The Spatial Distribution of Nitrogen Oxides in Hillsborough County, FL with Implications for the Social Distribution of Exposures

Student Paper 5

Haofei Yu, Amy L. Stuart

University of South Florida, 13201 Bruce B. Downs Blvd, MDC-56, Tampa, FL 33612

1 INTRODUCTION

The disproportionate distribution of air pollution exposure among population groups has long been a concern. Certain groups, such as ethnic minorities and the socioeconomically disadvantaged have been found more likely to reside in close proximity to air pollution emission sources and to live in areas with higher air pollution concentrations [1]. Therefore they may potentially be subject to higher risk of adverse health effects due to exposure to air pollution [2]. Environmental justice issues have been identified as one of the seven challenges facing the air quality management system in the United States [3]. In addition, air quality has also found to be affected by urban growth patterns. Different urban forms may lead to distinct spatial distribution of air pollution concentrations [4].

To mitigate the health effects of air pollution and to improve urban planning toward an equitable and sustainable direction, studies focusing on exposure to air pollution, especially the distribution of exposure among different population groups, are needed. Much of the previous work on inequalities in air pollution exposure has used air pollution monitoring data and or statistical regression analysis. These methods fail to characterize the pollutant concentration variation over small scales [5] or lack predictive capabilities.

In this paper, a spatially-resolved concentration distribution of oxides of nitrogen is obtained by dispersion modeling. The estimated distribution is then combined with demographic data to investigate the disparities in residential exposure to NOx air pollution in the Tampa, FL area. NOx is chosen as the study pollutant because it has been identified as an important urban air pollutant and it may trigger respiratory responses for susceptible individuals [6]. The study region is Tampa, FL, which is a fast growing area with a diverse population. The methods and results of the study are discussed in the following sections.

2 METHODS

Point and on-road mobile source emissions in Hillsborough County and the five surrounding counties are included in the modeling. Point source information was obtained from the 2002 EPA National Emission Inventory (NEI). Temporal allocation factors from the emissions

modeling clearinghouse [7] were applied to each point source to estimate hourly-resolved point source emissions.

Based on the availability of the 2002 traffic count data, roadways in Hillsborough County were categorized into major roadways and minor roadways. A bottom-up approach was employed to estimate the emissions from major roadways. Major roadway links were first rediscretized into segments that would be modeled as area sources. To reduce the total number of emission sources, a linear regression algorithm, allowing a maximum aspect ratio of 10, was developed and applied. The emission rate of each segment was calculated by combining traffic count data, segment length, and emission factors. Emission factors were estimated by the EPA MOBILE6.2 model and vary by road function class, road speed and month.

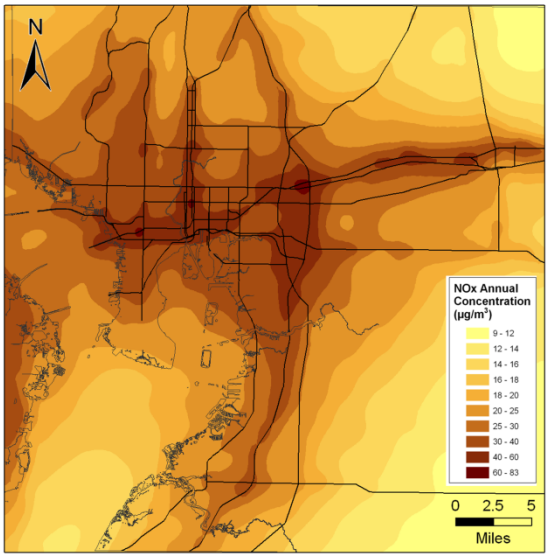
The estimated 2002 total emissions from major roadways account for 77% of the total on-road mobile source emissions for the study area in 2002 national emission inventory. Using a top-down approach, the remaining mobile source emissions were spatially allocated to a 1 km by 1 km grid network overlaid on the study area. Emissions were allocated proportionally to minor roadway density [8]. Additionally, mobile source emissions from the five surrounding counties were included in the modeling using a similar top-down method. To account for the temporal variation of traffic count, a monthly traffic count variation profile was derived and incorporated in the modeling.

The non-steady state Gaussian dispersion model, CALPUFF, was used to estimate the spatial NOx distribution in Hillsborough County. The meteorological data used in the modeling were obtained from VISTAS (Visibility Improvement State and Tribal Association of the Southeast). They have 4 km spatial resolution and 1 h temporal resolution. The CALPUFF model was run for 2002 with a receptor grid with 1 km resolution covering Hillsborough County. The modeling domain was extended out 60 km to capture pollutant re-circulation due to the land sea breeze.

The modeled annual concentration distributions were compared with demographic block-group data from the 2000 census to explore potential inequalities in exposure to outdoor NOx. The population-weighted average exposure was estimated for specific subgroups in the following categories: race/ethnicity (black, Hispanic, white and Asian), age (less than 18, 18-65 and greater than 65) and socioeconomic level (income below and above poverty). Race/ethnicity and socioeconomic groups were selected because disparities between these groups have previously been documented [9]. The age groups were selected because young and elder populations can be susceptible to air pollution. Additionally, the subgroup inequality index [9] was calculated and used to explore variations in the exposure disparities. The index was extended to calculate disparities by concentration levels rather than proximity (as discussed in the caption of Figure 3.)

3 RESULTS AND DISCUSSION

Figure 1. The modeled annual NOx concentration for Hillsborough County



The modeled annual average NOx concentrations for 2002 are shown in Figure 1. A roadway dominated pattern is observed, the highest pollutant concentrations were found near the roadways, especially roadways with the highest traffic volumes and the intersections of the major interstates. The distribution indicates that the mobile source emissions likely contribute significantly to ground level NOx air pollution.

Figure 2 shows the estimated population-weighted exposure to NOx for race/ethnicity, age and socioeconomic groups. The weighted exposure for the black, Hispanic and below poverty groups are higher than the county average, while exposures for white and Asian groups are lower than the county average. Little difference was seen between age groups.

Figure 2 The estimated population-weighted exposure to NOx for race/ethnicity, age and socioeconomic groups.

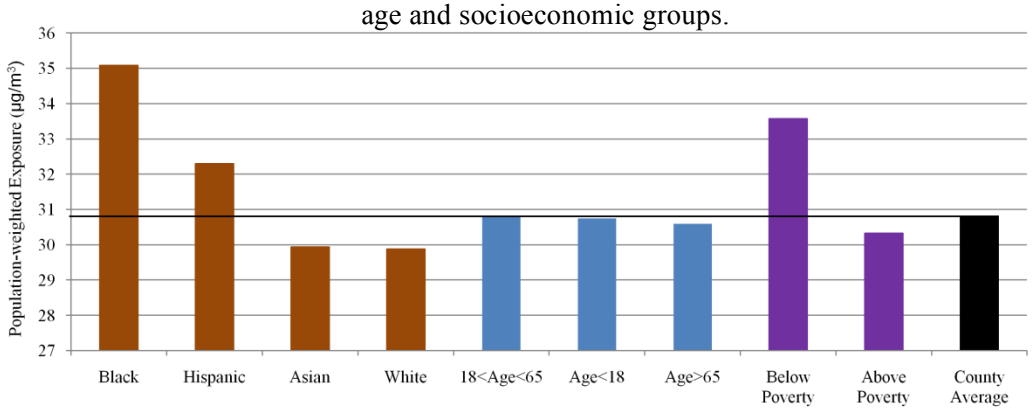
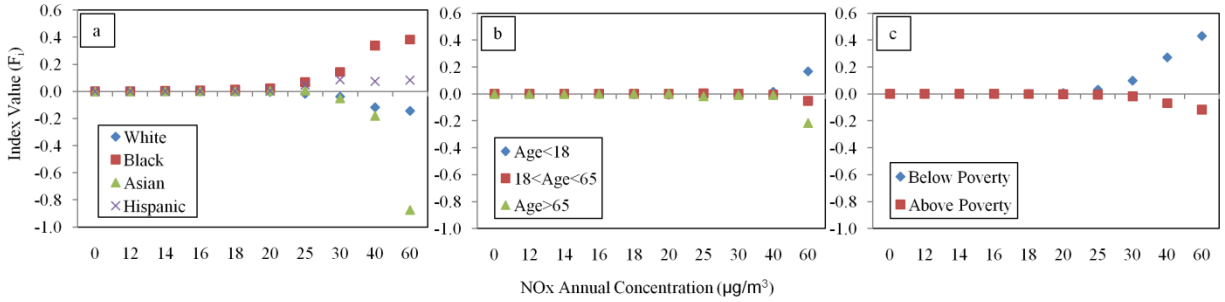


Figure 3 shows the estimated inequality indices for each subgroup. There is a higher fraction of the black and below poverty populations living in areas with the highest NOx concentrations. The same disparities are also observed for the Hispanic and young age groups, with smaller magnitude. The Asian group has a very low tendency of living in areas with the highest NOx concentrations.

The methods developed in this study can be used to investigate air quality and air pollution exposures. We are planning to apply them to study the air quality impact of different urban growth scenarios.

Figure 3. Estimated inequality index for race/ethnicity (a), age (b), and socioeconomic (c) groups. The index value is calculated as $F_i = \log(Z_i/T_i)$, where Z_i is the fraction of the total population living within an exposure area that is a specific subgroup, and T_i is the fraction of the total population of Hillsborough County that is that subgroup. Here, an exposure area is the area with modeled concentrations greater than a specific concentration level.



4 SUMMARY

The spatial distribution of NOx air pollution concentrations in the Tampa, FL area was modeled. Based on the modeling results, residential exposures to NOx for race/ethnicity, age and socioeconomic population groups were estimated. Exposure analyses show that black, Hispanic and below poverty population groups are likely exposed to higher NOx concentrations compared with county average. Additionally, the white and Asian groups may be exposed to lower NOx concentrations.

However, there are also a few limitations of this study. The traffic count data used in the mobile source emission estimation process is the Annual Averaged Daily Traffic (AADT). Although a monthly traffic variation profile is applied, the resolution of the traffic count is still of concern. In addition, the spatial resolution of the meteorological data used in this study is 4 km, which may not be enough considering the fact that the resolution of the receptor network is 1 km.

5 ACKNOWLEDGEMENT

This material is based upon work supported by the National Science Foundation under Grant No. 0846342. Funding was also provided in part by a USF University Graduate Fellowship and a College of Public Health Doctoral Fellowship. The authors would like to acknowledge the use of the services provided by Research Computing, University of South Florida.

6 REFERENCES

1. Mennis, J. L.; Jordan, L., The Distribution of Environmental Equity: Exploring Spatial Nonstationarity in Multivariate Models of Air Toxic Releases. *Annals of the Association of American Geographers* **2005,** *95* (2), 249-268.
2. Keating, M. *Air of Injustice: How Air Pollution Affects the Health of Hispanics and Latinos*; League of United Latin American Citizens.: Washington, D.C., 2004.
3. National Research Council *Air Quality Management in the United States*; Washington, DC, 2004.
4. Hixson, M.; Mahmud, A.; Hu, J.; Bai, S.; Niemeier, D. A.; Handy, S. L.; Gao, S.; Lund, J. R.; Sullivan, D. C.; Kleeman, M. J., Influence of regional development policies and clean technology adoption on future air pollution exposure. *Atmospheric Environment* **2010,** *44* (4), 552-562.
5. Isakov, V.; Touma, J. S.; Burke, J.; Lobdell, D. T.; Palma, T.; Rosenbaum, A.; Ozkaynak, H., Combining Regional- and Local-Scale Air Quality Models with Exposure Models for Use in Environmental Health Studies. *Journal of the Air & Waste Management Association* **2009,** *59* (4), 461-472.
6. Health Effects Institute *Special Report 17: Traffic-related air pollution: A critical review of the literature on emissions, exposure, and health effects*; Boston, MA, 2010.
7. U.S. Environmental Protection Agency Emissions Modeling Clearinghouse Temporal Allocation. http://www.epa.gov/ttn/chief/emch/temporal/index.html (accessed January 11th).
8. Saide, P.; Zah, R.; Osses, M.; Ossés de Eicker, M., Spatial disaggregation of traffic emission inventories in large cities using simplified top-down methods. *Atmospheric Environment* **2009,** *43* (32), 4914-4923.
9. Stuart, A. L.; Mudhasakul, S.; Sriwatanapongse, W., The Social Distribution of Neighborhood-Scale Air Pollution and Monitoring Protection. *Journal of Air & Waste Management Association* **2009,** *59*, 591-602.