee et al., 2015). We evaluate and compare the MRCOG's 2012 baseline and 2040 Trend and Preferred scenarios in this study. The Preferred Constrained scenario was omitted since it was very similar to the Preferred scenario.

3. Methodology

MRCOG used an integrated land-use and travel demand model to evaluate a 2012 baseline scenario and the three future scenarios described above. UrbanSim, an agent based land-use microsimulation model, was used to model parcel level land-use change, including changes in the distribution of employment and housing across the study area. A traditional trip based 4-step model was used to forecast travel demand for three different time periods: AM peak, PM peak, and the remaining off-peak hours. The models were integrated in the sense that UrbansSim provided employment and population forecasts to the travel demand model and the travel demand model provided origin-destination travel costs to UrbanSim. We then use the output of these models to estimate vehicle emission rates, fine particulate matter concentrations (PM2.5), and population exposure to PM2.5. Our methodology quantifies concentrations and exposure to primary, directly emitted, PM2.5 pollution from vehicle exhaust. It does not account for PM2.5 pollution that results from additional, secondary, reaction of vehicle related and other air pollutants that represent a more regional air quality concern. Details of the air quality modeling are discussed below.

3.1. Emission modeling

We use US EPA's Motor Vehicle Emission Simulator (MOVES) model, tailored with regional vehicle fleet and travel activity data, to create a PM2.5 emission rate lookup table tabulating emission rates in five mile per hour increments for urban restricted access, urban unrestricted access, rural restricted access, and rural unrestricted access roadway types. The lookup table is used to assign appropriate emission rates to each roadway segment with greater than one vehicle trip per minute. Lower volume links are assumed to contribute an insignificant amount of pollution. Each segment's total emission rate is then calculated by multiplying by each segment's traffic volume and length. Gram per meter squared per second emission rates for each segment (the input needed for the air dispersion modeling step) are then calculated by dividing by each roadway's estimated area (each roadway was assumed to be 15 m wide, except for limited access highways which were assumed to be 15 m wide in each direction) and the time period corresponding to the vehicle traffic volume estimates.

3.2. Dispersion modeling

US EPA's AERMOD dispersion model is used to estimate the concentration of traffic related PM2.5 over the study area. In a conventional analysis, AERMOD models the concentration contribution of each source at a receptor independently. In a large transportation network, such as Albuquerque's that consists of around 9093 roadway segments (emission sources) and a dense network of 172,700 receptors to capture near roadway concentration gradients, the result is more than 1.5 billion source-receptor pairs. Allowing AERMOD to model each source-receptor pair exceeds feasible computational times (months to years). To overcome this limitation, we use a novel rastering approach previously developed and demonstrated for Los Angeles County, California (Rowangould, 2015). This method breaks the modeling domain down into a large set of small 1 km^2 emission source grid cells. A 3 km grid of receptors with 100 m spacing (fine receptor network) is centered over each grid cell and buffered by a 11 km grid of receptors with 500 m spacing (course receptor network). This method divides the large modeling domain into hundreds of smaller modeling sub-domains. Each sub-domain is designed to be large enough to capture the expected extent of pollution dispersion from roadway sources within the sub-domain. The result is a significantly lower number of source-receptor pairs, increasing computational efficiently. Additionally, each of the sub-domains can be modeled in parallel, further increasing computational efficiency.

We setup AERMOD to model each roadway segment as an area source following US EPA PM2.5 hotspot modeling guidance (USEPA, 2010). Digital elevation model (DEM) data is obtained from the U.S. Geological Survey (USGS) and meteorological data is obtained from New Mexico Environment Department, Air Quality Bureau. The meteorological data represent hourly surface and upper air data for the years 2001 through 2004. Deviating from US EPA guidance, we only model the first and fifteenth day of each month in the meteorological data to further reduce computational times, an approach previously found to produce accurate annually averaged concentration estimates (Rowangould, 2015). We also estimated concentrations with the reduced number of meteorological records and the full records for five individual grid cells in different locations in the MRCOG region and found no significant difference in annual average concentrations.

The individual modeling results for each sub-domain are combined into two geo-spatial point data sets, one for the fine and one for the course receptor networks. The point concentration estimates are then transformed into raster data sets with a 20 m resolution using a spline interpolation procedure in ESRI ArcMap version 10.1. The two raster data sets are then summed to create a single regional PM2.5 concentration raster.

3.3. Exposure analysis

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

PM2.5 exposure is calculated by first estimating the area weighted average PM2.5 concentration in each US Census block. We then calculate the population of each US Census block by adding up the parcel level population estimates made by UrbanSim for each planning scenario. The parcel data from UrbanSim, however, does not include socioeconomic data necessary for our environmental justice analysis. Therefore, we obtain the racial makeup of each US Census block group from the 2012 American Community Survey. We also obtain median household income estimates for each travel analysis zone (TAZ), roughly the same as a US Census tract, for each scenario from MRCOG. We assign each census block containing our population and PM2.5 concentration estimates the same racial and income attributes as the larger census units that they fall within. The racial composition of each census block is assumed to remain constant since we do not have a method for forecasting changes in population growth by race.

4. Results

Primary PM2.5 emissions from vehicle exhaust generally contribute very little to the average concentration of PM2.5 across the Albuquerque metropolitan area but they can be a significant source of PM2.5 pollution near high volume roadways. The annual average concentration of primary PM2.5 from vehicle emissions was generally less than 1 $\mu g/m^3$ (Fig. 1). During this same time period, annual 24-h average ambient PM2.5 concentrations measured by the two federal reference monitors in the Albuquerque metropolitan area were 7.4 $\mu g/m^3$ (2012 data for US EPA monitor site: 35-001-0023) and 8.7 $\mu g/m^3$ (2013 data for US EPA monitor site: 35-001-0029). These monitors are located near arterial roadways but away from the region's two interstate highways and provide a rough estimate of the region's background PM2.5 concentration. Considering these data as the background concentration, concentrations near high volume roadways are estimated to be up to 11–14% higher than the 2012 background. While higher concentrations near roadways pose relatively greater health risks they are unlikely to exceed the annual PM2.5 National Ambient Air Quality standard of 12 $\mu g/m^3$.

The results also show significant spatial variation. Concentrations of primary PM2.5 are highest along the region's highways and major arterials which is expected given their high traffic volumes (Fig. 1). The highest concentrations occur along interstates 25 and 40, the two roadways running north-south and east-west through the middle of the maps in Fig. 1. The

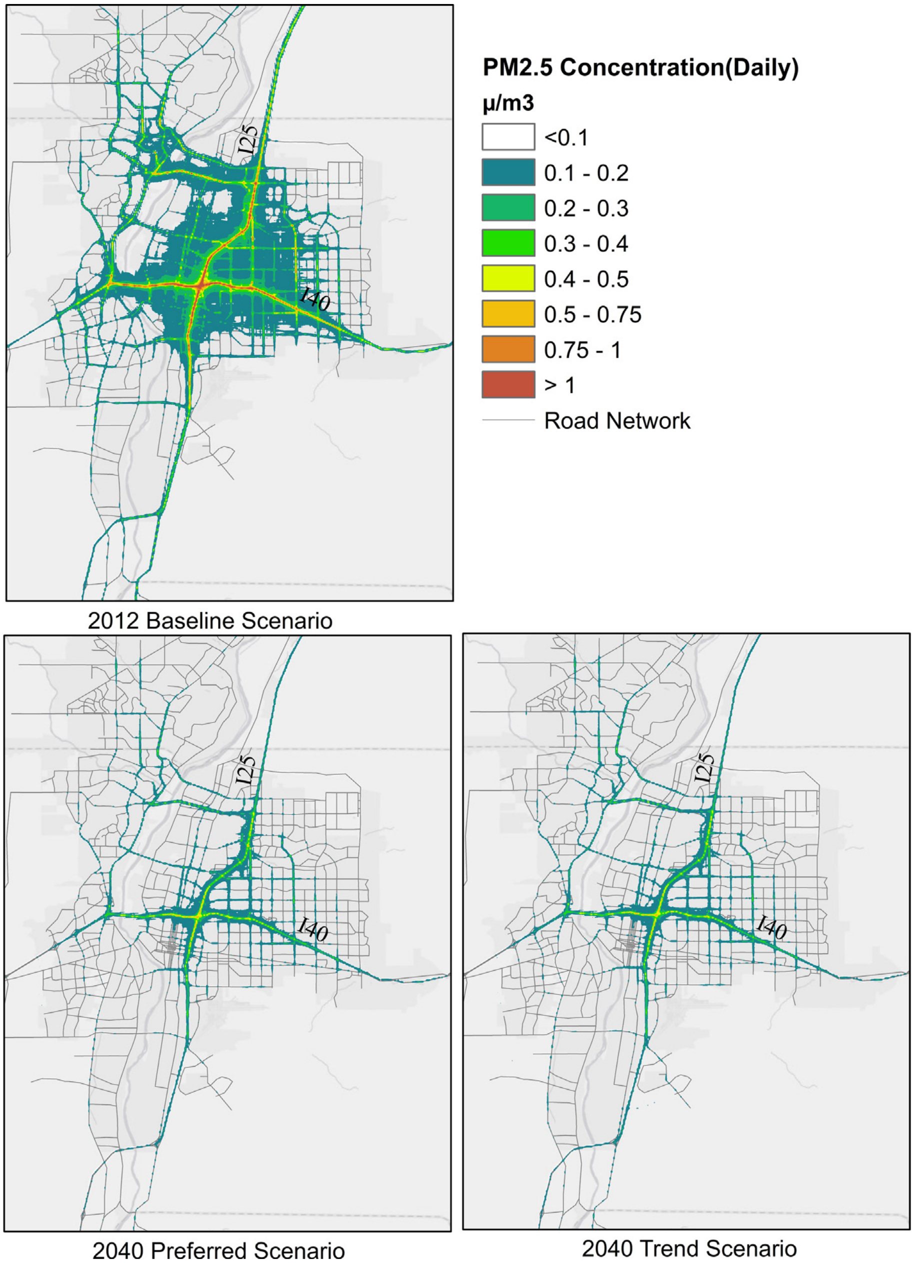

Fig. 1. Maps of daily average PM2.5 concentrations for each scenario.

maps in Fig. 1 also indicate that PM2.5 concentrations are expected to decline significantly across the entire region by 2040 in both planning scenarios. The large reduction is mostly due to reductions in per mile vehicle emission rates, rather than less driving. The MOVES model used to generate future year emission factors for our analysis projects large reductions in vehicle fleet average emission rates based on the scheduled phase in of approved, stronger, federal vehicle emission standards and the gradual replacement of older, more polluting vehicles, with new vehicles that achieve stronger emission standards. Total vehicle miles traveled (VMT) increases by 48% in the Trend scenario, and 40% in the Preferred scenario, over the 2012 Baseline scenario. The large increase in driving is the result of an expected 52% increase in the region's population by 2040. VMT per capita declines by 2% in the Trend scenario and 7% in the Preferred scenario. There is no apparent change in the relative spatial distribution of PM2.5 across the three scenarios.

The large reduction in PM2.5 concentrations also results in large reductions in population exposure (Fig. 2). The cumulative population exposure curves in Fig. 2 indicates most of the population is presently exposed to relatively low concen-

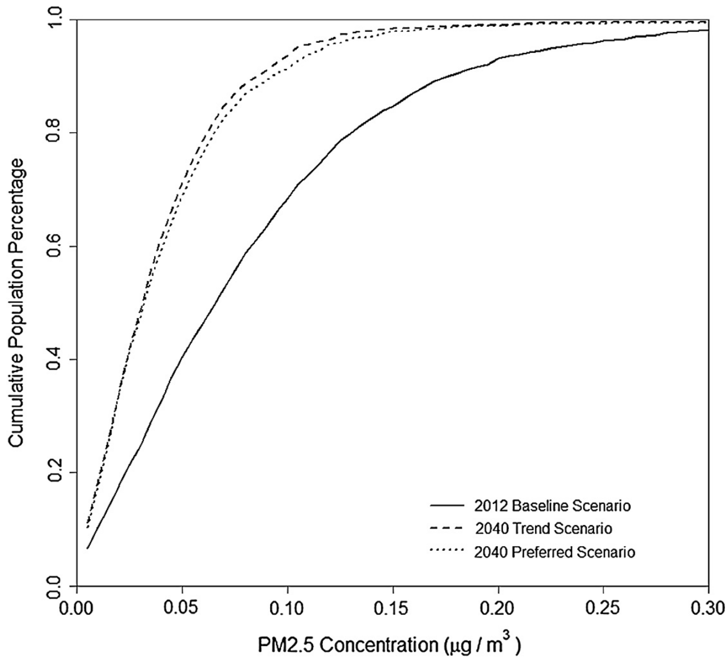

Fig. 2. Cumulative average daily PM2.5 exposure distribution for each scenario.

trations of directly emitted PM2.5 from vehicle exhaust, and that exposure declines by a large amount in the Trend and Preferred scenarios (i.e., the space between the baseline and 2040 scenario curves).

Table 1 compares aggregate regional emission, concentration and exposure results. These results are among the most interesting. PM2.5 emissions fall by 51% in the Trend scenario and 53% in the Preferred scenario as do average concentrations. The lower emissions and concentrations are expected from the Preferred scenario as it achieves the largest reduction in VMT and least amount of congestion (average network speed is 6 MPH higher than the Trend scenario and there are fewer hours of delay and congested network links). However, the Trend scenario achieves a 6% lower population weighted PM2.5 concentration (i.e., exposure) than the Preferred scenario.

The higher exposure level in the Preferred scenario, which achieves the lowest emission rates, is the result of two spatial processes. First, as seen in Fig. 3, the Preferred scenario results in slightly higher concentrations than the Trend scenario does along several portions of highways and arterials in the central part of Albuquerque. The Preferred scenario, which differs from the Trend primarily by incentivizing higher levels of infill, transit oriented, and mixed use development in existing activity centers also results in higher population densities. The preferred scenario's average population density is 7% higher than the Trend's. The combination of increasing population density and PM2.5 concentrations in central Albuquerque results in higher average exposure levels. Had the region been able to achieve the emission reductions of the Preferred scenario while maintaining the population distribution of the Trend scenario, the average exposure would have declined to 0.038 µg/m^3, a 3% reduction from exposure in the Trend. This result indicates that changing population patterns were the main driver of changes in exposure levels between the Trend and Preferred scenarios.

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

Table 1
Average daily PM2.5 emissions, concentrations, and exposures.

Scenario	Emission inventory (kg)	Mean concentration (µg/m^3)	Population weighted mean concentration (µg/m^3)					
			Total	White	Hispanic/Latino	Other non-White	Low income	High income
Baseline	300	6.4×10^{-3}	0.083	0.081	0.084	0.085	0.096	0.072
Trend	147	3.2×10^{-3}	0.039	0.037	0.040	0.041	0.046	0.030
Preferred	142	3.1×10^{-3}	0.041	0.039	0.042	0.041	0.050	0.030

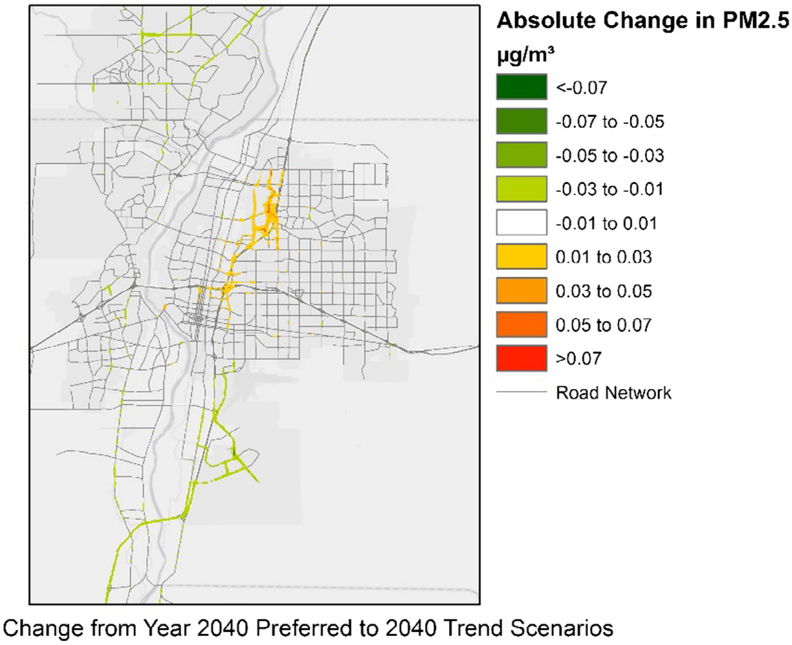

Fig. 3. Change in average daily PM2.5 concentration between year 2040 preferred and 2040 trend scenarios.

While we do not find significant differences in exposure by minority status, we do find significant differences in exposure by income level. We define high income areas as those census blocks that have a higher average household income than the Albuquerque average, and low income areas as those which have an average household income that is lower than the Albuquerque average. Table 1 shows that low income households in the Baseline scenario have on average 33% higher exposure than high income households. The exposure disparity by income group grows to 52% in the Trend scenario and 67% in the Preferred scenario. While the relative exposure disparity grows in the future year scenarios, the absolute size of the average disparity measured in $\mu m/m^3$ declines by a small amount and each income group experiences large reductions in average exposure. Furthermore, these results also indicate that low income households are exposed to nearly 9% higher concentrations under the Preferred scenario when compared to the Trend scenario while exposure for high income households remains constant. Fig. 5 shows the cumulative exposure distribution for each scenario and income group, indicating again that low income households are burdened with a disproportionately high level of exposure that changes little over time.

5. Discussion

Our analysis of the Albuquerque region's land-use and transportation planning process demonstrates the limitation of conventional regional air quality analysis that rely on aggregate emission inventories; the approach used by most metropolitan planning organizations in the United States and which is required by US EPA's transportation conformity process in air quality non-attainment areas. In the Albuquerque metropolitan area, we find that changes in aggregate emission inventories and average emission concentrations for primary PM2.5 do not correspond to changes in emissions exposure. A planning scenario with greater vehicle emissions (and higher concentrations) results in less exposure than a scenario with fewer emissions. Differences in land-use and, to a lesser extent, travel behavior account for the misalignment. These results indicate that current regional air quality analysis procedures and performance measures are potentially misleading and not well suited for evaluating the air quality and public health impacts of contemporary transportation and land-use strategies including infill and smart-growth development.

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

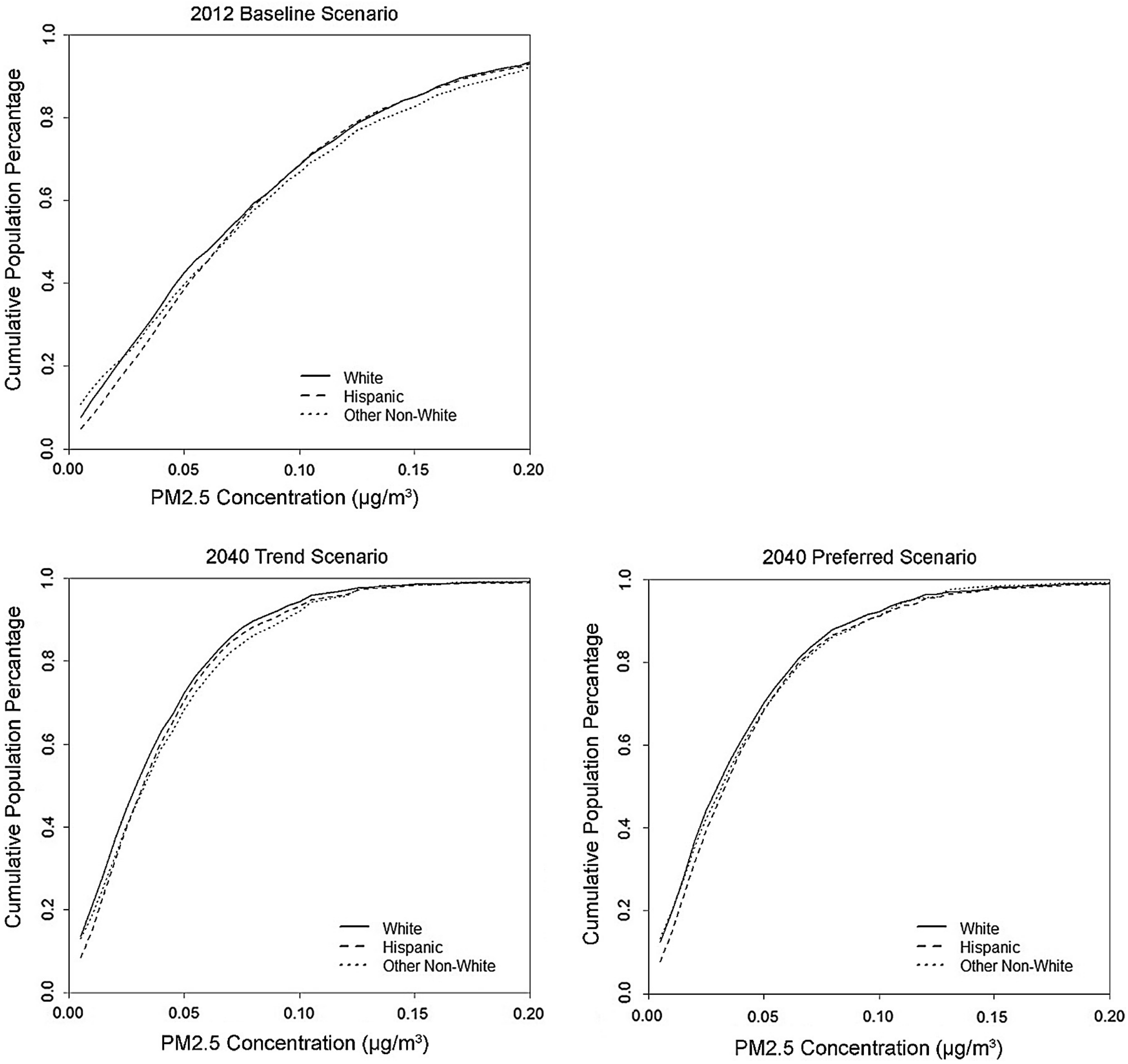

Fig. 4. Cumulative average daily PM2.5 exposure distributions by race/ethnicity group.

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

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

MPO's that do consider environmental justice concerns in their regional plans often rely on some type of buffer analysis. A common approach based on our experience is to draw spatial buffers around high volume roadways (where high concentra-

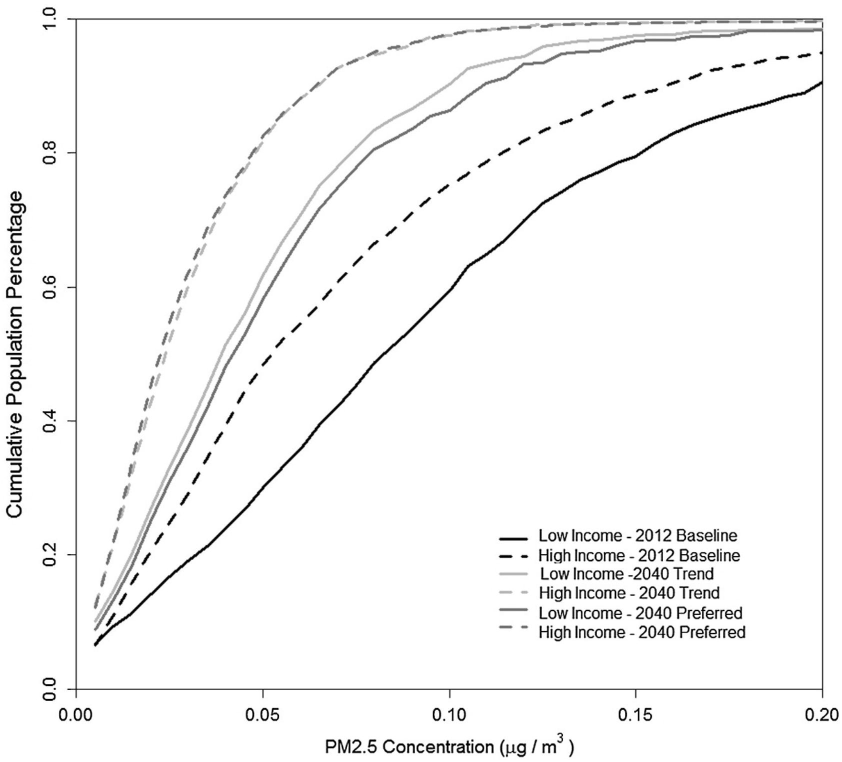

Fig. 5. Cumulative average daily PM2.5 exposure distributions by income group.

tions 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 or not there is an environmental justice concern then becomes subject to the choice of these thresholds which could be difficult to defend. For example, prior studies have considered a wide range of traffic volume and distance thresholds (Rowangould, 2013); however, MPOs would likely benefit from a more conclusive analysis to aid in decision making. Furthermore, vehicle emission rates and concentrations vary across regions due not only to traffic volume but also congestion levels, the density of roadways, the type of vehicles using roadways (e.g., amount of diesel truck traffic), topography, and varying climate and weather patterns. Most buffer approaches also fail to consider how vehicle emission rates change over time though the planning horizon. As time goes on and vehicle emission rates decline the correlation between traffic volume and near roadway emission concentrations will change significantly, making it difficult to estimate how environmental justice concerns change over time.

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

Finally, while our spatially detailed air quality analysis framework overcomes many limitations of prior methods and current practice, several limitations exist. The MPO in Albuquerque uses a standard 4-step trip based travel demand model. This model allows us to estimate spatially detailed maps of vehicle emissions concentrations across the region based on the projected movement and volume of vehicle traffic. The travel demand model, however, does not provide detailed information about the movement of individuals and where they spend their time. Our analysis estimated, as most prior studies have, exposure based on the concentration of vehicle emissions at each person's home location. While this is a limitation, we argue that it still provides a reasonable estimate of exposure. A recent study by Shekarrizfard et al. (2016) compares home based and dynamic exposure to nitrogen dioxide (NO_2) from vehicle emissions in Montreal, Canada and finds that home based exposure estimates on average underestimate daily exposure by a small amount. Larger errors are found for specific individuals and trip types. Prior studies have also shown that concentrations of vehicle emissions are highest in the evening and early morning hours (Hu et al., 2009; Rowangould, 2015; Zhu et al., 2006) which is also when most people are at home. Furthermore, most people spend the majority of their time in and around their home. In regions that use activity based travel demand models, it would be possible to account for the daily movements of the population and estimate a more refined exposure estimate (Dhondt et al., 2012; Shekarrizfard et al., 2016).

A second limitation is that exposure is based on the estimated ambient concentration of air pollutants, and not the concentration within buildings and vehicles, places where people spend a significant amount of time. Prior studies that measured air pollutants in various microenvironments find that concentrations in buildings and vehicles often exceed outdoor concentrations, though in some buildings they may be lower (Baek 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 the above mentioned activity data. Ideally, such ratios would be based on measurements made in the specific study area as they will vary with regional differences in building types and climate.

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

It should also be understood that exposure to primary PM2.5 pollution from vehicle emissions is only one source of the population's total PM2.5 exposure. Total exposure would have been higher if we included exposure to PM2.5 formed from additional reactions between vehicle exhaust emissions and other pollutants in the atmosphere. This requires different modeling methods that have less spatial resolution as explained above. However, we expect that the relative differences in exposure would remain similar since secondary PM2.5 pollution exhibits less spatial variation and represents a regional rather than near-roadway air quality challenge. Furthermore, we have not accounted for PM2.5 pollution originating from non-highway sources.

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

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