Science of the Total Environment 576 (2017) 148–158

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Impacts of compact growth and electric vehicles on future air quality and urban exposures may be mixed

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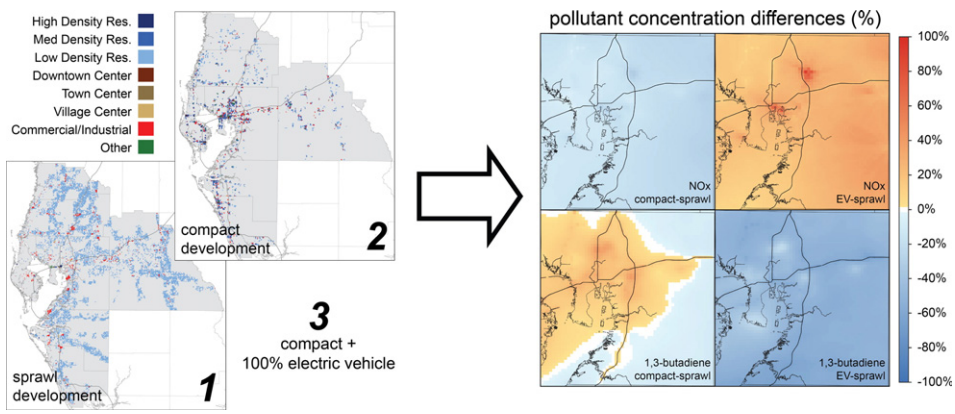
HIGHLIGHTS

- Impacts of urban design on future air quality and exposure were investigated.
- Compact urban form was predicted to have lower area-wide emissions than sprawl.
- Compact form lowered NO_x exposure but increased exposure to butadiene and benzene.
- Electric vehicles increased NO_x exposure, but lowered exposure to the other pollutants.
- Multiple pollutants and source types need to be considered during urban design.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 1 August 2016
Received in revised form 10 October 2016
Accepted 11 October 2016
Available online 23 October 2016

Editor: D. Barcelo

Keywords:
Air pollution exposure
Compact growth
Electric vehicles
Urban air quality
Urban form

ABSTRACT

'Smart' growth and electric vehicles are potential solutions to the negative impacts of worldwide urbanization on air pollution and health. However, the effects of planning strategies on distinct types of pollutants, and on human exposures, remain understudied. The goal of this work was to investigate the potential impacts of alternative urban designs for the area around Tampa, Florida USA, on emissions, ambient concentrations, and exposures to oxides of nitrogen (NO_x), 1,3-butadiene, and benzene. We studied three potential future scenarios: sprawling growth, compact growth, and 100% vehicle fleet electrification with compact growth. We projected emissions in the seven-county region to 2050 based on One Bay regional visioning plan data. We estimated pollutant concentrations in the county that contains Tampa using the CALPUFF dispersion model. We applied residential population projections to forecast acute (highest hour) and chronic (annual average) exposure. The compact scenario was projected to result in lower regional emissions of all pollutants than sprawl, with differences of −18%, −3%, and −14% for NO_x, butadiene, and benzene, respectively. Within Hillsborough County, the compact form also had lower emissions, concentrations, and exposures than sprawl for NO_x (−16%/−5% for acute/chronic exposures, respectively), but higher exposures for butadiene (+41%/+30%) and benzene (+21%/+9%). The addition of complete vehicle fleet electrification to the compact scenario mitigated these in-county increases for the latter pollutants, lowering predicted exposures to butadiene (−25%/−39%) and benzene

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http://dx.doi.org/10.1016/j.scitotenv.2016.10.079

(−5%/−19%), but also resulted in higher exposures to NO_x (+81%/+30%) due to increased demand on power plants. These results suggest that compact forms may have mixed impacts on exposures and health. 'Smart' urban designs should consider multiple pollutants and the diverse mix of pollutant sources. Cleaner power generation will also likely be needed to support aggressive adoption of electric vehicles.

1. Introduction

Exposures to ambient air pollution is associated with a wide range of adverse health effects ranging from minor respiratory tract irritation to increased mortality (Brunekreef and Holgate, 2002; Kampa and Castanas, 2008). Recent estimates suggest that ambient air pollution exposure is a leading environmental health risk factor, and contributes to over three million premature deaths per year worldwide (Forouzanfar et al., 2015). Rapid growth of urban areas around the world (Cohen, 2004) has contributed to these impacts. After 2020, population growth is predicted to occur almost exclusively in urban areas (United Nations, 2015). The United States is no exception to this global phenomenon. From 1980 to 2010, the US urban population increased by 49% and the area of urbanized land increased by 108%. From 2000–2010, 98% of US population growth occurred in urban areas (U.S. Census Bureau, 1983, 2013).

To better control urban air pollution and reduce adverse health effects of pollution exposure, many mitigation strategies have been proposed, among them is improved urban planning. The question of which urban form is most sustainable, i.e. which best accommodates the rapid expansion of cities while maintaining and improving socioeconomic services, and reducing negative environmental consequences such as urban air pollution, has been extensively discussed in the field of urban planning. Within about the last two decades researchers have also started to seriously investigate the impacts of urban form on air quality (Breheny, 1996). Characterization of urban form involves the consideration of many factors related to the types and spatial configuration of residences, destinations, transportation infrastructure, and other land uses (Newman and Kenworthy, 1999). Although indices quantifying sprawl have been developed (Ewing et al., 2002), due to the complexity involved, studies of comparative impacts on air quality (Borrego et al., 2006; Clark et al., 2011; De Ridder et al., 2008; Frank et al., 2000; Kahyaoğlu-Koračin et al., 2009; Liu, 2003; McDonald-Buller et al., 2010; Niemeier et al., 2011; Song et al., 2008; Stone et al., 2007, 2009) often simplify combinations of characteristics into categories representing two more abstract constructs: sprawl and compact urban form.

The sprawl form can be characterized by low-density single-use development, scattered and segregated destinations, lack of central activity centers, and sparse travel networks. Sprawl has been found to encourage the use of private motor-vehicles, while discouraging public transit and active travel (Ewing, 1997; Ewing and Cervero, 2010). Specifically, increased vehicle miles travelled and resultant mobile source emissions are usually associated with sprawl forms (Song et al., 2008). Conversely, compact urban form can be characterized by high density mixed-use developments in or near activity centers, and high accessibility to multi-modal travel networks (Ewing et al., 2002). Compact forms have gained popularity among urban planners as they have been shown to decrease impacts on agricultural lands and wetlands, conserve green spaces, and reduce energy and water use (Chang et al., 2010; Ewing and Rong, 2008; Westerink et al., 2012). Previous researchers have also suggested that compact form could potentially improve air quality and decrease pollution exposure by decreasing motor-vehicle use (through changes in travel mode choices toward public transit, walking and biking) and by decreasing travel distances (through changes in residential location choices) (Boarnet and Crane, 2001). Indeed, several studies of impacts on air quality have found that compact forms may decrease emissions and concentrations of some pollutants regionally (Borrego et al., 2006; De Ridder et al., 2008; Stone, 2008; Stone et al., 2007, 2009; Kahyaoğlu-Koračin et al., 2009; Bechle et al., 2011). However, other studies also predict that higher density urban forms could result in higher population-weighted residential exposures than sprawling forms, particularly for primary particulate components, due to the co-location of population and emissions (Schweitzer and Zhou, 2010; Hixson et al., 2010, 2012; McDonald-Buller et al., 2010; Clark et al., 2011; Martins, 2012). This is consistent with findings that proximity to traffic and active travel are associated with increased human exposure to some pollutants (Kaur et al., 2007). However, urban residents are simultaneously exposed to a variety of air pollutants, and impacts on exposure can differ between pollutants because spatial and temporal patterns of emissions and concentrations differ (e.g. Yu and Stuart, 2016). Studies on the impacts of urban form on multi-pollutant exposure remain limited and mechanisms are still too uncertain to adequately inform policy and planning choices.

One of the transportation choices that has been suggested as a potential remedy for near-road exposures is use of electric vehicles (EV). Due to their zero tailpipe emissions, EVs are generally considered to be a clean alternative to conventional vehicles. Previous studies suggest that wide adoption of EVs, i.e., fleet electrification, could decrease concentrations and exposures to a few important urban pollutants (Electric Power Research Institute, 2007b; Li et al., 2016; Tobollik et al., 2016), particularly in congested inner-cities (Jochem et al., 2016), and could decrease overall emissions of greenhouse gases (Electric Power Research Institute, 2007a; Stephan and Sullivan, 2008; Becker et al., 2009). However, fleet electrification increases electricity demand from power plants, and hence can increase emission from power plants (Electric Power Research Institute, 2007b; Alhajeri et al., 2011; Li et al., 2016). In a study of fine particulate pollution in several Chinese cities, Ji et al. (2015) found that this effect could lead to higher exposures for socio-economically disadvantaged populations living near coal-fired power plants. A few studies suggest that the balance of costs and benefits of fleet electrification likely depends of the power plant fuel mix, EV charging profiles, and urban geography (Funk and Rabl, 1999; Hawkins et al., 2012; Li et al., 2016; Tessum et al., 2014; Ji et al., 2015; Jochem et al., 2016). Overall, further studies are needed to better understand these interactions and their impacts on air quality and environmental health, particularly considering multiple types of pollutants.

The objective of this study was to inform understanding of impacts of urban growth form and fleet electrification on urban air quality and population exposures. To do this, we predicted impacts of three potential future urban development scenarios for the area surrounding Tampa, Florida in 2050 on three important urban pollutants (NO_x, benzene and 1,3-butadiene). We considered a sprawl scenario, a compact scenario, and the compact scenario with complete vehicle fleet electrification. We hypothesized that the compact scenario would result in increased exposures for urban residents, but that fleet electrification would effectively mitigate those exposures. For each scenario, we projected emissions using local visioning data, determined spatial concentration distributions using dispersion modeling, and estimated population-weighted human exposure to each pollutant. Results were compared across pollutants and scenarios to inform knowledge on both the effects of urban and transportation design choices on air pollution exposure, and the mechanisms of these effects.

2. Methods

2.1. Scope of study

The study area of this work is the region surrounding Tampa, FL. The area is the focus of a long-term modeling and measurement project on urban sustainability (e.g. Gurram et al., 2015; Stuart and Zeager, 2011;Yu and Stuart, 2016). The area is a growing metropolitan region with a diverse population. The region aspires to develop in a manner that will meet the needs of its population, attract an educated workforce, and conserve its natural resources. However, it has struggled to implement public transportation infrastructure and generally has a sprawling development pattern (Glaeser et al., 2001; Stuart et al., 2009). Hence, it provides a relevant case study for the many similar regions across the US (and more broadly) that are trying to manage their growth sustainably. A map of the study area is provided in the Supplemental materials (Fig. A-1).

NO_x, benzene and 1,3-butadiene are the focus pollutants of this study. They have significant impacts on human health and public welfare in urban areas in the US, with roadway vehicles contributing substantially to their emissions (ENVIRON International Corporation, 2006). NO_2 (a component of NO_x) is a US criteria pollutant (U.S. Environmental Protection Agency, 2008) and the latter two were identified within the subset of air toxics that present the greatest risk in urban areas (U.S. Environmental Protection Agency, 1999). Despite their importance to metropolitan air quality, the impacts of urban design on these pollutants have been less-well studied than $PM_{2.5}$ and ozone.

The future development scenarios for the Tampa area used for this work were based upon established regional visioning plans (One Bay, 2008) developed by One Bay, a collaborative organization comprising several metropolitan planning organizations in the region. The One Bay visioning process considered multiple alternative plans for the seven counties surrounding the Tampa Bay in 2050, including "business as usual" sprawl development and transit-oriented compact development. We used these as the basis for the sprawl and compact scenarios for this study. Under the sprawl scenario, new developments (after 2005) consist primarily of low-density residential areas spread throughout the region. Under the compact scenario, new developments are dominated by medium-density residential areas concentrated in current urban centers and along existing roadway corridors. Maps of the projected distributions of new developments for each scenario are provided as Supplemental materials (Figs. A-1 and A-2). For this study, we also defined an electric vehicle scenario that was based on the compact plan, but with 100% electrification of the vehicle fleet. This third scenario allowed investigation of the potential for fleet electrification to mitigate the spatial concentration of mobile source emissions that occurs under the compact scenario. For a final comparison, we used our previous results for the year 2002 (Yu and Stuart, 2016), as a baseline scenario.

2.2. Emission estimation

Emissions from four source categories (on-road vehicles, stationary point sources, stationary non-point sources and off-road mobile sources) were first projected to the year 2050 for each growth scenario for the seven-county region surrounding Tampa. One Bay visioning data, obtained from the Tampa Bay Regional Planning Council, provided the basis for projections under the sprawl and compact scenarios. The compact scenario also provided the basis for the electric vehicle scenario. However, on-road vehicle emissions were excluded and stationary point-source emissions were increased, due to the assumption of 100% electrification of the vehicle fleet. Finally, the projected off-road emissions were the same across all three scenarios. Methods used to project and to allocate the 2050 emissions spatially and temporally for each source category are presented below. Additional details and equations are provided in the Supplemental materials. Details of the emissions estimation for the baseline scenario are provided in Yu and Stuart (2013, 2016).

2.2.1. Roadway emissions

We applied a top-down approach to estimate future emissions from on-road mobile sources. First, we estimated county total on-road emissions for each scenario using the Motor Vehicle Emission Simulator (MOVES) (U.S. Environmental Protection Agency, 2015) for each of the seven counties included in the One Bay visioning plans (and each month of the year). We then allocated the estimated total annual emissions to a regular spatial grid of area sources covering the region. Grid resolution was 1 km within Hillsborough County and 5 km elsewhere, consistent with the baseline scenario modeling.

Several sets of input data were needed for county-level MOVES modeling of each future scenario; these include total vehicle counts disaggregated by vehicle type, vehicle miles travelled (VMT) by vehicle type, meteorological parameters, and fuel properties. We projected county-level vehicle counts to 2050 by scaling by the ratio of future to baseline residential population. We estimated the future residential populations by projecting household counts in each county and assuming an average household population of 2.46. Household counts were calculated as the product of projected land area times household density for each of 15 land-use types. The projected values of average household population, average household density by land-use type, and the scenario-specific area for each land-use type were obtained from the visioning data. We estimated county-level VMT by allocating total VMT in the seven-county region (available for each scenario from the visioning data) to each county based on the fraction of total vehicle trips generated in that county. County vehicle trips were calculated as the product of the vehicle trip generation rate (trips per acre) times the land area (acres) for 32 unique buildup types in each county. Vehicle trip generation rates for each buildup type were obtained directly from the visioning data, while projected land area of each buildup type was derived from the scenario-specific land use data. For the meteorological inputs, we used the 30-year average monthly temperatures and relative humidities, obtained from the National Mobile Inventory Model (NMIM) county database (U.S. Environmental Protection Agency, 2005). Fuel properties and all other MOVES input data were unchanged from the baseline scenario modeling.

After obtaining total vehicle emissions for the region, we allocated the emissions spatially to a regular grid of area sources using fractional weights for each grid cell derived from multiple linear regression modeling. Specifically, the grid cells were divided into three categories: cells within Hillsborough County that contain freeways, cells within Hillsborough County that do not contain freeways, and cells outside Hillsborough County. For each category and pollutant, we developed and applied a separate regression equation to estimate relative roadway emissions from a cell of that type (for a total of 9 regression equations). Candidate regression predictor variables included major roadway length (km), minor roadway length (km), and the areas (km^2) of 7 aggregated land use types with a cell. The final predictor variables and their coefficients were determined by regressing cell-specific data from the baseline scenario. Baseline pollutant emissions and roadway lengths were obtained from the baseline study, with baseline land use areas obtained from the Southwest Florida Water Management District (www.swfwmd.state.fl.us/data/gis/layer_library/). Once specified, the regression equations were applied to estimate relative emissions from each cell using projected values of the predictor variables from the future scenario data. Finally, we calculated the spatial weights for each cell as the ratio of that cell's emissions to the sum of emissions from all cells in the region. The specific variables and coefficients used for each regression are provided in Supplemental materials.

Temporal allocation of the on-road mobile source emissions to each hour of the year was achieved using the same month-of-year, day-of-

week, and hour-of-day variation profiles used in the baseline scenario modeling (Yu and Stuart, 2013, 2016).

2.2.2. Stationary facility (point source) emissions

Stationary point sources currently contribute little (0.2% and 0.5%, respectively in 2002) of the total emissions of 1,3-butadiene and benzene in the study domain. Hence, we excluded them from this analysis and only estimated future point source emissions for NO_x. We projected NO_x emissions by increasing the baseline emissions by the emissions resulting from the change in electricity demand. The total change in emissions was estimated as the product of the total change in electricity demand (GWh/yr) times an emissions factor (tons/GWh) that was calculated by averaging 2002 data on gross loads and annual emissions from the Environmental Protection Agency's air markets programs (ampd.epa.gov/ampd/). 2002 data were used to isolate the potential impacts of the future urban development scenarios on air pollution, and also due to lack of reliable data on power plant fuel mixes for the region of study in 2050. Increased emissions were allocated evenly between sources. Electricity demands for the future sprawl and compact scenarios were obtained directly from the visioning data. For the electric vehicle scenario, we estimated the increased electricity demand due to fleet electrification by multiplying projected VMT (miles) for each vehicle class under the compact scenario by average vehicle electricity consumption (Wh/mile) for electric vehicles of that class. We calculated the latter as the product of vehicle weight by class and a 0.065 Wh/mile/lb. electricity consumption factor.

To temporally allocate the total annual point source emissions for each future scenario to each hour of the year, we largely applied the same temporal profiles used for the baseline modeling, as provided by the U.S. Environmental Protection Agency (2007). The exception to this were for the diurnal (hour-of-day) variation profiles for the electric vehicle scenario. Here, we separated the total emissions due to electric vehicle charging from the remaining point source emission, and calculated and applied special diurnal profiles for the vehicle charging portion. Because vehicle charging (and resultant emissions) is expected to occur while a vehicle is parked, we calculated these profiles by inverting the available vehicle-type-specific diurnal allocation profiles for on-road mobile source emissions. The features of these inverted profiles are similar to vehicle charging profiles that have been applied in earlier studies (Alhajeri et al., 2011; Electric Power Research Institute, 2007a, 2007b; Stephan and Sullivan, 2008).

2.2.3. Other emissions (non-point and non-road)

We extrapolated annual county total non-point source emissions to the year 2050 separately for the sprawl and compact scenarios. For the electric vehicle scenario, non-point source emissions were set equal to those from the compact scenario. Specifically, we scaled the baseline emissions for each distinct source classification code using a total of nine surrogates. Surrogates included the area of different land use types (and combinations), population, and vehicle miles travelled (VMT). Sources and estimation method for this surrogate data for the baseline and future scenarios are discussed in Section 2.2.1. A detailed list of surrogates used for each source classification code is provided in the Supplemental materials.

For the off-road (also called non-road) source emissions, all future scenarios shared the same annual county total emissions projections. We used the National Mobile Inventory Model (NMIM) (U.S. Environmental Protection Agency, 2005) to estimate pollutant emissions for the majority of sources, using the default projected activity data. Additionally, we estimated emissions from three categories not included in the NMIM: aircraft, commercial marine vessels and locomotives. Aircraft and locomotive emissions were extrapolated to 2050 based on population, and commercial marine vessel emissions were extrapolated using the predicted annual total cargo weights handled by the Port of Tampa, the largest marine port in the study domain. Cargo weights in 2002 were obtained from the Tampa Port Authority. To project cargo weights from 2010 to 2050, we applied a 1.5% annual growth rate (Norbridge Inc., 2011).

In addition to total emissions, spatial and temporal distribution of pollutant emissions can be affected by urban form. For each future scenario, we developed and applied 22 spatial surrogates to allocate the county total non-point and off-road emissions to the regular grid of area sources mentioned previously. The spatial distribution of the electric vehicle scenario emissions was again set equal to that of the compact scenario. The spatial surrogates included population, household counts, and several land use types. The same baseline and future land use data discussed previously were used to develop spatial surrogates. A detailed list of these surrogates are provided in the Supplemental materials. Finally, to temporally allocate non-point and on-road emissions for the future scenarios, we use the same temporal profiles used for the baseline scenario modeling (Yu and Stuart, 2013, 2016).

2.3. Concentration modeling

To estimate concentrations of the selected pollutants for each future scenario, we applied the Gaussian puff dispersion model, CALPUFF (Scire et al., 2000). CALPUFF is an established non-steady-state chemical fate and transport model that can produce concentration estimates at high spatial resolution, which is desirable for exposure estimation. For each future scenario, we ran CALPUFF to produce one year of hourly-resolved concentrations on a regular spatial grid with 1 km resolution overlaying Hillsborough County, as well as at the centroids of census block groups. We used the same meteorological data and model configuration that were used for the baseline modeling. We treated reactivity of NO_x in the atmosphere using the MESOPUFF algorithm. For butadiene and benzene, we applied diurnally-varying effective loss rates that consider photolysis and reaction with hydroxyl radical, nitrate radical, and ozone. Wet and dry deposition were enabled. Details are provided in Yu and Stuart (2016).

2.4. Exposure estimation

To estimate human exposures to air pollution under the future scenarios, we first combined the modeled hourly concentrations to derive spatial fields of annual average and highest hour concentration throughout Hillsborough County. We used these summary fields to estimate chronic and acute population-weighted exposure to each pollutant by matching the spatially-resolved concentrations with projected block-group-level residential populations, as described in Yu and Stuart (2016). Block group populations for each future scenario were estimated by combining resolved baseline populations with projected changes in land use from the visioning data (as described in Section 2.2.1 for county total populations). Maps of the projected distributions of population density for each scenario are provided as Supplemental materials (Fig. A-2). Finally, we compared the results for the different scenarios to evaluate the impacts of urban form and vehicle fleet electrification on air pollution exposure.

3. Results

3.1. Projected 2050 emissions in the study region

The projected pollutant emissions for each of the three future scenarios, and the 2002 baseline scenario, are shown in Table 1. The spatial distributions of emissions within Hillsborough County for future scenarios are shown in Fig. 1.

Comparing the compact and sprawl scenarios, total regional emissions in 2050 (Table 1) are projected to be substantially higher for the sprawl scenario for all three pollutants. Higher regional emissions under sprawl conditions are largely due to substantially higher predicted vehicle mileage travelled (36%) and higher predicted electricity demand due to a larger built-up area. Nonetheless, differences between

Table 1
Annual emissions (tonnes[a]) of all pollutants.

Pollutant	Scenario	Regional[b] emissions				Hillsborough Co. emissions			
		On-road	Point	Other	Total	On-road	Point	Other	Total
NO_x	Baseline	140,000	87,100	42,100	269,000	44,400	50,900	10,920	106,000
	Sprawl	51,600	200,000	51,200	303,000	9780	79,100	11,110	100,000
	Compact	36,600	162,000	47,000	246,000	11,700	69,700	11,310	92,700
	Electric vehicle	0	268,000	47,000	315,000	0	95,900	11,310	107,000
Butadiene	Baseline	215	–[c]	183	398	62.3	–	30.1	92.4
	Sprawl	74.7	–	124	199	15.0	–	17.7	32.8
	Compact	64.8	–	128	193	18.0	–	17.9	35.9
	Electric vehicle	0	–	128	128	0	–	17.9	17.9
Benzene	Baseline	1850	–	1520	3360	534	–	328	863
	Sprawl	452	–	1640	2090	96.5	–	346	443
	Compact	394	–	1400	1790	116	–	355	471
	Electric vehicle	0	–	1400	1400	0	–	355	355

[a] Values are provided to three significant digits only; hence values shown may not exactly sum to the totals shown.
[b] This includes the total emissions from all seven counties.
[c] A dash indicates that these emissions were not included (because they account for less than 0.6% of total emissions of each of these pollutants).

pollutants and between scenarios are evident in the regional distribution of emissions (Fig. 1). For NO_x, total emissions within Hillsborough county (Table 1) are lower for the compact scenario than for the sprawl scenario, consistent with the regional results. However, this is due only to lower emissions from stationary point sources. Point sources dominate NO_x emissions overall (accounting for over 65% of total regional

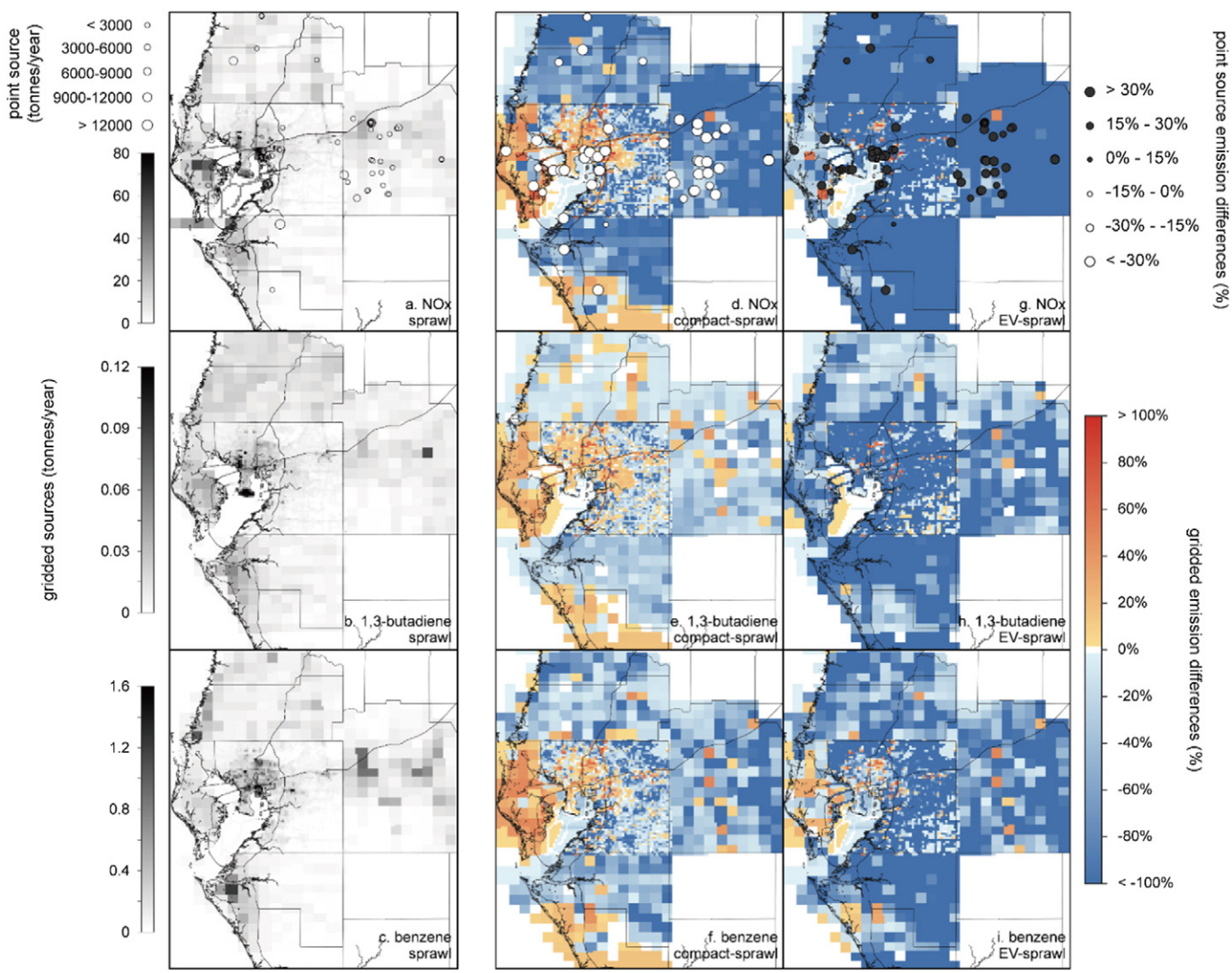

Fig. 1. Spatial distributions within Hillsborough County of projected emissions for the sprawl scenario (left column), and differences from these projected emissions for the compact scenario (middle column) and electric vehicle scenario (right column). The top row of subplots shows NO_x, middle row shows butadiene, and the bottom row shows benzene. Point sources were only included in the estimation for NO_x; for visualization, emissions from co-located point sources are aggregated. Limits shown in the figure do not represent actual minimum and maximum values.

emissions in both scenarios) and many of the highest-emitting point sources, primarily electricity generating units (EGU), are inside Hillsborough county.

Conversely, in-county emissions of all three pollutants from on-road and other sources (off-road mobile and non-point area) are projected to be higher under the compact scenario than the sprawl scenario, with a higher percentage of emissions from these sources distributed to Hillsborough county for the compact scenario than for the sprawl scenario. The redistribution of emissions to more-developed regions, including Hillsborough and Pinellas counties, is evident for all three pollutants in Fig. 1d–f. For butadiene and benzene, this resulted in higher in-county total emissions (Table 1) for the compact scenario than for the sprawl scenario because point source emissions were negligible.

For the electric vehicle scenario, total regional emissions and Hillsborough county emissions of butadiene and benzene are projected to be substantially lower than for both the sprawl scenario and compact scenario (Table 1). This is due to the elimination of on-road emissions (and the overall lack of point source emissions) for these pollutants. However, for NO_x, regional total and in-county emissions are projected to be higher under the electric vehicle scenario than for both the sprawl and compact scenarios. This is because a substantially higher electricity demand was required for the electric vehicle scenario, resulting in higher EGU point source emissions (Fig. 1g). For much of the region, area source emissions (on-road, non-road, and non-point) of all three pollutants (Fig. 1g–i) are lower for the electric vehicle scenario than for the sprawl scenario. Fleet electrification succeeds in alleviating much, but not all, of the increased density of emissions within Hillsborough County seen in the compact scenario result.

Compared with the 2002 baseline scenario, total regional emissions (and Hillsborough County emissions) of benzene and butadiene (Table 1) are projected to be lower for all future scenarios. This is primarily due to decreased on-road emissions of all pollutants under all future scenarios (less than 40% of baseline) due to improved vehicle technology, with a concomitant decrease in the contribution of on-road mobile sources generally. However, total regional NO_x emissions are projected to be lower than the baseline only for the compact scenario. NO_x emissions from stationary point sources increased substantially from the baseline under the sprawl and electric vehicle scenarios as a result of increased future electricity demand (assuming no improvements in power plant pollutant control). However, within Hillsborough County alone, total NO_x emission are slightly lower than the baseline for the sprawl scenario because of the disproportional contribution of mobile sources there.

3.2. Projected 2050 pollutant concentrations in Hillsborough County

Projected pollutant concentration fields in Hillsborough County are shown in Figs. 2 and 3 for the annual average and highest hour summary values, respectively. Areas of high concentrations for all pollutants in the sprawl scenarios fields (subplots a–c) are largely in the same locations as high emissions, but with a more diffuse areal pattern. An area with elevated annual average levels (a high) can be seen for all pollutants over downtown Tampa and the Port of Tampa, but is less diffuse for NO_x. Emissions from commercial marine vessels, and a few point sources of NO_x are substantial here. An additional high is also apparent for NO_x near a point source to the northeast of I-75, while the butadiene field has two additional highs located near the MacDill Air Force base and the Tampa International Airport. The highest hour fields contain similarly located highs, but with an additional area of elevated concentration to the east of the county (to the south of I-4 over Plant City). Compared with the 2002 baseline scenario (whose fields are shown in Yu and Stuart, 2016), the impact of roadways is less evident here.

Differences in concentration resulting from the other two future scenarios (compact and electric vehicle) compared with the sprawl scenario are also shown in Figs. 2 and 3. NO_x concentrations (subplots d in both figures) are predicted to be lower throughout the county for the compact scenario than for the sprawl scenario (18% and 15% lower for the spatial average of the annual mean and highest hour values, respectively). This is consistent with the reduction in both regional total and in-county emissions. However, for butadiene and benzene (subplots e and f), substantial areas of the county show higher concentrations under the compact scenario. The largest differences were found in the highest hour fields (Fig. 3) and were 113% and 79% for butadiene and benzene, respectively. The increase is due to the redistribution of emissions into the county under the compact scenario because of higher population and land development densities there rather than in the greater region. The electric vehicle scenario largely mitigated this redistribution for the latter two pollutants (subplots h and i), but resulted in elevated levels of NO_x through the county (subplots g), with a maximum increase of 344% for the highest hour NO_x field. This difference between pollutants can be explained by differences in the contributions of different source types (see Section 3.1). Similar features can be seen in both the annual average (Fig. 2) and highest hour (Fig. 3) fields, with more variable results for the latter.

3.3. Projected 2050 population exposure in Hillsborough County

Table 2 provides the estimated population-weighted county-level exposure concentrations for each pollutant and scenario. Impacts of the future scenario clearly differ by pollutant. The county population-weighted exposure concentrations for NO_x are lower for the compact scenario than for the sprawl scenario for both the chronic (annual average) and acute (highest hour) measures. With the addition of full vehicle electrification to the compact scenario, the weighted NO_x exposure concentration is substantially higher in the county than for all other scenarios (sprawl, compact, and baseline). This effect is magnified for acute exposures, for which the exposure concentration for the electric vehicle scenario is 1.8 times that of the sprawl scenario, and 2.2 times that of the compact scenario alone. Conversely for butadiene and benzene, the electric vehicle scenario has the lowest projected exposure concentrations of all scenarios, while the compact scenario without vehicle electrification has higher projected exposure concentrations than the sprawl scenario.

4. Discussion

4.1. Impacts of urban growth form on air quality

The results here predict lower future mobile source emissions of all pollutants considered when compared with the 2002 baseline case, regardless of the urban growth form. This decrease is due to changes in vehicle technology, not reductions in future travel, and is consistent with other studies of future scenarios where the MOVES model was used (Atlanta Regional Commission, 2010; Federal Highway Administration, 2012). Nonetheless, urban form is predicted to impact these potential benefits. Specifically, higher regional vehicle miles travelled and higher regional electricity demand under sprawling growth counteract the technology improvements for all pollutants; for NO_x, the effect was substantial enough to lead to a predicted future increase (rather than a decrease) in total regional emissions under sprawl (including all sources). This difference between pollutants in overall direction of change is due largely to the mix of types of sources contributing to each pollutant's emissions. Overall, we observed a regional emissions benefit of compact growth versus sprawl, consistent with previous studies (e.g. Frank et al., 2000; Stone et al., 2007; Niemeier et al., 2011). However, we also find that the benefit is more muted for benzene and butadiene compared with NO_x; hence generalization from studies of individual pollutants may overstate the large-scale emissions benefits of compact form.

Further, when considering the impacts on pollutant concentrations and human exposures at a more local scale, differences between pollutants are exacerbated. As suggested by previous work on other

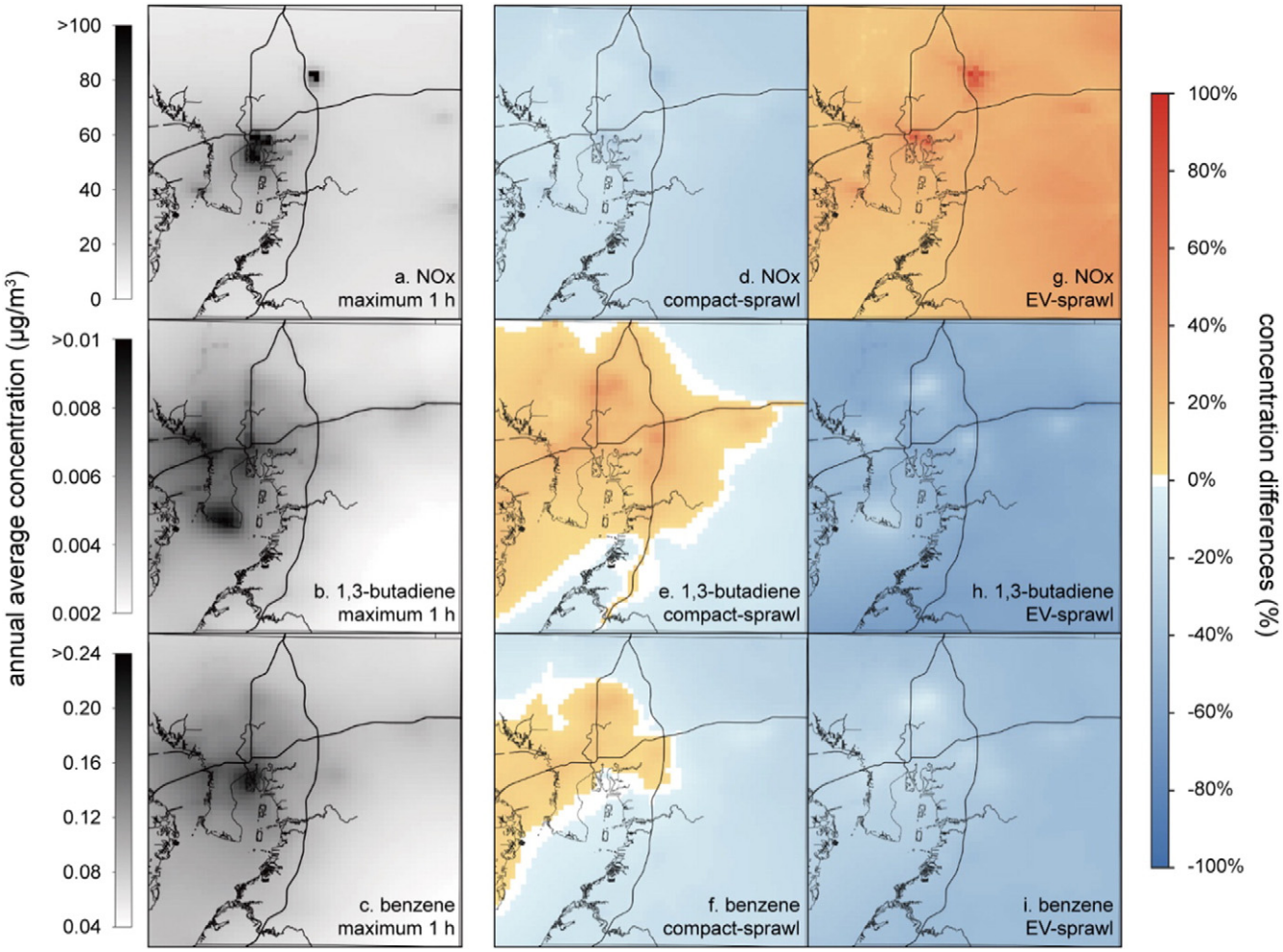

Fig. 2. Spatial distributions of the annual average pollutant concentrations for the sprawl scenario (left column), and differences from these concentrations for the compact scenario (middle column) and electric vehicle scenario (right column). The top row shows NO_x, the middle row shows butadiene, and the bottom row shows benzene. Limits shown in the figure do not represent actual minimum and maximum values.

pollutants (e.g. Hixson et al., 2010 for $PM_{2.5}$), we found that the compact growth form concentrated emissions and ambient levels of two of our focus pollutants (benzene and butadiene) in the populated region of Hillsborough County. Due to the colocation of people and pollution, this resulted in higher predicted acute and chronic population-weighted exposures to these pollutants under compact form. However, for NO_x, the effect of densification is muted and the compact form is predicted to have lower in-county emissions, ambient levels, and population-weighted exposures. Again, this difference between pollutants stems from differences in the types and locations of sources of each.

Compared with sprawling urban growth, it is clear that more compact urban form has many benefits to public health and the environment, from improved physical activity (Ewing et al., 2003) to better social connectivity (Leyden, 2003) to reduced resource use (Chang et al., 2010). However, from an air quality perspective, the impacts can be mixed. Compact form reduces overall emissions of air pollutants on a regional scale. Hence, it may help alleviate impacts of air pollution at this and larger scales, from exposures to regional-scale secondary pollutants (such as ozone and secondary fine particles) to global warming. However, it can also exacerbate exposures to primary pollutants that are disproportionately emitted from roadway vehicles. Hence, to meet its full potential benefit, compact form must be accompanied by changes to policy and transportation infrastructure that remove emissions from where people spend time. Example changes include implementation and promotion of public transit, no-vehicle zones in densely populated central areas, and more generally, infrastructure designs that prioritize the travel convenience and safety of pedestrians and bicyclists over the convenience and speed of motorists. This is doubly important when considering that non-vehicle modes of travel can exacerbate exposure and intake of some air pollutants, particularly for routes of travel that are near to roadways (e.g. Good et al., 2016).

Although roadway emissions are the main contributor to the increased density of air pollutants under compact form, it is also important to note that other sources play a role. Land-use policies and air pollution control regulations that help remove these emissions from people are also necessary. As an example, in this study, marine vessel emissions contribute to benzene exposure and airport emissions also contribute to butadiene exposure. If these sources were relocated from the more-populated central region to relatively remote areas, or if more stringent control technologies were required for these industries, human exposure to benzene and butadiene is expected to be reduced.

Overall, this work does not negate the role of compact form in promoting healthy and sustainable cities. However, it does highlight the complexities involved. Further, it strongly suggests that a suite of policy changes is needed to fully realize the benefits of compact form without also incurring air quality-related health costs.

4.2. The role of vehicle fleet electrification in reducing pollutant exposures

One potential strategy for reducing vehicular emissions near people is fleet electrification. Due to their lack of tailpipe emissions,

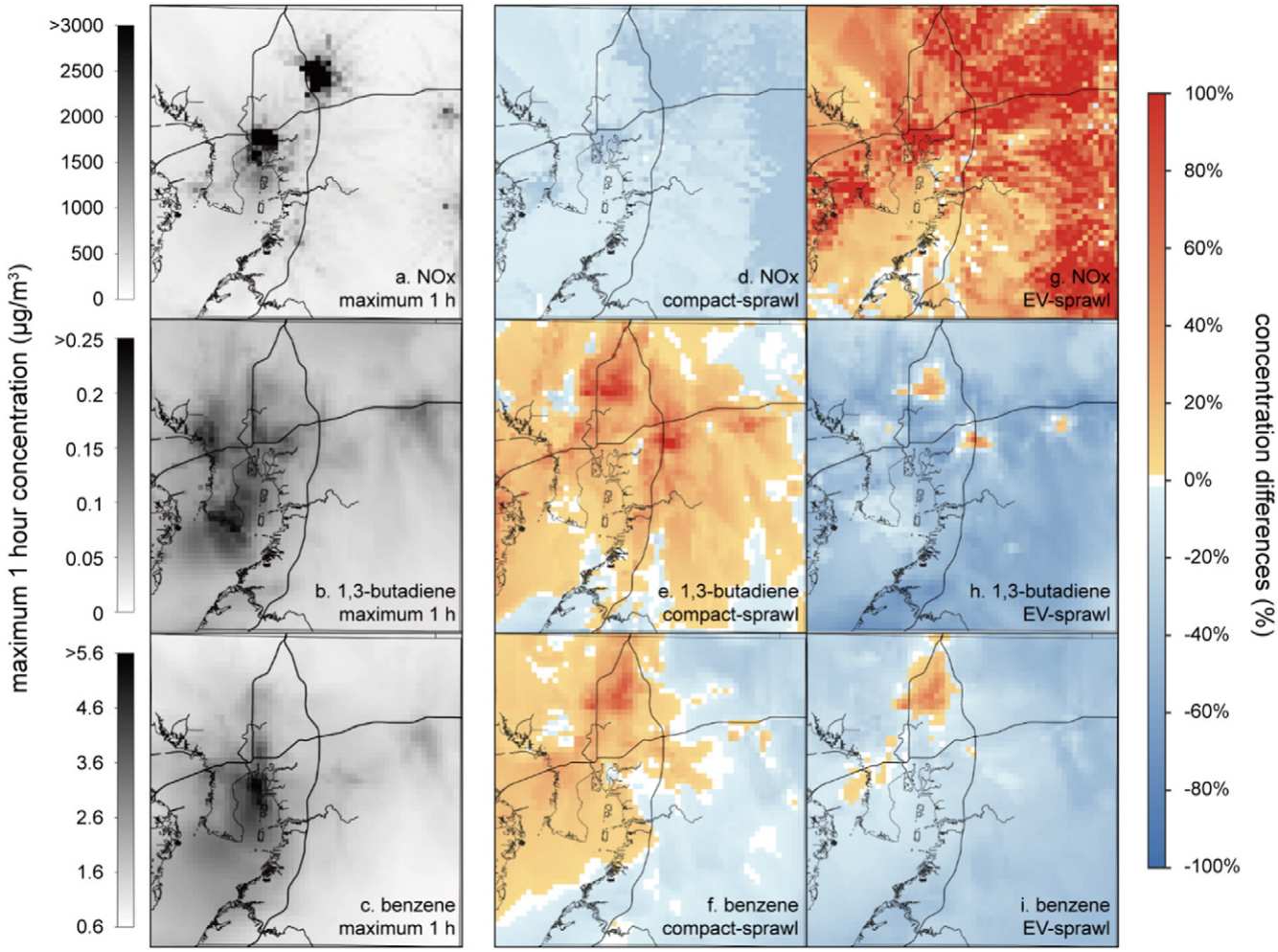

Fig. 3. Spatial distributions of the maximum hour pollutant concentrations for the sprawl scenario (left column), and differences from these concentrations for the compact scenario (middle column) and electric vehicle scenario (right column). The top row shows NO_x, the middle row shows butadiene, and the bottom row shows benzene. Limits shown in the figure do not represent actual minimum and maximum values.

electric vehicles are expected to improve air quality and reduce greenhouse gas emissions without drastically changing personal mobility. Hence, the purchase and use of electric vehicles have been encouraged through direct subsidies or tax benefits in many states in the US.

Consistent with previous studies (Funk and Rabl, 1999; Electric Power Research Institute, 2007b; Alhajeri et al., 2011; Hawkins et al., 2012; Tessum et al., 2014; Jochem et al., 2016), our results suggest that fleet electrification does not guarantee reductions in air pollution, and the balance of costs and benefits likely depends substantially on the power plant fuel mix. Here, we found that although emissions of butadiene and benzene were lower for the complete fleet electrification (EV) scenario, emissions of NO_x were higher than for any of the other scenarios (even the baseline scenario). Further, concentrations and population-weighted exposures to NO_x in Hillsborough County were up to three times higher. This was due to the increased demand for electricity generation by power plants, the substantial contribution of coal-fired power plants to electricity production in the area, and the location of many power plants in populated locales. Although recent local changes and expected future changes to the power plant fuel mix will reduce the impacts of coal, 39% of all electricity in the US was generated by coal in 2013, and this percentage has been projected to drop only slightly to 34% by 2040 (U.S. Energy Information Administration, 2015). Given the high growth rate of the US electric vehicle market – which is expected to continue for at least the next 10 years (Becker et al., 2009; Block and Harrison, 2014), coal may play an important role in producing the electricity needed to propel these vehicles. Hence, fleet electrification could increase exposures to NO_x (and the many other detrimental air pollutants known to be produced during coal combustion) unless improvements in power plant control also occur.

Table 2
Population weighted exposure concentrations (μg/m³).

Pollutant	Chronic[a]				Acute[b]			
	Baseline	Sprawl	Compact	EV	Baseline	Sprawl	Compact	EV
NO_x	17	19	18	27	310	550	460	990
Butadiene	0.017	0.0046	0.0060	0.0028	0.33	0.085	0.12	0.064
Benzene	0.24	0.11	0.12	0.089	4.1	1.9	2.3	1.8

[a] Calculated using the annual average concentrations.
[b] Calculated using the highest hour concentrations.

As with compact urban form, concomitant policy changes are likely needed to ensure the potential air quality benefits of electric vehicles for all pollutants. In the long term, these could include the replacement of existing plants with those that use cleaner fuels and renewable technologies (e.g. wind and sun) to produce electricity. Retrofitting existing power generation facilities and adding advanced emission control technologies can also contribute. In the study area, Tampa Electric has invested over a billion US dollars over the last decade on repowering and retrofitting projects that have resulted in large reductions in NO_x emissions (www.tecoenergy.com/csr/environment/airquality/). Finally, policies should consider the location of the displaced emissions from electric vehicles. In the study region, many stationary point sources of NO_x are located near populated areas, increasing the population-weighted exposure. Although not studied here, this displacement also has the potential to disproportionately affect socio-economically disadvantaged populations, who often live closer to point sources of pollution, including coal-fired power plants (e.g. Ji et al., 2015). Overall, electric vehicles are not a 'silver bullet' for mitigating vehicular air pollution; many other transportation planning and air quality management policies may be more effective at reducing the quantity of pollution near people while also mitigating total emissions released to the environment.

4.3. Limitations

There are several limitations to the findings of this study. Emission estimates for stationary point sources have the largest uncertainties. For the future scenarios, point source emissions were estimated by extrapolating from the baseline scenario using the projected electricity demands, but with emission factors (tons of emissions per GWh of load) assumed to be the same as in the baseline scenario. In reality, future emission rates are expected to be lower due to improved technology and increasingly stringent regulations on power generation units. As an example, the California Emission Forecasting System predicts that NO_x emissions from stationary point sources will decrease from 2000 to 2020, despite increased electricity demand. Although currently stayed by the U.S. Supreme Court, the Clean Power Plan is also expected to improve emissions controls, decreasing the use of coal, and increasing renewable energy production from wind and sun. Adoption of these cleaner power generation technologies was not considered here. If sufficient controls on power plant emissions, including alternative generation technologies, are implemented by 2050 in the Tampa region, this could mitigate the increased emissions of NO_x found here under the sprawl and electric vehicle scenarios. Overall, this would likely both reduce the advantages of the compact scenario over sprawl to regional emissions and reduce or eliminate the tradeoff between the benefits and costs of the electric vehicle scenario. Finally, we evenly distributed the increased power plant emissions in future scenarios due to lack of adequate data for spatial allocation. Hence, the results here provide hypothetical potential impacts of the specific scenarios on air pollution and mechanisms of those impacts, but should not be considered projections of actual expected air quality.

The on-road mobile source emissions and their spatial distribution are also uncertain. First, we did not include roadway network expansions or increased public transit usage in the future scenario estimates. This was because no such expansions were included in the One Bay visioning plan data and the long range transportation planning data suggest that even in 2050, public transit will only account for less than 1% of the area-wide total vehicle miles travelled. Both roadway network expansion and public transit use likely depend somewhat on urban form. Overall, we expect they could enhance the differences between scenario found here. However, due to lack of adequate data, we could not consider these secondary effects. Additionally, the total vehicle miles travelled in the study region for each future scenario was allocated to each county using vehicle trip generation rates by land-use type. Although individual travel behaviors such as trip length and trip frequency may vary with urban form (Milakis et al., 2008), the long-term impacts are not well established or quantified. Finally, we predicted the future spatial distributions of on-road mobile source emissions using multiple linear regression equations developed from current data; no travel demand analysis was performed. Hence, the adequacy of the roadway networks, trip generation rates, and regression equations for extrapolation to future scenarios and behaviors is unknown.

Several other limitations are inherent in our estimates of pollutant concentrations and exposures for the future scenarios. First, we used a dispersion model, CALPUFF, to estimate pollutant concentrations. Other models are available that can treat atmospheric chemistry in a more detailed manner, but many cannot achieve the high spatial resolution needed here. Additionally, our block group population projections were based on visioning data on household densities and coverage areas for each land use type. More comprehensive and rigorous models for urban growth are available, such as UrbanSim (The UrbanSim Project, 2011) and MoSeS (Townend et al., 2009), and could be applied to future studies of air quality. Additionally, for simplicity, we used a less explicit representation of major roadways for this study than for our baseline scenario studies (Yu and Stuart, 2013, 2016). Hence, the very near road impacts may be underestimated here. Finally, although we estimated and compared differences in emissions on a regional scale, we only estimated concentrations and exposures for Hillsborough County, due to model boundary limitations. Hence, we cannot quantify how regional population-weighted exposures would change between scenarios. Because Hillsborough County is one of the most populated counties in the region, we expect that the comparison of county-level exposures qualitatively applies to the region, but our quantitative results are limited to the local area.

5. Conclusions

In this study, we estimated and compared the impacts of sprawling growth, compact urban form, and 100% vehicle fleet electrification on emissions, ambient concentrations and human exposures to three important urban air pollutants (NO_x, benzene and 1,3-butadiene) for the area surrounding Tampa, FL. Emissions of the pollutants were first projected and allocated (spatially and temporally) for three potential future regional land use and transportation scenarios. Ambient concentrations of each pollutant were modeled using the CALPUFF dispersion model. Finally, the modeled pollutant concentrations were combined with projected population distributions for each scenario to estimate population-weighted exposures to each pollutant for Hillsborough County. The major findings from this study include:

1. Regional emissions of benzene and 1,3-butadiene in 2050 were predicted to be lower than the baseline (2002) scenario for all future scenarios, while emission of NO_x were only lower for the compact scenario. NO_x emissions were higher than baseline for the sprawl and electric vehicle scenarios due to increased power plant emissions resulting from increased electricity demand.
2. Area-wide emissions decreased for all pollutants under the compact scenario compared with sprawl. However, emissions and ambient concentrations of benzene and butadiene were disproportionally distributed to the central populated region of Hillsborough County.
3. In-county population-weighted chronic and acute exposures were lower for the compact scenario than the sprawl scenario for NO_x, but higher for benzene and butadiene.
4. Complete electrification of the vehicle fleet was predicted to mitigate the concentration of pollutant emissions, ambient concentrations and exposures within the county for benzene and butadiene. However, due to increased electricity demand, the electric vehicle scenario was conversely predicted to increase emissions, ambient concentrations, and exposures to NO_x (assuming no improvement in power plant emissions control.)

5. Effects of urban form on air quality differ by pollutant. Differences in the types and locations of emission sources that contribute to the ambient pollutant concentrations are important.
6. Impacts of vehicle fleet electrification on air quality are also pollutant specific, they may not always be beneficial, and they likely depend on the success of clean energy initiatives.

These findings suggest the importance of careful assessment of impacts on public health during urban planning, as well of the importance of considering multiple pollutants and emission source sectors during that assessment. The electric vehicle scenario results particularly highlight the importance of cleaner power generation concomitant with aggressive electric vehicle adoption. Although this study focuses specifically on Tampa, FL, many cities in the US and internationally have been undergoing rapid sprawl development. To address the negative consequences of sprawl, compact urban forms are gaining popularity worldwide. Further, the market for electric vehicles has been growing substantially as countries try to move toward a cleaner energy future. However, projections also suggest that coal-fired power plants will continue to contribute substantially to electricity generation capacity for several decades in some regions, including in the US (U.S. Energy Information Administration, 2015). Hence the findings here on the potential interplay of these factors in creating a healthy urban environment are likely applicable to many other regions. Overall, these findings contribute to our current understandings of the complex relationships among urban form, transportation, and air quality. As such, they help move the design of urban and transportation infrastructure in a more sustainable direction.

Acknowledgements

This material is based upon work supported by the National Science Foundation under grant 0846342. Funding was also provided in part by the University of South Florida. The authors acknowledge the use of services provided by Research Computing at the University of South Florida.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2016.10.079.

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