Working paper: Neighborhood-level risk perceptions of extreme heat events across the U.S.

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Abstract

Extreme heat is the leading weather-related cause of death in the U.S., a threat that is exacerbated by global warming. Yet many individuals fail to perceive extreme heat as a serious risk. Thus, understanding Americans' perceptions of heat risk and how such perceptions vary geographically and across different populations is a critical precursor to encouraging adaptive behaviors – such as staying hydrated or refraining from outdoor activity – during heat waves. Using a large original survey dataset of 9,217 respondents, we model Americans' perceived risk to their health from extreme heat in every populated census tract across the nation. Nationally, risk perceptions are higher in southern states where mortality from heat waves is also highest. However, the extent of variation within states and metropolitan areas is similar to variation between states. Locally, risk perceptions are higher in areas with greater poverty and among minority populations that are more vulnerable to environmental risks in general. We identify highly vulnerable areas where risk perceptions currently lag heat-related mortality; without concerted adaptation efforts such vulnerability is likely to expand and intensify as heat exposure increases. Comprehensive estimates of extreme heat risk perceptions at the census tract level can support communication, education, and adaptation initiatives in existing and emerging areas most vulnerable to heat in the U.S.

Main

Extreme heat events are the leading weather-related cause of death in the U.S. and are projected to become more frequent and intense over the 21st century [1, 2, 3]. Mortality and morbidity from heat exposure can often be mitigated, however, if individuals perceive the risk, have access to necessary resources, and take appropriate precautionary action [4]. Mitigating the effects of extreme heat can be as simple as increasing fluid intake, using a fan, finding a cooler location, or avoiding over-exertion. Yet, if individuals do not perceive heat exposure to be a problem, then they may be less likely to obtain necessary resources and take appropriate actions. Despite the

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importance of risk perceptions in driving behavior, little effort has been directed to mapping risk perceptions because of the difficulty in obtaining comprehensive social survey data across large areas at fine spatial scales. Thus, while substantial effort and resources continue to focus on mapping variations in a population’s exposure to and impacts from extreme heat [5, 6, 7, 8, 9], which remains vital, comprehensive high resolution heat risk perception maps with a national extent have thus far been beyond scientific reach.

Here we apply a small-area estimation model based on new nationally representative survey data to estimate health risk perceptions of heat waves for every state, county, and census tract in the U.S. The model employs individual and socio-environmental predictors of heat risk perceptions and is validated using independent tract-level survey data. Mapping risk perceptions reveals the importance of physical factors such as local climate and land cover, along with demographic factors such as age and gender in shaping Americans’ perceived risk to their personal, family’s, and community’s health during a heat wave. Risk perceptions exhibit substantial variation at multiple scales, with estimates across states showing similar variation to estimates across census tracts in major metropolitan areas. Results provide a new tool for communicators and decision makers to understand the geographic diversity in Americans’ judgments about the health risks of extreme heat.

Extreme heat is one of the most severe environmental hazards to public health: it is the leading cause of weather-related mortality in the U.S., and has numerous impacts on vital social systems including food, water, energy and infrastructure [1, 4]. Extreme heat events are also projected to intensify in frequency and severity due to climate change [2, 3, 10], with even greater impacts in urban areas, due to heat island effects [11, 12, 13] and air pollution [14]. Increasing urbanization, migration to climates more prone to extreme heat, and an aging population that is more vulnerable to heat stress compounds the problem in the U.S. [5, 15, 16].

Extreme heat typically becomes hazardous during heat waves, multi-day periods of excessively hot weather (often combined with high humidity) that, due to their severity or duration, pose risks to human health [17, 18]. The point at which temperature and humidity levels threaten health, however, varies depending on factors such as physiological sensitivity, the ability to take protective action, individual psychological factors, and individual exposure [9, 16, 19, 20, 21, 22]. Psychological factors that influence health risks include risk perceptions, which comprise beliefs and attitudes about the frequency, severity, and duration of extreme heat events, as well as the dangers of exposure. In addition to physical risk factors, previous research underscores the importance of such risk perceptions—among other social and behavioral factors—in increasing

vulnerability to hazards and the impacts of climate change [23, 24, 25, 26, 27]. Vulnerability to extreme heat varies geographically at local to regional scales due to a variety of factors including differences in physical exposure to hot weather driven by climate and land cover, variation in demographic and health status characteristics associated with heat sensitivity, and availability of air conditioning, among others [28]. Few studies, however, have focused on heat wave risk perceptions specifically, or systematically collected data on risk perceptions at the national scale to how perceptions vary geographically or across demographic groups. Previous research has used qualitative case studies of subgroups of the population or surveys in a small number of individual cities [29, 30, 31, 32, 33, 34]. There remains a large knowledge gap globally about heat risk perceptions and how to effectively communicate about the risk [35]. Societal vulnerability to extreme heat is increasingly understood as a function not only of demographics and access to resources, but also knowledge and perceptions [36]. Effective adaptation strategies to the risks of extreme heat, therefore, must address public perceptions and knowledge [13].

The urgency of understanding the determinants of heat wave vulnerability is compounded by global warming, which will exacerbate impacts due to higher average temperatures, more frequent temperature extremes, increased humidity, and increased weather variability [3, 37, 38]. Global warming will exacerbate extreme heat hazards in areas that already experience extreme heat, but the hazard will also spread to areas with little prior experience of health-threatening heat [2, 3]. In such areas, risk perceptions will likely lag the changing risk environment since they are strongly influenced by a variety of cognitive and intuitive factors including personal experience [27]. The gap between perceptions and changing baseline risk will compound vulnerability if it reduces the likelihood of individuals to take precautionary actions. Thus it is important to understand how people currently perceive the risk of extreme heat at the appropriate geographic scales necessary to target resources and reduce population vulnerability.

Small-area estimation from national survey data

We use new nationally representative survey data and multilevel regression and poststratification (MRP), a small-area estimation method, to provide high-resolution, nationwide estimates of risk perceptions. We collected U.S. national survey data ($n = 9217$) in 10 waves at two-week intervals during Summer 2015 using a representative online panel. Our survey instrument contained nine questions eliciting respondents' judgments of negative health effects from heat waves operationalized in terms of likelihood, severity, and worry. Respondents were asked to evaluate each aspect in terms of health risks to themselves (personal risks), family members (family risks),

and others in their community (community risks). Here we present an aggregate index of overall heat risk perception for all nine items (Cronbach’s $\alpha = 0.95$). Respondents who did not answer all nine questions were omitted from the analysis (n=368).

We apply MRP to the national survey data to generate estimates of heat risk perceptions at the census tract level for all populated census tracts in the U.S. MRP is an emerging method developed to estimate public opinion (or other population estimates) at sub-national levels using multilevel regression modeling of survey data in combination with census data and other geographically varying predictors [39, 40, 41]. Recent research has applied and validated MRP to estimate patterns in public opinion across a range of sub-national scales relevant to decision making in the context of climate change [42, 43].

Our results are validated by comparing model estimates against estimates from independently conducted surveys (in randomly selected geographies) in two census tracts and eight states.

Results

Our heat risk perception index ranged from 0 to 100, with higher values indicating higher risk perceptions. People with higher risk perceptions were 1) more likely to think that a heat wave would occur in their community; 2) more likely to think that a heat wave, were it to happen in their community, would affect the health of themselves, their family, and others in their community; and 3) more worried about the effects of heat waves. Nationally, the mean heat risk perception index was 40. At the state level, estimates ranged from 31 to 45. Overall, respondents perceived the risks of extreme heat to themselves (mean=34.6, SD=3.9) to be lower than risks to their family (mean=39.6, SD=3.4) or others in their community (mean=47.9, SD=3.5). An online visualization tool shows the spatial variations across the US at county and tract levels (Beta version for peer review: <https://bit.ly/2q5wDPS>).

Risk perceptions of extreme heat exhibit substantial variation from the local to regional scale in the U.S. At state level, there is a distinct north-south gradient in perceptions of harm from heat waves, with residents in southern states perceiving higher risk than those in northern states (Fig. 1). People in inland northern states in particular (e.g., North Dakota, Minnesota) exhibit lower risk perceptions than those in coastal states. Residents of Texas, Louisiana, and Nevada had the highest levels of perceived risk. Closer examination of state- (SD=3.8) and county-level (SD=4.2) heat risk perceptions also shows substantial variation (Fig. 2). The southernmost counties in Texas perceive the greatest potential harm from extreme heat, for example, as do counties in southern California and its Central Valley. In addition, highly populated counties

Figure 1: State level estimates of heat risk perception for the contiguous U.S. Values indicate mean estimated risk perception index for the population of each state ($SD=3.8$).

are important for determining the overall level of risk perception within a state. The gradient in extreme heat risk perceptions evident in the U.S. in both the state and county-level maps is consistent with the latitudinal temperature gradient and suggests that those living in warmer climates understandably perceive higher risks from extreme heat. Likewise, some of the lowest risk perceptions are in counties at high elevations with cooler climates, such as in the Rocky Mountains of Colorado, Wyoming, and Idaho. Lower-than-average risk perceptions are also evident in counties along the Appalachian Mountains. Such patterns highlight the influence of temperature as a key factor driving spatial variations in extreme heat risk perceptions; demographic influences, however, are also evident at the national scale. Higher-than average risk perceptions of extreme heat can be found, for example, in some counties with relatively high African American (e.g. along the Southern Black Belt in east-central Mississippi and Alabama) or Hispanic/Latino populations (e.g. in southern California and Texas).

Spatial patterns in heat risk perceptions also show strong features at the census tract level, with wide variation present even within the same counties (Fig. 3). Such patterns are not

Figure 2: County level estimates of heat risk perception for contiguous U.S. counties. Values indicate mean estimated risk perception index for the population of each county ($SD=4.2$).

Los Angeles County, California

Cook County, Illinois

Harris County, Texas

Maricopa County, Arizona

Difference from county average

Figure 3: Tract level estimates of heat risk perception for the four largest U.S. counties by population. Tracts are shaded by the difference from the average for each county. From top left: Los Angeles County, California (mean=45, SD=4.1), Cook County, Illinois (mean=39, SD=4.5), Harris County, Texas (mean=46, SD=3.9), and Maricopa County, Arizona (mean=43, SD=3.8).

wholly consistent with variations in temperature exposure. In examples from the four most populated counties, Los Angeles, California, Cook County, Illinois (Chicago), Harris County, Texas (Houston), and Maricopa County, Arizona (Phoenix), risk perceptions vary within counties by about 20 points ($SD=3.8 - 4.5$). In each case, the more densely populated urban tracts tend to exhibit higher relative risk perceptions than the suburban and rural areas surrounding the cities. Yet, while temperature changes may again partly explain these variations due to urban heat island effects, the spatial variability of risk perceptions within urban cores points to other factors. Close examination of the most densely populated areas (indicated by smaller tract sizes) reveals an urban core with relatively low risk perceptions of harm from extreme heat surrounded by a ring of tracts with higher perceived harm (especially, for example, in Harris County, Texas). Such a pattern reflects a feature of urban geography in many American cities explained primarily by differences in economic, demographic, and social factors [44]. Thus, within urban areas heat risk perceptions are strongly influenced by sociodemographics that are consistent with social vulnerability [45].

Model estimates were validated against independent mail surveys conducted in two census tracts in the communities of Brawley, Imperial County, California ($n=277$) and Peoria, Peoria County, Illinois ($n=364$). Tracts were selected by first stratifying all U.S. counties with heat-related mortality statistics recorded in the CDC WONDER database [46] into those with above- and below-average per capita mortality and above- and below-average risk perceptions. One county was then randomly selected from each of the two groups that had higher-than-average heat-related deaths and either lower- or higher-than average risk perceptions. That is, one county had high heat-related deaths and higher-than-average risk perceptions (Imperial County, CA), and the other had high heat-related deaths and lower-than-average risk perceptions (Peoria County, IL). One census tract was then randomly selected within each of the two counties. Compared against these tract-level surveys, the mean absolute error of our MRP model estimates was 2.7 points (for CA and IL) (Fig. 4). We also validated our estimates against independent online surveys conducted in eight states. States were selected by stratifying all 48 contiguous states and the District of Columbia into population quartiles, and randomly selecting two states within each quartile. Compared against these state-level surveys, the mean absolute error of our MRP model estimates was 1.6 points, and the correlation of the model estimates to the state-level survey results was $r=0.82$ (Fig. 5).

Within the two census tracts selected for our external validation surveys we see strong demographic patterns across race/ethnicity and gender. While white respondents have the lowest

Figure 4: External validation of estimated risk perception index with independent survey estimates in randomly selected tracts in Imperial County (Brawley), California (left) and Peoria County, Illinois (right). The mean absolute difference between MRP model estimates and the external survey results was 2.7 points. The risk perception index is generally higher in Brawley than in Peoria. In both census tracts, Hispanic females have the highest risk perceptions while white males have the lowest.

Figure 5: External validation comparison of estimated risk perception index with mean-centered independent survey estimates in eight randomly selected states. The mean absolute difference between MRP model estimates and the external survey results was 1.6 points. Estimates were correlated at $r=0.82$.

heat risk perceptions, Hispanic respondents have the highest risk perceptions in both tracts. Women tend to perceive higher risks from extreme heat than men. Estimated heat risk perceptions overall are 14 percentage points higher in the Imperial County, California tract than in the Peoria County, Illinois tract, which also illustrates regional-scale geographic differences.

Heat-related mortality data are available at the state level [46], which allows for a comparison between recent mortality and risk perception estimates. We see a generally positive relationship between risk perception and mortality from 1999-2015 (Fig. 6) ($r=0.57$). However, regional patterns are also evident in this comparison: most states in the South have higher risk perceptions than would be predicted by their per capita mortality, while most states in the Midwest have lower risk perceptions than would be predicted by their mortality rate. These patterns may indicate some degree of existing adaptation in states with high risk perceptions and lower than expected mortality. For example, the heat risk perception index is 10 points higher in California than Wisconsin, yet mortality is similar in the two states (0.2 per 100,000) despite greater population exposure to extreme heat in California. Similarly, mortality is comparable between Texas and Kansas (0.3 per 100,000), yet the heat risk perception index is 7.5 points higher in Texas.

U.S. population exposure to extreme heat will continue to grow in the 21st century under most climate scenarios, driven by both changes in climate, population growth, and shifts in population distribution to more exposed areas [5]. We compare our risk perception estimates at the census division level to an ensemble mean scenario of population exposure for 2041-2070 reported by Jones et al. [5]. Risk perception estimates and population exposure are highly correlated both under the base period (1971-2000; $r=0.77$) and future projections (2041-2070; $r=0.80$). Population exposure and risk perceptions are highest in the West-South Central division (including Texas, Oklahoma, Arkansas, and Louisiana). Risk perceptions are lower than expected, based on current and projected population exposure, in the Mountain division (including the states of Arizona, Nevada, Colorado, Utah, New Mexico, Montana, Idaho, and Wyoming).

Discussion and conclusions

The development of estimates of extreme heat risk perceptions that integrate sociodemographic as well as physical contextual factors can improve our understanding of spatial variability and scale-dependent patterns in these perceptions. The factors most important for determining the spatial patterns in risk perceptions appear to vary by geographic scale. At the state and county

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Figure 6: Risk perception as compared to heat-related mortality (MCD-ICD 10 code T67) at the state level, 1999-2015 [46].

Figure 7: Heat risk perception index by projected change in aggregate exposure to extreme heat across nine U.S. census divisions. Exposure projections courtesy Jones et al. (2015) [5].

level, risk perceptions are consistent with differences in average temperatures. At local (city and neighborhood) scales, however, variation in risk perceptions are more strongly influenced by sociodemographic factors. In both cases, differences in perceptions are consistent with variation in both physical and social vulnerability to the hazard.

Increasing atmospheric greenhouse gas concentrations that are causing global temperatures to rise are also having an effect on the U.S., where mean temperatures have increased by 1.3°F to 1.9°F since record keeping began in 1895 [47]. As the climate continues to warm, populations in northern states and at higher elevations will become more exposed to extreme heat [3]. The rate at which individual’s risk perceptions change, however, is unknown, and may lead to a growing gap between perceptions and exposure if risk perceptions do not keep pace with the changing climate. There is growing evidence that rising greenhouse gases are already affecting some characteristics (e.g., likelihood, severity) of heat waves [48] and projections of future climate change indicate that heat will become an increasing problem [49]. Populations in areas that already experience frequent extreme heat, such as the U.S. South and Southwest, will be more exposed to extreme heat, but may be able to leverage existing infrastructure and experiential knowledge to cope with more frequent hot weather. Populations in areas with lower exposure, such as those in northern states, may become increasingly at risk of negative health impacts from extreme heat as exposure exacerbates extreme heat events beyond the range of previous experience.

An analysis of city to national-scale trends in heat-related mortality found evidence that populations in the US have indeed become more resilient to heat over time, even when accounting for increases in the use of air conditioning [50]. Despite this increased resilience, however, an increase in average temperatures by 5°F (central climate projection) would lead to an additional 1,907 deaths per summer across 105 US cities [50]. A better understanding of the variation in Americans’ risk perceptions of extreme heat may help further improve resilience to increasing heat in the coming decades.

Mapping model estimates reveals that risk perceptions of extreme heat appear to be scale dependent. Local climate, land cover, and other contextual factors shape risk perceptions alongside demographic predictors, but physical factors appear to be more important in driving national scale responses, whereas sociodemographic predictors are more relevant at finer scales. In addition, variation among states is similar to variation among census tracts in major metropolitan areas. Comparisons between Americans’ current risk perceptions and future exposure to extreme heat suggest that residents of Mountain region states perceive less risk, on average, than those

in other states with comparable exposure levels. Given that risk perceptions motivate adaptive responses, future efforts designed to increase awareness about the health risks of extreme heat may become particularly important in Mountain states, as well as in South Atlantic states, where future exposure is expected to increase the most. These results provide insights and a new tool for communicators and decision makers to understand the geographic diversity in Americans' judgments about the health risks of extreme heat, and point towards the need for additional analyses that can help identify areas where gaps (or lack of concordance) between actual and perceived risk may exist, or may grow in the future.

Methods

We construct an aggregate index of heat risk perception using our three groups of three questions in an online survey instrument designed to elicit risk judgments of negative health effects from heat waves operationalized in terms of likelihood, severity, and worry. Respondents used a slider bar to indicate their answer on a 0-100 scale. Respondents answered each question for a) "Your health;" b) "The health of others in your family;" and c) "The health of others in your community." Our questions were as follows: 1) "A heat wave is a period of unusually and uncomfortably hot weather. Thinking about your local area, how likely is it, if at all, that each of the following will be harmed by a heat wave in the next five years? If you're not sure, just give your best estimate." Response options range from 0% ("Definitely will not be harmed") to 100% (Definitely will be harmed). We also include a separate response option of "[w]ill not be harmed because a heat wave will not occur." 2) "If a heat wave were to occur in your local area, how much, if at all, do you think it would harm the following?" Response options ranged from 0 ("Would cause no harm at all") to 100 ("Would cause extreme harm"). 3) "How worried, if at all, are you about the effects of heat waves on the following?" Response options ranged from 0 ("Not worried at all") to 100 ("Extremely worried"). The aggregate index of all nine items has high internal consistency (Cronbach's $\alpha = 0.95$).

Predicting heat wave risk perceptions at the tract level using multilevel regression and post-stratification (MRP) proceeded through several stages, from variable and model selection to testing and validation. In MRP, a multilevel regression model is fit to an individual-level dependent variable using a combination of individual-level demographic predictors, grouped random effects, and group-level predictors across geographic units within the dataset. In the second step, poststratification, the fitted model is applied to the population of the study area across each demographic-geographic type within the population, using census data cross-tabulated across

each type. Estimates for each demographic-geographic type can then be aggregated by their population to produce estimates for every geographic unit.

Our individual-level model uses age group, gender, and race/ethnicity as predictors, with an interaction term for age by gender by race/ethnicity. Individuals are grouped geographically according to their census tract, county, state, and census division. In addition to using fixed effects as in classical regression, the multilevel model uses random effects for grouping variables. Random effects are related to each other by their hierarchical structure and thus are partially pooled towards their group mean. Greater pooling occurs for smaller groups and when group-level variance is low. Group-level predictors are also used to improve model fit [40, 41] and are based on respondents' geographic location. Based on exploratory analyses employing Random Forest (RF) analysis [51] that considered dozens of potential geographically varying census, climate, and land cover variables suggested by previous research, we included educational attainment, poverty, and disability status; impervious surface land cover; and gridded long-term mean temperature as tract-level predictors. For poststratification we utilize 2015 5-year American Community Survey data cross-tabulated by age group, gender, and race/ethnicity across all states, counties, and U.S. census tracts. Although there is a strong theoretical basis for selecting several sociodemographic factors in a model of heat wave risk perceptions, census and other datasets provide many different measures of most factors. RF ranks variables by their predictive importance, which we compared for four indices including personal harm, harm to one's family, and community harm, and an overall risk perception index that combined these three, resulting in four indices. We also compared the RF results for both binary and continuous outcomes, resulting in a total of eight indices. Age, race/ethnicity, education, disability, various measures of income, temperature, and the proportion of impervious surfaces in the tract consistently ranked among the top ten predictors in the RF analysis. Model selection proceeded by comparing predictions and errors across the reduced variable sets identified from the RF analysis.

We specify our model as follows, predicting heat risk perceptions (y) for each individual i :

$$y_i \sim N \left(\gamma^0 + \alpha_{j[i]}^{\text{race}} + \alpha_{k[i]}^{\text{age}} + \alpha_{l[i], D=d}^{\text{gender}} + \alpha_{j[i], k[i], l[i]}^{\text{race.age.gender}} + \alpha_{t[i]}^{\text{tract}}, \sigma_y^2 \right),$$

where

$$\begin{aligned}
\alpha_j^{\text{race}} &\sim N(0, \sigma_{\text{race}}^2) \text{ for } j = 1, \dots, 5 \\
\alpha_k^{\text{age}} &\sim N(0, \sigma_{\text{age}}^2) \text{ for } k = 1, \dots, 10 \\
\alpha_l^{\text{gender}} &\sim N(0, \sigma_{\text{gender}}^2) \text{ for } l = 1, 2 \\
\alpha_{j,k,l}^{\text{race.age.gender}} &\sim N(0, \sigma_{\text{race.age.gender}}^2) \text{ for } j = 1, \dots, 5; k = 1, \dots, 10; l = 1, 2 \\
\alpha_t^{\text{tract}} &\sim N(\alpha_{r[t]}^{\text{region}} + \alpha_{s[t]}^{\text{state}} + \alpha_{c[t]}^{\text{county}} + \gamma^{\text{tmean}} \text{tmean}_t + \gamma^{\text{landcover}} \text{landcover}_t + \\
&\quad \gamma^{\text{education}} \text{education}_t + \gamma^{\text{lowincome}} \text{lowincome}_t + \gamma^{\text{disability65}} \text{disability65}_t, \sigma_{\text{tract}}^2) \text{ for } t = 1, \dots, 6994 \\
\alpha_r^{\text{region}} &\sim N(0, \sigma_{\text{region}}^2) \text{ for } r = 1, \dots, 9 \\
\alpha_s^{\text{state}} &\sim N(0, \sigma_{\text{state}}^2) \text{ for } s = 1, \dots, 51 \\
\alpha_c^{\text{county}} &\sim N(0, \sigma_{\text{county}}^2) \text{ for } c = 1, \dots, 1524
\end{aligned}$$

Each variable is indexed over individual i and over response categories j, k, l, r, s, c , and t for race, age, gender, state, region, county, and census tract geography variables, respectively. The tract variable is further modeled as a function of region, state, county, and a series of geography-level covariates including the mean of daily mean summer (JJA) temperature within the census tract (1981-2010) from the Daymet dataset [52], the mean percentage imperviousness within the tract in 2011 from the National Land Cover Dataset [53], the percentage of the adult population with a bachelors degree or higher in 2014 [54], the percentage of households receiving benefits from the Supplemental Nutrition Assistance Program (SNAP) in 2014 [54], and the percentage of residents age 65 and over with disability status in 2014 [54]. The tract-level estimates are aggregated to create the county-level and state-level estimates. The models are fitted using the `lmer` function in the R package `lme4`; the `lmer` function fits the model using restricted maximum likelihood.

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