Environment International 40 (2012) 79–87

Contents lists available at SciVerse ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Inequalities in cumulative environmental burdens among three urbanized counties in California

Jason G. Su [a,*], Michael Jerrett [a], Rachel Morello-Frosch [b,c], Bill M. Jesdale [b], Amy D. Kyle [a]

[a] 50 University Hall, Environmental Health Sciences, School of Public Health, University of California, Berkeley, CA 94720–7360, United States
[b] Department of Environmental Science, Policy and Management, University of California, Berkeley, CA 94720, United States
[c] Community Health and Human Development, School of Public Health, University of California, Berkeley, CA 94720, United States

ARTICLE INFO

Article history:
Received 4 June 2011
Accepted 10 November 2011
Available online 3 January 2012

Keywords:
Air pollution
Heat stress
Cumulative impacts
Inequality index
Environmental justice

ABSTRACT

Low-income communities and communities of color often suffer from multiple environmental hazards that pose risks to their health. Here we extended a cumulative environmental hazard inequality index (CEHII) – developed to assess inequalities in air pollution hazards – to compare the inequality among three urban counties in California: Alameda, San Diego, and Los Angeles. We included a metric for heat stress to the analysis because exposure to excessively hot weather is increasingly recognized as a threat to human health and well-being. We determined if inequalities from heat stress differed between the three regions and if this added factor modified the metric for inequality from cumulative exposure to air pollution. This analysis indicated that of the three air pollutants considered, diesel particulate matter had the greatest inequality, followed by nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$). As measured by our index, the inequalities from cumulative exposure to air pollution were greater than those of single pollutants. Inequalities were significantly different among single air pollutant hazards within each region and between regions; however, inequalities from the cumulative burdens did not differ significantly between any two regions. Modeled absolute and relative heat stress inequalities were small except for relative heat stress in San Diego which had the second highest inequality. Our analysis, techniques, and results provide useful insights for policy makers to assess inequalities between regions and address factors that contribute to overall environmental inequality within each region.

1. Introduction

Researchers and policy-makers have identified a higher frequency and magnitude of exposures to environmental stressors in communities of color and low-income communities (Institute of Medicine 1999; Morello-Frosch and Shenassa 2006). Such inequalities in environmental hazard exposures are increasingly recognized as potential determinants of health disparities (Finkelstein et al., 2005; Morello-Frosch and Jesdale, 2006; Morello-Frosch et al., 2011). Multiple environmental hazards may act cumulatively or interact in complex ways to magnify their risks to human health (National Research Council, 2009). For example, the synergy between ozone and other pollutants in causing health effects has been recently suggested (Mauderly and Samet, 2009). In previous work, we developed a cumulative environmental hazard inequality index (CEHII) to assess inequalities by racial-ethnic composition and by poverty status in exposure to multiple air pollutants in Los Angeles County (Su et al., 2009c). In this paper, we extend that method to compare inequalities in exposure to single and multiple environmental hazards in Los Angeles County with those in Alameda County and San Diego County. The environmental hazards are traffic-related air pollution (nitrogen dioxide or NO_2), fine particulate matter $PM_{2.5}$ (aerodynamic diameter less than 2.5 μm), and diesel particulate matter (diesel PM).

We broadened the method beyond air pollution by adding metrics for heat stress (both absolute and relative measures). Exposure to excessively hot weather is increasingly recognized as a threat to human health and well-being that will likely worsen with climate change (Harlan et al., 2006; Patz et al., 2005). Heat-related deaths are a chronic problem in arid climates (Center for Disease Control, 2005). Summer heat waves, sporadic periods of elevated temperatures outside the normal range of climate variability, occur throughout the world (Meehl and Tebaldi, 2004). They contribute to the global burden of disease and premature deaths (Confalonieri et al., 2007; Huynen et al., 2001; Medina-Ramon et al., 2006). More deaths are attributed to heat in temperate climates than in warm climates, probably because people in temperature zones are less acclimated to high temperatures (Rey et al., 2007; Saanen et al., 2007). Some research has found significant interactions between heat stress and high concentrations of air pollutants such as ozone and NO_2 (Basu, 2009; Theoharatos et al., 2010; Vaneckova et al., 2008). The highest

* Corresponding author. Tel.: +1 510 643 0102; fax: +1 510 642 5815.
E-mail address: jasonsu@berkeley.edu (J.G. Su).

0160-4120/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.envint.2011.11.003

morbidity and mortality associated with extreme heat appear to occur in cities, falling disproportionately upon marginalized groups, particularly the poor, minority populations, and the elderly (Center for Disease Control, 2009). Therefore, these disadvantaged communities may experience disproportionate burdens from both ambient air pollutant exposures and heat stress. In this paper, we applied the CEHII method to quantitatively assess inequalities in exposure to air pollution and heat stress in three urban counties.

2. Materials and methods

This section first describes the data sources used to develop metrics for air pollution and heat stress, and race-ethnicity or socioeconomic status. We then explain the techniques used to calculate inequalities in exposure to single and cumulative hazards.

2.1. Air pollution

We estimated NO_2 using land use regression models (Su et al., 2009a) to model spatial variation in traffic pollutants for the three regions, using detailed pollution data available from earlier studies (Ostro and Kim, 2008; Ross et al., 2006; Su et al., 2009b). Because $PM_{2.5}$, levels vary over large areas, and there were limited monitoring sites available, we used geostatistical interpolation to estimate exposure to $PM_{2.5}$ based on a network of 23 continually operating monitors (Krewski et al., 2009). Diesel PM concentrations at the census tract level were estimated by the US Environmental Protection Agency for 1999 (See National-Scale Air Toxics Assessment: http://www.epa.gov/ttn/atw/nata1999). Census tract level NO_2 and $PM_{2.5}$ mean concentrations were extracted from the corresponding model surfaces. To exclude extreme outliers that existed in the data, any pollutant within a census tract with a z-score greater than 5 was removed from analysis.

2.2. Absolute and relative summer heat stress

Increased temperature and radiation directly raise body temperature, and increased humidity slows cooling of the body by decreasing sweat evaporation (English et al., 2009). An increase in wind speed, by contrast, increases sensible and latent heat loss (Dikmen and Hansen, 2009). Therefore, high temperature, high humidity, and low wind speed increase an individual's risk of heat illness (Maloney, 1998). For summer heat stress, we used Steadman's (1984) apparent temperature, calculated by:

$$T_{ap} = -1.8 + 1.07 * T_{amb} + 2.4 * P - 0.92 * v + 0.042 * Q$$

where T_{ap} is the estimated apparent temperature and T_{amb} the measured ambient temperature, both in °C; P, v and Q are vapor pressure (kPA), wind speed (m/s), and solar radiation (W/m^2), respectively. In estimating daily heat stress, the daily maximum ambient temperature was used for T_{amb}, and daily average vapor pressure and wind speed for P and v, respectively.

Meteorological data were acquired from the California Irrigation Management Information System (CIMIS). Daily data in summer months (July, August, and September) from 123 monitoring stations for 2001–2005 were used to estimate summer heat stress. Literature suggests that when the temperature is above 40 °C, people working outside should take extreme caution (Harlan et al., 2006). The apparent temperature exceeding 40 °C was treated as absolute exceedance temperature (i.e., difference between apparent temperature and 40 °C). The total absolute extreme temperature exceedances were summarized for each monitoring station for a summer season and then divided by the number of days with temperature measured above 40 °C in the same period to derive a per day absolute temperature exceedances for that summer season. This value was estimated for each of the five years and then further averaged to reflect the five-year mean per day absolute temperature exceedances (°C per day).

Distance to coast (km), latitude (degrees), and elevation (m) data (Brody et al., 2008) were then used to model per day absolute temperature exceedances for the state of California using data from the 123 monitoring stations. The modeling results were then used to predict absolute daily temperature exceedances for each census tract for the counties of Alameda, Los Angeles, and San Diego.

An individual's response to heat is also conditioned by their local climate. We thus calculated the total temperature exceedances for each monitoring station based on its 1971–2000 historical normal maximum temperature for a summer season (i.e., July, August, and September). The total temperature exceedances were then divided by the number of days with temperature above historical normal maximum temperature in the same period to derive a per day relative temperature exceedances (°C per day) for that summer season. The estimations were conducted for the 2001–2005 summer seasons and daily relative temperature exceedances of a five-year mean were calculated and used for our analysis. Because of the lack of 30-year CIMIS meteorological data to derive historical normal maximum temperatures for each monitoring station, the historical normal maximum temperature data for the CIMIS monitoring stations were derived from the U.S. National Climate Data Center (NCDC) for 1971–2000 based on the closest distance principle. The relative daily temperature exeedances E_j for a summer season for at location j were calculated as follows:

$$E_j = \frac{1}{n}\sum_{i=1}^{n}\left(Tap_{ij} - \overline{T}_j^{\max}\right)$$

where $\overline{T}_j^{\max}$ is the mean historical normal maximum temperature from the months of July, August, and September at the j^{th} location. Tap_{ij} is the i^{th} day apparent temperature in the three-month period exceeding the mean historical normal maximum temperature at the j^{th} location, and n is the total number of days with apparent temperature greater than the mean historical normal maximum temperature. An inverse distance weighting function was used to assign the relative daily temperature exceedances from the 123 monitoring stations to the census tracts in the counties of Alameda, Los Angeles and San Diego.

2.3. Neighborhood racial/ethnic composition and poverty rate

We selected two widely used neighborhood composition metrics. The first metric, based on the 2000 US Census, was the census tract racial-ethnic composition, defined as the percentage of non-Whites in the population. The second metric was the proportion of the population with an income less than 200% of the federal poverty level, because on average, families need an income equal to about two times the federal poverty level to meet their most basic needs (Berstein et al., 2000). To reduce the complexity of the paper, only inequalities by racial-ethnic composition are described in the main text. Inequalities across neighborhood poverty gradients were similar and are included in Supplementary Figs. A1, A2 and A3.

2.4. Cumulative environmental hazard inequality index

To measure inequality related to racial-ethnic or socioeconomic measures, we modified a “concentration index” developed for the World Bank to estimate health inequalities across regions and groups