Impacts of Transit-Oriented Compact-Growth on Air Pollutant Concentrations and Exposures in the Tampa Region

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16. Abstract

The objective of this study was to model the potential impacts of alternative transit-oriented urban design scenarios on community exposures to roadway air pollution. We used a modeling framework developed previously for the study area that includes activity-based travel demand modeling (Tampa Bay ABM), a dynamic traffic assignment model (MATSim), a mobile-source emissions model (MOVES), a line-source dispersion model (RLINE), and a population exposure estimator to simulate ambient concentrations and population exposure to oxides of nitrogen (NO_x) under alternate urban design scenarios for Hillsborough County, Florida. Data from the 2040 transit plan envisioned by the Tampa Bay Area Regional Transportation Authority were added to the modeling system along with reassignment of household residence locations to parcels near to both employment centers and transit stops. Scenarios included a low-transit scenario (S1) that used the 2040 base residential distribution with 2010 bus services, an enhanced-transit scenario (S2) that applied the proposed 2040 bus services, and a compact-growth scenario (S3) that increased the residential density in S2 by redistributing 37% households to be near to jobs and bus stops. Results show slightly higher shares for active modes of travel for S2 and S3 compared to S1, with an increase of 7.1% for walking and 1.8% for transit under S3 specifically. Measures of travel under S3, including daily total travel distance and travel time, decreased compared to S1 by 9% and 2.1%, respectively. Pollution results were more mixed. Daily total emissions of NO_x and its overall mean ambient concentration were lower for S3 than S1 (by 11% and 9%, respectively), but mean population exposure was higher (by 29%), due to the collocation of people and pollution. Enhanced diesel bus services alone increased emissions, concentrations, and exposures to NO_x. This study suggests that a multi-faceted approach may be needed to ensure beneficial pollution outcomes of transportation and urban design interventions.

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Impacts of Transit-Oriented Compact-Growth on Air Pollutant Concentrations and Exposures in the Tampa Region

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1. Description of the Problem

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

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

To address this, a few studies modeled the impact of alternate urban forms and/or investment in transit infrastructure on vehicular emissions, concentrations, and population exposure. Stone et al. (2007) simulated vehicular activity in alternate hypothetical urban forms and found that compact forms lead to less vehicular travel and emissions. Hixson et al. (2009) used a GIS-based land use planning tool, a four-step travel demand model, and a source-oriented three-dimensional photochemical air quality grid model to estimate air quality and population-weighted exposure in the San Joaquin Valley. They found that compact growth, when pursued along with investments in high speed rail and adoption of clean technologies, results in lower emissions of non-methane organic gases, oxides of nitrogen (NO_x), and fine particles ($PM_{2.5}$) when compared to sprawling or business-as-usual urban forms. Additionally, they showed that compact urban forms helped reduce the $PM_{2.5}$ concentrations over most of their study region (except for urban centers) but increased the population-weighted exposure by 10–15% when compared with low-density development. Similarly, De Ridder et al. (2008a) combined spatial land use data obtained from satellite imagery with a four-step travel demand model and an atmospheric chemical transport model to study the impact of sprawling urban form on regional air quality and population exposure. They found that relocating 12% of the urban population to the greener peripheries resulted in a 17% increase in traffic volume, approximately 4% increase in ozone and PM_{10} levels, and 13% reduction and 1.2% increase in exposures for the group of individuals who moved out and who stayed, respectively.

More recently, Shekarrizfard et al. (2017) combined the travel demand model MOVES and the dispersion model CALPUFF to estimate the impact of transit and vehicle technology improvements on air quality and population exposure. Overall, they found that a large portion of reductions in vehicular emissions in the future transit investment scenario is due to improvements in vehicular technology, with transit investment accounting for an additional 3% reduction in the 2031 nitrogen dioxide (NO_2) levels; similarly, transit investment resulted in an additional 10% reduction in future-year population exposure to NO_2 (Shekarrizfard et al., 2017). Locally in Tampa, Yu and Stuart (2017) found that compact urban form development along with vehicle fleet electrification could have varied (in both strength and direction) impacts on air quality and population exposure depending upon the type of pollutant being studied. Finally, Stevenson et al. (2016) modeled the health benefits of compact cities and found that such cities can achieve overall health gains of 420–826 disability-adjusted life-years (DALYs) per 100,000 population.

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

Previously, studies have pioneered this approach by building frameworks that integrate activity-based travel demand models (ABM), dynamic traffic assignment models (DTA), mobile-source emission models, and dispersion models to estimate population-level exposures to traffic pollution (Beckx et al., 2009c; Dhondt et al., 2012; Hatzopoulou & Miller, 2010; Vallamsundar et al., 2016). The activity-based travel demand models, in particular, offer the capability to simulate the daily activity and travel patterns of individuals and their exposures to traffic-related pollution under different policy scenarios. Specifically, using the above ABM-DTA-emissions-dispersion framework, Dons et al. (2011a) studied the impact of altering shopping hours and Dhondt et al. (2013) explored the impact of fuel price increase on population exposure. Whereas these studies provide valuable insights into the effects of local policies on exposures, they did not fully exploit the land use and transportation-related features of this framework to understand the relationship between urban land use, transport design, and population exposure. This is a significant gap, especially considering that such transportation and air pollution frameworks are well-suited for simulating the impacts of alternate land use and transportation infrastructure scenarios on air quality and population exposure. In addition, the integrated transportation, air pollution, and exposure modeling framework we developed previously has desirable features, such as higher spatial and temporal resolution than previous frameworks, inclusion of meteorological conditions for an entire season (as opposed to only a few days in a year), and explicit modeling of exposures during travel (Gurram et al., 2018).

Hence, this study used our agent-based exposure modeling framework to understand the impact of transit-oriented compact-growth strategies on local air quality and exposure levels. It represents the next step in a multi-year ongoing case study of Tampa focused on understanding the links between urban form, transportation infrastructure design, exposures to traffic-related air pollution, and its social distribution (Evans & Stuart, 2011; Fridh & Stuart, 2014; Gurram et al., 2015; Stuart et al., 2009; Stuart & Zeager, 2011; Yu & Stuart, 2013, 2016, 2017). Specifically, this study uses the framework to predict the impact of implementing a future-year transit vision in conjunction with population reassignment strategies that reduce the distances between residences and work locations. Specifically, we predict the daily activity and travel patterns of individuals, vehicular emissions, air quality levels, and population exposure for different urban design scenarios. Thus, this study adds to the body of literature on sustainable urban forms that improve public health through policy interventions focusing on land use/urban form and transportation design.

2. Approach and Methodology

2.1 Scope

This study is focused on Hillsborough County, Florida, a county with an estimated population of 1.3 million containing the city of Tampa. It is a predominantly urban county, with an estimated 96.5% of the population residing in the urbanized areas (US Census Bureau, 2010b). The county provides an interesting setting to conduct this research due to the limited transit availability, dependence on automobile for travel, and unsatisfactory air quality record (American Lung Association, 2011).

Additionally, the metropolitan area of Tampa-St. Petersburg-Clearwater is listed in the top 100 sprawling metro areas in the US (Smart Growth America, 2014). The county is planning to expand the current interstate system by adding express toll lanes (Florida Department of Transportation, 2017). The impact of these automobile-oriented expansions on the county's air quality and population exposures, especially for the vulnerable population groups, is largely unclear.

The pollutant focus is NO_x as a surrogate for the more complex mix of traffic-related pollution in the study area. Additionally, NO_2 a component of NO_x, has been associated with a variety of adverse health outcomes including reduced lung function, wheezing, and asthma (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010).

2.2 Description of the Modeling Framework

For this work, we applied our integrated agent-based exposure modeling framework (Gurram, 2017; Gurram et al, 2018), which is comprised of activity-based travel demand simulation, dynamic-traffic assignment simulation, emissions estimation, and pollutant dispersion simulation, to predict the effect of alternate land use and transportation scenarios on regional travel, air quality, and population exposure. In our framework, the activity-based travel demand model DaySim is used to estimate the initial travel demand for the study region. DaySim employs the principle of utility-maximization and estimates individual daily activity and travel patterns using a suite of econometric models including multinomial and nested logit models. Since this initial travel demand from DaySim does not provide the travel route information for individuals, the dynamic traffic-assignment model MATSim is used to estimate the specific route of travel. In this process, MATSim also provides an updated set of activity and travel information that is consistent with the network travel conditions during the simulation along with the distribution of automobile and public transit vehicular volumes on the roadway network. The generated vehicular volumes are input to MOVES to estimate the hourly roadway link-level emissions. These link-level emissions are then input to R-LINE to estimate the hourly concentrations. To estimate the population exposures, diurnally-averaged hourly concentrations are spatially and temporally matched with the locations of individuals; exposures during travel are explicitly calculated using the travel route information from MATSim. A detailed description of the modeling framework is provided in Gurram (2017) and Gurram et al. (2018).

2.3 Specification of the Transportation Modeling Component

To accurately represent the vehicular emissions resulting from daily activity and travel patterns, it is important to consider the inter-regional travel. Thus, we focused on characterizing the travel within and between Hillsborough County and its surrounding counties. Our study used the Tampa Bay ABM (TBABM) developed for the FDOT District 7 jurisdiction (Gliebe et al., 2014). District 7 includes

Hillsborough, Pinellas, Pasco, Hernando, and Citrus counties. Hence, we obtained the travel demand for the full projected population in 2040 using TBABM.

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

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

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

2.4 Specification of the Air Pollution Modeling Component

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

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

2.5 Specification of the Alternate Urban Design Scenarios

We used three alternate urban land use, population redistribution, and transportation infrastructure scenarios to study the impact of transit-oriented compact-growth strategies on population exposure to NO_x. All scenarios were implemented for the 2040 model year. The three scenarios included a low-bus service (low-transit) scenario that implemented the 2010 bus-transit infrastructure (S1), an enhanced-bus service (enhanced-transit) scenario that used the planned 2040 bus-transit infrastructure (S2), and a transit-oriented compact (compact-growth) scenario that used the 2040 bus-transit infrastructure and increased residential density (S3). A summary of the scenarios and their distinct urban form and transportation characteristics are provided in Table 1. The enhanced-transit scenario (S2) was intended to capture the impact of additional bus service on the local air quality and population exposure; similarly, the compact-growth scenario aimed to capture the impact of both additional bus services and compact urban development on the regional air quality and population exposure. Details of the residential population distributions and transit infrastructure in each scenario are provided next. The modeling specifications discussed in the previous sections were held constant across the three scenarios.

Table 1 Summary of urban land use and transportation infrastructure characteristics for three alternate urban design scenarios

Urban Form and Transportation Characteristics	Scenario		
	Low Transit (S1)	Enhanced Transit (S2)	Compact Growth (S3)
Urban form	2040 base population distribution		Reallocated base population
	Lower residential density		Higher residential density
Transportation	2040 highway		
	2010 bus service		2040 bus service

2.5.1. Residential Population Distributions

Figure 1a shows the spatial distribution of the 2040 base residential density used in both the low-transit (S1) and enhanced-transit (S2) scenarios, while Figure 1b shows the spatial distribution of the difference in residential density between the compact-growth (S3) scenario and the other scenarios. For the 2040 base residential demographics used in S1 and S2, we applied the distribution determined by the Hillsborough County Planning Commission (Hillsborough Metropolitan Planning Organization, 2014). This distribution was developed by projecting out every five years from a base year of 2010 using population growth projections from the Florida Bureau of Economic and Business Research as the control totals, and the application of an attractiveness index for each transportation analysis zone (TAZ) based on the vacant developable acres (where the attractiveness was inverse-weighted by the square of distance between activity centroids and the vacant developable land).

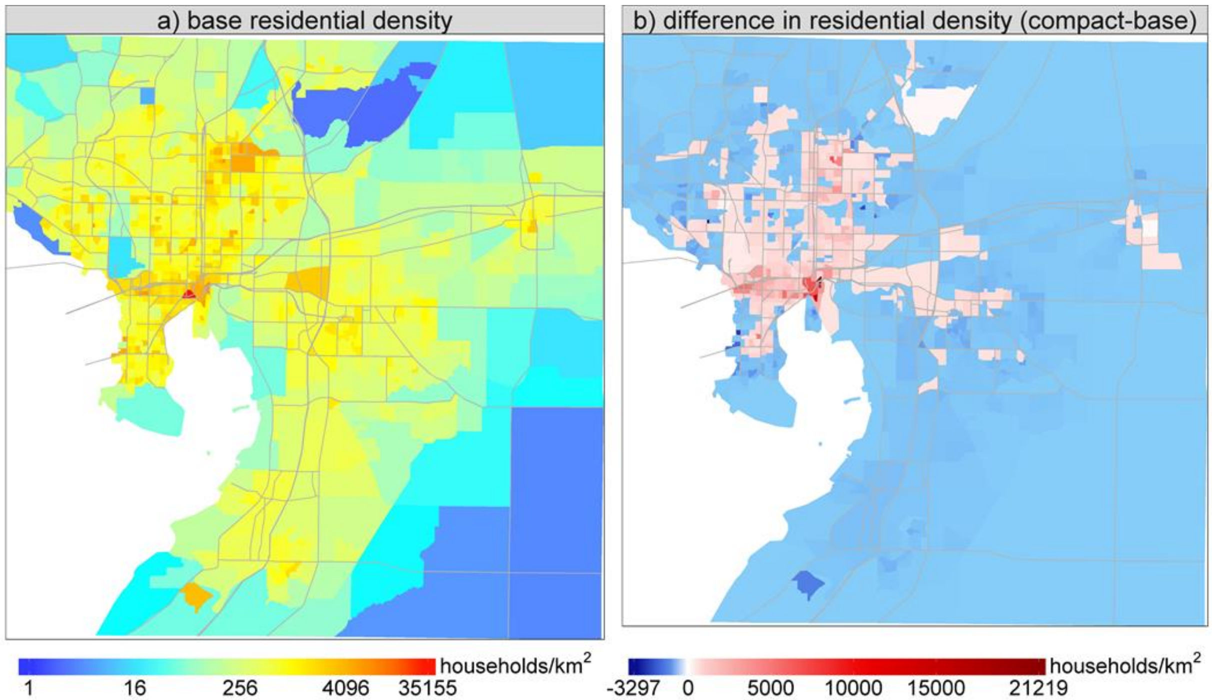

Figure 1 Spatial distribution of block group-level residential density in the 2040 base and compact-growth scenarios. a) base residential density for 2040, b) difference in residential density between the compact growth scenario (S3) and base scenario (used for the low-transit S1 and enhanced-transit S2 scenarios).

For the compact-growth (S3) scenario, we redistributed the households in the study region by developing and applying a new attractiveness index that incorporates some of the key urban form variables including density, diversity, and distance to transit (Ewing and Cervero, 2010). The index weighs parcels based on the number of service and retail jobs available near it, availability of a walk-accessible bus stop, and the distance to job locations and the nearest bus stop; the parcels that are closest to locations with both a high number of jobs and a bus stop have higher weights. Specifically, the attractiveness index (AI) for every parcel i in the study region was calculated as:

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

where k represents a parcel within a 0.5-mile buffer around the origin parcel, r_k is the number of retail and service type of jobs in the k^{th} parcel, t_i is 1 if no bus stops are present in a 0.5 mile buffer around the i^{th} parcel and 0 otherwise, D_{r_k} is the distance in feet between the i^{th} parcel and the k^{th} parcel, and D_{t_i} is the distance in feet between the i^{th} parcel and the nearest bus stop. For residential redistribution, 50% of households that fell in parcels with an attractiveness index below 75th percentile were randomly chosen (with uniform probability) for reallocation to new parcels. The new parcels were also randomly chosen from the set of all parcels with probability (p_i) given by:

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

Thus, about 37.5% of households in the study region were reallocated from parcels with a low attractiveness index to parcels with a high attractiveness index.

As shown in Figure 1, residences were more spread out for the 2040 base case compared with the compact-growth scenario. Due to the population reallocation, the residence density of several block groups that form the urban core of Hillsborough County increased. The mean residential density in the compact-growth scenario was 1199 households/km^2, an increase of 27% compared to the base residence density for 2040. The highest increase in residence density of 250% was observed for a block group in downtown near the Selmon Expressway. Conversely, the largest drop in residence density of 49% was observed in the Town 'N' Country area.

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

2.5.2 Transit Infrastructures and Services

Hillsborough county's current transit infrastructure and its plans for 2040 primarily involve bus transit. Hence, we compared the impact of the current and proposed bus transit. To control for the impact of vehicle and fuel technology on air quality, we also assumed the use of diesel-powered buses in both cases. Figures 2a and 2b show maps of the 2010 and 2040 bus transit infrastructures considered here, respectively. 2010 bus transit was used for the low-transit scenario (S1), and 2040 bus transit was used for the enhanced-transit (S2) and compact-growth (S3) scenarios. Both transit cases were based on the 2040 bus infrastructure and service plan provided by FDOT. The 2040 bus transit information was used as provided in the plan, while the 2010 transit information was created by reducing the frequency of services and removing the additional bus routes so that the 2010 transit information closely resembled District 7's original transit scheme for 2010. The 2010 bus services comprise 6284 bus stops, 94 routes, and 2811 km of bus-serviced roadways, and 2040 bus services include 8754 bus stops, 195 routes, and 5413 km of bus-serviced roadways.

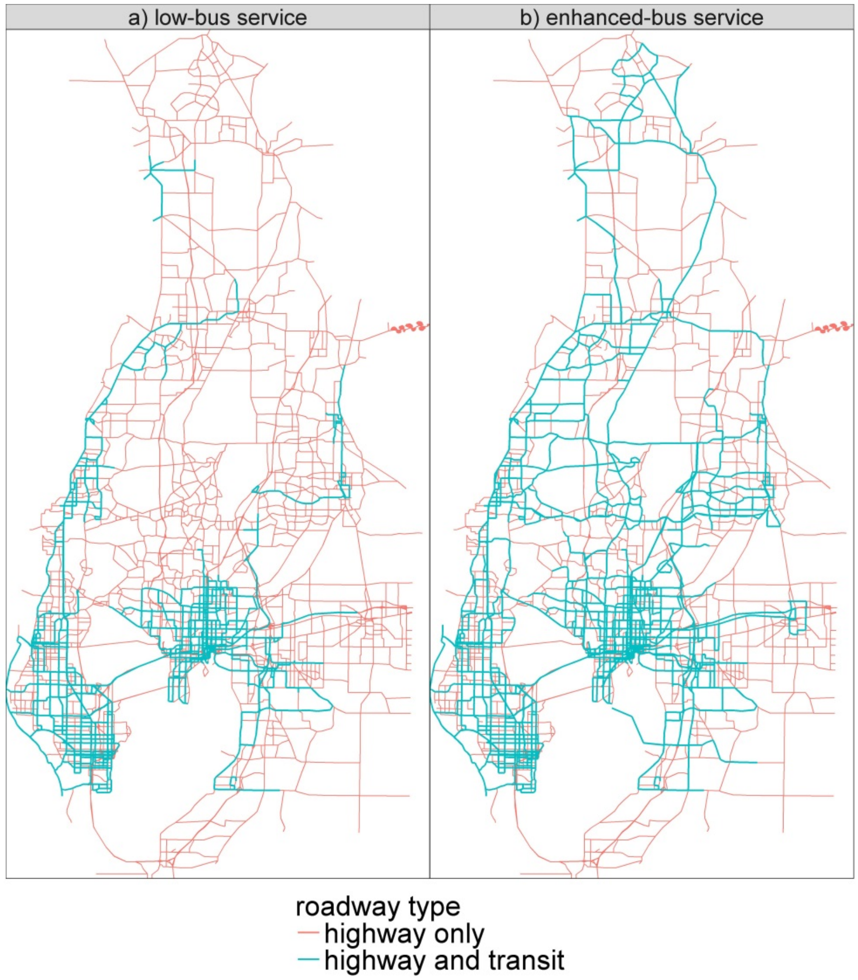

Figure 2 Highway and bus transit infrastructure in 2040 for low-transit and enhanced-transit scenarios

3. Findings

3.1 Mode Shares and Travel Characteristics for Alternative Urban Design Scenarios

The travel mode shares of daily personal trips for the three urban design scenarios are shown in Figure 3. The initial mode shares resulting from the DaySim model and the updated shares following the MATSim model are presented separately. The relative ranking of most of the mode shares is the same in the DaySim and MATSim models, with the exception of the bicycle mode, with MATSim comparatively lower than DaySim for the three scenarios.

Overall, in all of the scenarios, the car mode draws the highest share; however, its share drops from the low-transit scenario to the enhanced-transit scenario and further drops for the compact-growth scenario. This decline is more discernible in the MATSim model results, with the drop amounting to 2.3% and 9% from low-transit to enhanced-transit and compact-growth, respectively. In contrast to the car mode, both the walk and transit mode shares increased from the low-transit to the compact-growth scenarios; the mode share gain for walking is much higher compared to transit. Specifically, the increase

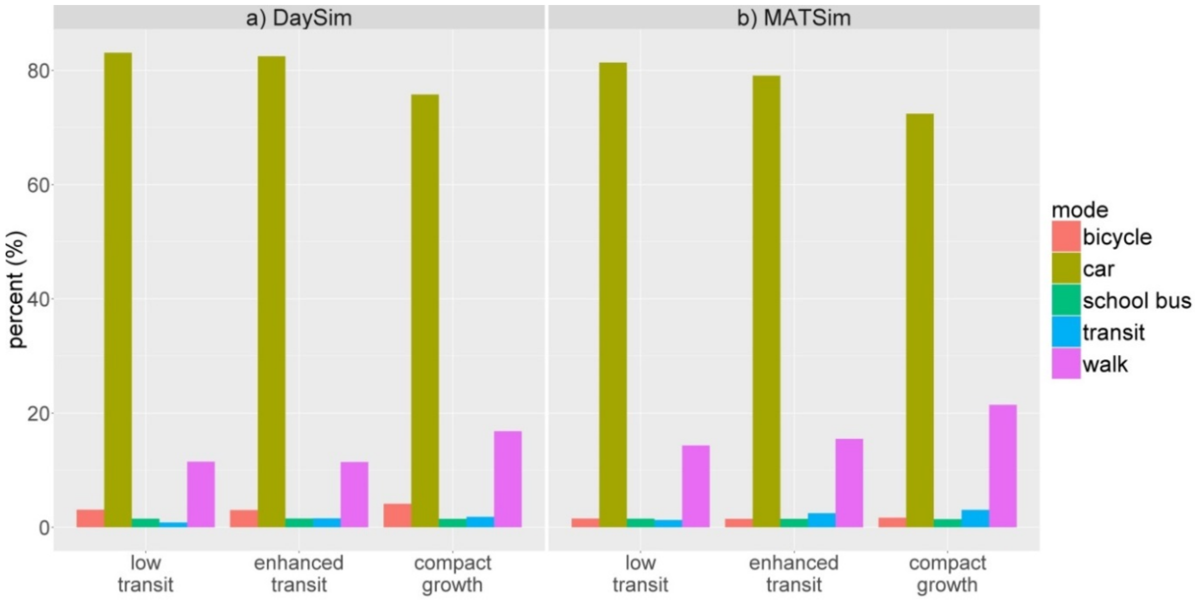

Figure 3 Mode shares for the low-transit, enhanced-transit, and compact-growth scenarios. Mode shares shown follow simulation in a) DaySim and b) MATSim.

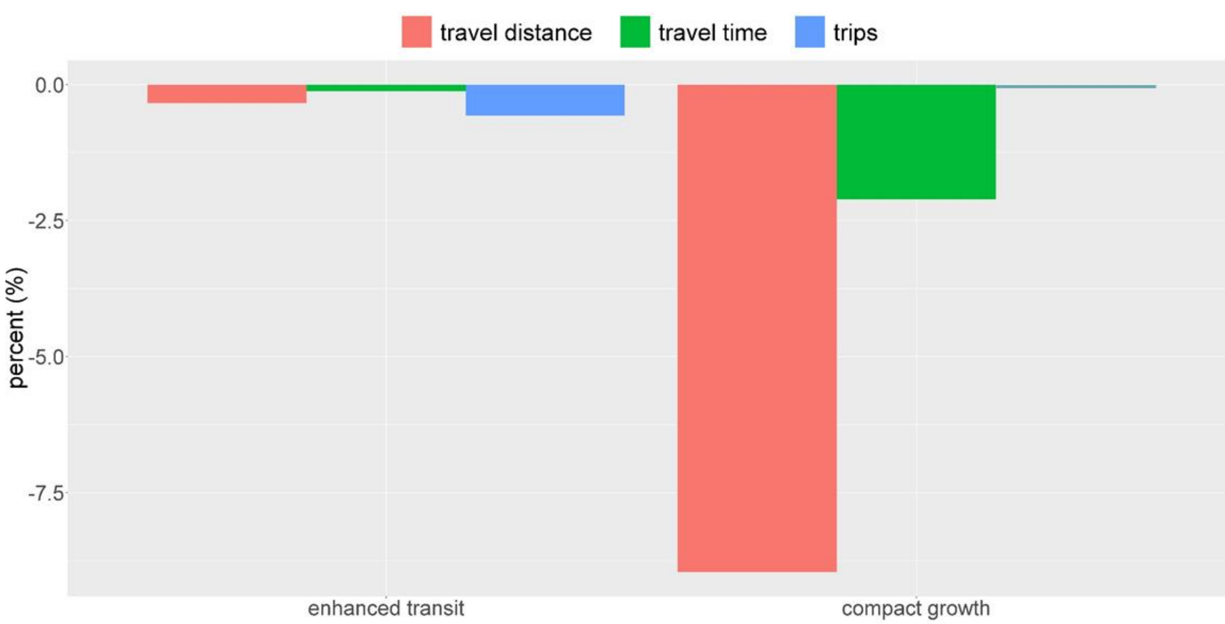

Figure 4 Percent change in cumulative travel distance, travel time, and number of trips for enhanced-transit and compact-growth scenarios compared with low-transit scenario.

in the share of walk mode from low-transit to enhanced-transit and compact-growth is 1.1% and 7.1%, respectively; the increase in transit share from low-transit to enhanced-transit and compact-growth is 1.2% and 1.8%, respectively. Similar to the walk and transit mode shares, the mode share for bicycle also generally increases from low-transit to compact-growth, although this increase is relatively low. The mode share for the school bus remains relatively constant across all the scenarios.

In addition to shifts in mode shares, the three urban design scenarios resulted in changes of other travel measures, including travel times and distances. The percent change in the travel measures for the enhanced-transit and compact-growth scenarios when compared with the low-transit scenario is shown in Figure 4. The total daily trips predicted in the enhanced-transit scenario is less than that in the low-transit scenario by 0.5%; however, the total daily trips in the compact-growth scenario is very similar to the low-transit scenario. Compared to the low-transit scenario, both the cumulative daily travel time and travel distance for the enhanced-transit and compact-growth scenarios are low, although the reductions in the enhanced-transit scenario are more muted compared to the compact-growth scenario. It should be noted that despite no reduction in the overall number of trips, the compact-growth scenario led to reductions in the travel distances and times.

3.2 Distributions of Emissions and Concentrations of NO_x

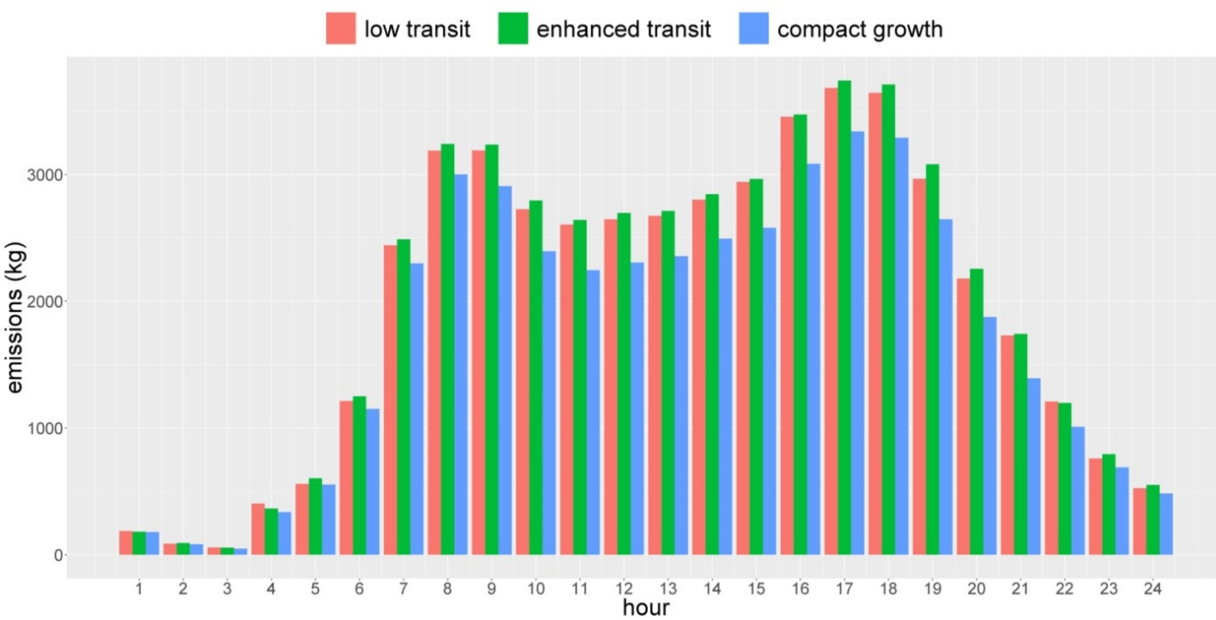

Figure 5 Diurnal NO_x emissions for the low-transit, enhanced-transit, and compact-growth scenarios.

Figure 5 shows the diurnal emissions for the alternate urban design scenarios. Emissions in all scenarios display a similar diurnal trend with a morning peak from 7:00–9:00 AM and an evening peak from 4:00–6:00 PM. The peak emissions in the evening were higher compared to the morning by 15% for the low-transit and enhanced-transit scenarios and 12% for the compact-growth scenario. The daily aggregate emissions in the low-transit, enhanced-transit, and compact-growth scenarios were 47.9, 48.7, and 42.8 tonnes, respectively; thus, the total emissions in the low-transit scenario were 2% less compared to the enhanced-transit scenario and 11% more compared to the compact-growth scenario. The emissions in all scenarios were higher compared to the daily auto-only emissions (20.4 metric tonnes) for 2010 estimated in Gurram et al. (2018). The higher emissions in the 2040 scenarios compared to 2010 can predominantly be attributed to an increase in auto-driver trips by 42%, 40%, and 30% for the low-transit, enhanced-transit, and compact-growth scenarios, respectively. Additionally, the emissions from bus-transit were also included in the 2040 scenarios.

Figures 6 and 7 show the diurnal cycle of the domain-average NO_x concentrations and the distribution of hourly NO_x concentrations for the three urban design scenarios, respectively. The morning peak for the diurnal concentrations led by 1 hour compared to the emissions; thus, the highest mean concentrations were observed from 6:00–8:00 AM. Similarly, the peak hour concentrations in the evening were observed from 5:00–6:00 PM as opposed to 4:00–6:00 PM for the emissions. The peak concentrations in the morning were higher compared to the evening; this trend is in contrast with the diurnal trend for emissions.

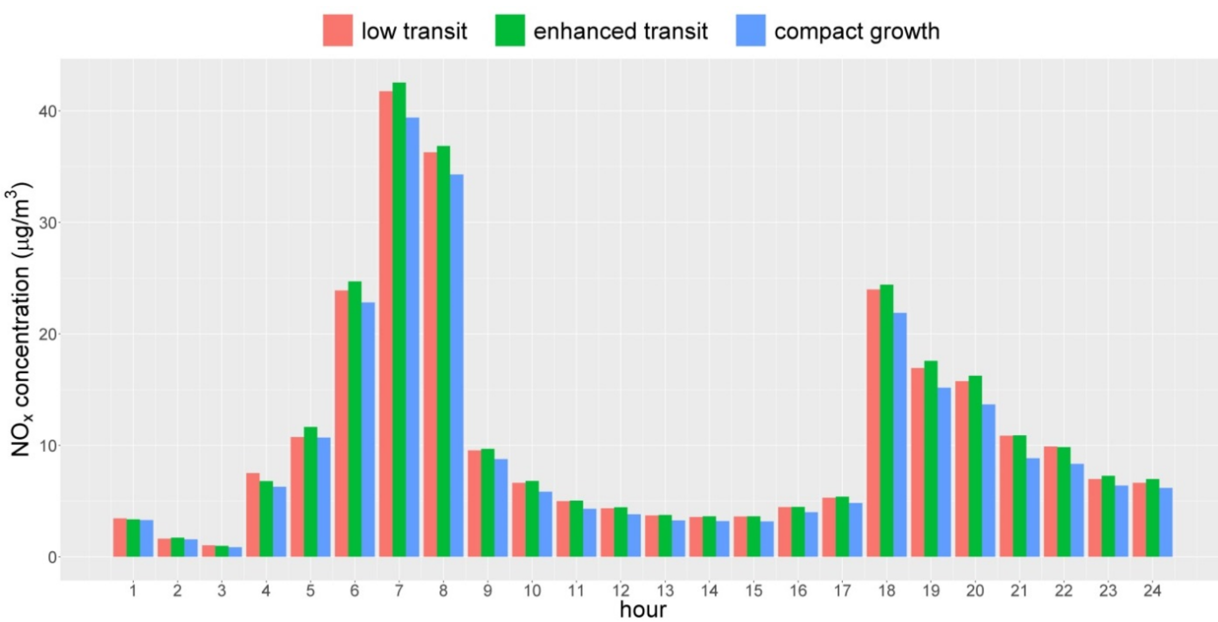

Figure 6 Diurnal cycle of domain-average NO_x concentrations for low-transit, enhanced-transit, and compact-growth scenarios.

The domain-average hourly-mean concentration in the winter season for the low-transit scenario was 10.7 µg/m^3. The hourly-mean concentrations in the enhanced-transit and compact-growth scenarios were 2% higher and 9% lower than the low-transit scenario, respectively. The maximum concentrations for the low-transit, enhanced-transit, and compact-growth scenarios were 5072, 5314, and 7321 µg/m^3, respectively, and were observed along the interstate corrirdors of I-275 and I-4 between 5:00–6:00 PM, as shown in Figure 8.

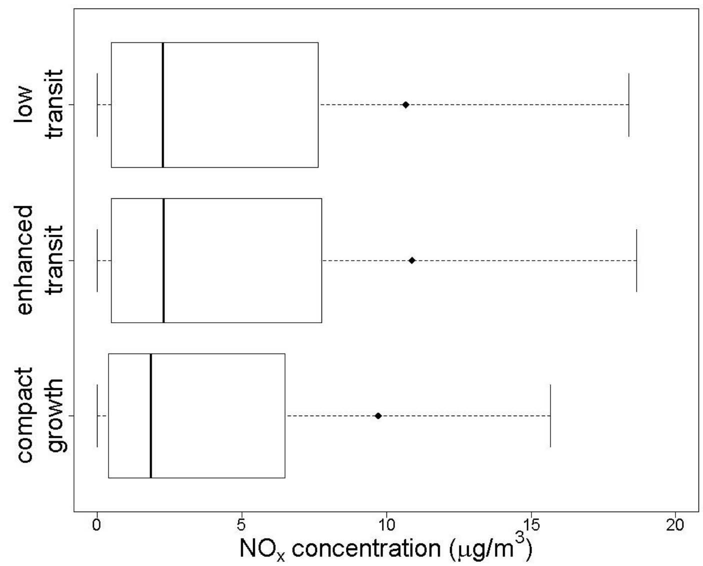

Figure 7 Distribution of hourly NO_x concentration for low-transit, enhanced-transit, and compact-growth scenarios.

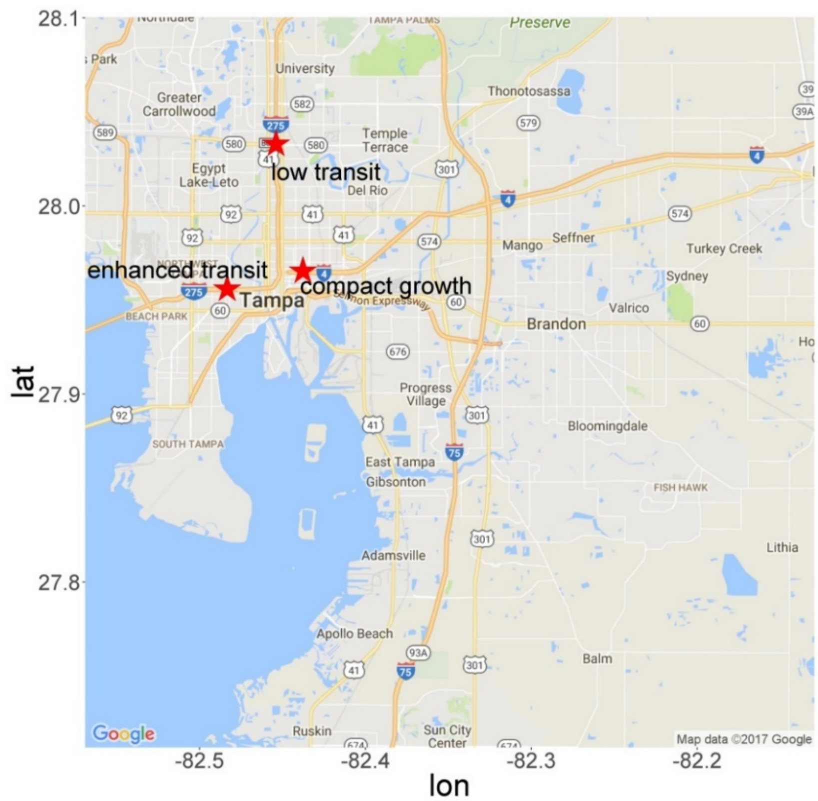

Figure 8 Spatial locations of maximum NO_x concentrations for low-transit, enhanced-transit, and compact-growth scenarios

Additionally, Figures 9, 10, and 11 show the spatial distribution of the differences in NO_x concentration between the enhanced-transit and low-transit scenarios, the compact-growth and low-transit scenarios, and compact-growth and enhanced-transit scenarios, respectively. Overall, NO_x concentrations in the low-transit scenario were higher compared to the enhanced-transit scenario in a few outer geography pockets surrounding Tampa's urban core. The concentrations in the enhanced-transit scenario were higher than the low-transit scenario within the urban core of Tampa, especially along the I-275 commute corridor. A similar and more accentuated trend was observed for the concentration differences between the compact-growth and low-transit scenarios. Concentrations in the compact-growth scenario were higher than the low-transit scenario almost entirely within Tampa's urban core along the I-275 starting from the USF area, I-4, and Dale Mabry Highway. For the rest of the county, the concentrations in the compact-growth scenario were lower compared with the low-transit scenario. The concentration differences between the compact-growth and enhanced-transit scenarios were very similar to those between the compact-growth and low-transit scenarios. The only difference is that the urban core area with higher concentrations for the compact-growth scenario (Figure 10) was spatially smaller compared with its size for the enhanced-transit scenario (Figure 11).

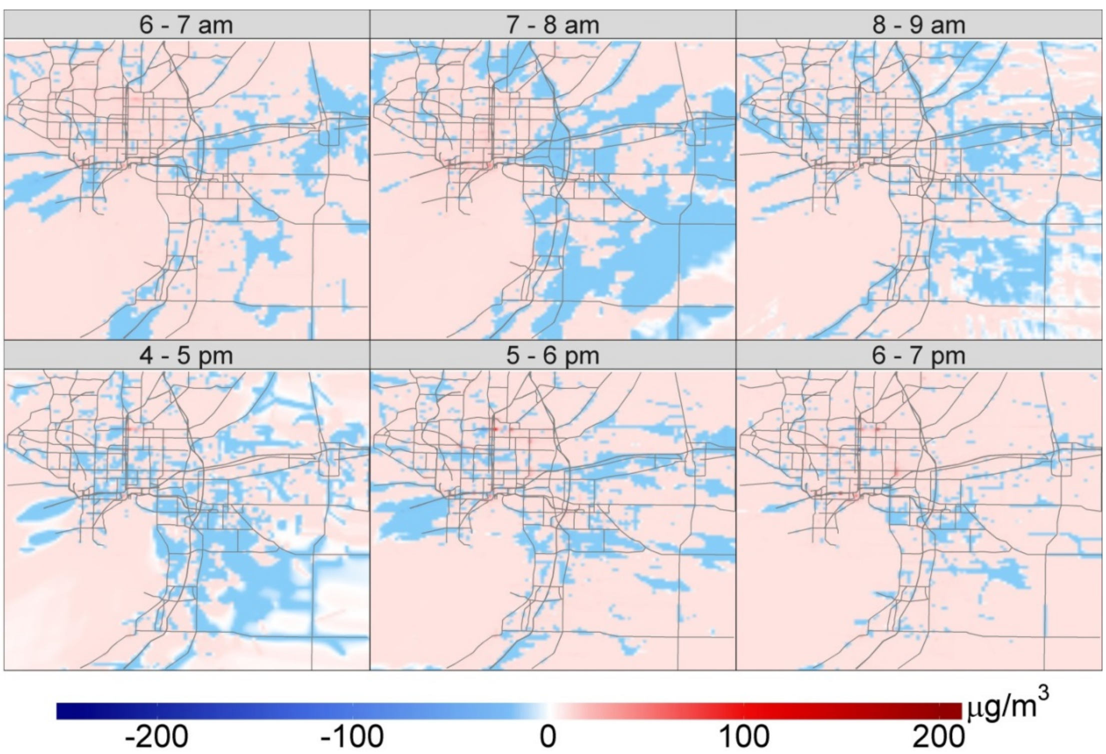

Figure 9 Spatial distribution of the difference in NO_x concentrations between enhanced-transit and low-transit scenarios (enhanced transit - low transit) for morning and evening peaks hours

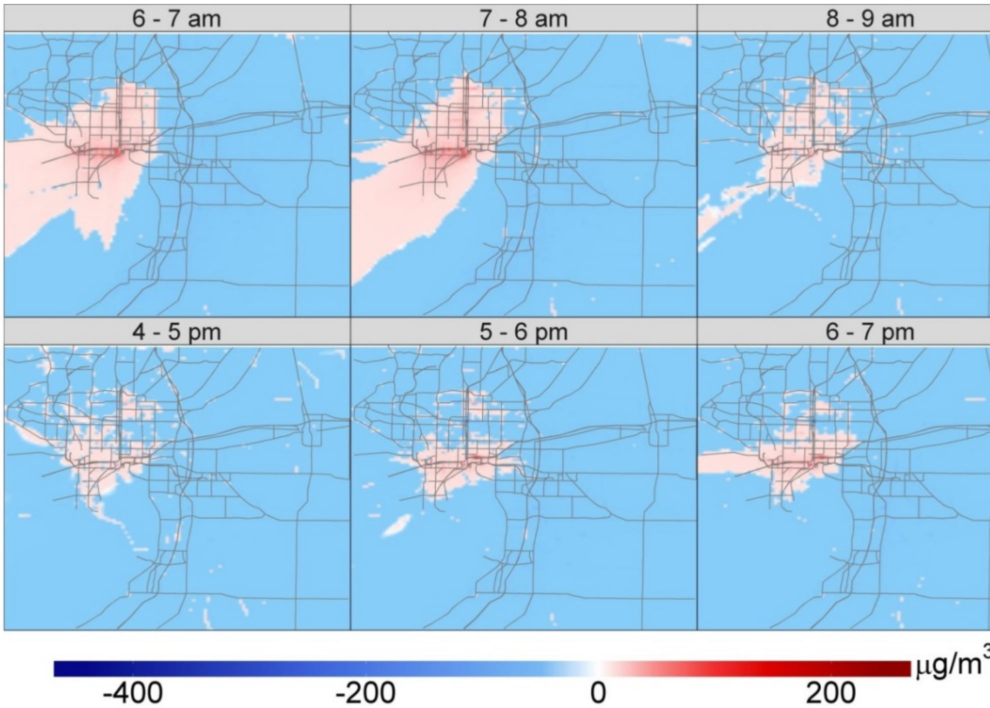

Figure 10 Spatial distribution of difference in NO_x concentrations between compact-growth and low-transit scenarios (compact growth - low transit) for morning and evening peaks hours

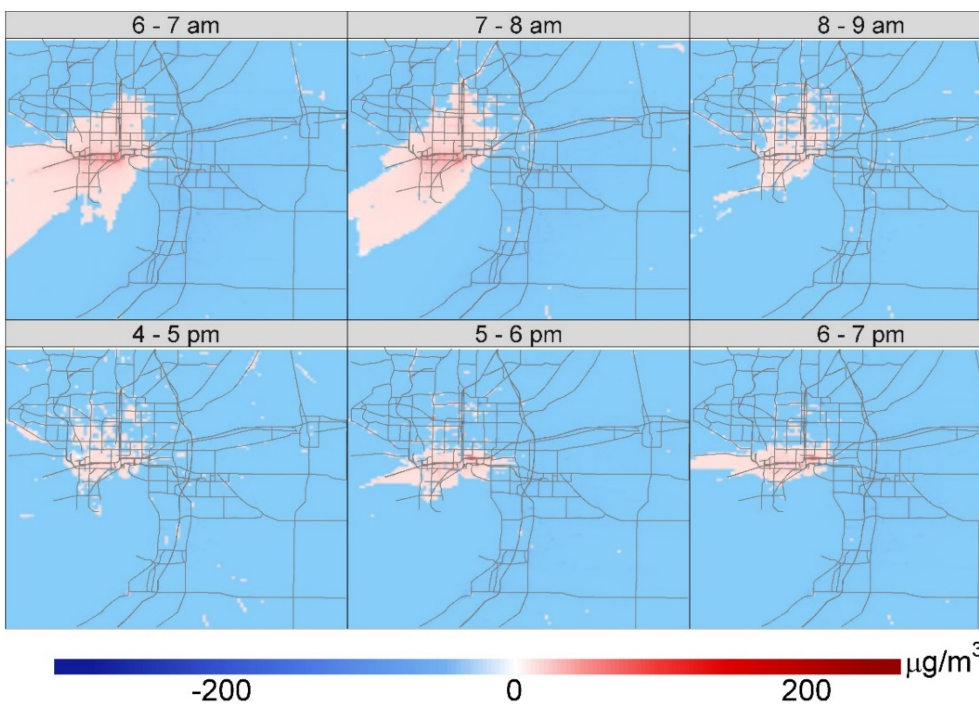

Figure 11 Spatial distribution of difference in NO_x concentrations between compact-growth and enhanced-transit scenarios (compact growth - enhanced transit) for morning and evening peaks hours

3.3 Population Exposure

Figure 12 shows the distribution of individual exposure to NO_x in the low-transit, enhanced-transit, and compact-growth scenarios. The mean population exposure concentration in the low-transit scenario was 22.7 μg/m^3, and the mean exposure concentrations in the enhanced-transit and compact-growth scenarios were higher than the low-transit scenario by 3.3% and 29%, respectively. The spatial distribution of the differences in daily exposure density between the enhanced-transit and low-transit scenarios and compact-growth and low-transit scenarios is shown in Figure 13. The mean exposure density for the enhanced-transit and compact-growth scenarios was approximately 3.3% and 33.3% higher than the low-transit scenario, respectively. The block groups with high exposure density in the enhanced-transit scenario compared with the low-transit scenario were interspersed throughout Tampa's urban core and the suburban areas. In contrast, the high exposure density block groups in the compact-growth scenario were concentrated primarily in the urban core of Tampa along I-275, I-4, and Dale Mabry Highway. The highest increase in exposure density in the compact-growth scenario were predicted in block groups near the Downtown, especially those between the Selmon Expressway and I-275. High exposure density was also predicted in the block group below Tampa International Airport. Low-exposure densities were predicted along the I-75 corridor in the southern part of the county.

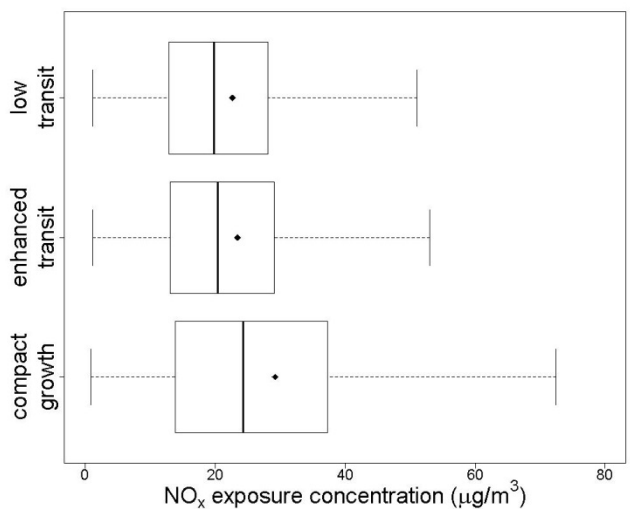

Figure 12 Distribution of population exposure for low-transit, enhanced-transit, and compact-growth scenarios. Lower whisker given by max(min(x), Q1–1.5*IQR), upper whisker given by min(max(x), Q3+1.5*IQR), where x represents vector of concentrations, Q1 is 25th percentile, Q3 is 75th percentile, and IQR is Q3-Q1.

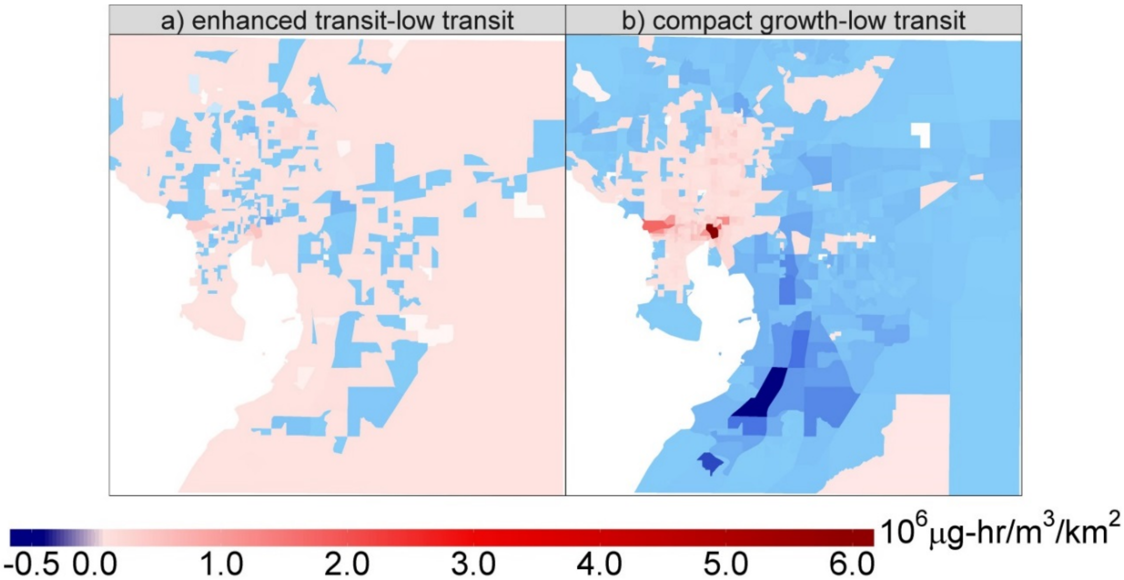

Figure 13 Differences in block group-level aggregated exposure densities between different scenarios. Exposure density differences are shown between a) enhanced-transit and low-transit and b) compact-growth and low-transit scenarios.

4. Discussion

This study provides complementary evidence on the impact of urban design that features transit-oriented compact-growth policies on population distribution, traffic emissions, concentrations, and population exposure. We used transportation and air pollution models to estimate high resolution spatiotemporal distributions of individuals, vehicular activity, and pollutant concentrations. In the study, an increase in household (and population) density was observed in the compact-growth scenario that employs transit-oriented population compaction policies; the population density in the compact-growth scenario was 7146 people/km^2, which represents an 8% increase compared to the 2040 base population distribution in the low-transit and enhanced-transit scenarios. This is similar to the findings of Stone et al. (2007), who reported a mean increase of 6.6–26.8% for different metropolitan statistical areas in their compact growth scenario; similarly, Hixson et al. (2009) created a high-density transit-oriented scenario with an estimated population density of 3935 people/km^2.

The drop in VMT in this study as a result of simulating transit-oriented compact-growth development was about 10%. This is consistent with the findings of Gim (2012), who performed a meta-analysis on the relationship between density and travel behavior and concluded that higher densities lead to reduced auto travel in the US (although muted compared to Europe). Additionally, Stone et al. (2007) estimated a median drop in VMT of 6% for a compact-growth scenario when compared to projected business-as-usual growth. Similar reductions in VMT due to increases in residential density were reported by Chattopadhyay and Taylor (2012).

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

Overall, air quality in the transit-oriented compact-growth scenario slightly improved. Emissions and concentrations in the compact-growth scenario were lower by 11% and 9%, respectively, compared to the low-transit scenario. This is consistent with the findings of Yu and Stuart (2017), who looked into the effects of compact growth on the regional emissions, concentration, and population exposure for the Tampa Bay area. They found that regional on-road NO_x emissions in the compact scenario were reduced by 29% compared to the sprawled-growth scenario. However, in their compact-growth scenario, a significant portion of the region-wide future population was reallocated to Hillsborough County; this resulted in 20% higher on-road NO_x emissions for the county in the compact-growth scenario compared to the sprawled-growth scenario. Similarly, Schweitzer and Zhou (2010) studied 80 metropolitan areas and reported lower ozone concentrations in the compact urban forms. Finally, Hixson et al. (2009) also reported reductions in NO_x emissions when pursuing a compact-growth scenario. However, in contrast to our expectations, the emissions and concentrations in our enhanced-transit scenario were higher compared to those in the low-transit scenario. We hypothesize that this is due to insufficient emissions offset as a result of lower travel mode shifts from car to bus. In addition to the low mode shift, the increased bus frequencies and the addition of new diesel-powered buses may have led to higher emissions. For example, the daily total NO_x emissions for the bus-only roadway links (i.e., only buses travel on these links) was 796 grams/meter for the enhanced-transit scenario as opposed to 73 grams/meter for the low-transit scenario, an increase of almost 1000%. Similarly, the enhanced-transit scenario recorded daily total emissions of 58,740 grams/meter (an increase of 68% compared to low-transit scenario) for bus links (i.e., other travel modes were allowed on these links apart from bus). However, for non-bus links (i.e., no buses travel on these links), the daily total emissions in the enhanced-transit scenario was 34,018 grams/meter, i.e., 38% lower compared to the low-transit scenario. This suggests that transit intensification strategies, if not targeted precisely, may lead to the deterioration of air quality; hence, transit investment in itself, which several studies use as a predictor for increased share of the transit mode (for example, Hixson et al. (2009)), may not always be a reliable indicator for increased transit use. We do not know if our air quality results will hold with other types of transit, such as CNG-powered buses, light rail, and heavy rail as the county plans to migrate its entire bus-fleet to compressed natural gas (CNG) by 2040. Nonetheless, compact urban design policies in conjunction with competent transit plans that displace a significant portion of auto drivers to the transit mode may hold the key for improving air quality.

Although the compact-growth scenario marginally improved the urban air quality in our study area, the population exposure was higher compared to the low-transit and enhanced-transit scenarios. This contrasts with Yu and Stuart (2017), who reported lower population exposure to NO_x from all source types for compact scenarios compared to sprawl scenarios for the same study region. However, they also reported higher exposures under compact scenarios for butadiene and benzene, suggesting that compact forms may have differential effects on population exposure depending on the mix of pollutant sources. Similarly, Schweitzer and Zhou (2010) reported higher neighborhood exposures to ozone and $PM_{2.5}$ in compact regions. Hixson et al. (2009) found 10–15% higher exposure to primary $PM_{2.5}$ components such as elemental carbon and organic carbon in high-density development scenarios. Thus, compact urban forms by themselves may not always lead to reductions in overall population exposure. Perhaps they need to be combined with other strategies such as development of public transit infrastructure that improves accessibility between activity locations, urban design that encourages alternate modes of travel including walk and bicycle, fuel and vehicle technologies that lead to lesser life-cycle emissions, and displacing pollutant sources from high-density population zones. A combination of these strategies may be needed to lower exposures and improve health outcomes especially for the vulnerable population groups.

4.1 Limitations

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

Although we simulated the traffic on roadways using MATSim, we did not include information on toll roads. This could have biased estimates of the spatial distribution of traffic. We also did not include the emissions from commercial traffic such as freight, shipping, and other on-road sources such as school buses or emissions from point and area sources. Thus, we do not know whether the predicted trends in concentrations and population exposure is representative of overall exposures.

The attractiveness index we developed in this study solely considers transit and job accessibility at the residence locations of individuals. However, Arrington and Cervero (2008) argued that transit accessibility between origin and destination is important for improving transit mode share. Additionally, we did not consider accessibility to other activity locations such as shops, hospitals, and entertainment places. Thus, our compact urban form may not entirely represent a mixed-use development.

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

4.2 Conclusions and Recommendations

This study investigated the impact of a transit-oriented compact-growth scenario on population distribution, vehicular travel and emissions, concentrations, and population exposure. We found that adding more diesel-powered bus routes and improving bus frequencies increased NO_x emissions, leading to higher exposures. Thus, the bus-transit plan adopted for Tampa may not be adequate to cause sufficient travel mode shifts and may, in fact, deteriorate the air quality, without other mitigating approaches. Additionally, the compact urban forms co-located individuals near to major roadway sources, thus exacerbating their exposures. Hence, there is a need for collaborative solutions from public health and urban design professionals that seek to improve air quality and population health. Future research efforts should consider alternate modes of transit, including light and heavy rail, which improve accessibility between locations and urban design plans that proliferate mixed-use neighborhoods.

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