Exposure and Inequality for Select Urban Air Pollutants in the Tampa Bay Area

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Exposure and inequality for select urban air pollutants in the Tampa Bay area
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HIGHLIGHTS
• We compare distributions of concentration and exposure for four urban air toxics.
• Patterns differ between pollutants with and without secondary contributions.
• Exposures to benzene and butadiene were higher for disadvantaged subgroups.
• Trends in exposure inequality for the aldehydes were complex and often reversed.
• Impacts of urban design choices on exposures may depend on pollutant type.

ABSTRACT
Air pollution exposure has been linked to numerous adverse health effects, with some disadvantaged subgroups disproportionately burdened. The objective of this work was to characterize distributions of emissions and concentrations of a few important urban air toxics at high spatiotemporal resolution in order to assess exposure and inequality. Benzene, 1,3-butadiene, formaldehyde, and acetaldehyde were the focus pollutants, with oxides of nitrogen (NOx) estimated for comparisons. Primary pollutant emissions were estimated for the full spectrum of source types in the Tampa area using a hybrid approach that is most detailed for major roadways and includes hourly variations in vehicle speed. Resultant pollutant concentrations were calculated using the CALPUFF dispersion model, and combined with CMAQ model output to account for secondary formation of formaldehyde and acetaldehyde. Census demographic data were applied to estimate residential pollution exposures and inequality among population subgroups. Estimated concentrations of benzene, 1,3-butadiene, and NOx were generally higher in urban areas and lower in rural areas. Exposures to these pollutants were disproportionately high for subgroups characterized as black, Hispanic and low income (annual household income less than $20,000). For formaldehyde and acetaldehyde, the patterns of concentration and exposure were largely reversed. Results suggest that disparities in exposure depend on pollutant type.

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Urban air toxics
Nitrogen oxides
Dispersion modeling
Air pollution exposure
Exposure inequality

1. Introduction
Acute and chronic exposure to urban air pollution have been linked with a wide range of adverse health effects (Pope et al.,...
2007; Brunkreerf and Holgate, 2002). Inequality in exposure to air pollution is a particular concern because prevalence rates of some effects associated with air pollution are high for socioeconomicly disadvantaged groups (Morello-Frosch et al., 2011). However, adequate characterization of disparities in exposure for the mix of air pollutants in urban areas, and mechanistic understanding of causes of these exposure disparities are lacking; this impedes development of potential solutions, such as ‘smart’ urban design.

To characterize human exposure in urban areas and inequalities in exposure between population subgroups, spatially-resolved pollutant concentrations over a large area are critical (Touma et al., 2006). However, regulatory monitoring networks are often too sparse to capture spatial variations at intra-urban scales (Stuart et al., 2009). Further, acute and chronic exposures can result in distinct health outcomes (Laumbach and Kipen, 2012); this requires concentrations at high temporal resolution, but covering a long time period. Finally, to improve understanding of disparities in exposure to the mix of urban air pollution, more studies are needed for urban air toxics, which are poorly characterized at high resolution and large scope.

Both Gaussian dispersion models and Eulerian chemical transport models are routinely used to estimate ambient air pollutant concentrations for air quality management and exposure assessment purposes (Ozkaynak et al., 2013). Both types of models are based on mass–balance equations and diagnose ambient concentrations from detailed information on emission of air pollutants and meteorology. Dispersion models are typically designed to characterize emission source geometry and to estimate concentrations at higher spatial resolution. This is beneficial for pollutants dominated by vehicular sources because their levels often peak in close proximity (hundreds of meters) to busy roadways (Gilbert et al., 2003). However, chemical transport models typically treat chemical reactivity in a more detailed manner; this is needed for pollutants with substantial reactive formation in the atmosphere. Recent work has attempted to combine the benefits of both types of models (Beever et al., 2012; Cook et al., 2008; Isakov et al., 2007; Isakov et al., 2009; Karamchandani et al., 2012; Stein et al., 2007; Touma et al., 2006). However, these efforts remain computationally intensive or limited in scope. Finally, one important hurdle to obtaining the benefits of dispersion modeling over large areas is the lack of tools that generate the necessary input data on emissions from a comprehensive set of source types involved. Hence, source types considered in previous work using dispersion models (e.g. McConnell et al., 2010) are often limited.

In this paper, we estimate detailed emissions, concentrations and exposures for the area surrounding Tampa, Florida USA; this area is the focus of a modeling and measurement project to improve understanding of impacts of urban design on exposure disparities (Gurram et al., 2015; Frith and Stuart, 2014; Yu and Stuart, 2013; Evans and Stuart, 2011; Stuart and Zeager, 2011; Stuart et al., 2009). Contributions of this paper include investigation of a few toxic air pollutants (benzene, 1,3-butadiene, formaldehyde, and acetaldehyde) that are important in many urban areas, but are understudied. These are investigated over an entire county and full year, but at high spatial and temporal resolution. Additionally, we describe a novel method of combining dispersion modeling with output from a chemical transport model to obtain concentrations at high resolution while capturing the effects of reactive pollutant formation. We also describe improvements to our approach that complete a toolset for estimating a comprehensive and detailed urban-scale emission inventory for a non-steady-state dispersion model. Finally, we update our findings for oxides of nitrogen (NOx) to enable comparison of exposures and inequality between several pollutants important to the mix of urban air pollution. Overall, our findings contribute to understanding of exposures that is necessary for appropriate urban design and air quality management.

2. Methods

2.1. Emission estimation

We estimated the emissions of a select set of urban air toxics (as defined by the U.S. Environmental Protection Agency) and NOx for the spatial domain of Hillsborough County, where the city of Tampa is located, and its surrounding area (Fig. 1). The estimation period was 2002, with hourly resolution. A comprehensive set of source categories were captured, including stationary point, on-road mobile, biogenic, non-point, and non-road mobile sources. Many details of our approach for estimating emissions were described by Yu and Stuart (2013), who considered only NOx. Because the pollutants here have different sources and are affected by different processes, our approach required substantial augmentation. Methods that were not described previously are the focus of this section.

2.1.1. Emissions grid specification

Emissions from point sources and from the busiest roadways inside Hillsborough County were estimated explicitly. All other emissions were allocated to a regular spatial grid of area sources. We used a 1 km resolution grid in Hillsborough County for all pollutants. For benzene, 1,3-butadiene (and NOx) we also estimated emissions for counties within a 50 km buffer of Hillsborough to capture their influence on concentrations in the county; a lower resolution (5 km) grid was used outside the county. For formaldehyde and acetaldehyde emissions, we rotated the 1 km resolution grid to correspond to cell boundaries from the grid of a reactive transport model (Fig. 1) and did not estimate emissions outside this grid.

2.1.2. On-road mobile sources

We applied an extension of our hybrid method (Yu and Stuart, 2013) to estimate hourly pollutant emission rates from on-road mobile sources. Specifically, we use vehicle activity and emission factors to calculate detailed link-level emissions for roadways with high vehicle activity (major roadways) in Hillsborough County. For all other roadways in the emissions domain, we allocate county-level emissions to a regular spatial grid. Improvements to the methods are described below; they include the generation of emission factors using an updated emissions simulator and the inclusion of hourly roadway speed variations. A summary of the underlying hybrid method is provided as supplemental materials.

The Motor Vehicle Emission Simulator, MOVES (U.S. Environmental Protection Agency, 2010a, 2010b) was applied to generate an emission factor look-up table for matching to roadway links and hours. We prepared MOVES input data using locally-specific information on vehicle population, vehicle mileage, and meteorological parameters. Specifically, we determined the distribution of vehicle population using registration data from the Florida Department of Highway Safety and Motor Vehicles (2002, 2003), and the distribution of vehicle miles traveled using county total data for 2002 from the Florida Department of Transportation (2003). Finally, we extracted the diurnal cycle of hourly temperature and humidity for each month of 2002 from the county database of the National Mobile Inventory Model (NMIM) (U.S. Environmental Protection Agency, 2005a). Default values were used for all other inputs.

Speed affects vehicular emissions substantially (Bai et al., 2007). Hence, we matched emission factors using the estimated hourly vehicle traveling speed on each link. Specifically, we generated MOVES emission factors using discrete speed bins that span the range of link traveling speeds (2.5 to 75 mph), followed by step-wise linear interpolation to calculate factors for specific speeds. We estimated traveling speeds for each link and hour by applying a widely-used empirical function from the Bureau of Public Roads (Gannett Fleming Inc., 2010a): $\rho_f = S_{fl}/[1 + \alpha_f (T_{fl}/C_f)^\beta]. S_{fl}$ is the free flow speed, $T_{fl}$ is the traffic volume, $C_f$ is the roadway capacity, and $\alpha_f$ and $\beta$ are empirical parameters.
Subscripts \( l \) and \( h \) specify the link and hour, respectively. We obtained information on roadway capacity for each link from the Florida Department of Transportation (2009). Free flow speed and the empirical parameters for each link were selected based on the area type and roadway type, which were retrieved from the Tampa Bay Regional Planning Model (Gannett Fleming Inc., 2010b).

2.1.3. Biogenic sources

Biogenic emissions can be substantial for acetaldehyde and formaldehyde (Guenther et al., 2012). We obtained the annual total biogenic emissions of formaldehyde for counties in the emissions domain from the 2002 National Emission Inventory (NEI). We used these same values for acetaldehyde because emission factors for both pollutants are identical in the system that generated biogenic emissions for the NEI, the Biogenic Emission Inventory System (BEIS, U.S. Environmental Protection Agency, 2010a).

Total emissions were allocated to each hour of the year and 1 km grid cell in the domain. For spatial allocation, emissions were assumed to be proportional to the forest land area (km\(^2\)) in each cell. Forest land use shapefiles were retrieved from the Southwest Florida Water Management District (2012). For temporal allocation, two variation profiles were applied: the annual profile by month and the diurnal profile by hour; profiles were derived from results from a stand-alone version of the BEIS (version 2.3). Specifically, we ran the BEIS model for each month to produce hourly emissions that we averaged by hour of day to generate a diurnal profile for that month.

BEIS input data on temperature, cloud cover and photosynthetically-active radiation (PAR) were derived from multiple sources. The diurnal cycle of hourly temperatures for each month was determined by averaging hourly values extracted from the NMIM county database. Hourly cloud cover was derived from surface meteorological observations from the 2002 dataset from VISTAS (Visibility Improvement State and Tribal Association of the Southeast, Morris et al., 2007). We extracted data from the two stations within Hillsborough County, and used their averages. We estimated photosynthetically active radiation (\( \mu \text{mol m}^{-2} \text{s}^{-1} \)) for each hour \( h \) in month \( m \), as \( \text{PAR}_{h,m} = S_{h,m} f_m F_p \), where \( S_{h,m} \) is the solar radiation intensity (W/m\(^2\)), \( f_m \) is the fraction of incoming solar radiation that is photosynthetically active, and \( F_p \) is a conversion factor (4.57 \( \mu \text{mol s}^{-1} \text{W}^{-1} \)) (Escobedo et al., 2009). Hourly solar radiation intensities (\( S_{h,m} \)) were obtained from the National Solar Radiation Database (National Renewable Energy Laboratory, 2007). Monthly PAR fractions (\( f_m \)) were retrieved from the Global Terrestrial Observing Network; we used the fraction of absorbed photosynthetically-active radiation (FAPAR) from satellite data provided by the Joint Research Centre of the European Commission (http://fapar.jrc.ec.europa.eu/).

2.1.4. Other sources

Annual total emissions for stationary point sources, non-road mobile sources (e.g. lawn mowers and recreational watercraft) and non-point sources (e.g. landfills) are available from the 2002 NEI. We allocated the totals spatiotemporally using the methods and surrogates provided by the U.S. EPA Emissions Modeling Clearinghouse, EMCH (U.S. Environmental Protection Agency, 2007a, 2007b), except as noted below.
emissions from commercial marine vessels were treated differently. Because the NEI process involved the estimation of total nationwide emissions before allocation to the 150 largest ports in the U.S (U.S. Environmental Protection Agency, 2005b), we instead used local data. Specifically, emissions estimated from vessel activity (Bryan, 2006) were allocated to grid cells covering marine ports and navigable waterways.

Additionally, to allocate emissions for area source types requiring a forest area spatial surrogate, we used data from Southwest Florida Water Management District (2012) because these data have higher resolution than the NEI data. Finally, stationary point source emissions of benzene and 1,3-butadiene account for less than 1% of the total pollutant-specific emissions in the study area. Hence they were excluded from the dispersion modeling to reduce the computational burden.

2.2. Concentration estimation

To estimate ambient concentrations at high spatial resolution while treating secondary formation of formaldehyde and acetaldehyde, we used a method that combined non-steady-state dispersion modeling with available concentration estimates from a chemical transport model. Details are presented below.

2.2.1. Dispersion modeling

We applied the CALPUFF dispersion model (Scire et al., 2000) to estimate high-resolution pollutant concentrations resulting from local emissions. CALPUFF is an established Gaussian puff model that represents the non-steady-state release, transport, and dispersion of pollutants from multiple sources. Many of the source parameters, modeling assumptions, and input data applied here are described by Yu and Stuart (2013). Here, we detail those methods that differ from the previous work. Previously-described methods are summarized, for context.

Concentrations of the focus pollutants were calculated for all hours of 2002 for a receptor network that included centroids of all census block group areas (n = 795) in Hillsborough County, all monitoring stations in the county, and a regular 1 km resolution grid. To facilitate the combination of results across models, the regular receptor grid used for simulations of formaldehyde and acetaldehyde was rotated and extended to cover all grid cells from the chemical transport model that overlapped the county.

All sources except major roadways and point sources were treated as 1 km² area sources on a regular emissions grid. Major roadway links in Hillsborough County were treated individually as rectangular area sources. Stationary point sources were also represented individually. CALPUFF-ready meteorological and geophysical data, originally from MM5, with one-hour temporal resolution and 4 km spatial resolution were used to drive CALPUFF (Yu and Stuart, 2013).

To account for reactive processing during dispersion, two approaches were used. The default reaction algorithm in CALPUFF (MESOPUFF II) was applied for NOₓ. For other pollutants, a diurnal cycle of hourly reactive loss rates for each season were calculated and applied. We calculated hourly loss rates considering pollutant reactions with hydroxyl radical (OH), nitrate radical (NO₃) and ozone (Finlayson-Pitts and Pitts, 1999; Jacobson, 2005; Seinfeld and Pandis, 1997). For acetaldehyde and formaldehyde, photoysis reactions were also included using temporally-resolved photolysis rate constants. Necessary data on reactant concentrations (monthly average ammonia concentrations, and hourly ozone, hydroxyl radical, and nitrate concentrations) and other rate calculation inputs (quantum yield, absorption cross section, solar zenith angle) were obtained from multiple sources. Details of the reactive loss rate calculations and data are provided in supplemental materials. Wet and dry deposition were also treated; parameter values are also listed in supplemental materials.

Due to the computational burden involved, the CALPUFF modeling process was split into 620 simulations that were executed in parallel on a high performance computing cluster. For pollutants other than NOₓ, the year was also split into 3 time periods (January–February, March–October, and November–December); two days of overlap were used between time periods for model spin up.

2.2.2. Treatment for secondary formation of aldehydes

Secondary formation in the atmosphere can substantially affect aldehydes, but is not treated by CALPUFF. However, the CMAQ model (Community Modeling and Analysis System) is designed to treat chemical and physical transformations in a detailed manner (but does not provide concentrations at high spatial resolution). Hence, we combined our CALPUFF aldehyde concentrations with available results from the CMAQ model for 2002 to take advantage of the information provided by both models.

A few methods have been applied in previous studies that combine results from an Eulerian chemical transport model and a Gaussian dispersion model (Beever et al., 2012; Cook et al., 2008; Isakov et al., 2007; Isakov et al., 2009; Stein et al., 2007), but no standard method has been established. We applied an empirical approach using CMAQ results obtained from the Community Modeling and Analysis (CMAS) center (https://www.cmascenter.org/) for 2002 with hourly, 12 km resolution (Boothe et al., 2006). For every hour of 2002, results from the CALPUFF and CMAQ models were combined as follows. First, the spatial average of the pollutant concentration estimated by CALPUFF at all receptors within the domain of the CMAQ results (see Fig. 1) was calculated and subtracted from the spatial average of concentrations modeled by CMAQ. This total difference was used to represent the overall contribution of secondary formation; this difference was allocated spatially to the CMAQ grid cell centroids proportional to the relative concentrations estimated by CMAQ. Contributions from secondary formation at all CALPUFF gridded receptor locations were then estimated from the difference values at the CMAQ centroids, using local third-order polynomial interpolation. The final concentration estimate at each CALPUFF receptor location was the sum of the CALPUFF estimate and the spatially-allocated contribution from secondary formation.

2.2.3. Model evaluation

To evaluate model performance, we compared the final estimated concentrations with available measured concentrations from 2002 obtained from the U.S. EPA Air Quality System Dataset. Measured data included 24-h samples with a typical frequency of six days from two monitoring sites in the county for the air toxics and hourly measurements of NOₓ at two sites. Annual cumulative distributions of the measurements and model results (with the hourly model output aggregated to match the air toxics measurements) were calculated and compared. Several common model performance statistics were also calculated from the paired comparisons of monthly and weekly average concentrations of NOₓ. Results show reasonable skill for all pollutants, with best performance for NOₓ and acetaldehyde, and worst performance for 1,3-butadiene. Small improvements in performance over our previous study (Yu and Stuart, 2013) were also found (for NOₓ). Details are provided as supplemental materials.

2.3. Exposure and inequality estimation

The estimated pollutant concentrations were combined with residential demographic data to estimate air pollution exposure, and exposure inequality among different population subgroups. The subgroups studied were groups characterized by annual household income (less than $20,000, $20,000 to $40,000, $40,000 to $60,000, $60,000 to $100,000, and more than $100,000), race/ethnicity (black, Hispanic and white), and age (less than 5, between 5 to 65, and more than 65 years old).

Subgroup exposures and inequality were evaluated at the block group level from both annual average and the highest hour concentrations. These temporal summary statistics were used to represent chronic and acute exposures, respectively. The exposure concentration used
for small block groups (with area less than 1 km$^2$) was the concentration at a model receptor at the block group centroid. For larger block groups, we averaged concentrations from all gridded receptors within the block group. Block group residential demographic data from the year 2000 U.S. census (Florida Geographic Data Library, 2008) were used to estimate population-weighted exposures and subgroup inequality index values for the study area. The population-weighted exposure ($X$) for each subgroup was calculated as $X_i = \sum_j \left( C_j p_{ij} / P_i \right)$, where $p_{ij}$ is the population of subgroup $i$ residing in block group $j$, and $P_i$ is the total population of subgroup $i$ in the county. The subgroup inequality index was calculated as $\kappa = \log \left( \kappa_0 / F_i \right)$, where $\kappa_0$ is the fraction that is subgroup $i$ of the total population residing in all block groups with concentration in the interval $k$, and $F_i$ is the fraction that subgroup $i$ comprises of the total county population. The index quantifies the degree of disproportionate exposure of a specific subgroup; it is described in detail in Stuart et al. (2009) and Yu and Stuart (2013). Concentration interval limits were selected to provide five (linearly) regular intervals with approximately 20% of the population residing within each interval.

3. Results and discussion

3.1. Distributions of emissions

Table 1 provides a summary of estimated emissions in the study domain for all categories of sources. Although all of the pollutants chosen here have large contributions from on-road mobile sources, contributions from other emission categories are substantial, and the relative contribution of each emission category differs by pollutant. On-road mobile sources (both inside and outside Hillsborough County) contributed over 50% of the anthropogenic emissions of all pollutants, and over 50% of the total emissions (including biogenic emissions) of NOx, benzene, and 1,3-butadiene. Inside the county, emissions from minor roadways were larger than emissions from major roadways. For formaldehyde and acetaldehyde, biogenic emissions had the largest contributions at 51% and 72%, respectively. For benzene and 1,3-butadiene, non-road mobile sources were the second most substantial contributing sector after on-road mobile sources, at 27% for 1,3-butadiene and 26% for benzene. Point sources contributed the least for all pollutants except NOx, for which they contributed 32%.

Fig. 2 shows the spatial distributions of emissions for benzene and acetaldehyde in Hillsborough County. Spatial distributions of NOx and 1,3-butadiene were similar to benzene, and distributions of formaldehyde were similar to acetaldehyde; they are provided as supplemental materials (Figure S3). For all pollutants, the busiest interstate highways, including I-4 and I-75, had the highest estimated major roadway emissions. The most apparent difference in the spatial distributions of emissions occurs for the other source category. Urbanized areas, especially downtown Tampa, generally had higher other source emissions for benzene, 1,3-butadiene, and NOx. Conversely, formaldehyde and acetaldehyde show higher emissions in more rural areas, due mainly to the dominance of biogenic sources (Table 1). In addition, emissions from shipping lanes are apparent for all pollutants except 1,3-butadiene. The number of point sources also differed between pollutants. It was much larger for NOx and benzene than 1,3-butadiene, formaldehyde, or acetaldehyde. Additionally, most of the point sources were located in or near urbanized areas for all pollutants except formaldehyde.

Overall, the results show substantial differences in the contributions of distinct source types to each pollutant and resultant differences in the spatial distributions of resolved emissions. Hence, when modeling exposures to the mix of urban pollution, it is important to consider a comprehensive and resolved emissions inventory.

3.2. Concentration distributions

Spatial distributions of the estimated annual average and the highest hour concentrations of benzene and acetaldehyde in Hillsborough County are shown in Fig. 3. Results for NOx and 1,3-butadiene were similar to benzene, and those of formaldehyde were similar to acetaldehyde; they are provided as supplemental materials (Figure S4). For benzene (1,3-butadiene and NOx), the highest concentrations are seen near the urban core area, particularly along major roadways. Roadway impacts are much less apparent for acetaldehyde (and formaldehyde). Instead, areas of high concentration were more diffuse and are primarily seen to the south and east of central Tampa for the annual average and highest hour values, respectively. Importantly, the local emissions (modeled by CALPUFF) contributed only 3.4% and 19% of the domain-averaged acetaldehyde concentrations, for the annual average and highest hour values, respectively. Hence, the majority of ambient acetaldehyde concentrations are attributable to secondary formation rather than direct emissions.

Our results suggest that the combination of dispersion modeling of local emissions with regionally-influenced reactive generation is needed for the estimation of acetaldehyes. By combining the results from dispersion modeling and a chemical transport model, we were able to benefit from the advantages of both models. This provides a demonstration of methods that are needed for many pollutants of public health concern that have substantial regional reactive generation, including PM$_{2.5}$, and many air toxics.

The presence of distinct spatial concentration distributions for different pollutants (e.g. benzene versus acetaldehyde) also supports the need to examine multiple pollutants during exposure and inequality estimation. Humans are exposed to a variety of airborne pollutants simultaneously. Because the concentration patterns differ, higher exposures for one pollutant may not indicate higher exposure for all pollutants.

3.3. Exposure and inequality

Table 2 provides the estimated population weighted exposures to benzene and acetaldehyde. The black subgroup was found to have the highest average exposure to benzene, with a value 17% higher than...
the county average for chronic exposures (annual mean concentrations) and a value 20% higher than the county average for acute exposures (highest hour concentrations). The subgroup with the lowest income (less than $20,000) ranked second highest in average benzene exposure among all subgroups. The white subgroup had the lowest average benzene exposure in the race/ethnicity category, with values lower than the

Fig. 2. Annual total emissions (tonnes) of benzene (a) and acetaldehyde (b).

Fig. 3. Concentrations (μg/m³) of benzene (a and c) and acetaldehyde (b and d). The top and bottom rows show the annual average and highest hour concentrations, respectively.
Population weighted exposure generally decreased to the county average with increase of annual household income. Benzene exposures for all age subgroups were generally close to the county average, with slightly higher acute exposure estimated for older people (age > 65).

For exposures to acetaldehyde, the black subgroup also had the highest chronic exposure on average, but the value was equivalent to that for older people (greater than 65 years). Further, for acute acetaldehyde exposures, the highest value was estimated for young children (less than 5 years), and average black exposure was equivalent to white exposure. However, average chronic and acute exposures to acetaldehyde for all subgroups were less than 1% greater than the county average.

**Table 2**  
Annual average and highest 1-hour population-weighted exposures to benzene and acetaldehyde for each population subgroup.

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Benzene (μg/m³)</th>
<th>Acetaldehyde (μg/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual mean</td>
<td>Highest 1-hour</td>
</tr>
<tr>
<td>Race/ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>0.28</td>
<td>4.85</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.26</td>
<td>4.27</td>
</tr>
<tr>
<td>White</td>
<td>0.23</td>
<td>3.88</td>
</tr>
<tr>
<td>Annual household income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;20K</td>
<td>0.26</td>
<td>4.51</td>
</tr>
<tr>
<td>20K–40K</td>
<td>0.25</td>
<td>4.21</td>
</tr>
<tr>
<td>40K–60K</td>
<td>0.24</td>
<td>3.99</td>
</tr>
<tr>
<td>60K–100K</td>
<td>0.23</td>
<td>3.79</td>
</tr>
<tr>
<td>&gt;100K</td>
<td>0.24</td>
<td>3.94</td>
</tr>
<tr>
<td>Age &lt;5</td>
<td>0.24</td>
<td>4.05</td>
</tr>
<tr>
<td>Age between 0</td>
<td>0.24</td>
<td>4.03</td>
</tr>
<tr>
<td>Age &gt;65</td>
<td>0.24</td>
<td>4.13</td>
</tr>
<tr>
<td>County average</td>
<td>0.24</td>
<td>4.05</td>
</tr>
</tbody>
</table>

**Fig. 4.** Index of subgroup inequality versus concentration for benzene and acetaldehyde. The concentration shown is the cutoff value used to define the area of exposure to this or a higher concentration value.
maximum was observed, suggesting that although they were disproportionately represented in the most polluted areas, they were primarily living in areas with intermediate concentration levels. Among the income category groups, the benzene inequality index value decreased with increase of income for all but the highest concentration interval. For the highest concentrations, the poorest group (income less than $20K) remained the most disproportionately exposed group, but the highest income group (income over $100K) ranked second. Estimated subgroup inequality index values for age subgroups were generally close to zero, with positive values for people older than 65 for the highest benzene concentration cutoffs.

The trends in the inequality index value for acetaldehyde were more complicated than for benzene. Specifically, they tended to reverse for the highest concentrations. Whites and intermediate incomes were disproportionately represented in these high concentration areas, while blacks and the lowest incomes were not. Interestingly, people older than 65 appear to have been disproportionately exposed to high annual average concentrations, but also disproportionately unexposed to higher maximum hour concentrations.

It is clear that the distinct exposure and inequality results for benzene (1,3-butadiene and NOx) versus acetaldehyde (and formaldehyde) found here are due to the differences in the spatial distributions of their concentrations (Fig. 3) compared with those of people’s residences. Differences in the factors that contribute to concentrations between pollutants, i.e., emissions versus reactive generation in the atmosphere, are particularly important. Benzene, 1,3-butadiene and NOx are largely primary pollutants. Hence, concentrations are expected to be higher near to sources. Furthermore, their emissions are dominated by on-road mobile sources (Table 1) resulting in concentrations that are higher near roadways and traffic (Fig. 3). Previous studies for the same area have shown that socio-economically disadvantaged subgroups tend to reside closer to major roadways (Stuart et al., 2009; Chakraborty, 2009), resulting in disproportionate exposures for these groups. Acetaldehyde and formaldehyde are also emitted by roadway vehicles, but secondary formation contributes substantially to their ambient concentrations. Hence, concentrations are not higher near roadways and other emission sources, resulting in a different pattern of exposure.

Exposure inequality results found here for benzene and 1,3-butadiene are consistent with those of our previous study focused on NOx alone (Yu and Stuart, 2013). However, the results for formaldehyde and acetaldehyde indicate that patterns of inequality differ by pollutant, and the relationships are complex. Additionally, the direction of disparity is somewhat reversed between the pollutants that substantially result from primary emissions over a short spatiotemporal scale (benzene, butadiene, and NOx) and those that have large contributions from secondary formation over a longer scale (formaldehyde and acetaldehyde). This is consistent with the findings of Marshall (2008), who also found reverse disparities for a secondary pollutant (ozone) compared with a few primary pollutants (benzene, butadiene, chromium particles, and diesel particles). Overall, these results suggest that care should be taken in summarizing inequality based on results from individual pollutants. Although many studies of inequality in air pollution exposure have relied on a single pollutant approach (e.g. Clark et al., 2014; Fann et al., 2011), a multiple pollutant approach is needed. However, categorization by type of pollutant may be helpful, considering both similarity in emissions sources and behavior in the atmosphere.

Specifically, it is clear from this and previous work that on-road mobile sources contributed substantially to the disproportionate exposures of disadvantaged subgroups to NOx, 1,3-butadiene and benzene. Since mobile source emissions are known to consist of many hazardous gases, it is reasonable to suspect that exposure inequalities found for NOx, 1,3-butadiene and benzene may also be generalizable to other mobile-source dominated primary pollutants.

### 3.4. Implications

These results have several implications for control strategies. For all pollutants studied, reduction of on-road mobile source emissions is likely to reduce air pollution exposures to some degree. Many strategies are available to reduce roadway emissions, from improved vehicular technologies to strategies that alleviate demand for motor vehicle use. The latter include public transit infrastructure and promotion of non-motorized commute modes including walking and biking. However, these rely on an urban form that is compact and dense. Conversely, many metropolitan areas in the U.S. today contain sprawling developments and isolated communities connected over large distances by large roadways. Hence, people are increasingly dependent on cars for daily activity. From 1980 to 2010, total vehicle mileage traveled increased by 108%, which is three times the population increase during the same period (Federal Highway Administration, 2013). These trends exacerbate the need for reductions in emissions through alternative transportation modes, while making them more difficult.

One of the advantages cited by proponents of compact urban design, characterized by high density and mixed land use developments, is improvements in air quality. Indeed studies have found that high-density urban areas promote the use of public transit systems, and non-motorized commute modes (Schwanen et al., 2004). A few studies have also shown it to be associated with lower on-road mobile source emissions (McDonald-Buller et al., 2010; Niemeier et al., 2011) and lower measured or modeled concentrations of some pollutants (Clark et al., 2011; Hixson et al., 2010; Martins, 2012). Therefore, compact urban design may be a promising strategy for reduction of concentrations and exposures.

However, there are still few studies of the effects of compact design and transportation policies on air pollution inequality, particularly considering multiple pollutants. Reduction of emissions from motor vehicles will likely help reduce exposures for many pollutants, particularly traffic-related primary pollutants (NOx, benzene, and 1,3-butadiene here). However, high-density development can collocate people with emissions from congested centrally-located roadways and intersecions, increasing pollutant exposures. A substantial contributor to inequality in exposures to traffic pollution is residential segregation in which disadvantaged groups live in close proximity to these roadway sources (e.g. Stuart et al., 2009). Compact growth may not necessarily help alleviate inequality, which requires reduction in emissions near areas where disadvantaged population subgroups spend time. Additionally, effects on overall exposures may be much less for secondary pollutants with substantial regional biogenic emissions (formaldehyde and acetaldehyde here), and effects on inequality may be substantially different, even opposite.

### 4. Conclusions

In this study, spatiotemporal distributions of emissions and concentrations of select urban air toxics and NOx in the Tampa area in 2002 were investigated. These were applied to estimate human exposures to air pollution and differences by pollutant in the social distribution of exposure among income, race/ethnicity, and age subgroups. Innovations presented here include improvements to the emissions estimation approach, and combination of CALPUFF modeling with CMAQ results to allow study of pollutants with substantial secondary production in the atmosphere. Major findings from this work are as follows:

1. The high-resolution spatial distributions of emissions show distinct patterns. For NOx, 1,3-butadiene and benzene, higher emissions were found in urbanized areas; for acetaldehyde and formaldehyde, higher emissions were found in rural area. Differences in contributing sources are responsible for the differences observed.

2. On-road mobile sources were found to contribute substantially to modeled ambient concentrations of NOx, 1,3-butadiene and benzene.
For acetaldehyde and formaldehyde, processes not included in CALPUFF modeling, specifically atmospheric formation, contribute substantially to pollutant concentrations.

3. Disproportionate exposures were found for black, Hispanic and low income (annual household income less than $20,000) population subgroups, for NO$_3$, 1,3-butadiene and benzene. Complex exposure patterns with reverse disproportionality at the highest concentration levels were found for acetaldehyde and formaldehyde, due primarily to their distinct spatial distribution of estimated concentrations.

Although the specific conditions of emissions and meteorology have likely changed somewhat since the period of the data considered here, results suggest the need to consider multiple pollutants (or pollutant types) in studies of inequality and for other assessments of the potential health impacts of urban development policy. Methods and results presented here should contribute to improved urban design, transportation planning, and air quality management toward a sustainable and equitable direction.

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Appendix A. Supplementary data

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References


