Impacts of Estimated Travel Activity on Air Pollutant Concentrations and Human Exposures in the Tampa Region

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Extended Abstract

INTRODUCTION
Air pollution is now the world’s largest single environmental health risk (United Nations Environment Programme, 2014). The 2014 World Health Organization (WHO) report attributes about 3.7 million deaths to ambient air pollution (World Health Organization, 2014). Within the urban context, motor vehicles are a significant contributor to ambient air pollution and have been linked with adverse health impacts (HEI Panel on the Health Effects of Traffic-Related Air Pollution, 2010). Therefore, it is important to measure population exposure to air pollution.

Personal monitoring, for which individuals wear exposure measurement devices, is the gold standard for exposure estimation. However, personal monitoring campaigns are often limited to small sample sizes due to high costs. Alternatively, studies also use centralized monitoring station measurement data to estimate individuals’ exposures. However, this approach cannot capture important spatial variations in pollutant concentrations, especially for traffic-related air pollutants (Monn, 2001), leading to exposure misclassification. Further, forecasting, necessary for exploring urban design solutions that could potentially result in lower exposures, has turned out to be a challenge. To overcome these limitations, modeling techniques are used to estimate pollutant emissions, spatiotemporal distributions of concentrations, and the resulting exposures (Hatzopoulou and Miller, 2010).

This study is part of an overarching project (Gurram et al., 2014; Yu and Stuart, 2016) that aims to understand and predict interactions between design of urban transportation infrastructure, spatiotemporal distribution of traffic-related pollutant emissions and concentrations, human exposure to air pollution, and the social distribution of exposures in Tampa, Florida. Here, we describe and demonstrate an integrated transportation and air pollution modeling framework that brings together activity-based travel demand simulation, dynamic traffic assignment simulation, mobile source emission estimation, and dispersion modeling to estimate group-level exposure to mobile source pollution for the Tampa region. We also demonstrate the first stages of the framework resulting in concentration estimates and discuss its planned application to alternative urban growth scenarios.

METHODS
Hillsborough County, Florida is our study area. The geographic context of the county is presented in Figure 1. The freeway road I-275, acts as a major commuter corridor connecting north of Tampa to the central business district at the south. The freeway roads I-75 and I-4 run along the north-south and east-west directions, respectively, and serve as major highways for intra-city, inter-city and inter-state travel. The county has a diverse mix of air pollution sources and population demographics, few public transportation options, an unsatisfactory air quality record, and a sprawling urban form. These attributes make it a good test bed for investigating alternate transportation design scenarios that may improve air quality in the region. In this study, we focus on oxides of nitrogen ($\text{NO}_x$) as a surrogate for traffic-related air pollution.

The modeling framework is shown in Figure 2. It comprises three components: transportation modeling, air pollution modeling, and exposure modeling.
Transportation Modeling

The transportation modeling component includes an activity-based travel demand model (DaySim) and a dynamic traffic assignment model (MATSim). As part of the Second Strategic Highway Research Program, Resource Systems Group (RSG) has developed the Tampa Bay activity-based travel demand model (simply called, Tampa ABM), which is based on the DaySim framework (Gliebe et al., 2014). We used this model in our study.

Figure 1. The study area of Hillsborough County, Florida. (Source: Gurram et al. 2015)

Figure 2. The integrated modeling framework for air pollution exposure estimation.
The Tampa ABM comprises a set of discrete choice models that are used to describe and predict the long-term location choices (work location, auto ownership levels) and daily activity and travel choices (daily activity and travel scheduling, mode of travel, timing of travel, and destinations of travel) of all residents in the study region. Inputs to the ABM include detailed demographic characteristics, land use data, and transportation system characteristics of the study region (Bradley et al., 2010). The demographic inputs come from a population synthesizer called PopGen (Ye et al., 2009) that generates a synthetic population of individuals and households to match aggregate-level distributions of both household- and person-level characteristics from the U.S. Census. The 2010 census summary files and the American Community Survey’s 2006-10 Public Use Microdata Sample (PUMS) data were used to synthesize the population. Demographic variables that were not controlled in PopGen (e.g., household car ownership and individual employment characteristics) were estimated using econometric models based on local data. Similarly, the Florida Department of Revenue’s tax assessor records, household census records, and employment data provided by InfoGroup, for the year 2010, were used to generate the land use data. Following this, the transportation system characteristics (including travel time and travel cost attributes for different modes of travel) for 2010 were obtained from the Tampa Bay Regional Planning Model. All these data were input to the Tampa ABM to simulate the activity and travel patterns for one day for each synthetic individual in the study region. The outputs from the ABM include the set of all activities undertaken in the data, detailed spatial coordinates of the activity locations, time-of-day for activities, activity durations, and the mode of travel between these activity locations.

Although Tampa ABM provides detailed information on activity-travel patterns, it does not estimate travel routes between the fixed-activity locations. The route information is essential both for emissions and human exposure estimation. To estimate the travel route information, we used the traffic assignment model MATSim (Balmer et al., 2008). We processed the trip file outputs from the Tampa ABM using SPSS and Java to provide the initial travel demand for MATSim. Additionally, the road network for the Tampa Bay area was also processed to create the network inputs for MATSim. MATSim estimates travel routes for all trips generated for an individual by maximizing the overall schedule utility of the individual while considering capacity constraints on the transportation network. In doing so, an individual’s travel plan (including the routes) is penalized if the MATSim-simulated travel schedule differs from the travel schedule provided by the Tampa ABM. At each iteration, MATSim drops the travel plans with high penalties and estimates new travel plans by modifying either the trip schedules or the travel routes. Since a majority of travel in Tampa is by automobile (with close to 90% mode share), only the automobile trips were simulated in MATSim. Overall, the travel schedules and routes of 9.7 million trips made by approximately 2.3 million residents of the study region during a 24-hour period were simulated. The outputs for this model include hourly traffic volumes and travel times on a typical weekday for each roadway link, and the spatial coordinates for each individual along their travel paths.

**Air Pollution Modeling**

Once roadway link traffic volumes have been simulated, hourly distributions of mobile source emissions and the concentrations can be estimated. To estimate the mobile source emissions, the 2014 MOVES model (Office of Transportation and Air Quality, 2014) was utilized. Specifically, seasonal-average diurnal cycles of hourly emissions were estimated by running MOVES in batch mode at the project scale for all roadway links in Hillsborough County. First, the hourly traffic volume and speed for each roadway link, obtained using MATSim, were input to the MOVES model. Speeds were estimated using the travel time output data. Second, the 2010 Hillsborough County meteorological data provided with MOVES were aggregated across all the days from each season to generate averaged diurnal cycle of hourly temperature and relative humidity for a representative day of that season. County-specific default fuel formulation data and the national default vehicle age distribution data for the year 2010 were also used. Here, we ran MOVES to estimate NOx emissions on an average winter day (including the months of November through March).

Emissions output from MOVES were input to R-LINE, along with the necessary meteorological inputs, to calculate the hourly distributions of concentrations. Specifically, link-level emissions were
modeled as line sources using the roadway length and width characteristics. Meteorological surface data for the year 2010 were prepared using the AERMET program by utilizing raw data from the National Climatic Data Center for the Tampa International Airport. Concentrations were generated for each hour of the meteorological record for a regular grid of receptor locations with 500 m resolution throughout the study area. Output values were averaged to generate the diurnal cycle of hourly concentrations.

**Exposure Modeling**

The exposure modeling step involves combining the spatiotemporal locations of hypothetical individuals with the spatiotemporal distribution of pollutant concentrations to estimate person-level exposures. The outputs from DaySim and MATSim can be merged to create a sequential activity-record for each person. Specifically, the activity records contain the location coordinates, time-of-day, and activity durations both for fixed location activity and the travel activity, for each individual. This information is combined with the concentration maps to generate time-weighted exposure measures for the representative individuals in the study region.

**RESULTS**

The hourly-varying average diurnal cycle of NO\(_x\) concentrations in 2010 resulting from passenger cars is presented in Figure 3. Temporally, NO\(_x\) concentrations have two peaks; one during the morning (5 to 9 am) and the other during the evening (5 to 10 pm) peak hours. Spatially-averaged hourly concentrations are generally higher during the morning peak, but the evening peak lasts longer than the morning peak. Note that emission estimates during the evening peak hours were found to be higher than emissions during the morning peak hours. Lower mixing heights could be a reason for the higher morning concentrations. Although the results here are not directly comparable with available measured concentrations (because we modeled NO\(_x\), not NO\(_2\), and we have only included passenger car emissions), the diurnal profile of the modeled concentrations is similar to that of measurements at a near-road monitor in the area, with some differences in the shape and timing of the evening peak.

Spatially, higher concentrations are observed along the major freeway corridors including I-75, I-275, and I-4. This is expected, as these freeway corridors experience high traffic volumes. High concentrations are also observed along the road network near the university area, downtown area, and Brandon, a suburban location near Tampa. The highest modeled concentration of 3814 µg/m\(^3\) was found approximately 2 miles from the intersection of I-275 and I-4 (on January 7\(^{th}\) for the 5:00 to 6:00 pm hour). Although the results here are not directly comparable to the National Ambient Air Quality Standards (NAAQS), they suggest that NO\(_2\) concentrations could reach levels of acute health effect concern. (Assuming a NO\(_2\) to NO\(_x\) ratio of 0.4, an approximation for near-road conditions, the 98th percentile value of the 1-hour daily maximum, also at this location, is about 980 µg/m\(^3\); this substantially exceeds the NAAQS limit for hourly NO\(_2\)).

Overall, these results demonstrate the applicability of an integrated modeling framework, including activity-based travel demand (DaySim), dynamic traffic assignment (MATSim), mobile source emissions (MOVES), and dispersion (R-LINE) models to estimate mobile source concentrations at a high spatial and temporal resolution.

**FUTURE WORK**

The next steps of this study include addition of truck traffic to the currently modeled passenger traffic, followed by completion of the exposure estimation for NO\(_x\) for the winter season. Ultimately, we will estimate population exposure for alternative scenarios of urban land-use design and transport policies. Specifically, we will simulate exposures for the year 2050 under (1) a smart-growth oriented compact urban form with significant presence of public transport systems and (2) a sprawl-growth scenario with little presence of non-automobile modes of travel. The smart-growth scenario will include a new rail travel mode along with an expanded bus rapid transit service that connects commercial and residential locations with the rail line; these transit modes will be modeled after the Tampa Bay Area Regional
Transportation Authority’s long-term vision. A stringent land use policy that discourages leapfrog urban development will also be applied to this scenario. In the sprawl-growth scenario, the existing highway network will be expanded with no additional public transportation options. A flexible land use policy that allows for leapfrog development will also be applied. Results from this work are expected to improve current understanding of the interactions between urban transportation design and exposure to traffic related air pollution.

Figure 3. Diurnal cycle of mobile source NO\textsubscript{x} concentrations in Hillsborough County in 2010.

REFERENCES


