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 objective risk. For example, we know which parts of the U.S. 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 perceptions align with objective risk? 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 U.S. 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 the Severe Weather and Society Survey. This enables us to measure, map, and compare perceptions of risk from multiple weather hazards in geographic areas across the country.

Keywords: Extreme weather, risk perceptions, geography

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. These weather and climate disasters included three tropical cyclones, three severe thunderstorms, three tornadoes, two hail storms, two inland floods, a crop freeze, 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) 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). Thus, 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. How do concerns about drought, heat waves, and flooding vary across the country? Do these risk perceptions align with objective indicators of exposure, such as those collected by NOAA? 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 our ongoing national surveys where we apply a novel methodology in survey research to fill this gap.

1.1 Risk Perceptions

Risk perceptions can be defined as intuitive risk judgments about the probability of an event and how concerned people are with its consequences (Slovic, 1987; Sjöberg, Moen, & Rundmo, 2004). Further, risk perceptions have been measured in a number of different ways. Rooted in a psychometric paradigm, risk perceptions can be considered in terms of (i) the risk domain (e.g., technologies such as nuclear energy, activities such as football, or natural hazards such as tornadoes and hurricanes) and (ii) the characteristics that define them (e.g., whether the risks are new, understood, catastrophic, etc.; Fischhoff et al., 1978). For decades, risk perception research has focused on the characteristics of risks, and how people view risks *on average* (Boholm, 1998; Fischhoff et al., 1978; Sjöberg, Moen, & Rundmo, 2004). More recent research has proceeded to identify which factors best predict individual differences in risk perceptions (e.g., experience, education, worldviews, demographics). As such, measures of individual differences in risk perceptions have recently been developed and tested (Blais & Weber, 2006; Kahan, 2015).

Individual differences can have a profound influence on how people perceive risks. For example, the white-male effect (or the notion that white men tend to view hazards as less risky than their female and minority counterparts) has been demonstrated across many domains, including severe storms and floods (Flynn, Slovic, & Mertz, 1994). The American Preparedness Survey also found that women, African-Americans, and people with lower socio-economic status (i.e., those earning less than $25,000 a year) are more worried about the impacts of climate change (Petkova et al., 2016). This relationship may be due to differences in power, status, trust, or other cultural differences (Flynn, Slovic, & Mertz, 1994; Keown, 1989). For example, the white male effect can be explained by differences in cultural theory (Kahan, 2007; Kahan, Jenkins-Smith, & Braman, 2011) and political ideology (McCright & Dunlap, 2011; 2013).

Understanding the individual differences that help explain risk perceptions can improve risk management because these perceptions can function as motivation for behavior. For example, depending on the type of risk, individuals may try to avoid, ignore, or plan ahead for an event (Slovic, 1987; Wachinger, Renn, Begg, & Kuhlicke, 2013). While extreme weather and climate hazards may be viewed as “uncontrollable” or “involuntary,” other voluntary activities (e.g., caffeine, smoking, football) require a choice to engage in the activity. Since natural hazards and extreme weather events can happen to anyone and at any time, the individual does not have control over *whether* the event occurs; they only have control over how they *respond or prepare* for the given event.

The literature on how individual risk perceptions are related to engaging in protective actions and behavior has found that people are not likely to engage in protective behaviors if they do not believe a given risk is threatening (Lindell & Perry, 2012; Mileti & Sorensen, 1990; Murphy et al., 2009). This relationship has been observed for numerous extreme weather and climate hazards, including hurricanes (Burnside, Miller, & Rivera, 2007; Dow & Cutter, 2000), earthquakes (Lindell, Arlikatti, & Prater, 2009; Mileti & O’Brien, 1992; Rüstemli & Karanci, 1999), and floods (Ramasubramanian et al., *in press*; Whitmarsh, 2008). That being said, the variables influencing personal preparedness and protective behavior are many, and often include (i) trust in experts and information sources (Siegrist & Cvetkovich, 2000), (ii) cultural and demographic differences (e.g., age, gender, income; Wachinger et al., 2013), as well as (iii) media, and the quality and quantity of the risk information provided (Clarke & Short, 1993).

Furthermore, exposure and vulnerability are context specific, and likely influence risk perceptions (Cardona et al., 2012). For example, those who have experienced a natural disaster in the last five years are more likely to be worried about the effects of climate change (Petkova et al., 2016; Van der Linden, 2015). While some extreme weather and climate hazards threaten specific geographic areas (e.g., hurricanes primarily threaten the east coast), other hazards (e.g., snow and ice) are less geographically specific and can threaten large portions of the country. This relationship between risk and geography is fairly well documented with research that identifies the geographic distribution of risk across different hazards (e.g., Boruff et al., 2003; Gensini & Brooks, 2018; Howe, Marlon, Wang, & Leiserowitz, 2019). Taken together, these findings support the notion that geography and other individual differences will likely influence risk perceptions of natual hazards and climate disasters.

Previous research indicates that exposure to local weather risks and subjective local weather risk perceptions are well aligned (Shao, 2016; see also Brody et al., 2008; Ripberger et al., 2017). However, little robust information about the geographic distribution of *subjective* risk perceptions exists. Risk perceptions of extreme weather and hazard events may or may not align with objective indicators of risk or exposure. A recent study by Howe and colleagues (2019) provides important evidence that subjective perceptions of health risks from extreme heat exhibit strong geographic patterns that relate to but do not directly overlap with objective indicators of risk. For example, though the study finds that people who live in especially warm climates have the highest risk perceptions, people who live in cooler climates often face greater health risks from extreme heat. This discrepancy suggests a possible mismatch between objective risk and subjective risk perceptions, which may be driving maladaptation to heat risks in portions of the country (For similar concerns in the UK, see Wolf et al., 2010).

The following perspective 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, broadcasters, emergency managers) develop messaging strategies and education initiatives that are specific to the communities they serve. The maps also provide important information about the geographic relationship between objective risk and subjective risk perceptions that will motivate future research on community resilience to extreme weather and climate events.

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 across extreme weather and climate hazards. This analysis uses data from the 2017 and 2018 surveys (n = 2,000 & 3,000, respectively). Both surveys were implemented online to demographically representative samples of adults (age 18+) that reside in the continental US (CONUS). The samples were provided by Qualtrics, and further information about data collection and preliminary frequency information can be found in Silva et al. (2017; 2018).

At the beginning of each 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,

[1] https://github.com/oucrcm/wxsurvey

flooding, hurricanes, and wildfires—were presented in a random order for each participant. The question wording is provided below:

"*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?*"

2.1.2. Validation Survey Data

The data we use to validate the estimates come from an additional independent oversample of 50 survey respondents that reside in a random set of 30 National Weather Service County Warning Areas (CWAs) across the US (n = 1,500). The same sampling methodology and survey questions were used to collect the estimation and validation data.

2.2. Multilevel Regression and Poststratification (MRP)

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 CWAs as the geographic unit of analysis because they define the zones for which each 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:

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

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

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

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

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

$$\alpha_s^{CWA} \sim N(\alpha_n^{region} + \gamma^{exposure}, \sigma_{CWA}^2), s = 1, \ldots, 115$$

$$\alpha_n^{region} \sim N(0, \sigma_{region}^2), n = 1, 2, 3, \text{ or } 4$$

The models have three levels. Risk perceptions (y) vary as a function of an individual's demographic profile (*gender*, *age*, *race*, and *ethnicity*) and geographic location (*CWA*). *CWA* effects vary in relation to NWS *region* and *exposure* (see below for details); and *region* effects are random intercepts with no predictors. Following estimation, we use the parameters from these models to predict risk perceptions for each demographic-geographic combination. For example, one demographic-geographic combination is female, age 18 to 34, white, non-Hispanic in the NWS Norman, OK CWA. 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) in 115 CWAs, resulting in 4,140 unique predictions (2 x 3 x 3 x 2 x 115 = 4,140).

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.[2] These frequencies (N) provide the weights we use to produce the MRP estimates for each CWA:

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

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

2.2.1. Storm Events Database (Exposure)

We use the NCDC Storm Events Database to calculate proxies for objective risk across all but one of the hazards (NOAA, 2019). Specifically, we use data from the last 20 years (1999 - 2018) to calculate the mean days per year that each CWA experiences a heat, cold, snow/ice, tornado, flood, hurricane, or wildfire event (See Appendix 1 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 these calculations may provide information about the probability of hazards in CWAs, they do not address 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

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[2] County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin are available here: https://www2.census.gov/programs-surveys/popest/datasets/2010-2016/counties/asrh/.

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, hurricane events concentrate along the Eastern and Southern coastlines, 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 0.85 or above, while the remaining two are 0.71 and 0.68. While relatively high, we double check the validity of the heat risk perception estimates by comparing them to the estimates that Howe et al. (2019) identified using different survey measures and data. We do this by aggregating county estimates[3] from the previous study to CWAs and then compare the previous estimates to the current estimates. Figure 2(b) plots this comparison. As in Figure 2(a), the comparison reveals a strong positive correlation between the measures (r = 0.74). In combination, these comparisons corroborate the validity of the risk perception estimates.

[Figure 2]

3.4. Comparing 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 relatively moderate relationship between perception and exposure to snow/ice, wildfire, and extreme cold 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 most discrepent communities (i.e., positive and negative residuals) observed 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

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

New Orleans, LA CWAs perceive more flood risk than exposure suggests; the opposite is true in the San Diego, CA and Grey, ME CWAs, where residents perceive less risk than exposure suggests. More exploration is necessary, but these results may 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). 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 objective natural hazard risks and subjective risk perceptions across geographic regions of the continental United States (CONUS). The geographic maps we present can help to build a vulnerability radar for weather risks, which will support hazard communications. For example, this information on risk perceptions could help inform forecasters and broadcast meteorologists who are interested in effectively communicating risks to their respective communities. Furthermore, CWAs where individuals have discrepant beliefs (e.g., believe they are safe from heat waves, but actually face higher 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 changes before and after interventions (i.e., intervention effectiveness).

While the implications for this study are many, there are a few limitations that provide opportunities for future research. First and foremost, we use exposure as a rough proxy for objective risk. Previous research (including evidence from this perspective), suggests that people evaluate *both* event frequency (probability) and severity (consequences) when formulating perceptions of risk (Weinstein et al., 2000). It is therefore important that future work attempt to capture severity when measuring objective risk. Data limitations will likely complicate this task. Here, we use the Storm Evemts Database to measure exposure. As we note with drought, inconsistancies 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). 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 there are individual differences in risk perceptions and related decision making constructs (e.g., knowledge, risk literacy, risk perceptions, and reception, comprehension, and response of warnings). As such, 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.

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. Taken together, these methods provide the ability to better inform stake holders and the public of risks and uncertainties, ultimately supporting resilient decision making.

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FIGURES

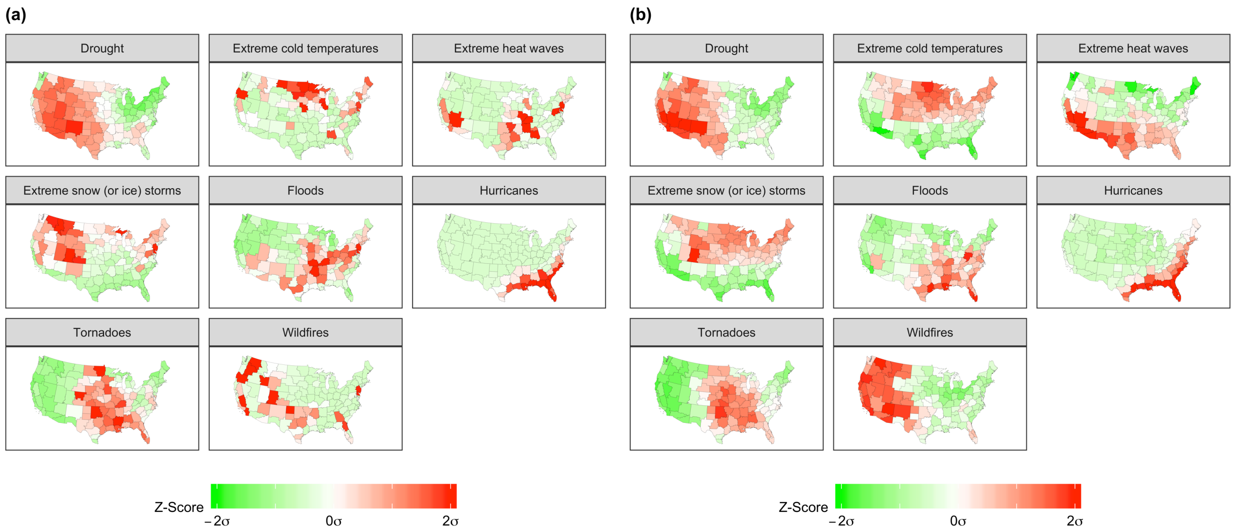

Figure 1: Mapping (a) exposure to and (b) risk perceptions from weather and climate hazards by CWA.

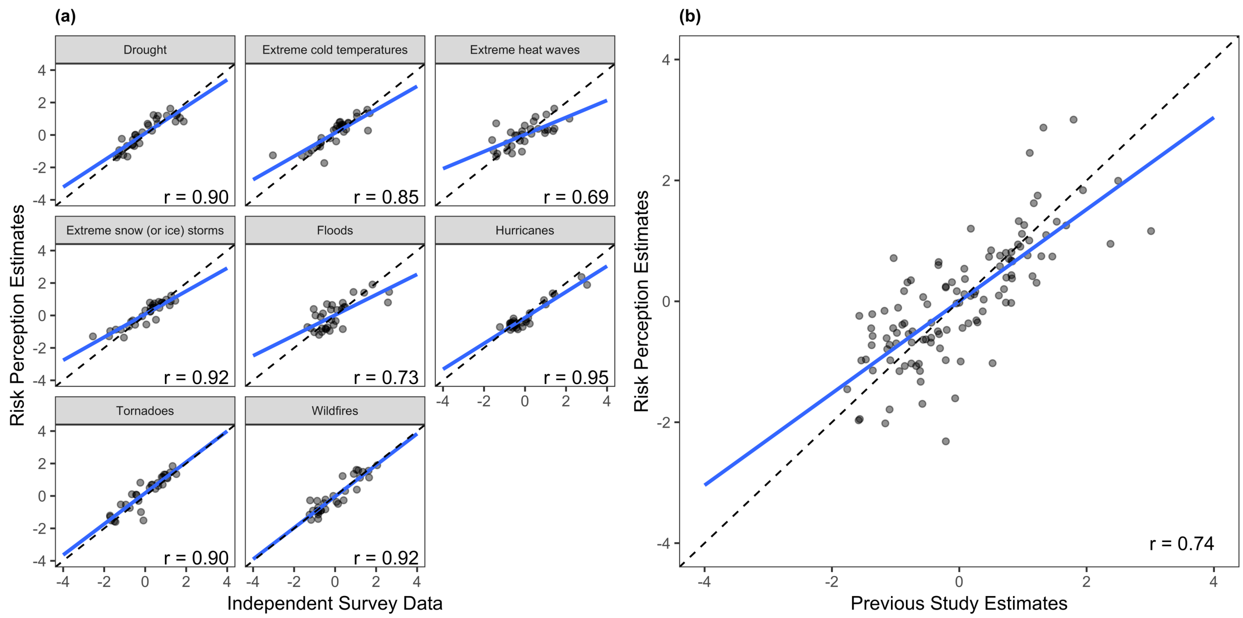

Figure 2: Comparison of risk reception estimates to (a) independent survey data and (b) previous study estimates for heat risk perceptions.

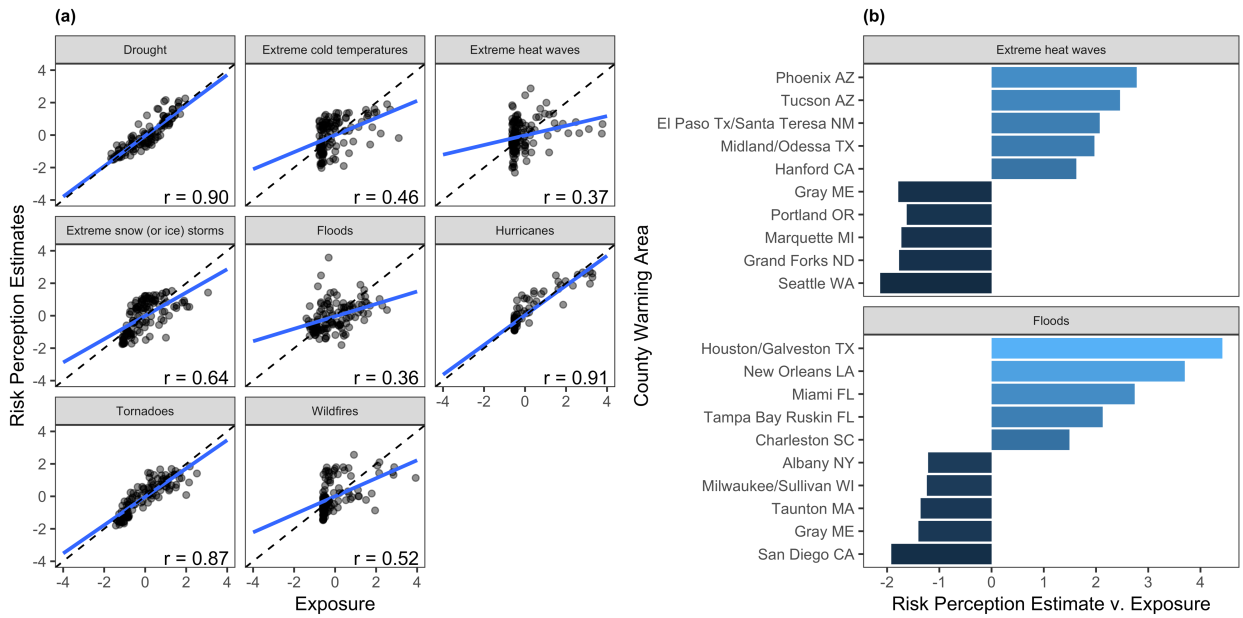

Figure 3: Comparison of (a) risk perception estimates to exposure to (b) identify possible perception-exposure misalignments.

APPENDIX

Category	Corresponding Event Types in the NCDC 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 NCDC Storm Events Database and the US Drought Monitor that we associate with each category of hazard.