Estimating Human Exposures to Traffic-Related Pollution using an Integrated Transportation and Air Pollution Modeling Framework: Application to the Tampa Region

Extended Abstract # 308

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INTRODUCTION

Air pollution is now the world's largest single environmental health risk. The recently released World Health Organization (WHO) report attributes about 7 million worldwide premature deaths to air pollution; 4.3 million deaths are attributable to household air pollution and 3.7 million deaths attributable to ambient air pollution[1]. Within the urban context, motor vehicles are a significant contributor to ambient air pollution and have been linked with adverse health impacts[2]. Therefore, it is important to measure and model population exposure to air pollution.

Personal monitoring, where 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 can inaccurately characterize the spatial distributions of pollutant concentrations, especially for traffic-related air pollutants that exhibit considerable spatial variation[3], leading to exposure misclassification. Besides, due to the descriptive nature of these studies, exploring urban design solutions which could potentially result in lower exposures has turned out to be a challenge. To overcome these limitations, some studies use modeling techniques to estimate pollutant emissions, spatiotemporal distributions of concentrations, and the resulting individual exposures[4].

This study is part of an overarching project that aims to understand and predict interactions between design of urban transportation infrastructure, human exposures to traffic-related air pollutants, and the social distribution of exposures[5,6]. 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 emissions estimation, and dispersion modeling to estimate individual- and group-level exposures to mobile source pollution for the Tampa region. We also demonstrate the first stages of the framework resulting in emissions estimates.

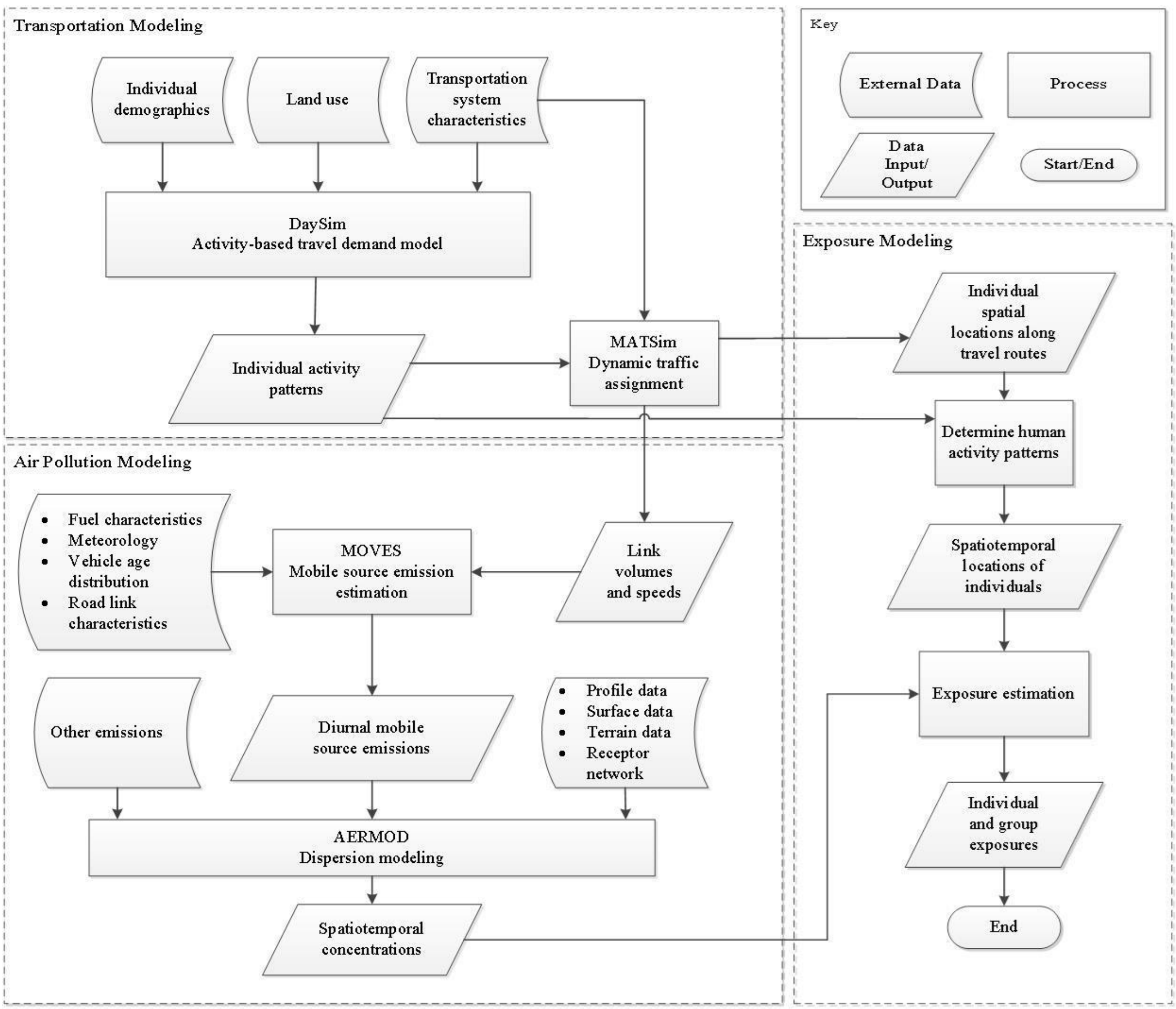
METHODS

Hillsborough County, Florida is our study area. 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 seek to improve the air quality.

Traffic-related air pollution is a complex mixture of many specific pollutants including oxides of nitrogen (NO_x), carbon monoxide (CO), particulate matter (PM), and benzene. In this study, we focus on oxides of nitrogen (NO_x) as a surrogate for traffic-related air pollution[2].

The modeling framework is shown in figure 1. It consists of three components: transportation modeling, air pollution modeling, and exposure modeling.

Figure 1. The integrated modeling framework for air pollution exposure estimation.



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[7]. We used this model in our study. The Tampa ABM is comprised of a set of discrete choice models that estimate the long term choices (work location, auto ownership levels) and short term activities (location, travel mode, daily scheduling) of households and individuals, using optimization techniques that assign higher probability to choices with greater utility. Inputs to the model include synthetic population, land use data, and travel system characteristics[8]. The synthetic population was generated using the 2010 census summary files and the American Community Survey's 2006-10 Public Use Microdata Sample (PUMS) 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 level of service variables, including travel time and travel cost, for 2010 were obtained from the Tampa Bay Regional Planning Model. Finally, the discrete choice models were estimated using pooled 2009 National Household travel Survey data for the Jacksonville and Tampa Bay areas. Activity-travel patterns for one day for each hypothetical individual in the study region are output from the model. They include detailed spatial coordinates for the fixed activity locations, time-of-day for activities, activity durations, and travel mode between these activity locations.

Although activity-based travel demand models provide detailed information on individuals' activity-travel patterns, they are generally inadequate for estimating 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 MATSim which is a dynamic traffic assignment model[9]. Specifically, we processed the trip file outputs from the Tampa ABM using SPSS and Java programming 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 the demanded trips by maximizing overall utility. In the optimization, an individual's travel plan is penalized if the 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 the trip schedules or the travel routes. The outputs for this model include hourly traffic volumes and travel times on a typical weekday for each link, and the spatial coordinates for each individual along their travel paths.

Air Pollution Modeling

Once link traffic volumes have been simulated, hourly distributions of mobile source emissions and the concentrations can be estimated. To estimate the mobile source emissions, we used the 2014 MOVES model[10]. Specifically, we estimate seasonal-average diurnal cycles of hourly emissions 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, are input to the MOVES model. Speeds are estimated using the travel time output data. Second, we aggregate the 2010 Hillsborough County meteorological data provided with MOVES, for the months 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, are also used. For the results shown below, we applied this framework to estimate NO_x emissions on an average winter day (including the months of November through March).

To estimate concentrations, emissions output from MOVES will be combined with the point source emissions and are input to AERMOD along with the necessary meteorological inputs to calculate the hourly distributions of concentrations. Specifically, the link-level emissions will be modeled as area sources using the roadway length and width characteristics obtained from the transportation network. Surface and profile data for the year 2010 are being prepared using the AERMET program by utilizing the raw data from the National Climatic Data Center for the Tampa International Airport and the Ruskin stations, respectively. Similarly, the terrain data and the receptor grid are being prepared using the AERMAP program. Using these inputs, concentrations will be generated for each hour of the meteorological record for a regular grid of receptor locations with 500 m resolution throughout the study area. Values will be averaged to generate the diurnal cycle of hourly concentrations for each season.

Exposure Modeling

In the exposure modeling step, we combine the spatiotemporal locations of hypothetical individuals with the spatiotemporal distribution of pollutant concentrations to estimate the person-level exposures. We merge the outputs from DaySim and MATSim 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 activities and the travel activity, for each individual. This information will be combined with the concentration maps to generate time-weighted exposure measures for all the representative individuals in the study region.

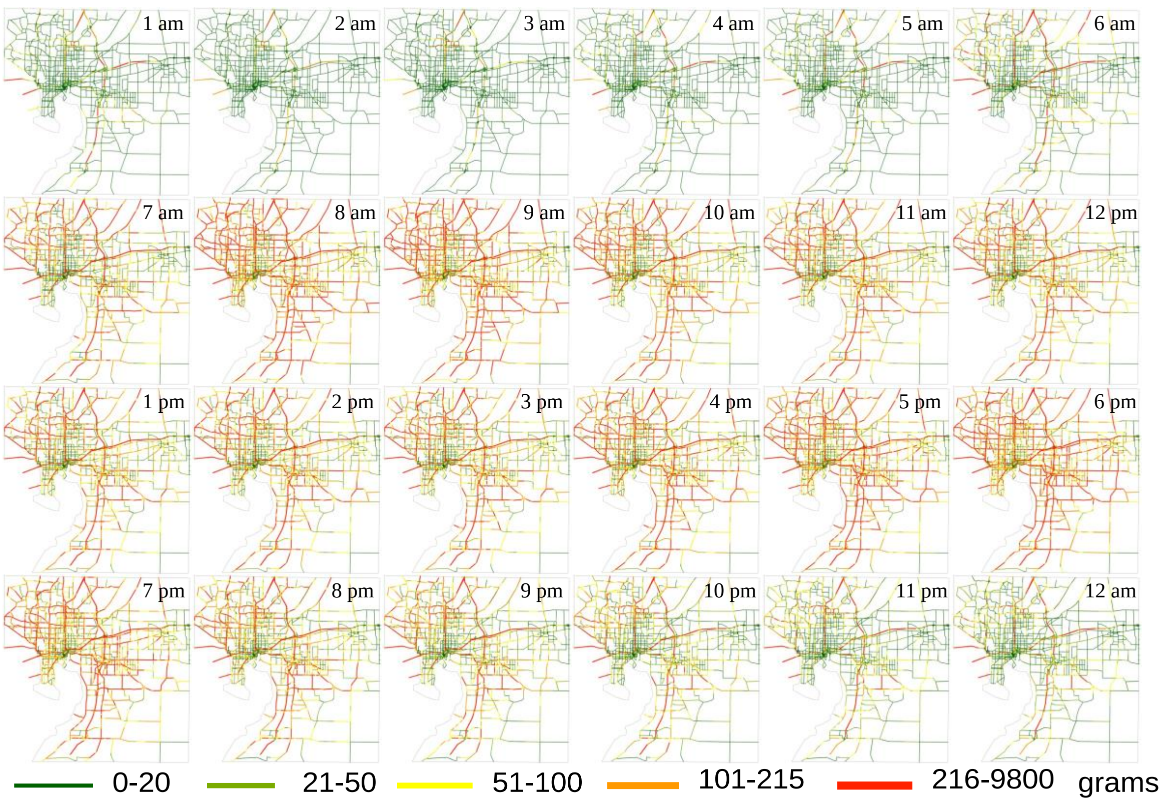
RESULTS

The link-specific NO_x emissions resulting from passenger cars on an average winter day are presented in figure 2. Emissions are higher during the morning (7 to 9 am) and the evening (4 to 7 pm) peak hours compared to the rest of the day. Additionally, emissions during the evening peak hours are higher compared to the emissions during the morning peak hours. This could be an artifact of the individual activity-travel patterns, because the evening commute has a higher propensity for stopping when compared to the morning commute[11].

Spatially, higher emissions 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 emissions are also observed along the road network near Brandon, a suburban location near Tampa. Emissions are somewhat low in the Tampa Downtown area. This may be an artifact of not using visitor and freight trips in the model, and is the subject of current study. Overall, these results demonstrate the integration of activity-based travel demand (DaySim), dynamic traffic assignment (MATSim), and mobile emission (MOVES) models to estimate mobile source emissions at a high resolution.

The next steps of this study include addition of truck trips, followed by completion of the concentration and exposure estimation for NO_x for the winter season. Ultimately, estimates of population exposure will be obtained for alternative scenarios of urban land-use design and transport policies. Exposures will be simulated 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 includes the availability of a new rail travel mode in the study region along with an expanded bus rapid transit service which connects the commercial and residence locations with the rail line. The rail mode will be modeled after the Tampa Bay Area Regional Transportation Authority's long term transit vision for the Bay area. Additionally, a stringent land use policy that discourages leapfrog urban development will be applied to this scenario. In the sprawled-growth scenario, no additional public transportation options will be added to the study region and the existing highway network will be expanded. Further, a flexible land use policy that allows for leapfrog development will be applied in this scenario. Hence, results should help improve understanding interactions between urban transportation design, air pollution, and health.

Figure 2. Diurnal cycle of mobile source NO_X emissions in Hillsborough County.



REFERENCES

1. World Health Organization. *Burden of disease from ambient air pollution for 2012*; Geneva, 2014.
2. HEI Panel on the Health Effects of Traffic-Related Air Pollution. *Traffic-related air pollution: a critical review of the literature on emissions, exposure, and health effects*; HEI Special Report 17; Health Effects Institute; Boston, MA, 2010.
3. Monn, C. *Atmos. Environ.* **2001**, *35*,1-32.
4. Hatzopoulou, M.; Miller, E.J. *Transport Res Transport Environ*. **2010**, *15*, 315-325.
5. Gurram, S.; Stuart, A.L.; Pinjari. A.R. *Air Qual Atmos Health*. **2014**, doi: 10.1007/s11869-014-0275-6
6. Yu, H.; Stuart, A.L. *J Air Waste Manage Assoc*. **2013**, *63*, 943-955.
7. Gliebe, J.; Bradley, M.; Ferdous, N.; Outwater, M.; Lin, H.; Chen, J. *Transferability of activity-based model parameters*; SHRP 2 Report S2-C10A-RW-2;Transportation Research Board; Washington, DC, 2014.
8. Bradley, M.; Bowman, J.L.; Griesenbeck, B. *J Choice Modelling*. **2010**, *3*, 5-31.
9. Balmer, M.; Meister, K.; Rieser, M.; Nagel, K.; Axhausen, K.W. Agent-based simulation of travel demand: Structure and computational performance of MATSim-T. *Proceedings of the 2nd TRB Conference on Innovations in Travel Modeling*, Portland, Oregon, June 22-24, 2008.
10. Office of Transportation and Air Quality. *Motor Vehicle Emission Simulator (MOVES) User Guide for MOVES2014*; EPA-420-B-14-055; U.S. Environmental Protection Agency; Research Triangle Park, NC, 2014.
11. Chu, Y.L. *Trans Res Rec J Trans Res Board*. **2003**, *1831*, 106-113.