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Exposure and inequality for select urban air pollutants in the Tampa Bay area

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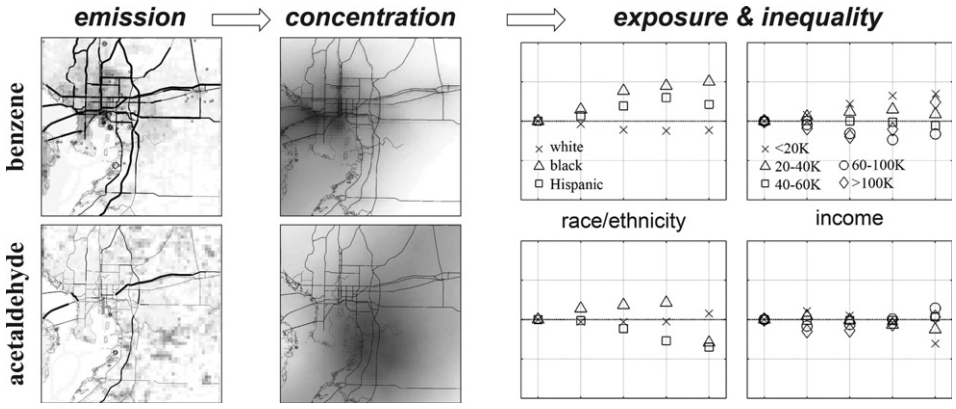
HIGHLIGHTS

- 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.

GRAPHICAL ABSTRACT



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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 (NO_x) 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 NO_x 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.

1. Introduction

Acute and chronic exposure to urban air pollution have been linked with a wide range of adverse health effects (Pope et al.,

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2002; Brunekreef 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 socioeconomically 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 (Beevers 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; Fridh 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 (NO_x) 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 NO_x 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 NO_x. 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 NO_x) 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 emissions 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): $S_{l,h} = S_{l,f}/[1 + \alpha_l (T_{l,h}/C_l)^{\wedge}\beta_l]$. $S_{l,f}$ is the free flow speed, $T_{l,h}$ is the traffic volume, C_l is the roadway capacity, and α_l and β_l are empirical parameters.