8-2018

Humans as Sensors: The Influence of Extreme Heat Vulnerability Factors on Risk Perceptions Across the Contiguous United States

Forrest Scott Schoessow
Utah State University

HUMANS AS SENSORS: THE INFLUENCE OF EXTREME HEAT VULNERABILITY FACTORS ON RISK PERCEPTIONS ACROSS THE CONTIGUOUS UNITED STATES

by

Forrest Scott Schoessow

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Geography

Approved:

Peter D. Howe, Ph.D. Major Professor	Claudia Radel, Ph.D. Committee Member
E. Helen Berry, Ph.D. Committee Member	Mark R. McLellan, Ph.D. Vice President for Research and Dean of the School of Graduate Studies

UTAH STATE UNIVERSITY
Logan, Utah

2018

ABSTRACT

Humans as Sensors: The Influence of Extreme Heat Vulnerability Factors on Risk Perceptions Across the Contiguous United States

by

Forrest Scott Schoessow, Master of Science

Utah State University, 2017

Major Professor: Dr. Peter D. Howe
Department: Environment and Society

Extreme heat events are the deadliest natural hazard in the United States and will continue to increase in both severity and frequency in the coming years due to the effects of climate change. As a result, the number of individuals residing in the United States exposed to deadly heat waves will continue to rise, underscoring the urgent need for decision-makers and risk managers to develop more comprehensive strategies to mitigate the negative impacts of extreme heat, as heat mortality is often preventable if appropriate actions are taken. The intensity and scope of extreme heat impacts hinges upon climatological, meteorological, and geographic exposure factors, as well as dynamic human factors, such as sensitivity and the efficacy of communities' adaptive policies. Failure to consider the human dimensions of extreme heat risk can lead to inadequate hazard communication, misguided management priorities, vulnerable populations being "left behind," and systemic underestimation of risk. Spatially-explicit risk perception data can aid the development of more sophisticated extreme heat risk assessments at the local level by capturing changes in dynamic sensitivity factors over time and space. In this study, a series of mixed effect models were specified that included meteorological, climatological, geographic, sociodemographic, temporal, or land cover variables – each representing different sensitivity, exposure, or adaptive capacity factors – as predictors of extreme heat risk perception. Results summarize the effect these dynamic and varied risk factors have on heat wave risk perception, report patterns of geographic variation in the response, and highlight subpopulations that tend to perceive themselves to be at the highest risk of being negatively impacted by extreme heat. Incorporating risk perceptions into risk assessment presents a more democratic way of identifying vulnerable populations, a necessary step toward enhancing hazard preparedness frameworks and risk management plans.

(165 pages)

PUBLIC ABSTRACT

Humans as Sensors: The Influence of Extreme Heat Vulnerability Factors on Risk Perceptions Across the Contiguous United States

Forrest Scott Schoessow

Extreme heat events are the deadliest natural hazard in the United States and will continue to get worse in the coming years due to the effects of climate change. As a result, more people will experience deadly heat conditions. This highlights the need for decision-makers to develop better strategies for preventing future losses. How badly individuals are affected by extreme heat depends on many circumstances, such as how high temperatures actually are, weather conditions, and location. For example, a dry 90 °F day in Phoenix is probably more tolerable than a humid 90 °F day in New Orleans for most individuals. However, some groups of people are more likely to be harmed by extreme heat than others, such as the elderly and those who work outdoors. This may seem straightforward, but uncovering less obvious clues that help explain how and why some groups are affected differently by extreme heat can be difficult, since much of the impact of extreme heat depends on people's judgements of the risk and their personal decisions. These human factors are typically not very easy to measure because different hazards affect different people in different ways at different times in different places. This study uses a large survey of the U.S. population and statistical methods to explore how weather, time, space, and personal experience with heat affect different people's judgment of risk. Whether different groups understand their high or low risk status has

important implications for decision-makers responsible for crafting plans to reduce extreme heat risk in their local community.

ACKNOWLEDGMENTS

My profound thanks and gratitude go out to: Dr. **Peter Howe**, Department of Environment and Society and the Ecology Center. Thank you for expanding my understanding, my perspective, and my horizons. The Department of Environment and Society and the School of Research and Graduate Studies, for their generous funding which helped to make this all possible. **Yajie Li**, **Emily Esplin**, and everyone in the Human-Environment Spatial Analysis Lab (Neil too). Our collaborators at Yale School of Forestry and Environmental Studies and the Yale Program on Climate Change Communication, Yale University. Dr. **Claudia Radel**, Department of Environment and Society and the Ecology Center—for keeping the door open, hearing me out, and exposing me to wonderful, fantastic new realms of geographic thought. Dr. **Eddy Berry**, Department of Sociology—for always keeping it 100% real and helping me navigate the wild world of academia. Dr. **Susan Durham**, Department of Biology and the Ecology Center—for sharing your time, your willingness to edify, and your invaluable wisdom regarding all things multilevel and statistical. Dr. **Rob Davies**, Utah Climate Center—for providing invaluable mentorship and helping me keep the big picture in sight. Dr. **Tom Edwards**, Department of Wildland Resources and the Ecology Center—Thank ye, Grand Wizard of R for your time, dedication, and teachings. **Ben Crabb**, M.S., Remote Sensing and GIS Laboratories at Utah State University—for always being down to talk space-time dynamics. Dr. **Will Pearse**, Department of Biology and the Ecology Center—for helping me tackle mixed effect model comparisons. Dr. **Courtney Flint**, Department of Sociology and the Ecology Center—for getting me stoked on methods. Dr. **Andrew**

Tredennick, Department of Wildland Resources and the Ecology Center—for the invaluable data science consultations. **Mikey Kettinger**, M.F.A., David R. Jones, **Alex T. Ross**, Gary Grice, and Thomas Forsberg—for providing invaluable creative inspiration. The medical staff at the USU Student Health Center—for forcing me to understand that coding for 70+ hours straight can and will kill me. My family; my darling sisters, Lexi and Teague; my brilliant mother, **Grace Schoessow**, M.S.; my lionhearted father, **Scott Schoessow**—for making this all possible through their endless support and encouragement. My wife-to-be, the ever-so-humble, **Beth Shirley**, M.A., Presidential Doctoral Research Fellow, Department of English—for inspiring me, helping me make sense of my own words, generally keeping me alive, and providing the best sounding board I could ever ask for.

Forrest Scott Schoessow

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Extreme heat events are the deadliest natural hazard in the United States (U.S.) (CDC, 2016; Jones *et al.*, 2015; Smith, 2013, p. 271) and will continue to increase in both severity and frequency in the coming years due to the effects of climate change (EPA, 2016; IPCC, 2014; Mora, *et al.*, 2017; NWS, 2015; Vose *et al.*, 2017). As a result, the number of individuals residing in the U.S. exposed to deadly heatwaves will continue to rise, underscoring the urgent need for decision-makers and risk managers to develop more comprehensive strategies to mitigate the negative impacts of extreme heat, as heat mortality is often preventable if appropriate actions are taken. Extreme heat risk levels are rising across the contiguous United States due to both natural and human factors. Rising physical exposure levels across the contiguous United States and their complex interaction with social sensitivity factors (such as age, race/ethnicity, and sex) create unique risk levels for different subpopulations distributed across the country. Furthermore, recent studies have demonstrated the influence of human activity on the development and severity of extreme heat events (Angelil *et al.*, 2017; Dole *et al.*, 2014; Hoerling *et al.*, 2013; Jeon *et al.*, 2016; Knutson *et al.*, 2013; Rupp *et al.*, 2012) and examined how individual behavior and risk judgements can lead to highly variable impacts across similarly placed and exposed populations.

The definition of Risk has evolved significantly in hazards literature over the past few decades. Recently, hazards scholarship has reexamined the nature of Risk to incorporate the influence of such human factors. Recent literature has defined natural hazard Risk as a function of Vulnerability (composed of Exposure and Sensitivity factors) minus Adaptive Capacity factors (IPCC, 2014; Jones *et al*., 2015; Melillo *et al*., 2014; Tierney, 2014, p. 12). More generally, risk is described as, "A condition in which there is a possibility that persons or property could experience adverse consequences" (Lindell *et al*., 2006, p. 84). Extreme heat hazards have highly variable impacts determined by the dynamic space-time patterns of exposure, complex individual-level sensitivity factors, and the adaptive capacity of the exposed populations. Accurate, locally-relevant vulnerability data describing the distribution of both the physical and human determinants of vulnerability are required in order to minimize future losses. Yet, while we have improved our ability to predict climate changes and extreme heat events on a global scale by better understanding the dynamic properties and interactions of the earth's natural systems, insufficient research has been conducted to integrate the equally dynamic properties of human systems into more comprehensive risk assessments. Failure to consider the human dimensions of extreme heat risk can lead to inadequate hazard communication, misguided management priorities, vulnerable populations being "left behind," and systemic underestimation of risk.

As a greater proportion of the population will be physically exposed to extreme heat events in the coming years, and despite growing evidence that the increase in frequency and intensity of extreme heat events can be at least partly attributed to human activity (Dole *et al*., 2014; Jeon *et al*., 2016; Knutson *et al*., 2013; Rupp *et al*., 2012; Vose *et al*., 2017), it is unlikely that sufficiently aggressive mitigation steps can immediately be taken to alter this reality and reverse the overall trend of rising extreme heat events. Nevertheless, we cannot simply "fix" the weather or "repair" the climate. While it is technically possible to alter our physical environment and therefore our degree of exposure to a certain extent—reducing impervious surface coverage or augmenting evapotranspiration potential in urban areas, for example—we have little command over meteorological and climatological processes that are so highly variable across time and over space. Furthermore, the costs associated with actively modifying our physical environment (and subsequently urban climates) to reduce exposure to extreme air temperatures far outweigh those associated with targeted risk reduction programs aimed at identifying and confronting human sensitivity factors—particularly socioeconomic inequalities—that contribute to vulnerability and increase total risk. Vulnerability must be attenuated, and adaptive capacity must be built to reduce future losses and strengthen resilience across the contiguous United States.

Minimizing the negative impact of extreme heat events on the most vulnerable subpopulations of any given geographic area is a complicated endeavor. To increase chances of success, the risk reduction process must seek to address the cumulative impact of both human and physical factors that contribute to vulnerability as well as to promote protective behaviors that mitigate unnecessary exposure. However, the strength and distribution of individual-level sensitivity factors is particularly difficult to measure due to the dynamic nature of human systems. Traditional vulnerability studies often lack the critical psychosocial data such as risk perceptions that are required to more completely account for the role human risk judgment plays in determining individual vulnerability (Howe *et al*., 2013; Mora *et al*., 2017). The information contributed by this research will help identify vulnerable subpopulations, target risk communication products and the allocation of additional necessary resources to vulnerable populations (CDC, 2016; EPA, 2016; Howe *et al*., 2015; Melillo *et al*., 2014). A more comprehensive understanding of extreme heat risk that includes these critical psychosocial data is vital to enhancing adaptive capacity and strengthening community resilience.

Personal behavior and preparedness can either attenuate or exacerbate vulnerability. Ideally, risk perception mirrors reality because we only respond to the hazards we perceive. Risk perception is a determinant of individual risk decision-making and influences the likelihood of an individual engaging in personal protective behaviors. Consequently, it is important to understand what factors influence risk perception and their distribution. This knowledge gap presents a major challenge for decision-makers seeking to minimize negative impacts in their communities by using risk reduction strategies that target the most vulnerable subpopulations. As large population areas increasingly incorporate vulnerability considerations into a more impact-based assessment of heat risk (shifting away from more simple frequency and magnitude-based predictions of exposure), risk perceptions play an increasingly important role in understanding the drivers of vulnerability and these factors' distribution throughout the populace. This is primarily for three reasons: (1) "We know people generally do not respond to hazards that they do not perceive" (FEMA, 2017, p. 4); (2) Differences in risk perception in different subpopulations "highlights the need for effective risk communication" (FEMA, 2017, p. 12); (3) Risk perceptions provide empirical data that helps researchers better understand the individual-level sensitivity factors that help determine personal vulnerability.

Addressing human sensitivity factors via targeted risk communication is a cost-effective method of reducing hazard vulnerability, minimizing loss, and enhancing resiliency. In order to achieve this, decision makers need space-time-specific vulnerability information which can be used to identify at-risk subpopulations, describe their distribution, examine their context, and develop targeted risk communication strategies. Mitigation and risk reduction decisions occur at different spatial scales, so it is necessary to have reliable vulnerability information specific to the appropriate level of decision-making. For example, when an NWS local office issues an extreme heat advisory, this may automatically activate risk mitigation resources which often include communications aimed at increasing hazard awareness among specific populations (Hawkins *et al*., 2017). In these circumstances, maps and geographic information systems are vital tools which enable decision makers to situate contextual knowledge of the hazard in their districts and coordinate the appropriate degree of response alongside local agencies (Lindell *et al*., 2006, ch. 10).

Support for natural hazards risk management policy, engagement with risk communication products like the NWS heat alert system, and the likelihood of an individual engaging in protective behavior are greatly influenced by public beliefs and attitudes that can be better understood by studying the distribution risk perception and its determinants (California Governor's Office of Emergency Services, 2001, p. 10; FEMA, 2017; Howe *et al*., 2015; Lindell *et al*., 2006, p. 86). It is important to understand the space-time distribution of vulnerability factors before the risk communication process begins, because the more vague the information presented, the more likely it is to reinforce existing beliefs (FEMA, 2017, p. 8; Slovic *et al*., 1979). The creation of reliable, locally relevant data on public heat risk perception is necessary in order for decision makers and scientists to more comprehensively assess actual extreme heat risk for different subpopulations and evaluate which mitigation and adaptation strategies might be most effective in those communities. Federal guidelines describe risk communication as the most effective way to "correct" misperceptions of risk and note that, "With an understanding of the perceptions and misperceptions of risk made by their constituents, hazards risk managers can work to correct those misperceptions and address the public's fears and concerns" (FEMA, 2017, p. 13). Effective risk communication strategies encourage individuals to adopt proactive, protective behaviors, such as limiting their exposure by staying indoors, staying hydrated, and checking in on loved ones. Local communication strategies that promote protective behavior at the individual and community-level and are key to reducing hazard risk. Examples might include campaigning to increase awareness of local cooling shelters or addressing individual decision-making and behaviors that can exacerbate sensitivity factors or lead to greater exposure.

This study examines the first and second order effects of natural and human factors on extreme heat risk perception by using a suite of multilevel regression models to examine empirical and existing data collected across the contiguous United States for the heat season of 2015. This study uses time-stamped, georeferenced, U.S.-nationally-representative survey data to examine the spatial and temporal variation of perceived risk at multiple scales and provides locally-relevant estimates of unique subpopulations' risk perceptions for risk managers and scientists. This research contributes an evaluation of how human and natural factors shape risk perceptions and divides these drivers into three classifications: Exposure, Sensitivity, and Adaptive Capacity. These variables are evaluated independently and alongside one another in different controlled sets, specific to their unique, local geographical context. Results summarize the effect these dynamic and varied risk factors have on heat wave risk perception and report patterns of geographic variation in the response. Additionally, this study provides extreme heat risk perception estimates for unique subpopulations at multiple sub-national scales across the contiguous United States—previously systematically constrained only at the national level. This generation of localized heat risk perception knowledge helps provide decision makers with context-rich information at scales appropriate for more targeted risk communication and hazard preparedness campaigns.

CHAPTER 2

LITERATURE REVIEW

2.1. EXTREME HEAT

Extreme heat exposure is a serious problem that is getting worse. While there is no universal definition of what constitutes a heat wave; these events are commonly understood to be periods characterized by excessively high levels of temperature and/or humidity that jeopardize human health due to severity of exposure or duration (CDC, 2016; Hawkins *et al*., 2017; Keller and DeVecchio, 2015; Liss *et al*., 2017; Robinson, 2001; Smith *et al*., 2013; White-Newsome *et al*., 2014). Mora and colleagues (2017) found that about 30% of the global population is exposed to deadly heat conditions for at least 20 days each year, and this number is expected to increase to between 48–74% by 2100 based upon climate projections under different greenhouse gas emission scenarios. Others have concluded that if temperatures continue to rise as expected, a greater proportion of U.S. citizens will be exposed to deadly heat conditions in the future (Lehner and Stocker, 2015; Rauber et al., 2008, p.544). The many health risks associated with extreme heat events—exacerbation of pre-existing health issues, depletion of food and water supplies, as well as the significant levels of stress placed upon local resources—cannot be overstated (CDC, 2016; IPCC, 2014; NWS, 2015).

Extreme heat is a commonly experienced hazard with both immediate and delayed negative health impacts that can result in many fatalities during pronounced heat waves. In July 1995, during a five-day extreme heat event in Chicago, Illinois, over 700 deaths were recorded in excess of historical norms for the same time period, representing an increase of 85% from the previous year (Klinenberg, 2003; Semenza *et al*., 1996). In May 2015, record temperatures throughout southern India led to at least 2,320 confirmed fatalities (Mazdiyasni *et al*., 2017; Ratnam *et al*., 2016). In 2010, a prolonged heat wave affected much of the Northern Hemisphere during the months of July and August. In Moscow, Russia city officials reported a total of 10,935 deaths attributed to the extreme temperatures, representing an increase of 60% from the previous year (Shaposhnikov *et al*., 2014). And in August 2003, a particularly severe heat wave affected much of western Europe claiming more than 70,000 lives (Robine *et al*., 2008). Despite these high numbers, heat deaths are likely underreported due to heat's tendency to exacerbate preexisting medical conditions which often leads to misdiagnosis and improper data recording (Aström *et al*., 2011; Liss *et al*., 2017; Mora *et al*., 2017). The intensity and scope of these impacts hinges upon geographic factors, population dynamics, time, scale, and the efficacy of communities' adaptive policies (EPA, 2016; IPCC, 2014; Klinenberg, 2003; Reid *et al*., 2012; Semenza *et al*., 1996; Smith, 2013, p. 86-88; Tierney, 2014, p. 5).

2.2. HAZARD RISK

Risk is a function of Vulnerability minus Adaptive Capacity; as stated above, vulnerability is comprised of two factors: Exposure and Sensitivity. Thus, Risk = Vulnerability {{ *f* (Exposure + Sensitivity }} – Adaptive Capacity (Åström *et al*., 2011; Basu and Ostro, 2008; IPCC, 2014; Jones *et al*., 2015; NWS, 2015; Tierney, 2014, p. 12). In the context of weather-related hazards such as extreme heat, these individual components of risk have been defined by various scholars as follows:

1. Exposure: the likelihood of being subjected to the hazardous event (Anderson and Bell, 2009, 2011; Harlan *et al*., 2014; IPCC, 2014; Jones *et al*., 2015; Medina-Ramon and Schwartz, 2007; Tierney, 2014, p. 12);
2. Sensitivity: the likelihood of being negatively affected by exposure; or the factors which govern the severity of the impact (Grothmann and Reusswig, 2006; IPCC, 2014; Johnson *et al*., 2012; Jones *et al*., 2015; Klinenberg, 2003; Reid *et al*., 2012; Tierney, 2014, p. 12); and
3. Adaptive capacity: the ability of individuals or a group to take actions that mitigate hazard risks (Bobb *et al*., 2014; IPCC, 2014; Jones *et al*., 2015; Kalkstein and Sheridan, 2007; Tierney, 2014, p. 12).

The risk of extreme heat is usually formally assessed through one of two approaches: through traditional physical risk assessments, which mainly seek to measure the likelihood, frequency and magnitude of exposure, or through impact-focused risk assessments, which seek to quantify the potential severity of negative impacts to the exposed population (Smith, 2013, p. 86-88). These approaches complement one another; the risks associated with climate change and natural disasters can be more comprehensively assessed by supplementing traditional physical examinations of hazard exposure (e.g., Gill and Malamud, 2014; Hawkins *et al*., 2017; Mora *et al*., 2017; Van Westen, 2000) with analyses that seek to incorporate dynamic human vulnerability factors (e.g., age, sex, race, economic status, geography, etc.) (e.g., Buscail *et al*., 2012; Cardona *et al*., 2012; Cutter *et al*., 2003, 2008; Howe *et al*., 2015; IPCC, 2014; Masato *et al*., 2015; Reid *et al*., 2009; Semenza *et al*., 1996; Tomlinson *et al*., 2011; Weber *et al*., 2015; Wolf and McGregor, 2013).

2.3. RISK ASSESSMENT

There are difficulties in balancing these two types of risk assessments (traditional and impact-focused). Because the factors are complex and systems are interdependent, discrepancies between traditional risk assessments and impact-focused assessments that often consider risk perceptions of the public can lead to problems in the evaluation, management, and mitigation of hazard impacts by decision-makers (Smith, 2013, p.81). This is because risk factors are dynamic: they change over time and across space, affect different populations in unique ways, and are tied to human decision-making processes. For example, there is evidence that heat-related hospitalization and mortality rates are highest during the first heat wave of the summer (Anderson and Bell, 2009; Hawkins *et al*., 2017; Liss *et al*., 2017; Rauber *et al*., 2008, p. 526; Smith, 2013, p. 271). Additionally, growing urban populations will likely be exposed to more intense and frequent extreme heat events due to heat island effects (CDC, 2016; IPCC, 2014; Li and Bou-Zeid, 2013; Tomlinson *et al*., 2011), and the aging of the U.S. population will increase the percentage of the population considered vulnerable to heat (Basu, 2009; Jones *et al*., 2015; Lehner and Stocker, 2015; Mora *et al*., 2017; Rauber *et al*., 2008, p. 544). These impact factors are often not accounted for in traditional, physical risk assessments. Some authors have explicitly acknowledged their inadequate handling of dynamic human factors in their risk analyses, often citing difficulties in measurement or spatial-temporal data compatibility (Gill and Malamud, 2014; Hawkins *et al*., 2017; Jones *et al*., 2015; Liss *et al*., 2017; Mora *et al*., 2017). Adding further complexity to evaluating risk on a national scale, the U.S. is a large, geographically diverse country, and global environmental changes will impact different regions and their respective populations in different ways (Melillo *et al*., 2014; Medina-Ramon and Schwartz, 2007; Reid *et al*., 2009).

Trying to strike the appropriate balance between localized approaches to extreme heat hazard management which recognize the concerns of the public about future impacts and top-down, statistical assessments of the hazard that favor quantitative probabilistic frequency estimates is a major task for hazard managers and decision-makers (Cardona *et al*., 2012; Hawkins *et al*., 2017; Smith, 2013, p. 86-88; Weber *et al*., 2015). While objective assessments can effectively detect spatial and temporal trends related to a hazard phenomenon and human exposure, risk perceptions are an important source of data at the extreme local level, where individuals best understand their unique contextual environments and hazard mitigation needs (Tierney, 2014, p. 46). Risk perception data provides an informative contextual element to the human dimensions of risk management (Smith, 2013, p.71), and are increasingly sought after by government officials and risk managers (Reid *et al*., 2012; White-Newsome *et al*., 2014; Wolf *et al*., 2010), many of whom are actively seeking to streamline and revise hazard loss reduction plans by placing greater emphasis on engaging with subpopulations most likely to be negatively impacted (CDC, 2016; EPA, 2016; Hawkins *et al*., 2017; IPCC; 2014; Liss *et al*., 2017; Masato *et al*., 2015; Smith, 2013, p. 86-88; Weber *et al*., 2015). A critical missing piece in risk assessment is individual perceptions and behavioral indicators. Incorporating individuals' risk perceptions into hazard management strategies presents a more democratic approach toward lessening hazard impacts and emphasizes the need to address sensitivity factors, vital components of vulnerability. This necessitates a shift away from probability–likelihood-based models toward a more impact-based assessment of risk.

2.4. SENSITIVITY FACTORS

The drivers of sensitivity are particularly challenging to factor into formal risk assessments. This knowledge gap presents a major challenge to decision-makers seeking to minimize negative impacts because sensitivity factors largely determine the degree to which extreme heat exposure will negatively impact subpopulations (Cardona *et al.*, 2012; IPCC, 2014; Jones *et al.*, 2015; Klinenberg, 2003; Mora *et al.*, 2017; Semenza *et al.*, 1996; Tierney, 2014, ch. 1–4). For example, it is generally well understood that certain subpopulations characterized by different sensitivity factors—the elderly, infants, individuals with disabilities or preexisting medical conditions, the homeless and poor, and the socially isolated—are more vulnerable to periods of prolonged or excessive heat (CDC, 2016; EPA, 2016; Gronlund, 2014; Gronlund *et al.*, 2014, 2016; IPCC, 2014). The best way to manage risk and assess vulnerability of these subpopulations involves combining an understanding of the physical properties governing heat (exposure) with sound judgment based upon knowledge of sensitivity factors (Cardona *et al.*, 2012; CDC, 2016; EPA, 2016; IPCC, 2014; Melillo *et al.*, 2014). Many high population areas have already shifted towards developing assessments of heat risk that are more impact-based (rather than strictly frequency and magnitude-based predictions of exposure), but lack quantitative data characterizing the distribution of key sensitivity factors. Risk perceptions play an important role in understanding the drivers of extreme heat vulnerability (particularly sensitivity factors), identifying at-risk subpopulations, and providing localized knowledge of how these factors are distributed throughout different communities.

Many hazards and risk researchers have highlighted that disasters are the outcome of social, political, and economic conditions interacting with a natural hazard (Cardona *et al*., 2012; Tierney, 2014, p.39; White *et al*., 2001). This intersecting of dynamic human factors and exposure has been described as the “social production of risk” (Tierney, 2014, ch. 4). Cardona and colleagues have asserted that vulnerable populations are at risk not only from extreme heat exposure, but also, “as a result of marginality, of everyday patterns of social interaction and organization, and access to resources” (Cardona *et al*., 2012, p. 71; IPCC, 2014). It is this unique combination of sociodemographic factors, their interactions, and personal circumstances that contributes to vulnerability and directly affects the impact of heat hazards.

This study will analyze empirical heat risk perception data and evaluate the relationship between key factors often cited in the literature as major contributors to heat vulnerability (summarized in Table I) as well as their influence on individual risk perceptions. For example, age of respondent was included in the models as a sensitivity factor. Older individuals are statistically more likely to be negatively impacted by extreme heat exposure as they tend to be more physiologically susceptible to heat risk, more limited in their ability to access health services due to mobility constraints, and more prone to social isolation (Anderson and Bell, 2011 Gronlund, 2014; Gronlund *et al*., 2014, 2016; Harlan *et al*., 2006; Johnson *et al*., 2009; Kovats and Hajat, 2008; Liss *et al*., 2017; Reid *et al*., 2009; Semanza *et al*., 1996; Smith, 2013; Staffogia *et al*., 2006; Uejio *et al*., 2011; Weber *et al*., 2015; White-Newsome *et al*., 2014; Wolf and McGregor,

Table I. Summary of Sensitivity Factors Known to Influence Extreme Heat Risk and Their Directionality

Predictor	+/-	Details	Reference
Age (65+)	+	The elderly face higher risk of negative physiological impacts from exposure to hazard and are more likely to be limited in their ability to access health services due to mobility constraints	Anderson and Bell, 2009, 2011; Buscail et al., 2012; CDC, 2016; Cutter et al., 2003; EPA, 2016; Harlan et al., 2006; IPCC, 2014; Johnson and Wilson, 2009; Keller and DeVecchio, 2015, p. 319; Klinenberg, 2003; Kovats and Hajat, 2008; Medina-Ramon et al., 2006; Melillo et al., 2014; Reid et al., 2009, 2012; Safi et al., 2012; Semenza et al., 1996; Smith, 2013, p. 271; Staffogia et al., 2006; Tomlinson et al., 2011; Uejio et al., 2011; Weber et al., 2015; White-Newsome et al., 2014; Wolf and McGregor, 2013
Sex (♀)	+	Women tend to have a slower recovery time when a hazard strikes than men due to greater pressure to address family care; unequal socioeconomic conditions; and less mobility – additionally, women tend to be more susceptible to heat exposure due to physiological differences in thermoregulation, transpiration capacity	Burse, 1979; Canoui-Poitrine et al., 2006; Kovat and Hajat, 2008; Safi et al., 2012; Smith, 2013, p. 272; Staffogia et al., 2006; Kaciuba-Uscilko and Grucza, 2001
Education	–	Less educated individuals often face greater often face greater difficulty in accessing health services and information regarding the nature of the hazard	Anderson and Bell, 2009, 2011; CDC, 2016; Cutter et al., 2003; EPA, 2016; IPCC, 2014; Medina-Ramon et al., 2006; Melillo et al., 2014; Reid et al., 2009, 2012; Smith, 2013, p. 85–86; Weber et al., 2015
Race/Ethnicity (non-white)	+	Minority groups often reside in more hazard-prone areas, are predisposed to having less power to cope with negative impacts of hazards due to socioeconomic inequalities, difficulties accessing health services, and limited mobility	Anderson and Bell, 2009, 2011; Curriero et al., 2002; Cutter et al., 2003; IPCC, 2014; Klinenberg, 2003, p. 80–81; Melillo et al., 2014; Reid et al., 2009, 2012; Safi et al., 2012; Tierney, 2014, p. 21; Weber et al., 2015; Wolf and McGregor, 2013
Work Status (disabled)	+	Individuals with a source of income are less sensitive to negative hazard impacts; while disabled persons are more susceptible to negative impacts	CDC, 2016; Cutter et al., 2003; EPA, 2016; IPCC, 2014; Keller and DeVecchio, 2015, p. 319; Klinenberg, 2003, p. 80–81; Melillo et al., 2014; Safi et al., 2012; Semenza et al., 1996
Home Size	–	Larger homes are more likely to have the resources required to cope with hazard	Cutter et al., 2003; Klinenberg, 2003, p. 80–81; Reid et al., 2009, 2012; Semenza at al., 1996; Weber et al., 2015

2013). Women face greater heat risk due to both physical and socioeconomic factors. Women tend to be more susceptible to periods of extreme or pronounced heat due to physiological differences in thermoregulation, namely transpiration capacity (Burse, 1979; Staffogia *et al*., 2006). Women also face significant socioeconomic disadvantages that contribute slower recovery times when a hazard strikes due to greater pressure to address family care, mobility constraints, and unequal socioeconomic conditions (Canoui-Poitrine *et al*., 2006; Kovats and Hajat, 2008; Smith, 2013). Less educated subpopulations tend to face greater natural hazard risks in general due to difficulties they face in accessing health services and hazard information (Anderson and Bell, 2011; Cutter *et al*., 2003; Reid *et al*., 2009; Weber *et al*., 2015). Socioeconomically disadvantaged persons, particularly disabled individuals, are significantly more likely to be negatively affected by natural hazards, including extreme heat, due to a lack of resources required to cope with the hazard (Anderson and Bell, 2009, 2011; Cutter *et al.*, 2003; Harlan *et al.*, 2006; Kovats and Hajat, 2008; Johnson *et al.*, 2009; Liss, 2017; Reid *et al.*, 2009; Smith, 2013; Uejio *et al.*, 2011; Weber *et al.*, 2015; White-Newsome *et al.*, 2014). Conversely, several studies have suggested that individuals or families living in larger homes tend to have greater access to the resources required to cope with heat hazards (Cutter *et al.*, 2003; Klinenberg, 2003, p. 80-81; Reid *et al.*, 2009, 2012; Semenza *et al.*, 1996; Weber *et al.*, 2015). Due to social, political, and economic advantages minority populations (not identifying as White or Caucasian) typically are more sensitive to extreme heat risk (Anderson and Bell, 2012; Cutter *et al.*, 2003; Reid *et al.*, 2009; Weber *et al.*, 2015).

2.5. EXPOSURE FACTORS

Exposure is "The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected" (IPCC, 2014, p. 5). While sensitivity factors affect the chances that different subpopulations are impacted in different ways when subjected to a natural hazard, the intensity and duration of extreme heat exposure significantly contributes to overall risk. Location is important to understanding extreme heat exposure levels, and it has been noted that, like many other weather-related hazards, a heat wave has a distinctive "geographic relativism to it" (Rauber *et al.*, 2008, p. 525). This relates to what has been described as the first law of geography: “Everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Individuals clustered together over space are more likely to experience similar heat conditions, as illustrated by the regional differences shown in Figure 1.

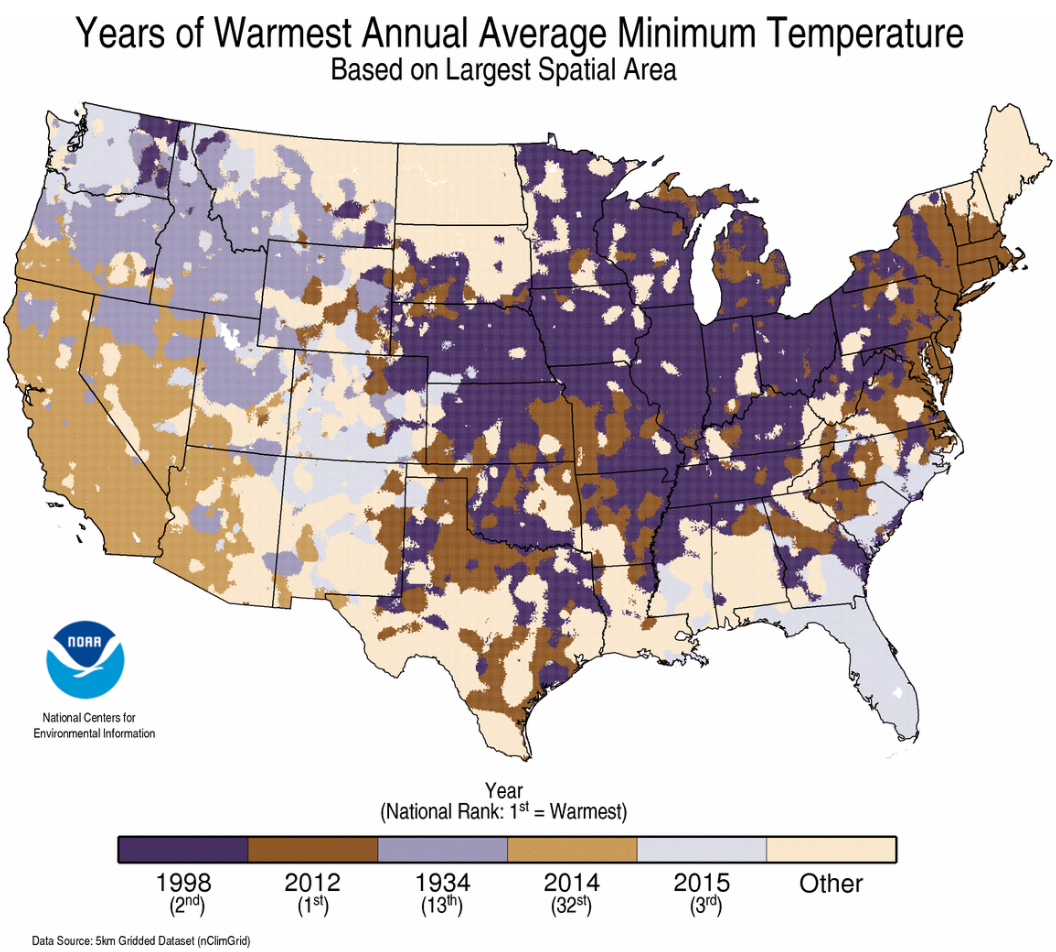
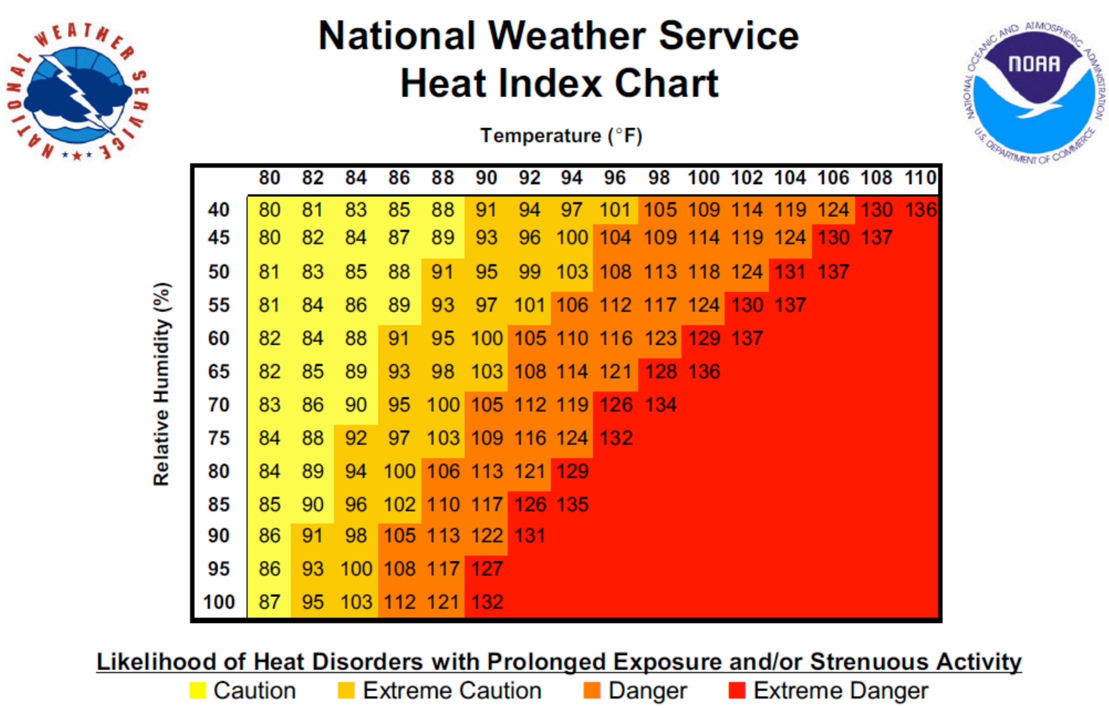


Fig. 1. Spatial distribution of greatest historical positive deviations in yearly average minimum temperature across the contiguous U.S. (NOAA, 2016).

Like sensitivity factors, exposure factors are dynamic and highly variable across time and space. However, these factors are generally better understood, thanks in part to modern technological advances that have enabled researchers to expand and enhance their avenues of inquiry. Many factors contributing to exposure levels have natural properties that have been observed, measured, and constrained: temperature levels, air pressure, humidity, solar insolation, radiative surfaces, albedo effect, air speed, elevation, proximity to large water bodies, etc. (Rauber *et al*., 2008, ch. 27; Van Westen, 2000). Knowledge of these natural properties helps explain how the human body interacts with extreme heat conditions.

The typical human body maintains a core temperature around 37 (± 0.5) °C at rest (Mackowiak *et al*., 1992; Sund-Levander *et al*., 2002). The body seeks to maintain this optimum core temperature via thermoregulation and has four ways to rid itself of excessive heat: evaporation, radiation, conduction, and convection (Hall, 2015, p. 914-915). However, even at rest, the average human body is generating heat by producing roughly 80–100 Watts to maintain the metabolic rate required in order to support the functioning of vital organs (Harris and Benedict, 1918; Roza and Shizgal, 1984). Therefore, if the human body is exposed to temperatures above 37 (± 0.5) °C, the body's ability to thermoregulate and cool via radiation and conduction is dramatically reduced. This is explained by the second law of thermodynamics which states that no object can transfer or dissipate heat into an environment of equal or greater temperature (Planck, 1903, p. 77-85). A human body that is exposed to temperatures greater than 37 (± 0.5) °C will begin to absorb heat via radiation and conduction. Under extreme heat conditions above this temperature threshold, evaporative cooling via perspiration becomes the body's primary defense against hyperthermia (Hall, 2015, p. 914-915). However, when relative humidity approaches 100%, the air saturates with water vapor and perspiration becomes dangerously deficient in its ability to achieve adequate thermoregulation

(Rauber *et al.,* 2008, p. 525). This creates particularly dangerous situations for people, such as outdoor workers and athletes, who are required to exert themselves outdoors during heat waves. In order to communicate the effects of combined heat and humidity on the human body when describing environmental conditions, the heat index was developed. The index combines measurements of both air temperature and relative humidity to produce an "apparent temperature" estimate which approximates how hot the human body perceives current conditions to be (Rauber *et al.,* 2008, p. 524-526). For example, a 37 °C air temperature combined with 40% relative humidity becomes 38 °C on the heat index and a blistering 57 °C with 70% humidity (Fig. 2). When the heat index


National Weather Service
Heat Index Chart

Temperature (°F)

Relative Humidity (%)	80	82	84	86	88	90	92	94	96	98	100	102	104	106	108	110
40	80	81	83	85	88	91	94	97	101	105	109	114	119	124	130	136
45	80	82	84	87	89	93	96	100	104	109	114	119	124	130	137	
50	81	83	85	88	91	95	99	103	108	113	118	124	131	137		
55	81	84	86	89	93	97	101	106	112	117	124	130	137			
60	82	84	88	91	95	100	105	110	116	123	129	137				
65	82	85	89	93	98	103	108	114	121	128	136					
70	83	86	90	95	100	105	112	119	126	134						
75	84	88	92	97	103	109	116	124	132							
80	84	89	94	100	106	113	121	129								
85	85	90	96	102	110	117	126	135								
90	86	91	98	105	113	122	131									
95	86	93	100	108	117	127										
100	87	95	103	112	121	132										

Likelihood of Heat Disorders with Prolonged Exposure and/or Strenuous Activity
Caution   Extreme Caution   Danger   Extreme Danger

Fig. 2. Heat index chart (courtesy of National Weather Service and the National Oceanic and Atmospheric Administration [NWS, 2005]).

climbs to these hazardous levels, individuals who experience prolonged exposure and are unable to adequately thermoregulate are most likely to suffer the negative effects of hyperthermia (Mora *et al*., 2017).

The spatial-temporal variation inherent to weather-related hazards greatly affects where and when different subsets of the population are exposed to prolonged or excessive periods of dangerous heat, as previously mentioned. Since heat conditions vary greatly across scales, time, and space it is often helpful to reference historical averages when describing the temperature trends that characterize different spatial-temporal units (e.g., the mean daily maximum temperature for a given month at the state level). This allows for place-based seasonal differences in extreme heat conditions to be characterized and examined in the context of their human impacts. More heat-related deaths and injuries are recorded during the first few heat waves of each year (Hawkins *et al*., 2017; Liss *et al*., 2017; Rauber et al., 2008, p. 526; Smith, 2013, p. 271) before individuals can acclimate to elevated temperatures over the course of the warm season. Population spatial dynamics also play an important role in determining degree of exposure, as people are not static entities and often choose to migrate seasonally (Jones *et al*., 2015). The environment in which people are situated has a direct effect on the frequency and degree to which they are exposed to extreme heat.

Urban environments with high population densities and other highly-developed areas with a higher proportion of impervious surfaces (pavement, concrete, etc.) are exposed to a higher degree of heat risk due to the urban heat island effect (UHI) (CDC, 2016; EPA, 2016; IPCC, 2014; Melillo *et al*., 2014). The UHI, a consequence of human development, describes cities' tendency to absorb and retain greater amounts of heat due to impervious surface properties, lack of cooling vegetation, decreased airflow due to human-built obstructions, and elevated exhaust emission levels from highly concentrated human activity. These factors, known to amplify heat exposure, are predominantly responsible for the extreme difference in temperatures between rural and urban environments (Fig. 3), where daytime city temperatures can be up to 5.6 °C higher than those recorded in the surrounding rural areas (CDC, 2016; EPA, 2016; IPCC, 2014; Tomlinson *et al*., 2011; Weber *et al*., 2015). Vegetation and tree coverage provides shade and helps drive down temperatures at night via evaporative cooling which reduces the likelihood of a sustained urban heat island effect (CDC, 2016; EPA, 2016). These nocturnal cooling processes play an integral role in helping to naturally reset the high surface and air temperatures from the previous day and play an important role in preventing prolonged or intense heat waves. The urban heat island effect is most apparent at night when air temperature differences between cities and rural areas can be as high as 12.2 °C (CDC, 2016; EPA, 2016). This illustrates the extreme importance of the aforementioned exposure factors that relate to human-built environments. When daily lows positively deviate from seasonal averages, daily highs are typically elevated, temperatures are less likely to "reset" via nightly cooling, and populations are more likely to be negatively impacted due to the unexpected nature of anomalous heat conditions (Rauber *et al*., 2008, p. 526; Smith, 2013, p. 271; Weber *et al*., 2015; White-Newsome *et al*., 2014).

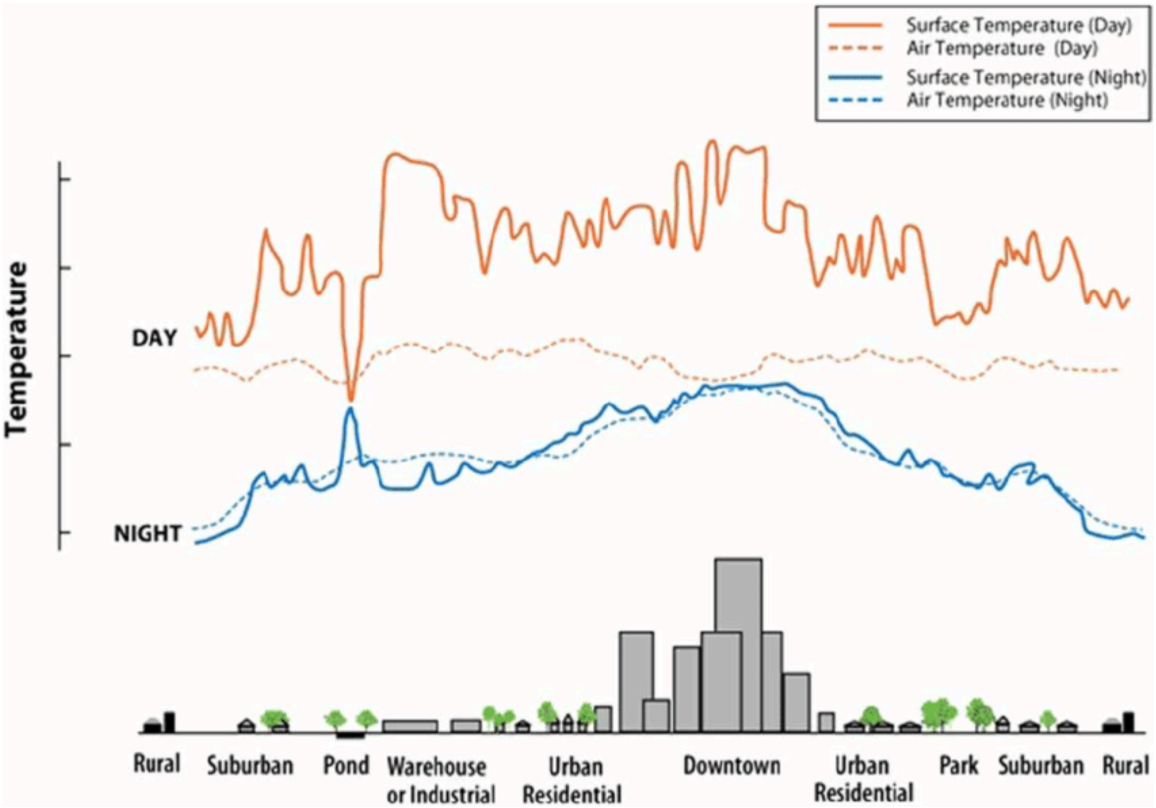


Fig. 3. Urban heat island profile, courtesy of the Environmental Protection Agency (CDC, 2016; EPA, 2016).

Table II summarizes the exposure factors evaluated in this study and the hypothesized directionality of their effect on extreme heat risk perceptions based upon how they augment heat risk individually. These factors include: Heat index measurements aimed at capturing the effect of humidity in the model (Anderson and Bell, 2009, 2011; EPA, 2016; Hawkins *et al*., 2017; Keller and DeVecchio, 2015, p. 316; Rauber *et al*., 2008, p. 525-526). Population density (Anderson and Bell, 2009, 2011; Buscail *et al*., 2012; CDC, 2016; EPA, 2016; IPCC, 2014; Kilbourne *et al*., 1982; Klinenberg, 2003, p. 80-81; Melillo *et al*., 2014; Rauber *et al*., 2008, p. 526-530; Safi *et al*., 2012; Smith, 2013, p. 272; Tan *et al*., 2007; Tomlinson *et al*., 2011; Weber *et al*., 2015) as well as impervious surface coverage and vegetation coverage (Bobb *et al*., 2014;

Table II. Summary of Exposure Factors Known to Influence Extreme Heat Risk and Their Directionality

Predictor	+/-	Details	Reference
Day of Year	−	First seasonal heatwave is responsible for greater negative impacts; fewer people are ready for their first experience of the warm season with extreme heat as compared to subsequent heatwaves. People tend to acclimate to warmer temperatures over the course of the warm season	Anderson and Bell, 2011; Hawkins et al., 2017; Liss et al., 2017; Rauber et al., 2008, p. 256; Smith, 2013, p. 85-86, 271
Heat Index	+	Index measures human body's perception of air temperature and factors in relative humidity alongside air temperature	Anderson and Bell, 2009, 2011; EPA, 2016; Hawkins et al., 2017; Keller and DeVecchio, 2015, p. 316; Rauber et al., 2008, p. 525-526
Impervious Surfaces	+	More developed environments with more impervious surface coverage are more likely to face higher degree of heat exposure due to the UHI effect.	Bobb et al., 2014; Buscail et al., 2012; CDC, 2016; EPA, 2016; Hawkins et al., 2017; IPCC, 2014; Keller and Devecchio, 2015, p. 317; Kilbourne et al., 1982; Klinenberg, 2002, p. 80-81; Melillo et al., 2014; Rauber et al., 2008, p. 526, 530; Reid et al., 2009, 2012; Smith, 2013, p. 272; Tan et al., 2007; Tomlinson et al., 2011; Weber et al., 2015
Tree Coverage	−	Great tree canopy and vegetation cover helps drive down temperatures when interacting with nightly lows; reduces threat of UHI effect	
Population Density	±	Urban environments with high population density face a higher degree of heat exposure due to the urban heat island effect which affects more people, which places greater stress on health service providors.	Anderson and Bell, 2009, 2011; Buscail et al., 2012; CDC, 2016; EPA, 2016; Hawkins et al., 2017; IPCC, 2014; Melillo et al., 2014; Kilbourne et al., 1982; Klinenberg, 2002, p. 80-81; Rauber et al., 2008, p. 526, 530; Safi et al., 2012; Smith, 2013, p. 272; Tan et al., 2007; Tomlinson et al., 2011
Mean Temperature for the week before response	±	Recent experience with extreme heat increases likelihood that this memory will influence or change judgement of risk	Smith, 2013, p. 81; Tierney, 2014, p. 18; Tversky and Kahneman, 1975; Weinstein, 1989
Seasonal Mean Temp. (May - Oct.)	+	Experience with extreme heat increases likelihood that this memory will influence judgement of risk	Anderson and Bell, 2009, 2011; EPA, 2016; Hawkins et al., 2017; IPCC, 2014; Rauber et al., 2008, p. 524-527; Smith, 2013, p. 84-86
Temperature Anomaly (deviation from 30-yr. seasonal avg. low)	±	Nightly lows are linked to cooling processes (with vegetation) that helps to reset high surface temperatures	Rauber et al., 2008, p. 526, 530; Reid et al., 2009, 2012; Smith, 2013, p. 272; Tan et al., 2007; Tomlinson et al., 2011; Weber et al., 2015; White-Newsome et al., 2014

Buscail *et al.*, 2012; CDC, 2016; EPA, 2016; IPCC, 2014; Keller and DeVecchio, 2015, p. 317; Kilbourne *et al.*, 1982; Klinenberg, 2003, p. 80-81; Melillo *et al.*, 2014; Rauber *et al.*, 2008, p. 526-530; Reid *et al.*, 2009, 2012; Safi *et al.*, 2012; Smith, 2013, p. 272; Tan *et al.*, 2007; Tomlinson *et al.*, 2011; Weber *et al.*, 2015) are known to influence temperature levels.

In addition to accounting for the heat index and anomalous temperature values, seasonal averages for each respondent's unique location were incorporated into the model. This was done in order to account for any influence experience with extreme heat may have on judgements of risk. Previous studies have acknowledged that such personal experience with a hazard may increase the likelihood that this memory will influence judgment of risk (Anderson and Bell, 2009, 2011; EPA, 2016; Hawkins *et al*., 2017; IPCC, 2014; Rauber *et al*., 2008, p. 524-527). Furthermore, Howe and Leiserowitz (2013) found that individuals are capable of detecting local changes in climate and weather patterns. Additionally, the average maximum temperature at each respondent's unique location for the week before the survey was evaluated as a separate variable, in order to address theories that recent experience and thus a clearer memory of the exposure incident may introduce additional bias to risk evaluation and judgment (Smith, 2013, p. 81; Tierney, 2014, p. 18; Tversky and Kahneman, 1973, 1974; Weinstein, 1989).

2.6 ADAPTIVE CAPACITY FACTORS

Adaptive capacity refers to the ability of an individual or a group to make "actual adjustments, or changes in decision environments, which might ultimately enhance resilience or reduce vulnerability to observed or expected [hazards]" (Adger *et al*., 2007, p. 720). Resilient communities with greater adaptive capacity are more likely to be capable of mitigating disaster by working to address vulnerability factors. As heat waves increase in frequency and severity, exposure levels will inevitably rise; this in turn will challenge the adaptive capacity and preparedness of communities with vulnerable subpopulations (IPCC, 2014; Melillo *et al*., 2014). Governmental disaster response preparedness does not necessarily translate into individual hazard exposure preparedness (Tierney, 2014, p. 7-10; Wolf *et al*., 2010); therefore, steps to increase resilience and enhance adaptive capacity must be proactively taken at multiple scales in order to ensure the meaningful reduction of future losses.

Because health impacts will differ greatly depending upon location, degree of exposure, and underlying sensitivity factors unique to each respective locale (or its denizens, as individuals or as a whole), building adaptive capacity is a challenging mission. It is by identifying, understanding, and addressing sensitivity factors that decision-makers are most likely to meaningfully reduce the vulnerable proportion of their respective populaces and reduce overall hazard risk for their communities. “Emphasizing that risk can be reduced through vulnerability is an acknowledgement of the power of social, political, environmental, and economic factors in driving risk” (Cardona *et al*., 2012, p. 72; IPCC, 2014). This responsibility primarily falls upon government officials and decision-makers who are duty-bound to make every effort to lower the number of known threats to the populace (Smith, 2013, p. 71). However, steps can also be taken by individuals within their communities towards enhancing their individual adaptive capacity, thereby strengthening the resilience of the community as a whole and helping to minimize future loss (CDC, 2016; EPA, 2016; IPCC, 2014; Melillo *et al*., 2014). For example, individuals are advised to seek cool environments, minimize sun exposure, stay hydrated, check in on loved ones young and old, wear lightly-colored, loosely-fit clothing, and reschedule outdoor activities earlier or later in the day (CDC, 2016; EPA, 2016).

Other adaptive capacity factors relate to the strength of any given community’s “safety net,” or its ability to absorb and deal with unexpected loss. For example, wealthier, whiter neighborhoods are typically less likely to be negatively impacted by extreme heat conditions; whereas poorer neighborhoods with more elderly residents are less likely to be able to cope. While urban residents are exposed to higher degrees of heat risk due to the UHI, they are also more likely to have more immediate access to health and human services than their rural counterparts (EPA, 2016; White-Newsome *et al*., 2014).

One of the most prominent and accessible government-sponsored initiatives aimed at strengthening adaptive capacity has been the development of a national extreme heat watch, warning, and advisory alert system by the National Weather Service (NWS). This public service is designed to provide the general populace with timely and reliable predictions of where and when heat waves will occur and communicate heat risk mitigation strategies that could be employed depending upon time and location (Hawkins *et al*., 2017; NWS, 2005. There are three levels of heat alert defined by the NWS: Warnings, Watches, and Advisories (WWAs). According to the NWS, each of their forecast offices across the U.S. (n = 122) issues some or all of these alerts depending upon their local area's unique circumstances. While the criteria that determine whether an alert should be issued or not may vary significantly for different weather forecast areas, the National Weather Service has summarized the conditions which are generally required for each alert level:

> "**Excessive Heat Warning** — Take Action!
> An Excessive Heat Warning is issued within 12 hours of the onset of extremely dangerous heat conditions. The general rule of thumb for this Warning is when the maximum heat index temperature is expected to be 105 °F [40.6 °C] or higher for at least 2 days and night time air temperatures will not drop below 75 °F [23.9 °C]; however, these criteria vary across the country, especially for areas not used to extreme heat conditions. If you don't take precautions immediately when conditions are extreme, you may become seriously ill or even die.

> **Excessive Heat Watches** — Be Prepared!
> Heat watches are issued when conditions are favorable for an excessive heat event in the next 24 to 72 hours. A Watch is used when the risk of a heat wave has increased but its occurrence and timing is still uncertain.
>
> **Heat Advisory** — Take Action!
> A Heat Advisory is issued within 12 hours of the onset of extremely dangerous heat conditions. The general rule of thumb for this Advisory is when the maximum heat index temperature is expected to be 100 °F [37.8 °C] or higher for at least 2 days, and night time air temperatures will not drop below 75 °F [23.9 °C]; however, these criteria vary across the country, especially for areas that are not used to dangerous heat conditions. Take precautions to avoid heat illness. If you don't take precautions, you may become seriously ill or even die" (NWS, 2005).

This information is often used by community health service providers, social workers, and local media who may be more capable of effectively communicating heat-related hazard information directly to the most vulnerable subpopulations (Klinenberg, 2003; Semenza *et al*., 1996). Local NWS forecast offices frequently collaborate with community partners to determine when an extreme heat alert should be issued for a local area and how to best communicate the risks associated with the hazard. For example, the NWS acknowledges that "residents of Florida are much more prepared for 32 °C+ weather than residents in Alaska" (NWS, 2005) and is working towards incorporating vulnerability considerations such as these into more local forecast offices' alert systems across the U.S. (Hawkins *et al*., 2017; Liss *et al*., 2017).

WWAs are not consistently issued when extreme heat conditions are present. In some cases, weather forecast areas bordering one another will issue some or no alerts while the other makes different issuance choices. Whether or not an alert was issued for the area an individual resides will not affect their degree of exposure or geographic proximity to extreme heat conditions, but it can affect whether or not hazard-specific risk information is communicated to said individual. This is both a strength and limitation of the national alert system for heat. One on hand, when weather forecast offices issue less alerts this helps to prevent "alert fatigue"—the point at which the populace ceases to pay attention to alerts that have been issued too liberally (Masato *et al*., 2015). However, this can also place vulnerable subpopulations at a disadvantage by depriving them of potentially valuable hazard mitigation information, particularly as the frequency and severity of heat waves rise.

Table III summarizes the adaptive capacity factors that are included in this study's model due to their effect on an individual's ability to cope with extreme heat exposure. Income was included in the model as it is known that wealthier individuals are more likely to have or acquire sufficient means to cope with hazards (Anderson and Bell, 2009, 2011; CDC, 2016; Cutter *et al*., 2003; EPA, 2016; Harlan *et al*., 2006; IPCC, 2014; Johnson *et al*., 2009; Klinenberg, 2003, p. 80-81; Kovats and Hajat, 2008; Melillo *et al*., 2014; Reid *et al*., 2009, 2011; Safi *et al*., 2012; Smith, 2013, p. 272; Tierney, 2014, p. 236; Uejio *et al*., 2011; Weber *et al*., 2015; White-Newsome *et al*., 2014). Non-English-speaking households and immigrant communities tend to have less access to hazard information or emergency assistance, often reside in more hazard-sensitive areas, and tend to have less power to cope with negative impacts of hazards due to socioeconomic and inequalities (Anderson and Bell, 2009, 2011; CDC, 2016; Cutter *et al*., 2003; EPA, 2016; IPCC, 2014; Klinenberg, 2003, p. 84; Melillo *et al*., 2014; Reid *et al*., 2009, 2011; Safi *et al*., 2012; Tierney, 2014, p. 236; Wolf and McGregor, 2013). The proportion of unemployed persons and of vacant homes in a particular areal unit are statistics that generally indicate its respective level of social cohesion, a major adaptive capacity factor

Table III. Summary of Adaptive Capacity Factors Known to Influence Extreme Heat Risk and Their Directionality

Predictor	+/-	Details	Reference
Income	–	Wealthier individuals are more likely to have or acquire sufficient means to cope with hazards	Anderson and Bell , 2009, 2011; CDC, 2016; Cutter et al., 2003; EPA, 2016; Harlan et al., 2006; IPCC, 2014; Johnson and Wilson, 2009; Klinenberg, 2003, p. 80–81; Kovats and Hajat, 2008; Melillo et al., 2014; Reid et al., 2009, 2012; Safi et al., 2012; Smith, 2013, p. 272; Tierney, 2014, p. 236; Uejio et al., 2011; Weber et al., 2015; White-Newsome et al., 2014
% Non-English-speaking households	+	Population tends to have less access to information and emergency help. Immigrant and minority groups often reside in more hazard-prone areas and tend to have less power to cope with negative impacts of hazards due to socioeconomic inequalities	Anderson and Bell, 2009, 2011; CDC, 2016; Curriero et al., 2002; Cutter et al., 2003; EPA, 2016; IPCC, 2014; Klinenberg, 2003, p. 84; Melillo et al., 2014; Reid et al., 2009, 2012; Safi et al., 2012; Tierney, 2014, p. 4–9; Weber et al., 2015; Wolf and McGregor, 2013
% Unemployed	+	Individuals without a source of income are less likely to be able to cope with hazard impacts; disabled persons are more susceptible to negative impacts	Anderson and Bell, 2009, 2011; Cutter et al., 2003; EPA, 2016; Klinenberg, 2003, p. 80–81; Safi et al., 2012; Semenza et al., 1996
% Vacant homes	+	High vacancy rates indicate there is less likely to be a reliable support network at the local level and more cases of social isolation. The urban poor face significant obstacles in acquiring information and health services	EPA, 2016; Klinenberg, 2003, p. 80–82; Smith, 2013, p. 271; Tierney, 2014, p. 236
Were any extreme heat alerts issued in summer days before response?	±	Residing within an extreme heat alert area may increase likelihood that the memory of personal experience with the hazard will bias judgement of risk	Howe, 2011; Smith, 2013, p. 84–86; Tierney, 2014, p. 18–20; Tversky and Kahneman, 1975; Weinstein, 1989
% of summer days where extreme heat aleart was issued before response	±		
Was extreme heat alert issued during week before response?	±	Residing within an area recently issued an extreme heat alert may increase likelihood that the recent memory of personal experience with the hazard will change or bias judgement of risk	

(Tierney, 2014, p. 236). Individuals without a source of income are less likely to be able to cope with negative hazard impacts (Anderson and Bell, 2009, 2011; Cardona *et al.*, 2012; Cutter *et al.*, 2003; EPA, 2016; IPCC, 2014; Klinenberg, 2003, p. 80-81; Melillo *et al.*, 2014; Safi *et al.*, 2012; Semenza *et al.*, 1996). High vacancy rates indicate there is less likely to be a reliable support network at the local level and more cases of social isolation (EPA, 2016; Klinenberg, 2003, p. 80-81; Smith, 2013, p. 271; Tierney, 2014, p. 236). Lastly, personal experience with extreme heat conditions which triggered an NWS alert is expected to influence risk perception values. Residing within an extreme heat alert area may increase the likelihood that a recent memory of personal experience with the hazard will influence judgment of risk either positively or negatively depending upon the outcome of the experience (Howe, 2011; Smith, 2013, p. 84-86; Tierney, 2014, p. 18-20; Tversky and Kahneman, 1974; Weinstein, 1989).

2.7. HUMANS AS SENSORS

Perception data aids understanding of changes in sensitivity factors over time and space. Humans are capable of detecting changes in local weather and climate patterns (Howe *et al.*, 2013b) and are more familiar with their respective group's unique situation. Moreover, "Risk perception is a precursor to the behavior change that constitutes adaptation," so understanding these perceptions can help decision-makers evaluate which subpopulations are least prepared to adapt (Howe, 2011). Looking at human survey data in this way and considering human participants as sensors can aid in the development of more precise and localized human vulnerability indices. For example, a perception of low risk could be associated with increased risk, as the group may be unprepared to adapt; similarly, it could be associated with low risk, as the group has better information on their own situation. These are important considerations that may augment our traditional understanding of the spatial distribution of vulnerability.

Previously, many scholars have stressed the importance of measuring risk perceptions as a way of adding the missing human data component to risk assessments, leading to a greater understanding of factors contributing to total vulnerability (Adger, 2006; Bubeck *et al.*, 2012; Chowdhury *et al.*, 2011; Grothmann and Patt, 2005; Howe *et al.*, 2013; Kates, 1971; Nitschke *et al.*, 2013; Slovic *et al.*, 2000; Wachinger *et al.*, 2013). However, few studies have specifically assessed the factors contributing to extreme heat risk perceptions by using representative survey data. To date, previous literature examining extreme heat risk perception data is largely limited to localized qualitative case studies or surveys confined to a handful of the U.S.' metropolitan areas (Abrahamson *et al*., 2009; Nitschke *et al*., 2013; Sampson *et al*., 2013; Semenza *et al*., 2008; Sheridan, 2007; Wolf *et al*., 2010). Despite contemporary access to an ever-growing collection of biophysical exposure data, vulnerability studies typically lack the critical psychosocial data such as risk perceptions that are required to more completely account for the role human risk judgment plays in determining individual vulnerability (Hogarth and Einhorn, 1992; Howe *et al*., 2013, Mora *et al*., 2017).

As mentioned in Section 2.3, many government officials and decision-makers want to identify vulnerable populations and address their unique needs, but find it challenging to balance between top-down risk management strategies and tailored, local approaches to risk reduction. As officials move towards embracing impact-based risk assessment methods, scholars have called for a more targeted approach to communicating heat hazards (Hawkins *et al*., 2017; Liss *et al*., 2017; Mora *et al*., 2017; White-Newsome *et al*., 2014; Wolf *et al*., 2010) and recommended the development of revised heat alert systems that are both person- and location-specific (Buscail *et al*., 2012; Liss *et al*., 2017; Masato *et al*., 2015; Reid *et al*., 2012; Tomlinson *et al*., 2011; White-Newsome *et al*., 2014; Wolf *et al*., 2010). These proposed changes require a clearer understanding of how vulnerability and adaptive capacity factors vary across subpopulations. Wilhelmi and Hayden (2010, p. 4) have asserted that

> "improving health outcomes related to exposure to extreme heat requires moving beyond the spatial analysis of quantitative aggregate demographic data toward understanding knowledge, attitudes and practices regarding extreme heat. Because awareness of extreme heat does not necessarily

> translate into action to reduce vulnerability, household-level perceptions of risk to extreme heat … need to be better understood."

This thesis seeks to address this gap in the heat risk literature by evaluating variations in risk perceptions for different groups across the U.S. Quantitative analysis of spatially-explicit risk perception data can aid the development of more sophisticated human vulnerability indices at the local level and can capture changes in dynamic sensitivity factors over time and space while also controlling for exposure and adaptive capacity factors. This thesis aims to provide a model for how future studies could proceed in incorporating risk perceptions into their analyses ***by*** using georeferenced and time-stamped survey data collected by "human sensors." This research identifies and isolate the effects of specific vulnerability factors related to sociodemographic, meteorological, climatological, temporal and geographic factors in order to better assess adaptive capacity, enhance resilience, and reduce extreme heat risk at different scales. The results of this study will help decision-makers better understand which groups of people are most likely to be negatively impacted by extreme heat and to target their efforts at risk mitigation on behalf of these subpopulations.

CHAPTER 3

METHODS AND ANALYSIS

3.1. RESEARCH QUESTIONS AND HYPOTHESES

Research Question I: How do key sensitivity factors known to be important contributors to overall heat vulnerability (summarized in Table I) contribute to extreme heat risk perceptions across the contiguous United States?

Hypothesis I: Individual-level sensitivity factors that have been found to be associated with greater personal risk of heat-related impacts in previous studies will positively influence heat wave risk perceptions across the study area and be a source of statistically significant variation (from the national mean).

Research Question II: How much variation in risk perception occurs at regional, state, and individual-levels?

Hypothesis II: Risk perceptions will demonstrate statistically significant variation across geographic units in the contiguous United States, and states that have a higher degree of exposure to extreme heat events will have higher risk perceptions.

Research Question III: How do key exposure factors known to be important contributors to overall heat vulnerability (summarized in Table II) influence extreme heat risk perceptions across the contiguous United States?

Hypothesis III: Respondents located in areas more likely to experience a higher degree of exposure will report higher risk perceptions (for example, due to geographic location, higher average seasonal temperatures or the effects of the urban heat island).

Research Question IV: How do key adaptive capacity factors known to affect an individuals' ability to cope with hazards (summarized in Table III) influence extreme heat risk perceptions across the contiguous United States?

Hypothesis IV: Adaptive capacity factors measured at the individual-level, such as income, will negatively influence extreme heat risk perception (e.g., as income levels increase, risk perception score will decrease). Contextual-level factors (those measured at the census tract level, e.g., number of unemployed, number of vacant homes) which are known to negatively influence overall adaptive capacity (and positively influence total extreme heat risk) will negatively influence extreme heat risk perceptions.

3.2. STUDY AREA AND DATA SOURCES

3.2.1. Nationally-representative heat wave risk perception survey data

This study examines heat wave risk perceptions across the contiguous U.S. during the warm months of 2015 and makes extensive use of empirical, nationally-representative survey data (Fig. 4) that was collected during the warm months of 2015. The survey was administered online over the course of 20 weeks, beginning in May, biweekly with unique panel respondents selected through probability-based sampling. The overall sample size was n = 10,532. However, due to the panel design of this survey, response data was collected more than once for some individuals. These response values were filtered from the dataset before analysis and the final sample size was n = 8,789. Individual identifiers were removed from the data and the precise geographic coordinates of respondents were "jittered" within a radius of 150m to ensure anonymity.

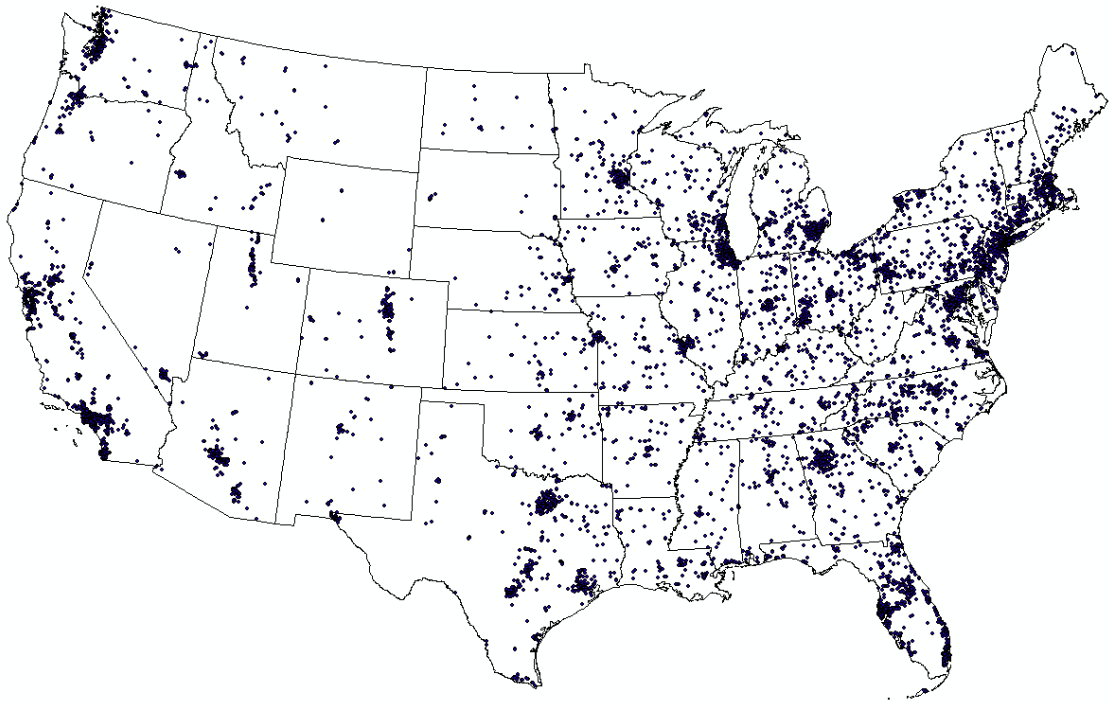


Fig. 4. Distribution of survey respondent locations.

This time-stamped, geo-referenced survey was composed of three questions measuring heat wave risk perceptions on three scales, measuring perceived risk to the individual respondent, their family, and their community and collected data on the demographic characteristics of each respondent. Seven of these demographic variables (Sex, Age, Race/Ethnicity, Income, Education, Work Status, Household Size) were used in this study's models along with temporal and geographic data recorded for each response. The structure of these variables is detailed in Section 3.3. The risk perception values associated with each of the survey questions were combined for each unique respondent to create the overall risk perception index used as the dependent variable in this study (Cronbach's alpha = 0.95). The quantitative outcome of the survey and index formulation is heat wave risk perception values on a scale of 0–1 with 1 representing the highest degree of perceived risk to heat. Across the U.S., the mean risk perception score is 0.42 (Fig. 5).

3.2.2. Contextual-level data sources

The 2015 meteorological and 1985–2015 climatological estimates of daily and monthly temperatures, corrected for elevation using the Parameter-elevation Relationships on Independent Slopes Model (PRISM), and gridded at 800 meter spatial resolution were utilized courtesy of the PRISM Climate Group at Oregon State University (PRISM Climate Group, 2015) to create three exposure variables: mean maximum daily temperature (avg. max. temp.) recorded during the week before the survey at each respondent's unique location at 800m (weekmeanb4survey_PRISM), maximum temperature recorded on the day of the survey at each respondent's unique

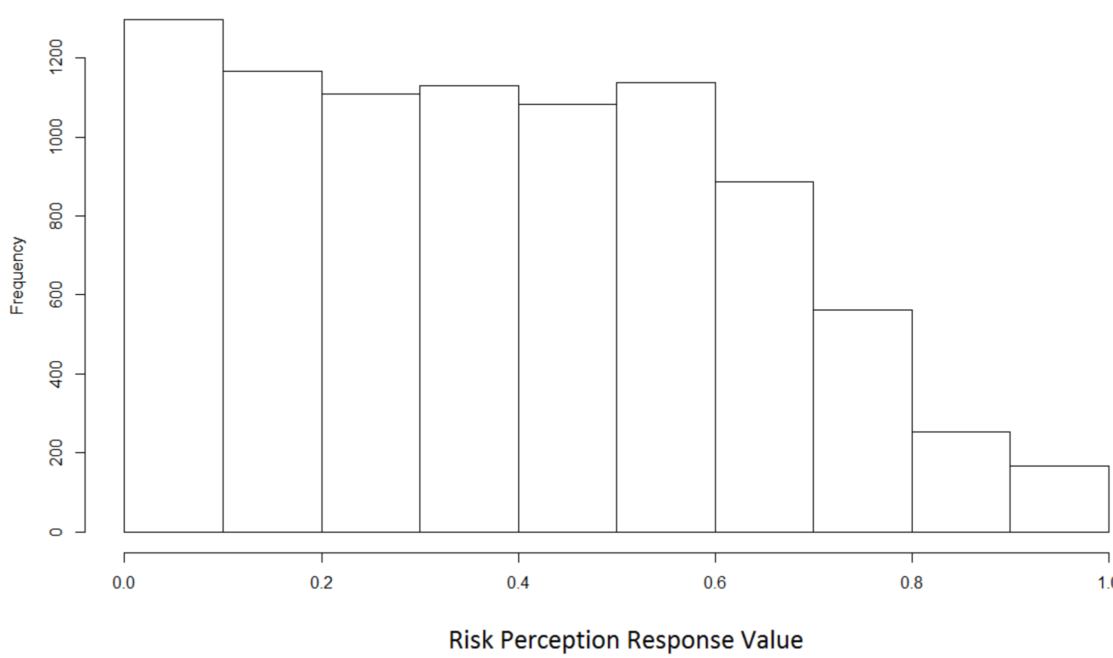


Fig. 5. Distribution of risk perception response values.

location at 800 m (Syday_Tmax) and mean seasonal temperature at the tract-level (TR.prism.tmean).

The National Weather Service (NWS) heat-related Watch-Warning-Advisory spatial polygon data for 2015 were utilized courtesy of the Iowa Environmental Mesonet at Iowa State University of Science and Technology (National Weather Service Hazards Alert Database, 2015) to create three adaptive capacity variables summarizing the presence of Watch, Warning, or Advisory heat alerts in the areas where survey responses were collected: Total percentage of days for which each respondent's location was issued an extreme heat alert before the survey (pct_WWAdaysb4survey), True/False: Were any heat alerts issued during the week before the survey response for each respondent's unique location? (weekb4survey_WWA), and True/False: Were any heat alerts issued on any day before the survey response for each respondent's unique location? (WWAb4survey).

Thirty meter vegetation and impervious surface estimates, calculated at the census travel level using gridded data from the 2011 National Land Cover Database were utilized courtesy of the Multi-Resolution Land Characteristics Consortium, U.S. Geological Survey (National Land Cover Database, 2011) to extract cell values to respondent location points, creating two exposure variables that indicate susceptibility to the urban heat island effect: Tract-level impervious surface coverage log-transformed (TR.impervious.mean.log) and Tract-level tree coverage square-root-transformed.

Population density estimates (popden) dated 2000, gridded at 1000 kilometers spatial resolution, representing persons per square kilometer were used to create an exposure variable courtesy of the Center for International Earth Science Information Network at Columbia University (CIESIN, 2005).

Census tract-level statistics from across the contiguous U.S. were acquired from the 2015 American Community Survey, courtesy of the U.S. Census Bureau (American Community Survey, 2017), and were used to create three adaptive capacity variables: Total proportion of unemployed individuals (TR.Employment.unemployed), Total proportion of vacant homes (TR.Housing.vacant), and Total proportion of non-English-speaking households (TR.Language.nonEnglish).

Two exposure variables, Deviation of average minimum temperature recorded during the month of the survey from the seasonal average at the tract-level (TR.tmin.anom.mav7) and County-level average seasonal heat index estimates (CO.HI.daily.MaySep), were created for all respondent locations across the contiguous U.S. using data provided by the 2000–2010 North America Land Data Assimilation System (NLDAS); courtesy of the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction (NCEP) Environmental Modeling Center (EMC), the National Aeronautics and Space Administration (NASA) Goddard Space Flight Center (GSFC), Princeton University, the National Weather Service (NWS) Office of Hydrological Development (OHD), the University of Washington, and the NCEP Climate Prediction Center (CPC); accessed via the Wide-ranging Online Data for Epidemiologic Research (WONDER) portal developed by the Centers for Disease Control and Prevention (CDC) (NLDAS, 2012).

3.3. DATA CHARACTERISTICS

3.3.1. Sensitivity Variables

Table IV characterizes the structure of the seven individual-level sensitivity variables included in this study's Sensitivity Model. Data for these variables were collected during the nationally-representative heat wave risk perception survey.

Table IV. Descriptive Statistics for Predictors of Sensitivity Model

Categorical Variable	Levels	Frequency	% of total
Sex	Female	4347	49.5
	Male	4442	50.5
Age	18-24 years	1142	13.0
	25-34 years	1602	18.2
	35-44 years	1751	19.9
	45-65 years	1316	15.0
	65+ years	2978	33.9
Race/Ethnicity	2+ Races/Ethnicities, Non-Hispanic	277	3.1
	Black, Non-Hispanic	670	7.6
	Hispanic	899	10.2
	Other, Non-Hispanic	378	4.3
	White, Non-Hispanic	6565	74.7
Education	Less than high school diploma	758	8.6
	High school graduate, GED, or alternativ	2523	28.7
	Some college or associates degree	2455	27.9
	Bachelors degree or higher	3053	34.7
Income	< $15,000	751	8.5
	$15,000-$29,999	998	11.4
	$30,000-$49,999	1387	15.8
	$50,000-$74,999	1739	19.8
	$75,000-$99,999	1330	15.1
	$100,000-$149,999	1776	20.2
	$150,000 or more	808	9.2
Work Status	Disabled	573	6.5
	Not Working	928	10.6
	Retired work	1311	14.9
	Seeking Job	585	6.7
	Working	5392	61.4
Household Size	One bedroom	1523	17.3
	Two bedroom	3067	34.9
	Three bedroom	1710	19.5
	Four + bedroom	2489	28.3

3.3.2. Exposure Variables

Degree of exposure is highly variable over space and time and is subject to a dynamic set of natural factors. The variables considered in this study are presented in Table V. 2015 was the hottest year on record at its conclusion (CDC, 2016; EPA, 2016). However, it is unlikely that exposure to extreme heat conditions was uniform across the U.S. population. Looking at localized survey data alongside contextual-level weather data that captures the variability of meteorological conditions over time and space provides the most context for the data itself and for model interpretation. In order for meteorological, climatological, and land cover data to be incorporated into the study models as controls for exposure factors cell values for all gridded contextual exposure data were extracted to each survey respondent location point —by month, week, or day (depending upon the temporal resolution of the contextual data) (Fig. 6).

Table V. Descriptive Statistics for Predictors of Exposure Model

Continuous Variable	Metric	N	Mean	Std. Dev.	Median	Min	Max
Day of year	Julian days	8789	228.91	44.88	233.00	156.00	298.00
Heat Index	F° (tract level)	8789	90.10	3.64	89.40	79.70	100.76
Impervious Surfaces	Avg. % developed imp. surface (tract-level)	8789	2.50	1.52	3.05	-5.06	4.56
Tree Coverage	Avg. % tree canopy cover (tract level)	8789	4.72	2.10	4.65	0.19	9.59
Seasonal Mean Temp. (May - Oct.)	C° (tract level)	8789	21.74	3.40	21.26	9.72	32.26
Temp. Anomaly	C° (2015 month avg. 30 year avg at tract-level)	8789	1.08	1.85	0.99	-5.70	7.48
Population Density	Persons per km²	8789	17.42	38.15	8.13	0.00	635.30
Max. Temp. (Day of Survey)	C° (800m PRISM)	8789	29.00	4.87	28.20	13.74	44.83
Avg. Max. Temp. (Week before survey)	C° (800m PRISM)	8789	27.45	5.34	28.14	7.11	44.52

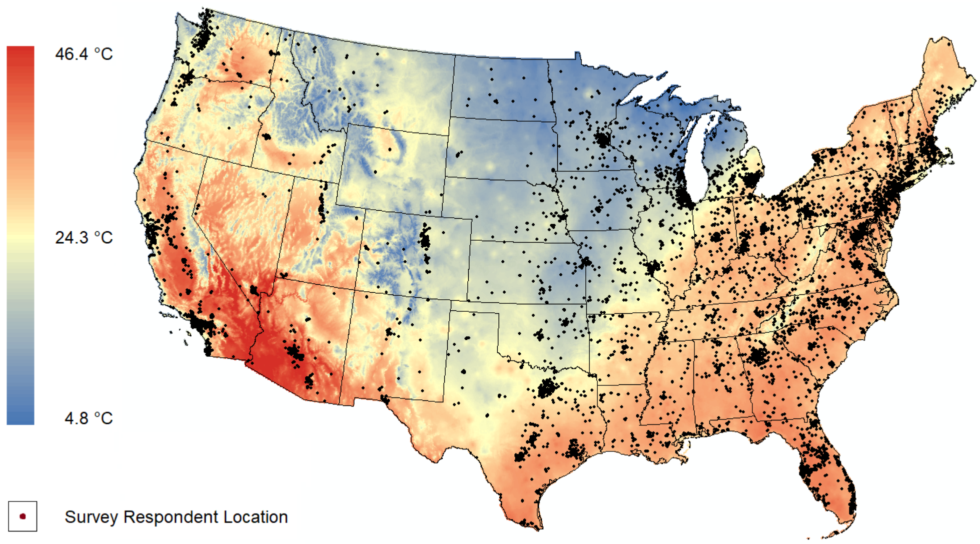


Fig. 6. Distribution of all survey response locations and PRISM max. temperature data for 31 May 2015 at 800 m spatial resolution. Extreme heat conditions can be observed in the southwest along the California and Arizona border.

It is important to note that variability exists on a wide range of scales and that survey respondents each likely experienced unique heat conditions despite their sometimes-close proximity to one another. Figures 7–9 demonstrate this extreme variability at three scales: region, state, and county. These figures, each, contain a different subset of survey respondents, each of whose locations fall within these respective scales (Midwest, Ohio, Franklin County). In each figure, the plots reflect the maximum daily temperatures recorded on May 27–31 at each respondent's unique location. All axes contained in Figures 7–9 represent these localized daily temperatures in °C. A high degree of variability remains present for each these geographic subsets of the survey population regardless of scale.

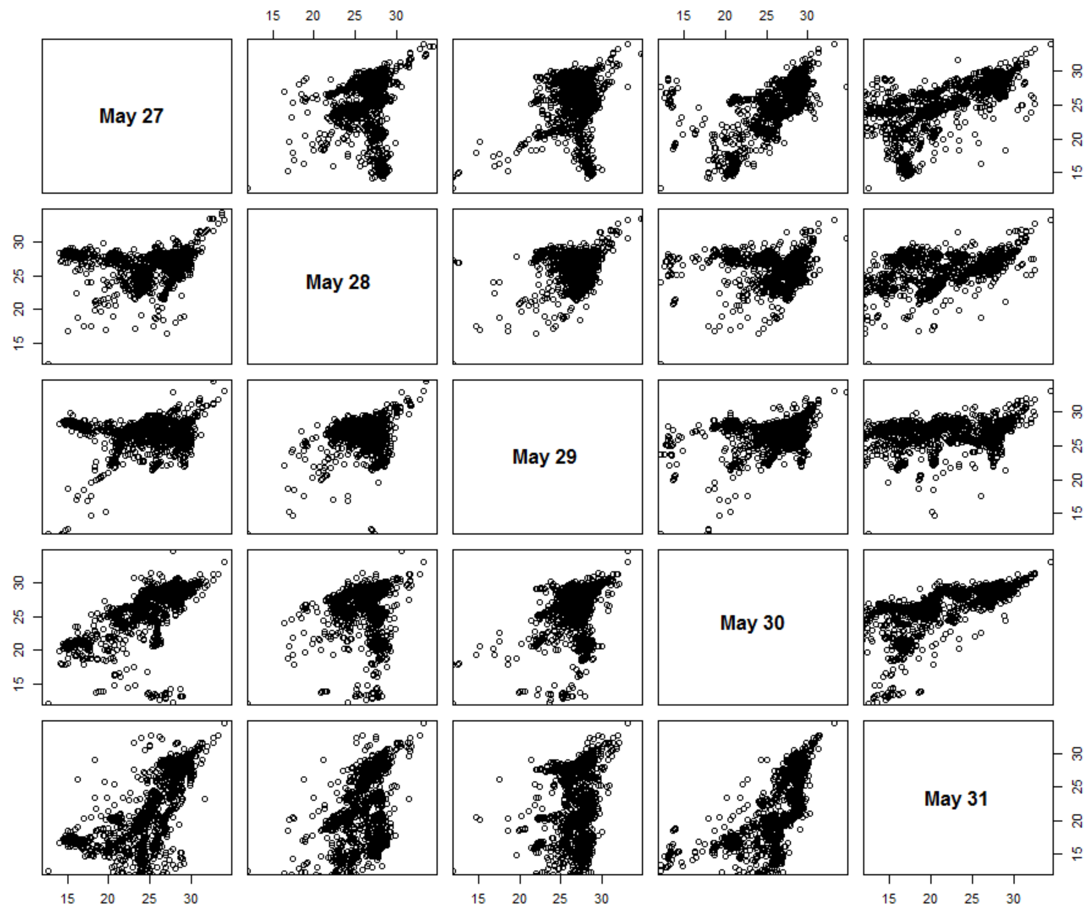


Fig. 7. Variability of max. temperatures (°C) at the locations of each unique Midwest survey respondent over five consecutive days.

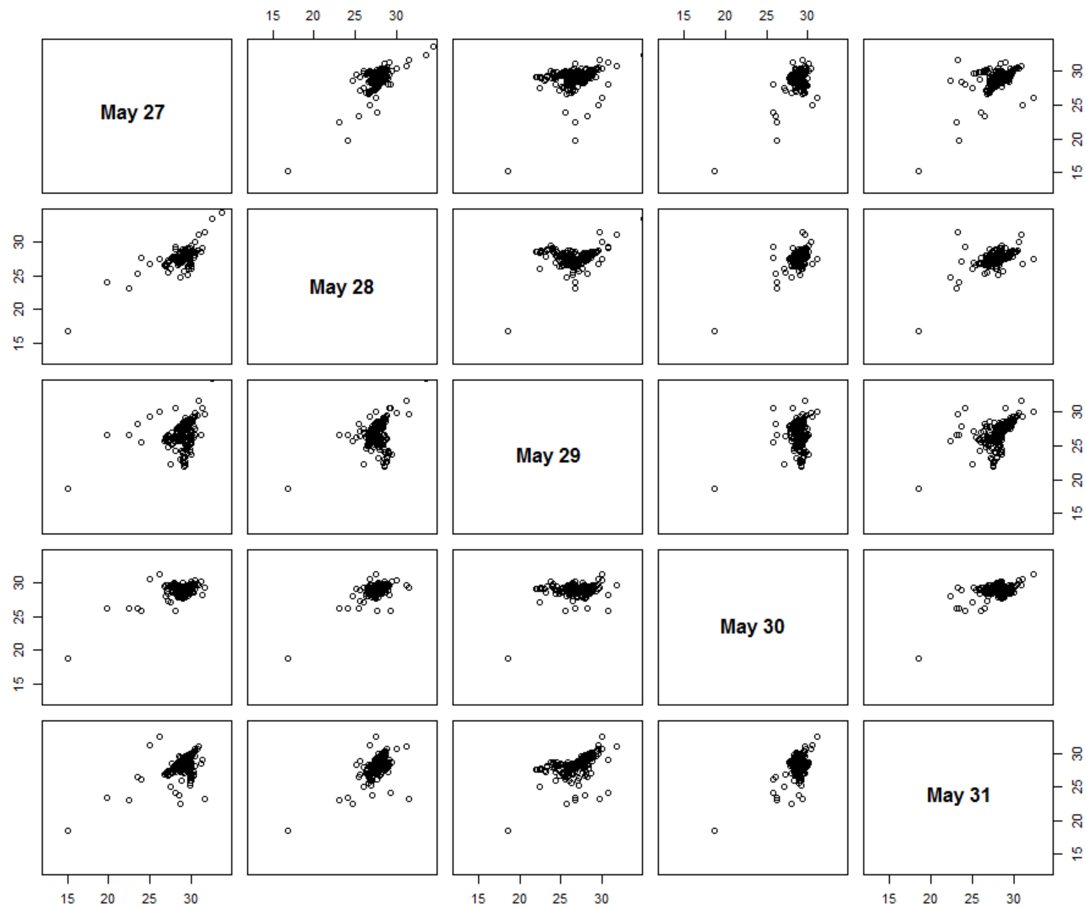


Fig. 8. Variability of max. temperatures (°C) at the locations of each unique Ohio survey respondent over five consecutive days.

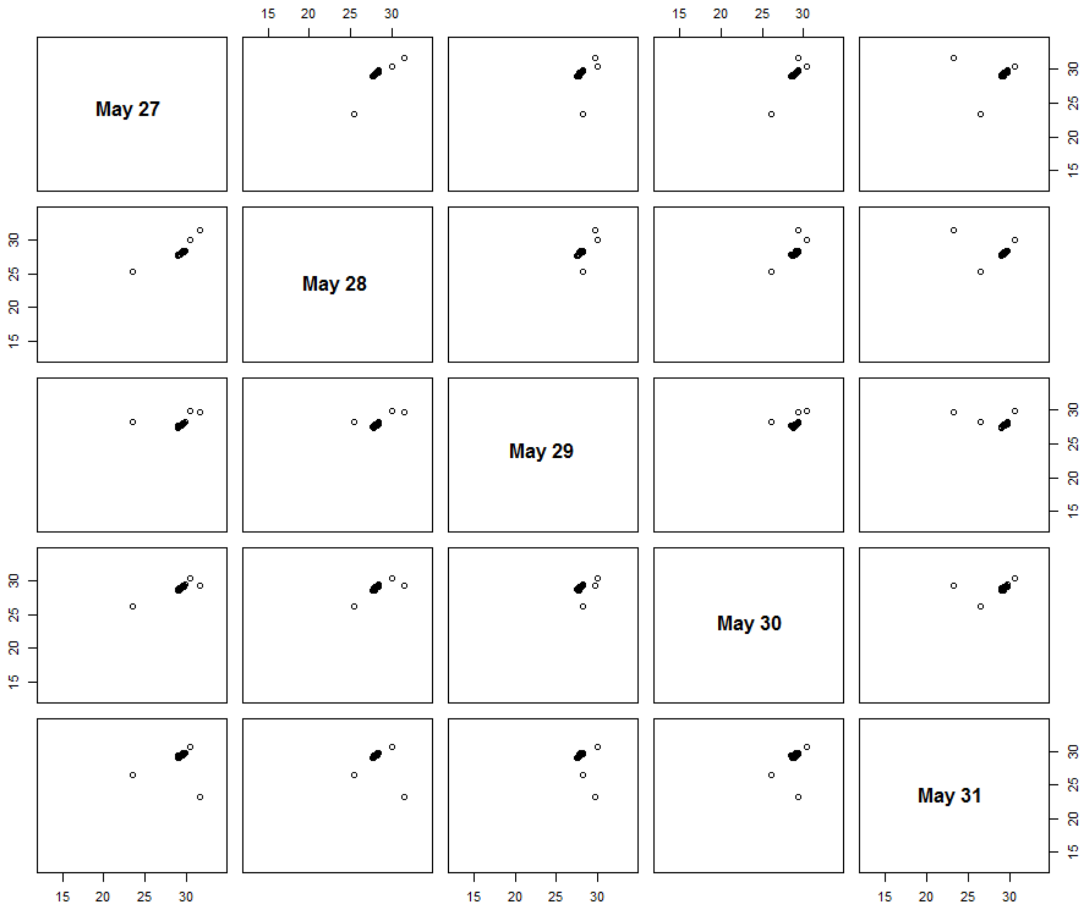


Fig. 9. Variability of max. temperatures (°C) at the locations of each unique Franklin County, Ohio survey respondent over five consecutive days.

Looking at the study area over the course of the study period (contiguous U.S., May–October, 2015) broad patterns emerge in heat conditions that are captured by the exposure variables included in this study: state-level average minimum temperatures were unusually high across the most of country, no estimates were below their average levels, but were the highest on record throughout the West (Fig. 9); whereas, state-level maximum temperatures were near average for much of the Mississippi and Ohio watershed areas and the highest on record in Washington and Oregon (Fig. 10).

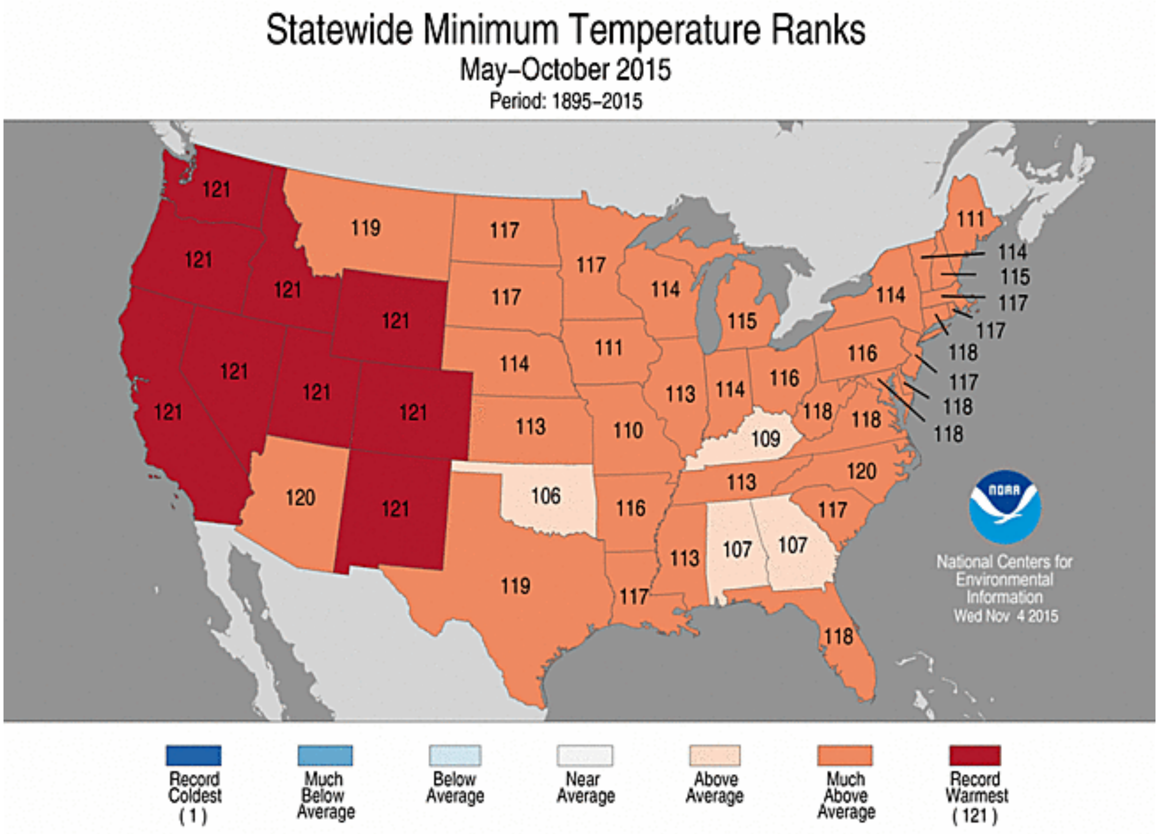


Fig. 10. Ranking of statewide minimum temperatures recorded from May–October, 2015. Note that for nine states in the West, record highs were recorded. Ranking numbers identify the count of years for which the 2015 recorded average minimum temperature (May to October) was greater (1895–2015) (NOAA, 2016).

Finally, on a still larger spatial and temporal scale, the exposure variable summarizing deviations of average minimum and maximum temperature recorded during the month of the survey from the 30-year seasonal average at the tract-level (TR.tmin.anom.mav7) are respectively depicted in Figures 11 and 12 by region.

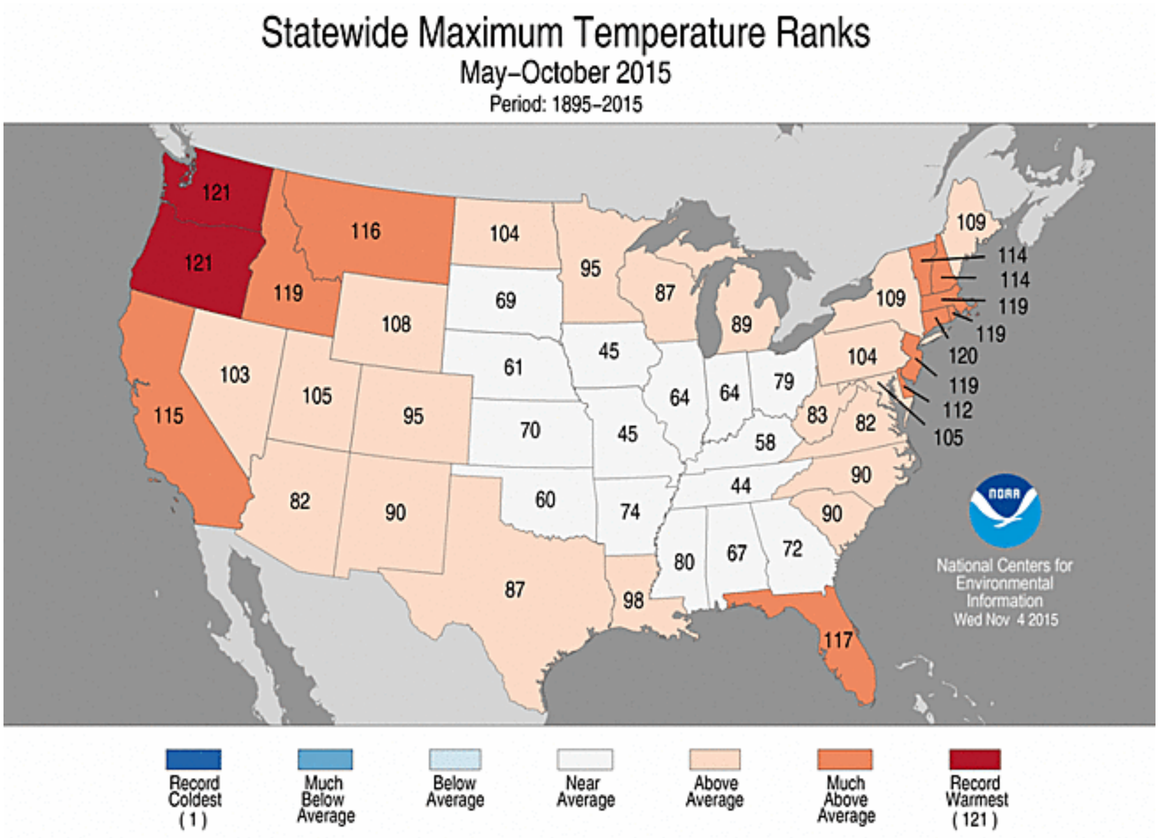


Fig. 11. Ranking of statewide maximum temperatures recorded from May–October, 2015. Note that record highs were recorded for this time period for two states (OR, WA). Ranking numbers identify the count of years for which the 2015 recorded average maximum temperature (May to October) was greater (1895-2015) (NOAA, 2016).

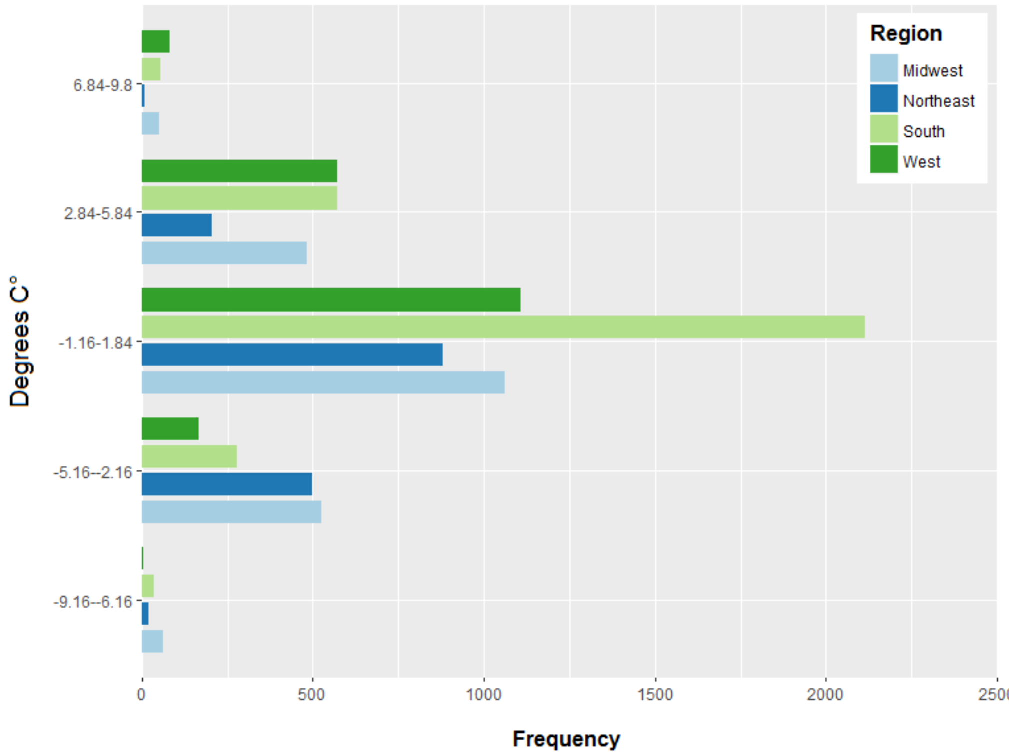


Fig. 12. Summary of deviations of 2015 monthly temperatures from 30-year averages across all unique response locations by region.

3.3.3. Adaptive Capacity

Descriptive statistics for continuous and categorical adaptive capacity predictors are detailed in Tables VI–VII.

Table VI. Descriptive Statistics for Continuous Adaptive Capacity Model Predictors

Continuous Variable	N	Mean	Std. dev	Median	Min	Max
% Non-English-speaking Households (tract level)	8789	7.22	9.68	3.40	0.00	71.00
% Unemployed (tract level)	8789	8.94	5.06	8.00	0.00	76.00
% Vacant homes (tract level)	8789	10.23	8.81	8.10	0.00	100.00
% Summer days where extreme heat alert was issued at respondent location before survey	8789	0.05	0.05	0.03	0.00	0.25

Table VII. Descriptive Statistics for Categorical Adaptive Capacity Model Predictors

Categorical Variable	Levels	Frequency	% of total
Heat alert issued during week before survey at respondent location	FALSE	8409	95.7
	TRUE	380	4.3
Heat alert issued during summer 2015 before survey at respondent location	FALSE	2456	27.9
	TRUE	6333	72.1
Income	< $15,000	751	8.5
	$15,000-$29,999	998	11.4
	$30,000-$49,999	1387	15.8
	$50,000-$74,999	1739	19.8
	$75,000-$99,999	1330	15.1
	$100,000-$149,999	1776	20.2
	$150,000 or more	808	9.2

Similar to Figure 5, Figure 13 shows max. temperature cell values at 800 m and the location of survey respondents. However, this graphic shows the average maximum temperature values recorded for Washington state from 27–28 June 2015 during an extreme heat event and the spatial distribution of NWS heat alerts issued for this two-day period.

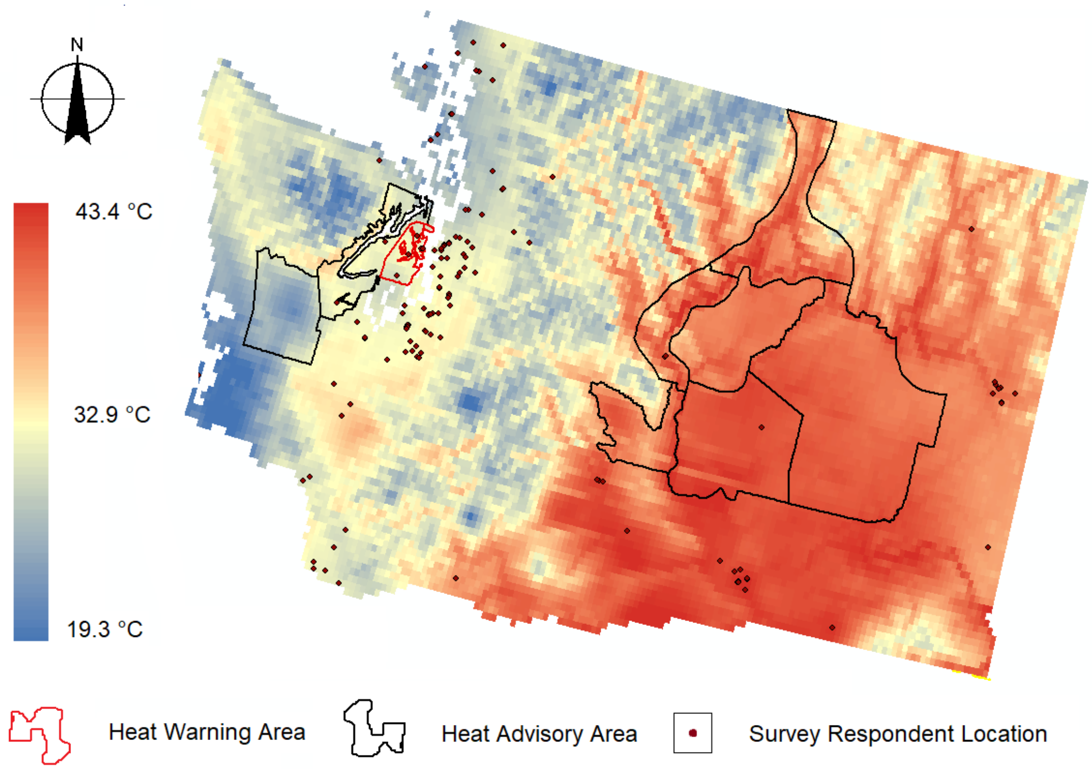


Fig. 13. Spatial distribution of extreme heat conditions, heat warning areas, heat advisory areas, and survey respondents on 27–28 June 2015.

Examining the NWS heat alert dataset as spatial polygons in this way allowed for the extraction of alert statistics for each survey respondent for each day of the study period. Figure 14 summarizes the regional distribution of NWS heat alert across the survey sample population.

Considering georeferenced, time-stamped risk perception data alongside NWS alert system data and PRISM meteorological data may enhance understanding of how changes in the dynamic components of heat risk over time and space influence extreme heat risk perceptions.

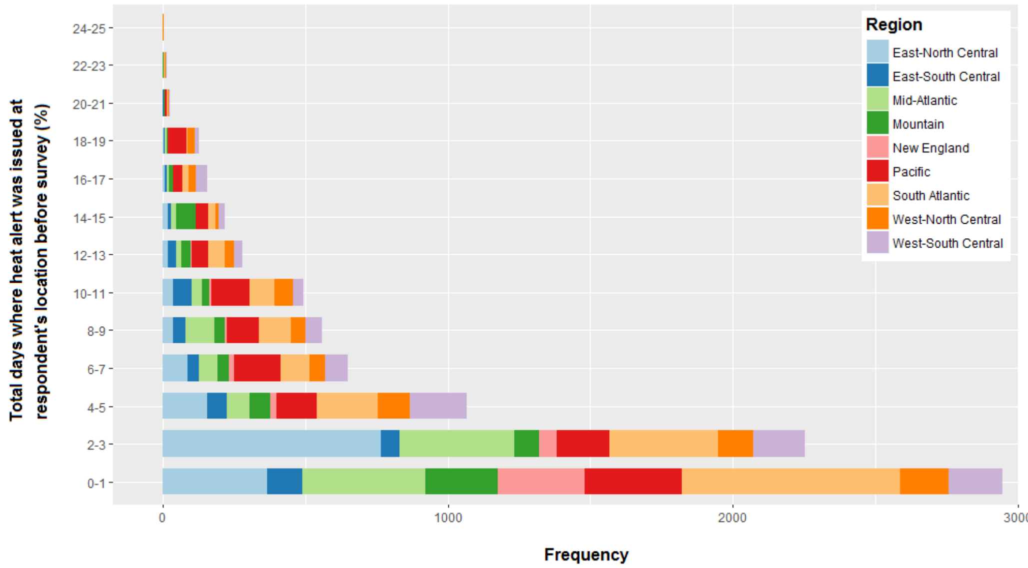


Fig. 14. Total percentage of days when an extreme heat Watch, Warning, or Advisory (WWA) alert was issued by the National Weather Service at all respondents' unique locations within Weather Forecast Areas (WFAs).

3.3.4. Summary of Data Characteristics

As stated in the Literature Review, past research has shown that experiential factors were strong predictors of individual risk estimates and that local seasonal weather patterns can be accurately detected by individuals (Howe *et al*., 2013; Howe and Leiserowitz, 2013; Leiserowitz, 2006; Smith and Leiserowitz, 2014). Figures 15–17 show whether a heat alert was issued during the week before survey response for each respondent's unique time and location alongside the mean temperature for each respondent's associated time and location. These graphics indicate that respondents in the West and South were subjected to higher temperatures and were alerted more frequently of extreme heat conditions. The random effects of the model results will allow for examination of whether the subpopulations of different regions tend to report risk perception values higher or lower than the national average due to the recent memory of

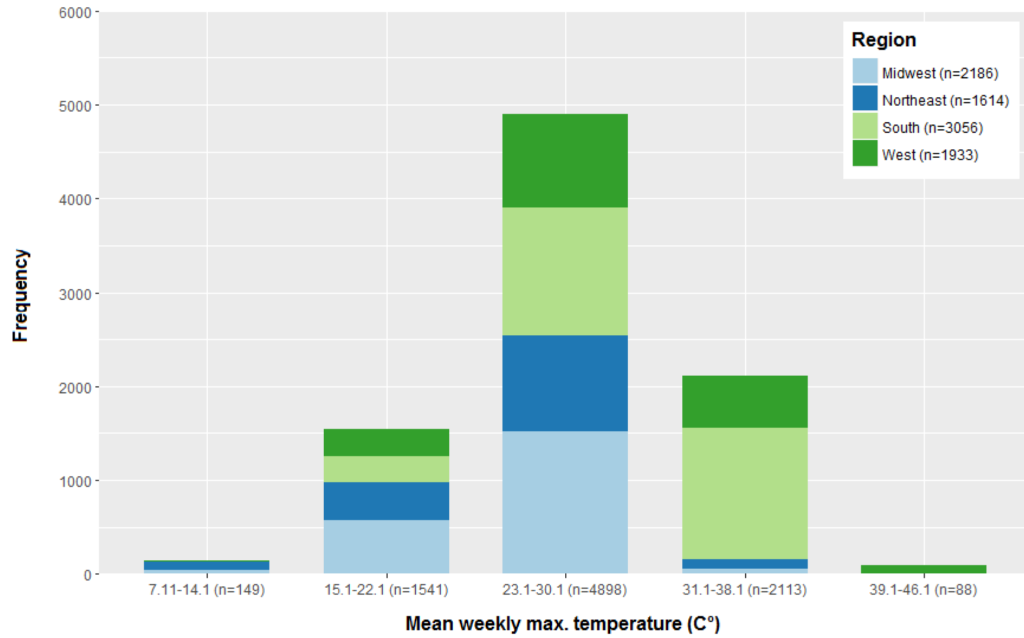


Fig. 15. Summary of average maximum temperature estimates for the week before response data was collected across all unique response locations by region.

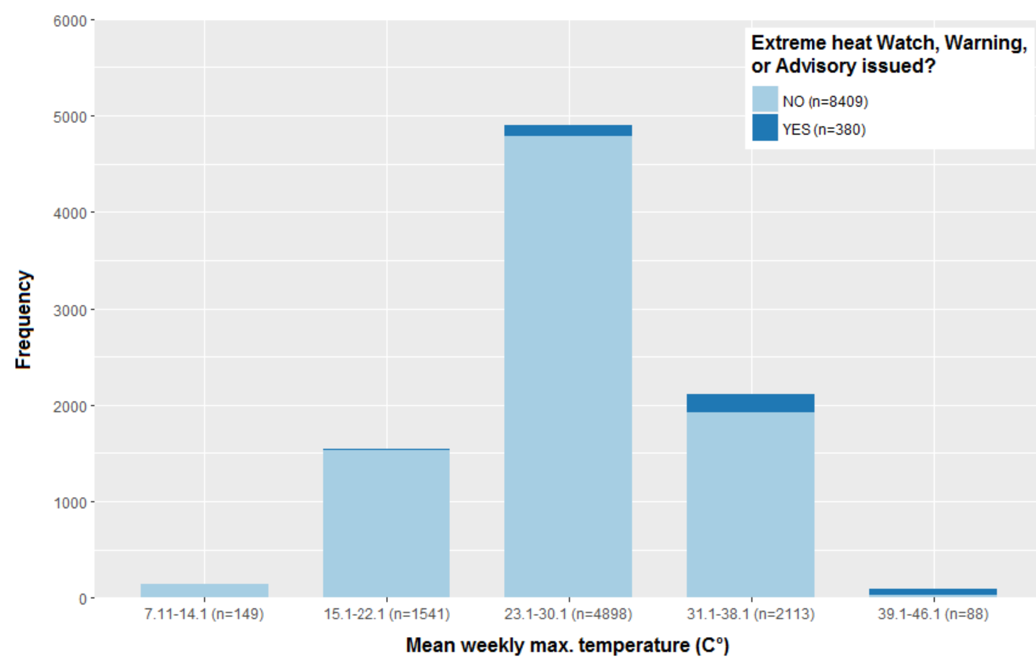


Fig. 16. Summary of average maximum temperature estimates for the week before response data was collected across all unique response locations, color coded by variable weekb4survey_WWA [YES or NO: Were any heat alerts issued during the week before the survey response for each respondent's unique location?]

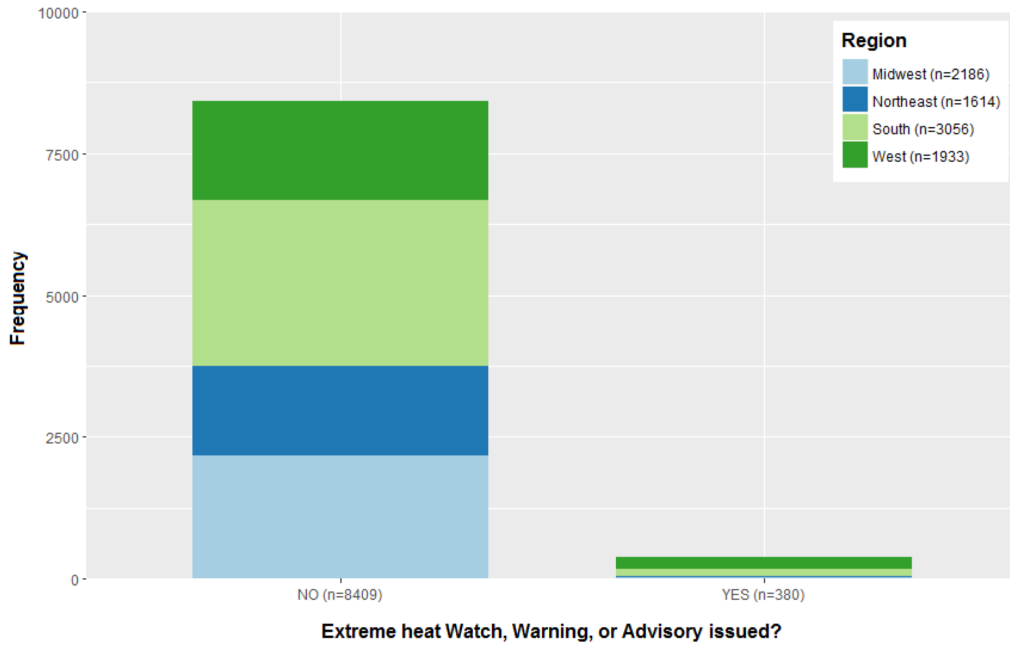


Fig. 17. weekb4survey_WWA [YES or NO: Were any heat alerts issued during the week before the survey response for each respondent's unique location?] by region

extreme heat conditions. This ability to distinguish multilevel variables containing a spatial component is one of the strengths of using mixed effect models for geographic analysis of survey data.

3.4. METHOD OF ANALYSIS

3.4.1. Overview of Analysis Techniques

A series of multilevel linear regression models were specified to measure the relationship between sensitivity, exposure, adaptive capacity, geography, and time factors on individual-level risk perceptions. Table VIII details which factors were tested in each model. The first model, testing sensitivity factors, contains only random effects, while subsequent models include controls for exposure and adaptive capacity factors as additional random and fixed effects. The final, maximal model (testing sensitivity,

Table VIII. Overview of Predictors included in study models

	Predictors Included in Model	Sensitivity Model	Exposure Model	Vulnerability Model	Adaptive Capacity Model	Maximal Model
Sensitivity Factors	Sex	X		X		X
	Age	X		X		X
	Race	X		X		X
	Education	X		X		X
	Work Status	X		X		X
	Household Size	X		X		X
	Sex : Race : Education	X		X		X
Exposure Factors (+ Geography / Time)	Day of Year		X	X		X
	Population Density		X	X		X
	Impervious Surfaces		X	X		X
	Tree Coverage		X	X		X
	Seasonal Mean Temp.		X	X		X
	Temp. Anomaly		X	X		X
	Heat Index		X	X		X
	Max Temp.		X	X		X
	(Day of Survey)		X	X		X
	Average Max Temp. (Week before survey)		X	X		X
	Census Tract		X	X		X
	County		X	X		X
	State		X	X		X
	Subregion (9)		X	X		X
	Region (4)		X	X		X
Adaptive Capacity Factors	# NonEnglish-speaking Households (tract level)				X	X
	# Unemployed (tract level)				X	X
	# Vacant homes (tract level)				X	X
	% Summer days spent in extreme heat alert area				X	X
	Experienced extreme heat alert in week before survey (Y/N)				X	X
	Experienced extreme heat alert in 2015 before survey (Y/N)				X	X
	Income				X	X

Note: Shaded predictors indicate those specified as random effects

exposure, adaptive capacity, geography, and time factors) contains all previously tested random and fixed effects in accordance with the literature and parameterized according to statistical best practices for confirmatory hypothesis testing (Barr *et al*., 2013; Gelman and Hill, 2007, ch. 11-12; Hofman, 1997; Winter, 2013; Zurr *et al*., 2010). The same methods and statistical techniques described in detail below for the initial model build were consistently applied to each subsequent model build and during the interpretation of all results. All analyses were performed using the R programming language and environment using the lme4 statistics package (Bates *et al*., 2015).

In the initial sensitivity model, a random-intercept model was fitted comprised solely of categorical random effect predictors that are each assumed to follow a Gaussian distribution and are composed of different levels (Barr *et al*., 2013; Hofmann, 1997; Winter, 2013). The model's coefficients (effects) associated with these predictors and their sublevels are random effects estimated with partial pooling—also known as linear unbiased prediction (Barr *et al*., 2013; Gelman and Hill, 2007, ch. 12; Goldberger, 1962; Hofmann, 1997; Jiang, 1997; Robinson, 1991; Winter, 2013). By using random effects, the structure of the data in each level is accounted for through partial pooling techniques so that group-level variations in the dataset can be examined. By treating the extreme heat risk factors addressed in the study hypotheses as random effects, the effect of data-clustering in the subgroupings of each predictor can be assessed in relation to their deviance from the overall mean (average risk perception score across the U.S. sample population) (Barr *et al*., 2013; Goldberger, 1962; Jiang, 1996; Hofmann, 1997; Robinson, 1991). This type of model is a natural fit for examining the multilevel structure of risk ecologies across the U.S. (Tierney, 2014, p. 45).

3.4.2. Model Specification

Analysis began by constructing a random intercept model which included all individual-level sensitivity factors measured in the representative survey as random effects (Fig. 18).

$$Y_{m,\ldots,x_i} = \mu + \alpha_m^{age} + \alpha_n^{sex} + \alpha_o^{race} + \alpha_p^{income} + \alpha_q^{education} + \alpha_r^{work} + \alpha_s^{hhsize} + \alpha_t^{work:race} + \alpha_u^{hhsize:work} + \alpha_v^{sex:race:education} + \alpha_w^{state} + \alpha_x^{region} + \varepsilon_i, \text{for } i = 1, \ldots, 8789$$

where …

$$\alpha_m^{age} \sim N(0, \sigma_{age}^2), \text{for } m = 1, \ldots, 5$$

$$\alpha_n^{sex} \sim N(0, \sigma_{sex}^2), \text{for } n = 1, 2$$

$$\alpha_o^{race} \sim N(0, \sigma_{race}^2), \text{for } o = 1, \ldots, 5$$

$$\alpha_p^{income} \sim N(0, \sigma_{income}^2), \text{for } p = 1, \ldots, 7$$

$$\alpha_q^{education} \sim N(0, \sigma_{education}^2), \text{for } q = 1, \ldots, 4$$

$$\alpha_r^{work} \sim N(0, \sigma_{work}^2), \text{for } r = 1, \ldots, 5$$

$$\alpha_s^{hhsize} \sim N(0, \sigma_{hhsize}^2), \text{for } s = 1, \ldots, 4$$

$$\alpha_t^{work:race} \sim N(0, \sigma_{work:race}^2), \text{for } t = 1, \ldots, 5$$

$$\alpha_u^{hhsize:work} \sim N(0, \sigma_{hhsize:work}^2), \text{for } u = 1, \ldots, 20$$

$$\alpha_v^{sex:race:education} \sim N(0, \sigma_{sex:race:education}^2), \text{for } v = 1, \ldots, 40$$

$$\alpha_w^{state} \sim N(0, \sigma_{state}^2), \text{for } w = 1, \ldots, 51$$

$$\alpha_x^{region} \sim N(0, \sigma_{region}^2), \text{for } x = 1, \ldots, 4$$

Fig. 18. Sensitivity Model formula. Colons denote specified interaction effects.

Predictors were dropped from the model based on tests of model fit. Model fit was assessed using chi-square tests on the log-likelihood values through iterative ANOVA testing to compare models reduced by one variable (subject to the ANOVA testing) and determine that variable's statistical significance via reduction in the residual sum of squares (Barr *et al*., 2013; Bates *et al*., 2015; Bliese and Ployhart, 2002 Winter, 2013). Table IX shows the models specified in order to complete these tests. Variables were retained based upon iterative significance testing and their importance in the literature referenced when constructing these confirmatory hypothesis tests.

Table IX. Model Specifications for Log-Likelihood Significance Tests of Sensitivity Model Predictors

Model	**Script**
Maximal Model (null)	riskp ~ (1 | age2) + (1 | sex) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Age	riskp ~ (1 | sex) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Sex	riskp ~ (1 | age2) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Race/Ethnicity	riskp ~ (1 | age2) + (1 | sex) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Income	riskp ~ (1 | age2) + (1 | sex) + (1 | race) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Education	riskp ~ (1 | sex) + (1 | race) + (1 | income) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Work Status	riskp ~ (1 | age2) + (1 | race) + (1 | income) + (1 | edu) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Household Size	riskp ~ (1 | age2) + (1 | sex) + (1 | income) + (1 | edu) + (1 | work) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Work : Race/Ethnicity	riskp ~ (1 | age2) + (1 | sex) + (1 | race) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Household Size : Work Status	riskp ~ (1 | sex) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1|sex:race:education) + (1 | State_name) + (1 | reg4)
Sex : Race/Ethnicity : Education	riskp ~ (1 | sex) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1 | State_name) + (1 | reg4)
State	riskp ~ (1 | age2) + (1 | race) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | reg4)
Region	riskp ~ (1 | age2) + (1 | sex) + (1 | income) + (1 | edu) + (1 | work) + (1 | hhsize) + (1 | work:race) + (1 | hhsize:work) + (1|sex:race:education) + (1 | State_name)

Note: (1|age) symbolizes an intercept that is different for every age group.

The significance of between-group variance in risk perceptions was tested by comparing the null (full Sensitivity Model) to a series of models each missing one random effect term (n =10). For each successive comparison, a log-likelihood ratio was calculated as 2[log-likelihood of the null model – log-likelihood of reduced model *n* (missing the random effect under scrutiny). The output log-likelihood test statistic distribution approximates a chi-squared distribution with *k*(null) – *k*(reduced) degrees of freedom, where *k* represents the number of random effects parameters to be estimated for each respective model (Barr *et al*., 2013; Bates *et al*., 2014; Bliese and Ployhart, 2002; Pinheiro and Bates, 2000; Winter, 2013). Table X summarizes the results of the predictor tests for the sensitivity model.

Table X. Log-Likelihood Significance Tests Results for Sensitivity Model Predictors

Predictor	df	AIC	BIC	logLik	Deviance	X df	X^2	$P(>X^2)$
Null Model	14	-464.97	-365.8	246.5	-493			
Age	13	-461.03	-368.97	243.51	-487.03	1	5.9366	$p < .015$ *
Sex	“	-459.39	-367.33	242.69	-485.39	“	7.5767	$p < .006$ **
Race/Ethnicity	“	-464.9	-372.84	245.45	-490.9	“	2.0665	$p = .151$
Income	“	-379.67	-287.61	202.84	-405.67	“	87.296	$p < .0001$ ***
Education	“	-466.97	-374.91	246.48	-492.97	“	0	$p = 1$
Work Status	“	-466.84	-374.78	246.42	-492.84	“	0.1297	$p = .719$
Household Size	“	-466.97	-374.91	246.48	-492.97	“	0	$p = 1$
Work : Race/Ethnicity	“	-460.45	-368.4	243.23	-486.45	“	6.5122	$p < .011$ *
Household Size : Work Status	“	-462.22	-370.16	244.11	-488.22	“	4.7454	$p = .029$ *
Sex : Race/Ethnicity : Education	“	-448.9	-356.84	237.45	-474.9	“	18.067	$p < .0001$ ***
State	“	-441.55	-349.49	233.77	-467.55	“	25.419	$p < .0001$ ***
Region	“	-456.48	-364.42	241.24	-482.48	“	10.488	$p = .001$ **

Notes: Significance codes: 0 ‘***’ 0.001 ‘**’ 0.05 *

By using random effects associated with individual-level geographic and socio-demographic factors, the model was able to account for some degree of spatial autocorrelation and overcome assumptions of independence that would normally be violated if geographically-nested data were to be analyzed using traditional linear regression modeling (Gelman and Hill, 2007, ch. 11; Hofmann, 1997). By specifying geographic levels (Region, State) as random effects, all coefficients were allowed to vary from individual to individual around a group mean (geographic—e.g., state, county, etc.). Visual inspection of residual plots did not present indications of heteroscedasticity or obvious deviation from normality (Figures can be found in Appendix A).

The random effects describe the grouping of sociodemographic factors and hierarchical nature of geographic terms incorporated in the model (respondents within state within region). As a result, this study can contribute a nationally-representative exploration of the inter-group variation of risk perception values across sociodemographic factors thought to influence heat vulnerability as well as geographic factors. The outcome variable is Risk Perception values on a scale of 0–1 with 1 representing the highest degree of perceived risk to heat. Across the U.S., the mean risk perception score is 0.42. Random effects included in this model provide a direct measure of how much of the reported Risk Perception scores' variance around this mean is explained by group-level differences.

3.4.3. Maximal Model Specification and Model Comparison

Table XI describes the models that were specified with different risk component controls while building towards the appropriate maximal model [preferred over more parsimonious but perhaps less explanatory alternative models (Barr *et al*., 2013)] which factors the influence of all previously evaluated predictors for sensitivity, exposure, and adaptive capacity.

Table XI. Overview of Model Builds Using Standard lme4 R Script

Model	Script
Sensitivity	riskp ~ sex + (1|race) + (1|age2) + (1|edu) + (1|work) + (1|hhsize) + (1|sex:race:edu)
Exposure	riskp ~ yday + CO.HI.daily.MaySep + TR.impervious.mean.log + TR.tree.mean.sqrt + TR.prism.tmean + TR.tmin.anom.mav7 + I(popden/100) + Syday_Tmax + weekmeanb4survey_PRISM + (1|TractCE) + (1|CountyFP) + (1|State_name) + (1|reg9) + (1|reg4)
Vulnerability (Sensitivity + Exposure)	riskp ~ sex + yday + CO.HI.daily.MaySep + TR.impervious.mean.log + TR.tree.mean.sqrt + TR.prism.tmean + TR.tmin.anom.mav7 + I(popden/100) + Syday_Tmax + weekmeanb4survey_PRISM + (1|race) + (1|age2) + (1|edu) + (1|work) + (1|hhsize) + (1|sex:race:edu) + (1|TractCE) + (1|CountyFP) + (1|State_name) + (1|reg9) + (1|reg4)
Adaptive Capacity	riskp ~ TR.Language.nonEnglish + TR.Employment.unemployed + TR.Housing.vacant + pct_WWAdaysb4survey + weekb4survey_WWA + WWAb4survey + (1|income) + (1|CWA) + (1|TractCE)
Maximal Model	riskp ~ yday + CO.HI.daily.MaySep + TR.impervious.mean.log + TR.tree.mean.sqrt + TR.prism.tmean + TR.tmin.anom.mav7 + I(popden/100) + Syday_Tmax + weekmeanb4survey_PRISM + TR.Language.nonEnglish + TR.Employment.unemployed + TR.Housing.vacant + pct_WWAdaysb4survey + weekb4survey_WWA + WWAb4survey + sex + (1|income) + (1|race) + (1|age2) + (1|edu) + (1|work) + (1|hhsize) + (1|sex:race:edu) + (1|CWA) + (1|TractCE) + (1|CountyFP) + (1|State_name) + (1|reg9) + (1|reg4)

Fixed effect parameters were specified which capture the effect of exposure and adaptive capacity treatments on mean risk perception response values of the representative sample population. The random effects parameters capture variance among sociodemographic, spatial, temporal, exposure and adaptive capacity groupings (among factors such as State, personal experience with a heat alert, or education level.) By parameterizing and incorporating both fixed and random effects in this multilevel model, the model takes on the necessary hierarchical structure for assessing individual-level effects on Risk Perception for each particular higher contextual-level unit/group (Barr *et al*., 2013; Bates *et al*., 2015; Gelman and Hill, 2007, ch. 11; Hofmann, 1997).

Following this final model build, the sequential model build will be evaluated by a model comparison ANOVA test. Residuals of the mixed effect models will also be evaluated for spatial autocorrelation in order to test for additional spatial variation in risk perceptions not explained by the selected predictors. Geographic patterns of spatial autocorrelation in the residuals (correlation between risk perceptions for individuals from the same locale), if present, may indicate unobserved contextual factors that affect individual's risk perceptions (Bivand *et al.*, 2008, ch. 9).

CHAPTER 4

RESULTS

4.1. SENSITIVITY MODEL

Sex was a statistically significant predictor of risk perception (*Variance* (σ^2) = 0.0005, $Std.\ Dev.\ (\sigma) = 0.021$, $X^2(1) = 7.577$, $p < 0.006$) and consequently its subgroups deviated from the mean (0.422 +/– 0.05) by 0.017 positively for Females (+3.9%) and negatively for Males (-3.9%) (Table XII).

Age was also a statistically significant predictor of risk perception (σ^2 = 0.0001, $\sigma = 0.01$, $X^2(1) = 5.937$, $p < 0.05$) and random effects indicate that older individuals tend to have slightly higher risk perceptions in relation to the mean (Fig. 19). More specifically, risk perceptions for individuals older than 45 tended to be roughly 2% higher than the mean (0.422 +/– 0.05) (Fig. A.1).

Table XII. Sensitivity Model Results Summary

Fixed Effects	$\boldsymbol{\beta}$	**Lower 95% CI**	**Upper 95% CI**	**Standard Error**	**t value**
Intercept (Natl. Risk Perception Mean)	0.42217	0.3676927	0.4766383	0.02779	15.19
Random Effects	**Levels (#)**	**Variance ($\boldsymbol{\sigma^2}$)**	**Std. Dev. ($\boldsymbol{\sigma}$)**	**Total variance**	**p**
Residual	-	0.054484	0.23342	92.16%	
Income	7	0.0013013	0.03607	2.20%	p < .0001 ***
Work : Race/Ethnicity	25	0.0006026	0.02455	1.02%	p = 0.01 *
State	49	0.0005149	0.02269	0.87%	*p < 0.0001* ***
Race	5	0.0004898	0.02213	0.83%	p = 0.15
Region	4	0.0004874	0.02208	0.82%	p = 0.001 **
Sex	2	0.0004509	0.02123	0.76%	p < 0.006 **
Household Size : Work Status	20	0.0002823	0.0168	0.48%	p < 0.03 *
Sex : Race : Education	40	0.0002612	0.01616	0.44%	*p < .0001* ***
Work Status	5	0.000134	0.01158	0.23%	p = .72
Age	5	0.0001087	0.01043	0.18%	p = .01 *
Education	4	0	0	0.00%	p = 1
Household Size	4	0	0	0.00%	p = 1

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

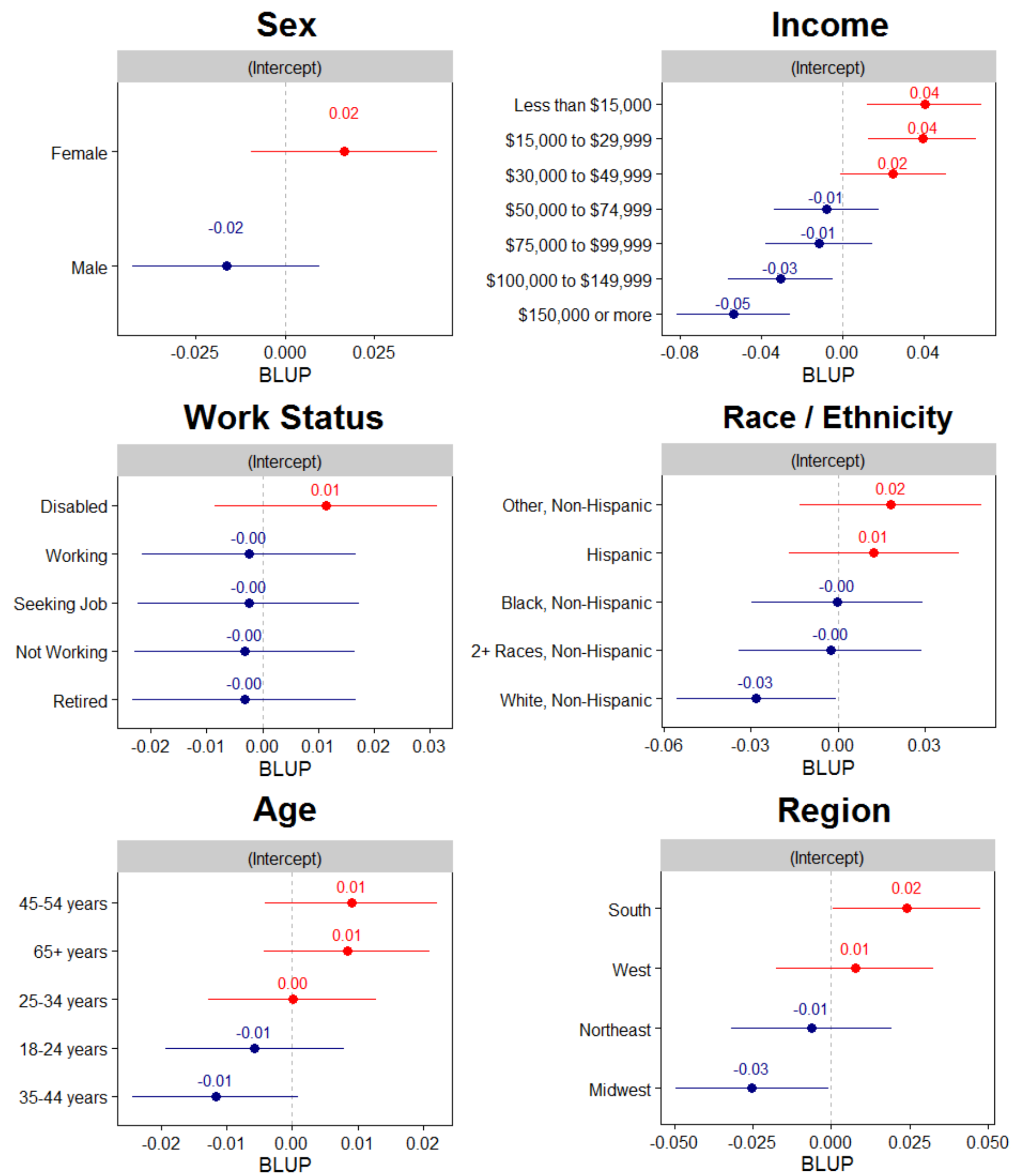


Fig. 19. Random effects of sensitivity model predictors.

While **Race/Ethnicity** was not a statistically significant predictor of overall risk perception in this model ($\sigma^2 = 0.0006$, $\sigma = 0.022$, $X^2(1) = 2.067$, $p = 0.151$), random effect estimates indicated some degree of variation in response values for different race/ethnicity categories. White respondents tended to report substantively lower risk perceptions than all other race/ethnicity categories (Fig. 19) and the national average (-6.7%) (Fig. A.1).

Income was included as a sensitivity factor in this model and was found to be a statistically significant predictor of individual heat wave risk perceptions ($\sigma^2 = 0.0013, \sigma = 0.036, X^2(1) = 87.296, p < 0.001$) and random effects indicate that wealthier individuals tend to have substantively lower risk perceptions in relation to less affluent individuals (Fig. 19) and to the national average (Fig. A.1). For example, respondents earning more than $150,000 each year tend to have risk perceptions 12.8% lower than the national average, while respondents earning less than $15,000 tend to have risk perceptions 9.3% higher than the national average (Fig. 20).

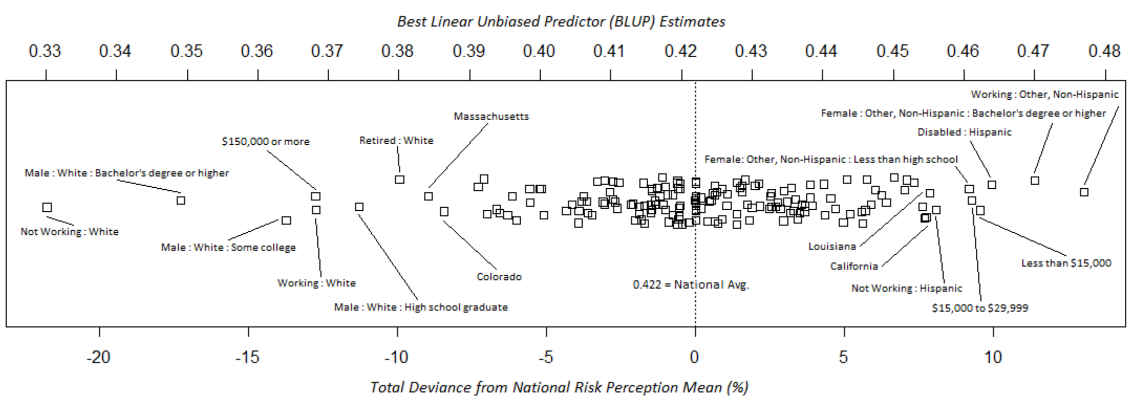


Fig. 20. Random effect estimates across subpopulations for Sensitivity Model.

While race, education ($\sigma^2 = 0.0000, X^2(1) = 0, p = 1$), work status ($\sigma^2 = 0.0001, X^2(1) = 0.13, p = 0.719$) and household size ($\sigma^2 = 0.0000, X^2(1) = 0, p = 1$) were not found to be statistically significant predictors of risk perceptions at their respective individual-levels (Table X) in this model, their random effects were retained for interpretation in relation to established vulnerability literature and following statistical best practices (Barr *et al*., 2013; Winter, 2013; Zuur *et al*., 2010) in order to be parameterized in the model as part of three random interaction terms: Work by Race [or (1|work:race) in lme4 script], Household Size by Work (1|hhsize:work), and Sex by Race by Education (1|sex:race:edu). Random effects for interactions among predictor variables such as these capture their own variance in the linear model (Fig. 20). The best linear unbiased prediction for each subpopulation is summarizing level-specific random effects for all variance components representing those predictor variables (e.g., Sex by Race by Education ~ female Whites with a bachelor's degree).

Work status by Race/Ethnicity was a statistically significant predictor of risk perception ($\sigma^2 = 0.0006$, $\sigma = 0.025$, $X^2(1) = 6.152$, $p = 0.011$). For this factor, there are 25 subgroups that the sample population is distributed and fit within (5 work status categories by 5 race categories) which provides best linear unbiased predictor estimates for a wide range of generalized risk perception profiles (Fig. 21). For example, estimates for Work by Race/Ethnicity indicate that the disabled Hispanic subpopulation tends to have 9.9% higher heat risk perceptions than the national average; whereas working White respondents tend to report values 12.7% lower than the national average; and retired Black respondents tend to have 1.4% higher risk perceptions than the national average. As depicted in Figure 21, across the 25 subgroups, deviation from the mean was highest for Disabled, Hispanic subpopulation (+9.9%) and lowest for Not Working, White subpopulation (–21.8%).

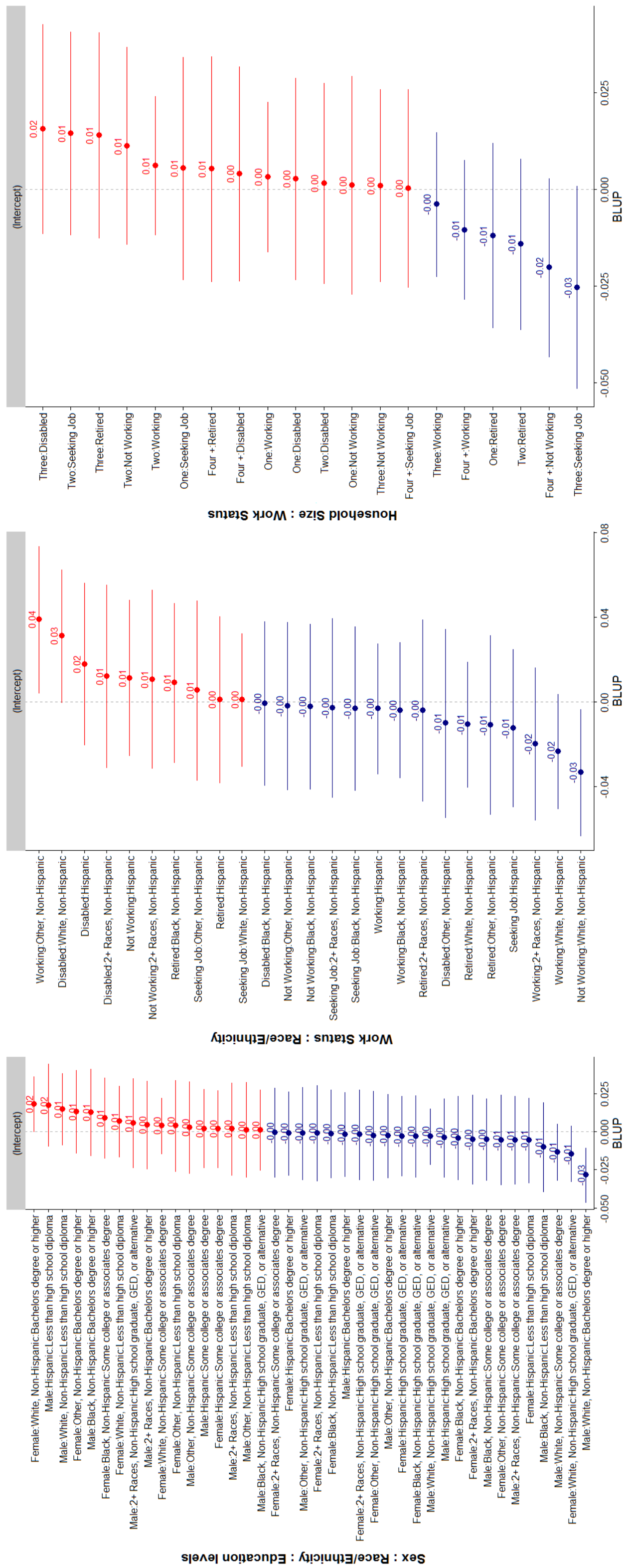


Fig. 21. Random effects of Sensitivity Model interaction predictors.

Household size by Work status was also a statistically significant predictor of heat wave risk perception ($\sigma^2 = 0.0003, \sigma = 0.017, X^2(1) = 4.745, p = 0.029$). There were 20 levels overall for this interaction predictor (4 levels for household size and 5 levels for work status). Again, generalizable profiles were obtained by calculating each respective subpopulation's best linear unbiased predictor estimate (Figure 21). Since Household Size was not a statistically significant predictor and its random subgroup effect size was estimated to be 0, the best linear unbiased predictor estimate was adjusted solely by crossed effects within the Work Status predictor's subgroups. Deviation from the national mean (0.422 +/– 0.05) across the 20 subpopulations ranged from a high of 6.4% (Disabled and living in a one-person household) to a low of -6.6% (Seeking a job and living in a three-person household). Risk perceptions for those who were retired and living in a one-person household were 3.6% lower than the national average, as compared to 3.3% higher for those were disabled and living in a one-person household.

Sex by Race/Ethnicity by Education was a statistically significant predictor of risk perception ($\sigma^2 = 0.0003, \sigma = 0.016, X^2(1) = 18.067, p < 0.001$). This predictor has 40 subgroups and for each the best linear unbiased predictor estimate was adjusted by its respective crossed effects within the Sex, Race/Ethnicity, and Education predictors' subgroups. Deviation from the national mean (0.422 +/– 0.05) across the 40 subgroups ranged from a high of +11.4% (Female by Other, Non-Hispanic by Bachelor's degree or higher) to a low of -17.3% (Male by White, Non-Hispanic by Bachelor's degree or higher). All subgroups containing White males ranged from -7.1% to -17.3%. In addition to the examples shown in Figures 20-21, the risk perception estimates for every subpopulation, detailed in their entirety, can be found in Appendix A, Figures A1-A2.

4.2. Geographic Variation of Sensitivity Model Results

Estimates of deviance from the mean in subpopulations can also be estimated across geographic units using the same techniques. By specifying geographic units as random effects, the structure and distribution of the individual-level data collected in each group level (state, region) is accounted for using partial pooling techniques to examine group level variations in the dataset. Thus, by treating geographic units as random effects, the natural degree of data clustering that can be expected within different states is assessed in relation to each state's deviance from the overall mean perceived heat risk across the U.S. (0.422 +/– 0.05). Respondents' state of residence was a statistically significant predictor of risk perception variation ($\sigma^2 = 0.0005$, $\sigma = 0.023$, $X^2(1) = 25.419$, $p < 0.001$). Across states, risk perceptions tend to be highest in California (7.9% higher than the national average) and lowest in Massachusetts (-9.0%). The states which tended to be closest to the national average were Pennsylvania (+0.6%), Iowa (+0.4%), Connecticut and Georgia (-0.6%). Which region respondents resided in was also a statistically significant predictor of risk perception and explained variation beyond that at the state level ($\sigma^2 = 0.0005$, $\sigma = 0.022$, $X^2(1) = 10.488$, $p = 0.001$). The Midwest tends to have lower risk perceptions than the national average (-6.0%) while the South has higher risk perceptions (+5.7%). Geographic estimates are summarized in Figure 22.

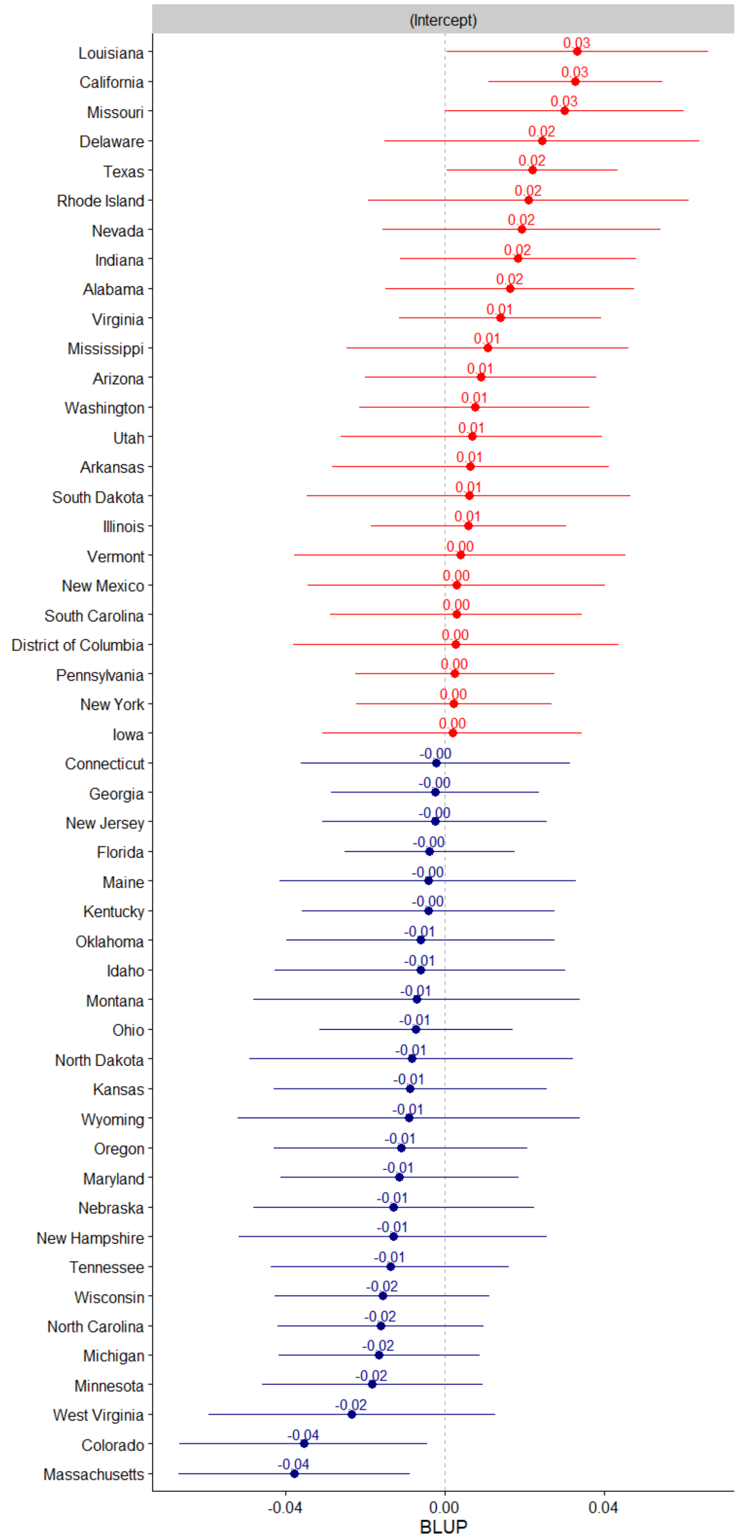


Fig. 22. State-level risk perception estimates while controlling for sensitivity.

A large Variance Partitioning Coefficient value (closer 1 than 0*)* indicates that much of the variance is due to unique individual-level circumstances not captured by the random effects specified. The Variance Partitioning Coefficient can be obtained by dividing the residual variance at the individual-level (0.0545) by the total variance across all levels (0.0591). The residual error term captured 92.16% of response variation (σ^2 = 0.0545, SD = 0.233) around the mean of (0.422 +/– 0.05) (Table XII). While unexplained individual-level circumstances drive most of the variation in risk perception (as is expected when examining any complex dependent variable using survey data) clustering of individual response values around group-level factors (age, sex, race) allows for the examination of the total influence of known vulnerability factors on risk perceptions. As expected, the variance of factor Income accounted for the greatest proportion of total variance among geographic and sociodemographic predictors at 2.2% of the total variance. However, contrary to expectations, the variance of factor Age (σ^2 = 0.0001, σ = 0.01) was rather low, accounting for only 0.18% of total variance.

4.3. ADDING CONTROLS FOR EXPOSURE AND ADAPTIVE CAPACITY

Following this initial model build, additional controls representing Exposure and Adaptive Capacity factors were sequentially added into the modeling environment as fixed and random effects. Additionally, a revised sensitivity model was specified (Table XIII) in order to allow for optimal comparison with subsequent model builds. The revised model, Sensitivity Model 2.0, treats the factor Sex as a fixed effect, drops the predictor Income (which was then added to the Adaptive Capacity Model), and retains only one

Table XIII. Results of Log-Likelihood Testing of Sensitivity Model 2.0 Predictors

Predictor	df	AIC	BIC	logLik	Deviance	X df	X²	P(> X²)
Null Model	8	-279.41	-215.1	148.71	-297.41			
Sex	9	-271.75	-215.1	143.88	-287.75	1	9.6614	$p < .002$ **
Age	"	-276.2	-219.55	146.1	-292.2	"	5.2118	$p = .02$ *
Race/Ethnicity	"	-260.85	-204.2	138.43	-276.85	"	20.557	$p < .0001$ ***
Education	"	-281.18	-224.53	-148.59	-297.18	"	0.2324	$p = .6$
Work Status	"	-224.76	-168.11	120.38	-240.76	"	56.648	$p < .0001$ ***
Household Size	"	-271.35	-214.7	143.67	-287.35	"	10.066	$p < .002$ **
Sex : Race/Ethnicity : Education	"	-265.09	-208.44	-140.54	-281.09	"	16.326	$p < .0001$ ***

Notes: Shaded cells indicate random effects. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

interaction term (Sex by Race/Ethnicity by Education). Table XIII summarizes the strength of Sensitivity Model 2.0's predictors and the models.

While the results for Sensitivity Models 1.0 and 2.0 differed somewhat (Table XIV), the directionality of their respective random effects generally remained consistent.

Table XIV. Sensitivity Model 2.0 Results Summary

Fixed Effects	β	**Lower 95% CI**	**Upper 95% CI**	**Standard Error**	**t value**
Intercept *(Natl. Risk Perception Mean)*	0.465021	0.41401	0.51604	0.026028	17.866
Sex (Male)	-0.036654	-0.01764	-0.01764	0.0097	-3.778
Random Effects	**Levels (#)**	**Variance (σ^2)**	**Std. Dev. (σ)**	**Total variance**	**p**
Residual	-	0.05448	0.23342	94.13%	
Race/Ethnicity	5	0.00139	0.03730	2.40%	$p < .0001$***
Work Status	5	0.00129	0.03598	2.24%	$p < .0001$***
Sex : Race/Ethnicity : Education	40	0.00036	0.01892	0.62%	$p < .0001$***
Household Size	4	0.00018	0.01327	0.32%	$p < .0001$***
Age	5	0.00010	0.01005	0.17%	$p = .02$*
Education	4	0.00007	0.00845	0.12%	$p = .6$

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

4.3. EXPOSURE MODEL

The predictors included in the Exposure Model are shown in Table VIII. Table XI details how these predictors were specified in the R coding environment to analyze influence of exposure variables on extreme heat risk perception, respectively. Again, predictors were individually evaluated using log-likelihood tests (as described in section 3.4.2). The results of these tests are shown in Table XV.

Table XV. Results of Log-Likelihood Testing of Exposure Model Predictors

	df	AIC	BIC	logLik	Deviance	X df	X^2	$P(> X^2)$
Null Model	8	-580.47	-467.17	306.24	-612.47			
Day of Year	9	-578.42	-472.2	304.21	-608.42	1	4.0478	$p < .05$ *
Population Density	“	-578.54	-472.32	304.27	-608.54	“	3.932	$p < .05$ *
Impervious Surfaces	“	-575.25	-469.03	302.62	-605.25	“	7.2191	$p < .001$ **
Tree Coverage	“	-581.89	-475.67	305.94	-611.89	“	0.5791	$p = .45$
Mean Seasonal Temp.	“	-573.7	-467.48	301.85	-603.7	“	8.7661	$p = .003$ **
Temperature Anomaly	“	-582.04	-475.82	306.02	-612.04	“	0.4308	$p = .5116$
Heat Index	“	-582.27	-476.05	306.13	-612.27	“	0.199	$p = .66$
Max Temperature (Day of Survey)	“	-582.1	-475.88	306.05	-612.1	“	0.3743	$p < .05$ *
Avg. Max Temperature (Week before survey)	“	-573.52	-467.3	301.76	-603.52	“	8.9471	$p < .003$ **
Census Tract	“	-218.6	-112.38	124.3	-248.6	“	363.87	$p < .0001$ ***
County	“	-564.8	-458.58	297.4	-594.8	“	17.673	$p < .0001$ ***
State	“	-582.25	-476.03	306.12	-612.25	“	0.2241	$p = .636$
Subregion (9)	“	-581.06	-474.85	305.53	-611.06	“	1.4045	$p = .24$
Region (4)	“	-582.47	-476.25	306.24	-612.47	“	0	$p = 1$

Notes: Shaded cells indicate random effects. Significance codes: 0 ‘***’ 0.001 ‘**’ 0.05 ‘*’

Table XVI details the results of the Exposure Model. Day of Year was a statistically significant predictor of risk perception (β = -0.0001, $X^2(1) = 4.05$, $p < 0.05$). Population density (β = 00.0002, $X^2(1) = 3.93$, $p < .05$) and impervious surfaces (β = 0.0063, $X^2(1) = 7.22$, $p < 0.001$) were statistically significant predictors of risk perception, which suggests that residing in an urban environment positively influences risk perception as hypothesized (Fig. 23). Average seasonal temperature (β = 0.0082,

Table XVI. Exposure Model Results Summary

Fixed Effects	***β***	**Lower 95% CI**	**Upper 95% CI**	**Standard Error**	**t value**
Intercept (Natl. Risk Perception Mean)	0.22319	-0.08396	0.53035	0.15671	1.424
Day of Year	-0.00012	-0.00025	0	0.00006	-2.012
Heat Index	-0.00098	-0.0052	0.00325	0.00216	-0.453
Impervious Surfaces	0.00632	0.00175	0.0109	0.00233	2.708
Tree Coverage	0.00151	-0.00236	0.00538	0.00198	0.766
Mean Temp	0.00823	0.00313	0.01333	0.0026	3.161
Temp Anomaly	0.00096	-0.00189	0.00381	0.00145	0.659
Population Density	0.00019	0	0.00038	0.0001	1.991
Max Temp. (Day of survey)	0.00066	-0.0014	0.00271	0.00105	0.626
Average Max Temp. (Week before survey)	0.00197	0.00068	0.00326	0.00066	2.996
Random Effects	**Levels (#)**	**Variance (σ^2)**	**Std. Dev. (σ)**	**Total variance**	**p**
Residual	-	0.03595	0.18961	62.11%	
Census Tract	6368	0.02024	0.14227	34.97%	*p = < .0001****
County	1496	0.00147	0.03837	2.54%	*p = < .0001****
Subregion (9)	9	0.00016	0.01257	0.27%	*p = .636*
State	49	0.00006	0.00799	0.10%	*p = .24*
Region (4)	4	0	0	0.00%	*p = 1*

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

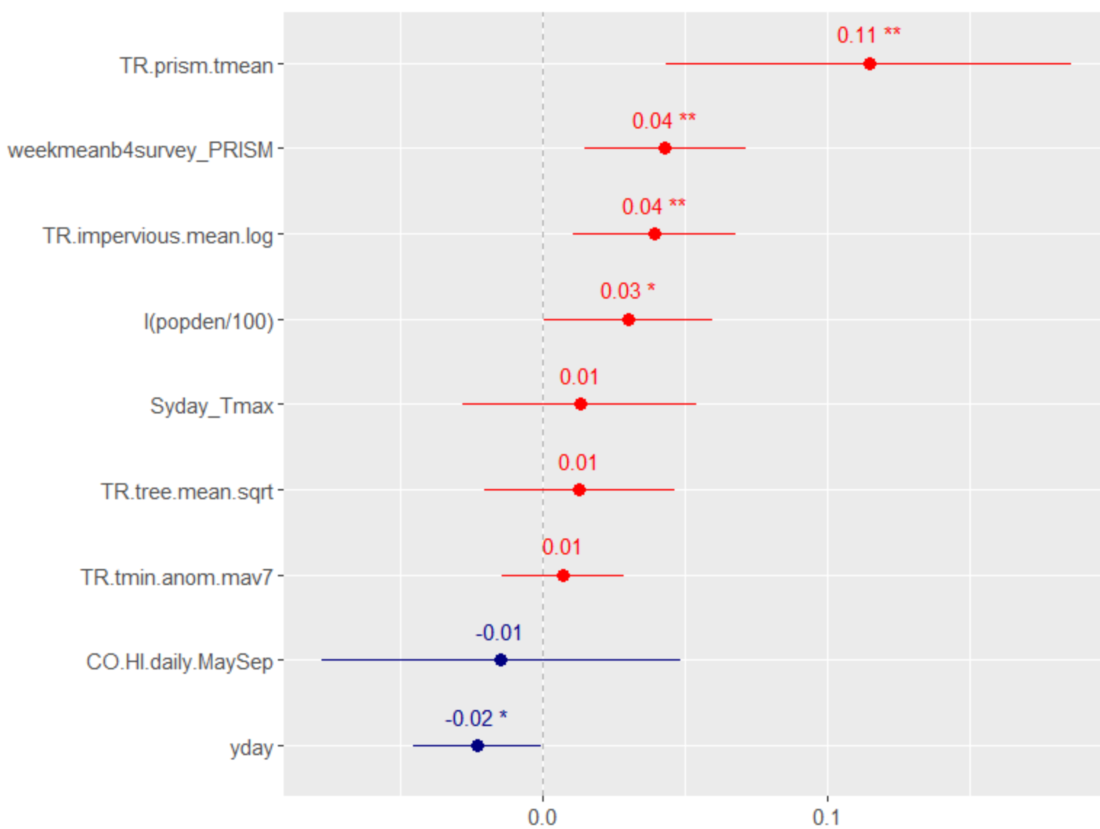


Fig. 23. Standardized fixed effects of Exposure Model.

$X^2(1) = 8.77$, $p = 0.003$), max temperature on the day of the survey ($\beta = 0.0007$, $X^2(1) = 0.37$, $p < 0.05$), and the average max temperature during the week before the survey ($\beta = 0.002$, $X^2(1) = 8.95$, $p < 0.003$) were statistically significant predictors of extreme heat risk perception.

Heat Index, Tree Coverage, Temperature Anomalies, and Temperatures on the day of the survey were not found to statistically significant predictors of risk perception and did improve model fit. Appendix B contains summary results (Table B.I, Fig. B.1) and diagnostics (Fig. B.2) for the Exposure Model.

Predictors positively influencing heat wave risk perceptions in the Maximal Model include: Population density, Avg. max. temperature recorded during the week before the survey at each respondent's unique location, Max. temperature recorded on the day of the survey at each respondent's unique location, Tract-level mean impervious surface coverage, Tract-level average seasonal temperature, Deviation of minimum temperature recorded during the month of the survey from the seasonal average at the tract-level, and Tract-level mean tree coverage (Figs. 23-24). Predictors negatively influencing heat wave risk perceptions in the Maximal Model include: County-level average seasonal heat index and Day of year (Figs. 23-24).

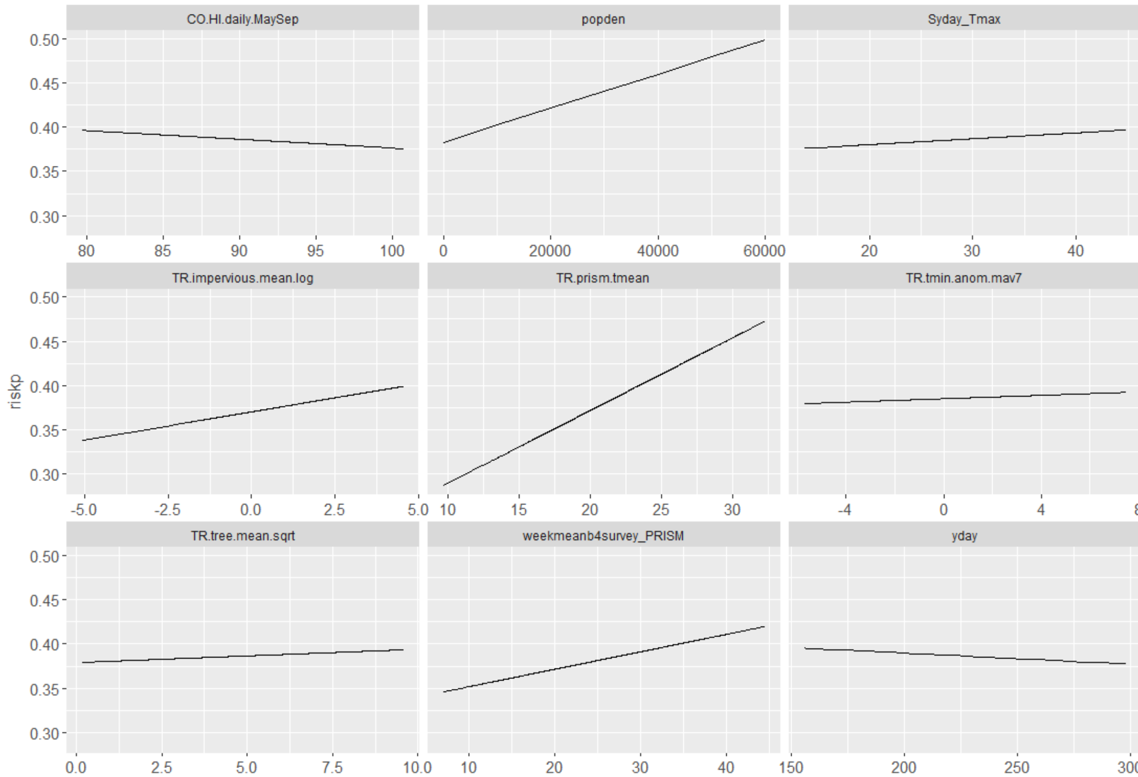


Fig. 24. Marginal effects of Exposure Model predictors.

4.4. VULNERABILITY MODEL

Since vulnerability is a function of both exposure and sensitivity, a mixed effect Vulnerability Model was specified to include controls from both the Sensitivity and Exposure Model builds as random and fixed effects (Table XI). Once again, predictors were individually evaluated using log-likelihood tests, the results of which are detailed in Table XVII.

Table XVIII details the results of the Vulnerability Model. The directionality of each fixed effect specified in the Vulnerability Model is summarized in Figure C.3 of Appendix C.

Table XVII. Results of Log-Likelihood Testing of Vulnerability Model Predictors

Predictor	df	AIC	BIC	logLik	Deviance	X df	X²	P(> X²)
Null Model	23	-877.9	-715.03	461.95	-923.9			
Day of Year	22	-876.11	-720.32	460.05	-920.11	1	3.7907	*p < .05* *
Population Density	"	-878.39	-722.6	461.2	-922.39	"	1.506	*p = 0.22*
Impervious Surfaces	"	-874.87	-719.09	459.44	-918.87	"	5.0248	*p < .025* *
Tree Coverage	"	-878.46	-722.67	461.23	-922.46	"	1.4414	*p = 0.23*
Mean Temp.	"	-871.71	-715.92	457.85	-915.71	"	8.1919	*p < .004* **
Temp. Anomaly	"	-879.19	-723.41	461.6	-923.19	"	0.7045	*p = 0.4*
Heat Index	"	-879.32	-723.53	461.66	-923.32	"	0.5782	*p = 0.45*
Max Temp. (Day of Survey)	"	-879.76	-723.97	461.88	-923.76	"	0.1359	*p = 0.71*
Average Max Temp. (Week before survey)	"	-869.22	-713.44	456.61	-913.22	"	10.675	*p < .001* **
Sex	"	-870.6	-714.82	457.3	-914.6	"	9.2935	*p < .002* **
Age	"	-877.7	-721.91	460.85	-921.7	"	2.1967	*p = 0.14*
Race/Ethnicity	"	-868.57	-712.78	456.29	-912.57	"	11.326	*p < .001* ***
Education	"	-879.9	-724.11	461.95	-923.9	"	0	*p = 1*
Work Status	"	-812.57	-656.78	428.28	-856.57	"	67.332	*p < .0001* ***
Household Size	"	-867.32	-711.53	455.66	-911.32	"	12.576	*p < .0004* ***
Sex : Race/Ethnicity : Education	"	-858.12	-702.34	451.06	-902.12	"	21.774	*p < .0001* ***
Census Tract	"	-532.68	-376.89	288.34	-576.68	"	347.22	*p < .0001* ***
County	"	-867.81	-712.03	455.91	-911.81	"	12.084	*p < .0005* ***
State	"	-879.45	-723.66	461.72	-923.45	"	0.4528	*p = 0.5*
Subregion (9)	"	-879.39	-723.61	461.7	-923.39	"	0.5044	*p = 0.48*
Region (4)	"	-879.9	-724.11	461.95	461.95	"	0	*p = 1*

Note: Shaded cells indicate random effects. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

The most statistically significant predictors of risk perception for the Exposure Model [Day of Year, Impervious surfaces, Seasonal average temperature, Population density, and Personal experience with heat (average max. temperature for the week before the survey at respondent's location)] and the Sensitivity Model 2.0 [Sex, Race/Ethnicity, Work Status, Household Size, Sex by Race/Ethnicity by Education] largely remained powerful explanatory variables in the Vulnerability Model. Age is a notable exception. Additionally, the percentage of total variance from the mean captured by the residual term (59.9%) is markedly lower than the estimate for the initial Sensitivity Model (92.2%). Controlling for exposure factors when examining heat risk perceptions substantially improved the ability to predict individual risk perceptions. Figure 25 shows

Table XVIII. Vulnerability Model Results Summary

Fixed Effects	β	Lower 95% CI	Upper 95% CI	Standard Error	t value
Intercept					
(Natl. Risk Perception Mean)	0.35003	0.06021	0.63988	0.14788	2.367
Sex	-0.03426	-0.05344	-0.01507	0.00979	-3.5
Day of Year	-0.00012	-0.00024	0	0.00006	-1.948
Heat Index	-0.00154	-0.00547	0.00239	0.00201	-0.767
Impervious Surfaces	0.00518	0.0007	0.00967	0.00229	2.264
Tree Coverage	0.00228	-0.00141	0.00597	0.00188	1.212
Mean Temp.	0.00786	0.00301	0.0127	0.00247	3.179
Temp. Anomaly	0.0012	-0.00159	0.00399	0.00143	0.843
Population Density	0.00012	-0.00007	0.0003	0.00009	1.231
Max Temp. (Day of survey)	0.00039	-0.0016	0.00238	0.00102	0.381
Avg. Max. Temp. (Week of survey)	0.00212	0.00085	0.00338	0.00065	3.273
Random Effects	**Levels (#)**	**Variance (σ^2)**	**Std. Dev. (σ)**	**Total variance**	**p**
Residual		0.03482	0.1866	59.89%	
Census Tract	6368	0.01913	0.13833	32.90%	$p < .0001$***
County	1464	0.00116	0.03402	2.00%	$p < .0005$***
Age	5	0.00006	0.00768	0.10%	$p = .14$
Race/Ethnicity	5	0.00075	0.02742	1.29%	$p < .001$***
Education	4	0	0	0.00%	$p = 1$
Work Status	5	0.00144	0.038	2.48%	$p < .0001$***
Household Size	4	0.00022	0.01476	0.38%	$p < .0004$***
Sex : Race/Ethn : Education	40	0.00038	0.01939	0.65%	$p < .0001$***
State	49	0.00009	0.009357	0.15%	$p = .5$
Subregion (9)	9	0.00009	0.00928	0.15%	$p = .48$
Region (4)	4	0	0	0.00%	$p = 1$

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

the estimated standardized fixed effect of Sensitivity (Sex) and Exposure factors included in the Vulnerability Model.

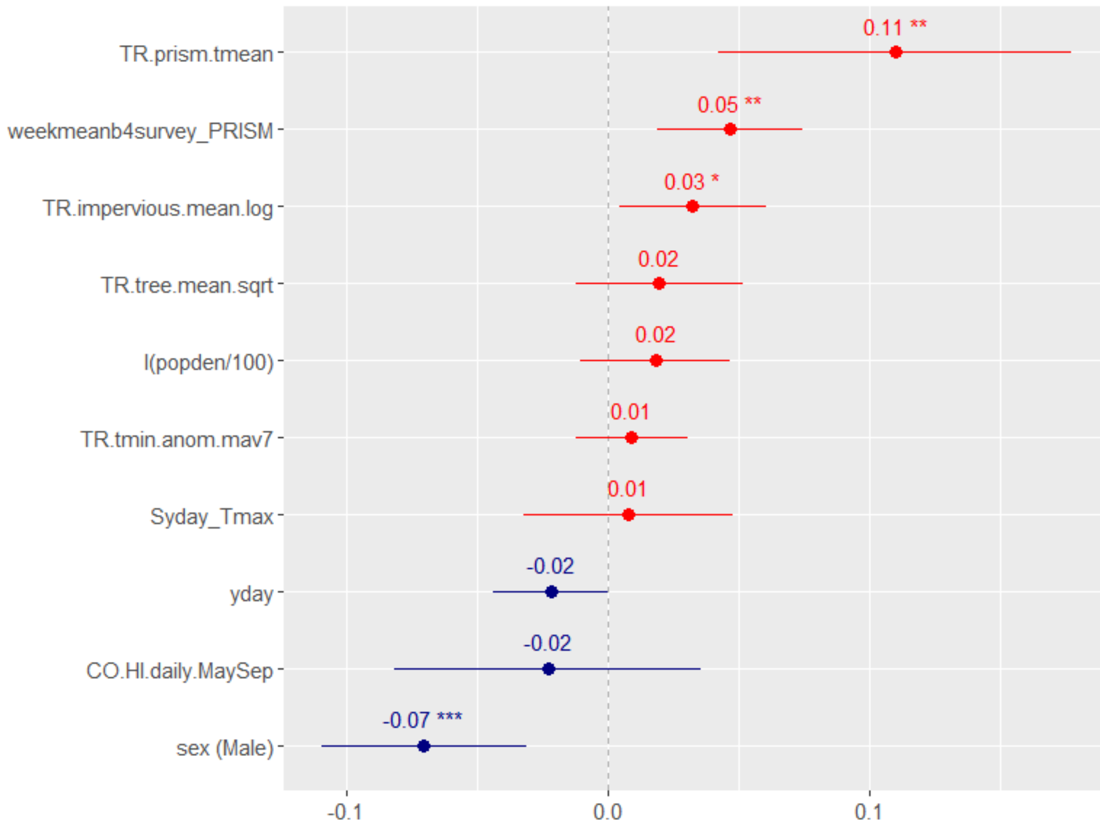


Fig. 25. Standardized fixed effects of Vulnerability Model.

4.5. ADAPTIVE CAPACITY MODEL

In this model, known adaptive capacity factors were parameterized (Table VIII) and modeled independent of any sensitivity or exposure controls in order to examine their isolated effects on extreme heat risk perceptions. Predictors were once again individually evaluated using log-likelihood tests, the results of which are presented in Table XIX.

Table XX summarizes the results of the Adaptive Capacity Model. Number of non-English-speaking households ($\beta = 0.0015$, $X^2(1) = 18.77$, $p < 0.0001$) and number of

Table XIX. Results of Log-Likelihood Testing of Adaptive Capacity Model Predictors

Predictor	df	AIC	BIC	logLik	Deviance	X df	X²	P(> X²)
Null Model	11	-680.64	-602.75	351.32	-702.64			
% Non-English-speaking Households (tract-level)	10	-663.88	-593.07	341.94	-683.88	1	18.765	$p < .0001$ ***
% Unemployed (tract-level)	"	-666.93	-596.11	343.46	-686.93	"	15.718	$p < .0001$ ***
% Vacant homes (tract-level)	"	-679.55	-608.74	349.78	-699.55	"	3.0932	$p < .08$
% Summer days spent in extreme heat alert area	"	-682.12	-611.3	351.06	-702.12	"	0.5268	$p = .47$
Experienced extreme heat alert in week before survey (Y/N)	"	-681.39	-610.57	350.69	-701.39	"	1.258	$p < .26$
Experienced extreme heat alert in 2015 before survey (Y/N)	"	-681.06	-610.25	350.53	-701.06	"	1.5799	$p < .21$
Income	"	-543.68	-472.87	281.84	-563.68	"	138.96	$p < .0001$ ***
County Warning Area	"	-628.47	-557.66	324.24	-648.47	"	54.173	$p < .0001$ ***
Census Tract	"	-276.85	-206.04	148.43	-296.85	"	405.79	$p < .0001$ ***

Note: Shaded cells indicate random effects. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

Table XX. Adaptive Capacity Model Results Summary

Fixed Effects	*β*	Lower 95% CI	Upper 95% CI	Standard Error	t value
Intercept *(Natl. Risk Perception Mean)*	0.35845	0.32392	0.39298	0.01762	20.347
% Non-English-speaking Households (tract-level)	0.0015	0.00084	0.00217	0.00034	4.442
% Unemployed (tract-level)	0.00237	0.00121	0.00354	0.00033	3.982
% Vacant homes (tract-level)	-0.0006	-0.00127	0.00007	0.00034	-1.761
% Summer days where extreme heat alert was issued at respondent location before survey	-0.05119	-0.18817	0.08578	0.06988	-0.733
Extreme heat alert issued in week before survey at respondent location (TRUE)	0.01399	-0.01043	0.03841	0.01246	1.123
Extreme heat alert issued in summer 2015 before survey at respondent location (TRUE)	0.00919	-0.00514	0.02352	0.00731	1.257
Random Effects	**Levels (#)**	**Variance (*σ*²)**	**Std. Dev. (*σ*)**	**Total variance**	**p**
Residual		0.03572	0.18899	60.45%	
Census Tract	6368	0.02028	0.14241	34.32%	$p < .0001$***
Income	7	0.00161	0.04017	2.72%	$p < .0001$***
County Warning Area	115	0.00148	0.03847	2.50%	$p < .0001$***

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

unemployed individuals ($\beta = 0.0024$, $X^2(1) = 15.72$, $p < 0.0001$) at the census tract level were statistically significant predictors of risk perception. Income, measured at the individual-level by the nationally-representative survey, was also a statistically significant predictor ($\sigma^2 = 0.0016$, $\sigma^2 = 0.04$, $X^2(1) = 138.96$, $p < 0.0001$).

The statistically significant effect of two tract-level variables, Number of non-English-speaking households and Number of unemployed individuals, is illustrated in Figure 26 which shows the standardized fixed effect estimates for the Adaptive Capacity model predictors.

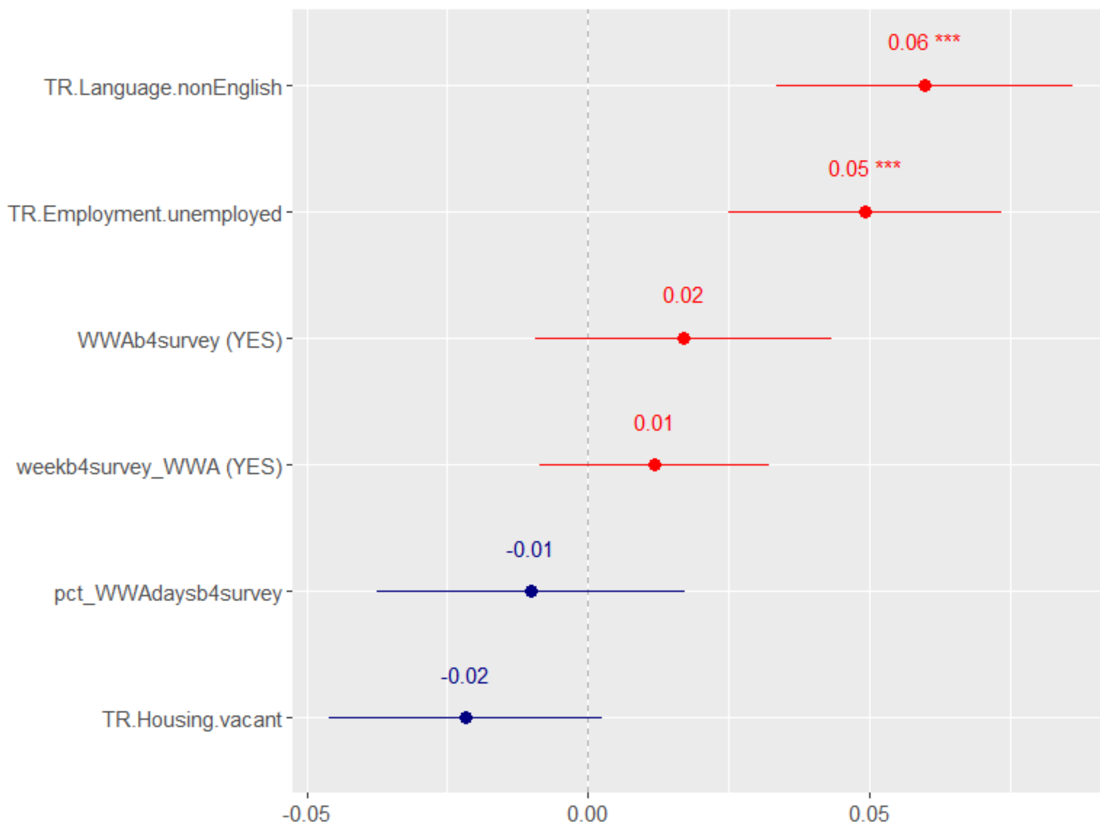


Fig. 26. Standardized fixed effects of Adaptive Capacity Model.

Predictors positively influencing heat wave risk perceptions in the Adaptive Capacity Model include: Tract-level unemployment and Number of non-English-speaking households at the tract-level (Fig. 27). Predictors negatively influencing heat wave risk perceptions in the Adaptive Capacity Model include: Total percentage of days for which each respondent's location was issued an extreme heat alert before the survey and Number of vacant homes at the tract-level (Fig. 27). Appendix D contains summary results (Table D.I, Fig. D.1) and diagnostics (Fig. D.2) for the Adaptive Capacity Model.

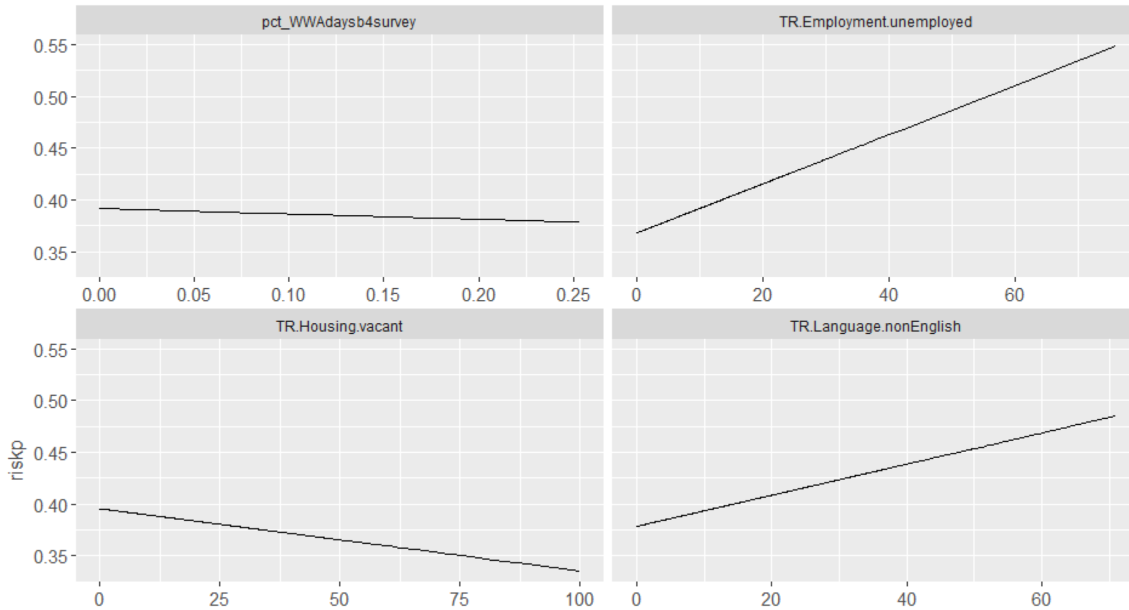


Fig. 27. Marginal effects of Adaptive Capacity Model predictors.

4.6. MAXIMAL MODEL

The final, maximal model was specified to include all factors known to influence extreme heat risk from the sensitivity, exposure, and adaptive capacity models as random and fixed effects (Table VIII). Rather than seeking to achieve the most parsimonious model, all theoretically important factors were retained as controls in accordance with statistical best practices for fitting linear mixed effect models (Barr *et al*., 2013; Bates *et al*., 2014; Bliese and Ployhart, 2002; Winter, 2013; Zuur *et al*., 2010 to help reduce bias and error. Again, predictors were individually evaluated using log-likelihood tests and their results are detailed in Table XXI.

Table XXI. Results of Log-Likelihood Testing of Maximal Model Predictors

	Predictor	df	AIC	BIC	logLik	Deviance	X df	X^2	P(> X^2)
Sensitivity Factors	Null Model	31	-953.88	-734.36	507.94	-1015.9			
	Sex	30	-945.82	-733.38	502.91	-1005.8	"	10.063	$p < .002$ **
	Age	"	-950.27	-737.83	505.13	-1010.3	"	5.616	$p = .018$ *
	Race/Ethnicity	"	-943.02	-730.58	501.51	-1003	"	12.866	$p < .0004$ ***
	Education	"	-955.88	-743.44	507.94	-1015.9	"	0	$p = 1$
	Work Status	"	-921.53	-709.09	490.76	-981.53	"	34.352	$p < .0001$ ***
	Household Size	"	-953	-740.56	506.5	-1013	"	2.8856	$p = .09$
	Sex : Race/Ethnicity : Education	"	-938.82	-726.38	499.41	-998.82	"	17.059	$p < .0001$ ***
Exposure Factors (+ Geography / Time)	Day of Year	"	-951.83	-739.39	505.91	-1011.8	1	4.0529	$p < .045$ *
	Population Density	"	-955.66	-743.23	507.83	-1015.7	"	0.2171	$p = .64$
	Impervious Surfaces	"	-952.8	-740.36	506.4	-1012.8	"	3.0819	$p = .08$
	Tree Coverage	"	-953.21	-740.77	506.6	-1013.2	"	2.6758	$p = .10$
	Mean Temp.	"	-947.46	-735.03	503.73	-1007.5	"	8.4177	$p < .004$ **
	Temp. Anomaly	"	-955.3	-742.86	507.65	-1015.3	"	0.5828	$p = .45$
	Heat Index	"	-955.13	-742.69	507.57	-1015.1	"	0.7511	$p = .39$
	Max Temp. (day of Survey)	"	-955.62	-743.19	507.81	-1015.6	"	0.2586	$p = .61$
	Average Max Temp. (Week before survey)	"	-945.39	-732.95	502.69	-1005.4	"	10.493	$p = .001$ **
	Census Tract	"	-620.2	-407.77	340.1	-680.2	"	335.68	$p < .0001$ ***
	County	"	-947.58	-735.15	503.79	-1007.6	"	8.2977	$p = .004$ **
	State	"	-954.91	-742.48	507.46	-1014.9	"	0.9689	$p = .33$
	Subregion (9)	"	-955.85	-743.41	507.92	-1015.9	"	0.0357	$p = .85$
	Region (4)	"	-955.88	-743.44	507.94	-1015.9	"	0	$p = 1$
Adaptive Capacity Factors	% Non-English-speaking Households (tract-level)	"	-953.23	-740.79	506.62	-1013.2	"	2.649	$p = .1$
	% Unemployed (tract-level)	"	-951.24	-738.81	505.62	-1011.2	"	4.6382	$p = .03$ *
	% Vacant homes (tract-level)	"	-954.07	-741.63	507.03	-1014.1	"	1.8119	$p = .18$
	% Summer days spent in extreme heat alert area	"	-954.88	-742.44	507.44	-1014.9	"	1.0037	$p = .32$
	Experienced extreme heat alert in week before survey (Y/N)	"	-955.81	-743.37	507.9	-1015.8	"	0.0741	$p = .79$
	Experienced extreme heat alert in 2015 before survey (Y/N)	"	-955.3	-742.86	507.65	-1015.3	"	0.5821	$p = .45$
	Income	"	-883.33	-670.89	471.66	-943.33	"	72.555	$p < .0001$ ***
	County Warning Area	"	-955.77	-743.33	507.88	-1015.8	"	0.1124	$p = .74$

Note: Shaded cells indicate random effects. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

The results of the maximal model are presented in Table XXII. Sensitivity factors specified as random effects—Age ($\sigma^2 = 0.0001, \sigma = 0.01, X^2(1) = 5.62, p = 0.018$), Race/Ethnicity ($\sigma^2 = 0.0008, \sigma = 0.028, X^2(1) = 12.87, p < 0.0004$), Work Status ($\sigma^2 = 0.001, \sigma = 0.031, X^2(1) = 34.35, p < 0.0001$), and interaction Sex : Race/Ethnicity : Education ($\sigma^2 = 0.0003, \sigma = 0.016, X^2(1) = 17.06, p < 0.0001$)—remained statistically significant predictors of extreme heat risk perception.

When controlling for sensitivity and adaptive capacity, exposure factors specified as fixed effects—Day of Year ($\beta = -0.0001, X^2(1) = 4.05, p < 0.045$), Mean Temperature ($\beta = 0.008, X^2(1) = 8.42, p < 0.004$), and Average Maximum Temperature during the

Table XXII. Maximal Model Results Summary

Fixed Effects	β	Lower 95% CI	Upper 95% CI	Standard Error	t value
Intercept *(Natl. Risk Perception Mean)*	0.33897	0.05779	0.62017	0.14346	2.363
Day of Year	-0.00012	-0.00024	0	0.00006	-2.014
Heat Index	-0.00172	-0.00551	0.00206	0.001933	-0.892
Impervious Surface	0.00426	-0.00045	0.00897	0.00249	1.771
Tree Coverage	0.00313	-0.00047	0.00673	0.00184	1.702
Mean Temp.	0.00788	0.00312	0.01264	0.00243	3.242
Temp. Anomaly	0.00109	-0.0017	0.00388	0.00142	0.767
Population Density	0.00004	-0.00014	0.00023	0.0001	0.468
Max Temp. (Day of survey)	0.00055	-0.00145	0.00255	0.00102	0.54
Average Max Temp. (Week before survey)	0.00212	0.00084	0.0034	0.00065	3.242
# NonEnglish-speaking Households (tract level)	0.00061	-0.00012	0.00133	0.00037	1.666
# Unemployed (tract level)	0.00131	0.00012	0.0025	0.00061	2.165
# Vacant homes (tract level)	-0.00047	-0.00116	0.00021	0.00035	-1.352
% Summer days where extreme heat alert was issued at respondent location before survey	-0.06941	-0.20155	0.06274	0.06742	-1.029
Extreme heat alert issued in week before survey at respondent location (TRUE)	-0.0034	-0.02785	0.02106	0.01248	-0.272
Extreme heat alert issued in summer 2015 before survey at respondent location (TRUE)	0.00551	-0.00835	0.01938	0.00707	0.779
Sex	-0.03347	-0.0506	-0.01633	0.00874	-3.828
Random Effects	**Levels (#)**	**Variance (σ^2)**	**Std. Dev. (σ)**	**Total variance**	**p**
Residual		0.03465	0.18616	59.78%	
Census Tract	6368	0.01862	0.13646	32.13%	*p < .0001****
Income	7	0.0012	0.03461	2.07%	*p < .0001****
County	1464	0.00104	0.03227	1.79%	*p = .004***
Work Status	5	0.00096	0.03106	1.66%	*p < .0001****
Race/Ethnicity	5	0.00083	0.02877	1.43%	*p < .0004****
Sex : Race/Ethn : Education	40	0.00025	0.01566	0.43%	*p < .0001****
State	49	0.00015	0.01213	0.26%	*p = .33*
Age	5	0.00012	0.01073	0.21%	*p = .018**
County Warning Area	115	0.00006	0.00801	0.10%	*p = .74*
Household Size	4	0.00006	0.00752	0.10%	*p = .09*
Subregion (9)	9	0.00002	0.00481	0.03%	*p = .85*
Education	4	0	0	0.00%	*p = 1*
Region (4)	4	0	0	0.00%	*p = 1*

Notes: Observations = 8789. Significance codes: 0 '***' 0.001 '**' 0.05 '*'

week before survey data were collected ($\beta = 0.0021$, $X^2(1) = 10.49$, $p = 0.001$)—remained statistically significant predictors of extreme heat risk perception (Fig. 28).

Among adaptive capacity factors, the random effect of Income was the only predictor to retain significance ($\sigma^2 = 0.0012$, $\sigma = 0.035$, $X^2(1) = 72.56$, $p < 0.0001$) and captured the greatest proportion of total variance amongst all random explanatory variables at 2.07% (Fig. 29).

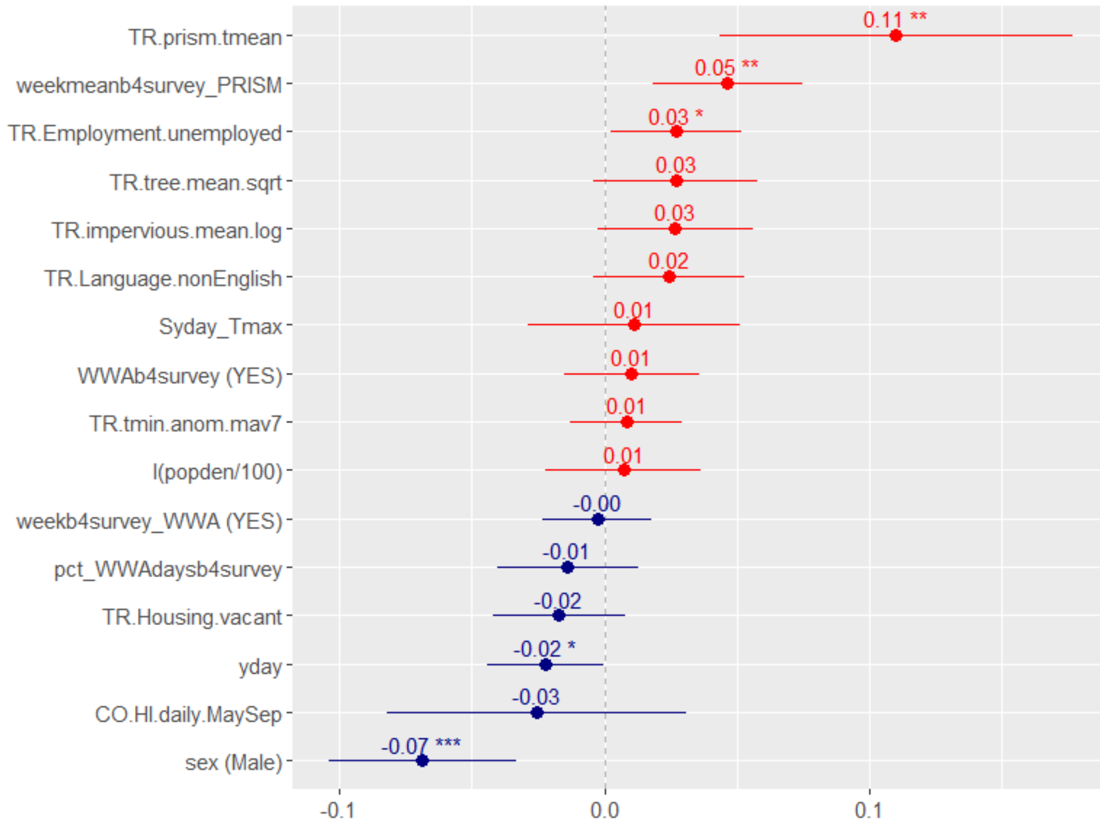


Fig. 28. Standardized fixed effects of Maximal Model predictors.

Predictors positively influencing heat wave risk perceptions in the Maximal Model include: Population density, Avg. max. temperature recorded during the week before the survey at each respondent's unique location, Max. temperature recorded on the day of the survey at each respondent's unique location, Tract-level unemployment, Tract-level mean impervious surface coverage, Number of non-English-speaking households at the tract-level, Tract-level average seasonal temperature, Deviation of minimum temperature recorded during the month of the survey from the seasonal average at the tract-level, and Tract-level mean tree coverage (Fig. 30). Predictors negatively influencing heat wave risk perceptions in the Maximal Model include: County-level

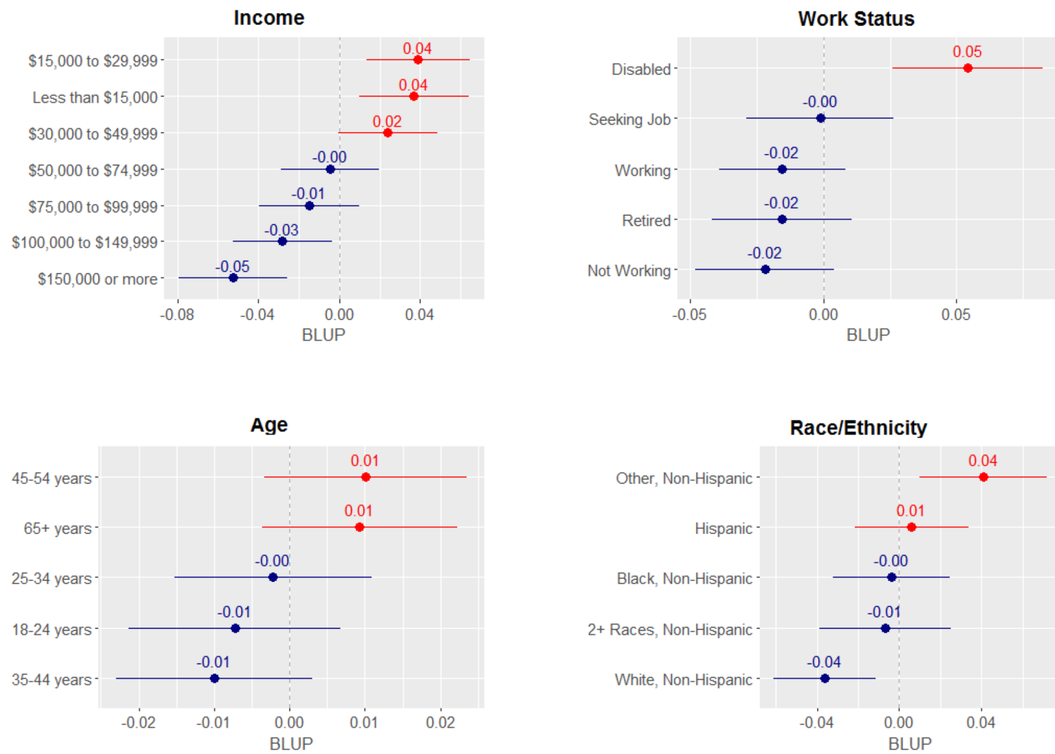


Fig. 29. Random effects of Maximal Model predictors

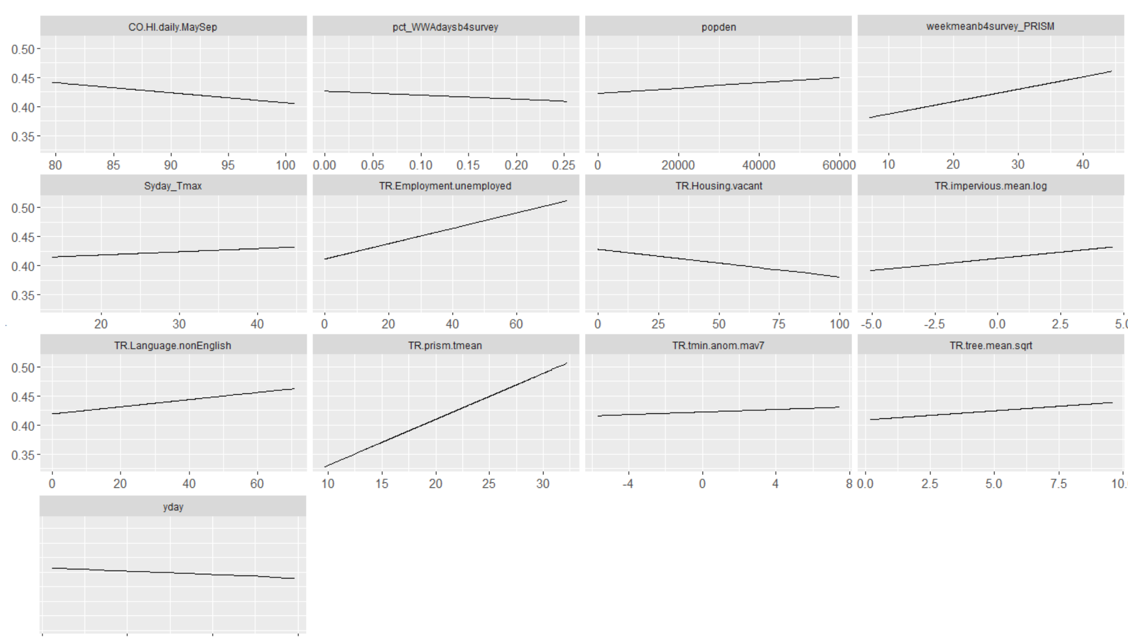


Fig. 30. Marginal effects of Maximal Model predictors.

average seasonal heat index, Total percentage of days for which each respondent's location was issued an extreme heat alert before the survey, Number of vacant homes at the tract-level, and Day of year (Fig. 30). Appendix E contains summary results (Table E.I, Figs. E.1-6) and diagnostics (Figs. E.7-8) for the Adaptive Capacity Model.

4.7. MODEL COMPARISON

Using log-likelihood based tests, each successive model build was assessed to compare explanatory power and model fit. Table XXIII demonstrates that each successive model specification improved upon the initial sensitivity models (1.0 and 2.0) and resulted in a better fit of the data by controlling for exposure and adaptive capacity factors. Statistically, compared to Sensitivity Model 1.0, the Vulnerability Model provided a substantively better fit of the risk perception data (X2(6) = 417.26, p < 0.00001) and explained 40.11% of total variance (Table XVIII) compared to 7.84% for Sensitivity Model 1.0 (Table XII).

Table XXIII. Maximal Model Comparisons

Model	df	AIC	BIC	logLik	Deviance	X df	X^2	$P(> X^2)$
Sensitivity Model 2.0	8	-279.41	-215.1	148.71	-297.41			
Sensitivity Model 1.0	9	-271.75	-215.1	143.88	-287.75	1	9.661	$p < .002$ **
Vulnerability Model	"	-276.2	-219.55	146.1	-292.2	"	5.212	$p = .02$ *
Maximal Model	"	-265.09	-208.44	-140.54	-281.09	"	16.33	$p < .0001$ ***

Notes: Significance codes: 0 '***' 0.001 '**' 0.05 '*'

The Maximal Model also reflected a statistically significant (albeit minimal) improvement on the fit of the risk perception data when compared to the Vulnerability Model ($X^2(8) = 91.98$, $p < 0.00001$) and explained 40.22% of total variance [32.13% at the census tract level, 1.79% at the county level, and 0.26% at the state level] (Table

XXII) compared to the Vulnerability Model's 40.11% [with 32.90% at the census tract level, 2.00% at the county level, and 0.15% at the state level] for the Vulnerability Model (Table XVIII).

The independent variable and explanatory predictors in this study revolve around a complex construct: risk. Because of this, in order to accurately and responsibly measure their effect and directionality, many predictors included in these mixed effect models required estimation of interactions between and across multiple dynamic variables that vary over space and time on different levels. Additionally, model misspecification and use of statistics aggregated to areal units can leave spatially patterned information in the model residuals. Therefore, it was prudent to test for spatial dependencies or data clustering in the modeled residuals. Moran I tests were conducted using the R programming language and environment using the spdep spatial statistics package (Bivand and Piras, 2015; Bivand *et al.*, 2013). Results indicate negligible influence of spatial clustering in the modeled residuals, with Moran I statistics decreasing from a high of 0.075 ($p < 0.00001$) for the Sensitivity Model 1.0 to a low of -0.023 ($p < 0.00001$) for the Maximal Model. Plots for these tests for all models can be found in the Appendices.

CHAPTER 5

DISCUSSION

Previous research is missing contextualized, locally-relevant vulnerability data detailing the distribution of extreme heat risk perception across the contiguous United States. To address this gap, using national survey data a series of mixed effect models were specified that included meteorological, climatological, geographic, sociodemographic, temporal, or land cover variables—each representing different sensitivity, exposure, or adaptive capacity factors—as predictors of extreme heat risk perception. The primary goals of this study were to (1) evaluate the spatial and temporal distribution of extreme heat risk perception across the contiguous United States, (2) generate risk perception estimates for unique subpopulations, and (3) describe the influence of important risk components—natural exposure variables as well as human sensitivity and adaptive capacity factors—on extreme heat risk perception.

The intensity and scope of extreme heat impacts hinges upon climatological, meteorological, and geographic exposure factors as well as dynamic human factors such as sensitivity and adaptive capacity. This thesis models the influence of these factors on risk perception using a suite of multilevel regression models. Four hypotheses were tested through the estimation of explicit directional relationships using mixed effect models. Each hypothesis looks at a different subset of variables thought to be determinants of heat risk perception, using the R = (E+S) – AC framework to classify important extreme heat risk factors and evaluate their influence on extreme heat risk perceptions. Generally speaking, a combination of human and physical factors tends to influence risk perceptions at both individual and contextual-levels. However, individual-level factors (such as sex, income, or work status) tend to influence risk perception more than contextual-level factors (such as seasonal average temperature, day of year, NWS alerts, or location-specific weather patterns). In other words, human sensitivity factors tend to exert more influence upon risk perception than environmental exposure or adaptive capacity factors.

5.1. RESEARCH QUESTION I

One of the principal objectives of this study was to determine how key sensitivity factors known to be important contributors to overall heat vulnerability (summarized in Table I) influence extreme heat risk perceptions across the contiguous United States. A series of linear mixed effect models were constructed to evaluate Hypothesis I (Individual-level sensitivity factors that are important contributors to heightened personal risk of heat-related impacts will positively influence heat wave risk perceptions across the study area and be a source of statistically significant variation from the national mean). This study quantifies the degree of first-order variation present among sensitivity effects contributing to risk perception at the individual-level. The results estimate the influence of sensitivity factors on risk perceptions, with and without controls for exposure and adaptive capacity factors. Most of the hypothesized directionalities of effect in personal sensitivity factors were observed via measurement of mean risk perception variation at their respective subpopulation groupings, or their random levels (Fig. 31).

		Sensitivity 1.0	Sensitivity 2.0	Exposure	Vulnerability	Adaptive Capacity	Maximal
Sensitivity	Sex (♀)	+ **	+ **		+ **		+ **
	Age (65+)	+ *	+ *		+		+ *
	Race/ethnicity (non-white)	+	+ ***		+ ***		+ ***
	Education	○	○		○		○
	Work status (disabled)	+	+ ***		+ ***		+ ***
	Home size	○	— **		— ***		○
Exposure	Day of year			— *	— *		— *
	Population density			+ *	+		+
	Impervious surface coverage			+ **	+ *		+
	Tree coverage			+	+		+
	Seasonal mean temp. (May-Oct.)			+ **	+ **		+ **
	Temp. Anomaly (2015 v. 1985-2015)			+	+		+
	Mean daily max. temp. (week of survey)			+ **	+ **		+ **
Adaptive Capacity	% Non-English-speaking homes					+ ***	+
	% Unemployed					+ ***	+ *
	% Vacant homes					—	—
	% Summer days spent in WWA before survey					—	—
	WWA, week before survey? (True)					+	—
	WWA, in 2015 before survey? (True)					+	+
	Income	— ***				— ***	— ***

Fig. 31. Directionality of known risk factors based upon estimates generated by mixed effect models. Directionality symbols: (+) positive relationship observed, (–) negative relationship observed, (0) no relationship observed; P-value symbols: *** = < .001, ** = < .01, * = < .05.

Most of the studied individual-level sensitivity factors influenced heat wave risk perceptions—either positively or negatively, as hypothesized—in a statistically significant manner across the study area (Fig. 31) and accounted for a statistically significant proportion of total variance around the national average. Risk perception response values for subpopulations known to be at increased risk tend to deviate from the national average in line with the directionality of effect suggested by previous scholars (Tables I-III). Sex, a factor which previous studies have identified as an important determinant of extreme heat sensitivity (Burse, 1979; Canoui-Poitrine *et al*., 2006; Kovats and Hajat, 2008; Safi *et al*., 2012; Smith, 2013, p. 272; Staffogia *et al*., 2006) is an important determinant of risk perception; women perceive themselves to be at greater risk than men. Racial or ethnic minority groups are known to be at increased risk of being negatively impacted by extreme heat (Anderson and Bell, 2009, 2011; Cutter *et al*., 2003; IPCC, 2014; Klinenberg, 2003, p. 80–81; Melillo *et al*., 2014; Reid *et al*., 2009, 2012; Safi *et al*., 2012; Tierney, 2014, p. 21; Weber *et al*., 2015; Wolf and McGregor, 2013) and also tend to have significantly higher risk perceptions. Previous studies have found that individuals with a source of income are less sensitive to negative hazard impacts, while disabled persons are more susceptible to negative impacts (CDC, 2016; Cutter *et al*., 2003; EPA, 2016; IPCC, 2014; Keller and DeVecchio, 2015, p. 319; Klinenberg, 2003, p. 80–81; Melillo *et al*., 2014; Safi *et al*., 2012; Semenza *et al*., 1996). As hypothesized, respondents with higher income tend to have lower heat risk perceptions than the national average, individuals with lower incomes tend to have higher risk perceptions, and persons with disabilities have substantively higher risk perceptions than any other work status-specific subpopulation. Specific risk perception estimates for all subpopulations (every random level) measured in the initial Sensitivity Model are provided in Tables A.I–II of Appendix A.

The relatively low variance across subpopulations (e.g., age, education groups) is partially a consequence of the conservative nature of mixed effect models which rely upon partial pooling and combinations of individual-level and contextual-level characteristics that tend to pull subpopulation estimates toward their respective national averages. Despite this, a few at-risk subpopulations tended to have lower risk perceptions than were expected (Fig. 32). Some factors known to increase vulnerability, such as age and education, did not tend to exert statistically significant influence over risk perceptions as expected. Age, a factor which previous studies have identified as an important determinant of extreme heat sensitivity (Anderson and Bell, 2009, 2011; Buscail *et al*., 2012; CDC, 2016; Cutter *et al*., 2003; EPA, 2016; Harlan *et al*., 2006; IPCC, 2014; Johnson *et al*., 2009; Keller and DeVecchio, 2015, p. 319; Klinenberg, 2003; Kovats and Hajat, 2008; Medina-Ramon *et al*., 2006; Melillo *et al*., 2014; Reid *et al*., 2009, 2012; Safi *et al*., 2012; Semenza *et al*., 1996; Smith, 2013, p. 271; Staffogia *et al*., 2006; Tomlinson *et al*., 2011; Uejio *et al*., 2011; Weber *et al*., 2015; White-Newsome *et al*., 2014; Wolf and McGregor, 2013), was found to be a statistically significant predictor of heat risk perceptions. However, age did not exhibit a profound impact on extreme heat risk perception; the most senior subpopulation (≥ 65 years of age) did not report markedly higher risk perception than younger subpopulations. This apparent underestimation of extreme heat risk by vulnerable subpopulations presents barriers to bringing these subpopulations into the risk reduction process and could be indicative of these populations being less likely to proactively implement protective behaviors. Future extreme heat risk research would benefit from examining the relationship between risk perception and personal medical histories alongside space-time-explicit hospitalization data.

Less-educated individuals often face greater difficulty in accessing health services and information regarding the nature of natural hazards (Anderson and Bell, 2009, 2011; CDC, 2016; Cutter *et al*., 2003; EPA, 2016; IPCC, 2014; Medina-Ramon *et al*., 2006; Melillo *et al*., 2014; Reid *et al*., 2009, 2012; Smith, 2013, p. 85–86; Weber *et al*., 2015),

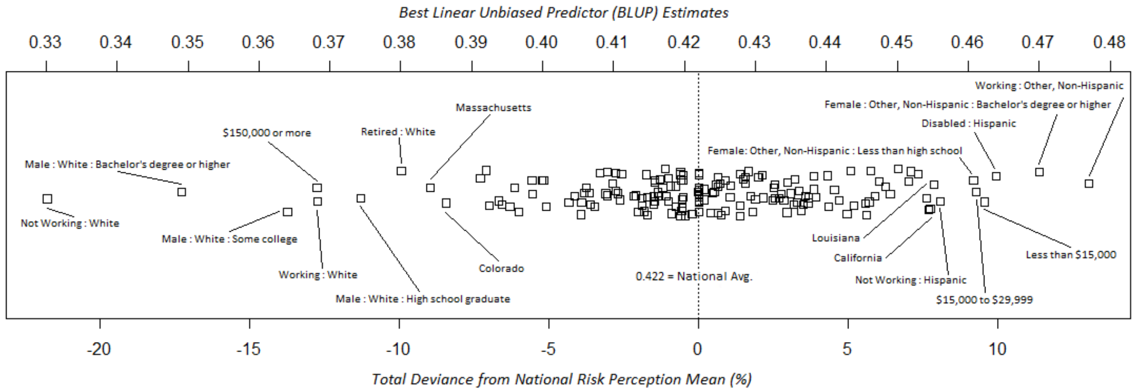


Fig. 32. Risk perception estimates for subpopulations from the initial Sensitivity Model, with the most extreme subpopulations labeled.

yet no relationship was observed between education level and heat risk perception. However, despite a statistically insignificant role in predicting heat risk perception as an independent factor, education was an important component of the statistically significant interaction predictor Sex by Race by Education. Additionally, previous research has identified home size as an important predictor of hazard risk; those with larger homes are more likely to have the resources required to cope with environmental hazards (Cutter *et al.*, 2003; Klinenberg, 2003, p. 80–81; Reid *et al.*, 2009, 2012; Semenza *et al.*, 1996; Weber *et al.*, 2015). Home size had a statistically significant negative effect on risk perception in two of four models but had no effect on risk perception when also controlling for income (and therefore will likely be considered an adaptive capacity factor in future tests).

The United States population is aging and is predicted to have over 88 million individuals at 65 years of age or older by the year 2050 (Ortman *et al.*, 2014). Additionally, the contiguous United States is predicted to experience more frequent and severe heat waves over the coming years (EPA, 2016; IPCC, 2014; NWS, 2015; Mora, *et* *al*., 2017; Vose *et al*., 2017). When vulnerable subpopulations underestimate risk, targeted risk communication campaigns become vitally necessary. In the context of extreme heat, they become even more urgent, given that the elderly do not recognize themselves to be at much higher risk. Data such as this underscores the value of systematically measuring risk perceptions at different levels and the importance of effective risk communication given that a hazard must first be perceived as a risk before any protective actions are likely to be taken (FEMA, 2017, p. 11).

What should an emergency manager do if a hazard presents a high risk to a community but the population in that community believes the risk to be much lower than it actually is? Situations like this present difficult challenges for decision-makers. Risk perception data highlights misperceptions and identifies vulnerable subpopulations. FEMA describes risk communication as the best way to counteract misperceptions about risk and reports, "The presence of differing risk perceptions [between the public and decision-makers] highlights the need for effective risk communication as a component of mitigation and preparedness" (FEMA, 2017, p. 12). Ultimately, ignoring risk perception data stands in the way of successful risk communication (California Governor's Office of Emergency Services, 2001, p. 10); and as Lindell et al. have noted, "Risk analysts and emergency managers must understand how different segments of the population at risk think about a hazard if they are to be effective in communicating with their audience" (Lindell *et al*., 2006, p. 86). Failing to consider community participation or input in the risk management process can reduce the likelihood of achieving a risk reduction solution that both the decision-making agency and the community find equitable and effective (California Governor's Office of Emergency Services, 2001, p. 29).

5.2. RESEARCH QUESTION II

The second objective of this study was to evaluate how much variation in risk perception occurs across the contiguous United States at different scales. Risk perceptions were expected to demonstrate substantive variation across geographic units in the contiguous United States, and subpopulations living in states with histories of heightened exposure to extreme heat events were expected to have higher risk perceptions. The results of this study provide support for this hypothesis and indicate that extreme heat risk perceptions demonstrate statistically significant non-random spatial patterns. As expected, risk perceptions demonstrated statistically significant geographic variation across the U.S. at different scales. Geographic predictors significantly influenced risk perception and accounted for a statistically significant proportion of total variance across all models. Additionally, the directionality of sensitivity factor relationships with risk perception was maintained even after controlling for geography. Different people experience different environmental conditions in different places and subsequently tend to report different risk perception levels.

On the whole, despite rising exposure levels, the national average (0.433) is below the median scale value (0.5) and lower than expected. Nevertheless, public risk perception trends across the U.S. generally reflected actual risk levels for many subpopulations. Random effect estimates for the subpopulations (including those specific to geographic units) were calculated in relation to the national average baseline (Fig. 32). For example, the risk perceptions of black men with college degrees, Iowans of 25–34 years of age, and working individuals who live alone tend to be closest to the national average. Deviations from the national average among particular subpopulation profiles, especially at the extremes, are of particular interest because what we perceive as real is real in its consequences (Thomas and Thomas, 1928). For example, risk perceptions among disabled Hispanic individuals, individuals earning less than $30,000 annually, and the populations of Louisiana and California tend to exhibit the greatest positive deviation from the national average. On the other hand, risk perceptions for white, working, men earning over $150,000 annually, and the populations of Colorado and Massachusetts exhibited the greatest negative deviation from the national average, which suggests they may be less likely to make preparations for extreme heat risk. Highlighting the distribution of misperceived risk can aid the development of subpopulation-specific risk communication products.

5.3. RESEARCH QUESTION III

The third objective was to evaluate how key exposure factors known to be statistically significant contributors to overall heat vulnerability influence extreme heat risk perceptions across the contiguous United States. It was hypothesized that respondents located in areas more likely to experience a higher degree of exposure would report higher risk perceptions (for example, due to geographic location, higher average seasonal temperatures or the effects of the urban heat island). The degree to which personal experience with exposure factors influences heat risk perceptions was quantified in an independent exposure model (Table XV) and while controlling for sensitivity and adaptive capacity factors (Table XVI). A statistically significant relationship was observed between individual risk perceptions and local, contextual-level predictors that vary over time and across space (e.g., maximum weekly temperature patterns). Many of the complex human-environmental factors incorporated into the Exposure Model were found to be statistically significant predictors of risk. For example, subpopulations situated in more densely-populated areas with greater impervious surface coverage—who are more likely to experience a higher degree of heat exposure due to the urban heat island effect (CDC, 2016; Liss *et al*., 2017)—were found to have higher extreme heat risk perceptions. Additionally, results demonstrate that the geographic distribution of extreme heat risk perception tends to coincide with observed local temperatures, and spatial analysis of the responses indicates that the distribution of extreme heat risk perceptions was non-random. Contextual-level heat exposure factors tend to affect risk perception in a logical direction across the United States.

In their 1979 publication *Rating the Risks*, Slovic and colleagues memorably began with, “People respond to the hazards they perceive” (Slovic *et al*., 1979). FEMA cites this line as critical for two reasons: “First, its converse is also true. People generally do not respond to the hazards that they do not perceive. Second, it has been found that these stated perceptions are based primarily upon inaccurate sources of information […] as opposed to personal experience and expert knowledge” (FEMA, 2017, p. 4). In training documents, FEMA advises that the general public typically does not consider contextual-level factors when evaluating risk. However, previous research has suggested that personal experience with extreme heat conditions may influence risk perception (Smith, 2013, p. 81; Tierney, 2014, p. 18; Tversky and Kahneman, 1973, 1974; Weinstein, 1989). Furthermore, studies have demonstrated the capacity of “human sensors” to detect changes in local environmental factors and found localized perceptions to be consistent with observations of local seasonal weather patterns and timing (Howe *et* *al*., 2013; Howe and Leiserowitz, 2013; Leiserowitz, 2006; Smith and Leiserowitz, 2014). The results of this study contribute additional evidence suggesting individuals' capacity to assess localized environmental conditions and changes. Results support the hypothesis that risk perceptions exhibit non-random geographic patterns in part due to different individual experiences with highly-variable weather and climate components of exposure. Individuals living in warmer climates that typically experience higher degrees of exposure tend to have higher risk perceptions. Additionally, two variables capturing recent experience with heat (mean daily temperature experienced during week before response data was collected and on the day of the survey) were statistically significant and positive predictors of risk perception. These results indicate that recent experience with elevated temperatures may lead to increased risk perception, and they lend strength to previous research that has suggested that changes in temperature may have a causal influence on environmental perceptions (Howe *et al*., 2013). Indeed, while the findings of this study cannot conclusively demonstrate causal relationships between the exposure conditions experienced by respondents and their perceptions, a distinct and logical pattern of directionality in the effect of recently experienced temperature changes on risk perception was observed across the contiguous United States.

FEMA's training documents again refer to Slovic and colleagues (1979), when stating, "Disaster management experts' risk perceptions correspond closely to statistical frequencies of death. Laypeople's risk perceptions are based in part on frequencies of death, but there are many other qualitative aspects that affect their personal rating of risks" (FEMA, 2017, p. 5). This is worth mentioning because while it is true that many factors affect risk perception, public risk perceptions generally did a better job of reflecting "experts' risk perceptions" than was expected.

Results of this study indicate that heat risk perception levels across many of the nation's subpopulations tend to accurately reflect the directionality of risk factor relationships described in statistical risk assessments. Time of year is a good example. The earliest heatwaves of the warm season are typically responsible for greater negative impacts when compared to subsequent heatwaves. This is partly due to a greater proportion of the national population being underprepared for extreme heat exposure earlier in the year. People tend to acclimate to warmer temperatures over the course of the warm season (Anderson and Bell, 2011; Hawkins *et al*., 2017; Liss *et al*., 2017; Rauber *et al*., 2008, p. 256; Smith, 2013, p. 85–86, 271). This is a complex contextual-level factor, yet results indicate that time of year negatively predicts risk perception—extreme heat risk perception decreases over the course of the warm months across the contiguous United States, reflecting observed mortality trends, despite temperature levels rising (and therefore presumably exposure levels). This finding may reflect previous observations that despite conditions worsening, individuals are less likely to be caught off guard after the beginning of the warm season (Liss *et al*., 2017). This has implications for risk communication campaigns in geographic areas which were previously unaccustomed to extreme heat events but are likely to face increased exposure in coming years. Negative heat impacts are not necessarily less severe in cooler regions of the contiguous United States than in hotter regions (Anderson and Bell, 2009; Anderson *et al*., 2013; White-Newsome *et al*., 2014). Furthermore, all regions of the CONUS are predicted to experience more frequent extreme heat events, particularly in southern latitudes (Vose *et al.*, 2017).

There were several unexpected findings related to exposure factors. First, greater tree canopy coverage helps drive down temperatures when interacting with nightly lows, thereby reducing the threat of the UHI effect; yet, the positive relationship observed between risk perception and local proportions of tree coverage at the tract level was not statistically significant independent of the significant effect found with impervious surface coverage. Second, temperature deviations (between nightly low temperatures recorded at the tract-level during the 2015 study period and the 30-year seasonal average low temperature) were not found to have a statistically significant influence on risk perception. Third, the heat index—which remains the primary metric used by the NWS to express the human body's perception of relative humidity alongside air temperature—did not exert significant influence on risk perception. This may be partly due to the low spatial resolution of the data (aggregated at the county level) as well as its correlation to mean temperature, which did show a significant effect.

This study is, to our knowledge, the first to investigate how localized personal experience with key meteorological and climatological factors known to be important contributors to overall heat risk (e.g., Heat Index, Daily Max. Temp., Seasonal Avg. Min. Temp) contribute to heat risk perceptions using time-stamped, georeferenced, CONUS nationally-representative, empirical survey data. Additionally, the methods detailed could be adapted to a wide range of human-natural systems evaluation applications by building space-time-explicit indices of environmental conditions unique to each respondent's geographic position at multiple scales. Results provide further evidence of "human sensors'" capacity to pick up on local environmental changes when making complex evaluations of risk. The findings of this study indicate that extreme heat risk perceptions demonstrate statistically significant non-random spatial patterns, which appear to reflect the substantive influence of personal experience with extreme heat exposure. The results of the Exposure Model indicate that states with a history of extreme heat exposure and experience tended to have higher heat risk perceptions. In contrast, states historically unaccustomed to extreme heat exposure did not necessarily tend to have higher risk perceptions (Fig. 22) despite evidence suggesting they will experience more frequent and longer-lasting extreme heat events in the future (Vose *et al*., 2017). Given these findings, future research should examine the effect of elevation on extreme heat risk perception as warming trends at higher elevations may be underestimated due to a lack of historical observational data as well as orographic factors not being considered in many regional climate forecast models (Pepin *et al*., 2015; Vose *et al*., 2017). On the whole, place-dependent exposure factors rooted in their respective geographic contexts were strong predictors of extreme heat risk perception, suggesting that risk communication plans that incorporate localized risk perception data may help to break down barriers to bring a greater proportion of the populace in the risk reduction process.

5.4. RESEARCH QUESTION IV

How do key adaptive capacity factors known to affect an individuals' ability to cope with hazards (summarized in Table III) influence extreme heat risk perceptions across the United States? I hypothesized that adaptive capacity factors measured at the individual-level, such as income, would negatively influence extreme heat risk perception (e.g., as income levels increase, risk perception score will decrease). Additionally, contextual-level factors (those measured at the census tract level, e.g., proportion of unemployed individuals, proportion of vacant homes) which are known to positively influence total extreme heat risk (by negatively influencing overall adaptive capacity) were predicted to negatively influence risk perceptions. The influence of these factors was measured independently (Table XIV) and while controlling for sensitivity and exposure factors (Table XVI). At the individual-level, income maintained a statistically significant negative effect on extreme heat risk perceptions in both the independent adaptive capacity model (Table XIV) as well as in the Maximal Model (Fig. 25), where Income captured the highest proportion of total variance among non-geographic predictors. At the community-level, a higher unemployment rate maintained its positive fixed effect on risk perceptions (Figs. 27, 30).

Wealthier individuals—who are more likely to have or acquire sufficient means to cope with hazards (Anderson and Bell, 2009, 2011; Cutter *et al.,* 2003; Harlan *et al.,* 2006; Klinenberg, 2003, p. 80-1; Melillo *et al.,* 2014; Reid *et al.,* 2009, 2012; Safi *et al.,* 2012; Smith, 2013; Tierney, 2014, p. 4-9; Weber *et al.,* 2015; Wolf and McGregor, 2013)—tend to have lower risk perceptions in general than the average American. Individuals without a source of income—who are less likely to be able to cope with hazard impacts (Anderson and Bell, 2009, 2011; Klinenberg, 2003, p. 80-1; Safi *et al.,* 2012; Semenza *et al.,* 1996) —tend to have higher heat risk perceptions. Non-English-speaking subpopulations—who tend to have less access to information and emergency help, often reside in more hazard-prone areas, and have less power to cope with negative impacts of hazards due to socioeconomic inequalities (Anderson and Bell, 2009, 2011; Curriero *et al.,* 2002; Cutter *et al.,* 2003; IPCC, 2014; Klinenberg, 2003, p. 80-1; Melillo *et al.,* 2014; Reid *et al.,* 2009, 2012; Safi *et al.,* 2012; Tierney, 2014, p. 4-9; Weber *et al.,* 2015; Wolf and McGregor, 2013) —tend to have higher heat risk perceptions. Additionally, while a high vacancy rate at the tract-level can indicate that there is less likely to be a reliable support network and more cases of social isolation (EPA, 2016; Klinenberg, 2003, p. 80-82; Smith, 2013, p. 271; Tierney, 2014, p. 236), risk perceptions were not significantly higher among subpopulations with a higher proportion of vacant homes. This could partly be due to error within the American Community Survey dataset. While there may be significant uncertainties associated with an individual ACS tract-level estimate, on average, this uncertainty appears to be attenuated across the contiguous United States. However, this limitation may also indicate that this variable was misclassified when it should have been a community-level sensitivity factor. Further research examining the efficacy of community-level adaptive capacity measures and their effect on risk perception is necessary. Because this study was primarily concerned with investigating the influence of vulnerability factors on risk perception, many adaptive capacity factors at both the individual and community-levels were unavailable and should be examined in future studies. These include: access to affordable air conditioning, duration of outdoor activity, involuntary degrees of exposure, likelihood of engaging in protective behavior, awareness of risk communication programs.

The Exposure Model results revealed that personal experience with heat conditions measured via climatological and meteorological variables at 800 m spatial resolution were found to have statistically significant positive influences on heat risk perception. However, in the Adaptive Capacity Model, no variables concerning personal experience inside an active NWS heat alert area improved the fit of the model. Recent experience with heat was found to influence risk perceptions, but being geographically situated in an alert area was not. NWS risk communication products should be expected to increase risk perception. However, results indicate that the current hazard alert system does not tend to increase extreme heat risk perception across the contiguous United States. This finding may have serious implications for the design of the National Weather Service's weather-related hazard risk communication product system—particularly as temperatures observed during extreme heat events are projected to increase at a greater rate than average temperatures over the coming years (Vose *et al.,* 2017), making preventable loss mitigation a top priority for many weather forecast offices (WFOs).

There may be a geographical explanation for the NWS risk communication products' apparent lack of influence on public risk perception. Firstly, simple proximity to or presence within a Watch, Warning or Advisory alert area does not necessarily translate into awareness of the risk message. The apparent lack of effect of WWAs on risk perception could simply be due to lack of awareness of the alerts. This, in turn, could be related to the mode or media in which these communication products are disseminated by the NWS. Secondly, in most cases, NWS weather forecast offices issue WWAs to specific subpopulations within administrative area boundaries (such as counties) whereas the actual meteorological patterns provoking biophysical exposure are highly variable over space and time—even at the individual-level—and recorded as gridded data. Consequently, there are many difficulties in defining alert areas that are capable of appropriately aggregating and issuing warnings with consistent accuracy ahead of highly localized weather patterns—chiefly, the modifiable areal unit problem (Openshaw, 1984).

Arbitrary political boundaries used to define WWA alert areas and unstandardized issuance parameters methods unique to each WFO for declaring either a Watch, Warning or Advisory may help explain limited correlation between local extreme temperatures and issuance of WWA alert (Hawkins *et al.,* 2017). This may, in turn, lead to "alert fatigue" (also known as "warning fatigue"), a condition in which members of the public become overwhelmed by the number of alerts or warnings and then become desensitized which can then lead to important hazard warnings being ignored or missed in the future or lead to delayed response times (Sendelbach and Funk, 2013). Warning fatigue can negatively impact the public's trust in WFOs and decrease the perceived credibility of hazard alert products issued during future scenarios—especially when warnings are issued but individuals are not affected (Dillon *et al.,* 2014; Mackie, 2013). Although the old adage, "better safe than sorry," may be true in most environmental hazard scenarios, more research is required to find the balance between a sufficient number of extreme heat alerts and the point of saturation across county watch areas (CWAs).

Public skepticism of WWAs may not help reduce extreme heat impacts going forward, especially if current WFO issuance thresholds remain the same despite rising temperatures and the frequency of extreme heat events. A recent NWS white paper (Hawkins *et al.,* 2017) summarizes the results of an internal survey conducted across all 122 WFOs inquiring about what is working and what is not with the current extreme heat event alert system. The results of this survey highlight system-wide issues that may affect WWA product impact on risk perception—chiefly, the inconsistent manner in which local NWS offices issue alerts across the CONUS. Sixty-four percent of WFOs reported confusion related to inconsistencies in their extreme heat warning system (Hawkins *et al.,* 2017, p. 9-11). Additionally, Hawkins and colleagues acknowledge there are geographical limitations to the current system which likely contributing to inter-office and partner confusion: static issuance criteria for urban and rural populations situated within or across CWA borders despite substantively different microclimatic conditions, extreme population differences between CWAs sharing common borders, and WFO territories occasionally encompassing multiple CWAs are (Hawkins *et al.,* 2017, p. 11).

Hawkins and colleagues report some WFO decision-makers are considering revising their current extreme heat alert systems to address these issues. Specifically, the authors acknowledge a growing internal consensus around the need to address the inherently top-down, "one size fits all" nature of current government methods for warning of extreme heat events and discuss the need to examine potential locally-developed approaches (Hawkins *et al.,* 2017). Presently, 70% of WFOs have multiple classifications for heat alerts (e.g., Heat Watch, Heat Warning), while the remaining WFOs only issue one alert classification. Many offices report "confusion and frustration from inconsistency" related to the definition of these different classifications (Hawkins *et al.,* 2017, p. 9). As previously mentioned, the NWS still primarily relies upon the Heat Index for issuing heat-related alerts (45% of WFOs), but many WFOs are experimenting with developing their own local issuance criteria to overcome the static limitations of the Heat Index (Hawkins *et al.,* 2017). For example, novel measures of extreme heat event frequency, such as the Warm Spell Duration Index developed by Zhang and colleagues (2011), and severity, such as the Heat Wave Magnitude Index developed by Russo and colleagues (2014), may provide more reliable estimates of the potential impact of extreme heat events to local subpopulations (Vose *et al.,* 2017). NWS risk communication products' lack of influence on risk perception may well be related to any number of issues Hawkins and colleagues report.

The findings of this study have serious implications for NWS hazard risk communication product system design. 49% of WFOs surveyed have revised their issuance procedures and developed local, context-specific criteria for issuing EHE alerts (Hawkins *et al.,* 2017). These revisions are aimed at increasing the relevance of heat-related alerts to their respective WFA subpopulations, which would increase risk perception. Hawkins and colleagues acknowledge difficulties in defining target audiences as well as in examining the effectiveness of their risk communications (2017, p. 9-12). As WFOs contemplate revising their current warning systems to address these issues, risk perception data can help guide them. Additional research should be conducted to evaluate the effect of these WFO changes on their respective WFA subpopulation's risk perception estimates. Future research should be conducted to investigate how the findings of this study can be explained and situated in the proper context.

Careful work was conducted to create a rich multidimensional, space-time-explicit dataset for the warm months of 2015 by compiling empirical response data alongside locally relevant NWS alert data, meteorological data and climatological data. The methods and procedures developed to generate this dataset are detailed in this study and could be adapted to serve future research objectives related to risk perception, exposure patterns, and government alert issuance parameters. More research should be conducted to examine the relationship between forecasted weather conditions, WWA alert issuance, actual observed weather conditions, and individual awareness of these factors. Evidence suggests that additional research could be conducted to examine if

WWA alerts tend not to alarm the populace or motivate it, and measure how engaged the population is with these early warning systems. Research opportunities exist here for communication scholars.

Risk communication strategies are necessarily space-time–specific. The effectiveness of hazard alerts and their geographic boundaries have real impacts confronted by first responders—health and human service professionals, hospitals, city managers, and emergency response units—and institutions who have their own boundaries or jurisdictions, sometimes encompassing multiple CWA sections. Imminent threats result in warnings aimed at producing appropriate emergency responses, whereas long-term hazard threats lead to the development of hazard-awareness programs, aimed at producing long-term hazard adjustments, thereby increasing adaptive capacity (Lindell *et al.,* 2006, p. 85). It is essential that NWS alerts are maximally effective in their ability to issue timely, reliable, and relevant hazard information to their local areas in a consistent and clear manner. Extreme heat risk perception data can be used to enhance adaptive capacity in many ways: to improve extreme heat vulnerability indices, map at-risk populations, complement traditional technical risk assessments, and help communicators like WFOs to better tailor their alert products to those who need them most. The results of this study indicate that while, statistically, many vulnerable subpopulations tend to understand themselves to be at greater risk, the risk perceptions of some subpopulations are lower than would be expected (or desired) given their observed history of susceptibility to extreme heat risk. This is important because "If the public does not perceive a hazard to affect them personally, they are unlikely to take any personal measures to prepare or mitigate for that hazard" (FEMA, 2017, p. 12). Only by examining the components of risk and understanding how they collectively contribute to the negative impacts of extreme heat can holistic risk reduction plans be formed. Risk perception data can and should play an invaluable role in helping to inform this process.

CHAPTER 6

CONCLUSION

In 2001, Gilbert White and colleagues observed that humankind is reaching the point of "knowing better" while simultaneously "losing even more" in an assessment of the use, misuse, and disuse of knowledge in the hazards management arena, which cited increases in estimated losses and published knowledge. To address this issue and ensure a less hazardous future environment, he and his colleagues argued for a cultural and academic shift towards a greater appreciation of contextual risk factors (through both remote sensing data, historical observations, and human data); a greater effort to translate study results into real, measurable good on behalf of more peoples; and most importantly, shifting towards an understanding of "natural disasters" not as "natural" but dependent largely upon human exposure and sensitivity factors (White *et al.,* 2001). Now, 15 years later, many exciting advances in remote sensing and geographic information science (GISc) have been achieved and implemented, allowing more researchers access to more data and to a more complete understanding of Earth's myriad interconnected systems. We know that extreme heat events are becoming more frequent and severe (EPA, 2016; IPCC, 2014; NWS, 2015; Mora *et al.,* 2017; Vose *et al.,* 2017). We also know that human activity contributes to this reality (Angelil *et al.,* 2017; Dole *et al.,* 2014; Hoerling *et al.,* 2013; Jeon *et al.,* 2016; Knutson *et al.,* 2013; Rupp *et al.,* 2012). Human and physical systems cannot be unraveled when assessing hazards risk—their intertwined nature is at the core of hazards research. Examining this relationship in the context of extreme heat risk perception across the contiguous United States requires an interdisciplinary approach using mixed methods and multidisciplinary datasets.

Natural hazards have highly variable impacts as a result of dynamic space-time patterns of exposure, their interaction with complex individual-level human sensitivity factors, and the adaptive capacity of the exposed populations. The magnitude and scope of extreme heat impacts largely depends upon the vulnerability of the population—determined by physical exposure and human sensitivity factors. However, the risk associated with vulnerability to extreme heat can be reduced by adaptive capacity factors, particularly as heat mortality is often preventable if appropriate actions are taken. Negative impacts from many hazards can be mitigated through community resilience—namely, effective hazard alert systems. By understanding the distribution of extreme heat vulnerability, risk can be attenuated during the process of building adaptive capacity—by enhancing risk communication methods, reducing socioeconomic inequality to strengthen community resilience, or by allocating emergency resources to the most vulnerable subpopulations. This approach to loss reduction is especially important for mitigating weather-related natural hazard risk because it is probably going to be easier for us to reduce the influence of sensitivity factors and augment adaptive capacity than it is for us to reduce exposure by "fixing" the weather, "fixing" urban sprawl, or "fixing" climate change. The risk associated with the rising frequency and magnitude of extreme heat exposure is unlikely to be completely mitigated, even under the most favorable emissions scenarios (Mora *et al.,* 2017).

Decision makers need locally-relevant information about the distribution of any potential negative impacts to inform mitigation and risk reduction strategies. Different hazard exposure levels affect different individuals in different ways at different times in different places, depending upon the different decisions that they make. Seeking to meet this need, a variety of methods have been developed to downscale vulnerability estimates —for exposure factors (Hawkins *et al.,* 2017; Mora *et al.,* 2017; NLDAS, 2017; Russo *et al.,* 2014; Vose *et al.,* 2017; Weber *et al.,* 2015; Zhang *et al.,* 2011) and sensitivity factors (Anderson and Bell, 2009, 2011; Buscail *et al.,* 2012; Cutter *et al.,* 2003; Harlan *et al.,* 2006, 2013; Johnson *et al.,* 2012; Medina-Ramon *et al.,* 2006; Melillo *et al.,* 2014; Reid *et al.,* 2009, 2012; Semenza *et al.,* 1996; Weber *et al.,* 2015; Wolf and McGregor, 2013) alike—from national models to finer regional and local scales. However, mitigation and risk reduction strategies must also account for a host of complex individual-level social factors related to hazard awareness, risk judgement, and subsequent decision-making behaviors at sub-national levels (Howe *et al.,* 2015). Traditional risk assessment typically lacks data on risk perception and human behavior—both of which are important determinants of disaster impact. This is important because the decision to take action and engage in mitigation or risk reduction activities at both the individual-level and community-level is greatly influenced by individual beliefs, attitudes and risk perceptions (California Governor’s Office of Emergency Services, 2001, p. 10; FEMA, 2017; Howe *et al.,* 2015; Lindell *et al.,* 2006, p. 86). These determinants of protective action are in turn influenced by factors such as personal circumstances, environmental context, and community resilience. Quantitative risk perception data detailing how different people perceive different levels of risk at different times in different places helps to fill this gap.

This study delivers risk perception estimates across the contiguous United States and evaluates the influence of critical natural exposure variables and human sensitivity and adaptive capacity factors at both individual and contextual levels. Additionally, this thesis details interdisciplinary research methods that could be adapted to examine the individual and contextual-level determinants of risk perception and hazards vulnerability at multiple geographic scales. Mitigation and risk reduction decisions are made by or on the behalf of different subpopulations that experience unique circumstances at different spatial scales (e.g., tract, county, or state-level) —so it is necessary to have reliable vulnerability information specific to the appropriate level of decision-making. The creation of reliable, locally relevant data on public heat risk perception is necessary in order for decision makers and scientists to more comprehensively assess actual extreme heat risk for different subpopulations and evaluate which mitigation and adaptation strategies might be most effective in those communities.

Whereas national vulnerability statistics cannot reveal sizeable differences in risk perception estimates between states or demographic groups, this study utilizes empirical United States-nationally representative survey data and multilevel regression techniques to estimate extreme heat risk perception for at-risk subpopulations at scales more relevant to local decision makers. For example, Missourians and Indianans gauge heat risk to be far higher than Coloradans and West Virginians. Extreme heat risk perception exhibits substantive, non-random patterns of geographic variation across the contiguous United States that appear to be strongly influenced by a combination of both individual-level sensitivity factors, contextual-level exposure factors, and personal experience with extreme heat—many of which were previously-untested.

Ideally, risk perception mirrors reality. However, this is often not the case (Kasperson *et al.*, 1988). In these circumstances, “Failure to correct risk perception could result in misguided or improper prioritization of risk, such that lower risks are given greater resources than more important risks where resources could have made a greater impact on risk reduction" (FEMA, 2017, p. 13). Low risk perception increases vulnerability because people do not respond to the hazards they do not perceive. In other words, what we believe to be real is real in its consequences and shapes our behavior—reactively or proactively. Low risk perception among at-risk subpopulations is especially worrisome and must be addressed in order to reduce loss. When vulnerable subpopulations, such as the elderly, do not perceive themselves to be at greater risk from extreme heat, this presents barriers to bringing them into the risk reduction process and effectively communicating the hazard. Estimating risk perception variation across different subpopulations gives us clues as to how these groups might be expected to behave in response to a hazard. Spatially-explicit risk perception data helps map misperception among vulnerable subpopulations, evaluate their unique circumstances, and develop more effective risk communication products at multiple scales.

Risk communication is key to reducing hazard risk. Effective risk communication strategies address irrational human behavior and decision-making that can exacerbate sensitivity factors or lead to greater exposure by promoting protective behavior at the individual and community-level. For example, the protective behaviors promoted by risk communication products might include acknowledging risk, avoiding unnecessary exposure, or developing personal heat-safety plans. The first steps in designing effective risk communication programs are identifying vulnerable subpopulations, studying their distribution, and evaluating their unique circumstances – risk perception data helps accomplish these goals (California Governor's Office of Emergency Services, 2001, p.

14). The development of more effective hazard alert systems is essential. Generally, government officials and their media outlets are charged with providing the general public with timely and reliable predictions of where and when heat waves will occur as well as with information concerning heat risk mitigation strategies they might seek to employ (Keller and DeVecchio, 2015, p. 319; Smith, 2013, p. 86-88). However, in order to develop more effective risk communication products, risk perceptions need to be understood first.

It is important to understand the space-time distribution of vulnerability factors and draw upon the contextual knowledge generated by risk perception studies before the risk communication process begins because the vaguer the information presented, the more likely it is to reinforce existing beliefs (FEMA, 2017, p. 8; Slovic *et al.,* 1979). These risk communication strategies would be enhanced if locally-relevant, space-time-specific vulnerability data were accessible. The spatial distribution of extreme heat risk in different local contexts is likely to change over time due to the dynamic nature of sensitivity and exposure factors; and therefore, vulnerability maps should be updated periodically (Reid *et al.,* 2012). Quantitative knowledge of the directionality and effect of vulnerability factors on risk perception, such as those examined in this study, can better equip policymakers, government officials, and risk managers with the information they need to cater local emergency services to the most vulnerable populations, with the goal of minimizing future impacts on those most likely to be impacted negatively. This creation of contextualized vulnerability knowledge plays an essential role in empowering members of vulnerable communities to strengthen resilience and is a necessary first step toward enabling policymakers to more effectively implement targeted strategies for risk reduction and communication.

The results of this study demonstrate that the relationship between the most important determinants of extreme heat risk and public risk perception generally reflects the degree and directionality of effect documented in expert risk assessments. Risk perception data also highlights subpopulations that tend to misperceive risk. The contextualized vulnerability knowledge generated by representative risk perception data also reveals local-level metrics that decision-makers can use to better tailor their hazard impact mitigation strategies and improve local adaptive capacity—for example, to elderly and less educated individuals who tend to misperceive extreme heat risk. Studying the landscapes of beliefs and values as well as how past experiences and socio-environmental contexts might influence future action can and should inform policy as well as our understanding of dynamic vulnerability at a range of temporal and spatial scales.

Extreme heat risk is rising across the contiguous United States, but total hazard risk can be reduced by targeted interventions aimed at strengthening adaptive capacity and addressing human vulnerability factors. In order to do this, researchers, risk managers, and community members will need to work together closely in order to enhance adaptive capacity and address vulnerability factors. Building networks, partnerships, and support systems will be required to achieve maximal risk reduction by exchanging and communicating information across group lines and reaching out to build adaptive capacity. This highlights the need for data compatibility—a strength of using quantitative risk perception data that is both space-time-explicit and representative of the national population. This study details an interdisciplinary approach for generating unique subpopulations risk perception estimates that will be useful to decision-makers at multiple scales using novel mixed methods to integrate multidisciplinary datasets which reflect the inherent inseparability of human and physical systems in the risk production. Leveraging advances in both the natural and social sciences to develop a more holistic understanding of the drivers and distribution of extreme heat vulnerability across the contiguous United States is vital to minimizing future loss in the face of rising exposure levels.

REFERENCES

Abrahamson V, Wolf J, Lorenzoni I, Fenn B, Kovats S, Wilkinson P, Adger WN, Raine R. Perceptions of heat wave risks to health: Interview-based study of older people in London and Norwich, UK. Journal of Public Health, 2009; 31(1):119–126. doi:10.1093/pubmed/fdn102.

Adger WN. Vulnerability. Global Environmental Change, 2006; 16(3):268–81. doi:/10.1016/j.gloenvcha.2006.02.006.

Adger WN, Agrawala S, Mirza MM, Conde C, o'Brien K, Pulhin J, Pulwarty R, Smit B, Takahashi K. Assessment of adaptation practices, options, constraints and capacity. Climate Change, 2007; 717-43.

American community survey. United States Census Bureau, 2017. Available at: http://ftp2.census.gov. Accessed on July 2017.

Anderson AA, Myers TA, Maibach E, Cullen H, Gandy J, Witte J, Stenhouse N, Leiserowitz A. If they like you, they learn from you: How a brief weathercaster-delivered climate education segment is moderated by viewer evaluations of the weathercaster. Weather, Climate, and Society, 2013; 5(4):367–77. doi:10.1175/WCAS-D-12-00051.1.

Anderson GB, Bell ML. Weather-related mortality. Epidemiology, 2009; 20(2):205–13. doi:10.1097/EDE.0b013e318190ee08.

Anderson GB, Bell ML. Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. Environmental Health Perspectives, 2011; 119:210–8. doi:10.1289/ehp.1002313.

Angelil O, Stone D, Wehner M, Paciorek CJ, Krishnan H, Collins W. An independent assessment of anthropogenic attribution statements for recent extreme temperature and rainfall events. Journal of Climate, 2017; 30:5-16.

Åström DO, Bertil F, Joacim R. Heat wave impact on morbidity and mortality in the elderly population: A review of recent studies. Maturitas, 2011; 69(2):99–105.

Barr DJ, Levy R, Scheepers C, Tily HJ. Random effects structure for confirmatory hypothesis testing: Keep it maximal. Journal of Memory and Language, 2013; 68(3):255–78. doi: 10.1016/j.jml.2012.11.001.

Basu R. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environmental Health, 2009; 8(40). doi:10.1186/1476-069X-8-40.

Basu R, Ostro BD. A multicounty analysis identifying the populations vulnerable to mortality associated with high ambient temperature in California. American Journal of Epidemiology, 2008; 168(6):632–37. doi:10.1093/aje/kwn170.

Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. Journal of Statistical Software, 2015; 67(1):1–48. doi:10.18637/jss.v067.i01

Bivand R, Hauke J, Kossowski T. Computing the Jacobian in Gaussian spatial autoregressive models: An illustrated comparison of available methods. Geographic Analysis, 2013; 45(2):150-79.

Bivand R, Piras G. Comparing implementations of estimation methods for spatial econometrics. Journal of Statistical Software, 2015; 63(18).

Bivand RS, Pebesma EJ, Gómez-Rubio V. Applied Spatial Data Analysis with R. New York: Springer, 2008.

Bliese PD, Ployhart RE. Growth modeling using random coefficient models: model building, testing, and illustrations. Organizational Research Methods, 2002; 5(4):362–87. doi: 10.1177/109442802237116.

Bobb JF, Peng RD, Bell ML, Dominici F. Heat-related mortality and adaptation to heat in the United States. Environmental Health Perspectives, 2014; 122(8):811–6. doi:10.1289/ehp.1307392.

Bubeck P, Botzen WJW, Aerts JCJH. A review of risk perceptions and other factors that influence flood mitigation behavior. Risk Analysis, 2012; 32(9):1481–95. doi:10.1111/j.1539-6924.2011.01783.x.

Burse RL. Sex differences in human thermoregulatory response to heat and cold stress. Human Factors, 1979; 21(6):687–99.

Buscail C, Upegui E, Viel J-F. Mapping heatwave health risk at the community level for public health action. International Journal of Health Geographics, 2012; 11(38). doi:10.1186/1476-072X-11-38.

California Governor's Office of Emergency Services. Risk Communication Guide for State and Local Agencies. State of California, 2001.

Canoui-Poitrine F, Cadot E, Spira A. Excess deaths during the August 2003 heat wave in Paris, France. Revue d'epidemiologie et de sante publique, 2006; 54(2):127-35.

Cardona OD, van Aalst MK, Birkmann J, Fordham M, McGregor G, Perez R, Pulwarty RS, Schipper ELF, Sinh BT. Determinants of risk: exposure and vulnerability. Pp. 65-108 in Field CB, Barros V, Stocker TF, Qin D, Dokken DJ, Ebi KL, Mastrandrea MD, Mach KJ, Plattner G-K, Allen SK, Tignor M, Midgley PM (eds). Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge (UK) and New York (US): Cambridge University Press; 2012.

CDC. Climate Change and Extreme Heat: What You Can Do to Prepare. Report No.: 430-R-16-061. Washington, DC: United States Environmental Protection Agency, 2016. Available at: https://www.cdc.gov/climateandhealth/pubs/extreme-heat-guidebook.pdf.

Chowdhury PD, Haque CE, Driedger SM. Public versus expert knowledge and perception of climate change-induced heat wave risk: A modified mental model approach. Journal of Risk Research, 2011; 15(2):149–68. doi: 10.1080/13669877.2011.601319.

CIESIN. 1000-kilometer gridded population density estimates. Center for International Earth Science Information Network at Columbia University, 2005.

Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J. A place-based model for understanding community resilience to natural disasters. Global Environmental Change, 2008; 18(4):598–606.

Cutter SL, Boruff BJ, Shirley WL. Social vulnerability to environmental hazards. Social Science Quarterly, 2003; 84(2):242–61.

Dillon RL, Tinsley CH, Burns WJ. Near-misses and future disaster preparedness. Risk Analysis, 2014; 34(10):1907–22.

Dole R, Hoerling M, Kumar A, Eischeid J, Perlwitz J, Quan XW, Kiladis G, Webb R, Murray D, Chen M, Wolter K, Zhang T. The making of an extreme event: Putting the pieces together. Bulletin of the American Meteorological Society, 2014; 95:427–40.

EPA. Excessive Heat Events Guidebook. Report No.:430-B-16-001. Washington, DC: United States Environmental Protection Agency; 2016. Available at: https://www.epa.gov/sites/production/files/2016-03/documents/eheguide_final.pdf.

FEMA. Comparative Emergency Management Training. Session 10: Risk Perception. Washington (DC): United States Federal Emergency Management Agency; 2017. Available at: https://training.fema.gov/hiedu/docs/cem.

Gelman A, Hill J. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge: Cambridge University Press, 2007.

Gill JC, Malamud BD. Reviewing and visualizing the interactions of natural hazards. Reviews of Geophysics, 2014; 52(4):680–722. doi:10.1002/2013RG000445.

Goldberger, AS. Best linear unbiased prediction in the generalized linear regression model. Journal of the American Statistical Association, 1962; 57(298):369–75.

Gronlund CJ. Racial and socioeconomic disparities in heat-related health effects and their mechanisms: A review. Current Epidemiology Reports, 2014; 1(9):165–73. doi:10.1007/s40471-014-0014-4.

Gronlund CJ, Zanobetti A, Schwartz JD, Wellenius GA, O'Neill MS. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992–2006. Environtal Health Perspectives, 2014; 122(11):1187–92. doi:10.1289/ehp.1206132.

Gronlund CJ, Zanobetti A, Wellenius GA, Schwartz JD, O'Neill MS. Vulnerability to renal, heat and respiratory hospitalizations during extreme heat among US elderly. Climate Change, 2016; 136(3–4);631–45. doi:10.1007/s10584-016-1638-9.

Grothmann T, Patt A. Adaptive capacity and human cognition: The process of individual adaptation to climate change. Global Environmental Change, 2005; 15(3):199–213. doi:10.1016/j.gloenvcha.2005.01.002.

Grothmann T, Reusswig F. People at risk of flooding: Why some residents take precautionary action while others do not. Natural Hazards, 2006; 38(1–2):101–20. doi:10.1007/s11069-005-8604-6.

Hall JE. Guyton and Hall Textbook of Medical Physiology, 13th ed. Philadelphia: Elsevier Health Sciences, 2015.

Harlan SL, Brazel AJ, Prashad L, Stefanov WL, Larsen L. Neighborhood microclimates and vulnerability to heat stress. Social Science and Medicine, 2006; 63(11):2847–63. doi:10.1016/j.socscimed.2006.07.030.

Harlan SL, Chowell G, Yang S, Petitti DB, Morales Butler EJ, Ruddell BL, Ruddell DM. Heat-related deaths in hot cities: Estimates of human tolerance to high temperature thresholds. International Journal of Environmental Research and Public Health, 2014; 11(3):3304–26. doi:10.3390/ijerph110303304.

Harlan SL, Declet-Barreto JH, Stefanov WL, Petitti DB. Neighborhood effects on heat deaths: Social and environmental predictors of vulnerability in Maricopa County, Arizona. Environmental Health Perspectives, 2013; 121(2):197–204. doi:10.1289/ehp.1104625.

Harris JA, Benedict FG. A biometric study of human basal metabolism. Proceedings of the National Academy of Sciences, 1918; 4(12):370–3.

Hawkins MD, Brown V, Ferrell J. Assessment of NOAA national weather service methods to warn for extreme heat events. Weather, Climate, and Society, 2017; 9(1):5–13. doi:10.1175/WCAS-D-15-0037.1.

Hoerling M, Chen M, Dole R, Eischeid J, Kumar A, Nielsen-Gammon JW, Pegion P, Perlwitz J, Quan XW, Zhang T. Anatomy of an extreme event. Journal of Climatology, 2013; 26: 2811–32.

Hofmann DA. An overview of the logic and rationale of hierarchical linear models. Journal of Management, 1997; 23(6):721–827. doi:10.1177/014920639702300602.

Hogarth RM, Einhorn HJ. Order effects in belief updating: The belief-adjustment model. Cognitive Psychcology, 1992; 24(1):1–55.

Howe PD. Hurricane preparedness as anticipatory adaptation: A case study of community businesses. Global Environmental Change, 2011; 21(2):711–20.

Howe PD, Leiserowitz A. Who remembers a hot summer or a cold winter? The asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the U.S. Global Environmental Change, 2013; 23(6):1488–500. doi:10.1016/j.gloenvcha.2013.09.014.

Howe PD, Markowitz EM, Lee TM, Ko C-Y, Leiserowitz A. Global perceptions of local temperature change. Nature Climate Change, 2013; 3:352–6. doi:10.1038/nclimate1768.

Howe PD, Mildenberger M, Marlon JR, Leiserowitz A. Geographic variation in opinions on climate change at state and local scales in the USA. Nature Climate Change, 2015; 5:596–603. doi:10.1038/nclimate2583.

IPCC. Summary for Policymakers. Pp. 1-32 in Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge (UK) and New York (US): Cambridge University Press; 2014.

Jeon S, Paciorek CJ, Wehner MF. Quantile-based bias correction and uncertainty quantification of extreme even attribution statements. Weather and Climate Extremes, 2016; 12: 24–32.

Jiang J. A derivation of BLUP—Best linear unbiased predictor. Statistics & Probability Letters, 1997; 32(3):321–4. doi: 10.1016/S0167-7152(96)00089-2.

Johnson DP, Stanforth A, Lulla V, Luber G. Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. Applied Geography, 2012; 35(1–2):23–31. doi:10.1016/j.apgeog.2012.04.006.

Johnson DP, Wilson JS, Luber GC. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. International Journal of Health Geographics, 2009; 8(57):1–13. doi:10.1186/1476-072X-8-57.

Jones B, O'Neill BC, McDaniel L, McGinnis S, Mearns LO, Tebaldi C. Future population exposure to US heat extremes. Nature Climate Change, 2015; 5:652–5. doi:10.1038/ nclimate2631.

Kalkstein A, Sheridan S. The social impacts of the heat–health watch/warning system in Phoenix, Arizona: Assessing the perceived risk and response of the public. International Journal of Biometeorology, 2007; 52(1):43–55. doi:10.1007/s00484-006-0073-4.

Kasperson RE, Renn O, Slovic P, Brown H, Emel J, Goble R, Kasperson J, Ratick S. The social amplication of risk: A conceptual framework. Risk Analysis, 1988; 8(2):177–187. doi:10.1111/j.1539-6924.1988.tb01168.x.

Kates RW. Natural hazard in human ecological perspective: Hypotheses and models. Economic Geography, 1971; 47(3):438–51. doi:10.2307/142820.

Keller E, DeVecchio D. Natural hazards: Earth's processes as hazards, disasters, and catastrophes, 4th rev. ed. Blodgett RH: Pearson Higher Education AU; 2015.

Kilbourne EM, Choi K, Jones TS, Thacker SB. Risk factors for heatstroke: A case-control study. Journal of the American Medical Association, 1982; 247(24):3332–6.

Klinenberg E. Heat wave: A social autopsy of disaster in Chicago. Chicago: University of Chicago Press; 2003.

Knutson TR, Zeng F, Wittenberg AT. The extreme March-May 2012 warm anomaly over the eastern United States: Global context and multimodel trend analysis. Bulletin of the American Meteorological Society, 2013; 94(4): S13–7.

Kovats RS, Hajat S. Heat stress and public health: A critical review. Annual Review of Public Health, 2008; 29:41–55. doi:10.1146/annurev.publhealth.29.020907.090843.

Lehner F, Stocker TF. From local perception to global perspective. Natural Climate Change, 2015; 5(8):731–734.

Leiserowitz AA. Climate change risk perception and policy preferences: The role of affect, imagery, and values. Climate Change, 2006; 77(1–2):45–72. doi:10.1007/s10584-006-9059-9.

Li D, Bou-Zeid E. Synergistic interactions between urban heat islands and heat waves: The impact in cities is larger than the sum of its parts*. Journal of Applied Meteorology and Climatology, 2013; 52(9):2051–64. doi:10.1175/JAMC-D-13-02.1.

Lindell MK, Perry RW, Prater C, Nicholson WC. Fundamentals of Emergency Management. Washington, DC: Wiley; 2006.

Liss A, Wu R, Chui KKH, Naumova EN. Heat-related hospitalizations in older adults: An amplified effect of the first seasonal heatwave. Scientific Reports, 2017; 7:39581. doi:10.1038/srep39581.

Mackie B. Warning fatigue–myth or misunderstanding: Insights from the Australian bushfires. Canadian Risks and Hazards Network, 2013; 5(1), 51–5.

Mackowiak PA, Wasserman SS, Levine MM. A critical appraisal of 98.6 F, the upper limit of the normal body temperature, and other legacies of Carl Reinhold August Wunderlich. Journal of the American Medical Association, 1992; 268(12):1578–80.

Masato G, Bone A, Charlton-Perez A, Cavany S, Neal R, Dankers R, Dacre H, Carmichael K, Murray V. Improving the health forecasting alert system for cold weather and heat-waves in England: A proof-of-concept using temperature-mortality relationships. PloS One, 2015; 10(10):p.e0137804.

Medina-Ramón M, Schwartz J. Temperature, temperature extremes, and mortality: A study of acclimatization and effect modification in 50 US cities. Occupational Environmental Medicine, 2007; 64(12):827–33. doi:10.1136/oem.2007.033175.

Medina-Ramón M, Zanobetti A, Cavanagh DP, Schwartz J. Extreme temperatures and mortality: Assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. Environmental Health Perspectives, 2006; 114(9):1331–6.

Melillo JM, Richmond TT, Yohe G. Climate Change Impacts in the United States. Third National Climate Assessment, 2014.

Mora C, Dousset B, Caldwell IR, Powell FE, Geronimo RC, Bielecki CR, Counsell CW, Dietrich BS, Johnston ET, Louis LV, Lucas MP. Global risk of deadly heat. Nature Climate Change, 2017; 7:501–6. doi:10.1038/nclimate3322.

National Land Cover Database, 2011. Multi-Resolution Land Characteristics Consortium. United States Geological Survey, 2011. Available at: https://www.mrlc.gov.

National Weather Service. Silver Spring (MO): National Oceanic and Atmospheric Administration, c2001. NWS: Heat Watches, Warnings, and Advisories, 2005. Available at: http://www.nws.noaa.gov/om/heat/ww.shtml. Accessed on 24 July 2017.

National Weather Service Hazards Alert Database. Ames: Iowa Environmental Mesonet, Iowa State University of Science and Technology, 2015. Available at: https://mesonet.agron.iastate.edu. Accessed on 5 July 2017.

Nitschke M, Hansen A, Bi P, Pisaniello D, Newbury J, Kitson A, Tucker G, Avery J, Dal Grande E. Risk factors, health effects and behaviour in older people during extreme heat: A survey in South Australia. International Journal of Environmental Research and Public Health, 2013; 10(12):6721–33. doi:10.3390/ijerph10126721.

NOAA National Centers for Environmental Information. State of the Climate: National Climate Report for 2015, 2016. Available at https://www.ncdc.noaa.gov/temp-and-precip/us-maps/. Accessed on 5 October 2015.

North America Land Data Assimilation System (NLDAS) Daily Air Temperatures and Heat Index. Centers for Disease Control and Prevention WONDER, 1979–2011, 2017. Available at: https://wonder.cdc.gov/nasa-nldas.html. Accessed on 24 July 2017.

Openshaw S. The Modifiable Areal Unit Problem. Concepts and Techniques in Modern Geography. Norwich, England: Geobooks, 1984.

Ortman JM, Velkoff VA, Hogan H. An Aging Nation: The Older Population in the United States. United States Census Bureau, Economics and Statistics Administration: US Department of Commerce, 2014.

Pepin N, Bradley R.S, Diaz HF, Baraër, M, Caceres EB, Forsythe N, Fowler H, Greenwood G, Hashmi MZ, Liu XD, Miller JR. Elevation-dependent warming in mountain regions of the world. Nature Climate Change, 2015; 5(5):424.

Pinheiro JC, Bates DM. Nonlinear Mixed-Effects Models. Pp. 273–304 in Mixed-Effects Models in S and S-PLUS, 1st ed. New York: Springer; 2000.

Planck M. Treatise on thermodynamics. OGG A, translator. London: Longmans, Green, and Co., 1903.

PRISM Climate Group. Corvallis: Oregon State University, PRISM Climate Group, 2015. Available at: http://prism.oregonstate.edu. Accessed on 5 July 2017.

Ratnam JV, Behera S, Ratna S, Rajeevan M, Yamagata T. Anatomy of Indian heatwaves. Scientific Reports, 2016; 6:24395. doi:10.1038/srep24395.

Rauber RM, Walsh JE, Charlevoix DJ. Severe and hazardous weather: An introduction to high impact meteorology, 4th rev. ed. Dubuque: Kendall Hunt Publishing Company, 2008.

Reid CE, Mann JK, Alfasso R, English PB, King GC, Lincoln RA, Margolis HG, Rubado DJ, Sabato JE, West NL, Woods B, Navarro KM, Balmes JR. Evaluation of a heat vulnerability index on abnormally hot days: An environmental public health tracking study. Environmental Health Perspectives, 2012; 120(5):715–20. doi:10.1289/ehp.1103766.

Reid CE, O'Neill MS, Gronlund CJ, Brines SJ, Brown DG, Diez-Roux AV, Schwartz J. Mapping community determinants of heat vulnerability. Environmental Health Perspectives, 2009; 117(11):1730–6. doi:10.1289/ehp.0900683.

Robine J-M, Cheung SLK, Le Roy S, Van Oyen H, Griffiths C, Michel J-P, Herrmann FR. Death toll exceeded 70,000 in Europe during the summer of 2003. Comptes Rendus Biologies, 2008; 331(2):171–8. doi:10.1016/j.crvi.2007.12.001.

Robinson GK. That BLUP is a good thing: The estimation of random effects. Statistical Science, 1991; 6(1):15–32.

Robinson PJ. On the definition of a heat wave. Journal of Applied Meteorology, 2001; 40:762–75. doi:10.1175/1520-0450(2001)040<0762:OTDOAH>2.0.CO;2.

Roza AM, Shizgal HM. The Harris Benedict equation reevaluated: Resting energy requirements and the body cell mass. American Journal of Clinical Nutrition, 1984; 40(1):168–82.

Rupp DE, Mote PW, Massey N, Rye CJ, Jones R, Allen MR. Did human influence on climate make the 2011 Texas drought more probable? Bulletin of the American Meteorological Society, 2012; 93:1052–4.

Russo SA, Dosio A, Graversen RG, Sillmann J, Carrao H, Dunbar MB, Singleton A, Montagna P, Barbola P, Vogt JV. Magnitude of extreme heat waves in present climate and their projection in a warming world. Journal of Geophysical Research: Atmospheres, 2014; 119:12,500–12.

Safi AS, Smith WJ Jr., Liu Z. Rural Nevada and climate change: Vulnerability, beliefs, and risk perception. Risk Analysis, 2012; 32(6):1041–59. doi: 10.1111/j.1539-6924.2012.01836.x.

Sampson NR, Gronlund CJ, Buxton MA, Catalano L, White-Newsome JL, Conlon KC, O'Neill MS, McCormick S, Parker EA. Staying cool in a changing climate: Reaching vulnerable populations during heat events. Global Environmental Change, 2013; 23(2):475–84. doi:10.1016/j.gloenvcha.2012.12.011.

Semenza JC, Rubin CH, Falter KH, Selanikio JD, Flanders WD, Howe HL, Wilhelm JL. Heat-related deaths during the July 1995 heat wave in Chicago. New England Journal of Medicine, 1996; 335(2):84–90. doi:10.1056/NEJM199607113350203.

Semenza JC, Wilson DJ, Parra J, Bontempo BD, Hart M, Sailor DJ, George LA. Public perception and behavior change in relationship to hot weather and air pollution. Environmental Research, 2008; 107(3):401–11. doi:10.1016/j.envres.2008.03.005.

Sendelbach S, Funk M. Alarm fatigue: A patient safety concern. AACN Advanced Critical Care, 2013; 24(4):378–386.

Shaposhnikov D, Revich B, Bellander T, Bedada GB, Bottai M, Kharkova T, Kvasha E, Lezina E, Lind T, Semutnikova A, Perhsagen G. Epidemiology, 2014; 25(3):359–364.

Sheridan SC. A survey of public perception and response to heat warnings across four North American cities: An evaluation of municipal effectiveness. International Journal of Biometeorology, 2007; 52(1):3–15. doi:10.1007/s00484-006-0052-9.

Slovic P, Fischhoff B, Lichtenstein S. Rating the risks. Environment: Science and Policy for Sustainable Development, 1979; 21(3):14–39.

Slovic P, Kunreuther H, White GF. Decision Processes, Rationality, and Adjustment to Natural Hazards. Pp. 1–31 in Slovic P (ed), The Perception of Risk. Sterling: Earthscan Publications; 2000.

Smith K. Environmental Hazards: Assessing Risk and Reducing Disaster, 6th rev. ed. New York: Routledge; 2013.

Smith N, Leiserowitz A. The role of emotion in global warming policy support and opposition. Risk Analysis, 2014; 34(5):937–48. doi:10.1111/risa.12140.

Smith TT, Zaitchik BF, Gohlke JM. Heat waves in the United States: Definitions, patterns and trends. Climate Change, 2013; 118(3–4):811–25. doi:10.1007/s10584-012-0659-2.

Stafoggia M, Forastiere F, Agostini D, Biggeri A, Bisanti L, Cadum E, Caranci N, de'Donato F, De Lisio S, De Maria M, Michelozzi P. Vulnerability to heat-related mortality: A multicity, population-based, case-crossover analysis. Epidemiology, 2006; 17(3):315–23. doi:10.1097/01.ede.0000208477.36665.34.

Sund-Levander M, Forsberg C, Wahren LK. Normal oral, rectal, tympanic and axillary body temperature in adult men and women: A systematic literature review. Scandinavian Journal of Caring Science, 2002; 16(2):122–8. doi: 10.1046/j.1471-6712.2002.00069.x.

Tan J, Zheng Y, Song G, Kalkstein LS, Kalkstein AJ, Tang X. Heat wave impacts on mortality in Shanghai, 1998 and 2003. International Journal of Biometeorology, 2007; 51(3):193–200. doi: 10.1007/s00484-006-0058-3.

Thomas WI, Thomas DS. The Child in America: Behavior Problems and Programs. New York: Knopf; 1928.

Tierney K. The social roots of risk: Producing disasters, promoting resilience. Redwood City: Stanford University Press; 2014.

Tobler, W. A computer movie simulating urban growth in the Detroit region. Economic Geography, 1970; 46:234–240

Tomlinson CJ, Chapman L, Thornes JE, Baker CJ. Including the urban heat island in spatial heat health risk assessment strategies: A case study for Birmingham, UK. International Journal of Health Geographics, 2011; 10:42.

Tversky A, Kahneman D. Availability: A heuristic for judging frequency and probability. Cognitive Psychology; 1973; 5(2):207–32. doi:10.1016/0010-0285(73)90033-9.

Tversky A, Kahneman D. Judgment under uncertainty: Heuristics and biases. Science, 1974; 185(4157):1124–31. doi:10.1126/science.185.4157.1124.

Uejio CK, Wilhelmi OV, Golden JS, Mills DM, Gulino SP, Samenow JP. Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. Health Place, 2011; 17(2):498–507. doi:10.1016/j.healthplace.2010.12.005.

Vose RS, Easterling DR, Kunkel KE, LeGrande AN, Wehner MF. Temperature Changes in the United States. Pp. 185–206 in Wuebbles DJ, Fahey DW, Hibbard KA, Dokken DJ, Stewart BC, Maycock TK (eds). Climate Science Special Report: Fourth National Climate Assessment, Vol. 1. Washington, DC: U.S. Global Change Research Program; 2017.

Wachinger G, Renn O, Begg C, Kuhlicke C. The risk perception paradox—Implications for governance and communication of natural hazards. Risk Analysis, 2013; 33(6)1049–65. doi:10.1111/j.1539-6924.2012.01942.x.

Weber S, Sadoff N, Zell E, de Sherbinin A. Policy-relevant indicators for mapping the vulnerability of urban populations to extreme heat events: A case study of Philadelphia. Applied Geography, 2015; 63:231–43.

Weinstein ND. Effects of personal experience on self-protective behavior. Psychology Bulletin, 1989; 105(1):31–50.

White GF, Kates RW, Burton I. Knowing better and losing even more: The use of knowledge in hazards management. Global Environmental Change. Part B: Environmental Hazards, 2001; 3(3–4):81–92. doi:10.1016/S1464-2867(01)00021-3.

White-Newsome JL, Ekwurzel B, Baer-Schultz M, Ebi KL, O'Neill MS, Anderson GB. Survey of county-level heat preparedness and response to the 2011 summer heat in 30 US states. Environmental Health Perspectives, 2014; 122(6):573–9.

Wilhelmi OV, Hayden MH. Connecting people and place: A new framework for reducing urban vulnerability to extreme heat. Environmental Research Letters, 2010; 5(1):014021. doi:10.1088/1748-9326/5/1/014021.

Winter B. Linear Models and Linear Mixed Effects Models in R with Linguistic Applications. arXiv:1308.5499. 2013. Available at: http://arxiv.org/pdf/1308.5499.pdf. Accessed on 5 July 2017.

Wolf J, Adger WN, Lorenzoni I. Heat waves and cold spells: An analysis of policy response and perceptions of vulnerable populations in the UK. Environment and Planning A, 2010; 42(11):2721–34. doi:10.1068/a42503.

Wolf T, McGregor G. The development of a heat wave vulnerability index for London, United Kingdom. Weather and Climate Extremes, 2013; 1:59–68. doi:10.1016/j.wace.2013.07.004.

Zhang X, Alexander L, Hegerl GC, Jones P, Tank AK, Peterson TC, Trewin B, Zwiers FW. Indices for monitoring changes in extremes based on daily temperature and precipitation data. Wiley Interdisciplinary Reviews: Climate Change, 2011; 2:851–870.

Zuur AF, Ieno EN, Elphick CS. A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution, 2010; 1(1):3–14. doi: 10.1111/j.2041-210X.2009.00001.x.

APPENDICES

APPENDIX A

SENSITIVITY MODELS

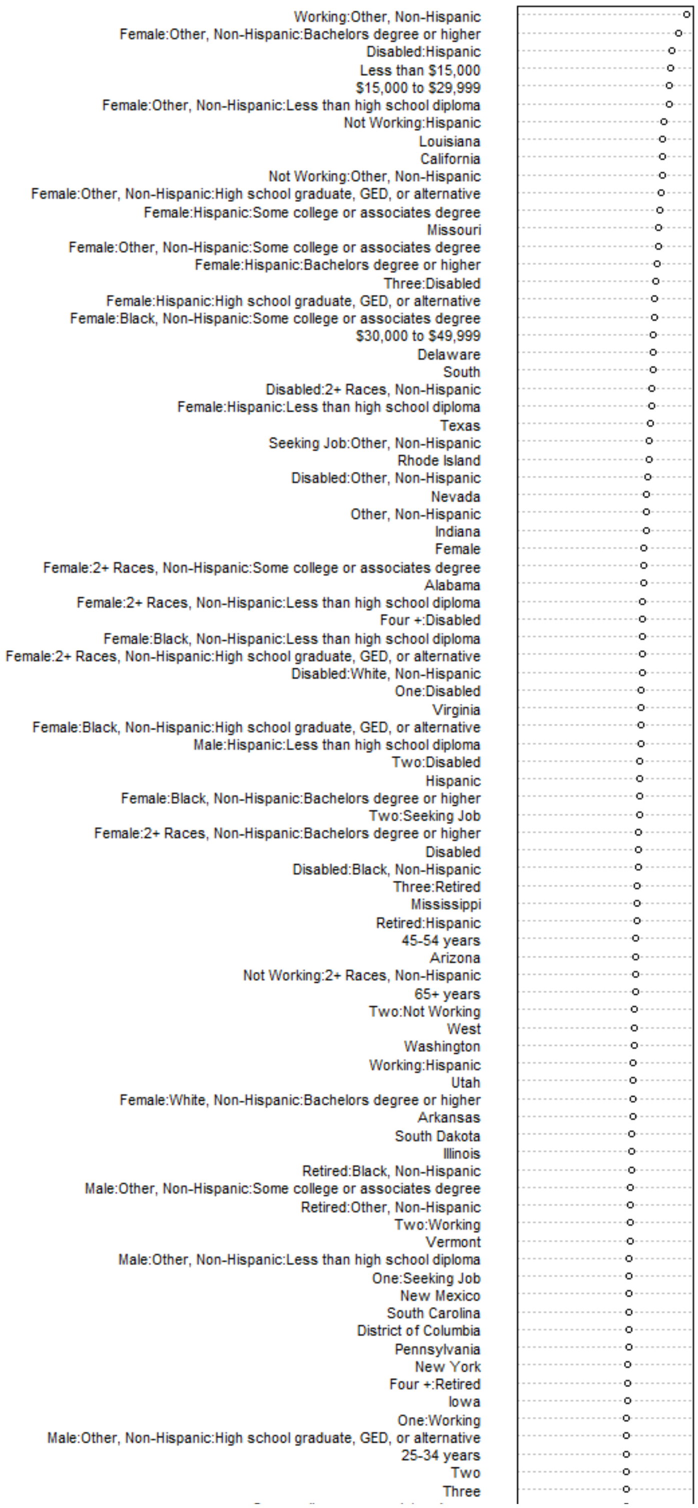


Fig. A.1. All BLUPs dotchart for Sensitivity Model, part 1.

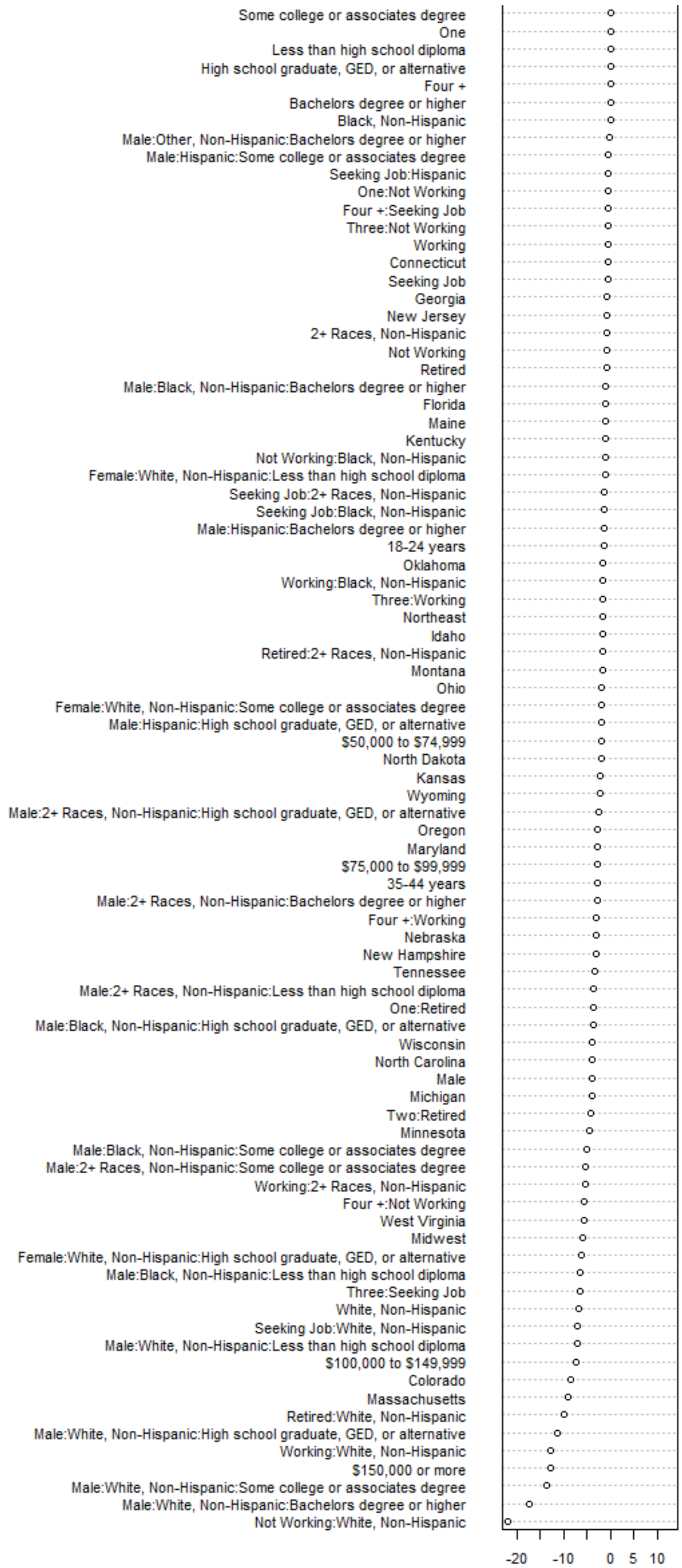


Fig. A.2. All BLUPs dotchart for Sensitivity Model, part 2.

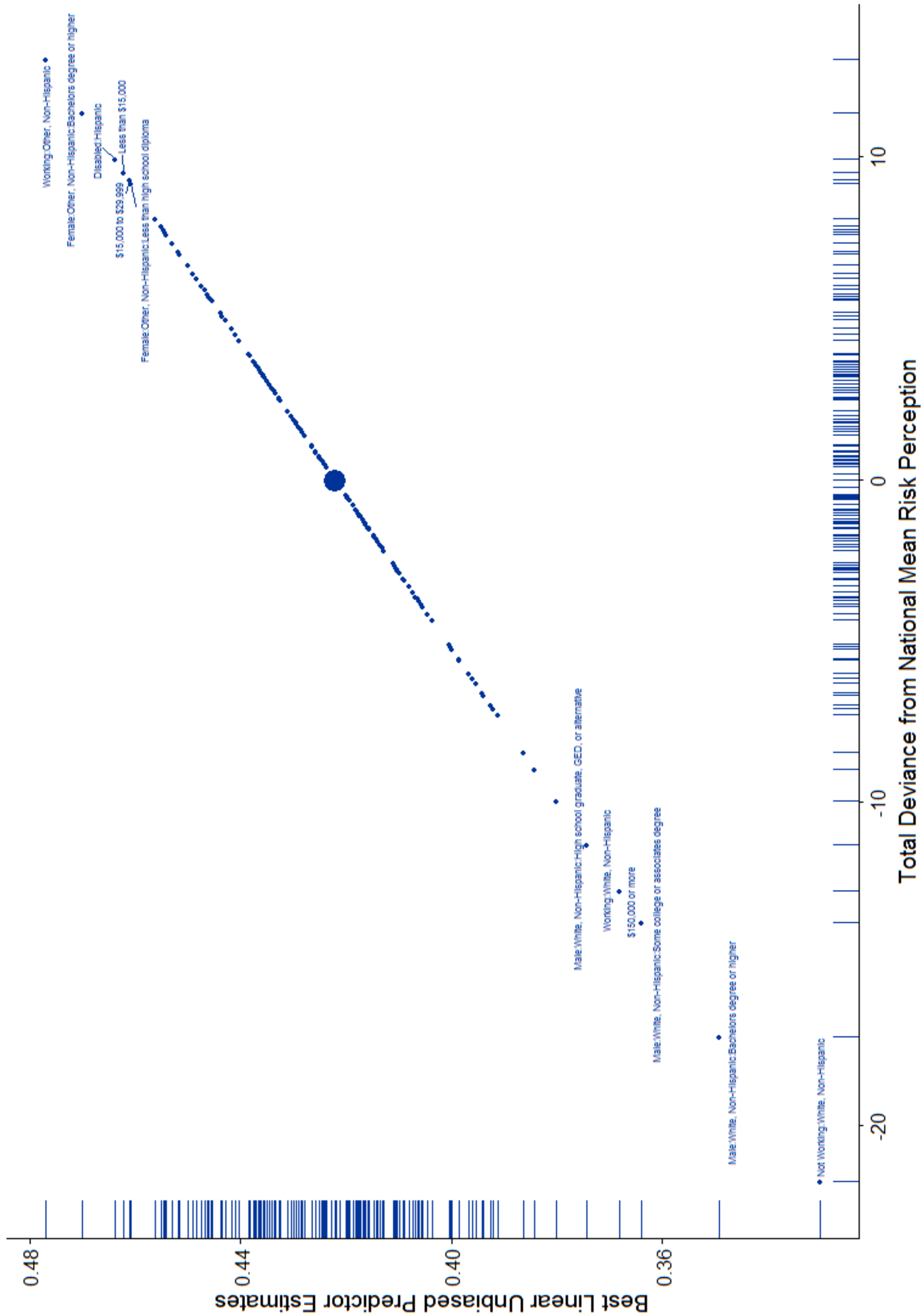


Fig. A.3. Random effect estimates for all subpopulations generated by the Sensitivity Model.

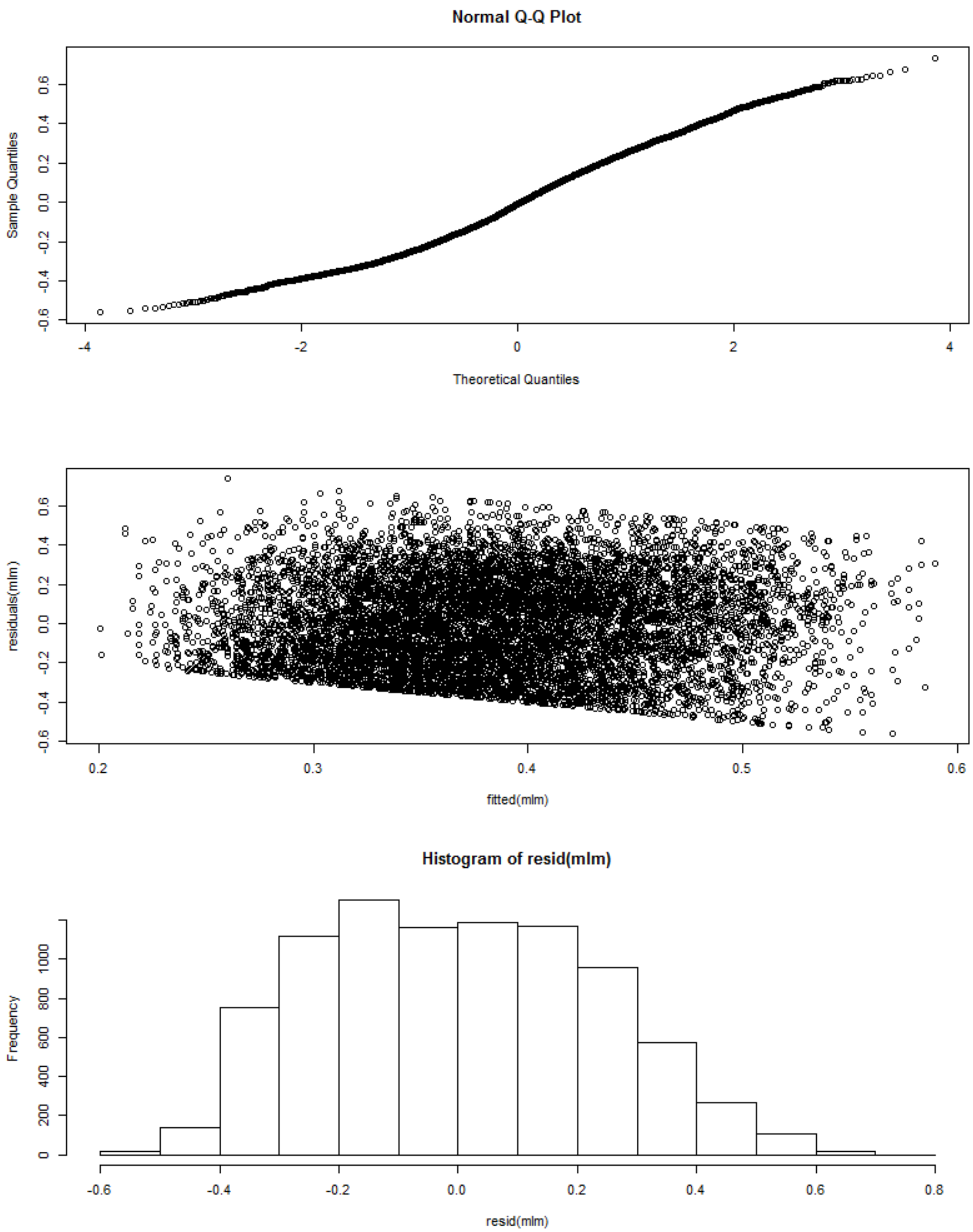


Fig. A.4. Diagnostic plots for Sensitivity Model.

APPENDIX B

EXPOSURE MODEL

Table B.I. Variance-Covariance Matrix for the Exposure Model

Predictor	(Intercept)	yday	CO.HI.daily.MaySep	TR.impervious.mean.log	TR.tree.mean.sqrt	TR.prism.tmean	TR.tmin.anom.mav7	I(popden/100)	Syday_Tmax	weekmeanb4survey_PRISM
(Intercept)	0.0245588393	-0.0000011107	-0.0003293004	-0.0000455956	0.0000086103	0.0002854858	-0.0000024838	-0.0000009752	-0.0000130558	-0.0000114978
yday	-0.0000011107	0.0000000038	0.0000000020	0.0000000002	-0.0000000022	-0.0000000116	-0.0000000278	0.0000000001	-0.0000000063	0.0000000191
CO.HI.daily.MaySep	-0.0003293004	0.0000000020	0.0000046516	0.0000004473	-0.0000005132	-0.0000043344	0.0000001225	0.0000000101	0.0000000897	0.0000000689
TR.impervious.mean.log	-0.0000455956	0.0000000002	0.0000004473	0.0000054493	0.0000017267	3.0500000000	-0.0000000340	-0.0000000488	0.0000001229	0.0000000255
TR.tree.mean.sqrt	0.0000086103	-0.0000000022	-0.0000005132	0.0000017267	0.0000039013	0.0000004799	0.0000000442	0.0000000338	0.0000001591	-0.0000000088
TR.prism.tmean	0.0002854858	-0.0000000116	-0.0000043344	-0.0000008809	0.0000004799	0.0000067758	0.0000000204	-0.0000000129	-0.0000010494	-0.0000002918
TR.tmin.anom.mav7	-0.0000024838	-0.0000000278	0.0000001225	-0.0000000340	0.0000000442	0.0000000204	0.0000021132	0.0000000018	0.0000000710	-0.0000002580
I(popden/100)	-0.0000009752	0.0000000001	0.0000000101	-0.0000000488	0.0000000338	-0.0000000129	0.0000000018	0.0000000094	0.0000000027	0.0000000023
Syday_Tmax	-0.0000130558	-0.0000000063	0.0000000897	0.0000001229	0.0000001591	-0.0000010494	0.0000000710	0.0000000027	0.0000011048	-0.0000001521
weekmeanb4survey_PRISM	-0.0000114978	0.0000000191	0.0000000689	0.0000000255	-0.0000000088	-0.0000002918	-0.0000002580	0.0000000023	-0.0000001521	0.0000004333

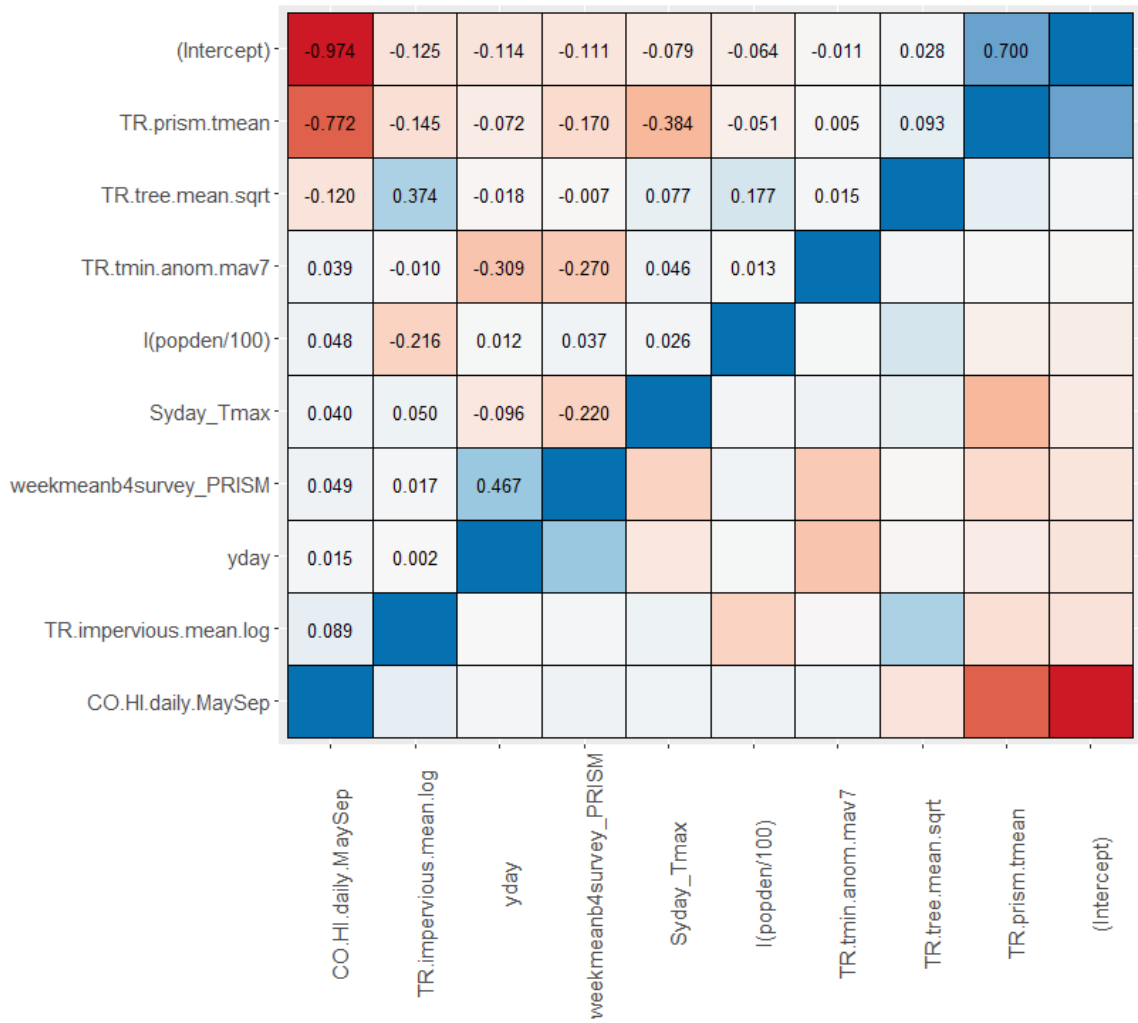


Fig. B.1. Fixed effects correlation matrix for Exposure Model.

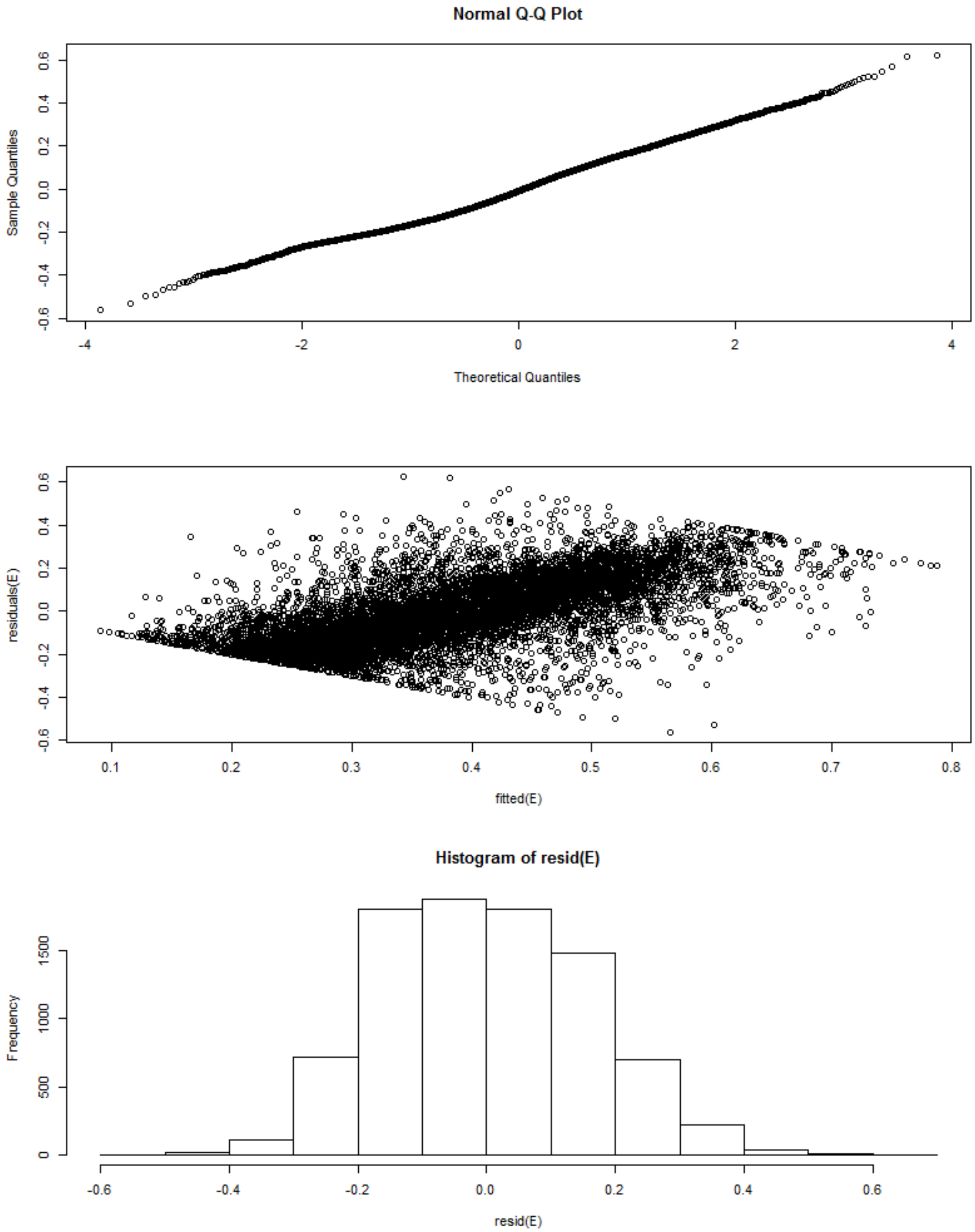


Fig. B.2. Diagnostic plots (qqplot, residuals, etc) for Sensitivity Model.

APPENDIX C

VULNERABILITY MODEL

Table C.I. Variance-Covariance Matrix for the Vulnerability Model

Predictor	(Intercept)	sexMale	yday	CO.HI.daily.MaySep	TR.impervious.mean.log	TR.tree.mean.sqrt	TR.prism.tmean	TR.tmin.anom.mav7	I(popden/100)	Syday_Tmax	weekmeanb4survey_PRISM
(Intercept)	0.0218676334	-0.0000581237	-0.0000010842	-0.0002847461	-0.0000434221	0.0000078916	0.0002515223	-0.0000025055	-0.0000009963	-0.0000141679	-0.0000115522
sexMale	-0.0000581237	0.0000958191	0.0000000002	0.0000001750	0.0000001355	-0.0000001216	-0.0000004337	-0.0000001520	-0.0000000143	0.0000001867	0.0000000358
yday	-0.0000010842	0.0000000002	0.0000000037	0.0000000021	0.0000000004	-0.0000000020	-0.0000000114	-0.0000000267	0.0000000001	-0.0000000060	0.0000000184
CO.HI.daily.MaySep	-0.0002847461	0.0000001750	0.0000000021	0.0000040214	0.0000003986	-0.0000004505	-0.0000038101	0.0000001225	0.0000000102	0.0000001107	0.0000000716
TR.impervious.mean.log	-0.0000434221	0.0000001355	0.0000000004	0.0000003986	0.0000052455	0.0000016012	-0.0000007911	-0.0000000314	-0.0000000443	0.0000001357	0.0000000259
TR.tree.mean.sqrt	0.0000078916	-0.0000001216	-0.0000000020	-0.0000004505	0.0000016012	0.0000035431	0.0000003305	0.0000000562	0.0000000300	0.0000001699	-0.0000000044
TR.prism.tmean	0.0002515223	-0.0000004337	-0.0000000114	-0.0000038101	-0.0000007911	0.0000003305	0.0000061090	0.0000000161	-0.0000000128	-0.0000010098	-0.0000002836
TR.tmin.anom.mav7	-0.0000025055	-0.0000001520	-0.0000000267	0.0000001225	-0.0000000314	0.0000000562	0.0000000161	0.0000020311	0.0000000017	0.0000000607	-0.0000002483
I(popden/100)	-0.0000009963	-0.0000000143	0.0000000001	0.0000000102	-0.0000000443	0.0000000300	-0.0000000128	0.0000000017	0.0000000087	0.0000000031	0.0000000023
Syday_Tmax	-0.0000141679	0.0000001867	-0.0000000060	0.0000001107	0.0000001357	0.0000001699	-0.0000010098	0.0000000607	0.0000000031	0.0000010321	-0.0000001461
weekmeanb4survey_PRISM	-0.0000115522	0.0000000358	0.0000000184	0.0000000716	0.0000000259	-0.0000000044	-0.0000002836	-0.0000002483	0.0000000023	-0.0000001461	0.0000004178

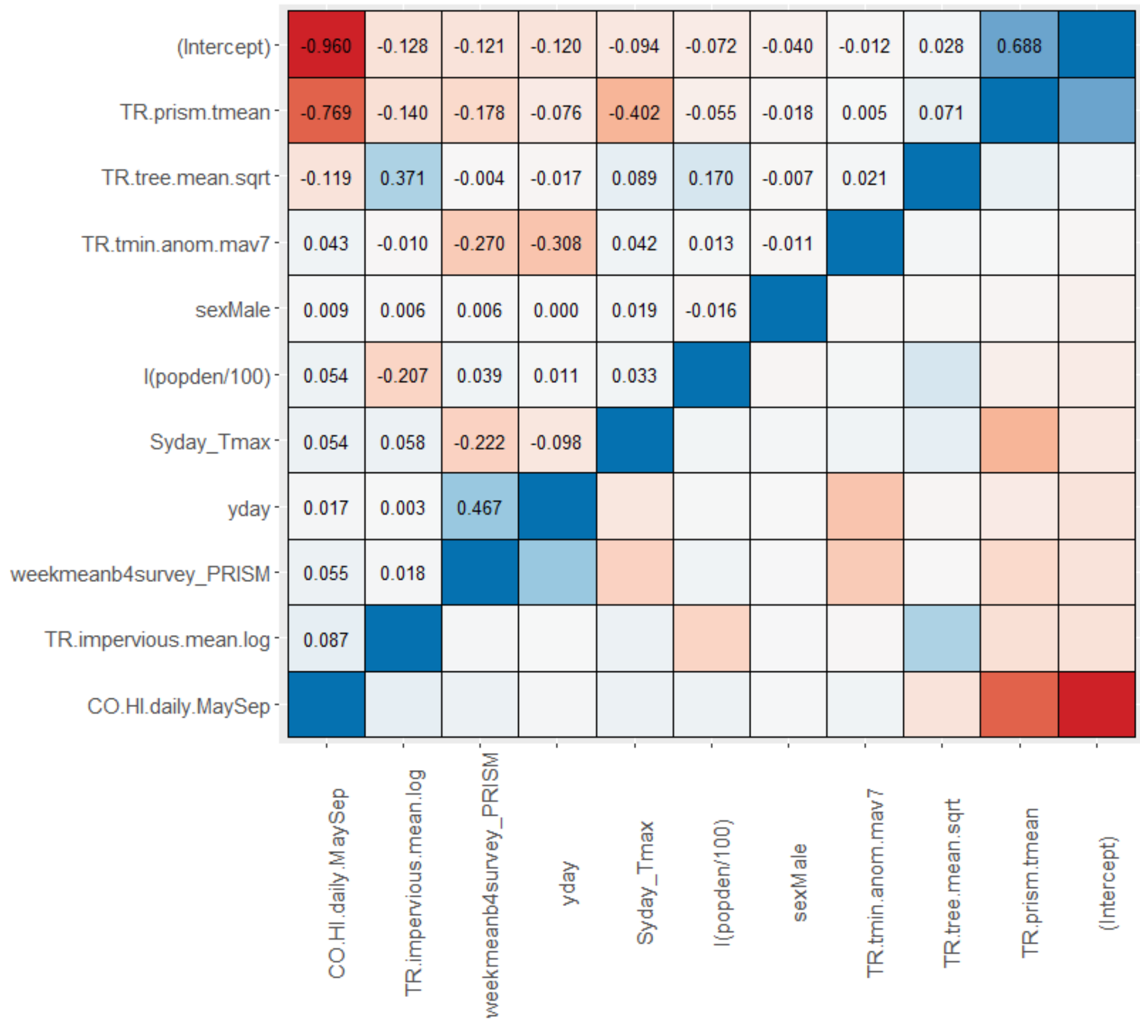


Fig. C.1. Fixed effects correlation matrix for Vulnerability Model.

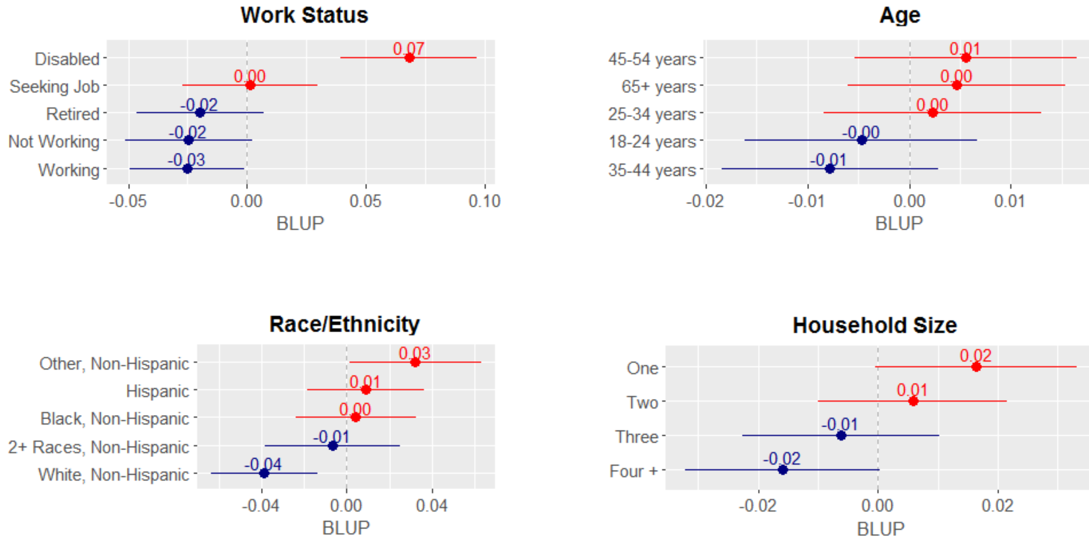


Fig. C.2. Random effects of Vulnerability Model predictors.

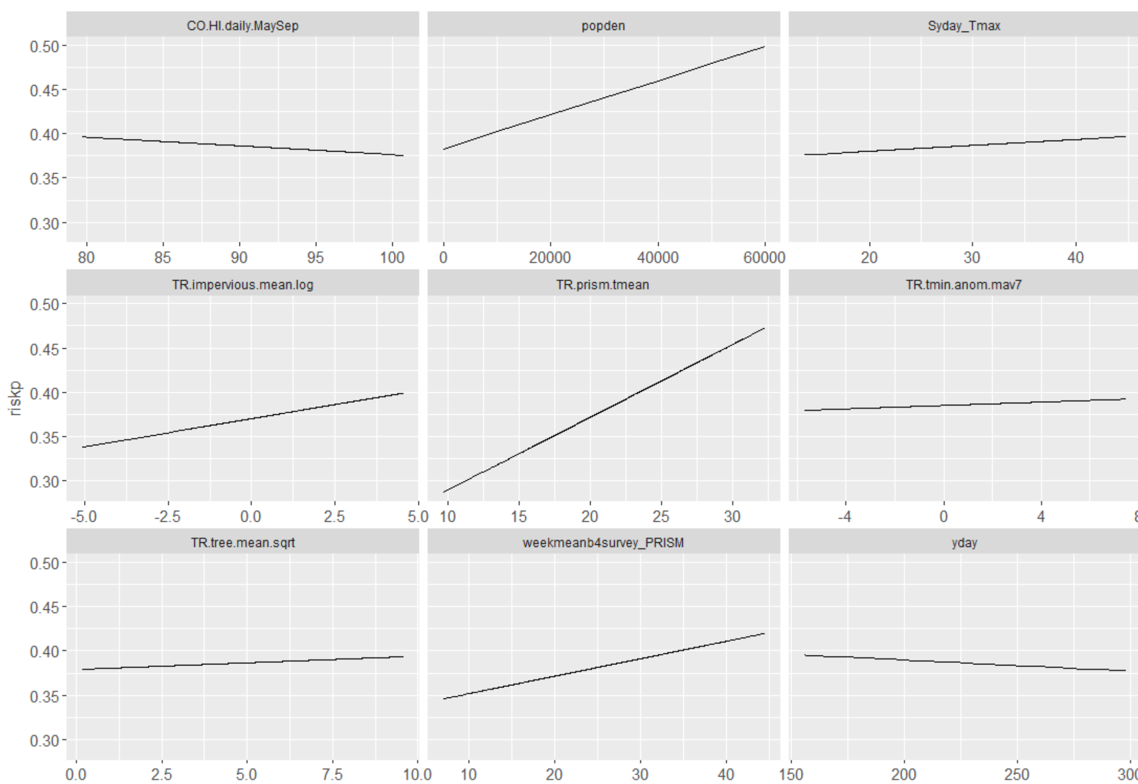


Fig. C.3. Marginal effects of Vulnerability Model predictors.

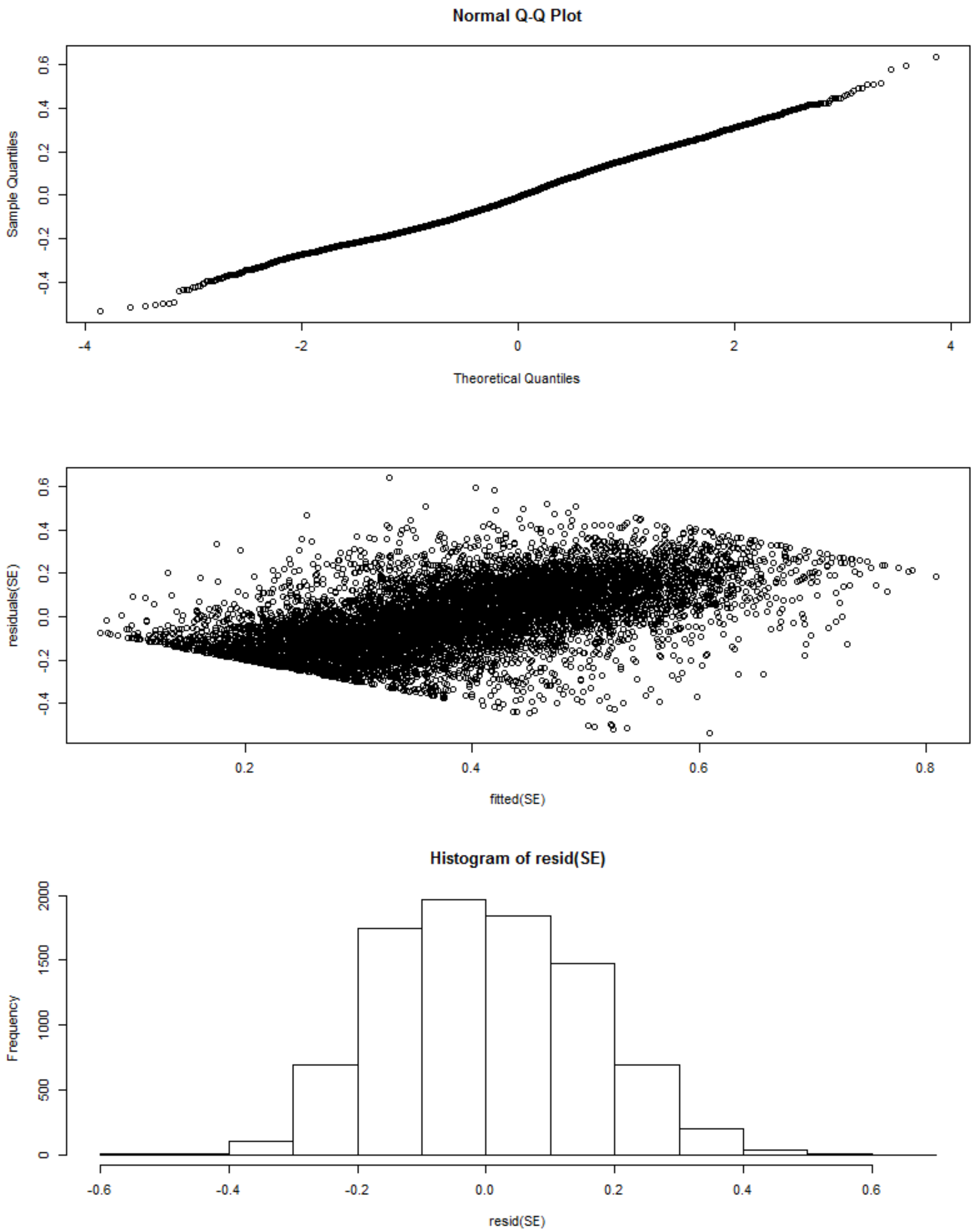


Fig. C.4. Diagnostic plots (qqplot, residuals, etc) for Vulnerability Model.

APPENDIX D

ADAPTIVE CAPACITY MODEL

Table D.I. Variance-Covariance Matrix for the Adaptive Capacity Model

Predictor	(Intercept)	TR.Language.nonEnglish	TR.Employment.unemployed	TR.Housing.vacant	pct_WWAdaysb4survey	weekb4survey_WWAYES	WWAb4surveyYES
(Intercept)	0.0003103405	-0.0000005468	-0.0000022771	-0.0000009658	-0.0000349512	-0.0000004475	-0.0000244288
TR.Language.nonEnglish	-0.0000005468	0.0000001144	-0.0000000312	0.0000000156	0.0000004973	-0.0000000709	-0.0000000717
TR.Employment.unemployed	-0.0000022771	-0.0000000312	0.0000003552	-0.0000000546	-0.0000009770	-0.0000000440	-0.0000000177
TR.Housing.vacant	-0.0000009658	0.0000000156	-0.0000000546	0.0000001166	0.0000005499	0.0000000329	0.0000000145
pct_WWAdaysb4survey	-0.0000349512	0.0000004973	-0.0000009770	0.0000005499	0.0048837510	-0.0000902791	-0.0002720717
weekb4survey_WWAYES	-0.0000004475	-0.0000000709	-0.0000000440	0.0000000329	-0.0000902791	0.0001552308	-0.0000008098
WWAb4surveyYES	-0.0000244288	-0.0000000717	-0.0000000177	0.0000000145	-0.0002720717	-0.0000008098	0.0000534423

Fig. D.1. Fixed effects corelation matrix for Adaptive Capacity Model.

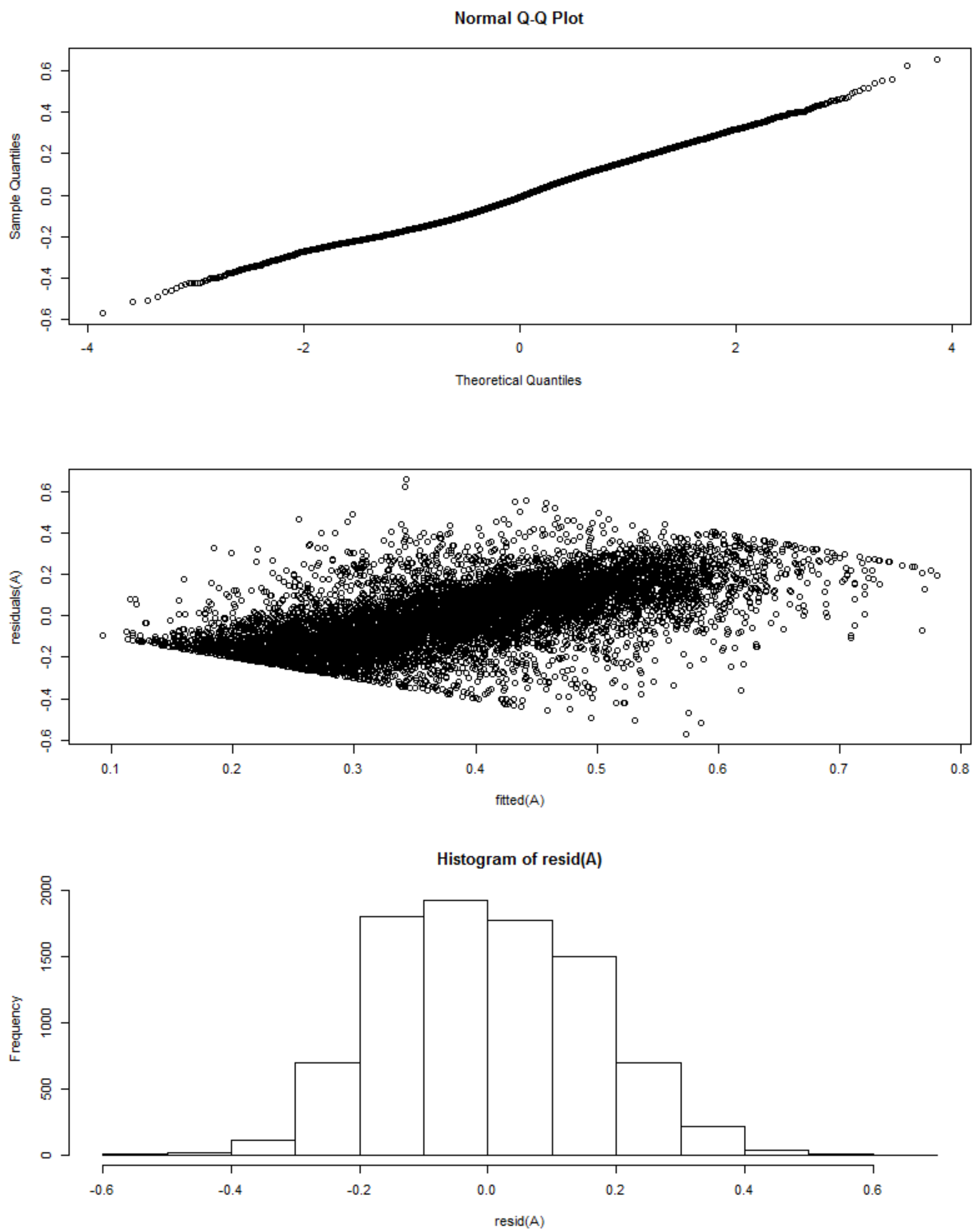


Fig. D.2. Diagnostic plots (qqplot, residuals, etc) for Adaptive Capacity Model.

APPENDIX E

MAXIMAL MODEL

Table E.I. Variance-Covariance Matrix for the Maximal Model

Predictor	(Intercept)	yday	CO.HI.daily.MaySep	TR.impervious.mean.log	TR.tree.mean.sqrt	TR.prism.tmean	TR.tmin.anom.mav7	I(popden/100)	Syday_Tmax	weekmeanb4survey_PRISM	TR.Language.nonEnglish	TR.Employment.unemployed	TR.Housing.vacant	pct_WWAdaysb4survey	weekb4survey_WWAYES	WWAb4surveyYES	sexMale
(Intercept)	2.06E-02	-1.05E-06	-2.65E-04	-3.83E-05	6.96E-06	2.38E-04	-3.17E-06	-7.96E-07	-1.84E-05	-1.17E-05	-2.69E-06	-4.31E-06	-4.53E-07	4.80E-04	-3.98E-06	3.77E-05	-4.88E-05
yday	-1.05E-06	3.70E-09	1.40E-09	6.00E-10	-1.70E-09	-1.08E-08	-2.65E-08	0.00E+00	-5.80E-09	1.82E-08	2.00E-10	-5.00E-10	2.00E-10	-1.84E-07	-5.90E-09	3.20E-08	-4.00E-10
Heat Index	-2.65E-04	1.40E-09	3.74E-06	2.96E-07	-3.97E-07	-3.57E-06	1.30E-07	8.10E-09	1.68E-07	7.01E-08	4.00E-08	4.35E-08	-1.09E-08	-3.26E-06	3.78E-07	-9.08E-07	1.64E-07
TR.impervious.mean.log	-3.83E-05	6.00E-10	2.96E-07	5.78E-06	1.52E-06	-7.33E-07	-2.68E-08	-4.08E-08	1.74E-07	4.00E-08	-1.10E-07	-1.79E-07	2.44E-07	-1.48E-06	-9.06E-08	2.45E-07	1.34E-07
TR.tree.mean.sqrt	6.96E-06	-1.70E-09	-3.97E-07	1.52E-06	3.37E-06	1.26E-07	5.90E-08	2.33E-08	1.93E-07	-4.60E-09	7.38E-08	-3.05E-08	2.16E-08	-4.42E-08	-6.21E-08	4.20E-07	-1.18E-07
TR.prism.tmean	2.38E-04	-1.08E-08	-3.57E-06	-7.33E-07	1.26E-07	5.91E-06	6.60E-09	-9.50E-09	-1.07E-06	-2.73E-07	-5.97E-08	-7.61E-08	-2.23E-08	-2.26E-07	2.01E-07	1.69E-07	-3.73E-07
TR.tmin.anom.mav7	-3.17E-06	-2.65E-08	1.30E-07	-2.68E-08	5.90E-08	6.60E-09	2.02E-06	2.10E-09	5.35E-08	-2.36E-07	-4.40E-09	1.63E-08	0.00E+00	9.48E-07	-1.14E-06	-1.77E-07	-1.33E-07
I(popden/100)	-7.96E-07	0.00E+00	8.10E-09	-4.08E-08	2.33E-08	-9.50E-09	2.10E-09	9.20E-09	4.30E-09	2.50E-09	-7.50E-09	2.00E-10	-2.10E-09	6.79E-08	-1.88E-08	-2.73E-08	-1.00E-08
Syday_Tmax	-1.84E-05	-5.80E-09	1.68E-07	1.74E-07	1.93E-07	-1.07E-06	5.35E-08	4.30E-09	1.04E-06	-1.49E-07	-1.48E-08	1.11E-08	2.50E-09	-6.03E-06	1.65E-07	2.95E-07	1.84E-07
weekmeanb4survey_PRISM	-1.17E-05	1.82E-08	7.01E-08	4.00E-08	-4.60E-09	-2.73E-07	-2.36E-07	2.50E-09	-1.49E-07	4.28E-07	-2.00E-10	-1.41E-08	6.60E-09	2.41E-07	-1.40E-06	-9.07E-08	3.37E-08
TR.Language.nonEnglish	-2.69E-06	2.00E-10	4.00E-08	-1.10E-07	7.38E-08	-5.97E-08	-4.40E-09	-7.50E-09	-1.48E-08	-2.00E-10	1.35E-07	-2.31E-08	8.10E-09	8.91E-07	-3.05E-08	-5.59E-08	-6.76E-08
TR.Employment.unemployed	-4.31E-06	-5.00E-10	4.35E-08	-1.79E-07	-3.05E-08	-7.61E-08	1.63E-08	2.00E-10	1.11E-08	-1.41E-08	-2.31E-08	3.68E-07	-5.77E-08	-6.88E-07	5.93E-08	1.54E-08	5.50E-08
TR.Housing.vacant	-4.53E-07	2.00E-10	-1.09E-08	2.44E-07	2.16E-08	-2.23E-08	0.00E+00	-2.10E-09	2.50E-09	6.60E-09	8.10E-09	-5.77E-08	1.23E-07	3.30E-07	1.14E-08	7.28E-08	-2.19E-08
pct_WWAdaysb4survey	4.80E-04	-1.84E-07	-3.26E-06	-1.48E-06	-4.42E-08	-2.26E-07	9.48E-07	6.79E-08	-6.03E-06	2.41E-07	8.91E-07	-6.88E-07	3.30E-07	4.55E-03	-9.26E-05	-2.54E-04	-5.19E-06
weekb4survey_WWAYES	-3.98E-06	-5.90E-09	3.78E-07	-9.06E-08	-6.21E-08	2.01E-07	-1.14E-06	-1.88E-08	1.65E-07	-1.40E-06	-3.05E-08	5.93E-08	1.14E-08	-9.26E-05	1.56E-04	-2.64E-07	-7.29E-07
WWAb4surveyYES	3.77E-05	3.20E-08	-9.08E-07	2.45E-07	4.20E-07	1.69E-07	-1.77E-07	-2.73E-08	2.95E-07	-9.07E-08	-5.59E-08	1.54E-08	7.28E-08	-2.54E-04	-2.64E-07	5.01E-05	4.44E-07
sexMale	-4.88E-05	-4.00E-10	1.64E-07	1.34E-07	-1.18E-07	-3.73E-07	-1.33E-07	-1.00E-08	1.84E-07	3.37E-08	-6.76E-08	5.50E-08	-2.19E-08	-5.19E-06	-7.29E-07	4.44E-07	7.64E-05

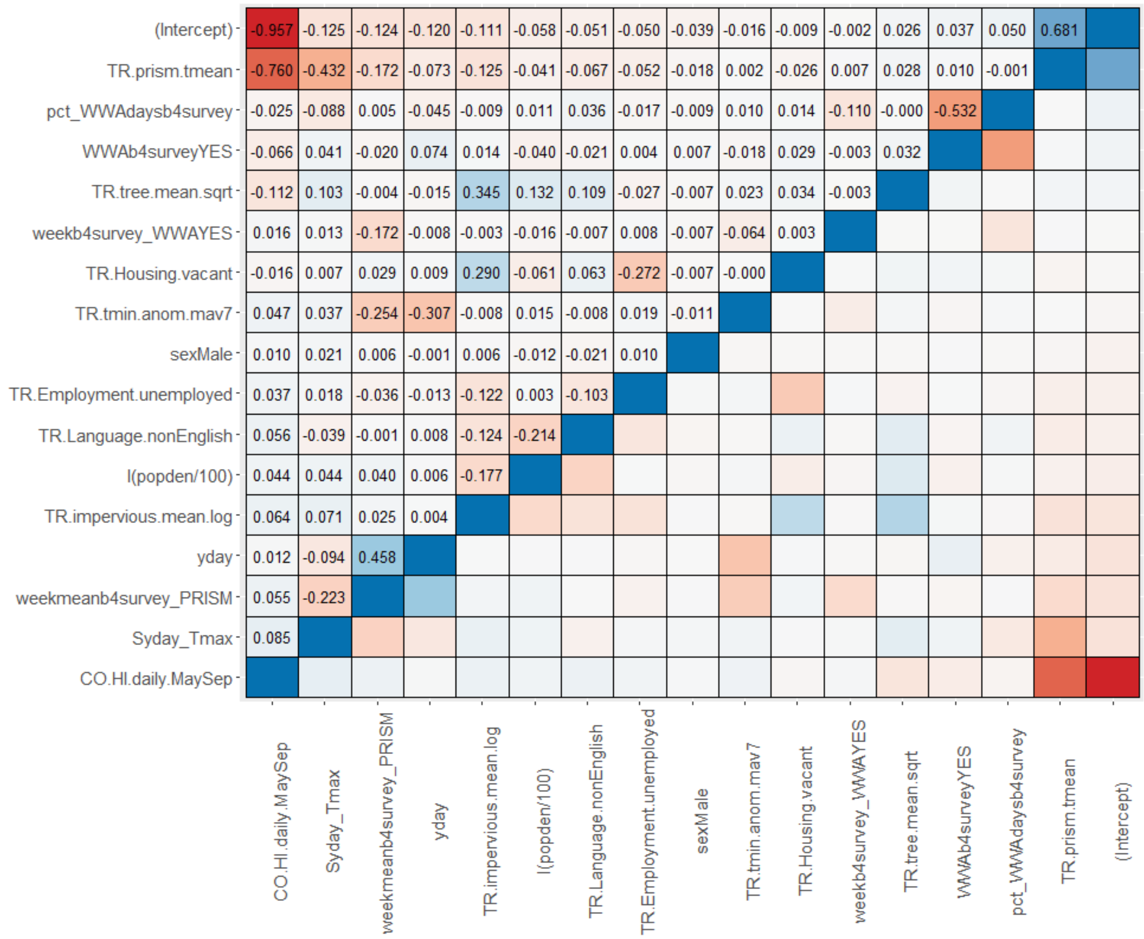


Fig. E.1. Fixed effects correlation matrix for Maximal Model.

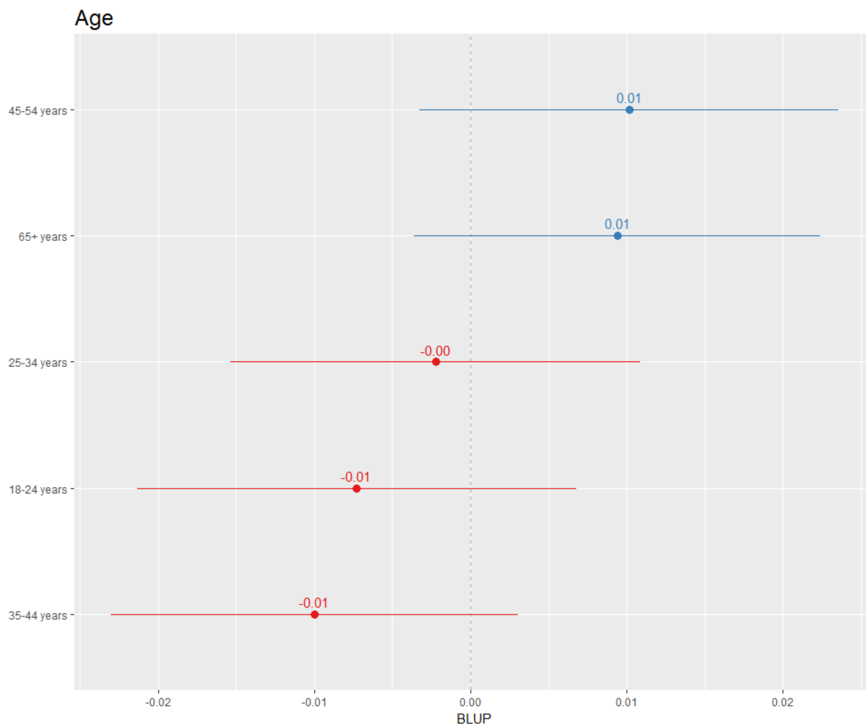


Fig. E.2. Random effect of age in Maximal Model.

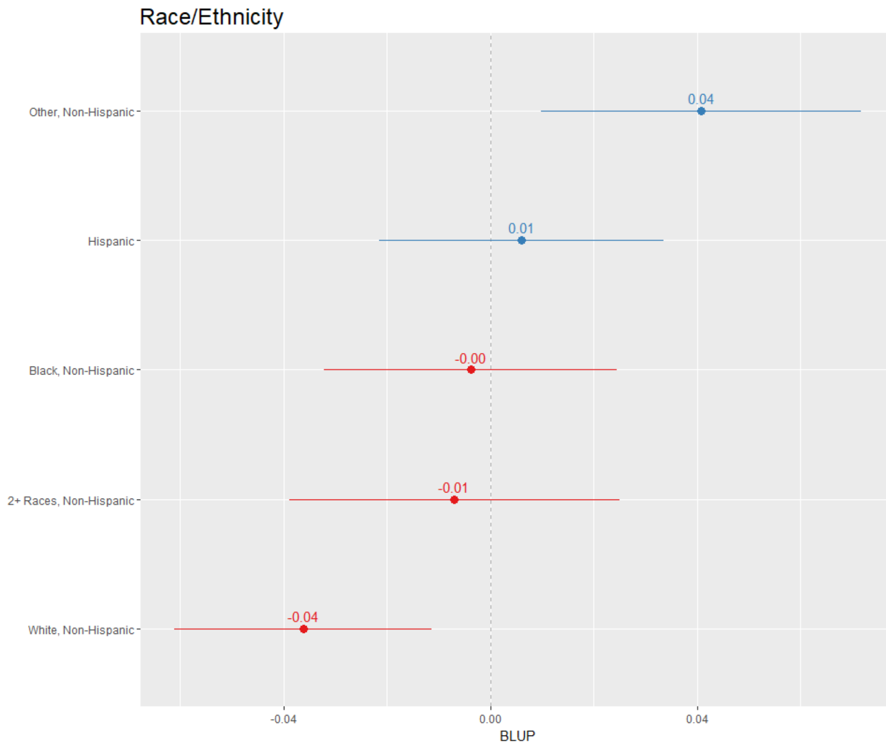


Fig. E.3. Random effect of race/ethnicity in Maximal Model.

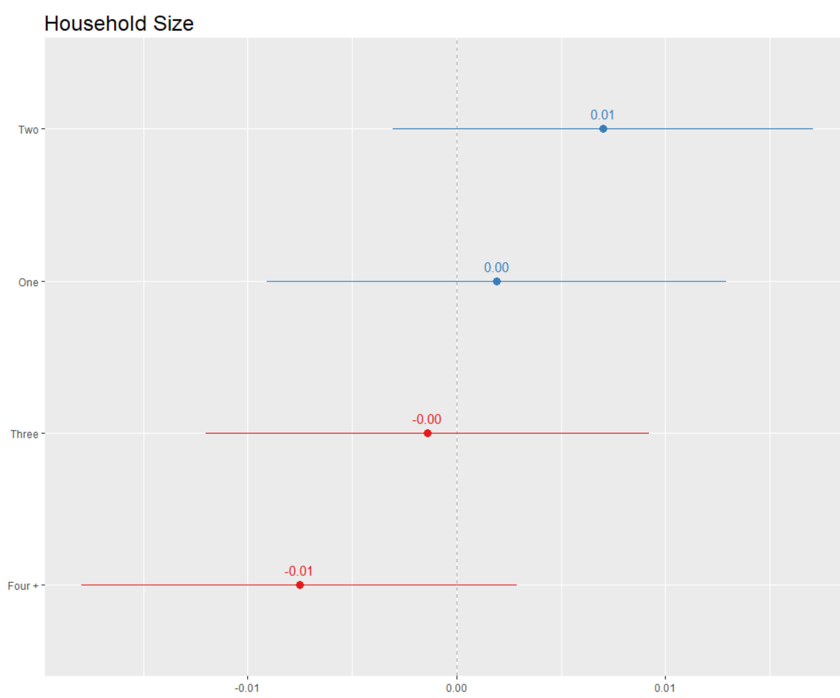


Fig. E.4. Random effect of household size in Maximal Model.

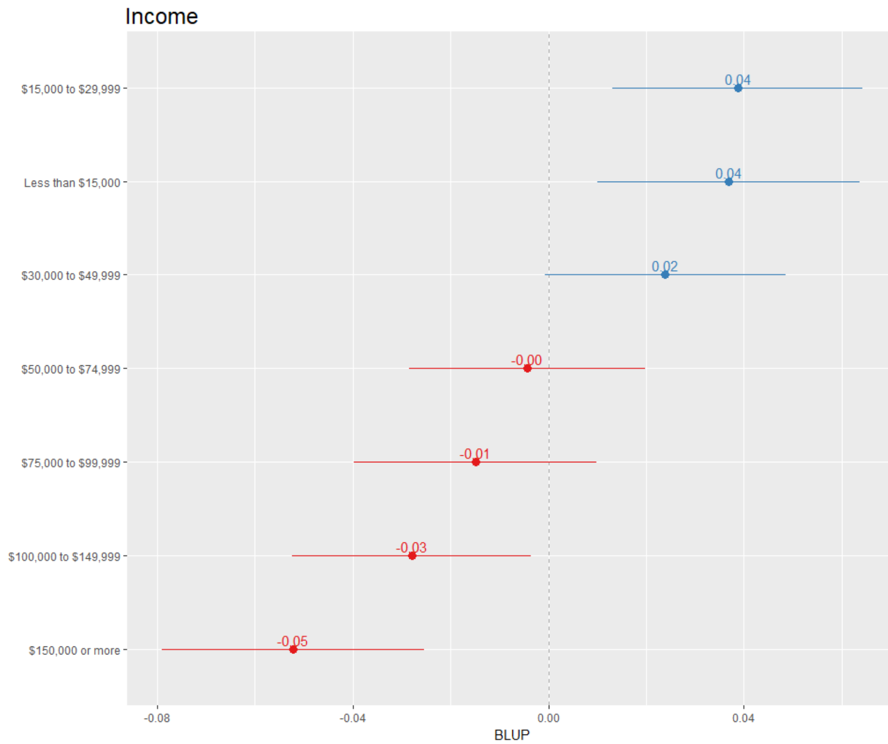


Fig. E.5. Random effect of income in Maximal Model.

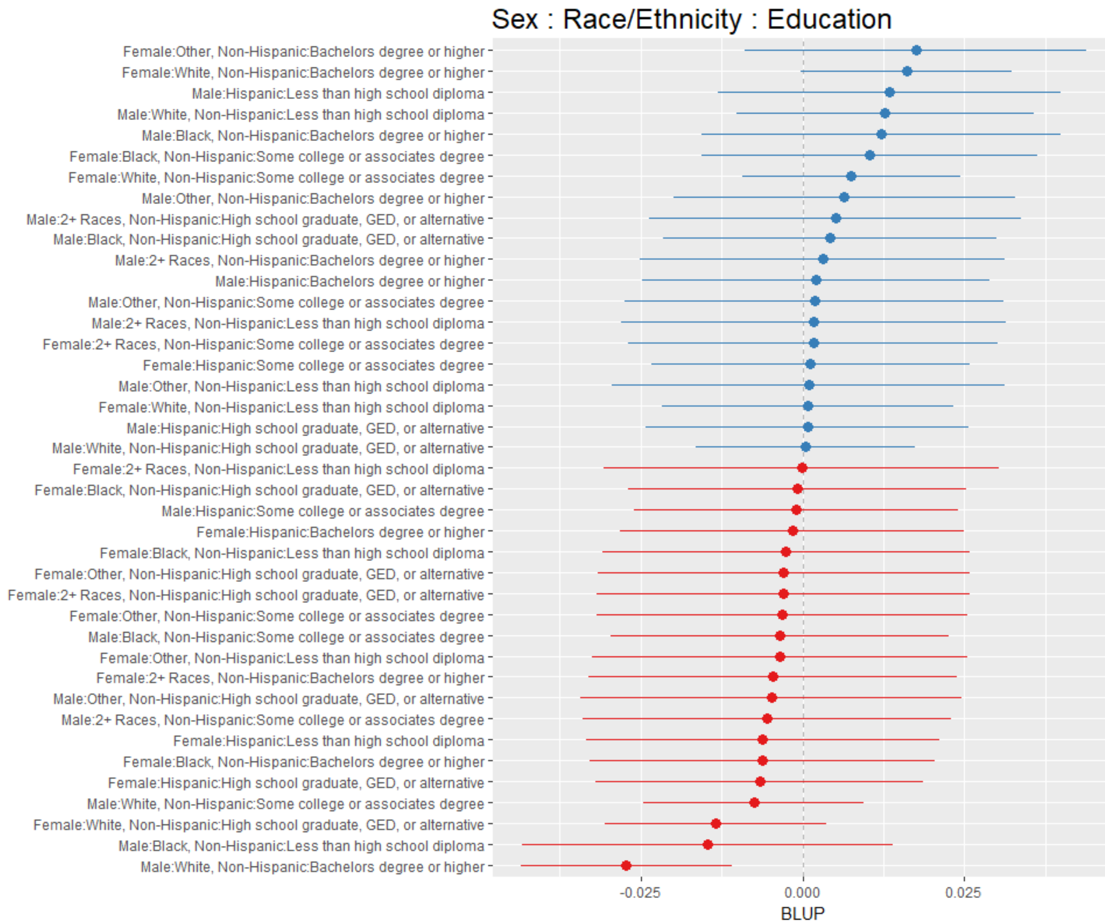


Fig. E.6. Random effects of interaction predictor in Maximal Model.

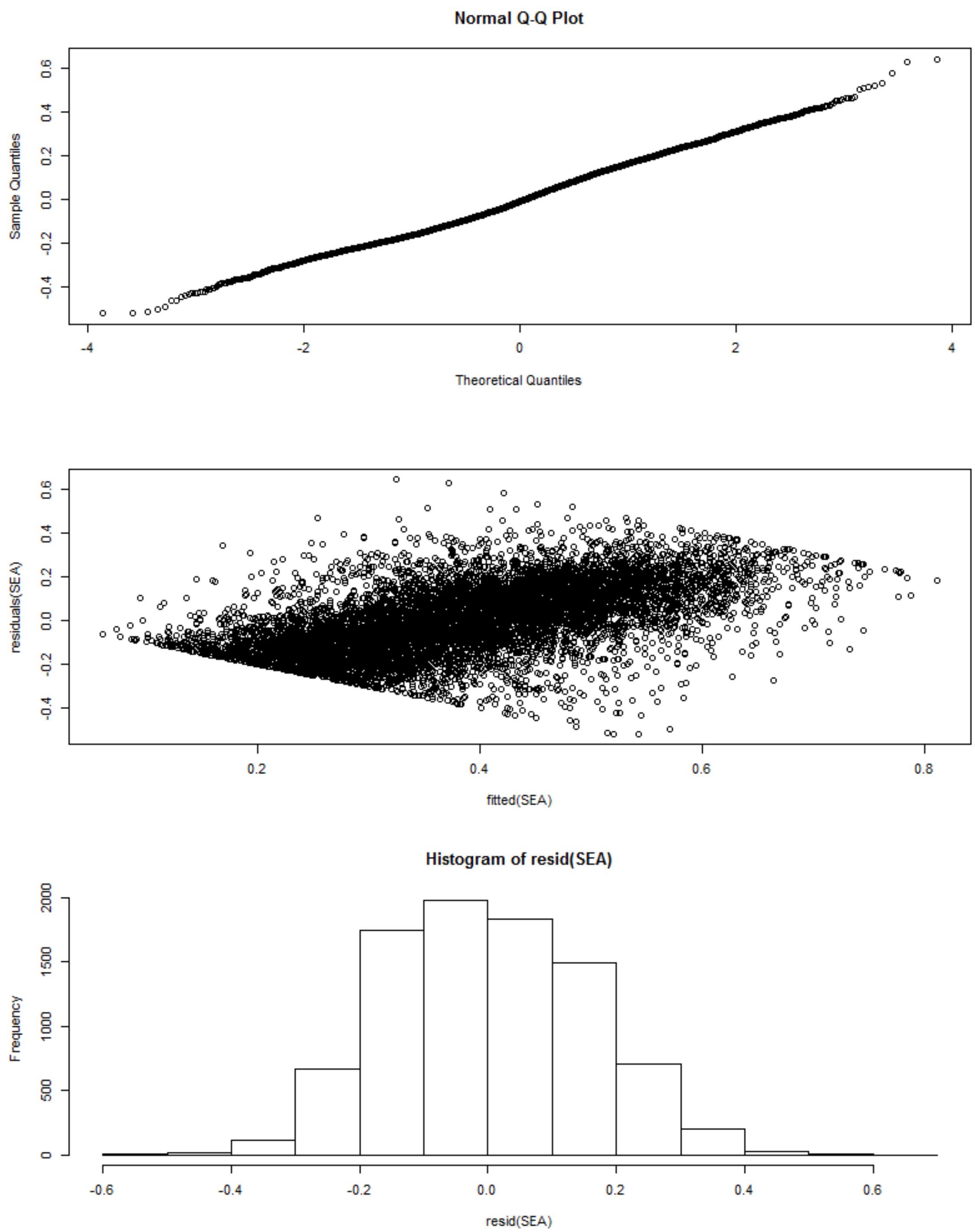


Fig. E.7. Diagnostic plots (qqplot, residuals, etc) for Maximal Model.

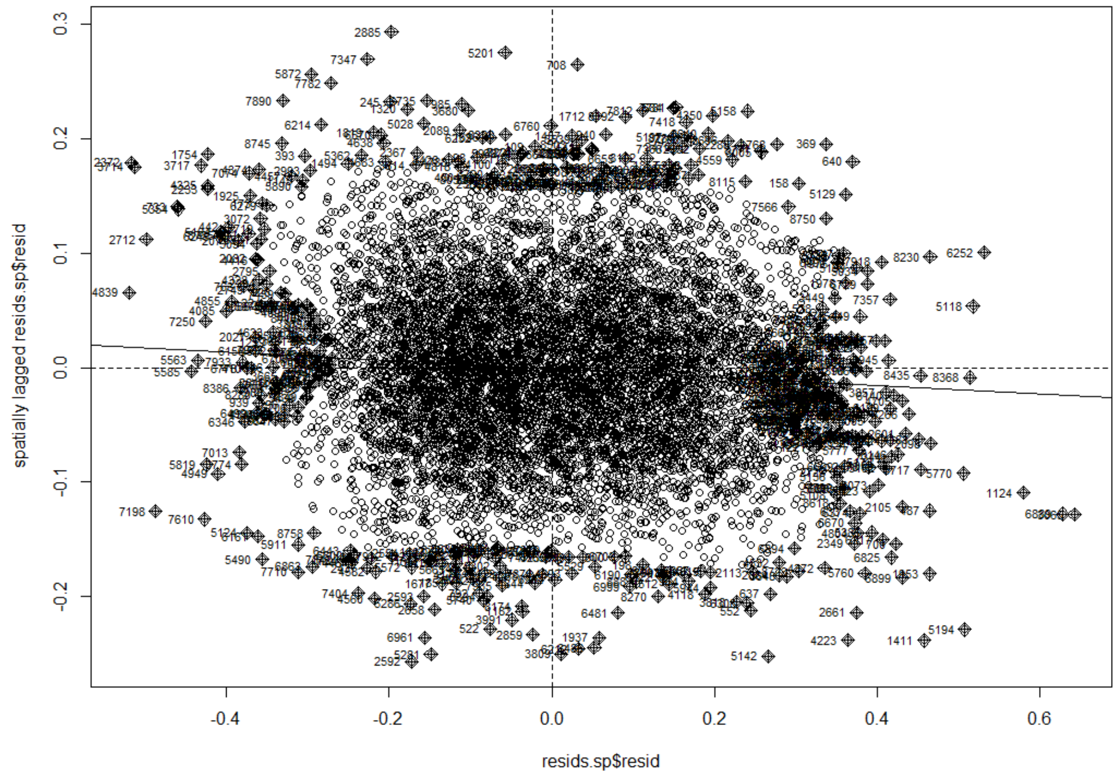


Fig. E.8. Moran's plot of spatial autocorrelation for the Maximal Model.