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Race, socioeconomic status, and air pollution exposure in North Carolina

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ABSTRACT

Background: Although studies suggest that exposure to pollutants is associated with race/ethnicity and socio-economic status (SES), many studies are limited to the geographic regions where monitoring stations are located.
Objectives: This study uses modeled predictive surfaces to examine the relationship between air pollution exposure, race/ethnicity, and measures of SES across the entire State of North Carolina.
Methods: The daily predictions of particulate matter $<2.5\ \mu m$ in aerodynamic diameter ($PM_{2.5}$) and ozone (O_3) were determined using a spatial model that fused data from two sources: point air monitoring data and gridded numerical output. These daily predicted pollution levels for 2002 were linked with Census data. We examine the relationship between the census-tract level predicted concentration measures, SES, and racial composition.
Results: SES and race/ethnicity were related to predicted concentrations of both $PM_{2.5}$ and O_3 for census tracts in North Carolina. Lower SES and higher proportion minority population were associated with higher levels of $PM_{2.5}$. An interquartile range (IQR) increase of median household income reduced the predicted average $PM_{2.5}$ level by 0.10 $\mu g/m^3$. The opposite relationship was true for O_3. An IQR increase of median household income increased the predicted average O_3 measure by 0.11 ppb.
Conclusions: The analyses demonstrate that SES and race/ethnicity are related to predicted estimates of $PM_{2.5}$ and O_3 for census tracts in North Carolina. These findings offer a baseline for future exposure modeling work involving SES and air pollution for the entire state and not just among the populations residing near monitoring networks.

1. Introduction

The United States Environmental Protection Agency (USEPA) defines environmental justice (EJ) as the “fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies” (USEPA, 2010). Disadvantaged populations are at increased risk for diabetes (Karter et al., 2002), cancer, infant mortality, and a myriad of other diseases (Institute of Medicine, 1999), and an increased burden of exposure to environmental stressors may exacerbate health disparities. The Institute of Medicine acknowledges that environmental risk factors are viewed as an additional health burden to these higher risk groups (1999). In an attempt to strengthen EJ efforts, the USEPA recently developed Plan EJ 2014, the USEPA (2011) strategy for addressing EJ issues and protecting human health and the environment in overburdened communities.

Over the past 12 years, much of the research surrounding EJ has hinged on the concern that poor or minority groups may be at an increased risk from exposure to environmental stressors (Downey, 2007; NEJAC, 2004; Ringquist, 2005; Stretesky and Hogan, 1998). A large body of research has shown that disparities exist in the distribution of exposure to environmental pollutants and hazards across race and income levels (Kramer et al., 2000; Mennis and Jordan, 2005; Morello-Frosch et al., 2002; Pastor et al., 2004; Perlin et al., 1999; Williams and Collins, 2001). When narrowing the EJ research to air pollutants, studies have been conducted across the US in Arizona (Grineski et al., 2007), California (Marshall, 2008) and several states in the Northeastern U.S. (Brochu et al., 2011; Gwynn and George, 2001; Yanosky et al.,

Abbreviations: AQS, Air Quality System; CMAQ, Community Multi-Scale Air Quality Model; EJ, Environmental justice; NDI, Neighborhood deprivation index; NHB, Non-Hispanic black; O_3, Ozone; PM2.5, Particulate matter $<2.5\ \mu m$ in aerodynamic diameter; SES, Socio-economic status; SHEDS, Stochastic human exposure and dose simulation; USEPA, US Environmental Protection Agency.

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2008). Few studies have focused on areas where air pollution levels are typically below federal standards, such as North Carolina.

Studies have shown that exposure to air pollution may elevate the risk of adverse health outcomes, including mortality (Bell et al., 2004; Dockery et al., 1993; Pope et al., 2002, 2004; Schwartz, 1994), cardiovascular and respiratory morbidity (Dominici et al., 2006; Peters et al., 2004; Tonne et al., 2007), and pregnancy outcomes (Bell et al., 2007; Gray et al., 2010; Pope and Dockery, 2006; Pope et al., 1995; Schulz et al., 2005). These health effects have been attributed to both short term and long term exposure to pollutants such as air borne particulate matter and ozone (Brunekreef and Holgate, 2002). As detrimental as environmental stressors are to human health, it is important to note that exposure to air pollution may not affect all individuals in a population the same way or even at the same rate (Bell and Dominici, 2008; Brunekreef and Holgate, 2002; Currie et al., 2009; Woodruff et al., 1997). Environmental pollutants can have a disparate effect among economically disadvantaged and minority populations (Sexton et al., 1993), groups that are also more likely to live in areas with higher levels of pollution, thus potentially detracting from their health (Gwynn and George, 2001; Perlin et al., 2001; Woodruff et al., 2003; Yanosky et al., 2008).

It is difficult to obtain an exact measure of personal air pollution exposure for assessing disparities. Health and EJ studies often use measurements obtained from monitoring stations as surrogates for individual exposure (Sram et al., 2005). There are many limitations to using measurements from monitored data. The collected measurements often have missing data as estimates are not always recorded every day. Additionally, the sparse network of monitoring stations misses large geographic regions and limits the population that can be assessed. Alternatively, proximity to major roadways has also been used as a metric for individual exposures due to the large contribution of traffic emissions to ambient air pollution (Hart et al., 2009; Karr et al., 2009; Miranda et al., 2012). Other studies have explored the use of modeling techniques for estimating exposure concentration measurements including the Community Multi-Scale Air Quality Model (CMAQ), the probabilistic NAAQS Exposure Model (pCNEM) and the stochastic human exposure and dose simulation (SHEDS-PM) (Berrocal et al., 2010b; Zidek et al., 2003, 2007).

In this study, we explore racial and socioeconomic disparities in exposure to air pollution across the State of North Carolina. Unlike previous studies of EJ dimensions of air pollution, which limit analysis of populations living near air quality monitoring stations, we use predictive surfaces of ozone (O_3) and particulate matter-$<2.5\ \mu m$ in aerodynamic diameter ($PM_{2.5}$) at the census-tract level covering all of North Carolina. This analysis seeks to provide a better understanding of the EJ dimension of air pollution exposure across the entire North Carolina population.

2. Methods

2.1. Exposure data

Daily fused predictions surfaces of $PM_{2.5}$ (daily average in $\mu g/m^3$) and O_3 (daily 8-h maximum in ppb) were obtained from the USEPA for 2002 (www.epa.gov/esd/land-sci/lcb/lcb_faqsd.html). A Bayesian space-time "downscaling" fusion modeling approach was used to develop these predictive surfaces (Berrocal et al., 2010a). The downscaling fusion model uses input data from two sources: point monitoring data and numerical model gridded output. The air quality monitoring data came from the Environmental Protection Agency Air Quality System (AQS) repository database, and the numerical output came from the Models-3/Community Multiscale Air Quality (CMAQ; http://www.epa.gov/asmdnerl/CMAQ) model run at the 12-km spatial resolution. An evaluation of the CMAQ model reveals overall agreement with the AQS network but with biased estimates (Mebust et al., 2003). The fused model combines the two data sources to attempt to adjust for the existing bias in the CMAQ model and produces predictions for census tract centroids across the entire State of North Carolina (Byun and Schere, 2006).

The term "downscaler" is used because adaptive smoothing of the areal CMAQ output is scaled to the point-level air monitoring data. The downscaler relates CMAQ output and air quality data using a spatial linear regression with bias coefficients (additive and multiplicative) that can vary in space and time. This approach to fusion modeling provides a new answer to the "change-of-support" problem where we would like to predict air pollution at a certain spatial resolution, but must reconcile the difference between point monitoring data and areal CMAQ output (Berrocal et al., 2010a, 2012). The fused output has complete spatial coverage of the study area at the census tract level. Further details and descriptions of the modeling technique and predictive performance can be found in Berrocal et al. (2012).

2.2. Demographic data

Measures of racial composition and socio-economic status (SES) for the general population of North Carolina were obtained from the 2000 US Census at the census tract level for the 1563 populated census tracts in the state (http://factfinder2.census.gov). The size of census tracts in North Carolina ranges from 0.4 to 3529.6 km^2 with a mean of 87.8 km^2 and a standard deviation (SD) of 171.3. Population density ranged from 2 to 4380 people per sq km with a mean of 442 people per sq km and SD of 550. Fig. 1 shows the 2000 population density for the State of North Carolina. SES variables obtained from the census included measures of poverty (percentage of census tract population below the poverty line), educational attainment (percentage of persons with less than a high school education) and measures of income (median household income). Racial composition for each census tracts was based on the tract percentage of those who self-reported as non-Hispanic black (NHB) and Hispanic. These variables were chosen based on associations between air pollution, race/ethnicity, and SES in previous studies (Miranda et al., 2011; Yanosky et al., 2008).

Table 1 shows the correlations between the SES and race/ethnicity variables. As expected, tract-level median household income was negatively correlated with both percent in poverty and percent less than high school education, with $r \sim -0.7$ in both cases. Percent in poverty was positively correlated with percent less than HS education and percent NHB, $r=0.61$ and 0.64, respectively. Correlations were significant in all cases ($p<0.0001$). We also included a neighborhood deprivation index (NDI) as a census level summary for living in a deprived neighborhood. The NDI was constructed as an aggregated measure of SES for North Carolina following the methodology described in Messer et al. (2006) and incorporates census SES variables. Using principal components analysis, the NDI was created as a standardized score having mean 0 and standard deviation of 1.

2.3. Statistical analysis

We examine the association between measures of SES, race/ethnicity, and average concentrations of O_3 and $PM_{2.5}$ at the census tract level using linear mixed regression models. We used the predicted $PM_{2.5}$ and O_3 concentrations as our outcome variables and examined the independent effect of SES, race/ethnicity on the level of each pollutant. We included a random intercept at the county level to account for unmeasured variation due to population-level characteristics. The census variables used in the models included: percent of population below the poverty line (poverty), median household income, percent of population with less than a high school (HS) level education, percent NHB, and percent Hispanic. We also included NDI as an independent covariate. We used the annual average $PM_{2.5}$ for the year 2002. For O_3 we consider both the annual average and also the average during the O_3 season for North Carolina, which is from April 1 through September 30. The model results were equivalent, and we present only those based on the O_3 season. All statistical analyses were performed using SAS 9.3 (SAS Institute, Cary NC).

3. Results

3.1. Race and SES summaries

Fig. 2 shows the spatial distribution of median household income and the percent in poverty by quintiles for census tracts in North Carolina. In the maps, darker shades are used to denote lower SES, for example lower income or higher poverty. In general, higher SES areas are located in the larger metropolitan regions of the state, while lower SES levels are clustered around the northeast and southern tracts of the state, as well as the far western Appalachian region. It is important to note that the smaller surface area of the census tracts clustered in metropolitan areas tend to mask the few tracts with lower SES characteristics. The maps of percent with less than high school education (not presented here)