Geographic Distributions of Extreme Weather Risk Perceptions in the United States

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ABSTRACT

Weather and climate disasters pose an increasing risk to life and property in the United States. Managing this risk requires objective information about the nature of the threat and subjective information about how people perceive it. Meteorologists and climatologists have a relatively firm grasp of the historical objective risk. For example, we know which parts of the US are most likely to experience drought, heat waves, flooding, snow or ice storms, tornadoes, and hurricanes. We know less about the geographic distribution of the perceived risks of meteorological events and trends. Do subjective perceptions align with exposure to weather risks? This question is difficult to answer because analysts have yet to develop a comprehensive and spatially consistent methodology for measuring risk perceptions across geographic areas in the US. In this project, we propose a methodology that uses multilevel regression and poststratification (MRP) to estimate extreme weather and climate risk perceptions by geographic area (i.e., region, state, forecast area, county). Then we apply the methodology using data from three national surveys (n = 9,542). This enables us to measure, map, and compare perceptions of risk from multiple weather hazards in geographic areas across the country.

KEY WORDS: Extreme weather, risk perceptions, geography

Social Media Summary:

Do risk perceptions of natural hazards (tornadoes, hurricanes, etc.) correlate with hazard frequency? Often, the answer is yes! See how we answer this question with data from large national surveys.

1. INTRODUCTION

Weather and climate disasters pose an increasing risk to life and property in the United States. In 2017, there were 16 weather and climate disasters with losses exceeding $1 billion each, including three tropical cyclones, three severe thunderstorms, three tornadoes, two hail storms, two inland floods, a crop freeze, a drought and two wildfires. The cumulative cost of these events was $309.5 billion, the most in US history (Smith, 2018). Reducing these costs and managing risk requires both *objective* information about the nature of the threat and *subjective* information about the risk perceptions of the diverse individuals affected by these threats. To improve hazard communication (e.g., forecasts) and decision support, those who are responsible for communicating information about the risks of extreme weather and climate disasters (e.g., emergency managers, broadcast meteorologists, warning forecast office meteorologists) need to understand how people think about and respond to risk.

Meteorologists and climatologists collect and compile data on the frequency and severity of extreme weather and climate hazards across the US (NOAA, 2019; National Drought Mitigation Center, 2019). As such, researchers have robust knowledge about the geographic distribution of objective risk from different weather and climate hazards across the country. By comparison, less is known about the geographic distribution of risk perceptions across weather hazards. This project is focused on understanding how risk perceptions vary geographically, irrespective of a single event, and the extent to which risk perceptions align with hazard exposure.

Using an all-hazards approach, we investigate the hazard exposure vs. risk perception relationship across eight different hazards in 115 geographic regions. This investigation allows us to statistically identify exposure-perception “gaps” across communities and hazards which could indicate vulnerability. In some cases risk perceptions may be low in comparison to exposure. This may indicate that these communities do not fully recognize the hazards they may see in the future. Alternatively, risk perceptions could be high in comparison to exposure. This may indicate that communities are overpreparing for some hazards at the possible risk of underpreparing for others. In both cases, one can imagine the value of local risk communication and education strategies that focus on closing these gaps in potentially vulnerable communities.

In addition to data about possible vulnerabilities across communities, investigation of the exposure-perception relationship across hazards provides valuable information about (i) the hazards that people perceive and worry about and (ii) the hazards that are historically present, but seem less notable. Extreme heat is one such example where past research indicates that exposure is relatively high in many places that tend to have low risk perceptions (Howe et al., 2019). A relatively low correlation between exposure to and perception of extreme heat may be an indicator of vulnerability that is applicable across communities. Recognizing this low correlation may help national organizations such as the Federal Emergency Management Agency and the National Weather Service (NWS) develop strategic risk communication and education campaigns to help people perceive hazards that they might otherwise overlook.

Furthermore, by measuring risk perceptions across the contiguous US, we can begin to address important questions: Do concerns about natural hazards vary systematically across the country? Do these risk perceptions align with objective indicators of exposure, such as those collected by the National Oceanic and Atmospheric Administration (NOAA)? Do individual risk perceptions correlate more strongly with risk exposure to certain hazards and not others? If so, which ones? Do these perceptions influence risk communication? These questions are difficult to answer because there is not yet a comprehensive and spatially consistent methodology for measuring risk perceptions across geographic areas in the US. This paper uses data from ongoing national surveys where we apply a novel methodology in survey research to fill this gap.

1.1 Weather and Climate Hazard Risk Perceptions

Risk perceptions represent intuitive judgments about the probability of a given risk (event) and concern about the consequences of that risk (event) if it were to manfiest (Slovic, 1987; Sjöberg, Moen, & Rundmo, 2004). Both theory and research indicate that risk perceptions are among the most important drivers of protective action in response to a wide variety of weather and climate hazards (Burnside, Miller, & Rivera, 2007; Dow & Cutter, 2000; Lindell, Arlikatti, & Prater, 2009; Lindell & Perry, 2012; Mileti & O'Brien, 1992; Mileti & Sorensen, 1990; Murphy et al., 2009; Rüstemli & Karanci, 1999; Ramasubramanian et al., 2019; Whitmarsh, 2008). As such, "best practice" guides to risk communication in specific communities often begin by emphasizing the importance of understanding risk perceptions (e.g., Perry & Lindell, 2003).

Differences among individuals *within* communities strongly influence weather and climate hazard risk perceptions. For example, research consistently shows that white men often view hazards as less risky than their female and minority counterparts (Flynn, Slovic, & Mertz, 1994). Age can influence risk perceptions as well, but the direction of the relationship is less consistent across hazards (Wachinger et al., 2013). For some hazards, risk perceptions seem to increase with age (Kellens et al., 2011); for others, there is no meaningful relationship (Plapp & Werner, 2006; Siegrist & Gutscher, 2006). These differences are likely driven by multiple mechanisms including variable access to resources, trust in authority, and worldviews (Kahan et al., 2007; Kahan, Jenkins-Smith, & Braman, 2011; Siegrist & Cvetkovich, 2000; Siegrist, 2019).

In addition to differences among individuals *within* communities, differences *between* communities can also influence risk perceptions. For example, a long line of research suggests that some communities develop “subcultures” through collective experiences that influence the ways in which people in a given community perceive and respond to disasters (Anderson, 1965; Sims & Baumann, 1972; Weller & Wenger, 1973; Granot, 1996; Engel et al., 2014; Bankoff, 2017). In addition to subcultures, differences in community *sensitivity* and *exposure* can perpetuate variation in risk perceptions between communities. Sensitivity indicates the extent to which demographic attributes, infrastructure, or other structures in a community generate vulnerabilities that predispose the community to loss during disasters (Cutter, Boruff, & Shirley, 2003). Exposure, by comparison, indicates the frequency with which humans in a given area come into contact with hazards, both historicially, and in the future (Burton, Kates, & White, 1993). Geography often influences exposure because many hazards are more (or less) common in given climates and landscapes. Exposure contributes to the *probability* side of the objective risk equation, whereas sensitivity contributes to the *consequences* side of the equation.

Previous research indicates a somewhat tenuous relationship between exposure and risk perception in the weather and climate domains. A few studies in specific communities indicate a modest relationship between flood risk perceptions related to exposure (Siegrist & Gutscher, 2006; Horney et al, 2010; Siebeneck & Cova, 2012; O’Neill et al., 2016; Royal & Walls, 2019). Other studies in different communities indicate little or no association between flood exposure and perceptions (Wallace, Poole, & Horney, 2016; Tanner & Arvai, 2018). While informative, these studies of the relationship between exposure and perceptions are subject to a variety of limitations. Most notably, most of the research in this area focuses on flooding, so we know relatively little about the connection between exposure and perceptions to other weather and climate hazards (but see Champ & Brenkert-Smith, 2016). Additionally, much of the research in the area focuses on people in specific communities, which limits the generalizability of the findings. A recent study by Howe and colleagues (2019) represents a notable exception to these limitations. It investigates the geographic distribution of heat risk perceptions in communities across the US, finding that subjective perceptions of health risks from extreme heat exhibit strong geographic patterns that relate to, but do not directly overlap with, extreme heat exposure.

The present study builds upon Howe et al. (2019) to measure and map public perceptions of risk from eight different extreme weather and climate hazards—extreme heat, drought, extreme cold, extreme snow (or ice), tornadoes, floods, hurricanes, and wildfires. The data and maps provided are publicly available[1] and the geographic relationships they depict will help risk communicators (e.g., forecasters, broadcast meteorologists, emergency managers) develop messaging strategies and education initiatives that are specific to the communities they serve. In addition, the data and maps facilitate academic research into the variety of factors explaining community perceptions of risk. To demonstrate this point, the analysis examines the relationship between hazard exposure and risk perceptions across hazards in the US.

2. METHODS

2.1. Data

2.1.1. Estimation Survey Data

The data we use to estimate subjective risk perceptions across geographic areas come from a national survey that is conducted annually by the Center for Risk and Crisis Management at the University of Oklahoma. This survey, called the Severe Weather and Society Survey, measures weather and climate risk perceptions and information reception, comprehension, and response

[1] For data access and interactive maps, see https://crcm.shinyapps.io/WxDash/.

across extreme weather and climate hazards. This analysis uses data from the 2017, 2018, and 2019 surveys (n = 2,003, 2,998, & 2,998, respectively). All surveys were implemented online to samples of adults (age 18+) that reside in the Contiguous US (CONUS). The samples were provided by Qualtrics, which uses quota sampling from opt-in panels based on demographic characteristics. While there is some debate in the literature about which sampling method is best, research suggests that the results from opt-in panels and probability samples are relatively comparable (Baker et al., 2013; Berrens et al., 2003; Chang & Krosnick, 2009; MacInnis et al., 2018). Of participants who started the survey, 79.9% went on to complete it. Further information about data collection and preliminary frequency information can be found in Silva et al. (2017; 2018; 2019).

At the beginning of the survey, participants responded to a battery of demographic questions and then rated eight extreme weather hazards on a five-point scale (no, low, moderate, high, or extreme risk). The eight hazards—extreme heat, drought, extreme cold, snow/ice, tornados, flooding, hurricanes, and wildfires—were presented in a random order for each participant. The question wording was: "*Thinking about all four seasons (winter, summer, spring, and fall), how do you rate the risk of the following extreme weather events to you and the people in your area?*" Note that this wording is intentionally nebulous; it does not instruct survey respondents to think of a specific definition or dimension of risk when providing a judgement. It also suggests that participants consider all four seasons, so as to encourage participants to avoid using common cognitive shortcuts (e.g., recency bias, availability heuristic, affect heuristic). As a result, the measure likely reflects the wide variety of factors that may influence participant risk perceptions, ranging from perceptions of exposure (the probability of an event) and sensitivity (vulnerability to an event) to perceptions of severity, consequences, and resilience. This variety reflects the subjective and heterogenous nature of risk perceptions, but it may complicate precise interpretation of the results.

2.1.2. Validation Survey Data

The data we use to validate the estimates come from an additional independent oversample of approximately 50 survey respondents that reside in a random set of 30 National Weather Service County Warning Areas (CWAs) across the US (n = 1,543). The same sampling methodology and survey questions were used to collect the estimation and validation data.

2.2. Multilevel Regression and Poststratification (MRP)

2.2.1. Methodology

Following Howe et al. (2019), we use Multilevel Regression and Poststratification (MRP) to estimate the distribution of geographic risk perceptions in the Contiguous United States (CONUS). MRP is an increasingly common technique in survey research that uses national data to estimate preferences, perceptions, and behaviors in small geographic areas (Buttice & Highton, 2013; Lax & Phillips, 2009; Zhang et al., 2015). The technique is particularly robust for domains in which geography (location) impacts the variable of interest. We use County Warning Areas (CWAs) as the geographic unit of analysis because they define the zones for which each NWS Weather Forecast Office (WFO) is responsible for issuing forecasts and warnings. In the current analysis, we include data from the 115 CWAs in the CONUS. As the name suggests, MRP involves two steps—multilevel regression and then poststratification. In step one, we estimate models for each of the hazards[2]:

$$y_i = \beta^0 + \alpha_{j[i]}^{gender} + \alpha_{k[i]}^{age} + \alpha_{j[i],k[i]}^{gender*age} + \alpha_{l[i]}^{race} + \alpha_{m[i]}^{ethnicity} + \alpha_{s[i]}^{area} \text{ , where}$$

$$\alpha_j^{gender} \sim N\left(0,\ \sigma_{gender}^2\right), j = 1 \text{ or } 2$$

$$\alpha_k^{age} \sim N\left(0, \sigma_{age}^2\right), k = 1, 2, \text{ or } 3$$

$$\alpha_{j,k}^{gender*age} \sim N\left(0, \sigma_{gender*age}^2\right), j = 1 \text{ or } 2 \text{ and } k = 1, 2, \text{ or } 3$$

$$\alpha_l^{race} \sim N(0, \sigma_{race}^2), l = 1, 2, \text{ or } 3$$

$$\alpha_m^{ethnicity} \sim N\left(0, \sigma_{ethnicity}^2\right), m = 1 \text{ or } 2$$

$$\alpha_s^{area} \sim N(\beta^{exposure} * exposure_s, \sigma_{area}^2), s = 1, \ldots, 115$$

The models have two levels. Individually, a participant's risk perception score for each hazard (y_i) varies as a function of the participant's demographic profile (*gender*, *age*, a *gender-age* interaction, *race*, and *ethnicity*) and geographic *area* (CWA). CWA effects vary in relation to *exposure*.[3] Following estimation, we use the parameters from these models to predict risk perceptions for each demographic-geographic combination. In all, the models provide estimates for two gender groups (male and female), three age groups (18 to 34, 35 to 59, and 60+), three race groups (white, black, other race), and two ethnicity groups (non-Hispanic and Hispanic), allowing us to make 36 demographic combinations in 115 CWAs across the country. For example, one

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[2] The models were fit using the rstanarm package in R. See Goodrich et al., 2018 for details.

[3] As As a robustness check for the results, we additionally run the MRP without hazard exposure as a predictor and replicate the results (see Supporting Information Figs. A1–A4).

demographic-geographic combination includes participants who are female, age 18 to 34, white, non-Hispanic and reside in the New Orleans County Warning Area (CWA).

In step two, we use poststratification to weight the predictions (θ) for each demographic-geographic combination (r). We use US Census data to identify the population frequency of each demographic-geographic combination. The population estimates were obtained from the U.S. Census Annual Population Estimates by Sex, Age, Race, and Hispanic Origin (US Census Bureau, 2018). These frequencies (N) provide the weights we use to produce the MRP estimates for each CWA:

$$Y_{CWA}^{MRP} = \frac{\sum_{r \in CWA} N_r \theta_r}{\sum_{r \epsilon CWA}}$$

This methodology allows us to estimate average area risk perceptions within each CWA for all eight hazards.

2.2.2. Exposure

We use the National Center for Environmental Information (NCEI) Storm Events Database to measure exposure across all but one of the hazards (NOAA, 2019). Specifically, we use data from the last 22 years (1996 - 2018)[4] to calculate the mean days per year that each CWA experiences a heat, cold, snow/ice, tornado, flood, hurricane, or wildfire event (See Table A1 for a list of the Storm Event types that we associate with each hazard). We use data from the US Drought Monitor to produce a comparable measure for drought (National Drought Mitigation Center, 2019). While

[4] Data from the US Drought Monitor only includes data from the last 20 years (1998-2018).

these calculations may provide information about the probability of hazards in CWAs, they do not address the sensitivity or consequences, so we adopt the term *exposure* in place of objective risk in the sections that follow.

3. RESULTS

3.1. Geographic Distributions of Exposure

The maps in Figure 1(a) plot exposure to weather and climate hazards by CWA. Most of the hazards exhibit a geographic pattern, but some of the patterns are more variable than others. For example, tornado events concentrate in the Midwest and Central Plains, cold temperature events are most common in the Upper Midwest, and drought events are more likely in the West. Wildfire, snow/ice, and flood events, by comparison, exhibit more geographic variation.

[Figure 1]

3.2. Geographic Distributions of Risk Perceptions

The maps in Figure 1(b) show the MRP estimates of average risk perceptions by CWA across the hazards. Consistent with Figure 1(a), most of the estimates exhibit a geographic pattern, but some are more variable than others. Hurricane risk perceptions, for example, are highest along the Eastern and Southern coastlines, where hurricane exposure is the greatest. Flood risk perceptions, by comparison, are a bit more diffuse.

3.3. Validating Estimates of Risk Perceptions

We validate the estimates of risk perceptions in two ways. First, we compare the risk perception estimates to observations from the independent validation sample we describe above (Section

2.1.2). The panels in Figure 2(a) plot bivariate relationships between the risk perception observations from the independent validation survey data and the original MRP risk perception estimates. There are consistently strong positive relationships between the two variables, but the correlations vary across the hazards. Six of the eight correlations are 0.90 or above, while the remaining two are 0.71 (Floods) and 0.79 (Extreme heat waves). While relatively high, we are able to double check the validity of the heat risk perception estimates by comparing them to the estimates provided by Howe et al. (2019) which uses different survey measures and data. By aggregating county estimates[5] from the previous Howe et al. (2019) study to CWAs and then comparing the previous estimates to the current estimates, Figure 2(b) plots the comparison of our heat risk data to Howe et al. (2019) heat data. As in Figure 2(a), the comparison reveals a strong positive correlation between the measures (r = 0.75). In combination, these comparisons corroborate the validity of the MRP risk perception estimates.

[Figure 2]

3.4. Comparing Risk of Hazard Exposure to Risk Perceptions

Do risk perceptions align with exposure or do perceptions misalign in ways that may complicate risk communication? The panels in Figure 3(a) address this question by plotting the bivariate relationships between risk perception estimates and exposure. There are strong relationships between risk perceptions and exposure to tornado, hurricane, and drought events; a moderate relationship between perception and exposure to snow/ice, wildfire, and extreme cold

[5] We weight the county estimates by population during the aggregation process.

events; and a fairly weak relationship between perceptions of risk and exposure to flood and heat events. The moderate and weak correlations suggest possible misalignments that may complicate communication and possibly jeopardize resilience in CWAs where risk perceptions are significantly lower (or higher) than we might expect based on exposure.

Figure 3(b) illustrates this point by plotting the five communities with the largest residuals (i.e., differences between risk perception estimates and exposure estimates) when modeling risk perceptions as a function of exposure to flood and heat events. Estimates suggest, for example, that residents of the Houston/Galveston, TX and New Orleans, LA CWAs perceive more flood risk than exposure suggests; the opposite is true in the San Diego, CA and Albuquerque, NM CWAs, where residents perceive less risk than exposure suggests. Similarly, estimates for Phoenix and Tucson, AZ suggest that residents perceive more heat risk than exposure suggests. One potential explanation for these results is the presence of unique disaster subcultures in these areas (Engel et al., 2014); for example, areas in Arizona such as Phoenix and Tucson may have a culture that is highly attentive to heat as a result of their average high heat, relative to other parts of the US, even if events that are considered extreme relative to this area may not be common. More exploration is necessary, but our results may also reflect a few well-known characteristics of risk perceptions: (1) that communities (in aggregate) weight event severity (consequences) more heavily than frequency (probability) when judging risk (i.e., probability neglect; Sunstein, 2001); and/or (2) that communities draw on recent or especially salient events when judging risk (i.e., availability heuristic; Tversky and Kahneman, 1973). Demuth's (2018) careful conceptualization of tornado experience may also help explain these residuals; specifically, she finds most measures of memorable experience and multiple experiences are positively associated with risk perceptions, but not all. For example, the 2017 Hurricane Harvey event in Houston/Galveston, TX, was a high *consequence* case that likely amplified residents' risk perceptions, even though the community's exposure is relatively modest in comparison to county warning areas that experience many floods of lower consequence.

[Figure 3]

4. CONCLUSIONS

The current study presents maps of natural hazard exposure and subjective risk perceptions across geographic regions of the Contiguous United States (CONUS). While many previous studies on exposure and perception have focused on very fine-grained differences in narrow geographic regions (e.g., cities and counties versus across the CONUS), the present study aims to provide more holistic evidence of varying risk perceptions across geographic regions.

For the first time, the current research demonstrates that concerns about natural hazards vary systematically across the country. Moreover, these risk perceptions generally align with objective indicators of exposure. Importantly, though potentially due to differences in measurement or measurement error, some risk perceptions correlate more strongly with exposure. Namely, while the perception-exposure relationship for hurricanes, tornadoes, and drought are strong (all correlations greater than 0.80), the perception-exposure relationship for flooding and heat are not as robust. One reason for the smaller perception-exposure correlations may be that individuals across the US are unaware of their exposure and therefore more at risk to making maladaptive decisions. Another may be that our measures of exposure to flooding and extreme heat risk are especially imprecise. For example, in areas such as Phoenix or Tucson, our models suggest risk perceptions are much higher than our exposure measure would predict. This could be due (at least partially) to threshold differences in the definition of an "event" or differences in reporting practices across NWS offices. Additionally, this measure of exposure does not account for respondents' higher levels of absolute heat exposure to which they may be calibrating their risk perceptions. Regardless, these results suggest that research into improving risk communication products for heat/floods may be more fruitful, than for other better understood hazards.

The geographic maps we present can help inform forecasters and broadcast meteorologists who are interested in effectively communicating risks to their respective communities. Furthermore, CWAs where individuals believe they are safe from heat waves, but actually face significant exposure might particularly benefit from educational or informational interventions. Having a standardized method to measure risk perceptions across time and space will support research interested in tracking the effectiveness of changes before and after interventions.

Implications asside, we recognize there are significant limitations to this study that may provide opportunities for future research. First and foremost, we use exposure as a rough proxy for objective risk. Previous research (including evidence from this study), suggests that people evaluate *both* event frequency (probability) and severity (consequences) when formulating perceptions of risk (Weinstein et al., 2000). However, the subjective risk perception prompt was relatively vague, asking simply, "…how do you rate the *risk* of the following extreme weather events to you and the people in your area?" This wording leaves it up to the participant to decide the extent to which they weigh the occurrence of the event in their area, and the potential impact of a hazard. It is therefore important that future work attempt to capture both frequency and severity when measuring objective and subjective risk. Data limitations will likely complicate this task. Furthermore, because the present study does not explicitly unpack what participants' judgments of risk are based on (e.g., consequences, frequency, recency), the current study is unable to provide holistic prescriptions on how communicators may improve risk communications or education materials.

Here, we use the Storm Events Database to measure exposure. Inconsistencies in reporting across space, time, and event type can make it difficult to reliably measure event frequency. These inconsistencies are even more apparent in attempts to measure event severity (e.g., fatalities, injuries, property and crop losses). More specifically, data from the Storm Events Database are aggregated from a variety of sources, including news stories and observer reports. Definitions of what counts as an "event" may vary, systematically or randomly, from one place to another, which likely impacts our measures of exposure. This limitation in the data may lead to cases where risk perceptions appear misaligned with the measure of exposure. Nonetheless, we expect that including information like this, if reliable, will improve (i) estimates of objective risk, (ii) MRP estimates of subjective risk perceptions (that partially rely on estimates of objective risk), and (iii) comparisons between the two.

While previous research on risk perceptions and risk communication has focused on averages (i.e., the notion that standard risk communication methods will work for *all* people), this research suggests that geographic location and experience with hazards might be important individual differences that influence risk perceptions. Given the relationship between risk perceptions, decision making and protective behavior, the present research suggests that some CWAs may be more vulnerable to uninformed decision making when responding to or preparing for natural hazards. While this paper cannot connect immediately the relationship between risk perceptions and protective behaviors, understanding the distribution of extreme weather and hazard risk perceptions can provide a basis for measuring response and protective action. Moreover, as precision for mapping differences in risk perceptions and objective risks increases, having a framework for conducting more holistic risk perception analyses will support future research on individual differences.

The current research also supports scientists (i.e., meteorologists, forecasters, emergency managers, and related social scientists) who are interested in effective methods for risk communication. Effective risk communication requires systematic, robust, and intimate knowledge of the community. This knowledge can be difficult and time consuming to obtain, and hard to pass on to employees who are transplants in the communities they serve. Tracking these constructs will provide systematic and reliable data across geographic areas in the US, which will support employees tasked with risk communication. In addition, it provides a method to track changes in skills and abilities over time, especially after implementing educational interventions, which will support the assessment of the effectiveness of new policies or decision support systems. Taken together, these methods provide the ability to better inform stakeholders and the public of risks and uncertainties, ultimately supporting resilient decision making.

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FIGURES

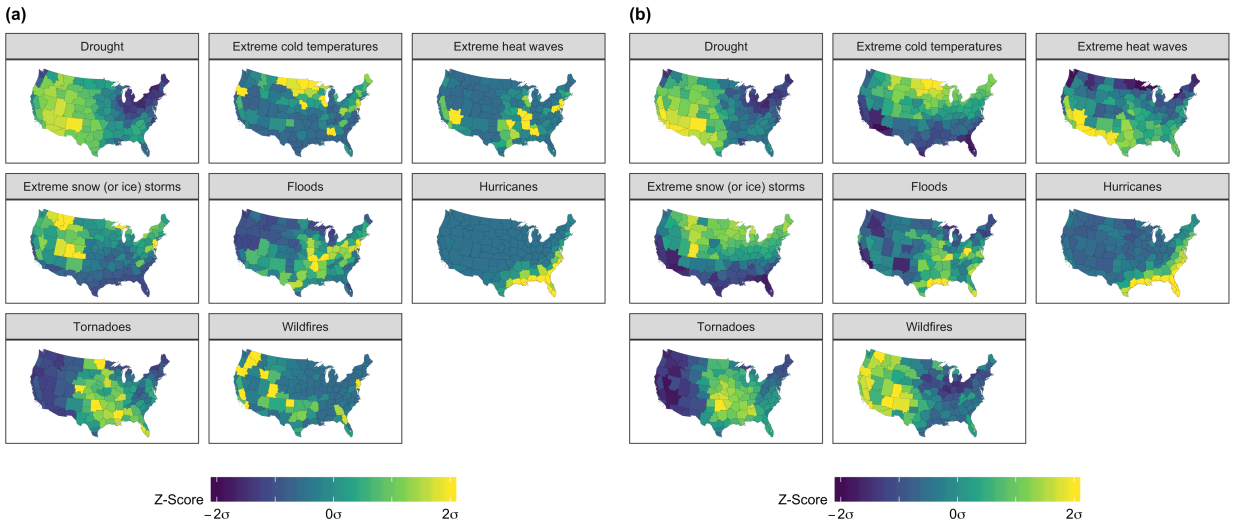

Figure 1: Mapping (a) exposure to and (b) risk perceptions from weather and climate hazards by CWA.

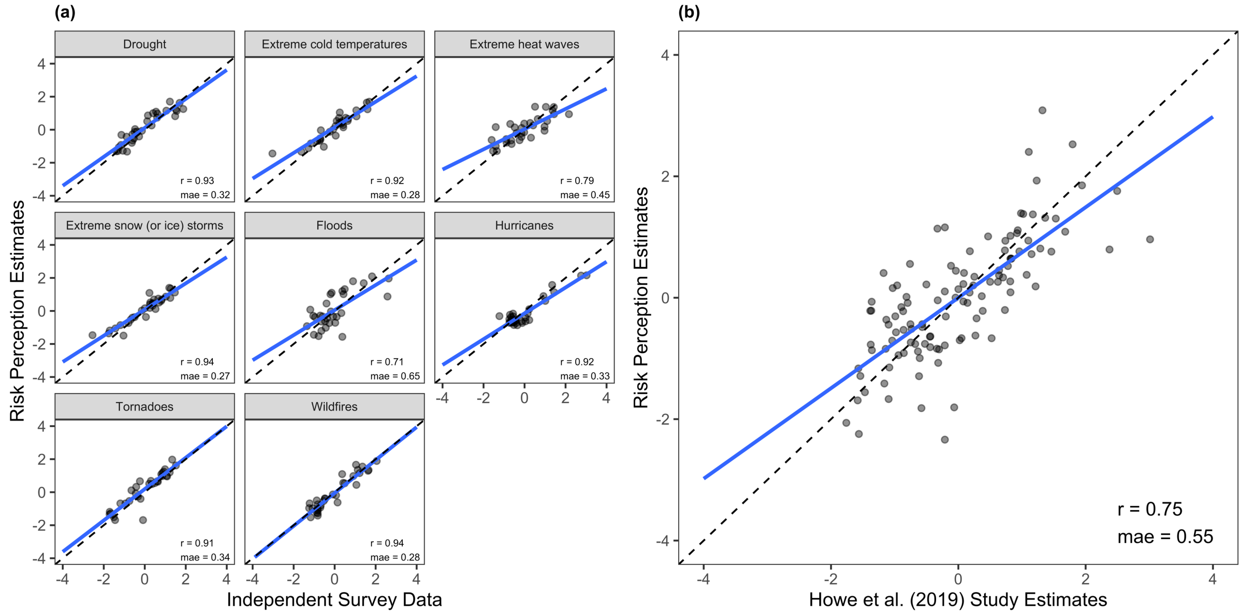

Figure 2: Comparison of risk perception estimates to (a) independent survey data and (b) previous study estimates for heat risk perceptions.

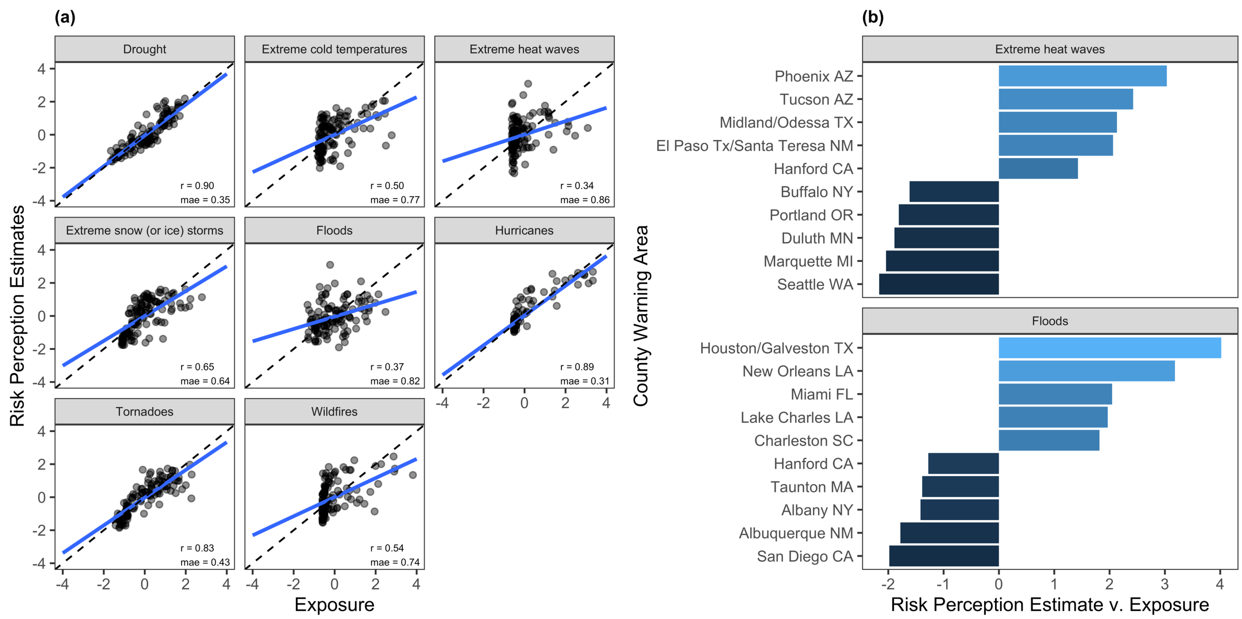

Figure 3: Comparison of (a) risk perception estimates to exposure to (b) identify possible perception-exposure misalignments.

Supporting Information

Category	Corresponding Event Types in the NCEI Storm Events Database and the US Drought Monitor Database
Extreme heat waves	Excessive Heat
	Heat
Extreme cold temperatures	Cold/Wind Chill
	Extreme Cold/Wind Chill
Extreme snow (or ice) storms	Blizzard
	Heavy Snow
	High Snow
	Ice Storm
	Lake-Effect Snow
	Winter Storm
	Winter Weather
Tornadoes	Tornado
Floods	Coastal Flood
	Flash Flood
	Flood
	Lakeshore Flood
	Surge/Tide
Hurricanes	Hurricane, Hurricane (Typhoon)
	Marine Hurricane/Typhoon
	Marine Tropical Depression
	Marine Tropical Storm
	Tropical Depression
	Tropical Storm
Wildfires	Wildfire
Drought	D1 (Moderate Drought)
	D2 (Severe Drought)
	D3 (Extreme Drought)
	D4 (Exceptional Drought)

Table A1: The storm event types from the NOAA NCEI Storm Events Database and the US Drought Monitor that we associate with each category of hazard.

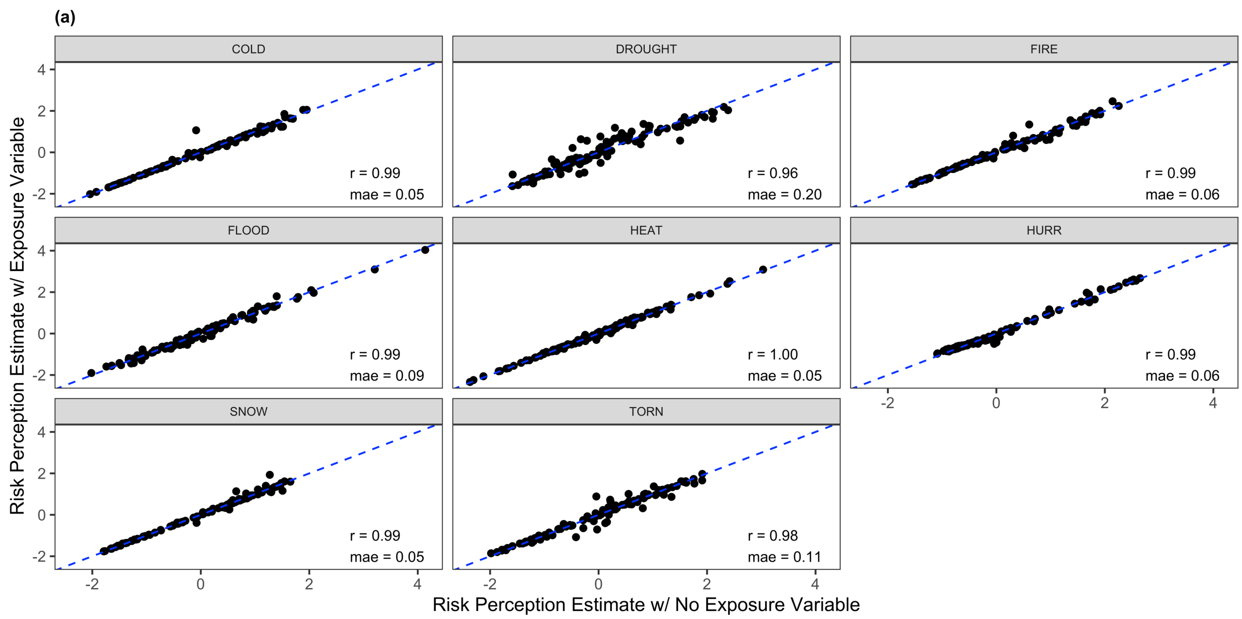

Figure A1. Comparison of MRP with and without exposure variable as predictor.

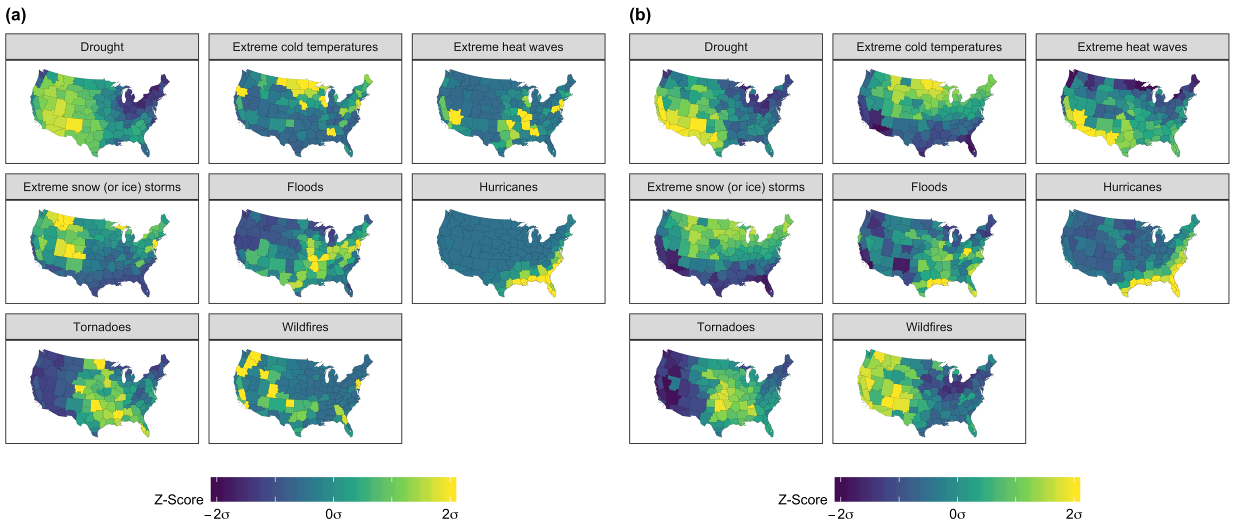

Figure A2. Replication of Figure 1 without Exposure variable as predictor.

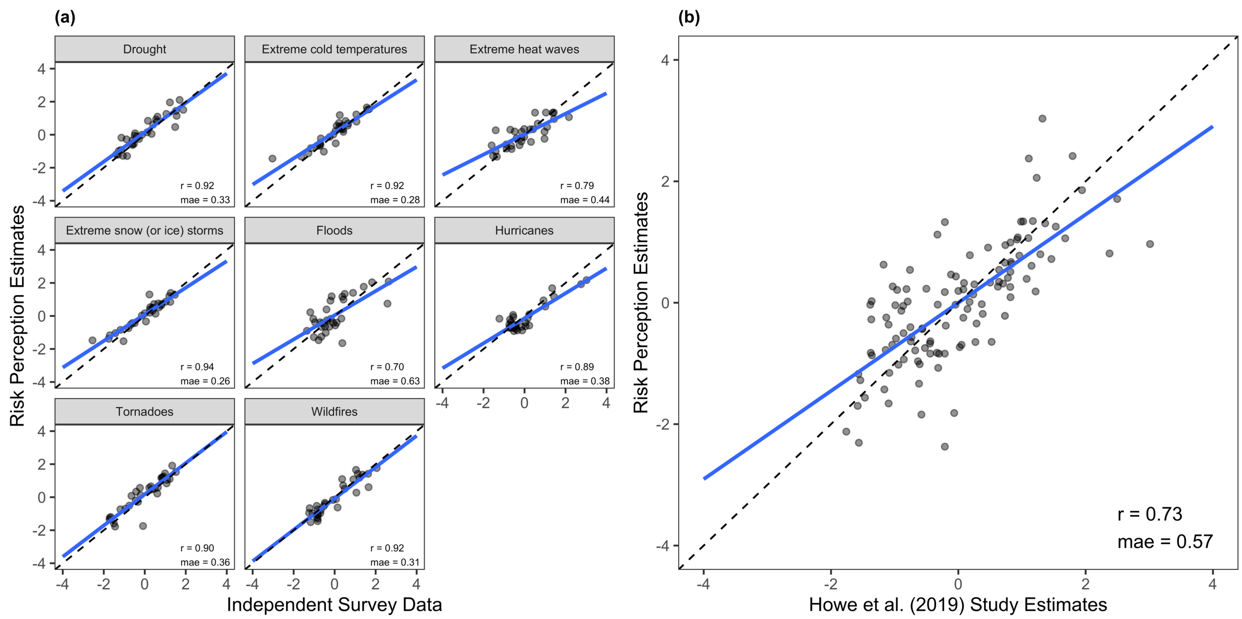

Figure A3. Replication of Figure 2 without Exposure variable as predictor.

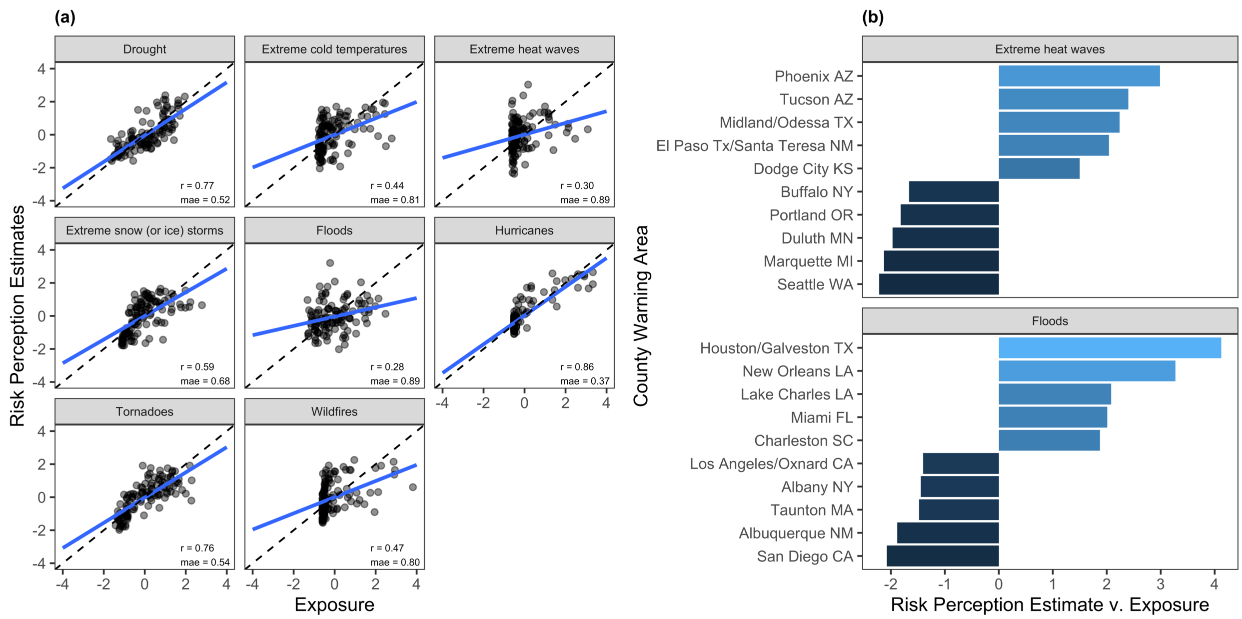

Figure A4. Replication of Figure 3 without Exposure variable as predictor.