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Abbreviations

AC - Air conditioning

AHS – American Housing Survey

BRFSS – Behavioral Risk Factor Surveillance System

CDC - Centers for Disease Control and Prevention

U.S. EPA – U.S. Environmental Protection Agency

GIS – Geographic Information System

IPCC – Intergovernmental Panel on Climate Change

MSA – Metropolitan Statistical Area

NLCD – National Land Cover Database

U.S. – United States

Outline of manuscript section headers

ABSTRACT

Background: The evidence that heat waves can result in both increased deaths and illness is substantial, and concern over this issue is rising due to climate change. Adverse health impacts from heat waves can be avoided and epidemiological studies have identified specific population and community characteristics that mark vulnerability to heat waves.

Objectives: We chose ten vulnerability factors for heat-related morbidity/mortality in the United States (U.S.): six demographic characteristics and two household air conditioning variables from the U.S. Census Bureau; vegetation cover from satellite images; and diabetes prevalence from a national survey. We then mapped and analyzed these in order to situate vulnerability to heat in geographic space and identify potential areas for intervention and further research.

Methods: We performed a factor analysis of the ten vulnerability variables, resulting in four factors that explained over 75% of the total variance. Values of increasing vulnerability were assigned for each factor to each of 39,794 census tracts and then added to obtain a cumulative heat vulnerability index value.

Results: We found substantial spatial variability of heat vulnerability nationally, with generally higher vulnerability in the Northeast and Pacific Coast and the lowest in the Southeast. In urban areas, inner cities showed the highest vulnerability to heat.

Conclusions: These methods provide a template for making local and regional heat vulnerability maps. After validation using health outcome data, interventions can be targeted at the most vulnerable populations.

INTRODUCTION

Exposure to extreme heat can overwhelm a person's ability to thermoregulate, resulting in physiological heat stress which sometimes leads to death (Luber et al. 2006). Studies of heat waves and mortality in the United States (U.S.) demonstrate that on days with increased temperature or periods of extended high temperatures, heat-related mortality (Chestnut et al. 1998), cardiovascular-cause mortality (Curriero et al. 2002; Medina-Ramon et al. 2006; Semenza et al. 1996), respiratory mortality (Mastrangelo et al. 2007), heart attacks (Braga et al. 2002), and all-cause mortality (Curriero et al. 2002) increase. During heat waves, calls to emergency medical services (Dolney and Sheridan 2006) and hospital admissions (Mastrangelo et al. 2007) have also increased.

The Intergovernmental Panel on Climate Change (IPCC) reports that heat waves have been increasing towards the end of the 20th century and are projected to continue to increase in frequency, intensity and duration worldwide (IPCC 2007), which could result in future increases in heat-related morbidity and mortality. However, heat-related deaths are preventable (Luber et al. 2006). Several cities have implemented heat emergency response plans, and mortality has decreased during subsequent heat waves (Ebi et al. 2004). But many elderly residents in four cities with heat wave warning systems reported that they did not take recommended actions during heat waves (Sheridan 2007), implying that interventions for the most vulnerable populations need improvement. Because not all populations are at equal health risk from heat, knowing where vulnerable populations are located can aid cities in targeting their resources most effectively, and, at the state and regional scale, can facilitate coordination of heat emergency plans. A national map of county-level heat vulnerability allows us to situate vulnerability to heat in geographic space and identify areas most in need of intervention.

While understanding vulnerability to heat at the individual biomedical level is important, understanding also how factors beyond individuals, including ‘place’, play into differing levels of risk may help in finding preventive solutions (Diez Roux 2004; Martinez et al. 1989; Smoyer 1998). Group-level variables (such as average income in a census tract) can influence health, independent of the influence of the same variable measured at the individual level (such as an individual’s personal or household income) (Diez Roux 2004; Smoyer 1998). Our vulnerability maps include data on both community properties (e.g. low green space) and population composition (e.g. high numbers of elderly residents) that may lead to vulnerability to heat.

The published literature on mapping heat vulnerability is scant. Vescovi et al. (2005) geographically overlaid climate variables with socio-economic variables in southern Quebec to estimate current vulnerable populations and then estimated future population vulnerability using climate and population projections. Overall, that study projected that the population at risk will increase. Harlan et al. (2006) investigated physical attributes of the environment, socio-economic characteristics, and an outdoor human thermal comfort index in Phoenix and found that neighborhoods with the highest temperatures and the least amount of open space and vegetation were also the most socio-economically disadvantaged. A recent publication mapped many heat vulnerability variables by county for the state of California (Climate Change Public Health Impacts Assessment and

Response Collaborative 2007). However, they did not make an index nor analyze the co-locations of their vulnerability variables. All three studies attempted to situate vulnerability in space, but at different spatial scales and with different variables.

Our study expands heat vulnerability mapping to a national scope, using variables shown in the epidemiological literature to increase vulnerability to heat-related health effects in urban areas. Our goal is to create a cumulative heat vulnerability index for nationwide comparison.

MATERIALS AND METHODS

Vulnerability Data Sources

Table 1 lists the data sources, vulnerability variables and level of aggregation of the datasets that were used in our analysis. We chose ten variables that have been demonstrated to modify the relationship between heat and health outcomes in the literature and for which national datasets were available (described in detail in the next sections). The true nature of some of the associations between these variables and whether effect modification is present consistently is still open to question because not all previous studies investigated the possibility of both confounding and effect modification by various vulnerability variables. However, the weight of available evidence and general plausibility pointed towards these ten variables as relevant to heat vulnerability. We included ten variables and used a factor analysis to deal with potential multicollinearities. All ten variables were calculated so that an increase in value denotes an increase in vulnerability.

Demographic and socioeconomic variables

The demographic and socioeconomic variables investigated included age, poverty, education, living alone, and race/ethnicity. Age is a vulnerability factor for heat waves as the very old have shown higher mortality during heat waves (Conti et al. 2005; Fouillet et al. 2006; Hutter et al. 2007; Naughton et al. 2002; Stafoggia et al. 2008; Whitman et al. 1997), higher rates of temperature-related deaths in temperature variability studies (CDC 2001; Medina-Ramon et al. 2006; Kim and Joh 2006) and higher hospital admission rates during heat waves (Knowlton et al. 2009; Semenza et al. 1999). However, not all studies found an increased risk for elderly U.S. residents (O'Neill et al. 2003).

Poverty and income related variables also modify the effects of heat in some studies. Community levels of poverty modified associations between heat and mortality for eleven Eastern U.S. cities (Curriero et al. 2002). A modest increase in risk of heat-related death was observed for those making less than $10,000 compared to those making more during the 1999 Chicago heat wave (Naughton et al. 2002). In Seoul, Korea, people of low income had higher mortality rates during hot weather (Kim and Joh 2006).

Individuals with at most a high school education had higher heat-related death rates than those with more years of education in studies of seven (O’Neill et al. 2003) and fifty U.S. cities (Medina-Ramon et al. 2006). In studies of area-level indicators of educational level, no significant effect modification was found for attained high school education in nine California counties (Basu and Ostro 2008), nor for the percent of residents of each city with a college education in 12 U.S. cities (Braga et al. 2002). The percent of residents in each city with a high school education, however, did modify the heat-mortality relationship for 11 Eastern U.S. cities (Curriero et al. 2002).

A sociological analysis of the 1995 Chicago heat wave found large numbers of the victims of the heat wave died alone (Klinenberg 2003) and an epidemiological study of the same heat wave found that people who did not leave home each day or lived alone had a higher risk of death compared to people with social contacts and access to transportation (Semenza et al. 1996). Similar results were found for the 1999 Chicago heat wave (Naughton et al. 2002). However, living alone did not modify the risk of heat-related death in Modena, Italy (Foroni et al. 2007) or in England and Wales (Hajat et al. 2007). Married people were less likely to die due to heat compared to those who were widowed, divorced, or never married in both Italy (Stafoggia et al. 2008) and France (Fouillet et al. 2006). While not all people who are single, widowed or divorced live alone, this may be a proxy for either living alone or not being checked on regularly during a heat emergency.

Comparisons of heat-related deaths by racial or ethnic groups show mixed results. The Centers for Disease Control and Prevention (CDC) found that Blacks had a higher age-adjusted heat-related death rate than Whites throughout the U.S. from 1979-1998 (CDC 2001). Kalkstein and Davis (1989) found strong correlations between heat mortality and percent non-White only in Southern cities (Kalkstein and Davis 1989). In Detroit, non-Whites had a higher risk of death on hot days (O'Neill et al. 2003; Schwartz 2005), and during the 1995 Chicago heat wave, non-Hispanic Blacks had higher death rates than non-Hispanic Whites (Whitman et al. 1997). In a case-control study, Blacks had a higher death rate than Whites; however both had higher rates than Hispanics (Basu and Ostro 2008). Modification of the relationship between heat and mortality by race, however, has not been found in all studies (Braga et al. 2002). Differential mortality rates may be partially explained by differences in air conditioning (AC) prevalence in homes by race. Sixty-four percent of the disparity in heat-related mortality between Blacks and Whites from four U.S. cities may be explained by the presence of central AC in one's home (O'Neill et al. 2005).

The 2000 U.S. Census demographic variables age, poverty, education, living alone and race/ethnicity were extracted from the Planner's Package Plus data product from Geolytics (East Brunswick, NJ). These data were aggregated at the census tract level for all tracts within the coterminous U.S.

Land cover

The existence of green space in a community has been associated with a decreased risk of heat-related illness and death. A case-control study of the 1980 heat wave in St. Louis and Kansas City, MO found a significant decrease in risk of nonfatal heatstroke associated with an incremental increase in greenery surrounding one's residence (Kilbourne et al. 1982). In Shanghai, a decrease in deaths in the 2003 heat wave compared to the 1998 heat wave was partially attributed to an increase in urban green area (Tan et al. 2007). Urban areas tend to have less green space and more impervious cover, which contribute to the urban heat island effect. This can further exacerbate a heat wave, and the higher city death rates during the 1966 St. Louis heat wave were hypothesized to be due to the hotter temperatures in the city (Clarke 1972). A national map of heat-related deaths in the elderly from 1979-1985 found that most of the high incidence areas were urban counties (Martinez et al. 1989), and in England and Wales, the relative risk of death was higher in urban than in rural areas (Hajat et al. 2007).

The 2001 National Land Cover Database (NLCD) was downloaded for the coterminous U.S. and aggregated at the census tract level by overlaying census tract polygons on the classified imagery (http://www.mrlc.gov/nlcd.php). Each 30 meter pixel from the NLCD was assigned to the census tract polygon in which its center was located. Percent green space for each census tract was calculated as the sum of land area classified as deciduous forest, evergreen forest, mixed forest, dwarf scrub, orchards/vineyards/other, pasture/hay, small grains, fallow, row crops, urban/recreational grasses, palustrine forested wetlands, and palustrine scrub/shrub wetlands divided by the total area for that census tract. Percent not green space was calculated as 100 minus the percent green space.

Diabetes prevalence

Pre-existing health conditions may lead to susceptibility to heat-related illnesses and death. These conditions include cardiovascular disease (Naughton et al. 2002; Semenza et al. 1996; Semenza et al. 1999; Stafoggia et al. 2006), diabetes (Schwartz 2005; Semenza et al. 1999), renal disease (Semenza et al. 1999), nervous disorders (Semenza et al. 1999), emphysema (Semenza et al. 1999), epilepsy (Semenza et al. 1999), cerebrovascular disease (Stafoggia et al. 2006; Stafoggia et al. 2008), pulmonary conditions (Semenza et al. 1996), and mental health conditions (Foroni et al. 2007; Semenza et al. 1996; Stafoggia et al. 2006; Stafoggia et al. 2008). However, for most of these variables, a consistent national dataset of prevalence does not exist currently, so we were only able to map diabetes prevalence.

We calculated diabetes prevalence from the 2002 Behavioral Risk Factor Surveillance System (BRFSS)'s state prevalence rates, which are reported by age, race and gender groups. From the 2000 census, we obtained population estimates for each age and race and multiplied these by the BRFSS state diabetes rate for that age and racial group obtaining an estimate of diabetes cases for that group in that county. These values were summed for all age and race groups in the county and divided by the county population to achieve an estimate of diabetes prevalence for each county in each state. Correlation between our county-level estimates and the few Metropolitan Statistical Area (MSA) estimates published by BRFSS was good (R^2=0.72).

Air conditioning

Home AC prevalence can be a strong protective factor against heat-related deaths (Curriero et al. 2002; Kaiser et al. 2001; Naughton et al. 2002; Semenza et al. 1996; Braga et al. 2001). While both room and central AC had negative correlations with heat-related mortality (Chestnut et al. 1998), central AC may have a stronger protective effect than room AC (Chestnut et al. 1998; O'Neill et al. 2003).

AC prevalence data were collected from both the metropolitan area and national surveys of the U.S. Census Bureau's American Housing Survey (AHS) for all counties (n=464) for which the MSA is indicated in the source data. We calculated the percent of households with central AC and with any AC by county, either as a direct estimate for the year 2002 or as an interpolation from values for neighboring years because the AHS survey is administered in different MSAs in different years.

Analysis

We obtained census tract level data for all variables except diabetes and AC prevalence, which were assigned to census tracts from county data because data for smaller areas was not available. We selected only the census tracts for which we had data for all variables, limiting us to counties with data from the AHS (i.e., urban areas: n=41,043). We then restricted our analysis to census tracts with populations of at least 1,000 people (n=39,794).

Spearman's correlation coefficients were calculated between the ten vulnerability variables. We then used principal components analysis to limit the number of variables and create independent factors for inclusion in a vulnerability index. A varimax rotation was used to minimize the number of the original variables that load highly on any one factor, and increase the variation between factors, thus making these new factors more statistically independent than the original variables. We retained four factors based on a combination of standard criteria including: eigenvalues greater than 1, a clear break in values in the scree test, and the percentage of variance explained by the factors. Factor scores were calculated for each of the four factors for each census tract using estimated scoring coefficients based on the factor analysis in SAS v9.1 (Cary, NC).

The calculated factor scores were normalized to have a mean of 0 and a standard deviation of 1. For ease of interpretation and to minimize the impact of outliers, we divided each factor into six categories based on standard deviations as shown in Table 2. We assigned scores to each category with 1 corresponding to the lowest vulnerability and 6 to the highest. Because we have no knowledge of nonlinearities in these relationships, we assumed linear relationships between each variable and vulnerability. In the absence of detailed understanding of the impacts of each factor on vulnerability, we assumed they each had equal impact and summed the assigned factor values for the four factors creating a cumulative heat vulnerability index value for each census tract.

Because heat may influence health differently depending on prevailing climate conditions, due to physiological and structural adaptations, the mean apparent temperature for MSAs was calculated from 1985 to 2003 and we assessed whether there was a significant relationship between this value and the cumulative heat vulnerability index.

RESULTS

Many of the ten vulnerability variables were highly correlated with each other as shown in Table 3. Factor analysis yielded four factors with primary loadings as follows (1) lower education/higher poverty/higher proportion people of color/lower green space; (2)

higher social isolation; (3) lack of AC; and (4) higher proportion elderly/with diabetes. These four factors explained 75.7% of the variability in the original ten vulnerability variables as shown in Table 4.

The cumulative heat vulnerability index values, summed from the four factors for each census tract, ranged from 7 to 22 with a mean of 13.94, a median of 14 and a standard deviation of 2.02. The 39,794 census tract-level cumulative vulnerability index values were fairly normally distributed. Figure 1 shows the geographic distribution of the cumulative vulnerability index nationally, with evidence of spatial clustering. Overall, higher vulnerability was seen in the Northeast and along the Pacific Coast, with some pockets of higher vulnerability in the Southeast and along the U.S./Mexico border. Thirteen census tracts had the highest cumulative heat vulnerability index values (21 or 22). Eight of these are in the San Francisco Bay Area (San Francisco County and Alameda County), two are in Cuyahoga County, Ohio, one is in Pierce County, Washington and one is in Los Angeles County, California. All of these census tracts are above the mean for all four factors. No census tract reached the highest vulnerability category for all four factors.

We then calculated each MSA's mean cumulative heat vulnerability index value and ordered them from lowest to highest, looking at the contributions of each Factor to the overall vulnerability. Only Factor 3 appeared to increase as the cumulative index increased (data not shown). To check whether AC was driving our vulnerability index, we did a factor analysis of vulnerability variables without AC and found that this yielded only three retained vulnerability factors, without the factor for AC as expected. Further analysis showed that while this did decrease vulnerability for the Pacific coast and the Northeast, the changes were minimal. Also, almost equal numbers of tracts showed increases as decreases. While this may imply that lack of AC is driving our vulnerability index, not all areas with low AC prevalence had high cumulative heat vulnerability values. Additionally, the importance of AC use in protecting against heat-related health outcomes is clear. Therefore removing it from our index would not improve our estimates of vulnerability.

Mean MSA values also highlight the regional variation in heat vulnerability with the most vulnerable 20 cities located on the Pacific coast or Northeast, topped by San Francisco, CA, New York, NY, and Los Angeles, CA. However, the least vulnerable 20 cities, while mostly in the Southeast (e.g. Austin, TX; Atlanta, GA; and Raleigh-Durham, NC), do include some cities from the Northeast and Midwest. For example, Minneapolis, MN was the third least vulnerable MSA and smaller MSAs in Massachusetts and New Jersey also fell in the least vulnerable ten.

Analysis by climatic region did not provide evidence for a trend in cumulative heat vulnerability by the mean apparent temperature from 1983-2003 by MSA (not shown). The only individual factor that showed a trend with apparent temperature was Factor 3 which decreased with increasing apparent temperature, as expected. However, the relationship was not very strong.

Figure 1 illustrates the national variability in heat vulnerability and variation within cities. In most cities, including those where most areas have low heat vulnerability, the downtown areas show the most vulnerability (Figure 2). While Dallas overall shows less heat vulnerability than the other cities, it contains areas of higher vulnerability in its central city. This pattern was found in many other low vulnerability Southeast and Midwestern cities. Local spatial autocorrelation analysis for individual MSAs showed significant clustering of high vulnerability in downtown areas and clustering of low vulnerability in outlying areas.

DISCUSSION

In our analysis of urban areas in the U.S., heat vulnerability varies nationally and is concentrated in central city areas. Epidemiological studies are increasingly assessing vulnerability of specific populations and geographic areas to heat waves. We used knowledge from previous epidemiological research to develop a map that can be used to focus interventions to prevent heat-related morbidity and mortality, and suggest directions for future research. Our analysis is an approach similar to methodologies used to map social vulnerability to environmental hazards (Cutter et al. 2003).

Epidemiological studies investigating different geographic regions in the same study have also found regional differences in response to heat (Basu et al. 2008; Conti et al. 2007; Curriero et al. 2002; Hajat et al. 2007; O'Neill et al. 2003), possibly due to ways in which the populations of those cities have adapted physiologically, socially and/or technologically to heat. However, most of these studies, when assessing modification of the heat-health relationship by vulnerability variables such as those used in this analysis (e.g. race, educational attainment), pool nationwide data rather than comparing vulnerabilities between regions, O'Neill et al. (2003) being one exception. Increased understanding of differential effect modification by geographic region could be used to further refine our heat vulnerability map.

Of the vulnerability factors created in this analysis, Factor 3 showed the most national spatial variability, and regions with the highest AC prevalence had some of the lowest cumulative heat vulnerability values. For example, areas along the West Coast showed very high vulnerability even though their current climates are temperate. In the event of a heat wave, they will likely have significant vulnerability to heat. Efforts should be made to create incentives for people to use their AC during heat waves, as the economic costs of AC use deter people who have AC in their homes from turning it on during a heat wave (Sheridan 2007). While AC can protect against heat, caution should be applied in promoting AC as the sole heat wave adaptation strategy. AC uses electricity, most of which comes from fossil fuel energy sources, and additionally exhausts waste heat to the local environment, thus increasing the urban heat island effect. Other modifications to the built environment such as tree and shrub planting, reflective paving surfaces, and natural ventilation can reduce heat exposure in a more sustainable manner.

While our map shows differences in heat vulnerability between regions of the country, it also highlights the higher vulnerability within the downtowns of metropolitan areas. Since heat warning systems and interventions are often implemented at the municipal or local level, identifying these regions within cities is essential. Heat waves can occur in any community, and with climate change, heat waves are projected to increase in frequency, duration and intensity in the U.S. (Meehl and Tebaldi 2004). Therefore municipalities should incorporate heat wave warning systems and interventions into their emergency planning procedures, focusing on ways to improve the compliance in the response, particularly of elderly adults, to such warnings (see Sheridan 2007).

Within-city analyses of heat vulnerability may give more information about local vulnerability than a national map. Also, relationships between variables may be different at smaller spatial scales, resulting in different vulnerability factors and thus different geographic variability. The methodology presented in this paper can be used for these local vulnerability maps. Identifying not only the most vulnerable populations in the community but also whether those areas already experience the hottest temperatures, as in Phoenix (Harlan et al. 2006), and ameliorating these local heat hotspots within the urban heat island with cool roofs and urban trees could go a long way towards mitigating heat. All metropolitan areas in this analysis, regardless of AC prevalence, had higher social vulnerabilities in their downtown core that make those areas more vulnerable to many exposures, heat being just one of them. Targeting these inequalities could lead to reductions in many health outcomes.

Our analysis introduces a methodology of vulnerability mapping for heat-related health outcomes that can serve as a template for future heat vulnerability maps at local and regional levels. The use of health data to validate our measures of heat-related vulnerability is an important next step. This could further highlight local or regional differences about which factors contribute most to vulnerability and therefore are important intervention targets. For example, the downtown area of Oakland with little green space and a high proportion of residents of color and people living in poverty, has not recently been the location of most of the heat-related health effects, possibly because these neighborhoods are located closer to the cooling breezes of San Francisco Bay (Paul English, personal communication, 2008). Thus local information is essential for ensuring the validity of this map at local scales. However, at regional and national scales, our map can provide guidance on locations for further analysis and intervention. At a national level, a method for weighting cities according to the probability of a heat wave can help determine which cities are most in need of heat wave intervention programs.

Our analysis was limited by the data available at the national level. Variables of pre-existing health concerns that denote vulnerability to heat such as cardiovascular disease or psychiatric disorders, are not currently available nationally, but may be in the future. Other vulnerability variables are likely to be available only through local surveys, such as degree of social connections between individuals within a community, or materials used in housing. Additionally, some variables such as crime rates merit further investigation as modifiers of heat and health associations in epidemiological analyses.

We limited our analysis to urban areas, in which the majority of heat wave health effects have occurred and for which we understand more about which conditions make individuals and communities more vulnerable. Sheridan and Dolney (2003), however, found that although higher absolute numbers of heat-related deaths occurred in urban counties in Ohio, the percentage increase in mortality during heat waves was greater in suburban and rural counties, thus highlighting an important area for future research. Rural populations may exhibit different patterns of vulnerability than urban populations.

With further information on the degree to which a given vulnerability variable modifies the heat-health relationship, more complex algorithms can be applied to more accurately value heat vulnerability, including differential weighting of the variables we examined or the inclusion of different or additional variables. We assessed whether summing the factor scores without rescaling and weighting them would create a different heat vulnerability map. This allowed for more gradation in vulnerability and finer stratification of regions, but AC prevalence still played a large role in cumulative heat vulnerability, and the same regions of the country and regions of cities showed comparatively higher and lower vulnerability.

CONCLUSIONS

Heat vulnerability varies spatially, on local, regional, national and international scales. With further validation at the local scale and evaluation with health outcome data, our methodology and results can help target resources for intervention. In our analysis, in addition to regional difference in heat vulnerability, higher vulnerability was seen within the downtown areas of all cities compared to suburban areas regardless of the city's overall vulnerability.

This study is a novel approach to map vulnerability to a health outcome related to climate change nationally and can be considered a first step towards tools that can help public health professionals prepare climate change adaptation plans for their communities. In addition to refinement of this method for heat vulnerability, further studies mapping vulnerability to other projected health impacts of climate change are needed.

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TABLES

Table 1: Heat-Health Vulnerability Data, 39,794 U.S. Census Tracts.

Category	Data Source (Year)	Variable Definitions	Mean (Range)
Demographic Variables	U.S. Census (2000)	% of population below the poverty line	12.57 (0.00 – 100.00)
		% of population with less than a high school diploma	19.97 (0.00 – 85.88)
		% of population of a race other than white	30.20 (0.00 – 100.00)
		% of the population living alone	10.28 (0.00 – 68.86)
		% of population 65 years of age or older	12.21 (0.00 – 94.28)
		% of population 65 years of age or older living alone	27.38 (0.00 – 100.00)
Land Cover	National Land Cover Database (2001)[a]	% of census tract area not covered in vegetation	61.15 (0.03 – 100.00)
Diabetes Prevalence	Behavioral Risk Factor Surveillance System (2002)	% of population ever diagnosed with diabetes	06.95 (2.38 – 11.10)
Air Conditioning	American Housing Survey (2002)[b]	% of households without central air conditioning	44.43 (2.10 – 95.13)
		% of households without any air conditioning	18.47 (0.00 – 95.13)

[a] From the 2001 national land cover datasets, % green space was calculated as the sum of land classified as deciduous forest, evergreen forest, mixed forest, dwarf scrub, orchards/vineyards/other, pasture/hay, small grains, fallow, row crops, urban/recreational grasses, palustrine forested wetlands, and palustrine scrub/shrub wetlands divided by the total area for that county, thus yielding a value we called % green space.

[b] Data were interpolated for 2002 for counties that were surveyed in years before and after 2002 to get a larger sample of air conditioning estimates for one year.

Table 2: Counts of Census Tracts for each Heat Vulnerability Factor by Categories Created by Observed Distributions

Categories		Number of Census Tracts (Percent)			
	Assigned Value	Factor 1 Social/environmental Vulnerability	Factor 2 Social isolation	Factor 3 Lack of AC	Factor 4 High proportion Elderly/diabetes
>=2 SD below mean	1	64 (0.16)	141 (0.35)	0 (0.00)	670 (1.68)
1 to 2 SD below mean	2	4163 (10.46)	4941 (12.42)	7567 (19.02)	5276 (13.26)
<1 SD below mean	3	20186 (50.73)	17296 (43.46)	14658 (36.83)	14633 (36.77)
<1 SD above mean	4	8117 (20.40)	12107 (30.42)	10239 (25.73)	13617 (34.22)
1 to 2 SD above mean	5	5208 (13.09)	3687 (9.27)	6136 (15.42)	4583 (11.52)
>2 SD above mean	6	2056 (5.17)	1622 (4.08)	1194 (3.00)	1015 (2.55)

SD - Standard Deviation

Table 3: Spearman's Correlation Values for Vulnerability Variables for Census Tracts Nationwide (N=39,794)

	Diabetes	Race Other Than White	Over 64 Years	Live Alone	Over 64 who Live Alone	Below Poverty Line	Less than HS Diploma	Not Green Space	No central AC	No AC of Any Kind
Diabetes	1.00									
Race other than white	0.25	1.00								
Over 64 years	0.13	-0.31	1.00							
Live Alone	0.07	-0.03	0.47	1.00						
Over 64 who live alone	0.06	0.06	0.22	0.69	1.00					
Below poverty line	0.27	0.64	-0.11	0.22	0.33	1.00				
Less than HS diploma	0.28	0.56	-0.05	-0.02	0.17	0.77	1.00			
Not green space	0.27	0.50	-0.02	0.23	0.24	0.43	0.35	1.00		
No central AC	0.11	-0.00	0.09	0.01	0.05	-0.01	-0.01	0.25	1.00	
No AC of any kind	0.11	0.02	-0.03	-0.03	0.01	-0.01	-0.03	0.25	0.85	1.00

All values are statistically significant $p<0.001$ except for those in gray

Table 4: Factor Loadings for Heat Vulnerability Variables for the Four Retained Varimax-Rotated Factors Based on Data from 39,794 Census Tracts

	Factor 1 Social/environmental Vulnerability	Factor 2 Social Isolation	Factor 3 Lack of AC	Factor 4 High proportion of Elderly/Diabetes
Diabetes	0.37	-0.10	0.07	0.78
Below poverty line	0.87	0.18	-0.05	-0.03
Race other than white	0.85	-0.05	0.03	0.02
Live alone	-0.06	0.91	-0.002	0.16
Over 64 who live alone	0.19	0.87	0.001	-0.06
Over 64 years	-0.32	0.38	-0.04	0.67
Less than HS diploma	0.85	-0.06	-0.05	0.07
Not green space	0.54	0.33	0.31	0.13
No central AC	0.02	0.02	0.92	0.06
No AC of any kind	-0.01	-0.03	0.92	-0.03

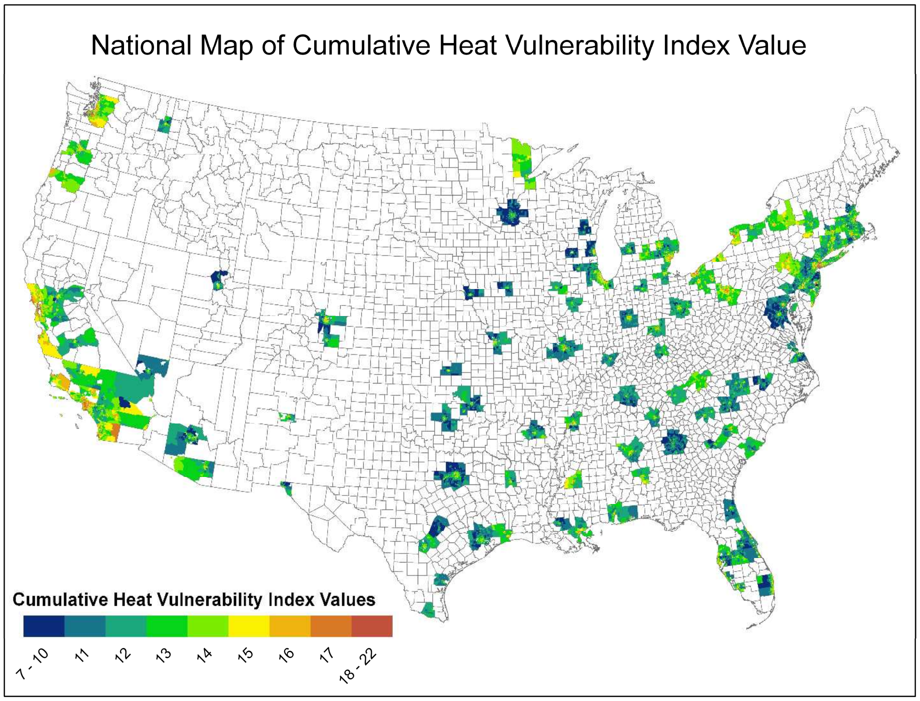
Values greater than 0.4 are the most significant loadings on that factor.

FIGURE LEGENDS

Figure 1: National Map of Cumulative Heat Vulnerability Index by Census Tracts (n=39,794)

Figure 2: Mean Cumulative Heat Vulnerability Maps by Census Tract for Four Selected Cities

FIGURES



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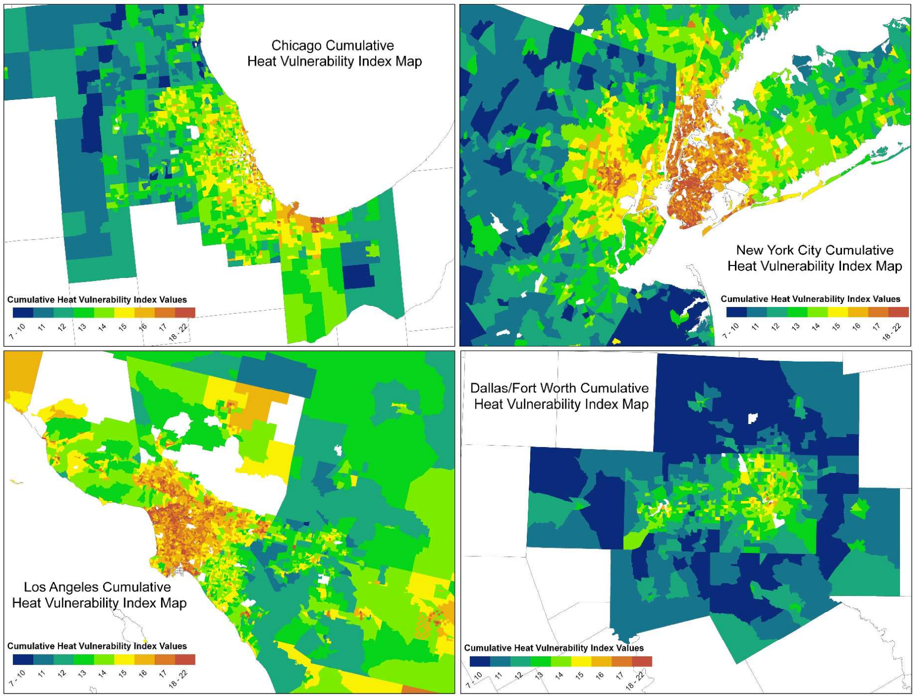

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