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Inequalities in cumulative environmental burdens among three urbanized counties in California

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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

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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

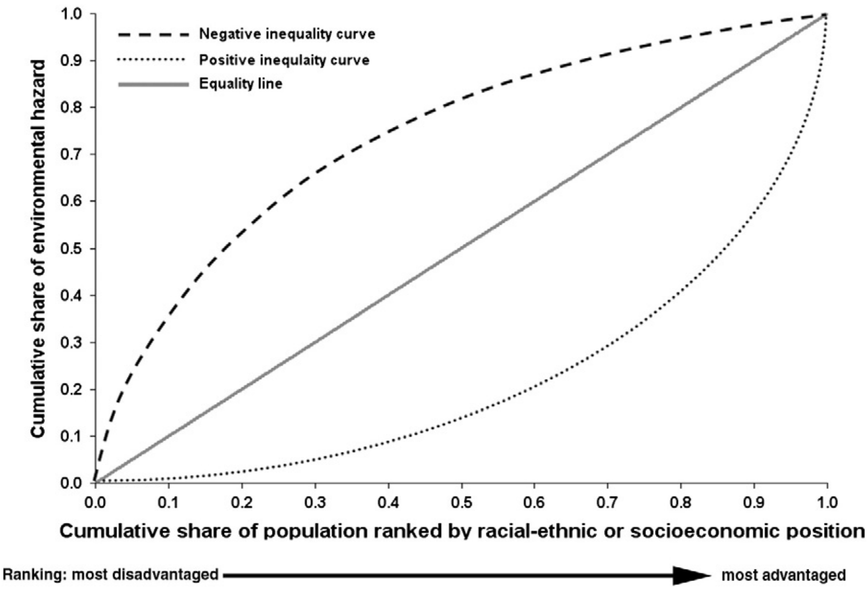

Fig. 1. Positive and negative inequality curves. A positive curve indicates that census tracts with a higher percentage of White residents or lower poverty rates have lower shares of environmental hazard. The negative curve indicates that census tracts with a lower percentage of White residents, or higher poverty rates, bear a higher proportion of the environmental hazards. The equality line indicates that environmental hazards are distributed equally among various groups of race-ethnicity or among various levels of poverty status.

in a population (O'Donnell et al., 2008) (Fig. 1). A summary measure of inequality is defined as twice the area between an inequality curve and the equality line:

$$I = 1-2\int_1^n e(s)ds$$

This measure gives a quantitative summary of inequality among groups, in which 0 indicates that all groups, or in our case all census tracts, have an equal share of environmental burden (i.e., no inequality), and 1 is the highest level of inequality, where one group or one census tract bears whole detrimental burden.

Such an index only captures inequalities associated with single factors. To measure the socioeconomic or racial-ethnic inequalities from multiple burdens, we calculated the cumulative environmental hazard inequality index (CEHII) (Su et al., 2009c). The index uses the cumulative proportion of the population – ranked by area-based racial-ethnic composition or socioeconomic strata, starting from the most disadvantaged – against cumulative environmental hazard burdens. We assumed the existence of fully multiplicative burdens (i.e., every pollutant was multiplicatively synergistic with every other pollutants). This methodological approach integrates multiple burdens and social data into a single index. Two inequality indices in exposure to multiple environmental burdens were investigated: one with the cumulative environmental burdens from three air pollutants NO_2, $PM_{2.5}$, and diesel PM; and another with the cumulative environmental burdens from air pollutants and heat stress metrics.

3. Results

This section first describes summer heat stress predictions (i.e., the absolute and relative heat stresses based on daily temperature exceedances) at the census tract level, followed by tract level descriptive statistics of race-ethnicity and air pollution. The inequalities from exposure to air pollution and heat stress in each of the three regions are summarized. Within-county inequalities are compared between NO_2, $PM_{2.5}$, diesel PM, and their cumulative environmental burdens, followed by adding in heat stress. Finally, the inequalities in exposure to single and cumulative burdens between the three counties are compared for the three air pollutant hazards and heat stress. The "t" statistical tests are used to assess the significance of differences in all the inequality indices discussed.

3.1. Prediction of heat stress

With a multiple linear regression model we found that distance to coast, elevation and latitude explained 74.6% (R^2) of variance in the absolute heat stress measure (based on temperature exceeding 40 °C) (Table 1). All three predictors had expected signs of correlation, the tolerance rates for collinearity were all greater than 0.85, and the Variance Inflation Facts (VIF) were all less than 1.17. Absolute heat stress was then predicted to the census tract level using the model from Table 1. Based on Fig. 2a–c, the absolute heat stress in the three counties generally increases when moving inland from coastal areas.

The relative heat stress measures (based on temperature exceeding local historical normal maximum temperature) from the weather monitoring stations were projected to the census tracts in the three counties by an inverse distance weighting function. The relative heat stress mapped in Fig. 3a–c demonstrates that these stresses are usually higher in places closer to the coastal areas and in low elevation regions.

3.2. Descriptive statistics

For neighborhood racial-ethnic composition, the census tract with the highest percentage of non-White population was in Los Angeles County with 99.6% (Table 2). The census tract with the

Table 1
Prediction of daily absolute temperature exceedances for the State of California using 123 meteorological monitoring stations.

Predictor	Coefficients		t	Sig.	Collinearity statistics	
	B	Std. error			Tolerance	VIF[a]
Constant	28.7784	3.5896	8.017	.000		
Latitude (degrees)	−.7323	.0994	−7.369	.000	.989	1.011
Elevation (m)	−.0018	.0002	−8.693	.000	.863	1.159
Distance to coastal line (km)	.0553	.0032	17.463	.000	.858	1.166

[a] VIF = variance inflation factor.

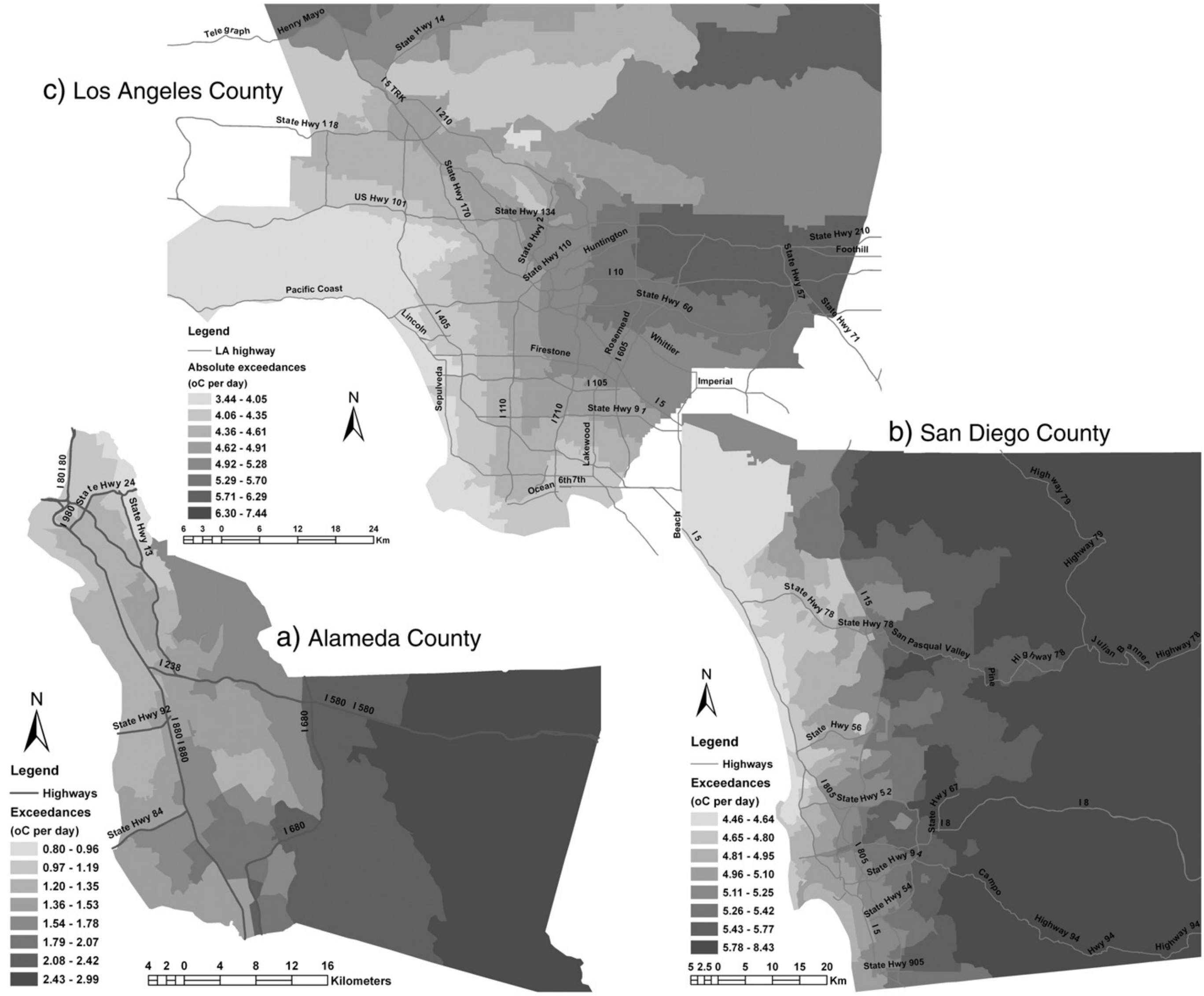

Fig. 2. Predicted absolute heat stress for the counties of Alameda (a), San Diego (b) and Los Angeles (c).

smallest non-White population had 0% non-Whites, also found in Los Angeles. Both Los Angeles and Alameda counties had more than 50% non-White populations (51.3% for Los Angeles and 51.5% for Alameda), but Los Angeles had the highest regional variation with a standard deviation of 28.7%. Los Angeles had the greatest maximum (47.8 ppb) and mean NO_2 concentrations (22.3 ppb) compared to Alameda County (maximum 21.78 ppb and mean 15.2 ppb) and San Diego County (maximum 29.32 and mean 13.5 ppb). The standard deviation was the smallest in Alameda (3.1 ppb). Similar to NO_2, the mean modeled concentrations of $PM_{2.5}$ and diesel PM were highest in Los Angeles County. Compared to San Diego County, Alameda County had lower mean modeled concentrations of $PM_{2.5}$ and diesel PM.

Los Angeles County had the greatest maximum absolute temperature exceedances (7.44 °C per day) but San Diego County had the greatest mean absolute temperature exceedances (5.18 °C per day). San Diego County had the greatest minimum absolute temperature exceedances (4.46 °C per day) but the smallest standard deviation (0.38 °C per day) among the three counties. By contrast, Alameda County had the lowest maximum (2.97 °C per day) and mean (1.47 °C per day) absolute temperature exceedances, although the standard deviation (0.42 °C per day) was higher compared to that of San Diego.

For relative heat stress, San Diego County had the highest maximum (3.64 °C per day) relative temperature exceedances. Alameda County, by contrast, had the greatest mean relative temperature exceedances (1.57 °C per day). Los Angeles County had the lowest mean relative temperature exceedances (1.14 °C per day) and its maximum relative temperature exceedances (2.11 °C per day) was between those of Alameda County and San Diego County. Overall, the degree of relative heat stress was lower compared to that of absolute heat stress.

3.3. Differences in inequality between NO_2, $PM_{2.5}$, diesel PM, heat stress, and their cumulative burdens within counties

Inequality curves for each of the three air pollutant estimates, the two heat stress indicators, and the cumulative burdens are displayed in Fig. 4a–c. The corresponding inequalities in exposure to single and cumulative environmental burdens, including the 95% confidence intervals, are shown in Table 3. Within county difference results are shown in Tables 4 and 5.

In Alameda county, among the three air pollutants, the greatest inequality existed for diesel PM (concentration index, referred as $C = -0.128$), followed by NO_2 pollution ($C = -0.045$) and $PM_{2.5}$ ($C = 0.003$) (Fig. 4a and Table 3). Although different in size, all the

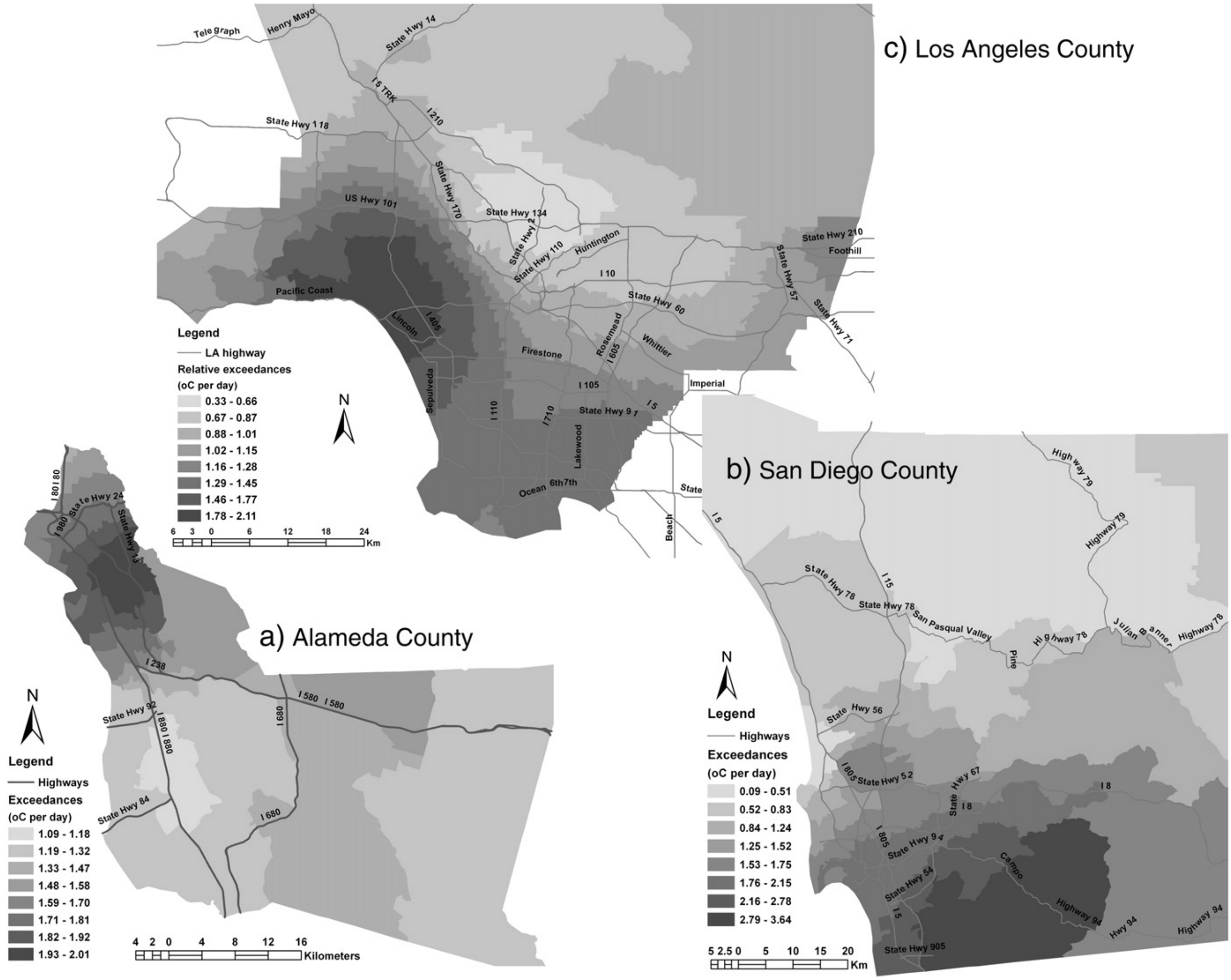

Fig. 3. Predicted relative heat stress for the counties of Alameda (a), San Diego (b) and Los Angeles (c).

single indices were significantly different from equality (Table 3). The inequality in cumulative exposure to three air pollutants (cumulative burdens A) was greater than for any single pollutant alone ($C = -0.179$). The negative signs associated with the inequalities indicated that neighborhoods with a higher proportion of non-Whites encounter greater exposure to these environmental hazards. For $PM_{2.5}$, however, neighborhoods with a higher proportion of non-Whites were exposed to lower modeled levels of air pollutants. Because the inequality from $PM_{2.5}$ was relatively small and had an opposite sign compared to inequalities from the other two air pollutants, the inequality in cumulative exposure to the three environmental hazards was only borderline significantly different from that of diesel PM ($t = 1.845$ and $p = 0.066$). All other inequalities in exposure to single pollutants were significantly different from one another and from the inequality in exposure to the three pollutants (Table 4).

Table 2
Descriptive statistics for race-ethnicity and heat stress at census tract level within counties.

Measures	Alameda				San Diego				Los Angeles			
	Min	Mean	Max	Std	Min	Mean	Max	Std	Min	Mean	Max	Std
% of population that is nonwhite	6.82	51.46	98.97	23.07	1.95	33.82	91.78	20.46	0.00	67.37	99.96	28.70
% of population that is Hispanic	0.36	17.88	81.39	14.19	0.00	26.38	96.11	21.57	0.00	43.37	99.61	29.52
% of population that is Black	0.00	16.95	84.26	20.32	0.00	5.36	60.76	7.02	0.00	9.48	96.18	15.80
% of population that is Asian	0.00	18.98	92.81	15.42	0.00	8.67	72.90	10.16	0.00	11.93	82.29	14.09
Traffic-related air pollution (NO_2) (ppb)	6.21	15.23	21.78	3.10	5.68	13.52	29.32	4.26	1.50	22.29	47.82	5.06
Air pollution fine particulates ($PM_{2.5}$) ($\mu g\ m^{-3}$)	11.43	11.81	13.21	0.25	11.89	14.00	16.06	0.85	6.58	20.26	24.26	2.68
Air pollution diesel PM ($\mu g\ m^{-3}$)	0.46	1.85	12.50	1.20	0.44	2.74	39.02	5.59	0.65	2.91	26.34	2.26
Absolute heat stress (°C per day)[a]	0.80	1.47	2.97	0.42	4.46	5.18	6.52	0.38	3.44	4.83	7.44	0.61
Relative heat stress (°C per day)[b]	1.09	1.57	2.01	0.28	0.09	1.47	3.64	0.75	0.33	1.14	2.11	0.33

[a] Refers to mean temperature exceedances for the days when apparent temperatures were above 40 °C for the summer months (July, August and September) in the 2001–2005 periods.
[b] Refers to mean temperature exceedances for the days when apparent temperatures were above the local historical normal maximum temperature for the same period as those used for calculating absolute heat stress.

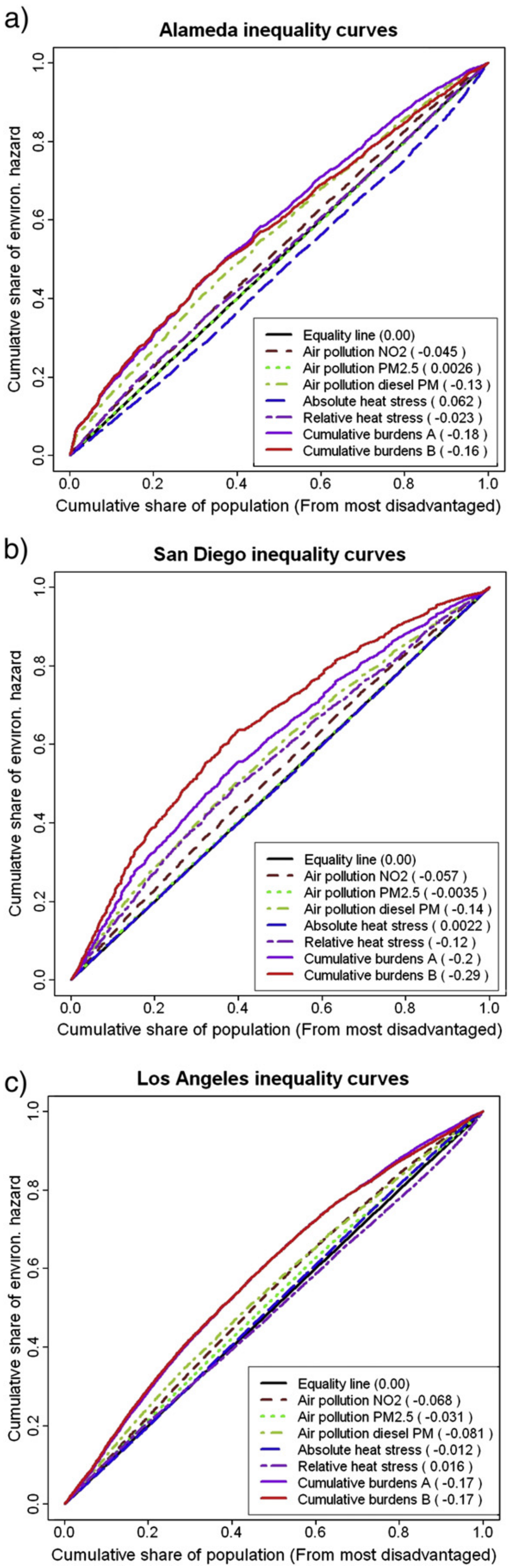

Fig. 4. Inequalities in exposure to NO_2, $PM_{2.5}$, diesel PM, absolute and relative heat stresses, and the cumulative environmental burdens from exposure to the three air pollutants (cumulative burdens A) and from exposure to both air pollution and heat stress (cumulative burdens B) in the counties of Alameda (4a), San Diego (4b) and Los Angeles (4c).

When heat stress was taken into account, we found (Fig. 4a and Table 3) that heat stress from absolute temperature exceedances had the second highest inequality ($C=0.062$), only lower than the inequality from diesel PM; however, the heat stress from relative temperature exceedances had the second lowest inequality ($C=-0.023$), only slightly greater than inequality from $PM_{2.5}$. Furthermore, the inequality from absolute heat stress took a positive sign, indicating neighborhoods with a greater proportion of Whites experienced higher absolute temperature exceedances. By contrast, the inequality from relative heat stress took a negative sign, indicating that neighborhoods with a greater proportion of non-Whites experienced higher relative temperature exceedances, although the level of inequality was smaller than that of absolute temperature exceedances. Based on the 95% confidence intervals in Table 3, inequalities from both absolute and relative heat stress were significantly different ($p<0.01$) from the equality line. In addition, inequalities from both absolute and relative heat stress were significantly different compared to inequalities from other single and cumulative environmental burdens ($p<0.01$) (Fig. 5). Because of the opposite direction in inequality for the absolute and relative heat stresses, the inequalities in exposure to the cumulative impacts from the three air pollutants and the two heat stress indices were not significantly different from those of the three pollutants ($t=0.646$ and $p=0.519$) (Table 5). The relative greater degree of inequality from diesel PM made it non-significant compared to that of the cumulative impacts from the three air pollutants and the two heat stress indices ($t=1.107$ and $p=0.269$). Heat stress and other single and cumulative burdens were significant different from one another (Table 5).

In San Diego, among the three pollutants, the greatest inequality was from diesel PM ($C=-0.138$), followed by NO_2 ($C=-0.057$) and $PM_{2.5}$ ($C=-0.004$) (Fig. 4b and Table 3). The cumulative inequality in exposure to the three pollutants was greater than for any single pollutants, and the inequality indices reflected that neighborhoods with a higher proportion of non-Whites experienced greater environmental hazard burdens. Comparing between the three environmental hazards and the cumulative burdens, all the inequalities were significantly different from one another ($p<0.05$) (Table 4). When heat stress was taken into consideration, we found that the inequality from absolute heat stress was the smallest ($C=0.002$) among all the indices considered (Table 3); however, the inequality from relative heat stress was the second highest ($C=-0.116$), only smaller than (but not statistically significantly different from) that of diesel PM ($t=1.249$ and $p=0.212$) (Table 5). The negative sign and the high degree of inequality from relative heat stress indicated that neighborhoods with a higher proportion of non-Whites experienced far greater relative temperature exceedances. By contrast, the absolute heat stress is non-significantly different from the equality line based on the 95% confidence interval in Table 3 (-0.001, 0.006). The addition of heat stress significantly increased the inequality from exposure to the three air pollutants (inequality changed from -0.199 to -0.293).

In Los Angeles county, although inequality from diesel PM ($C=-0.081$) was smaller than that of Alameda and San Diego counties, among the three environmental hazards considered, diesel PM exposure inequality was still the greatest in Los Angeles, followed by NO_2 (-0.068) and $PM_{2.5}$ (-0.031) (Fig. 4c and Table 3). The inequality in exposure to the three environmental hazards combined was greater than from any single factor. The inequalities had the following characteristics: (1) they were significantly different from

Table 3
Race-ethnicity inequalities in exposure to single and cumulative environmental hazards from air pollution and heat stress.

Inequality indicators	Alameda		San Diego		Los Angeles	
	Ineq. index	95% CI	Ineq. index	95% CI	Ineq. index	95% CI
NO_2	−0.045	(−0.057, −0.035)	−0.057	(−0.070, −0.044)	−0.068	(−0.072, −0.063)
$PM_{2.5}$	0.003	(0.001, 0.004)	−0.004	(−0.006, −0.0006)	−0.031	(−0.034, −0.028)
Diesel PM	−0.128	(−0.161, −0.095)	−0.138	(−0.167, −0.110)	−0.081	(−0.091, −0.072)
Cumulative burdens A[a]	−0.179	(−0.222, −0.136)	−0.199	(−0.239, −0.159)	−0.171	(−0.182, −0.159)
Absolute heat stress	0.062	(0.042, 0.082)	0.002	(−0.001, 0.006)	−0.012	(−0.015, −0.009)
Relative heat stress	−0.023	(−0.034, −0.011)	−0.116	(−0.136, −0.097)	0.016	(0.009, 0.024)
Cumulative burdens B[a]	−0.159	(−0.202, −0.115)	−0.293	(−0.337, −0.249)	−0.171	(−0.183, −0.159)

[a] Cumulative burdens A refers to the inequality of cumulative burdens from NO_2, $PM_{2.5}$ and diesel PM. Cumulative burdens B refers to the inequality of cumulative burdens from NO_2, $PM_{2.5}$, diesel PM, absolute and relative heat stresses.

equality; (2) they demonstrated that neighborhoods with higher proportions of non-Whites experienced greater environmental hazard burdens; and (3) they were significantly different from one another (Table 4). When heat stress was considered, it showed that inequalities from the absolute and relative heat stresses were in close range except for the direction of influence (−0.012 vs. 0.016). The effect of having opposite signs on the inequality index meant that the two heat stress indices canceled each other out in the cumulative inequality from heat stress. The combined heat stress thus did not contribute significantly to the overall inequality for the county: the difference between the cumulative burden inequalities with and without the addition of heat stress had a t value of 0.012 and a p value of 0.991 (Table 5).

3.4. Differences in inequality from exposure to air pollution, heat stress, and their cumulative burdens between counties

The degree of inequality in air pollution hazard decreased from diesel PM to NO_2 and to $PM_{2.5}$ for all the three counties (Fig. 3 and Table 3). Significant differences in inequality existed, however, between the three counties for $PM_{2.5}$ exposure ($p<0.05$, see Table 6). For NO_2, a significant difference was seen between Alameda and Los Angeles counties ($p=0.001$) and a marginally non-significant difference between San Diego and Los Angeles counties ($p=0.083$). By contrast, Alameda and San Diego counties were not significantly different in inequality from NO_2 exposure ($p=0.236$). For diesel PM, significant differences in inequality were seen between Alameda and Los Angeles counties ($p<0.001$) and between San Diego and Los Angeles counties ($p<0.001$), but not between Alameda and San Diego counties ($p=0.653$). All inequalities from cumulative burden in the three counties were greater than the corresponding single factor inequalities; however, no statistically significant difference existed for the inequalities from cumulative burdens between any two counties.

For absolute and relative heat stresses, the directions of inequality were always opposite for a given county. In Alameda, the degree of inequality from the absolute heat stress was about three times that of its relative heat stress. In Los Angeles, the inequality from absolute heat stress was very close in value to that of relative heat stress except for the direction of influence. In San Diego, relative heat stress created the highest degree of inequality for all the heat stress indices in the three counties ($C=-0.116$). The inequality from absolute heat stress in San Diego, by contrast, is not significantly different from that of the equality line. The small levels of inequality from heat stress in Alameda and Los Angeles counties meant that the addition of heat stress did not change the cumulative relationship these two counties had for the air pollution burdens. We calculated a t value of 0.482 and a p value of 0.630 for the air pollution burden inequalities between Alameda and Los Angeles; corresponding values became 0.681 and 0.496 when heat stress indices were added (Table 6). Because of the high impact from relative heat stress in San Diego County, the addition of heat stress made the inequalities in cumulative burdens significant between Alameda and San Diego counties ($t=3.866$ and $p<0.001$) and between San Diego and Los Angeles counties ($t=7.334$ and $p<0.001$) (Table 6).

Table 4
Within-county differences in inequality from exposure to NO_2, $PM_{2.5}$, diesel PM and the cumulative impacts using t tests.

County	Inequality indicators	$PM_{2.5}$		Diesel PM		Cumulative A[a]	
		(t)	(p)	(t)	(p)	(t)	(p)
Alameda	NO_2	8.010	<0.001	4.675	<0.001	5.830	<0.001
	$PM_{2.5}$			7.835	<0.001	8.194	<0.001
	Diesel PM					1.845	0.066
San Diego	NO_2	7.845	<0.001	5.027	<0.001	6.596	<0.001
	$PM_{2.5}$			9.173	<0.001	9.544	<0.001
	Diesel PM					2.418	0.016
Los Angeles	NO_2	12.569	<0.001	2.520	0.012	16.351	<0.001
	$PM_{2.5}$			9.821	<0.001	23.399	<0.001
	Diesel PM					11.771	<0.001

[a] Cumulative A refers to the inequality of cumulative burdens from NO_2, $PM_{2.5}$ and diesel PM.

Table 5
Identification of within-county differences in inequality from exposure to the two heat stress indices, the three air pollutants and their cumulative impacts.

Region	Inequality indicators	Absolute heat stress		Relative heat stress		Cumulative B[a]	
		(t)	(p)	(t)	(p)	(t)	(p)
Alameda	NO_2	9.132	<0.001	2.701	0.007	4.916	<0.001
	$PM_{2.5}$	5.857	0.001	4.210	<0.001	7.232	<0.001
	Diesel PM	9.753	<0.001	5.959	<0.001	1.107	0.269
	Cumulative A[a]	9.901	<0.001	6.819	<0.001	0.646	0.519
	Absolute heat stress			7.206	<0.001	9.021	<0.001
	Relative heat stress					5.899	<0.001
San Diego	NO_2	8.572	<0.001	4.919	<0.001	10.096	<0.001
	$PM_{2.5}$	2.434	0.015	11.200	<0.001	12.913	<0.001
	Diesel PM	9.535	<0.001	1.249	0.212	5.784	0.001
	Cumulative A[a]	9.808	<0.001	3.644	<0.001	3.095	0.002
	Absolute heat stress			11.699	<0.001	13.151	<0.001
	Relative heat stress					7.216	<0.001
Los Angeles	NO_2	18.795	<0.001	17.881	<0.001	15.481	<0.001
	$PM_{2.5}$	9.237	<0.001	11.324	<0.001	22.008	<0.001
	Diesel PM	13.527	<0.001	15.503	<0.001	11.332	<0.001
	Cumulative A[a]	26.496	<0.001	26.670	<0.001	0.012	0.991
	Absolute heat stress			6.566	<0.001	24.939	<0.001
	Relative heat stress					25.496	<0.001

[a] Cumulative A refers to the inequality of cumulative burdens from NO_2, $PM_{2.5}$ and diesel PM. Cumulative B refers to the inequality of cumulative burdens from NO_2, $PM_{2.5}$, diesel PM, absolute and relative heat stresses.

Table 6
Differences in inequalities in exposure to single and cumulative environmental hazards between Alameda, San Diego and Los Angeles counties using t tests.

Inequality indicators	Alameda vs San Diego		Alameda vs Los Angeles		San Diego vs Los Angeles	
	(t)	(p)	(t)	(p)	(t)	(p)
NO_2	1.186	0.236	3.287	0.001	1.736	0.083
$PM_{2.5}$	2.959	0.003	9.487	<0.001	10.146	<0.001
Diesel PM	0.450	0.653	3.320	<0.001	4.734	<0.001
Cumulative burdens A[a]	0.627	0.531	0.482	0.630	1.845	0.065
Absolute heat stress	7.641	<0.001	13.039	<0.001	4.467	<0.001
Relative heat stress	6.580	<0.001	3.809	<0.001	14.599	<0.001
Cumulative burdens B[a]	3.886	<0.001	0.681	0.496	7.334	<0.001

[a] Cumulative burdens A refers to the cumulative burdens from NO_2, $PM_{2.5}$ and diesel PM. Cumulative burdens B refers to the cumulative burdens from NO_2, $PM_{2.5}$, diesel PM, absolute and relative heat stresses.

4. Discussion and conclusion

In this study, inequalities by racial-ethnic composition from exposure to NO_2, $PM_{2.5}$, diesel PM and their cumulative impacts were compared both within and between counties. Additionally, burdens from absolute and relative heat stresses were added to these models. We treated absolute heat stress as experiencing extreme temperatures above 40 °C and relative heat stress as having extreme temperatures above local historical normal maximum temperatures.

Overall, our research corroborates other studies showing that communities of color bear greater environmental pollutants than predominantly White and more affluent communities (Marshall, 2008; Su et al., 2009c). Absolute heat stress, expressed in the mean per day temperature exceedances in excess of 40 °C, by contrast, followed the opposite direction in Alameda County: communities of color experienced less absolute extreme temperature exceedances. This might reflect that the White population in Alameda County mainly lived in the eastern suburbs further from the coast, leading to higher temperatures. San Diego County, however, did not have significant inequality based on absolute heat stress. In Los Angeles, although absolute heat stress was relatively small in scale, communities with higher proportions of non-White residents experienced greater levels of this type of heat stress. This is probably because those disadvantaged groups tend to reside further inland, especially in East Los Angeles.

Relative heat stress inequalities were among the smallest in the indices considered in this study for both Alameda and Los Angeles counties, indicating that relative heat stress alone might not be the only significant factor resulting in adverse environmental burdens for these two counties. Absolute heat stress in Los Angeles County is also a relatively small factor. In San Diego, however, we saw that neighborhoods with greater percentage of non-Whites experienced far greater inequality in relative temperature exceedances.

Inequalities from absolute heat stress always took an opposite sign compared to those of relative heat stress for a given county. These canceling effects in heat stress inequality, however, were not the same in the three counties. In San Diego County, the relative heat stress inequality was the highest, and absolute heat stress did not contribute significantly to the overall heat stress inequality. In Los Angeles County, the two heat stress indices canceled each other out. The canceling effect in Alameda County was between San Diego County (no cancelation) and Los Angeles County (almost total cancelation), due to the relatively greater absolute heat stress inequality (compared to its relative heat stress inequality).

In modeling heat stress, we used the meteorological data from monitoring stations. Generally weather stations are installed high enough to avoid wind obstruction and reduce impact from ground features. Our modeling process therefore did not take into consideration any ground features that might mitigate heat stress such as the presence of vegetation. Urban vegetation may provide shade, moderate temperature and help reduce heat-related illness for city dwellers (Blum et al., 1998; Cummins and Jackson, 2001; Nowak and Dwyer, 1997; Nowak et al., 1998). Land surface temperature is a measurement of how hot the land is to the touch. It differs from air temperature because land heats and cools more quickly than air. Land surface temperature should be more accurate in measuring actual heat stress felt by people on the ground. Future attempts to quantify heat stress will incorporate surface temperature derived from remote sensing data to detect small area variation of temperature. Heat stress is also related to housing characteristics and air conditioning (Kovats and Hajat, 2008). Air conditioning was found to be an important protective factor for heat related mortality (Semenza et al., 1996). Subsequent studies should also take these household variables into account given the availability of such data.

For the air pollutants NO_2, $PM_{2.5}$, and diesel PM, the inequalities within a county were significantly different in all three regions. The inequalities in cumulative environmental burdens with and without the impact of heat stress were also significantly different from those of single burdens, meaning there are corresponding significant differences in spatial distribution. Because of the relatively small effect from heat stress, the difference in cumulative inequalities with and without the burden from heat stress was not significant, meaning the addition of heat stress did not substantially influence the spatial pattern of the inequality. In this way, the inequality indices could be used to identify if significant spatial difference or correlation exists when combining multiple environmental burdens into one single index.

When we calculated the series of inequality indices using poverty status instead of racial-ethnic status, the results were similar (see Supplementary materials). This is not surprising because at the census tract scale, poverty and non-white were highly correlated ($r = 0.69$ in Alameda County and 0.77 in Los Angeles County). In San Diego County, by contrast, the inequality in exposure to relative heat stress was −0.044, much smaller than that of racial-ethnic gradient ($C = -0.12$). This demonstrates that though low income communities experienced greater exposure to relative heat stress, it was the communities of color had the greatest unfair exposure to this heat stress in San Diego County.

The single and cumulative environmental hazard inequality indices represent the relative degree of inequality in a region. Higher spatial variation of a pollutant would normally result in a greater inequality index, while the homogeneity of an environmental hazard in spatial distribution would create an index not significantly different from equality. If levels of environmental hazards in a region are largely above the National Ambient Air Quality Standard or above a known benchmark, normalization by benchmark standard or other techniques should be used to identify those hot spots. Special attention should also be paid to areas with very few environmental hazards as well as areas that lack a particular environmental hazard while other environmental hazard levels are high. The synergistic approach applied in our paper may inadvertently indicate that the cumulative impacts in such an area are lower, which in fact may not be the case.

In our analysis, any pollutant within a census tract with a z-score greater than 5 was removed. We also tested scenarios where no outliers were removed, and we did not see any large changes in inequality indices, but the curves were less smooth. For example, in San Diego, when all the census tracts were included we identified that the 10% of census tracts with the highest proportion of Whites had greater levels of estimated exposure to diesel PM (the curve lies under the equality line). After further investigation, we found that those communities were living on Coronado Island. Because of their proximity to the San Diego ports, Naval Complex, and San Diego International Airport, these communities had higher diesel PM exposure. This inequality, although, did not change the overall pattern that neighborhoods of predominantly non-Whites had higher inequality in environmental burdens.

Our research did not further classify minority population into African American, Hispanic, Asian, and other race-ethnicity groups. These individual groups might have different degrees of inequality compared to the overall non-White group; however, the techniques used here provide a way to assess race-ethnicity and poverty inequalities and assist decision makers in prioritizing efforts to address inequality issues.

Traditionally, epidemiological and environmental studies have focused on single environmental indices to examine the marginal associations between single burdens and health outcome. In reality, these burdens coexist and they might interact to synergistically worsen health status. Evidence for multiplicative burdens (Environmental Protection Agency, 2006; Mauderly and Samet, 2009) makes assessing single environmental or social factors problematic. Similarly, inequalities in exposure to multiple significant environmental hazards should also be applied to identify the cumulative burden inequality a region might experience. In Alameda County, census tracts with a high proportion of White residents experiencing greater heat stress than predominantly non-White census tracts, but when influences from multiple burdens were taken into consideration, it was the neighborhoods of non-Whites that had greater cumulative environmental burdens. Our research shows that inequalities from multiple environmental hazards were generally significantly different and greater than single hazard inequalities. This also demonstrates the importance of taking into account the cumulative burdens in assessing inequalities of a region for policy making.

Overall, our index allows for analysis of the environmental inequality from multiple hazard exposures. Although scientific evidence on the functional form of cumulative effects remains formative, the framework provides a screening assessment that incorporates cumulative burdens and social data into one indicator. Focusing on cumulative burdens may lead to policies that directly target communities of concern and consequently lead to improvements in public health.

Figures A1, A2 and A3 demonstrate the inequalities in exposure to the three environmental hazards (NO_2, $PM_{2.5}$ and diesel PM), the two heat stress measures and their cumulative impacts based on poverty gradient. Supplementary materials related to this article can be found online at: doi:10.1016/j.envint.2011.11.003.

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References

Basu R. High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ Health 2009;8:40.
Berstein J, Brocht C, Spade-Aguilar M. How much is enough? Basic family budgets for working families. Washington, DC: Economic Policy Institute; 2000.
Blum LN, Bresolin LB, Williams MA. From the AMA Council on Scientific Affairs. Heat-related illness during extreme weather emergencies. JAMA 1998;279:1514.
Brody SD, Zahran S, Vedlitz A, Grover H. Examining the relationship between physical vulnerability and public perceptions of global climate change in the United States. Environ Behav 2008;40:72–95.
Center for Disease Control. Heat-related mortality - Arizona, 1993–2002, and United States, 1979–2002, 54. Morbidity & Mortality Weekly Report; 2005. p. 628–30.
Center for Disease Control. Extreme heat: a prevention guide to promote your personal health and safety; 2009.
Confalonieri U, Menne B, Akhtar R, Ebi KL, Hauengue M, Kovats RS, Revich B, Woodward A. Human health 2007. In: Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE, editors. Climate change 2007: impacts, adaptation and vulnerability. Cambridge University Press Cambridge; 2007. p. 391–431.
Cummins SK, Jackson RJ. The built environment and children's health. Pediatr Clin North Am 2001;48:1241–52. x.
Dikmen S, Hansen PJ. Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? J Dairy Sci 2009;92:109–16.
English PB, Sinclair AH, Ross Z, Anderson H, Boothe V, Davis C, et al. Environmental health indicators of climate change for the United States: findings from the State Environmental Health Indicator Collaborative. Environ Health Perspect 2009;117:1673–81.
Environmental Protection Agency. Air quality criteria for ozone and related photochemical oxidants; 2006.
Finkelstein MM, Jerrett M, Sears MR. Environmental inequality and circulatory disease mortality gradients. J Epidemiol Community Health 2005;59(6):481–7.
Harlan SL, Brazel AJ, Prashad L, Stefanov WL, Larsen L. Neighborhood microclimates and vulnerability to heat stress. Soc Sci Med 2006;63:2847–63.
Huynen MM, Martens P, Schram D, Weijenberg MP, Kunst AE. The impact of heat waves and cold spells on mortality rates in the dutch population. Environ Health Perspect 2001;109(5):463–70.
Institute of Medicine (IOM). Toward Environmental Justice: Research, Education, and Health Policy Needs. Institute of Medicine, Committee on Environmental Justice, Health Sciences Policy Program, Health Sciences Section: Washington, DC; 1999.
Kovats RS, Hajat S. Heat stress and public health: a critical review. Annu Rev Public Health 2008;29:41–55.
Krewski D, Jerrett M, Burnett RT, Ma R, Hughes E, Shi Y, et al. Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality. Res Rep Health Eff Inst 2009:5-114. discussion 115–136.
Maloney SK. Heat storage, not sensible heat loss, increases in high temperature, high humidity conditions. World's Poult Sci J 1998;54:347–52.
Marshall JD. Environmental inequality: air pollution exposures in California's South Coast Air Basin. Atmos Environ 2008;42:5499–503.
Mauderly JL, Samet JM. Is there evidence for synergy among air pollutants in causing health effects? Environ Health Perspect 2009;117:1–6.
Medina-Ramon M, Zanobetti A, Cavanagh DP, Schwartz J. Extreme temperatures and mortality: Assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. Environ Health Perspect 2006;114(9):1331–6.
Meehl GA, Tebaldi C. More intense, more frequent, and longer lasting heat waves in the 21st century. Science 2004;305:994–7.
Morello-Frosch R, Jesdale BM. Separate and unequal: residential segregation and estimated cancer risks associated with ambient air toxics in U.S. metropolitan areas. Environ Health Perspect 2006;114:386–93.
Morello-Frosch R, Shenassa ED. The environmental "riskscape" and social inequality: Implications for explaining maternal and child health disparities. Environ Health Persp 2006;114(8):1150–3.
Morello-Frosch R, Zuk M, Jerrett M, Shamasunder B, Kyle AD. Understanding the cumulative impacts of inequalities in environmental health: Implications for policy. Health Affair 2011;30(5):879–87.
National Research Council. Science and decisions: advancing risk assessment. Washington, DC: National Academy Press; 2009.
Nowak DJ, Dwyer JF. Urban forestry. McGraw-Hill Yearbook of Science and Technology. New York: McGraw-Hill; 1997.
Nowak DJ, McHale PJ, Ibarra M, Crane DE, Stevens JC, Luley CJ. Modeling the effects of urban vegetation on air pollution. In: Gryning S, Chaumerliac N, editors. Air Pollution Modeling and Its Application XII. New York: Plenum Press; 1998.
O'Donnell O, van Doorslaer E, Wagstaff A, Lindelow M. The concentration index in Analyzing Health Equity Using Household Survey Data — a guide to techniques and their implementation. Chapter 8 Washington, D.C: The World Bank; 2008.
Ostro B, Kim JJ. Traffic pollution and children's health: Refining estimates of exposure for the east bay children's respiratory health study. Prepaired for the california air resources board and the california environmental protection agency; 2008. www.Arb.Ca.Gov/research/apr/past/03-327.pdf.
Patz JA, Campbell-Lendrum D, Holloway T, Foley JA. Impact of regional climate change on human health. Nature 2005;438(7066):310–7.
Rey G, Jougla E, Fouillet A, Pavillon G, Bessemoulin P, Frayssinet P, et al. The impact of major heat waves on all-cause and cause-specific mortality in France from 1971 to 2003. Int Arch Occup Environ Health 2007;80:615–26.
Ross Z, English PB, Scalf R, Gunier R, Smorodinsky S, Wall S, et al. Nitrogen dioxide prediction in Southern California using land use regression modeling: potential for environmental health analyses. J Exposure Sci Environ Epidemiol 2006;16:106–14.
Saanen J, Vroegop MP, van Deuren M, van Grunsven PM, van Vugt AB. Walking in the sun: heat stroke and heat exhaustion during the Four-Day March in Nijmegen, in 2006. Ned Tijdschr Geneeskd 2007;151:1549–52.
Semenza JC, Rubin CH, Falter KH, Selanikio JD, Flanders WD, Howe HL, et al. Heat-related deaths during the July 1995 heat wave in Chicago. N Engl J Med 1996;335:84–90.
Steadman R. A universal scale of apparent temperature. Journal of Climate and Applied Meteorology 1984;23:1674–87.
Su JG, Jerrett M, Beckerman B. A distance-decay variable selection strategy for land use regression modeling of ambient air pollution exposures. Sci Total Environ 2009a;407: 3890–8.
Su JG, Jerrett M, Beckerman B, Wilhelm M, Ghosh JK, Ritz B. Predicting traffic-related air pollution in Los Angeles using a distance decay regression selection strategy. Environ Res 2009b;109:657–70.
Su JG, Morello-Frosch R, Jesdale BM, Kyle AD, Shamasunder B, Jerrett M. An index for assessing demographic inequalities in cumulative environmental hazards with application to Los Angeles, California. Environ Sci Technol 2009c;43:7626–34.
Theoharatos G, Pantavou K, Mavrakis A, Spanou A, Katavoutas G, Efstathiou P, et al. Heat waves observed in 2007 in Athens, Greece: synoptic conditions, bioclimatological assessment, air quality levels and health effects. Environ Res 2010;110:152–61.
Vaneckova P, Beggs PJ, de Dear RJ, McCracken KW. Effect of temperature on mortality during the six warmer months in Sydney, Australia, between 1993 and 2004. Environ Res 2008;108:361–9.