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Heat & Social Inequity in the United States

Four Twenty Seven Climate Solutions
Nik Steinberg and Colin Gannon

Abstract: Due to the extensive influence of climate change on global temperatures, no risk is perhaps more apparent or more frequent and oppressive than heat waves. High temperature and humidity combinations can take a significant toll on the human body. Periods of extreme heat are expected to become more severe, last longer, and occur in places not accustomed to extreme heat. Current research and literature can be used to show where dangerous heat and humidity conditions are likely to be most prevalent and where populations vulnerable to heat stress reside. However, many complex factors, such as relative changes in temperature patterns or local socioeconomic conditions, must also be considered to provide a better understanding of overall heat vulnerability in a changing climate. Here, we utilize a multivariate approach to establish county-level risk scores by combining the social indicators of heat vulnerability with climate model projections of wet bulb globe temperature, a metric calibrated to human's response to conditions of high heat and humidity. This paper also serves as guide for understanding the methods, findings, and limitations associated with the Heat and Social Inequity Tool, an interactive series of maps available on the U.S. Climate Resilience Toolkit.

Introduction:

Climate change will increase the frequency and the severity of heat waves, and for many regions of the United States, heat waves are expected to become more frequent and often times more humid, limiting the human body's ability to sweat and cool down (Easterling *et al. 1997,2000b*; IPCC 2007; Gershunov and Guirguis 2012; Fischer and Knutti, 2015). While there are absolute limits to the amount of heat exposure humans can tolerate (heavy physical work can induce health effects at and above 26° C (WBGT))[1], individuals are acclimated to their local climate in physiological, behavioral, cultural and even technological terms (e.g., through ownership of air conditioning). Over time, populations may adjust to warmer and more frequent periods of excessive heat and their ability to cope may vary, challenging the so-called issue of relationship stationarity. Some populations may in fact adapt to higher temperatures through new technologies, behaviors, or physiological acclimation, but shifts in seasonality and low levels of social equity may inhibit and slow their pathway to heat adaptation.

Human vulnerability to extreme heat can be a difficult to effectively measure and quantify. Indicators of heat vulnerability are sensitive to scale and context. Evaluations of heat vulnerability generally evaluate the degree of vulnerability through an empirical investigation of the relationship between health outcomes and heat events (Ostro et al., 2010, Basu et al., 2010; Sheridan et al., 2011) or through multivariate, general indices that evaluate cumulative measure of heat vulnerability through a set of socioeconomic, demographic, and physical characteristics (Vescovi at al., 2005, Reid *et al.,* 2009; Cutter et al., 2010). Other investigations have sought to explore the determinates of negative heat-related health outcomes with multivariate indices, and vice versa (Chuang et al., 2016; Reid *et al.,* 2012). Here, we utilize the multivariate approach as a method to identifying counties vulnerable to changes in extreme heat.

Indicators of social vulnerability include characteristics of the population with strong associations to health impacts incurred in the past. In the U.S., positive associations have been identified between a number of individual factors and heat-related illnesses. Demographics are a key factor when identifying vulnerable populations and gauging a

[1] Heat Stress Standard ISO 7243

group's susceptibility to extreme heat. Illnesses from heat are strongly tied to age, social isolation, pre-existing medical conditions, poverty, job type, and other factors (Reid *et al*., 2009).

Poverty often serves as a proxy for heat vulnerability, and positive associations between income and heat morbidity have been identified throughout the U.S. (Curriero *et al.,* 2002). In our analysis, we found positive association between poverty and overall heat vulnerability when ranking (Spearman $\rho = 0.60$; $P = .0001$). Strong positive associations have also been observed among individuals with no high school diploma (Medina-Ramon *et al*., 2006 and O'Neil *et al.*, 2003). The elderly are particularly vulnerable, representing the largest demographic group to experience the ill effects of a heat wave (Gronlund *et al*., 2014; Bunker et al., 2016). Forecasts of an ageing population combined with longer life expectancies - the 60+ age groups is projected to make up 21.1% of the world's population by 2050 (United Nations 2013) - highlights the increasingly large volume of heat vulnerable individuals in the coming years. While the elderly make up a significant portion of vulnerable groups during a heat wave, heat-related illnesses are common among infants and young children (Schwartz 2005), athletes (Vanos *et al.,* 2010), people with pre-existing illnesses (Barrow and Clark 1998; Stafoggia *et al*. 2006), pregnant women (Basu *et al.,* 2016), and the homeless (Bassil and Cole 2010). Living conditions, including the quality of housing have also been shown to modify the heat exposure-response relationship (Evans *et al*., 2003; Howden-Chapman, 2004; Lawrence, 2004). When examining hospital visits following high ambient temperatures and heat waves in Chicago, the prevalence of diabetes was also shown to have a strong association with heat morbidity (Schwartz 2005 and Semenza *et al*., 1996). Direct and prolonged exposure to heat can also adversely affect outdoor laborers. These "effects tend to occur during outdoor labor as a result of accumulated heat load over a longer time period with little opportunity for rest" (Mengmeng *et al.,* 2014). Social isolation, whether amongst elderly populations or not, also holds strong associations to heat mortality in many cases (Semenza *et al*., 1996 and Naughton *et al*., 2002). Individuals living alone may not be checked on or be able to request the assistance of an in-home partner or family member during an emergency. Following the 1995 Chicago heat wave, several victims were found deceased and alone in their homes (Klinenberg 2003).

In the context of assessing the impacts of heat on human health, three interactive components are often used: *hazard* (i.e., the characteristics of heat that lead to varying levels of exposure), *population sensitivity* (i.e., the socioeconomic, demographic, and other medical factors that influence the susceptibility of populations), and *adaptive capacity* (i.e., communal, physical, and technological features that can reduce the risk of heat-related health risks). While adaptive capacity is critical to understanding vulnerability, mapping adaptation conditions lies outside the scope of this analysis and our findings merely cover the changing conditions of heat exposure through an examination of hazards and current social vulnerability. Yet the overall distribution of risk may similarly represent the ability to cope with changes in extreme heat.

This framework builds on previously proposed social vulnerability assessments (Klinenberg 2003; Wilhelmi *et al*., 2004; Cutter *et al*., 2008; English *et al*., 2013), utilizing spatially variable indicators to help contextualize social vulnerability in place. Yet a measure of vulnerability to climate change, and the differential outcomes it can exacerbate, hinges on climate measures that can effectively characterize the magnitude and rate of change in hazards such as heat.

In order to explore the relationship between population vulnerability and the influence of climate change, our analysis utilizes a simple technique known as the Delta Method, recognized by the Center for Disease Control (CDC) Building Resilience against Climate Effects (BRACE) framework. The Delta Method enables the comparison of climatic variables from a baseline period to a future period, while holding other variables constant. This method is often used to project future disease burdens by comparing relative changes in climate against existing levels of population vulnerability to show anticipated risks (Huang *et al.,* 2009; Knowlton *et al*., 2007; Barreca *et al*., 2014).

The result is a series of maps showing the dimensions of heat vulnerability in context of climate change and the cumulative risks of exposure to more frequent and severe heat episodes. Not everyone will be vulnerable to future heat risks, and what we find is that warmer temperatures will merely exacerbate existing economic, racial, and societal inequities; a phenomenon known as the 'Climate Gap' (Shonkoff *et al.,* 2009). We conclude that the growing threat of extreme heat brought on by climate change will disproportionately affect certain counties. We find counties with a greater share of low-income and non-white households and historically low acclimation to heat face the greatest heat risks.

Methods:

We chose eight variables that have been demonstrated to modify the relationship between heat and health outcomes in the literature and for which national data sets were available at the county scale.

Because some social vulnerability indicators were correlated (Table 2) we applied principal components analysis to reduce the dimensionality in the eight original variables and create independent factors based on the amount of explained variance A varimax rotation was used in order to make the new factors more statistically independent than the original variables. We retained three factors based on the percentage of variance explained by the factors and used a standard loadings cutoff of 0.3. Factor scores were then calculated for each of the three factors for each county and converted into percentiles for the story map visualizations. Social vulnerability indicators were derived from publicly available sources online and averaged over a 5-year period.

At the county-level, we utilize climate change projections to characterize warming conditions that are expected to bring more severe periods of extreme heat to many parts of the United States. Heat hazards were evaluated based on the number of future dangerous heat and humidity days and the relative change in their occurrence and severity, which are important indicators of vulnerability for populations not acclimated to high heat and humidity conditions (Knowlton *et al*., 2008). Here we use an indicator known as Wet Bulb Temperature (WBT); one of many indicators to assess the severity of heat and humidity combinations. The variables for computing WBT is based upon daily maximum near-surface air temperature, surface air pressure, and surface relative humidity.

To calculate historical and future wet bulb temperatures, we follow the methodology described in the ACP *Technical Appendix: Physical Climate Projections*. This approach uses the historical relationship between dry bulb temperature (air temperature) and wet bulb temperature during a baseline period (1981-2010) to simulate changes in local summer (June, July, and August) wet bulb temperature.

To establish the historical relationship between wet bulb temperature and dry bulb temperature, we use the North American Regional Reanalysis (NARR) dataset to calculate wet bulb temperature at each grid cell. The Davies-Jones (2008) formula is used to derive the wet bulb temperature in lieu of the Wobus method as used in the ACP, as the former tends to be a more accurate representation. Consequently, the NARR variables used to calculate wet bulb temperature are 2-m air temperature, 2-m relative humidity, and surface air pressure, at the three-hour interval.

We resample wet and dry bulb temperatures to a daily time step, and find the linear relationship between daily maximum wet bulb temperature and daily average temperature. This relationship is expressed as either a (1) simple linear model or a (2) piecewise linear model

(1) $T_w(T) = b_0 + \beta_0 T_d$

(2) $T_w(T) = b_1 + \beta_1 \, min(T_d, T_b) + \beta_2 \, max(0, T_d - T_b)$

where T_w is wet bulb temperature, T_d is dry bulb temperature, b_i are y-intercepts, β_i are slopes, and T_b is breakpoint.

The model with the smallest Bayesian information criterion (BIC) is used. Should the relationship yield a negative slope for either portion of the curve (this is particularly common on the right side of the break point), that model is discarded, and may revert to the simple linear model.

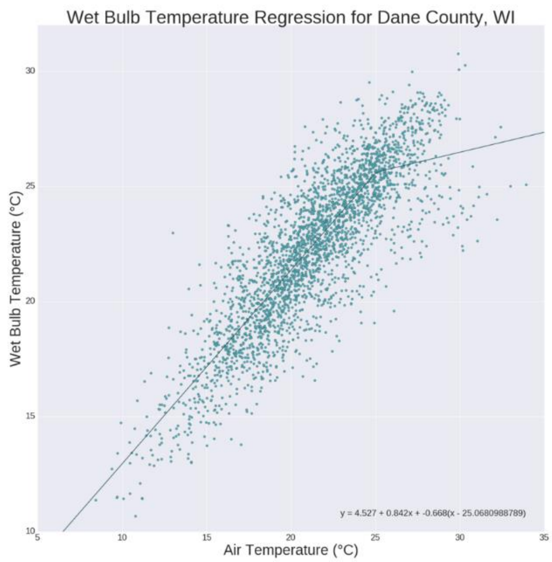


Figure 1. Piecewise linear regression between summer (June, July, August) daily average temperature means and maximum daily wet bulb temperature. The equation for the line of best-fit, shown in the bottom right of the graph, is derived by selecting the piecewise model with the smallest Bayesian information criterion (BIC).

Historical climate estimates and future projections are based on a suite of 20 CMIP5 models downscaled to the 1/8 degree across the continental United States (Reclamation, 2013). While this downscaling project provides improved resolution over the original CMIP5 model resolutions from which they are derived, the only variable outputs are daily maximum temperature and daily minimum temperature. Thus, to derive daily average temperature, we use an average of these two outputs.

"The historical regression calculated from equations (1) and (2) provides the distribution of T_w conditional on T_d for the baseline climatology. To account for the effects of climate change, we shift the conditional distribution upward by $\beta 0_0 \Delta T_f$, where ΔT_f is the local forced summertime temperature change given by $k\Delta T$. We use equation (3) to generate estimates of future wet bulb temperatures. Note that, for cases where the simple linear model best captures the distribution, this expression reduces to that model" (Rhodium Group, 2014)

(3) $T_w(T_d, \Delta T_f) = T_w(T_d - \Delta T_f) + \beta_0 \Delta T_f$

In equation 3, $k\Delta T$ is the estimated forced climate change for a given season. That is, for each summer season, we find the local temperature anomaly for that season relative to the global seasonal temperature anomaly, and find the line of best fit. This regression is used to adjust the local dry-bulb temperature as it relates to the global mean temperature. To find global mean temperature, we used an ensemble of 48 CMIP5 model projects, run over the historical and future time periods and averaged across the months of June, July, and August. We then fit outputs to the relevant spatial scales (county) and future time period (2020-2060) at five-year intervals.

Next, we measured the relative change in WBT severity and compared the average WBT during the baseline period against the average WBT by mid-century ($WBT_{2045\text{-}2049} - WBT_{1981\text{-}2005}$). We also evaluated the average relative increase in the number of days over the historical 95^{th} percentile WBT between baseline and projection period and the number of HHSI Category II days.[2] .

Final WBT temperatures are a multi-model mean of the 20 downscaled CMIP5 models. Each county is assigned the value of all $1/8^{th}$ degree climate model grid cells that intersects the spatial boundaries of the county. In some coastal counties, WBT values may be skewed by an intersection with grid cells that are not sufficiently resolved and thus mostly reflect ocean conditions. For these counties, we interpolate from the values of neighboring counties' WBT values, which are more reflective of the on-shore conditions that would be expected.

Each discrete vulnerability and heat hazard indicator was then standardized to make them comparable using an observed min-max scaling method (Cutter *et al.,* 2010). Distributions were then tested for skewness and refitted accordingly. The three heat hazard categories were then averaged and equally weighted against the PCA-adjusted social vulnerability scores. Normalized indicators were then scaled to a range of 0 to 100 where zero represents the lowest (or best) score for a specific indicator and one hundred corresponds to the highest (or worst) score. Percentiles are then used to classify the severity of vulnerability and show the relative distribution of heat vulnerability across counties (final map). The heat vulnerability score is a composite score calculated to reflect a county's existing vulnerability against forecasted levels (i.e., frequency and relative change of severity) of dangerous heat and humidity conditions.

Components	**Weighting**	**Heat Vulnerability Score**		
Heat & Humidity Exposure	50%	Relative	Changes (%) in the severity of maximum WBT (annual 95^{th} percentile) between 1981-2005 and 2045-2049	Average number of additional days above the historical 95^{th} percentile WBT between baseline and 2045-2049
		Absolute	Average number of days that exceed HHSI category II days in 2045-2049	
Social Vulnerability	50%		Composed of three factors: social isolation, economic opportunity, and living conditions	

Table 1. Weighting scheme used to calculate each county's Heat Vulnerability Score

[2] To estimate the number of future dangerous heat and humidity days, WBT is compared categorically using The Heat and Humidity Stroke Index (HHSI), a standardized method developed by The American Climate Prospectus (ACP) to indicate the relative human impact of combined heat and humidity. Ranges of WBT are divided into four HHSI categories--I: "Uncomfortable"; II: "Dangerous"; III: "Extremely dangerous"; IV: "Extraordinarily dangerous." (Rhodium Group, 2014). With the understanding that heat-related morbidity is positively associated with heat and humidity thresholds, we measured the average number of days in a five-year interval where WBT is projected to be equal to or greater than Category II, "Dangerous," utilizing the approach presented in the American Climate prospectus (2013) Technical Appendix A and downscaled temperature projections from Reclamation (2013)

Results:

We found that three social vulnerability factors explained > 72% of the total variance in the original 8 vulnerability variables: 1) social isolation (combined age 65 and over, age 65 and over and living alone, and housing stress), 2) economic opportunity (combined race, poverty, education, and diabetes), and 3) living conditions (combined race, poverty, and housing stress) (Table 1). We must assume linear relationships exist between each indicators and components with large variance explain dynamics in the data.

Table 1: Indicators for each factor of County Heat Vulnerability Score

Factor		Indicators[3]
1	Social Isolation	Age 65+
		Age 65+living alone
		Living alone
		Housing stress
2	Economic Opportunity	No high school diploma
		Diabetes
		Race
		Poverty
3	Living Conditions	Race
		Poverty
		Housing Stress

Table 2: Spearman's correlation values for 8 vulnerability indicators for US counties (n=3137)

	Age 65+	Age 65+, living alone	Race	Poverty	No high school diploma	Diabetes	Living alone	Housing stress
Age 65+	1							
Age 65+, living alone	0.84	1						
Race	-0.05	0.15	1					
Poverty	-0.05	0.15	1	1				
No high school diploma	-0.07	0.1	0.64	0.64	1			
Diabetes	0.22	0.3	0.53	0.52	0.6	1		
Living alone	0.47	0.64	0.17	0.16	-0.07	0.1	1	
Housing stress	-0.38	-0.35	0.3	0.3	0.19	-0.08	-0.05	1

Highlighted values indicate high correlation

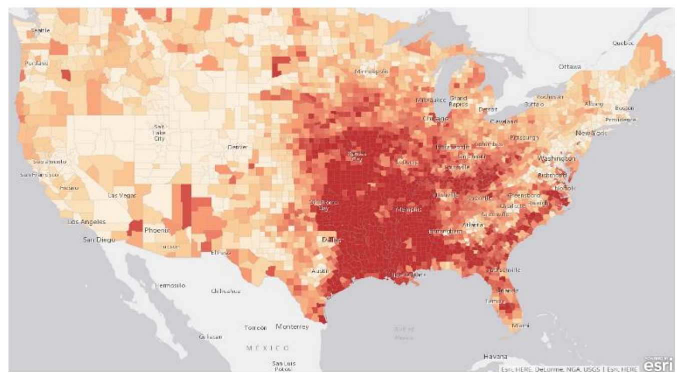
[3] Factors were created using a Principal Component Analysis. Indicators were grouped based on their loadings (Table 3).

Table 3: Factor loadings for the four retained varimax-rotated indicators for 3,137 US counties

	Factor 1	Factor 2	Factor 3
	Social Isolation	Economic Opportunity	Living Conditions
Age<65	0.82		
Age<65, living alone	0.97		
Living alone	0.70		
No high school diploma		0.78	
Diabetes		0.75	
Race		0.60	0.79
Poverty		0.60	0.80
Housing stress			0.43

Values greater than 0.3 are the most significant loadings

The heat vulnerability score, summed across all heat hazard and social vulnerability factors (Table 1), ranged from 9 to 87, with a mean of 43, a median of 42, and a standard deviation of 13. Overall, we find highly heat vulnerable counties were concentrated in the Great Plains, South, and Southeast regions of the United States, with the highest average state scores in Louisiana, Mississippi, and Arkansas (See Appendix for full list). Relative changes in the frequency and severity of heat, which composed of 50% of the heat hazards score, were dominant along the coastlines and northern states where the occurrence of very hot days is historically less common.



Map 1: Cumulative Heat Vulnerability Score

We found that racial and income disparities are associated with heat vulnerability, and counties with higher shares of low-income and non-white households were also relatively heat vulnerable (Figure 2). Of the country's ten most populous counties, Dallas County, TX and Cook County, IL are among the most vulnerable (see Appendix).

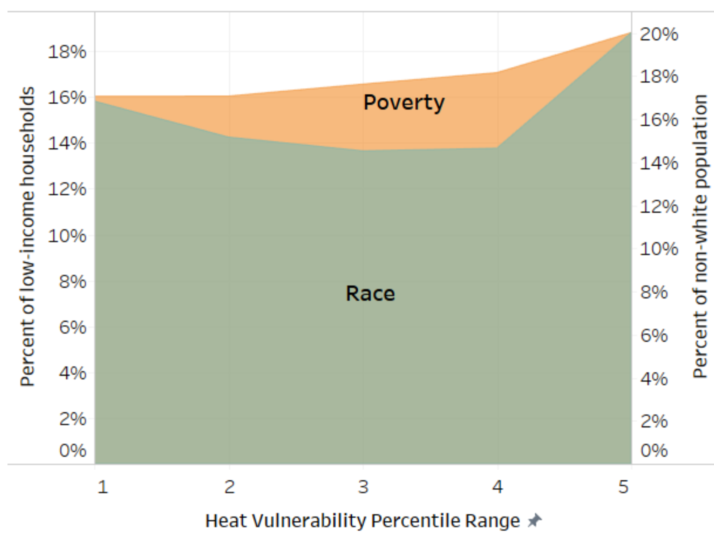


Figure 2. Distribution of counties by Heat Vulnerability Score (1=0-20%; 2=20-40%; 3=40-60%; 4=60-80%; 5=80-99%) and by percent non-white and low-income households.

Discussion:

Due largely to exposure to a high number of “dangerous”[4] heat and humidity days by mid-century, the South, Southeastern, Great Plains, and Midwest regions are likely to experience more extreme heat and humidity conditions than other parts of the country. Their experience with, and acclimated to, hot weather may however make them more resilient to these changes.

The rate and degree of temperature increase will vary widely across the United States with the most severe changes occurring in historically cool regions. The relative difference between historical and future extreme heat conditions is perhaps the most important indicator of human health when evaluating future heat risks as even incremental changes in climate that can generate a host of illnesses. For instance, regions such as the Pacific Northwest, Rocky Mountains, and northern Great Plains, will experience the most significant rise in heat extremes compared to the baseline period. Although generally temperatures will not be as high as they would be in the Southeast, the cooler regions will not be as well equipped to cope with increases in temperature.

Our analyses also focused on the different linkages to social vulnerability. The unique socioeconomic vulnerability factors associated with heat-related health are strongly tied to race, income, and living conditions. Low-income communities of color are also typically urban, impervious, absent of trees, and disproportionately exposed to heat-island risk factors (Harlan *et al.,* 2013). In rural counties, there are fewer epidemiological analyses to draw from, but no significant differences are evident when comparing the eight social vulnerability indicators across rural[5] and urban counties. Across the nation, social vulnerability varied widely, yet small clusters are evident within counties with majority African American residents in the South and Southeastern United States.

Conclusion:

There is no universal definition of what constitutes a heat wave. While a heat wave is a meteorological event, it should not be assessed independently of human impacts. From a climate change perspective, the lack of a unified index can cause confusion when discussing the complexities involved in evaluating and projecting the frequency and intensity of future heat extremes beset by changing climate. To ensure our analysis encompassed both the meteorological component and the local context, we focused on measures of extreme heat that capture both the relative change over time and an absolute heat-health risks regardless of place. Other trends not addressed here, such as urbanization, land use changes, and demographic shifts highlight the need for adaptation strategies designed around future conditions. Warming temperatures will challenge the effectiveness of traditional heat intervention strategies. Consequently, the extent to which heat impacts health and well-being will be largely determined local resources and capacity to implement interventions and raise public awareness. The indicators used here are a broad-brushed assessment of the climate effect on local heat exposure levels. Having identified local vulnerabilities, the next step is to evaluate heat vulnerability at a more local level and implement adaptation actions that address climate risk and social inequity as a shared threat to human health.

[4] Heat and Humidity Stroke Index (HHSI) Category II is equivalent to what might feel like the hottest summer day in the most humid parts of Texas or Louisiana.

[5] The definition of “rural” counties is based on the Office of Management and Budget (OMB) 2013 definition of “non metro” counties, which include Micropolitan (micro) areas, which are nonmetro labor-market areas centered on urban clusters of 10,000-49,999 persons all remaining counties, often labeled "noncore" counties because they are not part of "core-based" metro or micro areas.

Limitations:

Non-Stationarity

Some historical associations and thresholds of heat and human health may not hold under future climate scenarios as some adaptation measures continue to improve or demographic shifts and exposure levels change over time. Data used to determine the weighted exposure of populations (via public data) may not be representative of average condition or necessarily be indicative of future vulnerabilities.

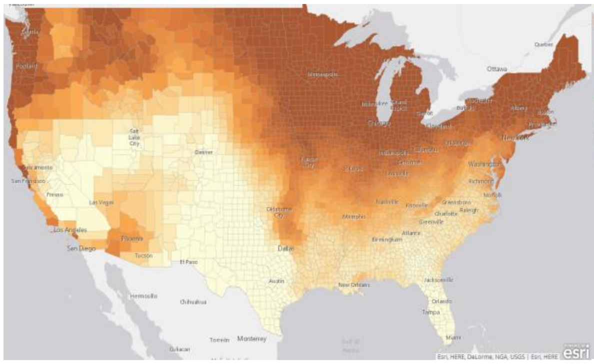
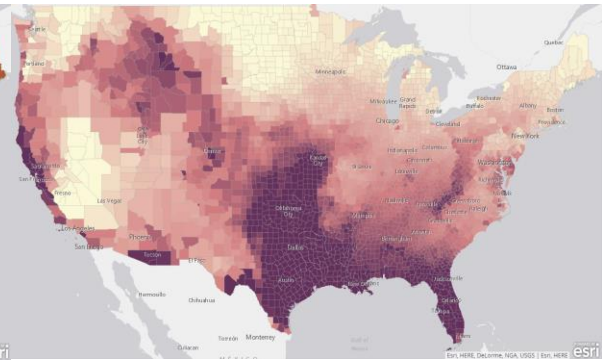
Data Availability

Our analysis was limited by the data available at the county scale nationwide. Due to rural-urban divides, heat relevant variables such as land cover (tree canopy, impervious pavement, and urban heat island effect) and accessibility (e.g., access to care physicians and centers) were excluded. Relevant medical conditions, such as psychiatric and cardiovascular illnesses were also not available nationwide. Measures of resilience, such as social capital or residential air conditioning were not available for non-urban areas. Also, epidemiological analysis that examines exposure-response rates merit further investigation to validate heat vulnerability scores.

Wet bulb temperature projections

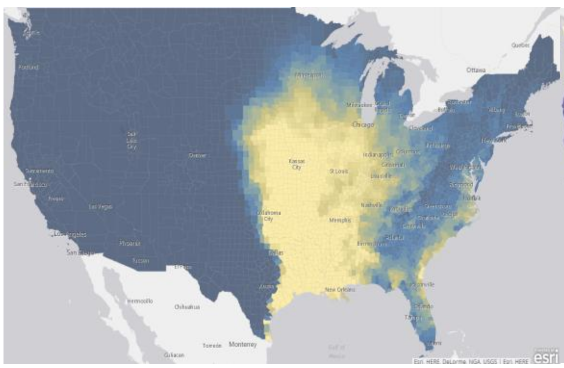
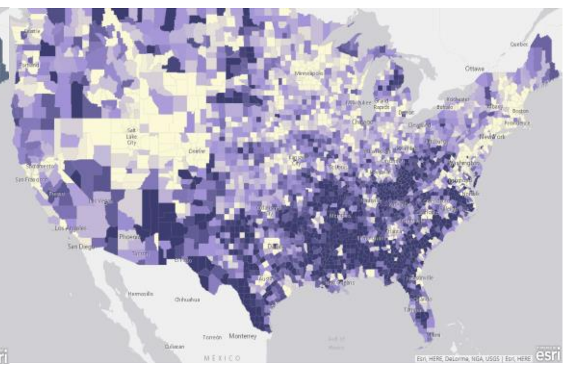
We follow the approach described in the American Climate Prospectus to project future wet bulb temperatures, although there are some limitations in this approach. We use the historical relationship between wet and dry bulb temperature to project future wet bulb temperatures given climate model output for dry bulb temperature. This relationship, a piecewise linear regression, may not hold in future climates, or change to varying degrees in different regions in the country. This approach also restricts the total range of outcomes, and thus does not fully capture either the abnormally hot or cool wet bulb temperatures for each dry bulb temperature. Additionally, there are inherent limitations in using climate models to project future climates, given the deep complexity and uncertainty in modeling the Earth's systems.

Appendix:

Map 2. Change in the severity of very hot days
Average change in the max wet-bulb temperature between 1981-2005 and 2045-2049

Map 3. Change in the frequency of very hot days
Average number of days over the historical 95th percentile in 2045-2049)

Map 4. Average number of days that exceed HHSI category II days in 2045-2049

Map 5. Social Vulnerability Score (2016)

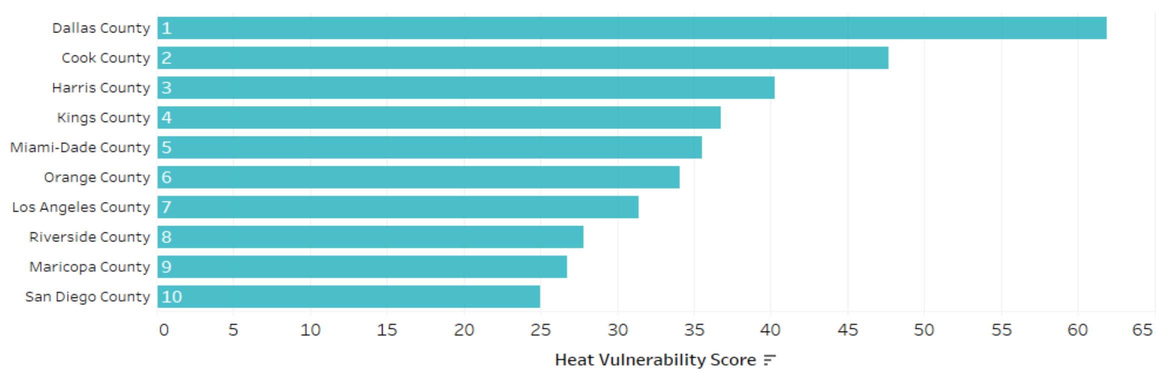


Figure 2. Ten most populous counties ranked by heat vulnerability score

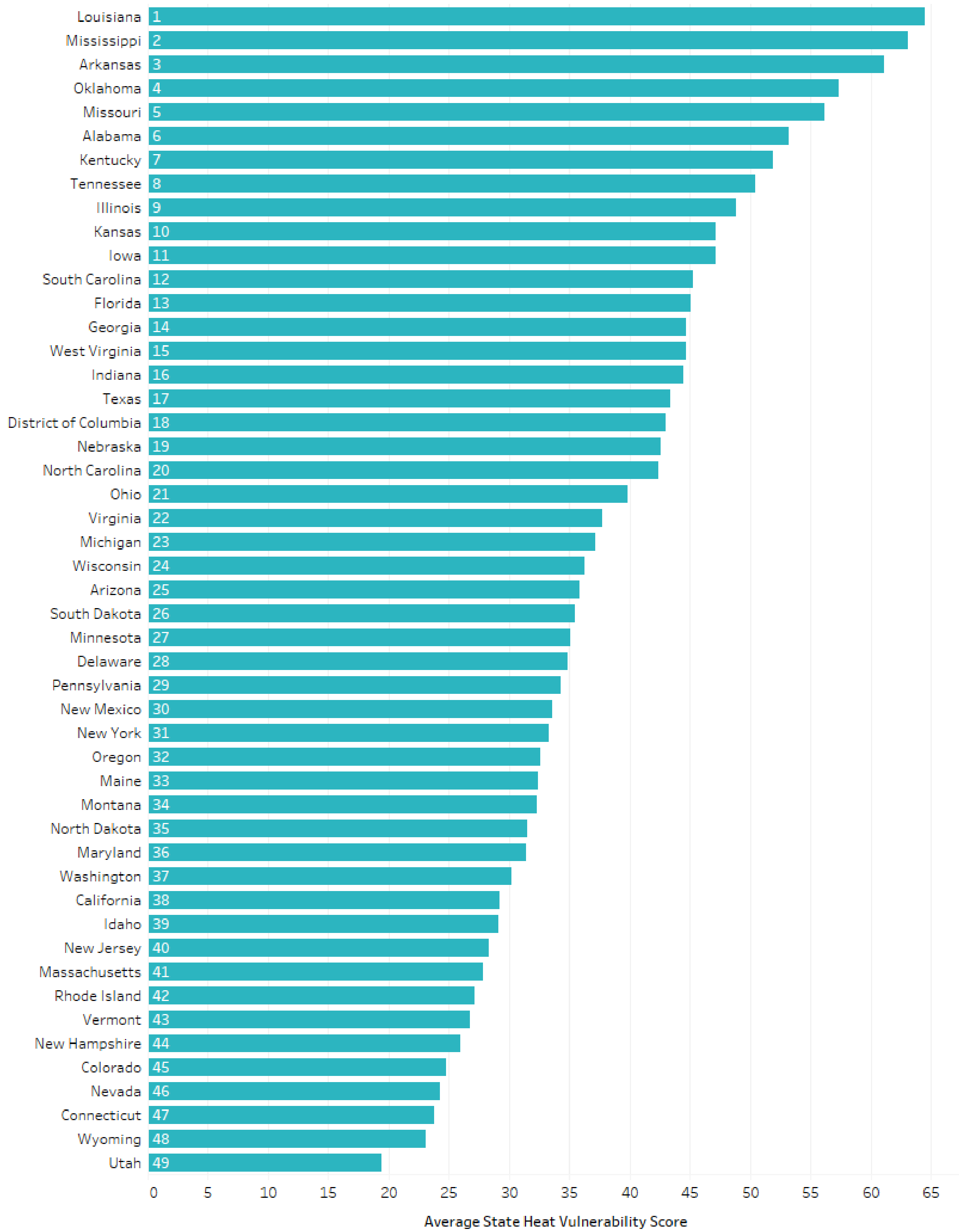


Figure 3. Ranking of heat vulnerability by state from high (1) to low (49)

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Vulnerability Indicators:

Housing stress: Percentage of households with at least 1 of 4 housing problems: overcrowding, high housing costs, or lack of kitchen or plumbing facilities (County Health Rankings & Roadmaps (CHR), averaged across 2014-2016

65+: Percent of residents 65 years and over (US Census, averaged across 2005-2014)

65+ living alone: Percent of households - one-person, 65 years and over (US Census, (averaged across 2005-2014)

Race: Percent of non-white residents (US Census, averaged across 2005-2014)

Living alone: Percent of households with only one-person (US Census, averaged across 2005-2014)

Below Poverty Line: Percent of people of all ages in poverty (US Census, averaged across 2005-2014)

No High School Diploma: Percent 25 years and over without finishing high school (US Census, 2006-2014)

Diabetes: Diagnosed diabetes prevalence (Centers for Disease Control, averaged across 2005-2013)

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