Vulnerability to Heat Stress in Urban Areas: A Sustainability Perspective

by

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ABSTRACT

Extreme hot-weather events have become life-threatening natural phenomena in many cities around the world, and the health impacts of excessive heat are expected to increase with climate change (Huang et al. 2011; Knowlton et al. 2007; Meehl and Tebaldi 2004; Patz 2005). Heat waves will likely have the worst health impacts in urban areas, where large numbers of vulnerable people reside and where local-scale urban heat island effects (UHI) retard and reduce nighttime cooling.

This dissertation presents three empirical case studies that were conducted to advance our understanding of human vulnerability to heat in coupled human-natural systems. Using vulnerability theory as a framework, I analyzed how various social and environmental components of a system interact to exacerbate or mitigate heat impacts on human health, with the goal of contributing to the conceptualization of human vulnerability to heat. The studies: 1) compared the relationship between temperature and health outcomes in Chicago and Phoenix; 2) compared a map derived from a theoretical generic index of vulnerability to heat with a map derived from actual heat-related hospitalizations in Phoenix; and 3) used geospatial information on health data at two areal units to identify the hot spots for two heat health outcomes in Phoenix. The results show a 10-degree Celsius difference in the threshold temperatures at which heat-stress calls in Phoenix and Chicago are likely to increase drastically, and that Chicago is likely to be more sensitive to climate change than Phoenix. I also found that heat-vulnerability indices are sensitive to scale, measurement, and context, and that cities will need to incorporate place-based factors to increase the usefulness of vulnerability indices and mapping to decision making. Finally, I found that identification of geographical hot-spot

of heat-related illness depends on the type of data used, scale of measurement, and normalization procedures. I recommend using multiple datasets and different approaches to spatial analysis to overcome this limitation and help decision makers develop effective intervention strategies.

Dedicated to My Family

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CHAPTER 1

INTRODUCTION

Climate change increases the risk of heat and its effects on human health in many ways, mostly adversely (McMichael et al. 2006). For instance, the increased length and intensity of extreme-heat events has made excessive heat one of the leading causes of deaths from natural disaster. Examples include the 1995 heat waves in Chicago that killed more than 700 (Klinenberg 2002), and the 2003 European heat wave that took the lives of over 22,080 people (Kosatsky 2005; Stone 2012). Large-scale urbanization and rapid population growth increase the risks to human health posed by climate change, especially in cities, because they change biophysical systems and ecosystems. One such change is the phenomenon of the urban heat island (UHI) effect, in which temperatures are higher in inner cities than in suburban areas. The UHI is one of the by-products of the human alteration of natural landscapes to landscapes of man-made materials like asphalt and concrete that retain heat (Stone 2012). The combination of global climate change and local environmental change threatens human survival over the long-term. A critical challenge to sustainability is to manage the increasing risk of excessive heat in urban areas, which will be home to more than 70 percent of the world's population by 2050 (The United Nations 2010).

In cities, heat stress is a result of a complex set of natural and human factors that interact to compromise the health of urban residents. Heat risks in urban areas are disproportionately distributed geographically and demographically (Reid et al. 2009). Several kinds of risk factors combine to determine the degree of human vulnerability to heat. The research presented in this dissertation comprises three empirical case studies that were conducted to advance our understanding of human vulnerability to heat in coupled human-natural systems. I used the theory of vulnerability as a framework for analyzing how various social and environmental components of a system interact to exacerbate or mitigate heat impacts on human health. The research goal was to contribute to the conceptualization of human vulnerability to heat by analyzing sensitivity, and by identifying connections between heat risks and the social and environmental factors that make a population susceptible to heat hazards. To advance vulnerability mapping applications, I tested several procedures that locate vulnerable areas geographically within a municipal boundary, the City of Phoenix, to help decision makers identify the areas most in need of proactive interventions.

Vulnerability can be defined as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (Wisner 2004, p.11), or "the degree to which a system or system component is likely to experience harm due to exposure to a hazard, either perturbation or stress" (Turner II et al. 2003, p.1084). Despite the slight differences between these two definitions of vulnerability, a majority of vulnerability scholars (Cutter et al. 2003; Eakin and Luers 2006; Polsky et al. 2007; Wisner 2004) agree that there are three pivotal components of vulnerability: exposure to threats, sensitivity to threats, and adaptive capacity to cope with threats. Cutter (1996), a pioneer in vulnerability-indicator studies, categorized contemporary research on vulnerability and sustainability science into two groups: the human-environmental research community and the natural-hazard-and-disaster (risk-hazard) research community (Cutter and Finch 2008). The first research community studies vulnerability caused by large-scale environmental processes, such as climate change, and how these processes, globally and locally, undermine the sustainability of a society by changing social-environmental systems, such as the food system or the livelihood system. This research community is concerned about social justice, equality, and opportunity (Eakin and Luers 2006). The risk-hazard research community clearly distinguishes the risk source (e.g., hurricane or tornado), and views changes in a population's socio-demographic characteristics and mobility as results of shifts in "riskscape" over time. Risk-hazard researchers have developed vulnerability-indicator systems that use underlying socioeconomic and demographic profiles as comparative metrics for evaluating people's susceptibility to natural hazards. Their approach can help those who plan for emergency preparedness, immediate responders, and those responsible for designing mitigations to help vulnerable populations recover from natural disasters. Social vulnerability is a consequence of social and political processes, and most of the time it reflects the geography of inequality and poverty (Cutter and Finch 2008; Glasmeier 2002). The consideration of inequality in risk-hazard studies, therefore, brings the two research communities together in the realm of sustainability science (Boone 2010).

The research presented in this dissertation straddles the two vulnerability-research communities. It includes the fundamental concerns of risk-hazard studies: "Where and what are the impacts?" and "Where are sensitive populations?" It also integrates the political-economy concerns of human-environmental studies: "How are people and places affected differently?" and "What are the consequences of differential susceptibility?"

My research was based on the definition of vulnerability as a function of exposure, human sensitivity, and adaptive capacity to heat. In this dissertation, physical exposure refers to proximity to excessive heat. Human sensitivity refers to the underlying characteristics of a population, and adaptive capacity refers to the ability of a population to cope with exposure to heat. By examining each component of vulnerability, this work contributes to the empirical literature on social vulnerability, and to applied human-environmental vulnerability research.

More intense, frequent, and longer lasting heat waves resulting from climate change threaten the sustainability of human society. My research contributes knowledge that can help us better understand this issue, which involves complex interactions among social and environmental conditions. It does so not only by investigating the systemic complexity of heat problems in coupled human-natural systems, but also by providing real-world solutions, which is the fundamental concern of sustainability science and scholarship. This dissertation includes three manuscripts that examine the components of vulnerability individually and jointly. The first manuscript (Chapter 2), “Sensitivity to heat: A comparative study of Phoenix, Arizona and Chicago, Illinois (2003– 2006),” is a sensitivity analysis of urban residents in the two cities. It argues that climate conditions, a city’s infrastructure, and residents’ demographic characteristics, socioeconomic status, and physiological acclimatization to temperatures all influence how an individual responds to heat, and how susceptible he or she is, to the impacts of heat. Using local climate data and information on daily heat-related emergency dispatches in statistical analyses, I: (1) examined extreme heat events in the two cities during the four-year study period; (2) identified the critical threshold temperatures beyond which heat-related emergency calls proliferated to an unmanageable status; and, (3) estimated how the two cities will be affected by climate change in the future. The threshold temperatures I identified can help municipal governments anticipate when they will need to deploy emergency services in response to extreme heat.

The second manuscript, “The contextual effects on the usefulness of a generic heat vulnerability index: A case study in Phoenix, Arizona,” (Chapter 3) contributes to our understanding of vulnerability to heat by reviewing heat-related vulnerability-indicator studies and testing a generic, national heat-vulnerability index (Reid et al. 2009), using data on heat-related hospitalizations in Phoenix, Arizona. The chapter compares the geographical differences between a map of vulnerability derived from a theoretical generic index and a map derived from actual heat-related hospitalizations. It also identifies local risk factors beyond the scope of the generic indicators. In Chapter 3, I argue that human vulnerability to heat is a complex and dynamic issue. The generic indicators of vulnerability are useful, but they are sensitive to scale, measurement, and context. While vulnerability mapping based on vulnerability indices is a pragmatic approach for highlighting the areas in a city where people are at the greatest risk of harm from heat, decision makers will need to query the characteristics of their cities to determine how closely vulnerability maps that are based on generic indicators reflect actual risk of harm.

Modeling and indicator studies cannot capture the complete story of heat vulnerability because it is a complex problem. Chapter 4, “Vulnerability mapping to mitigate and prevent heat-related illness,” presents an analytical and statistical tool that uses geospatial information on health data at two areal units (Census tracts and evenly distributed $1km^2$ grids) to identify the hot spots for two heat health impacts (heat-related emergency calls and heat-related hospitalizations). This research shows that (1) the two datasets capture different susceptible populations, and (2) different measurement and normalization approaches have different effects on the identification of vulnerable areas. Comparing the two health datasets with different standardized approaches, the research discusses some limitations of conducting geospatial analysis using heat-related illness, and extends exploration of the drivers that cause differential health consequences.

Chapter 5 discusses the complexity of vulnerability and the challenges involved in using indicators to evaluate actual risks of heat. It suggests an integration of multiple datasets and analytical approaches to improve our understanding of human vulnerability to heat. The chapter also provides recommendations and policy implications, from a sustainability perspective, to municipal authorities for mitigating heat stress and planning strategies to cope with future environmental change in complex urban systems.

CHAPTER 2

SENSITIVITY TO HEAT: A COMPARATIVE STUDY OF PHOENIX, ARIZONA AND CHICAGO, ILLINOIS (2003-2006)[1]

2.1 Introduction

Health and climatologically researchers are concerned about the adverse health effects associated with warmer temperatures resulting from climate change, and the impact of climate change on heat-related morbidity and mortality (Huang et al. 2011; Thacker et al. 2008). In the United States of America (USA), the total number of deaths resulting from excessive heat far exceeds the number due to other natural hazards (Thacker et al. 2008). The health impacts of excessive heat are expected to increase with the more frequent, intense, and longer-lasting heat waves predicted to result from climate change (Huang et al. 2011; Knowlton et al. 2007; Meehl and Tebaldi 2004; Patz 2005). Indeed, the twelve months between June 2011 and May 2012 comprised the warmest year in the contiguous United States since 1895 (National Climatic Data Center, National Oceanic and Atmospheric Administration (NOAA) 2012). Heat waves will likely have the most significant impacts in urban areas, where large numbers of vulnerable people reside and where local-scale urban heat island effects (UHI) both retard nighttime cooling and increase city warmth.

To mitigate the health effects of increasing temperatures, we need to know: 1) which populations of a city are at greatest risk, 2) how sensitive these populations are to temperature increase, and 3) what measures can be taken to prevent heat-related illness and death. Research studies have evaluated and predicted how climate change influences

[1] Co-authors of this manuscript were Patricia Gober, Winston Chow, and Jay Golden; this paper was submitted to *Urban Climate* in September 2012 and published in October 2013.

the health of urban residents, both in cities throughout in the U.S. (Greene et al. 2011; Hayhoe et al. 2010; Kalkstein and Greene 1997; Medina-Ramón and Schwartz 2007; Sheridan et al. 2012; Sheridan et al. 2009). These studies found that heat impact on mortality varies among cities and among different populations within cities. Large-scale studies that analyzed more than ten cities in different climate regimes confirmed that people in warm-climate areas are more acclimatized to heat (Curriero et al. 2002; Medina-Ramón and Schwartz 2007), and predicted that the majority of heat-related deaths due to climate change will occur in Southeastern and Northeastern cities (Greene et al. 2011). City-specific climate-mortality analyses complement research on regional and national scales. They emphasize sensitivity and adaptive capacities in a local context, yielding information that can help municipal governments implement interventions to reduce heat-related illness and death.

Little information is available to help municipal governments evaluate their current capacity for coping with heat or design adequate emergency-preparedness plans (although some researchers have suggested that increasing emergency-medical-service staffing is an effective heat mitigation strategy (Sheridan and Kalkstein 2004)). With climate change likely to exacerbate heat impacts on human health in the near future, cities need to become better prepared not only to respond to, but also to avoid, heat-induced emergencies. Our study used heat-related emergency calls as an indicator of heat-related illness in two cities in different climate zones (Phoenix, AZ, and Chicago, IL), to identify the temperature thresholds at which heat has widespread negative health impacts in each city. Because every city has unique social and physical environments, the temperature threshold varies among cities. If municipal governments were aware of the critical temperature at which heat causes health emergencies, they could plan more effectively to mitigate the effects of extreme heat on health, and to provide health- and life-saving responses to their residents. Planning for such measures as heat-wave warning systems, changes in the built environment, and care for vulnerable populations could be strengthened with knowledge of how often and when heat is likely to become a threat to health and life.

2.2 Theory and literature review

Although many researchers have examined the impact of heat on human health in case studies of individual cities (Alessandrini et al. 2011; Dolney and Sheridan 2006; Johnson and Wilson 2009; Metzger et al. 2010; Vaneckova et al. 2010), few have compared the heat slopes and threshold temperatures below which adverse health outcomes remain at a minimum, as we did in our study. Research on climate-related death and illness in urban areas seems to fall into three major categories. Studies in the first category investigated the historical exposure-response (or dose-response) relationship of temperature and health consequences (Alessandrini et al. 2011; Braga et al. 2001; Curriero et al. 2002; Davis et al. 2003; Medina-Ramón and Schwartz 2007), and/or identified the *threshold temperature* at which death rates are lowest (Honda et al. 2006; Kosatsky et al. 2006). They identified the association between temperature and mortality and considered the effects of both heat and cold on human health. Most found the temperature-mortality relationship to be nonlinear, with U, V, or J shapes (Kinney et al. 2008; O'Neill and Ebi 2009). The location of the low point of the curve, called the minimum mortality threshold, can be an indicator of adaptive capacity or acclimatization, and it varies by location. Higher minimum thresholds imply that the population is better adapted to heat, i.e., can tolerate a higher temperature while experiencing a lower number of adverse health outcomes. One study found that among 50 U.S. cities, heat effects in the hottest cities were much lower than those in cities with mild summers (Medina-Ramón and Schwartz 2007).

Studies in the second category concluded that not all urban populations are equally at risk from heat: human vulnerability to heat depends to some extent on the physical and social structure of the city. Humans can acclimatize to heat behaviorally (e.g., by foregoing outdoor activities) and culturally (e.g., by mitigating heat with air conditioning or changes in building design), as well as physiologically (Kovats 2008); this thread of research examines how altering behavior or culture affects vulnerability. For example, Curriero et al. (2002) found that the proportion of a city's population without a high school degree and the proportion living in poverty both correlated with mortality during extreme-weather events. They also found that weather-related mortality decreased with a higher prevalence of air conditioning (or heating) and a lower number of elderly residents. A sociological study of the 1995 Chicago heat wave, which took more than 700 lives, found that elderly people who lived alone were at a higher risk of death during the heat wave than those living in a family or group environment (Klinenberg 2002). Studies in the second category also found evidence that environmental, socioeconomic, and demographic risk factors affect the capacity of urban populations to *adapt to changes* in climate, and that these risk factors are not evenly distributed throughout the population (Bassil et al. 2009; Chow et al. 2012; Harlan et al. 2006; Reid et al., 2009; Uejio et al. 2011). For example, a study in metropolitan Phoenix (Chow et al. 2012) found heat vulnerability to be unevenly distributed, with a changing "heat landscape" from 1990 to 2000, and increasing vulnerability of Hispanics to heat stress due to demographic-pattern change and intensified UHI effects in traditionally minority neighborhoods.

Studies in the third category predicted the health consequences of a warmer future climate (Baccini et al. 2011; Cheng et al. 2008; Dessai 2003; Doherty et al. 2009; Gosling et al. 2009; Greene et al. 2011; Hayhoe et al. 2010; Jackson et al. 2010; Knowlton et al. 2007; Sheridan et al. 2012; Takahashi et al. 2007). For example, one study (Martens 1998) used the projected mean temperatures of 20 cities from three General Circulation Models (GCMs) to estimate changes in mortality rate due to temperature exposure, and concluded that global climate change will likely reduce mortality rates by decreasing death rates in winter in most of the study cities. Elderly people in cold climates would especially benefit, because of lower cardiovascular mortality rates during warmer winters. But subsequent studies, using data from as many as 50 U.S. cities, argued that the predicted drop in winter mortality rate would not compensate for increased summer mortality (Kalkstein and Greene 1997; Medina-Ramón and Schwartz 2007).

Some studies have taken a synoptic climatological or spatial synoptic classification (SSC) approach, which classifies weather conditions into different air-mass categories, to predict future relationships between climate and mortality. These approaches use a suite of meteorological conditions, including humidity, cloud cover, and wind speed, to represent an environment's weather conditions more accurately than temperature alone does (Greene et al. 2011; Hayhoe et al. 2010; Jan Kysely´ and Huth 2004; Kalkstein et al. 2008; Sheridan and Kalkstein 2004). Greene et al. (Greene et al. 2011) simulated future climate conditions and mortality in 40 large U.S. cites. Their results suggested that Southeastern and Northeastern cities would suffer a significant increase in both excessive heat events and heat-attributable mortality by the end of the twenty-first century, as the impact of climate change intensifies. Hayhoe et al. (2010) confirmed these findings in a case study of Chicago. They quantified the relationship between air mass and heat-related mortality in Chicago from 1961-1990, and applied three GCMs and two emission scenarios to estimate future mortality rates. Their results indicate that by the end of this century, Chicago's annual average heat-related mortality rate will be twice the 1995 level under the higher emission scenarios.

While such scenario-based research has helped policymakers to better understand the uncertainties surrounding heat-related mortality and to anticipate the range of possible future death rates, little research has studied the effect of a warmer climate on heat-related *illness*, which is a precursor of heat-related death. Heat stroke has a high case-mortality ratio, and progression to death can be rapid. If we could anticipate the incidence of heat-related illness, we could plan strategic and aggressive interventions to prevent such illness from progressing to mortality. Our cross-site comparison of heat slopes and estimates of heat-related illness provide a framework for assessing future heat impacts, and the need for context-based adaptation, in individual cities.

2.3 Materials and Methods

2.3.1 Study Areas

2.3.1.1 Phoenix, Arizona

The most populous city in Arizona, Phoenix is located in the Sonoran Desert in the southwestern United States. It has a hot, arid climate (Koppen classification *Bwh*) with extremely hot summers; the average maximum temperature in July is 41.0°C

(105.8°F). June is typically hot and dry, while July brings the monsoon season and increased humidity. Average annual precipitation (1971-2000) is low; about 21.1 centimeters (8.3 inches) at Phoenix Sky Harbor Airport (Arizona Department of Water Resources 2012). The extreme desert climate has not, however, hindered the city's growth. The widespread use of air conditioning after 1950, along with a growing dependable water supply, made it possible for Phoenix to grow and take on characteristics of an oasis city. Phoenix was one of the first U.S. cities to embrace evaporative-cooling and air-conditioning technologies, which became standard in housing built after World War II (Gober 2005).

Phoenix's population grew rapidly after 1945, from 65,000 in 1940 to 582,000 in 1970 (Gober 2005). Today, Phoenix is the sixth most-populous city in the U.S., with 1.5 million residents living within its 517 square miles. Phoenix has a low population density compared to most other major metropolitan areas in the U.S.: in 2010 it was 2,798 people per square mile. Demographically, the population is nearly evenly divided between two groups, Hispanics (40.8 percent) and non-Hispanic whites (46.5 percent). The remaining population is comprised of African-Americans (6.5 percent), Asians (3.2 percent), American Indians and Alaska Natives (3.2 percent), and Native Hawaiians and other Pacific Islanders (0.2 percent) (The US Census Bureau).

Since 1950, the Phoenix metropolitan area has undergone extensive land-cover and land-use change. Small individual city centers surrounded by agricultural land have merged into a large urban metropolis. Rapid urbanization has caused many environmental problems that threaten the area's long-term sustainability, including limited water resources, loss of native biodiversity, and an expanding urban heat island (UHI--the phenomenon of higher temperatures in the urban core than in outlying rural surroundings). Since 1990, the UHI effect has expanded and intensified, exacerbating already-extreme heat and raising nighttime temperatures by more than 6.0°C (Baker et al. 2002).

2.3.1.2 Chicago, Illinois

Chicago, Illinois is the largest city on the Great Lakes and the third largest city in the U.S; it has a hot-summer continental climate (Koppen classification *Dfa*). Although a much cooler city than Phoenix, Chicago was the site of a deadly heat wave in 1995, making it a useful area in which to study the relationship between heat and morbidity. As a cold-region city, Chicago provides a good counterpoint to Phoenix.

The average maximum July temperature is 29.4°C (84.9° F), 11.6°C lower than Phoenix. Average annual precipitation is about 93.7 centimeters (36.9 inches), four times greater than in Phoenix. The monthly average humidity in Chicago is constantly high, between 66 and 75 percent compared to 25 to 50 percent in Phoenix. Chicago's 2.7 million people reside on 234 square miles of land, resulting in a population density of 11,864 people per square mile, nearly four times that of Phoenix (The U.S. Census Bureau 2012). Compared to Phoenix, Chicago is a relatively old city, with a high-density urban center and low-density suburban areas. Non-Hispanic whites comprise 31.7 percent of Chicago's population, African-Americans 33.0 percent, and Hispanics 28.9 percent. Chicago's UHI effect is milder than Phoenix's, due to the proximity of Lake Michigan. The temperature gradient between Chicago's western suburbs and core downtown area is, on average, 1.7°C to 2.8 °C (3~5°F) (EPA 2009).

Chicago has a long history of segregation, poverty issues, and high crime-rates in poor neighborhoods—all obstacles to strong social networks and support, which are critical factors when it comes to adapting to heat stress (Harlan et al. 2006; Klinenberg 2002). In an analysis of deaths from the 1995 heat wave, Klinenberg (2002) concluded that the social structure in Chicago exacerbated the outcomes of the heat wave. Those most vulnerable to the heat wave were low-income African-Americans, the elderly, and those living alone in high-crime areas.

2.3.2 Data

We used historical temperature and heat-stress emergency-call data to identify and compare patterns in the health impacts of heat in Phoenix and Chicago. We studied daily variation in temperature and heat-related 911 emergency dispatches in each city to identify temperature-response effects (heat slopes) and the critical thresholds at which heat begins to harm health, and to assess heat-stress risk under different climate-change scenarios. Two pilot studies have examined heat-related emergency dispatches in Chicago (2003-2006) (Hartz et al. 2012) and Phoenix (2001-2006) (Golden et al. 2008), documenting annual, monthly, day-of-week, and time-of-day distribution of heat-stress calls and temperature metrics. Both studies found that high call volume was driven by high maximum temperature (Tmax) and apparent maximum temperature (ATmax), as well as maximum heat index, a combination of temperature and humidity. Hartz et al. (2012) examined the association between a set of climatic factors and indices and heat-stress calls in Phoenix and Chicago, using cubic and stepwise regression. Though their method was suitable for estimating the relationship between climate and heat-stress calls, they were unable to estimate accurately the change in the number of calls. By using a systematic approach to evaluate temperature-health association, we were able to compare residents' sensitivity to temperature increase in Phoenix and Chicago and estimate how the number of heat-related emergencies would increase in the event of higher temperatures.

We used temperature and daily heat-stress-call data (2003-2006) in a negative binominal model to generate curves that represent the relationships between temperature and heat-stress calls made. We then used these curves to identify heat slope and the threshold temperature beyond which the majority of heat-related health emergencies occurred. To evaluate the sensitivity of each city to heat, we estimated the number of heat-stress calls that would be made under maximum temperatures ranging from 1˚C to 5.5˚C higher than current temperatures—a plausible range predicted by two regional climate models (Georgescu et al. 2013; Lynn et al. 2007). The equations derived from the negative binomial models were used to calculate the number of heat-stress calls that would occur under warmer conditions in the two cities in July, the hottest month of the year. From these calculations, we estimated requirements for emergency medical support, and inferred measures that the cities could take to reduce vulnerability to heat stress in the future.

Research on the relationship between temperature and health has emphasized mortality (Braga et al. 2001; Curriero et al. 2002; Kovats 2008; O'Neill et al. 2003; O'Neill and Ebi 2009) because daily death statistics are collected on a national basis. However, an increase in the availability of local emergency-dispatch and hospital-admission records has stimulated research into morbidity patterns (Alessandrini et al. 2011; Bassil et al. 2009; Golden et al. 2008; Hartz et al. 2012; Uejio et al. 2011). We used heat-related emergency-dispatch calls (made from May through September, 2003-2006) as the indicator of heat-related illness. Both Chicago and Phoenix report and define heat-related calls consistently because their diagnosis procedure is based on a national standard (The Fire Department, City of Chicago 2012). We obtained dispatch data from the City of Chicago's Office of Emergency Management and Communications, and from the Regional Dispatch Center of the Phoenix Fire Department. Each record contains the address of the dispatch destination and the date and time when the call was made. Records include no detailed information on the victims, but the data were sufficient to allow us to evaluate residents' sensitivity to temperature change, and to suggest how the two cities' governments might plan ahead to reduce heat impacts and increase the capacity of their emergency-response systems.

A variety of temperature metrics have been used in epidemiological and health geography studies (Basu et al. 2005; Braga et al. 2001; Davis et al. 2003; Golden et al. 2008; O'Neill et al. 2003; Stafoggia et al. 2006); we chose daily maximum temperature and maximum heat index as metrics of extreme-heat events. Heat index, which combines air temperature and humidity, is a measure of human comfort. The human body uses an evaporative cooling process, sweating, to cool itself. High humidity reduces the evaporation rate and thus increases thermal discomfort (NOAA, office of Climate, Water, and Weather Service 2011).

There is no universally agreed-upon standard for heat waves, extreme-heat events, or temperature metrics that can be applied in human-health studies. Some researchers have argued that minimum temperature is more important than maximum temperature as a factor in heat-related mortality, because the human body benefits from cooling temperatures in the evening and nighttime (Kinney et al. 2008). If the minimum temperature is high at night, the body cannot recover from heat stress. However, studies in Phoenix and Chicago have shown that daytime maximum temperatures were slightly more correlated with heat-related morbidity than were nighttime minimums (Golden et al. 2008; Hartz et al. 2006; Hartz et al. 2012). A recently published paper on the association between heat-stress emergency calls and several climatic factors in Chicago and Phoenix noted that air-mass types are not associated with daily heat-stress calls in Phoenix due to low variability in weather conditions during hot months. Based on these studies, we chose maximum temperature as a metric of heat stress. We also used daily maximum heat index because of the high humidity in Chicago, where the combination of temperature and humidity may have a more significant effect on the body than temperature alone.

We calculated the heat index using the definition of the U.S. National Weather Service (Lans P. Rothfusz 1990):

$$HI = -42.379 + 2.04901523T + 10.14333127R - 0.22475541TR - 6.83783\text{x}10^{-3}T^2 - 5.481717\text{x}10^{-2}R^2 + 1.22874\text{x}10^{-3}T^2R + 8.5282\text{x}10^{-4}TR^2 - 1.99\text{x}10^{-6}T^2R^2$$

where T = ambient dry bulb temperature (°F)

R = relative humidity (integer percentage).

We used historical weather information from the National Climatic Data Center (NCDC). For Phoenix, we used data from the weather station at Phoenix Sky Harbor International Airport in central Phoenix. Chicago data came from the weather station at Midway Airport in southwest Chicago, about 9.5 miles from the downtown “Loop.” Although historical data from a single station may not fully represent the conditions for an entire city, data from these two stations are widely used by climatologists to represent the climate conditions of their cities.

2.3.3 Procedure

Extreme heat events and morbidity Heat waves have been defined in various ways, but definitions are usually based on the temperature exceeding specific threshold conditions and persisting for several consecutive days, so that there is no relief from the heat.

Table 2.1: Heat waves in Phoenix 2003-2006

Heat Waves	Date	Tmax(°C)	Number of Daily heat-stress calls	Average Tmax
Event 1	Sunday, July 13, 2003	45.6	7	46.4 °C
	Monday, July 14, 2003	46.7	9	(115.5 °F)
	Tuesday, July 15, 2003	46.1	20	
	Wednesday, July 16, 2003	47.2	8	
Event 2	Friday, July 15, 2005	45.0	11	45.1°C
	Saturday, July 16, 2005	45.0	12	(113.2 °F)
	Sunday, July 17, 2005	46.7	14	
	Monday, July 18, 2005	45.0	24	
	Tuesday, July 19, 2005	43.9	17	
Event 3	Thursday, July 13, 2006	45.0	17	45.2 °C
	Friday, July 14, 2006	45.6	17	(113.3 °F)
	Saturday, July 15, 2006	45.0	9	
	Friday, July 21, 2006	47.8	17	46.4 °C
Event 4	Saturday, July 22, 2006	46.7	23	(115.5 °F)
	Sunday, July 23, 2006	45.6	18	
	Monday, July 24, 2006	45.6	22	

Tmax=Daily maximum temperature

Threshold temperature is a designated upper percentile of the distribution of 30-year daily maximum temperatures (Meehl and Tebaldi 2004; Reid et al. 2009; Ruddell et al. 2010). We used the thresholds and criteria from Meehl and Tabaldi (Meehl and Tebaldi 2004) that were also used in other climatological studies (Huth et al. 2000; Ruddell et al. 2010). We calculated T1 (upper 2.5th percentile) and T2 (upper 19th percentile) from the 30-year

(1971-2000) distribution of daily maximum temperatures for Phoenix and Chicago between May and September, when most heat-related dispatch calls occurred. Phoenix T1= 45.0°C (113.0° F); Chicago T1= 35.0°C (95.0° F). Phoenix T2= 42.2° C (108.0° F); Chicago T2= 31.1 °C (88.0° F). The criteria for a heat wave are: 1) the daily maximum temperature reaches T1 for at least three consecutive days, 2) the average maximum temperature is above T1 during the entire heat event, and 3) the daily maximum is above T2 for every day of the entire period. According to these criteria, there were four heat waves in Phoenix and one in Chicago during the study period (Tables 2.1 and 2.2).

2.3.3.1 Evaluating temperature variables and heat-stress calls

Many longitudinal datasets with continuous dependent variables are modeled using Poisson regression, a model that is widely used for predicting continuous data in count format (D'Souza et al. 2004); however, if the data structure has a random dispersion pattern, the negative binominal regression could provide a better fit with the data than the Poisson regression (Bruno et al. 2007). The negative binomial regression model is ideal for an analysis that has a continuous and over-dispersed (the variance exceeds the mean value) dependent variable. The model is commonly used in biology and health studies to find patterns of a phenomenon, frequencies of events, disease spread, or change of population size over a period of time (Bruno et al. 2007; Mabaso et al. 2006; Rohr et al. 2008).

In Chicago and Phoenix, the number of heat stress calls varies enormously over the course of a year: 99.8 percent of Chicago calls and 93.6 percent of Phoenix calls occur between May and September. Therefore, we collected data for each day from May through September for our study (612 days in four years). The variances of heat stress-calls in the two cities far exceeded the mean value, indicating the problem of over-dispersion. We observed a large number of heat-stress calls made at the beginning of a heat wave, followed by a gradual decrease as the temperature returned to average. This data structure explained why the negative binominal model fit and predicted our data better than regular linear regression, quadratic regression, or Poisson regression, all of which are widely used in studies of temperature and health.

Table 2.2 Heat waves in Chicago 2003-2006

Heat waves	Date	Tmax(°C)	Number of Daily heat-stress calls	Average Tmax
Event 1	Monday, July 31, 2006	37.2	58	36.9 °C
	Tuesday, August 01, 2006	37.2	87	(98.3 °F)
	Wednesday, August 02, 2006	36.1	69	

Tmax=Daily maximum temperature

First, we used bivariance regression to examine relationships between heat metrics and heat-related dispatches in Phoenix and Chicago (Table 2.3). Air temperature is a stronger predictor of the daily variation in heat-stress calls in Phoenix than in Chicago. In Phoenix, Tmax, Tmin and Max heat index were good predictors of heat stress calls, with Pearson correlation values equal to 0.6 and p values below 0.01. Phoenix is usually hot and dry, so air temperature alone had the strongest relationship with heat-stress calls. The heat index, which incorporates humidity, was the strongest predictor of heat-stress calls in Chicago. The correlation coefficient between the heat-stress calls and the heat index in Chicago was 0.4. The correlations with Tmax and Tmin were lower than with the heat index in Chicago, but they were also statistically significant at the 0.01 level (Table 2.3).

Table 2.3 Pearson Correlation Matrix of heat-stress calls and climate variables in Phoenix and Chicago, May-September, 2003-2006.

		Number of heat-stress calls in Phoenix	Number of Heat-stress calls in Chicago
Tmax	Pearson Correlation	0.6**	0.3**
	Sig. (2-tailed)	0.00	0.00
Max_HI	Pearson Correlation	0.6**	0.4**
	Sig. (2-tailed)	0.00	0.00
Tmin	Pearson Correlation	0.6**	0.3**
	Sig. (2-tailed)	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). Tmax, Tmin, Max HI are daily maximum temperature, minimum temperature, and maximum heat index. (N=612 days)

We built two models for each city, one based on daily maximum temperature and the other based on maximum heat index using SAS 9.2, an integrated system of software product that perform statistical analysis. The models were designed to predict heat-stress calls and identify the temperature threshold at which heat-stress calls increase dramatically. Subsequently, we used the model to predict heat-stress calls under different future climate conditions.

The function of heat-stress calls and predictors is defined in Equation 1, using the negative binomial regression analysis:

$\hat{y} = \exp\{B_0 + B_1 X\}$ Equation (1)

Where $\hat{y}$ = the average (mean) number of heat-stress calls in a day

B_0 =intercept

B_1 = beta value

X = Maximum temperature or maximum heat index (°C)

2.3.3.2 Climate change and heat impacts on human health

One approach to projecting future heat morbidity is to use results derived from downscaled global climate models (GCM), but any contribution to decision making from this approach would likely be limited due to various uncertainties. For instance, GCM scenario combinations yield different projections of the future, depending upon which model is used, the scale of analysis, and the region involved. Trenberth (2010) noted the high degree of uncertainty associated with IPCC Assessment Report 4 climate model projections, and anticipated even higher levels of uncertainty associated with IPCC Assessment Report 5 projections due out in 2013. He argued that as the models become more complex, incorporating a greater number of variables from the climate system as well as the interactions among these variables (e.g., the release of greenhouse gases from melting permafrost and the fertilizing effect of atmospheric carbon dioxide on vegetation), the uncertainty of model results will increase, especially in the short term. Wilby and Dessai (2010) have noted that the ability to downscale models to finer scales does not imply that resulting future scenarios will be more reliable, and that the envelope of uncertainty is impossibly large for vulnerability assessment and climate adaptation, especially for municipal stakeholders. They have argued against using GCM results for assessment, instead favoring an approach that focuses on identifying the vulnerabilities and the sensitivities in the current system to a plausible range of climate change. We employed that strategy, using "what if" changes in future climate based on a reasonable range of temperature increase.

Using results from the negative binominal model of temperature-heat stress relationships, we conducted a hypothetical experiment, assessing the volume of heat-stress calls across a range of temperature increase from two regional climate model simulations (Georgescu et al. 2013; Lynn et al. 2007), and using the volume as an indicator of vulnerability and sensitivity to climate change. Other researchers have used model simulations to predict future summer temperatures in Phoenix (Georgescu et al. 2013) and Chicago (Lynn et al. 2007). Their results indicated that in Phoenix in 2050, the local maximum near-surface temperature warming in a high-development scenario (based on urban and population growth) could reach 4°C, while Chicago could expect an increase in the average summer temperature of approximately 5.5°C by 2080 as a result of anthropogenic climate change. Based on the results of these studies, we applied temperature increases from 1°C to 5.5°C to estimate the change in heat-stress calls from current status. As inputs into our model, we used each city's mean daily maximum temperature in July from 1980-1999, to represent the typical climatic experience of a city. Using this mean as a baseline, we then assessed the sensitivity of heat-stress calls to increases in maximum temperature. The goal of the analysis is not to project future mortality, but to provide sensitivity analysis and vulnerability assessment for the two cities, as a basis on which they might enhance their current emergency-response systems.

2.4 Results and discussion

2.4.1 Extreme heat events and heat-stress calls from 2003-2006

Since 1970, large-scale urbanization and land conversion has resulted in increased summer temperatures in metropolitan Phoenix, and further urbanization is likely to exacerbate surface warming (Georgescu et al. 2009; Grossman-Clarke et al. 2010; Ruddell et al. 2013). A study of historical threshold temperature change and climatic trends in Phoenix (urban) and Gila Bend (desert) in central Arizona found that Phoenix's climatic trend has deviated from its historical path, and shows an increased warming pattern (Ruddell et al. 2013). Warming is also a threat to Chicago, especially in terms of an increase in extremely hot days. Historical records from 1961-1990 indicate that oppressive air masses over Chicago occurred, on average, about 16 days each year, but a set of AOGCM simulations predicted that the frequency of oppressive--mass events is likely to increase dramatically in high-emission scenarios (Hayhoe et al. 2010). While the temporal limitations of our data prevent us from identifying climate trends in the two cities, we did find that Phoenix experienced more and longer-lasting excessive heat events than Chicago did. During our four-year study period, we observed four extreme heat events in Phoenix, all in July (Figure 2.1). In 2006, Phoenix experienced two heat waves in a single month, and the second one had a larger health impact than the first. We observed that numbers of heat-stress calls spiked in July, suggesting that more proactive interventions, medical services, and resources to mitigate heat stress are necessary in July than in other summer months. Chicago had only one extreme heat event in the four years studied. That event also occurred in July, and correlated with a four-year peak in daily number of heat-stress calls: 16.8 percent of total heat-stress calls in that year in Chicago occurred on a single day during this event (Figure 2.2).

Table 2.4 Descriptive analysis of heat-stress calls 2003-2006 (May-September)

	2003	2004	2005	2006	Daily average	Std.	Daily Maximum	Total
Phoenix	571	492	759	738	3.9	4	28	2560
Chicago	152	73	366	513	1.4	6.6	87	1104

Although Phoenix has a smaller population than Chicago, more Phoenicians made heat-stress calls than Chicagoans (2560 versus 1104 calls) (Table 2.4). In Phoenix, heat-stress calls were made on 530 days of 612 days (May-September, 2003-2006), but only on 111 days in Chicago. However, the maximum number of calls in a single day in Chicago was 87 (August 1, 2006), about 3.1 times the maximum number in Phoenix (28 calls on July 21, 2005), suggesting that heat stress was more concentrated during extreme events in Chicago and more a fact of everyday life in Phoenix.

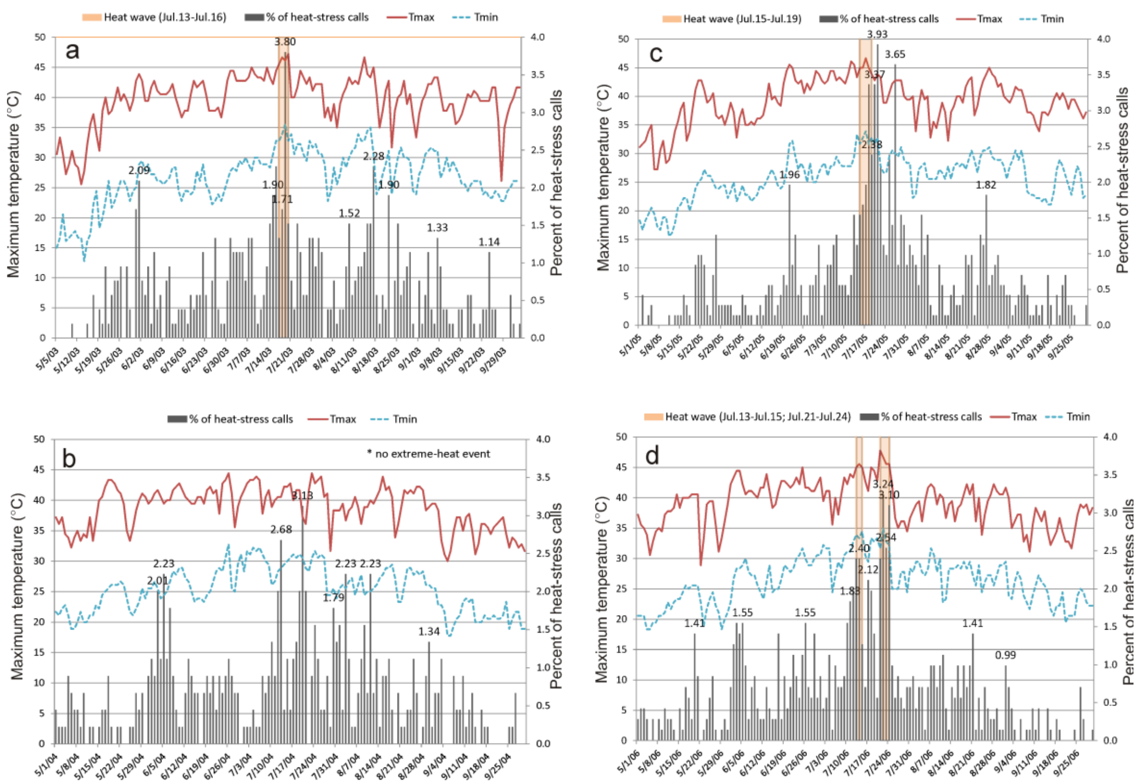


Figure 2.1 Temperatures and heat-stress calls in Phoenix from May to September (a) 2003, (b) 2004, (c) 2005, (d) 2006.

The daily distribution of heat-stress calls in the two cities was very different (Figures 2.1 and 2.2). Distribution in Chicago was highly concentrated during extreme-weather days, while calls in Phoenix were more dispersed. In Chicago, the first cluster of calls occurred in June during three summers, suggesting that Chicagoans may lack of attention to the health effects of heat on residents in early summer. The city could use mass media to increase people's awareness of the possible negative effects of heat exposure starting in June. Annually, peak call numbers were observed in late July and early August in Chicago. That suggests that during this time period, the city requires active plans to educate and inform people about heat stress, such as warning people in

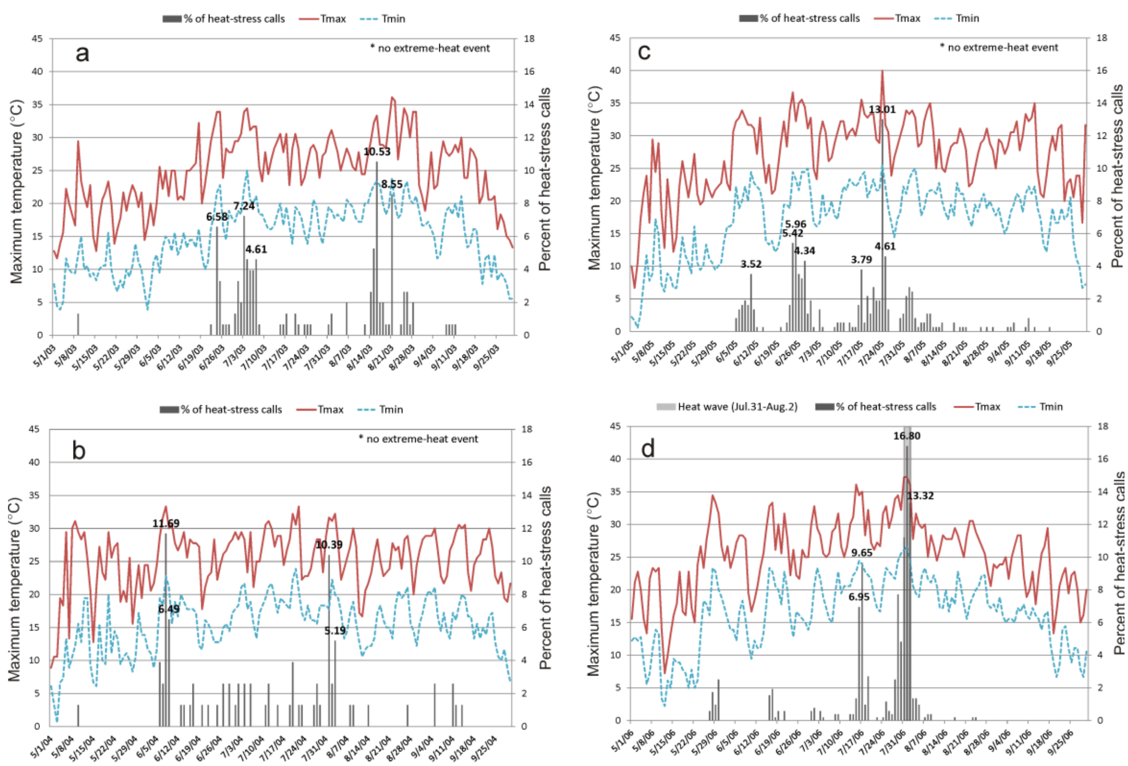


Figure 2.2 Temperatures and heat-stress calls in Chicago from May to September (a) 2003, (b) 2004, (c) 2005, (d) 2006.

advance that high temperatures are going to occur and that they should stay indoors.

Despite the fact that Chicago experienced fewer and shorter extreme heat events than Phoenix, our findings indicated that Chicago residents were more vulnerable to extreme heat than Phoenicians, especially when they faced: 1) a heat wave, or 2) a large diurnal temperature increase, or 3) extreme temperatures outside of their normal range of experience. For example, a large diurnal temperature increase in Chicago on July 24, 2005, with a dramatic temperature increase from 28.9°C (84.0°F) to 40.0°C (104.0°F), resulted in 48 calls in one day. The average maximum temperature for July over the past three decades was 29.5°C (85.1°F) in Chicago. Our findings revealed that 88.5 percent of Chicago heat-stress calls were made when the temperature was above 30.0°C (86.0°F), and call volume spiked when temperature reached 35.6 °C (96.1°F).

2.3.4 Model of heat-related illness

2.3.4.1 Phoenix Models

Our negative binomial models describe the rate of heat-stress-call increases when temperature rises. They also identify the critical temperature at which heat-stress calls will occur. Model results for Phoenix passed the omnibus test, model-effect test, and goodness-of-fit test. The ratio of the deviance to the degree of freedom (DF), Value/DF, of our Phoenix model using maximum temperature as a predictor is 1.0, and the p-value of the omnibus test was less than 0.0001. The Phoenix model using maximum heat index had the Value/DF of 0.9[2], and the p-value of the omnibus test was less than 0.0001. The omnibus test provided a test of the overall model, comparing it to a model without any

[2] The ratio of the deviance to DF, Value/DF, describes how well the model fits the data. If the model fits the data well, the ratio should be close to one.

predictors. A low p-value for this test indicated that the model was significantly improved with the predictor.

- Using maximum temperature as a predictor of heat-stress calls

$\hat{y}$ = exp $\{-6.84+0.203X_1\}$ (2)

When $Y=1$, $X_1=33.7$

- Using maximum heat index as a predictor of heat stress-calls

$\hat{y}$ =exp $\{-3.057+0.103X_2\}$ (3)

When $Y=1$, $X_2=29.7$

Where: $\hat{y}$ = daily average heat-stress calls

X_1= Maximum temperature (°C)

X_2 =Maximum heat index (°C)

Our models predicted the number of heat-stress calls using maximum temperature (Equation 2) and maximum heat index (Equation 3). Based on model results, we predicted that the Phoenix Regional Emergency Dispatch Center would start receiving heat-stress calls when the maximum temperature exceeded 33.7° C (92.7° F), or when the maximum heat index exceeded 29.7° C (85.5° F).

2.4.2.1 Chicago Models

The Chicago models described the relationship between temperature and the average daily number of heat-stress calls in Chicago, using maximum temperature (Equation 4) and maximum heat index (Equation 5) as predictors, respectively.

- Using maximum temperature as a predictor

$\hat{y}$ =exp $\{-17.296+0.573X_3\}$ (4)

When y=1, $X_3 = 30.2$

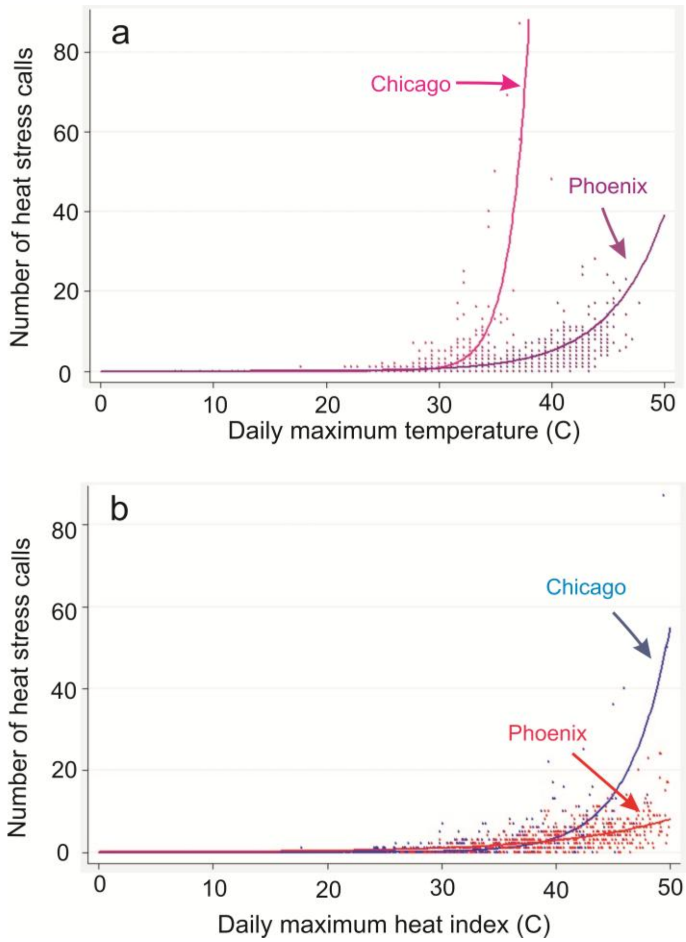


Figure 2.3 The results of the negative binominal model (a) using daily maximum temperature (b) using daily maximum heat index as a predictor.

- Using maximum heat index as a predictor

$\hat{y}$ =exp {-9.646+0.273X_4} (5)

When y=1, X_4 =35.3

Where: $\hat{y}$ = Daily average heat-stress calls

X_3= Maximum temperature (°C)

X_4 =Maximum heat index (°C)

The Chicago models fit the empirical data well, with the Value/DF ratios close to 1.0: the Value/DF ratio was 0.9 for the maximum temperature model and 0.8 for the maximum heat index model. Model results predicted that the Chicago Emergency Dispatch Center would receive at least one call per day when the maximum temperature was above 30.2° C (86.4° F), or when the maximum heat index was above 35.3° C (95.5° F). Heat-stress calls in Chicago would increase sharply when maximum temperature was above 32.0° C (89.6° F).

The model results, along with empirical data on the two cities, were plotted in Figure 2.3. Chicago's steeper curves indicate that Chicagoans are more sensitive to temperature increases than Phoenicians. When daily maximum temperature exceeds 35.0° C, heat-stress calls increase dramatically in Chicago. Heat-stress calls in Phoenix, however, gradually increase until the temperature reaches about 45.0° C. This 10° C difference in threshold temperature indicates that Phoenicians are indeed more acclimatized to high temperatures than Chicagoans; this finding echoes those of Curriero et al. and Medina-Ramon (Curriero et al. 2002; Medina-Ramón and Schwartz 2007).

2.3.5 Heat-stress calls under warmer climate conditions

Although our models showed that Phoenicians are more acclimated to heat than Chicagoans, they are not less *vulnerable* to heat. We used 20-year average daily maximum temperature in July as representative of residents' climatic experience in the hottest month of a year. The 20-year average for Chicago is 29.5° C and for Phoenix, 41.0° C. We used these temperatures as baselines, and calculated that Chicago and Phoenix would average 0.69 and 4.41 calls per day, respectively, at these temperatures

(Figure 2.4). Apparently, the prevalence of air conditioning in Phoenix (more than 90 percent of buildings are air conditioned) still cannot keep the number of heat-stress calls as low as in Chicago, which is a cold-climate city. Reducing the impacts of prolonged heat exposure in Phoenix would require proactive strategies to improve the city's current physical and social environments.

Despite the relatively lower number of heat-stress calls in Chicago, without adaptation, Chicagoans would suffer more negative health effects than Phoenicians if maximum temperatures increase substantially. With small increases in temperature, Phoenix would continue to outpace Chicago in the number of heat-related dispatches. However, if average temperatures were to increase by 4.8°C, Chicago would overtake

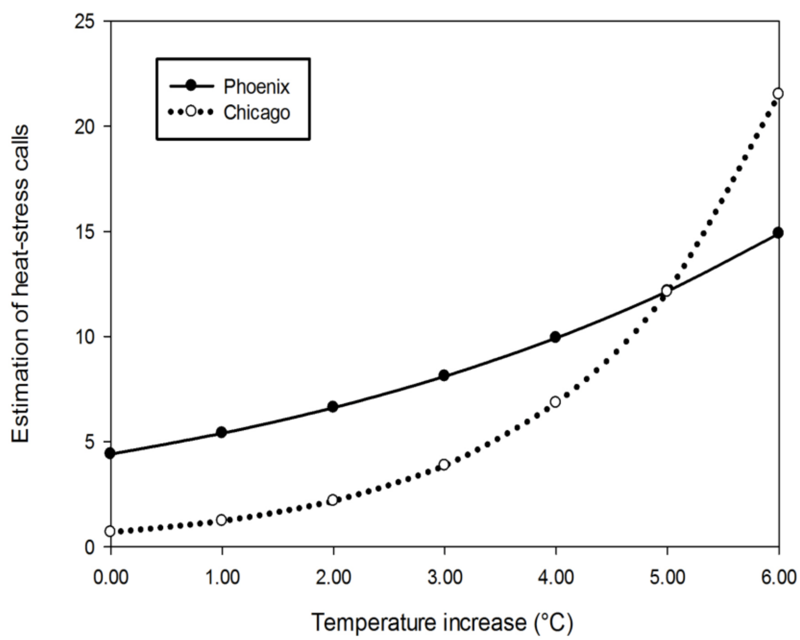


Figure 2.4 Estimates of daily heat-stress calls with increase temperatures.

Phoenix in the number of heat-stress calls (Figure 2.4). A warmer climate could seriously threaten human health and the existing emergency-response system in Chicago during extreme heat events.

2.5 Proactive heat mitigation strategies for the two cities

Willows and Connell (Willows and Connell 2003) have suggested that cities that fail to adopt new measures to cope with excessive heat in the future will become more vulnerable to temperature extremes. Our model results indicate that under current conditions, the critical threshold temperatures at which the Emergency Dispatch Centers start receiving heat-stress calls are 33.7°C (92.7°F) for Phoenix and 30.2°C (86.4°F) for Chicago. With a 5.5°C increase in temperature to 35.7°C, Chicago would experience an average of 16.2 heat-related calls per day. This number could climb higher because of the indirect influence of excessive heat on cardiovascular disease, cerebrovascular disease, electrolyte imbalance, renal failure, and respiratory illness (Reid et al. 2012). Because there are many kinds of emergency-dispatch requests other than heat-stress calls, and heat-stress calls will not be distributed at exactly the average rate on any given day, the capacity of Chicago's current Emergency Management Services (75 ambulances at 24 district stations (The Fire Department, City of Chicago 2012) will likely be challenged by both direct and indirect heat-related calls. A deadly heat wave in 2006 challenged Chicago's emergency response system with 87 heat-related calls in one day. If no adaptive action is taken by the City of Chicago to cope with heat-related events, residents' health could be seriously impacted.

Although the prevalence of air conditioning in Chicago (including central air and window units) reached 90 percent in 2009 (The US Census Bureau 2013), it does not follow that Chicagoans will be less vulnerable to extreme heat events. Lack of adequate capacity in Chicago's power system could exacerbate the impacts of heat. During the heat wave that occurred in July 1995, electric demand due to air-conditioning use created a peak demand for electricity and resulted in power outages. On the second day of the heat wave, area hospitals were overwhelmed with heat-stress victims and unable to keep up with the continuing emergency because of patient volume (Klinenberg 2002). The average duration of power outages in Chicago in 2011 was 89 minutes (not including storm-related blackouts). The overall duration was 366 minutes, affecting 2.8 million people in the greater Chicago area (Daniels 2012). To prevent overreliance on air conditioning that is vulnerable to power outages, Chicago (and municipal governments elsewhere) could enhance building codes to increase ventilation and require the use of materials that absorb less heat in building and housing design. We also suggest that Chicago's municipal government implement a two-stage strategy to reduce heat stress, based on the two threshold temperatures we found. Our model indicates that heat-stress calls start in Chicago when the temperature reaches 30.2°C, and that there is a 5°C difference between the start of calls and an unmanageable proliferation of calls. The recommended first-stage strategy would use existing municipal capacity to provide residents with information about how to prevent heat injuries. Chicago already has an Extreme Weather Notification System that provides registered members with recorded phone messages that communicate official warnings and information about City services to help residents to cope with heat. The City's Office of Emergency Management and Communication also makes and distributes a booklet to educate people about how to prepare for extreme-heat events, including what to do during power outages (Office of

Emergency Management and Communication, City of Chicago 2013). Our findings suggested that this warning information is especially important when the temperature is between 30°C and 35°C. The recommended second-stage strategy would be implemented when the temperature exceeds 35°C, and would require the city to take action to immediately reduce heat-stress by, for example, opening cooling centers and shelters, and providing support and care to vulnerable people living alone.

Chicago faces a set of challenges that results from the concentration of heat-stress calls during extreme-event periods, and from residents' greater sensitivity to increases in temperature, compared with Phoenix. Klinenberg (2002) noted the many cases of heat-related death among those living alone in Chicago. Climate change will likely only worsen the health consequences of social isolation of the elderly; it will also worsen the health consequences of the city's disadvantaged populations, who suffer from inadequate housing and a diminished welfare system. We suggest that Chicago provide more resources and services to its most vulnerable residents, the poor and the elderly, during heat waves, to reduce heat-related illness and death in the future.

In Phoenix, there is 11.3°C difference between the temperature at which the Emergency Dispatch Center starts receiving heat-stress calls (33.7°C) and the temperature beyond which the number of calls received increases dramatically (45°C). This suggests that Phoenix is more resilient to heat than Chicago because its residents have higher tolerance to temperature increases than do Chicagoans. Historically, Phoenix's summer daily maximum temperatures have changed little over time. Phoenix's challenge is that it routinely experiences high temperatures in the summer; in addition, the increasing UHI effect will have a significant impact on local climate. To cope with prolonged heat exposure in Phoenix, we recommend that the municipal government focus on UHI mitigation by providing daytime shade that reduces surface exposure to heat. The City of Phoenix has policies in place to reduce the UHI effect and enhance urban sustainability. By changing landscaping and using new building materials and designs, and by increasing shaded areas that help to mitigate the UHI effect and improve thermal comfort at street level, these policies aim to reduce UHI intensity and energy and water use in neighborhoods (Chow et al. 2012). To provide direct assistance to residents to mitigate heat stress, the Phoenix Heat Relief Network operates when temperatures consistently rise above 38.0°C (100.4°F), and the National Weather Service issues heat warnings that are featured prominently in news outlets. During hot days, homeless service agencies and faith-based communities distribute bottled water, provide temporary refuge for cooling, and give lightweight clothing, hats, and sunscreen to those in need (City of Phoenix 2013).

In Phoenix, interventions targeted at high-risk populations may be more effective in decreasing heat-related illness and death than interventions aimed at the general public. Baker et al. (Baker et al. 2002) found that in Phoenix, heat mainly affects people in outdoor spaces (probably because most of the city's indoor spaces are air conditioned in hot seasons), and we suggest that Phoenix focus on heat-mitigation strategies for outdoor spaces, such as providing shaded areas, accessible drinking water, and warning signs. Research and statistics (Chow et al. 2012; Harlan et al. 2006; Mrela and Torres 2010) indicate that most of the vulnerable population in metropolitan Phoenix is either Spanish-speaking, of low socioeconomic status, in the U.S. illegally, elderly, homeless, or some combination of the above.

2.6 Conclusion

We used the negative binomial regression model to determine how the volume of heat-stress calls in Phoenix and Chicago would be likely to change in response to temperature increase. Model results indicated that the threshold at which calls are likely to increase dramatically in Chicago is 35.0°C (95.0°F), and in Phoenix 45.0°C (113.0°F). The higher threshold for Phoenix may be due to the city's lower humidity and/or wide-spread use of air conditioning in residences, work places, and public buildings. The gentler slopes of the Phoenix models suggest that Phoenix's physical and social capacity to withstand heat is put to the test regularly, as evidenced by the regularity of heat-stress calls throughout the summer. Our results are consistent with Curriero et al.'s research (2002), which found that people in warmer regions are more adaptive to excessive heat than those in cold regions.

Our analysis identified the differences in the vulnerability and sensitivity of Phoenix and Chicago to heat stress. Our findings suggest that urban areas have different threshold temperatures at which heat-stress calls increase drastically, and that these differences are due not only to residents' physiological acclimatization, but also in some measure to the physical characteristics of a city's built environment and the demographic characteristics of its population. We conclude that both Chicago and Phoenix will need to increase adaptive capacity to cope with a warmer climate and reduce heat-related illness and death, especially among their most vulnerable populations. Phoenix needs to prioritize *outdoor* heat-mitigation strategies and those that protect its most vulnerable populations—the elderly, the homeless, Spanish speakers, those of low socioeconomic status, and those in the U.S. illegally—from heat-stress. Chicago needs to strengthen *indoor* heat-mitigation strategies, such as improving building ventilation and opening more cooling centers, increase the effectiveness of the public warning system, and provide social support so that vulnerable individuals can get help from others during heat waves before their situation requires emergency assistance. This study empirically demonstrated the need for improved adaptive capacity and suggested future strategies for achieving this goal. Municipal governments, as well as service agencies and organizations, can use model to inform their planning to reduce heat-related illness and death in the future.

CHAPTER 3

CONTEXTUAL EFFECTS ON THE USEFULNESS OF A GENERIC HEAT VULNERABILITY INDEX: A CASE IN PHOENIX, ARIZONA[3]

3.1 Introduction

Extreme hot weather events have become life-threatening natural phenomena in many cities around the world (Anderson and Bell 2011; Baccini et al. 2011; Harlan et al. 2013; Loughnan et al. 2013; Sheridan et al. 2012; US EPA 2006). Heat vulnerability indices (HVIs), composites of a large number of health, social, and environmental factors relevant to heat stress, have been developed to estimate the risk of heat-related health consequences at a range of spatial scales (Chow et al. 2012; Johnson et al. 2012; Loughnan et al. 2013; Reid et al. 2012; Reid et al. 2009). Application of HVIs at the neighborhood level allows public health practitioners and emergency responders to identify and locate populations that are at the highest risk of heat stress (Reid et al. 2009). Being able to visualize the spatial variation of heat vulnerability (i.e., on a map) enables local governments to allocate resources and increase assistance to people in the areas of greatest need. We investigated how generic indicators of heat-related risk are interrelated in Phoenix, Arizona, and analyzed the relative importance of different components of Reid et al.'s national heat vulnerability index in predicting hospital admissions and identifying hot spots of heat vulnerability at the neighborhood level. Study results may help the city focus its emergency services and climate-adaptation planning on neighborhoods at high risk of heat-related illness and mortality.

[3] This manuscript was co-authored with Patricia Gober and was submitted to *Environmental Health Perspectives* in November 2013.

Table 3.1: Literature on mapping heat vulnerability

Reference	Approach/conceptualization	Variables	Study area	Spatial unit	Test HVI with health data?
Vescovi et al. 2005	Integrated climate variables and socio-economic parameters through GIS tool to produce maps of estimated present and future public health risk to excessive heat.	temperatures, population above 65 yrs old, poverty, social isolation (single person household), education level.	Southern Quebec, Canada	Census subdivision	No
*Lindley et al. 2006	Proposed a framework/method to visualize areas that are vulnerable to heat hazards, as well as projected risks to heat.	maximum temperature, population above 75 yr old and living alone, population below four yrs. old, population with chronic illness, population with mental health problems or is bedridden, income disparity, land use type.	Greater London, the United Kingdom	Census block	No
*Reid et al. 2009	Used factor analysis to analyzed 10 heat vulnerability components, and add up factor scores as HVI.	prevalence of diabetes, race other than white, population above 65 yrs. old, living alone, population above 65 yrs. old and living alone, population below poverty line, population without high school diploma, no green space, no central AC, no AC any kind.	all Metropolitan statistical areas, USA	Census tract	No
*Rinner et al. 2009	Proposed 14 measures that represent exposure, sensitivity, and adaptive capacity to assess potential vulnerability to heat.	remotely sensed surface temperature, lack of tree canopy, green spaces, old dwellings without AC, high-density dwellings without AC, behavior, pre-existing/chronic illness, cognitive impairment, elderly residents, infants and young children, low-income households, rental households, socially isolated people, homeless, low education level, not English speaking, recent immigrants, radicalized groups, access to cooling centers.	Toronto, Canada	Census tract	No
Chow et al. 2011	Constructed a HVI by combining scores of five socioeconomic variables and three environmental factors	summer temperatures, vegetation index, population above 65 years old, median household income, population of foreign-born noncitizens, population living in different residences from 5 years prior.	Metropolitan Phoenix area, Arizona	Census track	No
Uejio et al. 2011	Used Generalized Linear and Mixed Models to identify important risk factors of heat vulnerability linked to heat mortality or morbidity.	selected 22 variables, including vegetation index, remotely sensed surface temperatures, impervious surface, housing density, single family detached homes, poverty, households renting, population above 65 yrs. old, population living alone, people with disabilities, linguistically isolated households, household with more than seven residents, percent ethnical minorities, population lives in different residences from 5 yrs. prior, vacant households, house age, housing value. Statistical results suggest four and 13 significant factors for Philadelphia and Phoenix respectively.	Philadelphia, PA; metropolitan Phoenix, AZ, USA	Census block groups	Heat-mortality identified by The Philadelphia Department of Health between July 8 and August 4, 1999 (n=64). Heat-related emergency calls identified by the City of Phoenix Regional Fire Department Dispatch Center between June to September, 2005 (n=637).

*Reid et al. 2012	Used Poisson regression to related HVI to heat and non-heat-related health conditions during extremely hot days in 5 states in the USA.	prevalence of diabetes, race other than white, population above 65 yrs. old, living alone, population above 65 yrs. old and living alone, population below poverty line, population without high school diploma, no green space, no central AC, no AC any kind	California, New Mexico, Washington, Oregon and Massachusetts, USA.	Zip-code area	Yes: counts of hospital admission due to electrolyte imbalance, cardiovascular, cerebrovascular disease, respiratory illness, nephritis and nephrotic syndrome, acute renal failure, heat-related illness, and internal causes of hospitalization, and number of daily mortality
Johnson et al. 2012	1. Used factor analysis to reduce components of excessive heat vulnerability index (EHVI) from 15 census 1990 variables , and three environmental indicators by adding up factor scores; 2. used the add-up EHVI to test the effectiveness of the EHVI using death rate during excessive heat event.	25 variables were selected at the beginning, but the final analysis keep 18 of them including females and males above 65 yrs. old, females and males above 65 yrs. old and living alone, white population, females head of household, mean family income in 1989, per capita income, mean household income, population above 25 yrs. old and without high school diploma; Asian population; population above 65 yrs. old and living alone; other race population; Hispanic population; Population above 25 yrs. old with a high school education; built-up index; vegetation index; Black population; remotely sensed surface temperature.	Chicago, Illinois	Census block group	Yes: heat mortality data from death certificate during a heat wave in July, 1995 (n=586). Residential heat death is defined by the Illinois State Vital Records Department.
Harlan et al. 2013	1. Used factor analysis to analyze neighborhood effects of population characteristics and biophysical environments; 2. derived a set of HVIs by adding up different risk factors to heat; 3. Examined the effects of HVIs on the presence of heat death in Binary logistic regression model.	ethnic minority, Latino immigrant, population below poverty line, population without high school diploma, population above 65 yrs. old, population with age above 65 and living alone, population living alone, no air conditioning, unvegetated area, remotely sensed surface temperature.	Maricopa County, Arizona	Census block group	Heat-mortality data from death certificate (n=455) between 2000-2008. Heat death is identified by a surveillance system specifically designed to identify heat-caused and heat-related deaths associated with weather in Maricopa County.
Loughnan et al. 2013	1. Identified threshold temperatures for eight Australian cities; 2. developed an index of vulnerability by combining risk scores; 3. used climate model output to predict changes of days with excessive heat; 4. estimated changes in risk related to changing population density and aging population.	population below 4 yrs. old and above 65 yrs. old, aged care facilities, socioeconomic status, urban design (non-single dwellings), proportion of single-person households, population need for assistance (disability), population density, ethnicity, remotely sensed surface temperature, land cover, accessibility to emergency service.	Brisbane; Canberra; Darwin; Hobart; Melbourne; Perth; Adelaide; Sydney, Australia	postal area	No

* including at least one health variable (preexisting health condition) as a component of HVI

3.2 Background

Vulnerability to hazardous natural events is a function of physical exposure, sensitivity, and adaptive capacity (Chow et al. 2012; Polsky et al. 2007; Turner II et al. 2003; Wisner 2004). Physical exposure describes proximity to environmental hazards, such as heat waves or natural disasters. Sensitivity is a characteristic of a population that influences the degree of susceptibility of a population, while adaptive capacity is the ability to cope with change or the impact of a hazardous event. Indicator studies use these concepts to develop measures of risk for local and national populations (Chow et al. 2012; Harlan et al. 2013; Johnson et al. 2012; Reid et al. 2012; Reid et al. 2009).

The social vulnerability index (SoVI) developed by Cutter et al. (2003) used demographic, housing, and neighborhood variables from the 1990 U.S. Census data to examine the social vulnerability to environmental hazards of 3,141 U.S. counties. Their approach to vulnerability indicators (Cutter and Finch 2008) guides scholars searching for indicators of heat risk.

Negative health consequences of heat result from interactions of human and natural factors. How HVI is conceptualized and measured differs from one study to another. In the past decade, at least 11 studies have developed different HVIs to map and visualize human vulnerability to heat (Table 3.1). Some researchers have used statistical and modeling approaches to identify the crucial risk factors they used for mapping vulnerability, while others assembled variables according to empirical analysis (e.g., ethnic minorities are generally more vulnerable than non-Hispanic whites) or social theories (e.g., low social cohesion may have negative impacts on residents' health) to evaluate an area's risk to heat. Most studies include as risk factors the key aspects of temperature and vegetation cover (exposure components); age and ethnicity (sensitivity components); and income (adaptive capacity). Aside from these common features of vulnerability, the concerns of different disciplines further differentiate the measures and conceptualization of heat vulnerability index. For example, Uejio et al. (2011) from the field of environmental modeling used indicators of the built environment and neighborhood stability to examine heat mortality and heat-related emergency services (EMS). They found that neighborhoods with a high proportion of ethnic minorities, social isolation, and vacant housing units experienced the highest heat-stress incidence. Epidemiologists emphasize human health conditions as risk factors; for example, diabetes, which increases susceptibility to heat (Reid et al. 2012; Reid et al. 2009; Rinner 2009). Public health experts and sociologists use variables such as prevalence of air conditioning (AC) and social infrastructure (i.e., access to health care facilities) as indicators of a society's adaptive capacities (Harlan et al. 2013; Loughnan et al. 2013; Reid et al. 2012; Reid et al. 2009). Different disciplinary perspectives capture different elements of exposure, sensitivity, and adaptive capacity, and thus produce different findings about what determines heat-stress vulnerability.

Reid and colleagues (2009) developed a composite HVI using a statistical approach that integrated factors known to be associated with risk of heat stress at a national scale. They selected six socio-demographic and economic indicators (poverty, educational level, minority status, living alone, elderly, and elderly living alone), two air-conditioning variables, a measure of vegetation density, and the prevalence of diabetes to create an HVI for metropolitan statistical areas that comprise 39,794 Census tracts across the U.S. They identified four dimensions of heat vulnerability: (1) social and environmental vulnerability—the aggregation of low education level, poverty, ethnic minority status, and lack of green space; (2) social isolation, which is measured by the proportion of people living alone; (3) AC prevalence; and (4) underlying health conditions, represented by the proportion of elderly in the population and the diabetes rate. Building upon this work, Reid et al. (2012) asked whether areas, at a ZIP-code scale, with high HVI scores had higher rates of mortality and morbidity during abnormally hot days. They evaluated the relationship in five states, California, New Mexico, Washington, Oregon, and Massachusetts. In California, Washington, and Massachusetts, heat-related illness was more strongly associated with the HVI on abnormally hot days than on other days. But in Oregon, rates of heat-related illness were the same on normally hot days and abnormally hot days. And in New Mexico, a one unit increase in the HVI was associated with a significant *decrease* in heat-related hospitalization on abnormally hot days. It is possible that local effects influence what the HVI measures in different places, and limit its usefulness as a predictor of adverse health outcomes in some areas.

Two local HVI studies have been conducted in Arizona, using measures similar to but not identical to Reid et al. (2009; 2012). Chow et al. (2012) constructed an HVI using seven indicators from three dimensions of heat vulnerability (physical exposure, adaptive capacity, and sensitivity) at the Census-tract level in metropolitan Phoenix. They then investigated geographical change in risk of heat stress between 1990 and 2000, and estimated the shift in vulnerability to heat of different ethnic populations. They demonstrated that metropolitan Phoenix has experienced a huge demographic change, and the change alone altered the “heatscape” in the region. The other Arizona study, by Harlan et al. (2013), examined neighborhood vulnerability indicators for 2,081 Census block groups in Maricopa County. Using 278 heat-death cases as dependent variables, they used binary logistic regression to validate a set of HVIs with different combinations of indicators. They concluded that socioeconomic vulnerability, being elderly or isolated, and surface temperature were strong predictors of death from heat exposure.

3.3 Aim and scope of the study

Measurement, scale, and context all influence the identification of risk factors. Different combinations of risk factors may cause the factors to relate to one another differently, producing a in the "vulnerability landscape." To better understand the relationships among risk factors and different scales, we tested Reid et al.'s (2009) national indicators in a local context. We investigated human vulnerability to heat in Phoenix, one of the nation's hottest cities. We also evaluated the extent to which the national indicators are useful for local planning and analysis in the City of Phoenix. By applying Reid et al.'s (2009) generic index to Phoenix, we were able to evaluate how accurately the generic index reflects actual risk of harm. We used the same variables as the national HVI studies (Reid et al. 2009 and 2012), but a few of them were measured differently at the census-tract scale. At this fine scale, we expected that our findings might be different from those of Reid et al. (2009; 2012) and the local research mentioned before. Harlan et al. (2013) also created and validated a set of HVIs at neighborhood level in Maricopa County, AZ, but the absence of the diabetes variable and the addition of temperature and biophysical variables (such as standard deviation of vegetation index) in that study limit its comparability with the national study.

We also asked where, and what kind of, neighborhoods are at risk of heat-related illness caused by factors *beyond* social and economic vulnerability, inadequate green space, social isolation, and diabetes. We used a multinomial logistic regression model, with heat-related hospital admissions for heat stress as the dependent variable, to answer the following questions: (1) How well does a national HVI explain heat-related hospitalizations in Phoenix? The municipal scale is highly relevant to intervention because it is the scale at which local governments determine resource allocation and enforce policies. (2) What is the relative importance of physical exposure, adaptive capacity, and sensitivity to the incidence of heat-related hospitalizations, given Phoenix's hot climate and high prevalence of air conditioning? (3) In which kinds of neighborhoods is the incidence of heat-related hospitalizations explained well or poorly by the HVI? (4) What conditions might be causing heat-related hospitalizations in Phoenix other than those included in the national HVI?

3.4 Materials and method

Our dependent variable came from the Arizona Department of Health Service's hospital discharge databases for 2004 and 2005. This dataset contains disease code, the International Classification of Diseases--Ninth Revision--Clinical Modification (ICD-9-CM) code, as well as the census tract number of the patient's residence, allowing us to calculate the rate of heat-related illness for each census tract, using ArcGIS 10. We geocoded 460 heat-related hospitalizations (ICD-9-CM codes 992.0-992.9, effects of heat and light) in 362 census tracts, and normalized the events using the population of each tract. Rates of hospitalization varied between 0 and 0.76%; the average rate was 0.03%. The distribution of the hospitalization rate was positively skewed, with a mode of 0, median of 0.02, mean of 0.03, and standard deviation of 0.05.

We used the variables used in Reid et al.'s (2009) national-scale research on heat vulnerability as our independent variables. Poverty, low education level, AC prevalence, and social isolation were indicators of adaptive capacity; ethnicity, age, and diabetes prevalence were indicators of a population's sensitivity to heat; and the density of green space indicated both physical exposure and adaptive capacity. Vegetation density has been shown to reduce neighborhood temperatures, particularly at nighttime (Shashua-Bar et al. 2009; Stabler et al. 2005). Other researchers have found a relationship between income and vegetation, which suggests that people in Phoenix use vegetation to mitigate the effects of heat (Harlan et al. 2006; Jenerette et al. 2007).

We used data from Census 2010 for our socio-economic and demographic variables, which included the percentage of population: living below the poverty line (poverty), above 65 years of age (elderly), ethnically other than non-Hispanic white (i.e., minority), having less than a high school diploma (low education), living alone, and living alone and more than 65 years old (elderly living alone). To determine poverty, the Census Bureau uses a set of annual income thresholds that vary by family size and composition. Official poverty thresholds do not vary geographically, but are adjusted according to the Consumer Price Index. Using these data, the poverty threshold for a household in Phoenix with two adults is $14,218 (U.S. Census Bureau 2013).

For AC prevalence, we aggregated parcel-level residential AC data from the Maricopa County Assessor's Office to the census-tract level. We measured the incidence of diabetes using the same hospitalization dataset that we used for heat stress. Using the principal diagnosis code (ICD-9-CM codes 250.0-250.9, Diabetes mellitus) and the cases' census tract numbers, we mapped 7727 cases of diabetes. Diabetes hospitalization rates varied from 0 to 5.52%; the average was 0.50%. Fifty-three (14.5%) of the census tracts had no hospital admissions for diabetes. We measured diabetes rates differently from Reid et al. (2012; 2009). They estimated diabetes prevalence based on age, race, and gender of a county's populations and the diabetes incidence rate of each group, which may have limited their conclusions by missing small-scale (neighborhood) effects on the disease.

We obtained vegetation index using a high-resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) image, with a 15-meter spatial resolution for the red and near-infrared bands used. We needed three ASTER images to cover the entire study area, and pieced together three images taken on June 16, 2005 and July 06, 2006 to represent Phoenix's summer vegetation. The normalized difference vegetation index (NDVI) was calculated using red and near-infrared bands in ERDAS IMAGINE 2011, a remote-sensing image-processing software. NDVI is widely used by ecologists and geographers to evaluate the vegetation cover of a large study area (Netzband et al. 2007). The NDVI value lies between -1 and 1, representing no vegetation coverage to high vegetation coverage, respectively.

3.4.1 Statistical analysis

Factor analysis was conducted using IBM SPSS 19. We used factor scores from this analysis as independent variables in the multinomial logistic regression (MLR), with health outcomes as dependent variables. Logistic regression is widely used in health studies in predicting the odds ratio of health outcomes (Warner 2002). We divided Phoenix's 362 census tracts into three categories based on the incidence of heat-related illness: zero-incidence tracts (146 tracts, 40.1%), moderate-incidence tracts (109 tracts, 30.1%), and high-incidence tracts (107 tracts, 29.6%). The distribution curve of hospital admissions is skewed to the right, with the mean at 0.03%. We used 0.5 standard deviation above the mean as the boundary between moderate and high-incidence neighborhoods. We then built an MLR model using factor scores as predictors (independent variables) of heat-related hospitalization.

3.5 Results

3.5.1 Correlation matrix

Spearman's correlation coefficients show the relationships among each of the 10 vulnerability indicators (Table 3.2). We found that diabetes-related hospitalization is highly correlated with the percentage of people below the poverty line, having less than a high school diploma, being of a race other than white, and being without central AC or AC of any kind. In the nationwide analysis, Reid et al. (2009) did not find such a strong correlation between diabetes prevalence and these variables (coefficient<0.3). Different measurements of diabetes and the demographic structure of Phoenix may have effects on our findings. Our fine-scale analysis revealed that hospitalization for diabetes had a very strong relationship with ethnicity and class, and marginal, socioeconomically disadvantaged groups in Phoenix suffered from diabetes more than others. Diabetes rates vary across ethnic groups, and minorities have higher rates (from 8.4% to 16.1%) than White Anglos (7.1%) (CDC 2012). As a chronic disease, diabetes can be managed with control programs and preventive actions; however, hospitalization data suggest that diabetes is not well-controlled among deprived Phoenicians.

Table 3.2 Spearman's correlation for vulnerability variables

	Diabetes	Race other than non-Hispanic white	Age above 65	Live alone	Elderly living alone	Below poverty line	Less than high school diploma	Low vegetation	No central AC	No AC of any kind
Diabetes	1.000									
Race other than white Anglo	.632**	1.000								
Age above 65	-.127*	-.543**	1.000							
Living alone	.343**	.055	.147**	1.000						
Elderly living alone	.270**	-.067	.521**	.574**	1.000					
Below poverty line	.734**	.790**	-.334**	.307**	.158**	1.000				
Less than high school diploma	.674**	.911**	-.420**	.088	.044	.825**	1.000			
Low vegetation cover	.322**	.336**	-.353**	.117*	-.026	.349**	.375**	1.000		
No central AC	.508**	.427**	-.047	.248**	.174**	.512**	.447**	.228**	1.000	
No AC of any kind	.516**	.421**	-.049	.260**	.173**	.498**	.434**	.258**	.929**	1.000

(Spatial unit: census tract; n=362) Correlation is significant (2-tailed) at the 0.05 level (*), and at the 0.01 level (**).

Another location-specific condition that was not accounted for in the large-scale analyses of (Reid et al. 2012; Reid et al. 2009) is AC prevalence, which is strongly negatively associated with poverty status and minority status in Phoenix, but not nation-wide. AC is vital to life and comfort in Phoenix, where summertime temperatures average 41ºC in July (Cerveny 1996). Although Phoenix's AC prevalence is above 90%, including central and window units (The US Census Bureau 2013), the nearly 10% of housing units without AC units are concentrated in economically disadvantaged neighborhoods in central Phoenix. We also found that neighborhoods in Phoenix with a higher proportion of elderly residents were likely to be wealthier, greener, and better educated than what Reid et al. (2009) found at the county scale for the nation overall. This difference could have to do with the influx of wealthy retirees into the Phoenix area and their tendency to live in retirement communities that often feature golf courses and outdoor recreational activities (Gober 2005).

3.5.2 Spatial Pattern of Heat Stress in Phoenix

We generated a map that displays the spatial distribution of hospitalization rates in the Phoenix (Figure 3.1). The map reveals a highly uneven rate pattern, with higher rates tending to be in the urban core rather than on the urban fringe. Urban-fringe neighborhoods in the northeast (Paradise Valley Village), northwest (North Gateway Village), and south Phoenix (South Mountain Village) have very low rates of heat-related hospitalization. Among the three neighborhoods with the highest hospitalization rates, one (neighborhood #3 in Figure 3.1), directly west of Sky Harbor Airport, is a low-income neighborhood with a median household income of $20,488 and a Hispanic population of almost 90%. However, the other two (#1 and #2 in Figure 3.1) are middle-class (with median household incomes of $40,104 and $37,514) neighborhoods, and their population of Hispanics are 25.7% and 52.3%, respectively.

3.5.3 Factor Analysis

Following Reid et al.'s (2009) analysis, we applied a Varimax rotation in the factor analysis to minimize the number of the original variables that load highly on any one factor and increase the variation among factors. We retained three factors (Table 3.3) with eigenvalues larger than one: poverty, ethnic minority, and low education (Factor 1); lack of AC and vegetation (Factor 2); and diabetes and social isolation, including elderly living alone (Factor 3). Factor 1 explained the highest amount of variance (44.7%), while Factor 2 and Factor 3 explained 19.98% and 10.46% of the variance, respectively. Together these three factors explained 75.14% of the total variance of the 10 vulnerability indicators, results similar to Reid at al.'s (2009) findings, where 75% of the total variance was explained by four factors.

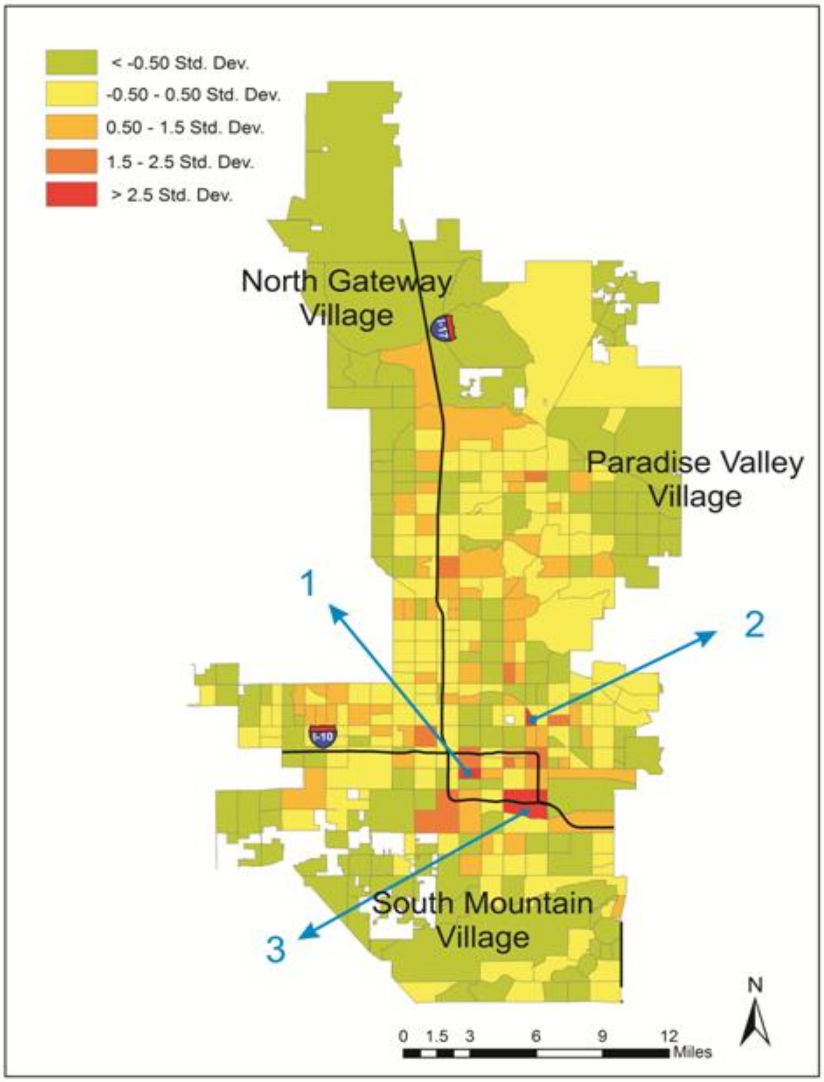
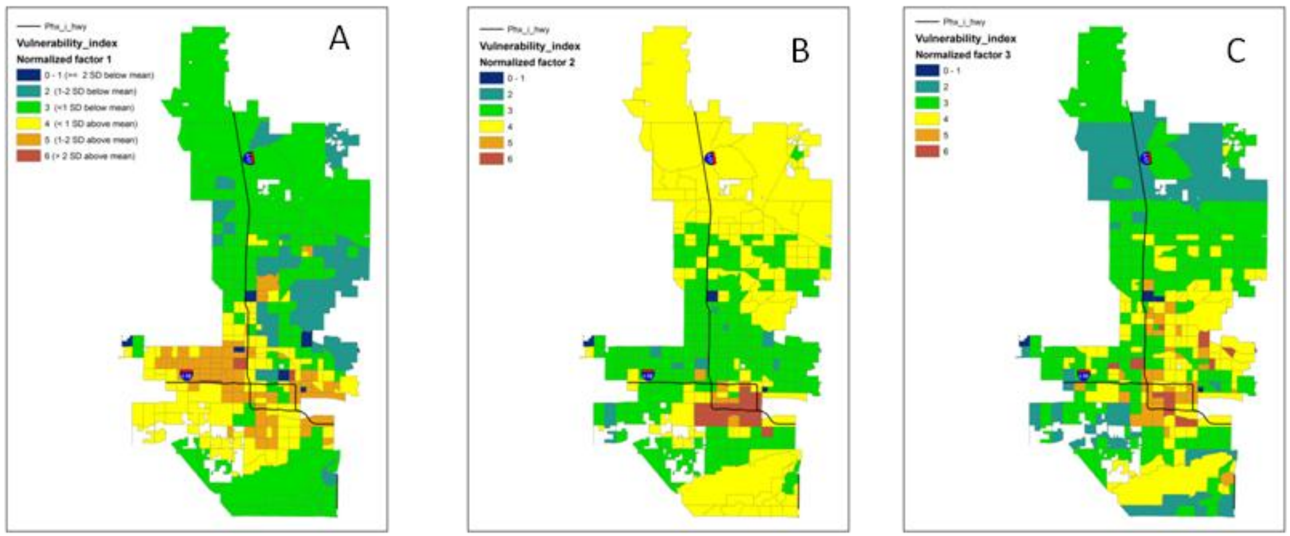


Figure 3.1 Spatial distribution of heat-related hospitalizations



*Red color represents high vulnerability

Figure 3.2: Maps of factor scores. A: Factor 1: Poverty, ethnic minority, and low-education level. B: Factor 2: Lack of AC and vegetation. C: Factor 3: Diabetes and social isolation.

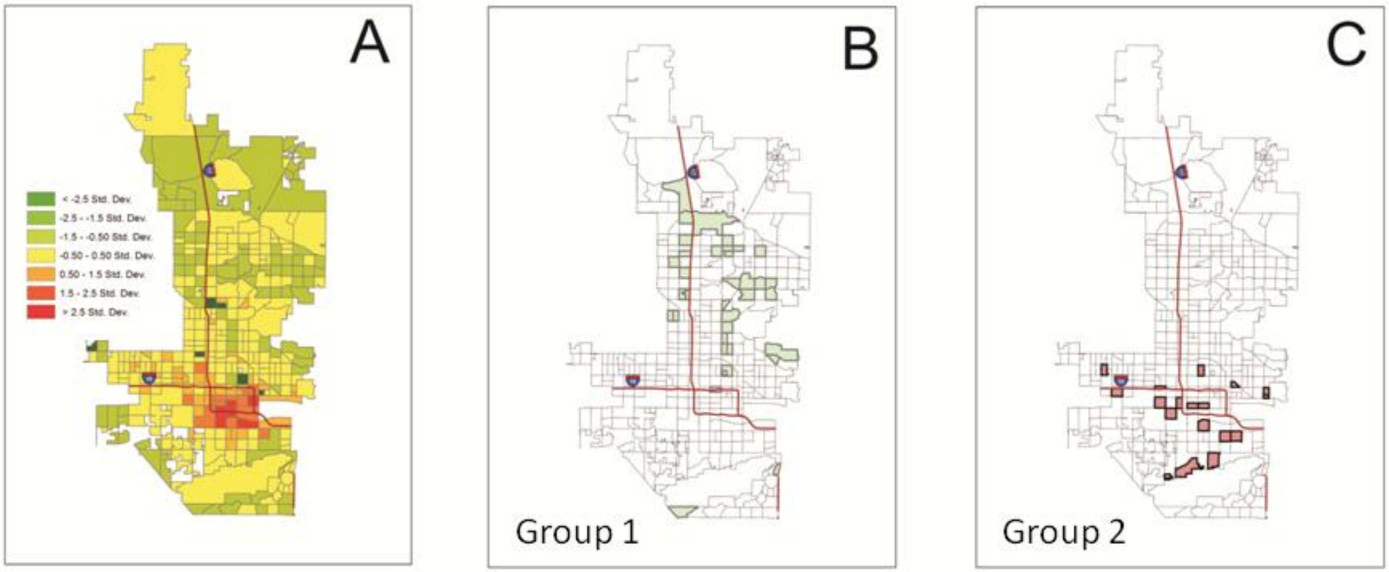


Figure 3.3 A: Map of heat-vulnerability index using the sum of the three factor scores. B: The high-incidence neighborhoods that are predicted as zero-incidence neighborhoods. C: The zero-incidence neighborhoods that are predicted as high-incidence neighborhoods.

Table 3.3 Factor analysis of 10 variables

Variables	Factor 1	Factor 2	Factor 3
Below poverty line	**0.797**	0.297	0.324
Ethnicity other than white Anglos	**0.926**	0.1	0.039
Less than high school diploma	**0.889**	0.18	0.142
Age above 65	**-0.653**	-0.154	0.485
No central AC	0.186	**0.919**	0.27
No AC of any kind	0.181	**0.921**	0.272
Low NDVI	0.44	**0.451**	-0.142
Age above 65 living alone	-0.057	0.101	**0.885**
Living alone	0.126	0.229	**0.627**
Diabetes	0.54	0.263	**0.585**

Factor 1: poverty, ethnic minority and low education; Factor 2: lack of AC and vegetation; Factor 3: diabetes and social isolation.

Poverty and minority status are fundamental elements of heat vulnerability, both locally and nationally, and they appear in Factor 1. Also included in Factor 1 is a negative relationship with elderly populations, because disadvantaged neighborhoods in Phoenix tend to have a large number of children and relatively few elderly residents. Factor 2 combines the lack of air conditioning with the lack of vegetation. This factor captures inner city neighborhoods (Figure 3.2B). Factor 2 can be considered a location factor. That is, people who live in the inner city are at higher risk from heat than people in other parts of the city. Factor 3 includes the combination of social isolation (especially of elderly people) and diabetes hospitalization. In Phoenix, demographic characteristics make the combination of social isolation and diabetes an important factor. In 2010, the number of people over 65 years old living in Phoenix was 121,943 according to the decennial census; among them, 31,791 people (about 27%) were living alone, giving Phoenix a higher proportion of elderly living alone than its neighboring cities (U.S. Census Bureau 2011).

The elderly population is at higher risk for diabetes (Arizona Department of Health Services 2008). Thus, Factor 3 can be explained by the history of retirement migration to Phoenix may have resulted in a large proportion of elderly living in social isolation, and the characteristics of this population are at high risk of diabetes hospitalization.

The sum of the three factor scores is displayed as an HVI map in Figure 3.3A. The areas with high HVI scores are clustered in the downtown Phoenix central business district and along the south side of the industrial corridor. These areas are home to marginalized populations and are of poor environmental quality (Grineski et al. 2007). Social deprivation may be associated with heat stress in the inner city of Phoenix.

3.5.4 MLR models

The results of the multinomial logistic regression show that the model using three factors as predictors outperforms the null hypothesis (a model without any predictor). The Bayesian Information Criterion (BIC) indicates that the model is “very strong” because the BIC value is above 10, with $p<0.01$. The model also passed the test of significance and goodness of fit, meaning that the data are consistent with the model assumptions. The overall likelihood ratio test shows that Factors 1 (socioeconomic deprivation) and 3 (social isolation) are statistically significant predictors of hospitalization rate.

Parameter estimates provide detailed information for the effect of each factor on the odds ratio, when the model compares response category with the reference group (Table 3.4). Only Factor 1, poverty and minority status statistically differentiates membership in a moderate-incidence tract from membership in a zero-incidence tract.

The Exp(B) coefficient indicates that a one-unit increase (mean ± 1) in Factor 1 increases the odds of being in the moderate incidence category by 99.6%.

Table 3.4 Multinomial logistic regression results (Parameter Estimates)

		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Moderate-incidence tract	Intercept	-0.178	0.141	1.609	1	0.205			
	FAC1	0.691	0.144	22.917	1	0.000	1.996	1.504	2.649
	FAC2	-0.172	0.21	0.674	1	0.412	0.842	0.558	1.270
	FAC3	0.165	0.168	0.972	1	0.324	1.180	0.849	1.638
High-incidence tracts	Intercept	-0.312	0.147	4.49	1	0.034			
	FAC1	1.007	0.152	43.829	1	0.000	2.738	2.032	3.689
	FAC2	0.183	0.145	1.579	1	0.209	1.200	0.903	1.596
	FAC3	0.691	0.166	17.405	1	0.000	1.996	1.442	2.761

a. The reference category is: 0 (zero-incidence tract).

When we compared high-incidence tracts to zero-incidence tracts, Factors 1 and 3 were significant variables affecting health outcomes. A one-unit increase in Factor 1 led to a 173.8% increase in the odds of a tract being a high-incidence tract rather than zero-incidence tract. Similarly, a one-unit increase in Factor 3 was associated with a 99.6% increase in the odds of a tract being a high-incidence tract relative to a zero-incidence tract. From these finding, we concluded that increasing proportion of the population living in poverty and ethnic minority status increases the incidence of heat stress, and that increases in both socioeconomic vulnerability (Factor 1) and social isolation and diabetes (Factor 3) increase the rate of heat-related illness, pushing an area into the high-incidence category.

We used the factor scores to predict the category (zero, moderate, and high incidence) of heat-related health outcomes for each tract. We then compared the predicted values and observed values. The classification table (Table 3.5) shows that our MLR model correctly predicts 78% of the zero-incidence neighborhoods, 26% of moderate-incidence, and 48% of high-incidence tracts. The overall accuracy rate in predicting heat-related outcomes was 54%, suggesting that heat hospitalization is a complex issue, and factors other than those in the standard vulnerability index contribute

Table 3.5 Accuracy assessments (Classification table)

Observed	Predicted			
	0	1	2	Percent Correct
0	115	14	17	78.8%
1	56	29	24	26.6%
2	35	21	51	47.7%
Overall percentage	56.9%	17.7%	25.4%	53.9%

*0= zero-incidence; 1=moderate-incidence; 2=high-incidence neighborhoods

to risk prediction; identifying those factors may improve intervention strategies.

Factor 2, with high loadings on lack of AC, is not a significant predictor of heat hospitalization in Phoenix. AC has been recommended as a mitigation strategy to reduce the effect of heat on health, because many studies found that AC prevalence is negatively associated with adverse health outcomes, especially on hot days (Keatinge 2003; McGeehin and Mirabelli 2001; Semenza et al. 1996; Semenza et al. 1999). However, having an AC unit installed in a house does not automatically translate into being able to use it to relieve heat-stress. According to a 2009 survey that interviewed 359 households in three socially vulnerable neighborhoods in metropolitan Phoenix (Hayden et al. 2011), many poor, minority families in Phoenix cannot afford to turn on their AC in the hottest season. In one neighborhood, more than 50% of respondents with AC indicated that they could not cool their homes during the summer because of the high electricity cost. In the two other neighborhoods, one-third of the respondents decided not to use AC in order to reduce the cost of their electricity bill (Hayden et al. 2011).

3.5.5 Unpredictable neighborhoods

We looked at the neighborhood characteristics of the 14% of census tracts that were oppositely misclassified by the model--35 neighborhoods predicted to be zero-incidence neighborhoods that were actually high-incidence neighborhoods (Table 3.6, Group 1; Figure 3.2B), and 17 neighborhoods that were predicted to be high-incidence areas but were actually zero-incidence areas (Table 3.6, Group 2 ; Figure 3.2C). Many members of Group 1 were wealthy neighborhoods on the urban fringe. Members of Group 2 were scattered in central and south Phoenix. The median household-income level of the 17 neighborhoods was $27,216. These neighborhoods have a higher proportion of Hispanic population than those in Group 1. Although neighborhoods in Group 2 were low-income, and the proportion of Hispanics and the diabetes rate there were higher than the City's average, they seemed to be resilient to heat. It is possible that these ethnic minority neighborhoods might have strong social networks that help residents get help before their health condition deteriorates due to heat. Several studies have pointed out that some socioeconomically disadvantaged groups and immigrants have strong internal social networks that foster social cohesion and fast recovery from disasters (Chamlee-Wright and Storr 2009; Klinenberg 2002; Li et al. 2010). A study of the deadly 1995 heat wave in Chicago found that busy and vital streets and high-density

Hispanic communities brought residents into contact with family, friends, and neighbors and provided a safety net in times of need (Klinenberg 2002). The same study compared two African-American communities, Englewood and Auburn Gresham, with similar poor, elderly populations, and found differing health outcomes of the heat wave. While Englewood suffered a large number of deaths during the heat wave, Auburn Gresham was far safer from heat death than many of the most affluent neighborhoods on the North Side of Chicago. Klinenberg (2002) concluded that strong ties to friends, family, and neighbors; pedestrian-friendly streets; and shops, restaurants, and community organizations are sources of community resilience that can save lives when a heat wave hits a city. Indeed, living in a neighborhood with a robust social infrastructure that provides an environment for mutual assistance could reduce negative health impacts, especially during disasters (Sampson 2011).

Table 3.6 Percent of Census tract with a value above the city's average in misclassified neighborhoods

Indicators (average)	**Group 1**	**Group 2**	**Phoenix City's average**
Median household income	60 % ($52,972)	0% ($27,216)	48,750
Proportion of non-Hispanic white	97 (69.16)%	6 (18.25) %	48.92%
Non-citizenship population	11 (8.6) %	71 (23.13) %	15.54%
Unemployment	23 (6.18) %	59 (8.84) %	7.52%
Proportion of renter	49 (40.93) %	65 (54.86) %	41.58%
Proportion of residents living in the same residence less than 5 years	**43 (44.18)** %	35 (47.85) %	46.24%
Vacancy rate	46 (12.44) %	71 (16.92) %	12.82%
Surface temperature	54% (26.06˚C)	76 (26.64˚C)	25.75%

Group 1: High-incidence neighborhoods but they were predicted to be zero-incidence neighborhoods.
Group 2: Zero-incidence neighborhoods but they were predicted to be high-incidence neighborhoods.
Values in parentheses: An average value for all neighborhoods in a group.

To better understand the risk factors beyond the scope of the national HVI, we looked at variables from other heat vulnerability studies which were not included in Reid et al.'s 2009 Study. These were the size of a census tract's non-citizen population, proportion of renters, residents living in the same residence less than five years, unemployment rate, vacancy rate, and nighttime surface temperature (Chow et al. 2012; Harlan et al. 2013; Klinenberg 2002). The first variable is a proxy for new immigrants who may have limited access to warnings, medical support, and resources that can help them gain relief from heat stress (Chow et al. 2012). Proportions of renters and new residents are measures of population mobility. Short-term renters and newcomers are likely to lack social support and assistance in their neighborhoods (Chow et al. 2012; US EPA 2006). Unemployment and vacancy rates are typically used as proxies for social stability of a neighborhood; unemployment rate captures the population's lack of stable economic resources and vacancy rate explains a neighborhood's prosperity. Klinenberg (2002) found that high unemployment, vacancy, and a high crime rate hinder residents from seeking help and prevent people from opening their windows for better ventilation during heat waves. We were not able to acquire crime-rate data at the census-tract scale for Phoenix, but we believe that unemployment and vacancy rates are adequate proxies for social stability. The last factor, nighttime surface temperature, represents the intensity of the urban heat island effect.

The above factors varied widely in the two groups of misclassified neighborhoods, so taking the averages of these variables for the two groups may not adequately represent the groups' characteristics. Thus, we used the city's average numbers for these variables as thresholds, and calculated the percentage of neighborhoods above the city average for each variable. Group 1 neighborhoods (shown in Figure 3.3B), with much higher expected hospital admissions than the HVI would have predicted, have a high proportion of white Anglos, but higher neighborhood mobility (43%) than Group 2 neighborhoods (35% mobility). High mobility may have a negative impact on heat-related hospitalization.

Many of the neighborhoods in Group 1 were in low-density areas on the urban fringe. The low-density environment offers a different lifestyle than does the urban core, one that may affect health outcomes of residents. However, more work is required to understand if the neighborhood design (low-intensity) and the life style (i.e., high car dependency) in these neighborhoods result in low social interaction and hinder the formation of social cohesion. Many neighborhoods in Group 2 (Figure 3.3C) were located in the city core, and had higher population densities and a higher proportion of Hispanic residents than neighborhoods in Group 1, but experienced no heat-related hospitalization. These neighborhoods may be good entry points for further research on neighborhood cohesion and sources of resilience.

3.6 Discussion

Using the three factors as predictors, our MLR model showed Factor 1, poverty/minority, and Factor 3, isolation/diabetes, to be the statistically significant determinants of hospitalization rates. In the case that compares zero and moderate-incidence neighborhoods, a one-unit increase in Factor 1 itself will almost double the odds of a zero-incidence neighborhood becoming a moderate neighborhood. When we compared zero-incidence neighborhoods with high-incidence neighborhoods, we found that Factor 1 and Factor 3 both had large impacts on the probability of being in high-incidence neighborhoods. When holding Factor 3 constant, a one-unit increase in Factor 1 almost triples the odds of a zero-incidence tract becoming a high-incidence area. We concluded that socioeconomic status (SES) and diabetes/social isolation are the crucial components of human vulnerability to heat in Phoenix when vulnerability is measured by hospitalization rates. This finding coincides with those of studies that found a strong association between poverty, minority, and heat-related illness (Curriero et al. 2002; Harlan et al. 2006; Jenerette et al. 2007; Uejio et al. 2011), and studies that have shown that diabetes complicates the human response to heat, resulting in heat-related illness and death (Schwartz 2005; Semenza et al. 1999). Our empirical analysis showed that the combination of SES (Factor 1) with social isolation and diabetes (Factor 3) aggravates the effects of heat on health and increases hospitalization rates. That is, low SES is the primary factor in human vulnerability to heat, and social isolation and diabetes aggravate the impact of heat. Thus, neighborhoods with these population characteristics will need interventions to help them adapt to future climate conditions and to respond more effectively to extreme hot weather events.

Our analysis reveals that proportion of dwellings with AC is not a contributor to heat-related hospital admissions, perhaps because the incidence of AC in Phoenix is so high or because having a unit does not translate into using the unit. AC may not be a significant predictor also because some heat-related illness may occur among those who work outside during the summer or are engaged in outdoor activity, and thus having an AC at home does not eliminate their risk of heat-related health problems. If this interpretation is correct, then reducing the risk of heat-related hospitalizations will require more than an increase in home AC units; it will also require more effective mitigation of risk for people who work or recreate outside, and identification of socially isolated, diabetes patients and concentration of effects in disadvantaged neighborhoods.

To enhance the predictability of HVI at the local level, we suggest that future studies incorporate the measurement of social mobility. In our misclassified neighborhoods, we found wealthy, white-Anglo neighborhoods with higher hospital admissions than the HVI would have predicted. Many of these neighborhoods have a proportion of households that have relocated to the neighborhood in the past five years that is higher than the city average. These new residents may lack information about how to cope with heat, and have limited support and social interaction in the neighborhood. Programs that enhance newcomers' awareness of the risks of heat may also reduce the incidence of negative health outcomes in highly transient neighborhoods.

Our findings provide information about vulnerable neighborhoods that can help the Phoenix city government plan for local interventions. We recommend a two-stage strategy to reduce heat-related hospital admissions in Phoenix. The first-stage should focus on immediate and short-term heat-mitigation among socioeconomically disadvantaged populations, especially in central Phoenix. We suggest that the municipal government relocate resources to neighborhoods with high risk to heat (high HVI scores) in the urban core. Intervention measures might include opening cooling centers during extreme heat events, providing educational information to the disadvantaged populations to prevent heat-related illness, and increasing the efficiency and affordability of AC and ventilation in residences. The second-stage policy should focus on long-term planning. Given that a high diabetes rate and high social isolation can exacerbate the rate of heat-related illness, diabetes-prevention programs and programs providing care for people living alone are likely to reduce heat-related hospital admissions. Preventive actions that target diabetes patients, such as providing them with information, affordable medical care and supports, may also reduce the negative impacts of heat on health.

3.7 Conclusion

Generic indicator systems can predict the risk of heat-related health problems adequately and provide a useful and meaningful picture of the spatial distribution of risk, but they are sensitive to scale, measurement, and context. Decision makers need to reflect on the particular aspect of their cities to determine how applicable the vulnerability maps reflect actual risk of harm. In our study of Phoenix, the variables used nationally allowed us to accurately classify about 54% of the census tracts based on heat-related hospital admissions. There is, however, a larger story about heat hospitalizations that is not well captured by the standard vulnerability measures. We found that neighborhood mobility, measured by the proportion of households that have moved in within the past five years, may be an important indicator of heat vulnerability. Further research can build upon our heat vulnerability map to identify the source of resilience to heat in Phoenix, and to further investigate the factors that put neighborhoods at risk for high levels of hospitalization due to heat-related illness.

CHAPTER 4

VULNERABILITY MAPPING TO MITIGATE AND PREVENT HEAT-RELATED ILLNESS

4.1 Introduction

More intense, frequent, and longer lasting heat waves are projected for the future (Meehl and Tebaldi 2004), and their impacts on human health have become an important concern in many disciplines, such as public health and human geography. Various actions can mitigate, or even prevent, the impact of high heat on health, including establishing real-time heat warning systems (Hajat et al. 2010; Hayhoe et al. 2004; Sheridan and Kalkstein 2004), increasing street-level comfort by planting trees and creating shade (Akbari 2002; EPA 2009; Shahmohamadi et al. 2011), and providing cool environments (especially for disadvantaged populations) by opening cooling centers and increasing green spaces in neighborhoods(Declet-Barreto et al. 2012; Klinenberg 2002). However, most municipalities lack information about where vulnerable populations are located in a city (Costello et al. 2009), and therefore, they are not adequately prepared for abrupt increases in heat-related illness (Ebi et al. 2009; O'Neill et al. 2010). Local initiatives to proactively prevent heat-related illness require easily interpretable information and analytical tools that can be incorporated into decision-making processes (O'Neill and Ebi 2009). This chapter argues that vulnerability mapping can provide visual information to decision makers about where preventive and mitigation strategies can best be applied.

The U.S. Environmental Protection Agency (EPA) identifies four factors that affect risk to excessive heat events: (1) *climate conditions*, (2) *demographic sensitivity*, (3) *place factors*, and (4) *behavior choices* (US EPA 2006). Regarding *climate*, increases in temperature, relative humidity, and days with oppressive air masses are all associated with heat-related illness and mortality (Chuang et al. 2013; Curriero et al. 2002; Golden et al. 2008; Greene et al. 2011; Hartz et al. 2012). A population's *demographic susceptibility* also plays an important role. The elderly, socioeconomically disadvantaged groups, ethnic minorities, people with underlying health conditions, and socially isolated individuals often experience higher rates of adverse health outcomes from heat than the general population (Curriero et al. 2002; Harlan et al. 2013; O'Neill et al. 2003; Uejio et al. 2011; EPA 2006). *Place factors* reflect locational considerations, for example, where an inner city area may be may be more susceptible to adverse health outcomes than a neighborhood on the city periphery due to urban heat island (UHI) effects and the density of residents in the urban core, or where cities have high mobility and lack social cohesion (Chuang and Gober 2013). *Behavior choices* include actions such as wearing inappropriate clothing, failing to stay hydrated, and engaging in outdoor activities during excessive heat events (EAP 2006).

The availability of climate data, census information, and standard measurements of the biophysical environment (i.e., remotely-sensed land-cover statistics) enable modelers to relate empirical health data to the risk factors that are thought to cause heat stress (Curriero et al. 2002; O'Neill et al. 2003; Uejio et al. 2011). Researchers also use risk factors to construct heat vulnerability indices using socioeconomic, demographic, and environmental characteristics (Harlan et al. 2013; Johnson et al. 2009; Reid et al. 2009; Uejio et al. 2011); the indices can be used to identify vulnerable areas on maps. Despite this wealth of information about risk factors and health outcomes, there is no universally agreed-upon standard for building heat-vulnerability indices: not for which variables to include, nor for how these variables are measured and collected, nor for the effects of place-specific characteristics such as climate, social structure, and the nature of the built environment.

Several studies have measured cities' vulnerability to heat using the concepts of sensitivity, adaptive capacities, and heat exposure (Chow et al. 2012; Chuang et al. 2013; Harlan et al. 2013). However, this approach cannot fully represent actual health outcomes, because heat vulnerability is a complex issue with many aspects (McMichael et al. 2006). Some researchers have attempted to link heat-stress factors to health outcomes, thus grounding vulnerability mapping in real-world health and mortality data (Harlan et al. 2013; Reid et al. 2012). We propose to build on this work by developing an analytical tool that uses evidence-based health data directly to help decision makers plan for effective interventions. Evidence-based data are the direct measurements of adverse health outcomes (O'Neill et al. 2009), including heat-related illness and death.

Mortality data is limited by privacy concerns and the small number of cases. Death certificates contain personal identification information, and heat-related deaths often occur only during short time spans or during an individual heat event (Harlan et al. 2013; Johnson et al. 2009; Uejio et al. 2011). Limited data reduces the power of statistical analyses and thus the ability to produce statistically significant results. To expand the sample size, recent studies have used emergency-dispatch records, hospitalization information, and emergency-room visits to depict actual heat-related events (Chuang et al. 2013; Dolney and Sheridan 2006; Golden et al. 2008; Hartz et al. 2012; Knowlton et al. 2008; Reid et al. 2012).

Dolney and Sheridan (2006) geocoded 911 emergency-calls made between 1999 and 2002 in Toronto and superimposed them on land-use maps to reveal the importance of behavior on heat stress. They found a higher volume of emergency calls in lakeside recreational areas on abnormally hot days than in the rest of the city, suggesting that people seek relief from heat at the waterfront or, alternatively, that outside activities emblematic of these places produce higher risk of heat exposure. The authors found that urban activity patterns may also affect heat stress. For instance, industrial areas and the city core experienced higher volumes of emergency calls during weekdays than on weekends, suggesting that the need to work outside may also be a factor in the geographic pattern of risk and poor health outcomes.

Extending the work of Dolney and Sheridan (2006), we distinguished vulnerable areas by identifying the areas with a high number of heat-related incidents, and their proximity to other high-risk areas. We used spatial statistics (hot-spot analysis) to analyze and compare two empirical datasets: heat-related emergency calls and heat-related hospital admissions in metropolitan Phoenix. The ultimate goal was to pinpoint vulnerable areas for future heat intervention and mitigation. In addition, we used this work as an opportunity to explore the differences in spatial patterns presented by the two different datasets, and how they were affected by differences in scale. The three experimental settings for spatial analysis were: (1) raw data contained in 1 km^2 grids; (2) raw data contained in Census tracts (CT); and (3) data standardized by population size at the CT scale. Hereafter, we use "1km^2 scale" to refer to the first setting, "CT scale" for the second setting, and "rate in CT" for the third setting. The results from this work provide decision makers with information about areas that may require enhanced intervention in the event of extreme heat. We compared the vulnerability maps we produced in this study to identify the pros and cons of various analytical approaches, including spatial resolution and normalizing by population size, on vulnerability mapping.

4.2 Data and methods

4.2.1 Heat-related emergency calls

We obtained heat-related 911-emergency-dispatch records (2459 cases in the years 2003 to 2006) from the Phoenix Fire Department Regional Dispatch Center. Each heat-related emergency record contains the date and time when the call was made and the locations to which EMS (emergency medical service) crews were dispatched. EMS providers treat patients wherever they are--at their homes, commercial buildings, shopping malls, parking lots, parks, and street intersections. EMS data are occurrence-based, capturing the locations from which calls for help originate. Emergency dispatch records thus reflect patterns of human mobility and activities, and they include the mobility and activity patterns of the city's homeless population.

4.2.2 Hospital admission data

Heat-related hospital admission data between 2004 and 2005 were obtained from the Arizona Department of Health Services Hospital Discharge Database. This database includes a patient's date of admission, disease diagnosis code (using the International Classification of Disease, 9th revision, ICD-9), and place of residence. In 2004 and 2005, there were 460 cases classified as heat-related illness (ICD-9: 992 Effect of Heat and Light) that had complete residence information. The hospitalization data is residence-based because they report the patient's address. Given that homeless people do not have a physical address in the hospitalization data (it is marked as “homeless” in the address column), the homeless are not included the hospitalization mapping.

4.2.3 Study area and spatial units

We confined our study area to the municipal boundary of the City of Phoenix, a basic political unit with a local government that implements interventions and policies for people’s health and well-being. We compared spatial patterns of heat stress for occurrence- versus residence-based data and across the three types of experimental designs (1 km^2 grids, CT scale, and rate by CT). The heat-dispatch data highlight the areas where vulnerable residents live and non-resident people congregate, or where activities linked to heat stress (e.g., working outside, engaging in recreational activities) occur, including activities of the homeless. The residence-based hospitalization data reflect neighborhood-level processes and the social patterns and health conditions of people in their home settings; they do not include the activities of the homeless. We superimposed the locations of homeless service centers, including shelters and food distribution stations, on maps of heat-related emergencies to see if activity patterns including those of the homeless differ in any substantial way from the neighborhood social patterns excluding the homeless. The size of the chronically homeless population (i.e., homeless for more than one year) was estimated at 1750 people in Phoenix in 2010, which accounted for almost 65% of the homeless population of Maricopa County (Maricopa Association of Governments 2011).

The areal sizes of CTs in Phoenix vary from 0.31km^2 to 321.8km^2, with a typical CT in central Phoenix covering about 2.5km^2 (1sq. mile). The shapes of CTs are irregular, and their boundaries are usually arterial streets, borders of agricultural areas, or the boundaries between different types of land use. Thus, sorting the data by CT helps us to understand the pattern of heat incidents within larger-scale boundaries. Census data provide population information that enables us to calculate the rates of incidents and the extent to which the non-normalized patterns we observe in CT's are a function of population density. Using rates by CT, we can account for the different densities in the central city versus suburban areas. Sorting the data with 1km^2 grids evenly distributed across the city captures the density of heat incidents at a finer scale and might provide a more specific target for intervention strategies. By using different methods of measuring the incidence of heat stress (hospitalizations versus 911 calls) at different spatial boundaries (km^2 versus Census tract), and with different methods of standardization (raw data versus data normalized by population), we were able to compare differences in the vulnerability maps resulting from these methods. We organized the health data and comparative analyses by their differences from the mean in standard deviation units. The maps show high incidence in shades of red and low incidence in shades of green.

4.2.4 Spatial analysis

We used Moran's Index (Moran's I) to test whether the heat incidents occur randomly or exhibit an ordered geographic pattern. Spatial autocorrelation is designed to identify systematic patterns, including dispersed, random, and clustered, in a variable's distribution. It measures the degree to which an attribute value of a spatial unit (e.g., number of heat-stress calls) is similar to its neighboring attribute values. Moran's I is a weighted correlation coefficient that measures global spatial autocorrelation (Guyon et al. 2010). It is based on cross-products of the deviations from the mean and is calculated for n observations on a variable x at locations i and j (Equation 1). The index falls between -1 (dispersed pattern) and +1 (clustered pattern), with zero indicating a random distribution. A positive value of Moran's I indicates that there is a more clustered pattern of heat stress incidents.

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad \text{Equation (1)}$$

Where $\bar{x}$ is the mean of the x variable, w_{ij} are the elements of the weight matrix, and S_0 is the sum of the elements of the $S_0 = \sum_i \sum_j w_{ij}$ weight matrix:

Assuming that locational factors (e.g., recreational land-use, low-vegetation and high heat-stress neighborhoods, or large open spaces) affect the distribution of heat incidents, we expect to see a stronger spatial autocorrelation in occurrence-based data than in residence-based data. This is because occurrence-based data reveal the actual geographic location of the heat event itself, while residence-based data show the place where heat victims live. Their residence may or may not be the place where heat incidents occur.

We used hot-spot analysis to highlight clusters of health outcomes. Hot-spot analysis measures the local spatial autocorrelation, and calculates Getis-Ord Gi* statistic (equations (2), (3) and (4)) by looking at each feature within the context of neighboring features, focusing on each unit of analysis by considering its value and the values nearby.

$$\mathrm{Gi}^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \qquad \text{Equation (2)}$$

Where x_j is the attribute value for feature $j, w_{i,j}$ is the spatial weight between feature i and j, n is the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \qquad \text{Equation (3)}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \qquad \text{Equation (4)}$$

Spatial analyses use threshold distance (fixed-distance weight) at 3 km (1.86 miles), which is roughly the distance for two continuous standard Census tracts in the city core. That is, all polygons (spatial units/neighborhoods) within a 3km radius of a measuring feature are considered its neighbors. The weight of a feature value is determined by the value of its neighbors.

4.3 Results

4.3.1 The nature of the two datasets

4.3.1.1 Spatial distribution of 911 calls

The distribution of emergency calls grouped within 1km^2 grids (by standard deviation; Figure 4.1A) has minimum and maximum values of 0 and 61, a mean value of 1.7, and a standard deviation (std.) of 3.8. The central business district and industrial corridor west of downtown Phoenix are contained within a rectangle bounded by two Interstate Highways and one State Route. Many government agencies and businesses are in the northern and central area of this rectangle, while industrial land and large warehouses are in the southern and western ends. The downtown area has a high population density during the daytime on weekdays, contributing to an elevated number of 911 calls. In addition, there are many low-income neighborhoods located in the urban center, as well as homeless shelters, food distribution centers, and health services. Urban heat island effects in the area (Brazel et al. 2007) may also contribute to the higher incidence of heat incidents here than in the peripheral areas of the city.

At the CT scale, the number of emergency calls ranged from 0 to 72, with a mean of 6.73 and std. of 7.51. When using CTs as the unit of analysis, the central core and South Mountain Park, in south Phoenix, show up as high-risk areas (Figure 4.1B). The census tract encompassing South Mountain Park had 26 heat-stress calls, the 6th highest volume of calls for a CT in the city. South Mountain Park is the largest municipal park in the U.S. (City of Phoenix 2013), with more than 50 miles of hiking, biking, and equestrian trails in a natural desert landscape. It appears that this large outdoor space experiences heightened risk of heat-related emergencies, perhaps due to its heavy use for outdoor recreation, relatively little water and shade, and the expansive natural-desert setting, which is quite unlike a typical city park.

Data standardized by population at the CT scale ranged from 0 to 7.36%, with mean of 0.22% and std. of 0.52. After dividing the number of calls by the CT population, the number of high-risk areas was reduced, but the South Mountain Park area remained a high-risk area. When we standardized by population, the patches of high occurrence on the city's periphery did not appear as high-risk areas. This wash-out effect may be caused by the large population size (large denominator) of some CTs on the city periphery, particularly large apartment districts.

Moran's I value for 911 calls was 0.42 at 1 km^2 scale, 0.4 at the CT scale, and 0.21 at the CT scale by rate, indicating that there was more clustering of actual occurrences than of the rate of occurrences. At least some of the clustering that occurred at these scales appears to be a function of residential densities, although it is evident that the central core still has higher rates than other parts of the city, even considering the core's higher population density. The fact that the South Mountain Park area continues to show up as a major hot spot in the normalized patterns demonstrates the limitations of using residential densities to normalize an occurrence-based process. Resident population count may not be indicative of the number of people in a given area, and 911 calls could be made by or for visitors to Phoenix, and thus their location in the city may affect the pattern of calls.

4.3.1.2 Spatial distribution of hospitalizations

The residences of those admitted to hospitals with heat-related illness are more scattered across Phoenix than 911 calls (Figure 4.2A, 4.2B and 4.2C). At the 1 km^2 scale, the count of hospitalization admissions have minimum, maximum, mean, and std. values of 0, 12, 0.31 and 0.8, respectively. At the CT scale, the counts of hospital admission ranged from 0 to 13, with a mean of 1.26 and std. of 1.53. For the hospitalization rates, the minimum and maximum are 0 and 0.76%, and the mean and std. are 0.03% and 0.05, respectively. Moran's I values for hospitalization are 0.25 (1km^2), 0.11(CT), and 0.1 (rate in CT). These Moran's I values represent slightly clustered patterns, with the most clustering occurring at the 1km^2 scale. The Moran's I values for hospitalization are smaller than the Moran' I values for 911 calls. This finding confirms our assumption that occurrence-based data reveals a stronger location effect on the spatial autocorrelation, because hospitalization reveals where heat victims live while 911 data identify the location of heat incidents.

South Mountain Park never appears as a high-risk area on the hospitalization maps. It is an affluent, suburban-like area with none of the residential high risk factors associated with heat stress. The failure of the downtown area to appear as an important node in mapping hospitalization may result from the fact that the city's homeless population is missing from the hospitalization data. It appears that the 911 call data capture the activities of those who are present in, but do not live in, downtown Phoenix, such as tourists, downtown workers, and the homeless.

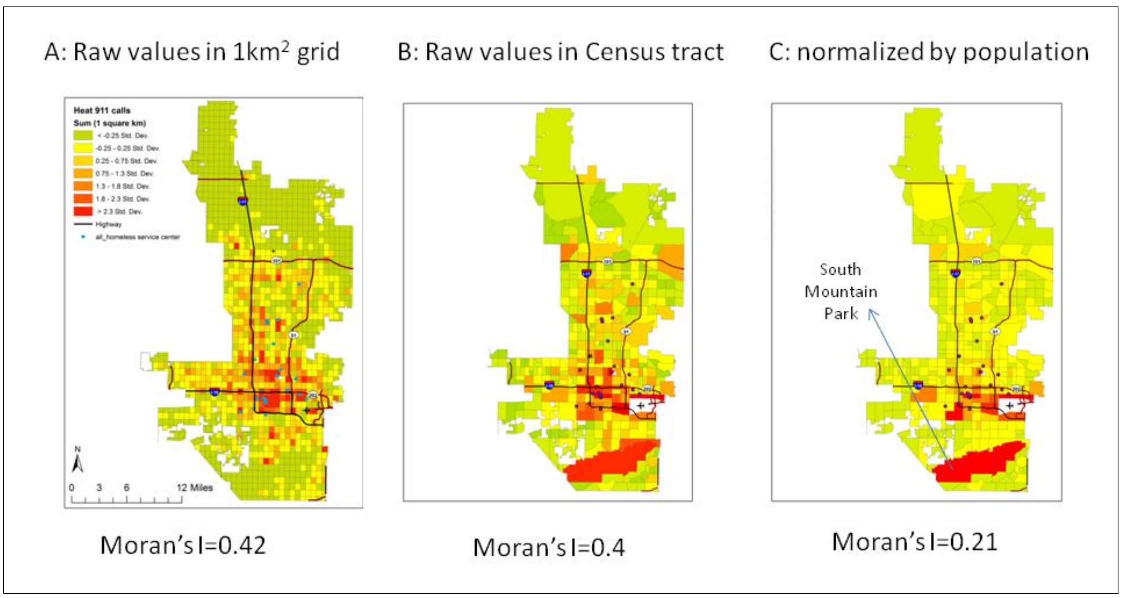


Figure 4.1 Spatial distributions of heat-related 911 calls

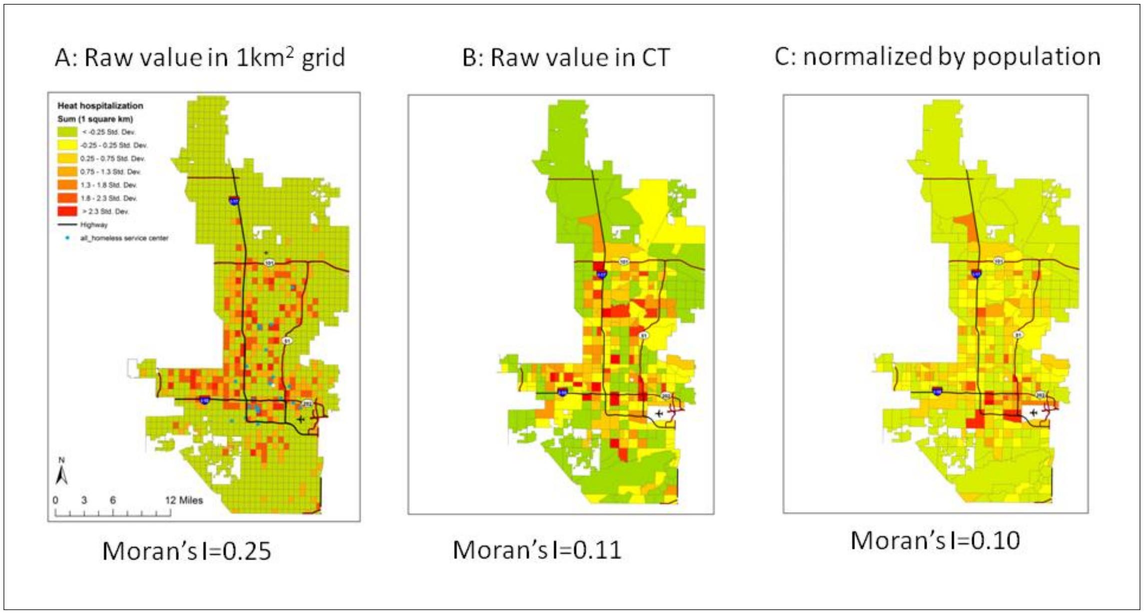
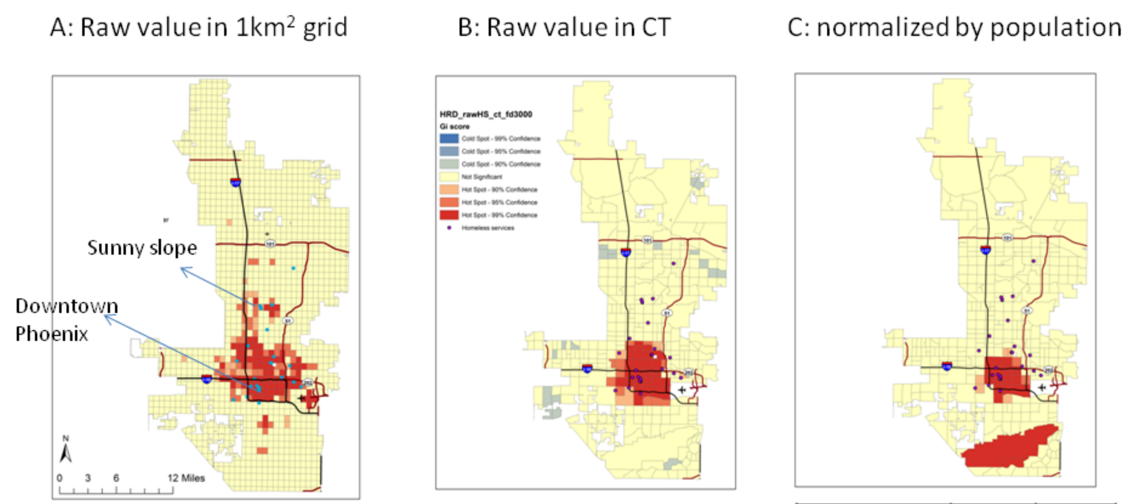


Figure 4.2 Spatial distributions of heat-related hospitalizations

4.3.2 Hot-spot analysis

4.3.2.1 Heat-stress emergency calls

Hot spots of 911 calls at the 1km^2 scale (Figure 4.3A) verified the high occurrence of 911 calls in the inner city, and underscored the need to focus interventions associated with temporary exposure, such as emergency services and heat alerts, in these areas. Almost all homeless service centers are located in the 911 hot spots. When we grouped 911 calls at the Census-tract scale, hot spots narrowed down to the heart of the city (Figure 4.3B), and cold spots appeared on the urban periphery. These cold spots disappeared when the data were normalized by population, and the urban core condensed even further to reflect the concentrated nature of 911 calls in the inner city as a function of urban activity patterns. The South Mountain Park area appears as a hot spot on the normalized map because of its low residential density (350 residents) combined with a high incidence of 911 calls (26). This combination produced a high rate of calls, which indicates the importance of warnings and emergency services for visitors to the park.



2B: socioeconomic characteristics	Cold spots	Hot spots
Median Household income	$70,779	$29,187
Living in different neighborhood in 5 years	38.66%	52.39%

2C: socioeconomic characteristics	Cold spots	Hot spots
Median Household income	N/A	$38,595
Living in different neighborhood in 5 years	N/A	49.30%

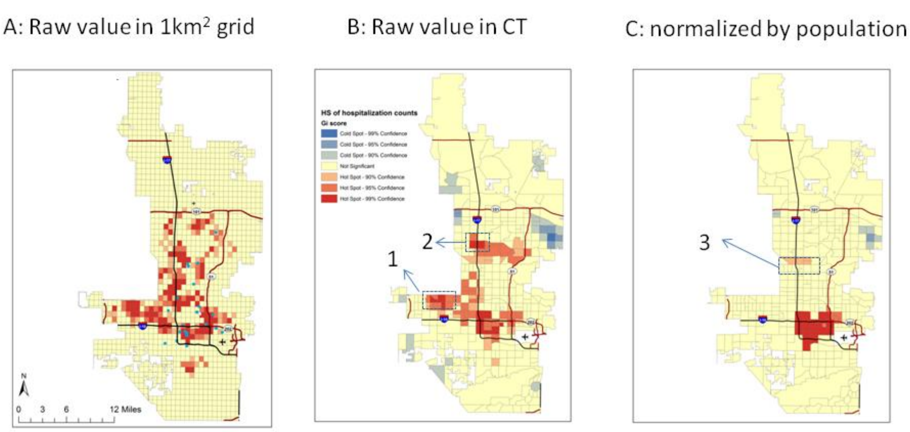
Figure 4.3 Hot spots of heat 911 calls

4.3.2.2 Heat-related hospitalizations

At the 1km^2 and CT scales, the patterns of hospitalization hot spots (Figure 4.4A and 4.4B) resembled the disorganized spatial distribution of heat-related hospital admissions (Figure 4.3A and 4.3B), although they showed some tendency to be concentrated in Central Phoenix rather than in more peripheral parts of the city. The analysis revealed a cluster of cold spots in affluent Paradise Valley Village[4] in northeast Phoenix, and smaller cold spots in peripheral areas. The concentration of hospitalization

[4] Paradise Valley Village's median household income is $68,332, higher than the citywide average of $54,745 (City of Phoenix 2013). This neighborhood has a high non-Hispanic white population (75.3%), compared to 46.50% for the city as a whole.

for inner-city residents shows up only when incidence is normalized by population (see Figure 4.4C). Region 3 in Figure 4.4C refers to a lower-middle-class apartment district where average incomes were lower than the city average ($34,806 versus $54,745), and the percentage of renters was higher (from 63.30-77.20% versus 41.10% for the city as a whole). The region also had a high percentage of non-citizens (30.6% versus 16.5% for the city as a whole), suggesting that it is an area where recent Mexican immigrants reside, with high residential instability (77.9% living in a different residence than they did five years ago, compared to the citywide average of 48.6%), which puts residents at high risk of heat hospitalization. Residents of these neighborhoods may be unfamiliar with the city's climate, work outside, lack financial resources to deal with heat or pre-existing disease, and have limited social support systems.



4B: socioeconomic characteristics	Cold spots	Hot spots
Median Household income	$78,981	$34,132
Living in different neighborhood in 5 years	39.01%	48.19%

4C: socioeconomic characteristics	Cold spots	Hot spots
Median Household income	$54,437	$26,220
Living in different neighborhood in 5 years	28.90%	53.21%

Figure 4.4 Hot spots of heat hospitalization

4.4 Discussion and conclusions

This study used two different types of health data in three experimental designs to identify hot spots of heat-related illness. The use of the different health datasets, areal units, and normalization approaches produced different but complementary results, which made it possible to draw conclusions that could not be drawn from a single set of data, areal unit, or normalization approach. Mapping occurrence-based data highlighted the areas which have high heat risk, while mapping residence-based data focused on the neighborhoods where heat victims (i.e., vulnerable populations) live. Both datasets and all experimental designs identified concentrations in downtown Phoenix, because this region is home to many socially vulnerable people, and is the center of the state's economy. Study results are consistent with those of other studies that have found a relationship between poor health conditions, such as high asthma mortality and hospitalization rates, or high tuberculosis rates (Carr et al. 1992; Grineski et al. 2007; Maantay 2007; Marder et al. 1992; McGowan and Blumberg 1995; Sotir et al. 1999; Weiss et al. 1992), and the co-location of heat stress and minority, disadvantaged, and impoverished neighborhoods. The results of this study, for both occurrence- and residence-based health outcomes, show that many of the hot-spot zones of heat-related illness overlap with low-income, minority communities in central Phoenix.

Excessive heat is one of the main causes of death among the homeless (Mrela and Torres 2010; Uejio et al. 2011). Effective intervention requires a better understanding of the travel patterns and behavior of this population. We found that the locations of homeless service centers are highly correlated with hot spots of heat emergency calls at

$1km^2$ and CT scales. If decision makers rely solely on hospitalization for heat-stress intervention, they may neglect this geographically mobile and vulnerable population.

The results of this study imply that plans for reducing heat stress should consider both residence-based and occurrence-based data. These two kinds of data reveal different dimensions of the heat problem in urban areas. The more concentrated patterns of the occurrence-based data reflect the more concentrated nature of urban-activity patterns, they include the homeless population, and they indicate that people using some outdoor recreational areas, including South Mountain Park, will require heat warnings, watering stations, information about appropriate attire and hydration, and access to emergency services. The residence-based data show the neighborhoods where people at highest risk for heat-health problems live. They indicate areas in need of more structural interventions, such as poverty reduction, health maintenance, and neighborhood development.

Normalization of data affects the results of hot-spots analysis. The hot spots of normalized hospitalization reveal not only the heavy concentration of heat-related illness in the central core of the city, but also that neighborhoods with a high percentage of new immigrants are at risk for heat-health problems. The latter finding suggests that people lacking knowledge of the area, resources to cope with heat, and strong social support networks may be at risk of hospitalization. These areas may also benefit from warnings, but also from access to cooling facilities, increasing the number of shaded areas, and more trees and vegetation to improve street-level comfort.

Although Phoenix is one of the hottest cities in the U.S., visitors and residents are often unaware of the dangers of prolonged heat exposure, especially when they engage in outdoor activities. Making warning information visible in recreational areas may be an effective and relatively low-cost way to remind people about the importance of keeping cool and staying hydrated in a desert city.

Hot-spot maps of heat vulnerability depend upon the type of data used, the scale of measurement, and normalization procedures. Overall, the 911 data provided a more focused geographic pattern, and revealed high-risk places like the South Mountain Park area, while vulnerable areas, such as high-risk immigrant neighborhoods and high renter-occupied neighborhoods, showed up most clearly in the hospitalization data. In the hospitalization data, heat stress as an inner-city problem showed up only when the data were normalized, pointing to the importance of normalization procedures to produce coherent maps. This result also highlights the importance of conveying to decision makers that incidence data implies different intervention strategies than residence data.

CHAPTER 5

CONCLUSION

Vulnerability to heat stress in urban areas is a complex and dynamic phenomenon. It is complex because it involves many components of coupled human-natural systems and their interactions. It is dynamic because many forces create changes in vulnerability to heat over time and space. These forces include demographic and global environmental change, technology development, and mobility within urban areas. Because of its complex and dynamic nature, we need to study heat vulnerability as a systems problem if we are to understand: 1) how it arises from the dimensions of exposure, sensitivity, and adaptive capacity to heat, and 2) how to mitigate or avoid its harmful consequences.

This dissertation has presented empirical evidence to demonstrate the complex and dynamic process of heat vulnerability. Temporal and spatial analysis identified the critical components that influence the formation of, and shifts in, heat vulnerability. The approach used in this study is characteristic of sustainability science, which emphasizes how processes and outcomes in multi-dimensional, human-nature systems are interconnected.

Quantifying connections between temperature and adverse health outcomes has posed a challenge in many disciplines because the relationship is often non-linear (Braga et al. 2001; Curriero et al. 2002; O'Neill and Ebi 2009). Although traditional risk-hazard research assumes a simple causal, dose-response relationship between exposure to a threat and its outcomes, many direct and indirect factors influence how an individual responds to heat stress; for example, humidity, income level, a city’s infrastructure, and residents’ acclimatization to local conditions. Thus, there is no universally agreed-upon threshold temperature at which urban systems will experience a drastic change in heat vulnerability. For instance, there is a ten-degree Celsius difference in the threshold temperatures for unmanageable proliferation of heat-stress calls in Chicago and Phoenix.

It is difficult for cities to anticipate and prepare for temperature increases using predictive climate models. Model outcomes depend on many variables and are affected by scale, and thus there is a high degree of uncertainty associated with their use for decision making and vulnerability assessment. Wilby & Dessai (2010) recommend vulnerability assessment and sensitivity analysis across a range of current conditions and plausible futures to overcome this limitation. When I analyzed sensitivities within a range between zero and five degrees Celsius temperature increase, I found that Chicago, a colder-regime city, is likely to be more sensitive to climate change than Phoenix, a warmer-regime city, assuming their adaptive capacities remain at the current levels. The results of my sensitivity analyses revealed that there is no one-size-fits-all solution to mitigate the impacts of climate change, and preventive strategies should be context-based.

Chapter 3 took on the difficult issue of how best to measure social vulnerability to heat stress. The literature contains various indicators related to physical exposure, sensitivity, and adaptive capacity, but the specific metrics vary across studies and research sites. I investigated Reid et al.'s 10-variable indicator framework and related it to empirical evidence of heat stress. This research tested a national heat vulnerability index developed by public-health experts in a local context. I found that the generic, national-indicator framework correctly classified only a little more than half (54%) of Phoenix neighborhoods. This finding highlights the effects of measurement, scale, and context on index reliability. The fact that the generic framework only correctly classified slightly more than half of Phoenix neighborhoods suggests that there is a need for further exploration of other factors that might mitigate or exacerbate the outcomes of heat stress. For instance, among the misclassified neighborhoods, I found that low social stability is relevant to high heat vulnerability in Phoenix. From this research I concluded that low adaptive capacity, as represented residential instability, can make advantaged neighborhoods vulnerable to heat stress. In some cases, high neighborhood stability appeared to reduce the negative impacts of high-temperature events. The modeling work described in Chapter 3 identified the neighborhoods that were hypothetically vulnerable but empirically resilient to heat stress. This finding provides a starting point for researchers to identify additional sources of neighborhood resilience. It also demonstrates the importance of evaluating positive factors, not just negative indicators, to understand vulnerability to heat stress.

The work described in Chapters 3 and 4 provides evidence that heat vulnerability is embedded in social vulnerability. The area of highest vulnerability to heat overlapped with low-income, minority neighborhoods in downtown Phoenix. People in these vulnerable areas not only suffered from higher rates of heat-related illness but also from poor environmental quality in terms of air pollution and toxic hazards (Bolin et al. 2000; Grineski et al. 2007). Adaptation programs that only attempt to reduce the rate of illness by, for example, providing cooling facilities, may work in the short term, but from a sustainability perspective, solutions to mitigate heat vulnerability should include more than reducing rates of illness. Strengthening social cohesion in poor neighborhoods and using planning and community-revitalization projects to increase urban quality-of-life may also reduce heat vulnerability.

One of my findings--that wealthy neighborhoods in Phoenix with less social stability and higher neighborhood mobility were more vulnerable to heat stress than disadvantaged but socially cohesive neighborhoods--extends the theoretical vulnerability framework by pointing out the possible importance of social cohesion on heat health effects. Future research can build upon my mapping results and design a qualitative approach to more fully understand other factors that make a neighborhood resilient.

Policy implications

As climate change continues to pose threats to human health through more intense, frequent, and longer-lasting heat waves (Meehl and Tebaldi 2004), decision makers can plan effective mitigations and adaptations that help urban residents cope with climate change. Mitigation strategies are policies and actions that help to reduce heat stress in urban areas. Examples of such strategies are shade trees, street-side canopies, and sufficient vegetation cover, all of which contribute to cooling the urban environment. Such strategies are especially important in inner-city and minority low-income neighborhoods, because people who live in these areas often lack resources (e.g., air conditioning) to cope with heat. Other urban-heat–island-mitigation strategies include cool roofing and paving projects that help reduce both surface temperature and the amount of energy used to cool buildings.

Adaptations to climate change are the actions that help people adjust to new climate conditions and events. The first line of defense in building capacity to adapt to climate change is to build a strong heat-warning system that provides easily accessible information to city residents. Such systems could incorporate the sensitivity analysis presented here, which is based on the relationship between temperature increase and adverse health outcomes, to anticipate the impact of a heat event. Information about the relationships between temperature and health outcomes can help city residents take preventive actions (for example, avoiding outdoor activities during an excessive-heat event), and help municipalities determine when to deploy extra services, such as emergency medical services.

My findings suggest a number of steps that cities could take to improve their preparedness for climate change. I list those steps below as possible starting points for conversations among public health practitioners, policy makers, planners, and government officials who are involved in dimensions of the heat-health problem.

(1) *Locate high-risk areas.* City governments can locate high-risk areas through comprehensive heat-vulnerability mapping, based on socioeconomic, environmental, and health dimensions.

(2) *Identify place-based dimensions of heat vulnerability*. Heat vulnerability cannot be adequately determined with generic indices, so individual cities will need to add place-based indicators to their analyses of local heat vulnerability. Social structures, demographic components, and neighborhood factors all influence the dynamics of vulnerability. A comprehensive understanding of contextual effects and local factors that make a neighborhood less or more resilient to heat would increase the predictability and usefulness of a heat vulnerability index during the decision-making process.

(3) *Identify remedies with co-benefits.* Poverty is a strong determinant of heat vulnerability. Therefore, programs that reduce poverty might also reduce the impacts of heat on human health. Likewise, programs that improve health might

also reduce vulnerability to heat. It has been shown that changing urban design to reduce automobile dependency and CO_2 emissions (for example, by increasing walkability in neighborhoods) can also reduce the risks of cardiovascular disease, obesity, and diabetes (Lathey et al. 2009), all of which that exacerbate heat stress.

(4) *Develop strategies to protect the homeless, the socially isolated, and urban refugees.* Disadvantaged populations and socially isolated individuals are highly vulnerable to heat. To help homeless people is especially challenging, because they are geographically mobile and often behave in unexpected ways. A proactive strategy would be to provide care to these populations, or at least to offer programs that educate them and their advocates about heat injury and ways to avoid it.

Social inequality creates many problems, especially for those with low socioeconomic status. My research describes the threats of excessive heat to those living in poor neighborhoods, and their vulnerability to it. Balancing social equality and increasing comfort level in poor neighborhoods by changing urban design may be a long-term process, but broadening accessibility to shelters and cooling centers in the meantime will reduce heat distress immediately. Heat vulnerability is an issue with many dimensions. No single discipline or research approach can solve the problem alone. To meet the needs of society while sustaining the life-support systems of our planet, we need improved dialogue between scientists and decision makers (Turner et al. 2003). The empirical information provided by my work could stimulate new dialogue between scientists and decision makers. But this dialogue may not solve problems unless stakeholder voices are included. Therefore, I close by suggesting that future research on heat vulnerability create opportunities for collaboration among scientists and stakeholders.

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APPENDIX A

STATEMENT OF PERMISSION

I declare that I have obtained explicit permission from the first authors and co-authors for including two peer-reviewed scientific journal manuscripts as chapters in this dissertation. They are:

- Patricia Gober (Chapters 2, 3, and 4);
- Winston Chow (Chapter 2);
- Jay Golden (Chapter 2);

December, 2013 Wen-Ching Chuang