Sociospatial Modeling for Climate-Based Emergencies: Extreme Heat Vulnerability Index

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Abstract Heat Waves and extreme heat are frequently not considered to be severe or adverse weather conditions. However, they are the leading cause of weather-related fatalities throughout the world. The misconception of heat is often due to the lack of visual evidence caused by destruction or risk, a commonly reported metric for hurricanes or similar forces. Heat Waves can be visualized through the Urban Heat Island, a phenomenon which exaggerates thermal impact within the built environment. This chapter explores and describes the Extreme Heat Vulnerability Index (EHVI), a local-area model designed for advance warning and mitigation practices related to extreme heat and socioeconomically vulnerable neighborhoods, through example data from Chicago, IL. The disadvantages and shortcomings of previous weather warnings are discussed, as well as how better vulnerability models can improve mitigation strategies to reduce loss of life and improve resource management. Mitigation practices from Chicago, Phoenix, Arizona, and other cities will be discussed to provide examples of the benefit of implementing vulnerability warnings.

Keywords Extreme heat · Urban heat island · Vulnerability modeling · Social vulnerability · Physical vulnerability · Disaster preparation · Disaster mitigation

1 Introduction

Vulnerability studies focusing on human health impacted by weather, or climate, variability have historically been studied from either the physical or social science fields. While both require a multidisciplinary approach, they are divided by the

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central focus of their fields. Physical vulnerability focuses on the configuration or magnitude of the adverse force, while social vulnerability concentrates on a population's ability to adapt or recover from the event regardless of its magnitude. This chapter discusses previous vulnerability assessment methods used to assess extreme heat's impact on human health, outlines data sources needed for such initial analysis projects, and discuss some of their resulting strengths and weaknesses.

Although it is not consistently considered a significant public health concern (Akerlof et al. 2010; Bassil and Cole 2010), heat is currently the greatest weather threat to health, particularly in urbanized areas (Pantavou et al. 2011; Peng et al. 2011). The increased risk is caused by heat induced hyperthermia, heat stroke, and dehydration. Heat also increases the risk of cardiovascular and respiratory morbidity and mortality, demonstrating its significant impact on population health (Luber and McGeehin 2008; Wilhelmi and Hayden 2010; Hondula et al. 2012). Heat vulnerability was chosen for this chapter because of its multifaceted impact on population health. To combat heat health risk, details describing a method of data fusion to improve heat wave mitigation (designed by the authors) combine previously distinct modeling methods for physical and social vulnerability. Our fused method is also applied at smaller resolutions of analysis than most previously implemented models in order to improve accuracy and application. This provides a model with unique benefits, as well as complications, due to the smaller spatial units of analysis. Additionally, this chapter discusses how public servants and volunteers can use vulnerability models to improve mitigation practices, enhance public awareness, and improve community engagement during extreme heat events.

2 Social Vulnerability

Populations who are less able to adapt or survive an oppressive event are identified as having a higher **Social Vulnerability**. This would suggest the vulnerable population's economic status and/or physiology makes them less capable of tolerating the stressful event. The oppressive event could take the form of an environmental stressor (common extreme weather examples include heat, flood, and tornado), could take the form of a financial hardship, such as unemployment, or illness. Models designed to identify socially vulnerable populations utilize social, economic, and various demographic variables to identify populations at an increased risk. The most prominent variables used for these studies include economic, education, race, or age classifications to identify vulnerability status (Cutter et al. 2003; O'Neill et al. 2005; Dolney and Sheridan 2006). It should be noted that many additional variables, subsets, or combinations of the variables could be used, as they will often change or hold different weight depending on the area of interest, for example: access to a heated shelter is less necessary in a southern climate. However, this example should provide a baseline to follow during this chapter (Cutter et al. 2010; Johnson et al. 2013).

Variables used to study social vulnerability identify populations who are less capable of surviving an oppressive event. Generalized examples of ‘at risk’ populations can include an elderly person with a decreased ability to properly regulate their internal temperature during extreme temperature conditions, or impoverished people’s hesitancy to seek medical attention at the onset of heat stroke symptoms (Center for Disease Control 2002, 2006; Changnon et al. 1996). Therefore, social vulnerability scientists work to identify which local socioeconomic attributes, and which combinations of them, are associated with an increased quantity of negative health outcomes during oppressive weather events.

Socioeconomic data is relatively easy to acquire through the U.S. Census Bureau. Historically, the United States federal government had collected data about the country’s population, once every ten years, beginning in 1790. This census was designed to document the distribution of the nation’s economic status, educational attainment, age, race, gender, and a multitude of other information. In 2010, the Decadal Census was converted to the American Community Survey; this new data collection method never collects a true census of the population, but will provide more frequent analytics about the nation’s population through survey collection methods (U.S. Census 2015). Rather than a full census every ten years, the American Community survey collects a sample survey from a small proportion of the population every year. The use of a sample survey suggests that all datasets going forward will only be estimates of the population dynamics; therefore, scientists will need to consider their implementation of this data carefully. Generalized population data derived from the historical census and American Community Survey is publicly available at designated political boundaries (such as counties, census tracts, and block groups) and is sufficient to use in the study of social vulnerability.

The U.S. Census political boundaries are established by political parties, politicians, as a method to organize citizens for voting and implementation of laws/government projects. Due to their organization, the U.S. Census boundaries maintain relatively equal population sizes between boundaries. Additional information on the boundary development and maintenance can be found through the Census website, but generally the division is: States > Counties > Census Tracts > Block Groups > Blocks > residential homes. The available datasets are not designed to allow for the identification of individual people, which is why only generalized data at the block or larger boundaries are available. Average characterizations of residential areas, such as the average income of all residents within the census boundary, provide valuable information about the people who live in a particular area. Population data can be used to identify vulnerable populations by identifying variables of groups who have not demonstrated historical resilience and adaptability to oppressive events. A quick background on some of the more commonly utilized variables will provide a better understand as to why such variables impact vulnerability, specifically during heat events.

2.1 Age

The average age of an individual, or the population in general, can indicate their probability of having pre-existing health conditions or requiring assistance for daily activities (Cutter et al. 2003; Naughton et al. 2002). This is particularly relevant for two age demographics: the very young (5 years and younger) and very old (65 years and older) have been identified in previous studies to experience higher rates of negative health impacts during oppressive weather events. Both the very young and very old must rely on others; often have limited mobility and motor functions which reduces their ability to maintain proper fluid levels or escape an oppressively hot environment (Center for Disease Control 2002; Naughton et al. 2002). Both the elderly and young populations have a higher rate of requiring mobility assistance (walkers, wheel chairs, or weak muscle functions), which requires additional assistance and supervision (Changnon et al. 1996; Ebi et al. 2003; Semenza et al. 1999). This implies more than vehicle transportation to the store; both elderly and young individuals may require the use of a walking aid to move between residential rooms and may have trouble with stairs or uneven surfaces. Limited mobility can make it difficult for them to acquire fluids or relocate to a cooler environment when necessary.

Additional physiological traits commonly present in elderly demographics (such as pre-existing health conditions like cardiovascular or diabetic diseases), can exacerbate health complications caused by external stressors (Ebi et al. 2003; Semenza et al. 1996). For example, during normal thermoregulation, blood vessels dilate to get closer to the skin and release heat; this causes a drop in blood pressure which can induce fainting spells/falls and numerous cardiovascular complications (CDC 2002). Common heat ailments therefore include increased pulse rates, fainting falls, heart attacks, and strokes. Similarly, diabetic individuals have lower kidney function, which can cause individuals to lose fluids at a higher than necessary rate through urination, increasing the risk of dehydration.

Men aged 65 and older have a documented reduction in thirst sensation, which can cause them to not realize how dehydrated they may have become during oppressive events (Semenza et al. 1999). Due to many of these conditions, Whitman et al. (1997) found at least 70 % of the mortalities from 1995 Chicago, Illinois heat wave consisted of individuals who were 65 years of age and older. Although mental and physical disabilities that impact survivability can be present at any age demographic, the rate of impairment is often higher in the elderly due to compounding health implications (Naughton et al. 2002; Semenza et al. 1999). The previously mentioned health complications can also make acclimation to weather difficult for both young and old individuals, which make them particularly vulnerable to early season heat waves (Changnon et al. 1996; O'Neill et al. 2005; Kalkstein and Greene 1997; Naughton et al. 2002).

2.2 Education

A population's level of education is often viewed as an indication of their attention to detail and general knowledge. Individuals who have completed higher levels of education may have a better understanding of human physical health, and a heightened ability to identify and respond to negative health indicators. For example, an individual with a college degree is expected to have taken (and paid attention during) a larger number of health classes. They will potentially have better healthy living habits resulting from those health lessons, and can identify health concerns in other people. People with a higher level of education may have a better ability for abstract thought, which can assist them in identifying inclement conditions (such as high ambient temperature and the need to hydrate) or identify medical issues in the people they are interacting without the need for additional external training, warnings, or alerts to do so. Increased level of education usually indicates better job security, income level, and residential settings, which further reduce their vulnerability (Harlan et al. 2006; McMichael et al. 2008). These improved homes will often have better insulation and their financial situation could allow for the opportunity for external cooling opportunities, like pool memberships or air conditioning (Davis 1997).

2.3 Income

An individual's financial situation is expected to be inversely related to their vulnerability (Changnon et al. 1996; Naughton et al. 2002). In other words, wealthier people are less vulnerable than poorer people. Individuals with higher incomes have increased accessibility to hospitals and generally have homes that include protective elements, like air conditioning (Davis 1997). Wealthier people may also have insurance or financial reserves to recover from oppressive events more quickly. It is often the wealthy, privately insured individuals, who are the first in a population to start rebuilding after a flood or tornado, because they have the ability to pay for repair work before federal disaster funding becomes available. Conversely, populations live in poverty have limited, or no, access too many protective amenities. Air conditioning use is one such amenity; lower income populations may not be able to afford running the utility even if it is present in their home. Air conditioning has been shown to decrease heat mortalities by 50–80 % during inclement weather (Semenza et al. 1996; O'Neill et al. 2005). People with lower incomes often take up residence in older and less insulated housing, which increases their exposure to inclement weather conditions. They also have less disposable income to spend at malls, movie theaters, or community pools which could provide relief during extreme heat events (Changnon et al. 1996). Similarly, low-income populations will be less likely to seek medical help due to a lack of insurance or expendable money.

These examples have provided a brief example of the potential range of social vulnerability. Although these traits have been presented distinctly, in the real world it may not be so clear. Elderly populations are often at increased risk due to their age and health risks and they may also commonly live on a fixed retirement income (Changnon et al. 1996). Elderly people may also live in their original home, built several decades ago, with minimal (or worn out) insulation and cooling systems (Davis 1997). These impacts can compound and increase risk. For these reasons, social vulnerability modeling should include multiple variables, rather than individual variables, to identify the compounding impact on populations.

3 Physical Vulnerability

The second type of vulnerability assessment is known as physical vulnerability, which focuses on the actual event or stressor which impacts a population. This modeling is focused on quantifying the event's oppressive force, intensity, and proximity. Common examples of physical variability studies include identifying flood zones, tornado path, or proximity to other site-specific hazards, such as wild fires. Physical vulnerability predominantly focuses on identifying the locations of hazard, and is often used more to document insurance and disaster relief rather than to understand the oppressive impact to the population. In contrast to social vulnerability, physical models do not indicate whether those who were impacted have the ability, be it financial or physical, to adapt or recover from the impact. However, physical modeling indicates how oppressive, or powerful, the extreme weather event is and will document the magnitude of impact. Simple examples of physical models can include the Fujita Scale (F-scale) for tornados or quantifying the difference between a 1 foot and 10 foot flooding event.

3.1 Heat Vulnerability

A common misconception about heat wave vulnerability is that there is a continuous, or even distribution, of temperature across an area (Johnson et al. 2011; Li et al. 2004; Zhang and Wang 2008; Went and Quattrochi 2006; Chen et al. 2006; Voogt and Oke 2003). This should be attributed to atmospheric meteorological forecasts and measurements, which are reported at county or larger boundary resolutions. The National Digital Forecast Database displays weather data at a 5 km resolution, suggesting the entire population within that boundary experiences the same thermal influence (NOAA—http://www.nws.noaa.gov/ndfd/). The urban heat island (UHI), a phenomenon where urban construction materials increase proximal temperatures (Luvall and Quattrochi 1998; Voogt and Oke 2003), disproves this notion. The discontinuity in heat distribution is caused by man-made, constructed materials (buildings, roads, parking lots) which absorb solar energy and re-emit it as thermal energy, or heat (Jensen 2007; Luvall and Quattrochi 1998).

To experience the impact of the UHI, an individual only needs to measure the temperature difference between a parking lot and a nearby grassy feature during a hot day. Advances in satellite imaging are now able to quantify the UHI's discontinuous nature, commonly known as the micro-UHI. The discontinuous thermal impact is derived from the density and quantity of constructed material within an area. Therefore, a dense commercial and high-rise apartment area will have a higher UHI than a neighboring suburban area (Chen et al. 2006; Zhang and Wang 2008). This quantifiable data can allow investigators to distinguish thermal difference between urban areas and incorporate the values into a vulnerability model (Johnson and Wilson 2009; Johnson et al. 2009, 2011; Cutter et al. 2003; Stanforth 2011). There are three important variables to consider for heat vulnerability modeling.

3.2 Micro-UHI

The thermal influence on a neighborhood, particularly within vulnerable populations, demonstrates the degree to which the local population may be affected. It is particularly relevant for individuals who live in dense urban areas, including high rise apartment facilities, that can absorb and store increased quantities of thermal energy (Cutter et al. 2003; Johnson et al. 2012; Zhang and Wang 2008). The thermal impact is particularly dangerous as built environments continue to emit heat throughout the night, which disrupts the normal diurnal thermoregulation process in humans (Sheridan 2002). Humans have evolved to use natural diurnal temperature changes to survive periods of high temperatures through nocturnal reduction in core body temperature. This process of diurnal thermoregulation reduces body temperature through exposure to cooler evening hours, and allows for the maintenance of safe body temperatures. Since the UHI disrupts this diurnal process by extending warm temperatures during evening hours, it requires individuals to use alternate means to regulate and maintain safe core body temperature, such as through air conditioning. The ability to quantify higher thermal risk areas is relatively unavailable without land surface temperature documentation from remote sensing devices. Although meteorological equipment can be used to quantify ambient temperature, they have significant spatial disadvantages.

Atmospheric temperature readings have a large spatial resolution, at least 5 km, which does not capture the micro-UHI, and in situ sensors do not provide a continuous coverage of a study area. However, Remote Sensing systems designed to document surface temperatures, such as the Landsat satellite series, can record land surface temperature (LST) and provide the continuous variable required to compare urban neighborhoods. It should be noted that thermal satellite or other remotely sensed data is a measure of the land surface temperature (LST) not the ambient air temperature. The two are believed to be related since the LST can heat the near surface air and increase ambient temperature where people live. However, due to the limited number of studies on the topic, a positive correlation between the two cannot be conclusively stated (Li et al. 2004; Voogt and Oke 2003; Weng and Quattrochi 2006). Therefore, documentation of the LST within urban areas can provide a good indication of thermal stress, but not necessarily the ambient temperature, in the local area. LST is a particularly relevant measurement for heat influence during periods of low wind and atmospheric mixing, which is common during heat waves and often exasperated by urban canyon geometry which blocks and channels winds within the city.

3.3 Built-up Environment

Similar to the measurement of LST, the built environment influences the impact of proximal land features on local residents. Dense urban areas may experience multiple negative health influences; increased surface runoff leads to surface refuse and dust/trash can accumulate on impermeable surfaces. For heat studies, impervious surfaces increase thermal stress and disrupt wind patterns, which would normally provide relief from the heat. Density of built environments can be quantified through remote sensing devices, similar to the methods used for heat (Zha et al. 2003). The normalized difference build-up index (NDBI) quantifies the density of constructed features (Jensen 2007). Although this particular algorithm has some inability to discern between constructed features and barren/rocky surfaces, it is not really an issue since barren surfaces are uncommon in urban areas and should therefore rarely impact urban analysis (Zha et al. 2003). The NDBI will identify many of the same areas as the UHI, but in that capacity it can be used to double check the LST measurements or assess mitigation practices like green roofs.

3.4 Vegetation

During photosynthesis, vegetation converts solar energy into glucose and stores the energy for later consumption. This removes a quantity of thermal energy from the local neighborhood and acts as a protective element (Davis 1997; Harlan et al. 2012). Vegetation can also store precipitation, reducing surface runoff, and reduce dust through soil stabilization with their roots. Stabilized soil can reduce surface refuse and asthmatic complications. Therefore, it is easy to understand the multiple ways why vegetation can improve the health and resilience of local populations. Quantification of vegetation can be obtained through many vegetation indexes used in remote sensing studies, the most common being the normalized difference vegetation index (NDVI) (Jenson 2007). This algorithm identifies healthy plant leaves, and is generalized enough for use across a wide variety of climates (Zha et al. 2003;

Jensen 2007). This type of index can identify areas where there is a protective element to local populations. Areas with more vegetation have a natural shield against the oppressive elements of heat to provide protection during inclement conditions (Luvall and Quattrochi 1998; Quattrochi and Luvall 1997; Voogt and Oke 2003; Chen et al. 2006) Fig. 1.

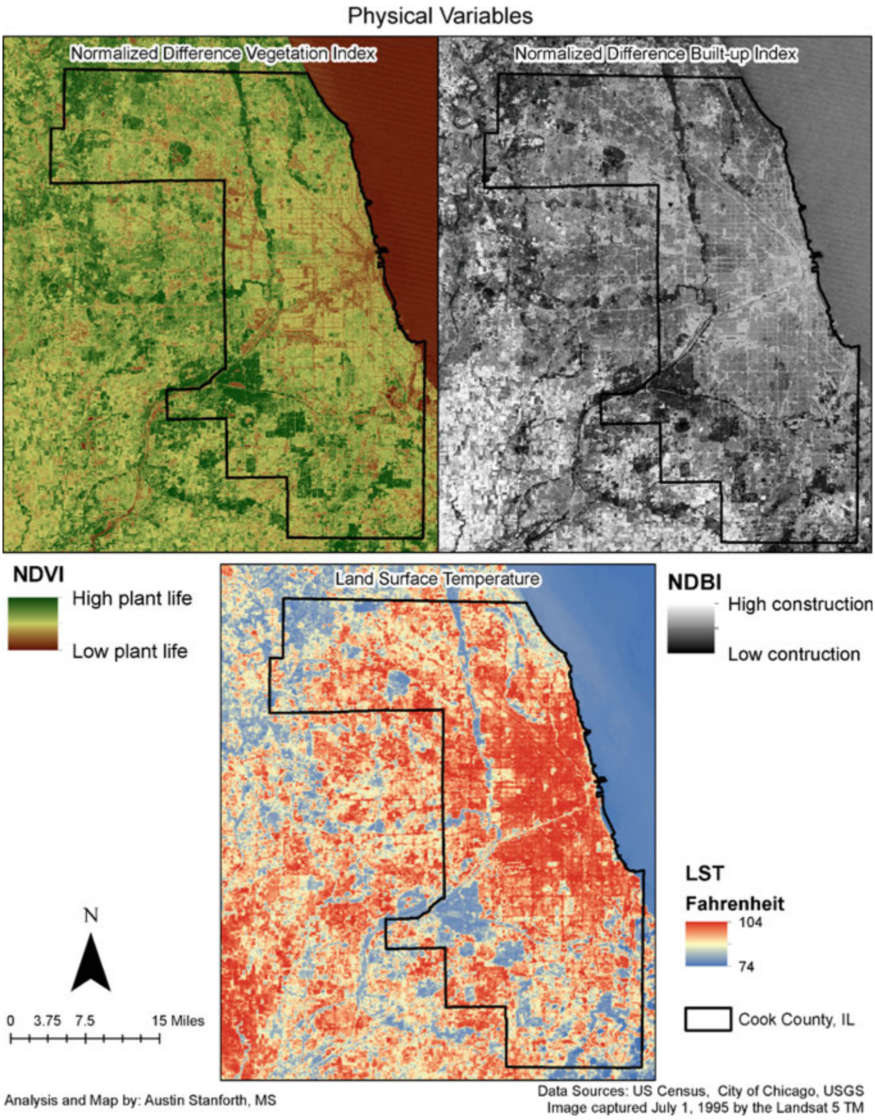

Fig. 1 Comparison images for the physical variables in and around Chicago, Illinois. Note how the *NDBI* and *LST* highlight similar surface feature spaces, while the *NDVI* highlights other regions?

4 Temperature Warnings

As previously mentioned, physical vulnerability studies place less emphasis on the individual or population's ability to adapt or recover from an event. Rather, they focus on the event or degree of influence imparted on the population. For heat waves, the degree of influence is simply the degree or temperature. This variable is often quantified and monitored through weather forecasts conducted by local branches of the National Weather Service (Johnson et al. 2012; Stanforth 2011). Due to the devastating loss of life previous heat waves have caused, the federal government has mandated the implementation of Heat Warning systems across the country (Ebi et al. 2004). Since weather forecasts often maintain a 5 km or larger resolution, this leads to practices that treat large non-uniform areas as continuous temperature patterns and do not factor in the discontinuous nature of urban features. The previously discussed remotely sensed environmental variables should demonstrate why this is an area of concern. Further complications arise as the national warning system often uses a standard specific temperature criteria across the continental United States. Due to the vast area and number of climate features, the application of a single temperature threshold is problematic (Robinson 2001). Discussion with habitants frequently suggest conditions considered uncharacteristically hot in the Pacific Northwest may not raise concern among populations of the dry, desert cities of the southwest (Personal correspondence 2010). This non-location specific implementation of warnings is another reason why heat wave warning systems have received very little interest from the public, because the advertised warnings may not describe inclement conditions in their location, so the population may lose interest.

Some researchers have developed regional, or location specific, warning systems. One of the most well-known, the Kalkstein Heat Health Watch Warning System, analyzes local weather patterns and uses statistical analysis to identify specific local weather conditions related to a significant increase in the reports of heat caused health concerns during previous extreme conditions (Kalkstein 1991; Kalkstein and Greene 1997; Kalkstein et al. 1996). The warning system then uses meteorological forecasts to identify the return of similar weather pattern forecasts to elicit warnings. Although the Kalkstein method has been used throughout the world, it has major shortcomings in its inability to identify 'at-risk' populations. The Kalkstein method uses meteorological forecast data, therefore maintaining the large resolution analysis; it also does not account for socioeconomic status to identify people who are more vulnerable during the projected risky weather pattern (Johnson et al. 2011, 2012; Stanforth 2011). This method can be efficient for the purpose of identifying when large inclement weather fronts are eminent and broadcasting a wide warning to all populations, but does not provide the means to improve mitigation or community prevention practices. The Kalkstein method should, however, receive credit for improving public outreach to emergency management authorities and public awareness of the risks of extreme heat conditions (Kalkstein et al. 2011).

An alternative warning forecast method is Robinson's threshold, which tracks an area's weather patterns over the course of several years. Conditions are considered extreme if they surpass the top distribution values of observed weather events (Robinson 2001). Similar to the Kalkstein method, Robinson's method uses large spatial resolution meteorological conditions. Although Robinson's (2001) method does not use health data to derive risk, it has fewer computational requirements, making it popular among researchers and emergency management offices alike. One consideration lacking in both of these mechanisms is consideration for the diversity of urban features. Due to the UHI, many locations within a city could experience heat wave conditions before their atmospheric forecast systems indicate a threat (Johnson and Wilson 2009; Johnson et al. 2009, 2012). To improve resilience methods, improvements in resolution and understanding of the mechanisms between social and physical space need to be undertaken.

5 Social-Spatial Vulnerability

The application of weather, social, and physical vulnerability derived warning systems, such as those previously mentioned, can improve a population's resilience. However, the application of a single method will not provide sufficient information to identify the best mitigation practices. Inquisitive minds may wonder, 'why not use multiple practices?' The combination of multiple practices within a single system should utilize the strengths of each and provide a better holistic approach (Johnson et al. 2009, 2011; Stanforth 2011). A few approaches have been made, such as those conducted by Reid et al. (2009) and Cutter et al. (2003), which incorporate both physical and social variables.

5.1 Social Vulnerability Index (SoVI)

Cutter et al.'s Social Vulnerability Index, or SoVI, is a national assessment of vulnerability whose smallest unit of measure is at the county level. It incorporates multiple socioeconomic variables, such as age and income. The SoVI includes generic environmental variables, such as urban density which are based on population calculations rather than the quantization of physical variables. It also maintains a large analysis resolution similar to those found in meteorological forecasts. Reid et al.'s (2009) method concentrated on the census tracts of urban areas, but uses a single analysis across the continental United States, similar to the inefficient national standardized heat wave meteorological warning. This study used Land Cover classification to identify the percent of area covered by vegetation as an indicator of environmental influence (Reid et al. 2009). However, since the classification map did not utilize imagery obtained during the time period of inclement weather conditions, the relationship between risk and the environment cannot be conclusively extrapolated. Reid's later publication suggested local-scale testing was a more optimal approach, and regional analysis could not account for small discrepancies in physical or vulnerable attributes (Reid et al. 2012). Despite the advancements over previous systems, both of the described methods maintain large spatial resolutions and do not incorporate temporally-specific environmental variables. To build a more holistic approach to vulnerability modelling, the system should incorporate temporally-specific and multidisciplinary data to assess the interaction of social and physical stressors.

The improved incorporation of multidisciplinary variables requires further understanding of different variable interrelationships. A few simple association examples can demonstrate the relationship between physical and social attributes. Income can impact the selection of available residences, e.g. lower income populations may only be able to afford to live in older or less insulated homes. Older residences commonly have no AC and low income neighborhoods are built in more dense configurations, similar to urban practices, which increases UHI (Davis 1997; Dolney and Sheridan 2006). These combined attributes can lead to a higher risk for heat vulnerability. Conversely, higher property values are often newer residences with more vegetated urban areas or have had more recent construction that can decrease UHI. The newer construction may also have better insulation and opportunity for AC utilization (Cutter et al. 2003; Harlan et al. 2006). Through these examples it's clear how social and environmental variables can be correlated, but variables that generally have little impact on each other can still increase a person's vulnerability. If you recall, our earlier discussion noted a person's age is not directly associated with a specific living condition, but is often related to their level of income.

Elderly populations often have decreased thermoregulation and mobility, which significantly increases risk if they live in an area with high ambient temperature. This is particularly relevant for elderly men, many of whom experience a reduction in thirst sensation and may refuse to use AC because 'it was not something they needed in their youth' (Semenza et al. 1999; Davis 1997). Should these stressors combine with a high risk due to income, such as living on a fixed retirement savings, the two variables could compound their impact to increase an individual's level of risk.

5.2 Extreme Heat Vulnerability Index

The previously discussed vulnerability models demonstrated how either social or physical stressors could be used to model vulnerability, and even how they could be interrelated. However, the large spatial resolutions used can negatively impact the analysis due to potential aggregation errors, a complication caused by averaging data over large areas (Stanforth 2011; Johnson et al. 2011; Reid et al. 2012). This spatial resolution limitation within extreme heat studies on urban populations could greatly affect their ability to determine localized variations in risk. A fine scale model would allow for the identification of specific socioeconomic variables that contributes to increased rates of morbidity and mortality in local populations. Therefore, analysis should focus on localized areas and the development of site specific warning systems which are necessary to better contribute to future mitigation plans (Johnson and Wilson 2009; Johnson et al. 2009). This desire to better understand micro-relationships between vulnerability variables motivated the creation of the Extreme Heat Vulnerability Index (EHVI).

First, a method to combine physical and social modeling must be considered. The previously mentioned Reid and SoVI models facilitated the development of spatially specific models, even though such models maintain large spatial regional or county study areas (Reid et al. 2009; Cutter et al. 2003; Harlan 2006). These models use a statistical data reduction method to assess the relationships between variables which could be described as 'indicators of vulnerability', including the financial and age variables found within the US Census data (Stanforth 2011; Johnson et al. 2012).

5.3 Statistical Modelling

Statistical modeling processes, such as the principal component analysis, can be used to identify trends in data sets. These trends can identify which variables are positively correlated to negative health impacts within a population. Two sets of data are required to perform such an analysis that includes both dependent and independent variables. Health data can account for the dependent variable; previous vulnerability studies have utilized both mortality and morbidity data (Kalkstein et al. 1996; Semenza et al. 1999). Although both can provide an indication of risk, mortality data can be easier to compile (Johnson et al. 2009, 2011; Stanforth 2011; Johnson et al. 2012). Morbidity records are protected by many privacy laws, including the federal Health Insurance Portability and Accountability Act (HIPAA), and can be easily confounded due to inconsistencies between hospital records for a patient's admittance and discharge. Mortality records and death certificates, although protected, are often a matter of public record and much more accessible. Furthermore, heat mortality records demonstrate the most extreme impact of a heat wave, which this type of modeling should focus on preventing. It should be admitted that some complications exist with heat mortality research, as there remains little standardization for heat mortality classification, and the quantities are often underreported (Bohnert et al. 2010; Iniguez et al. 2010).

5.4 Heat Contributing Mortality Causes

The use of all heat-related mortality causes includes those that list other primary causes of mortality which could have been exasperated by the heat (cardiovascular, asthmatic, diabetic, or similar). This inclusive list has been found to positively identify populations at increased risk during the study period (Whilhelmi and Hayden 2010). Inclusion of heat contributing mortalities is not believed to overestimate the weather's impact (Shen et al. 1998; Whitman et al. 1997). The independent variables consist of local sociodemographic and environmental variables. The social economic data can be obtained through the US Census website, www.census.gov, while satellite data can be acquired through the U.S. Geological Survey's online database, www.USGS.org. Similar data reduction methods used during the previously described SoVI analysis could be implemented into the EHVI study design using smaller spatial units, such as US Census Tracts and Block Groups. The use of census data is beneficial for this type of study because it provides socioeconomic data for analysis and provides boundaries to extract environmental variables through the use of a Geographic Information Science (GIS) system. Additionally, each U.S. Census boundary contains a unique identification code for a standardized identification system to statistically compare the areas among themselves (Stanforth 2011; Johnson et al. 2011). The U.S. Census data also provide a generally standardized population amount within each boundary, naturally reducing some bias from population density.

The EHVI study is unique among the previously described methods because it affords multiple environmental variables with the same weight as the social variables (Johnson et al. 2012). The EHVI uses a data reduction statistical method, in the Johnson et al. (2012) example the Principal Component Analysis (PCA) is used, to categorize variables based on their relationship to health outcomes (the dependent variable). These types of statistical data reduction techniques simplify the data to identify which variables are more correlated to the dependent variable (StatSoft 2015). The EHVI for Chicago was created using mortality from the July 12–16, 1995 heat wave as the dependent variable. This allowed for the statistical analysis to find variables which were correlated, or could be compared, to the population whose health experienced the greatest impact during that particular heat wave. Chicago has a humid continental climate, with an average daily July temperature of 75.56 °F. During the heat wave the temperature ranged between 86.06 and 104 °F, which does not allow for natural regulation of body temperature (Stanforth 2011). Over 700 mortalities were documented during this 5-day heat wave. Of those, 586 have been accepted as being directly or indirectly caused by the meteorological event (Centers for Disease Control 1995; Whitman et al. 1997; Shen et al. 1998; Stanforth 2011; Johnson et al. 2012). Geocoded (mapped or located) mortalities can act as the depending variable in the statistical analysis by extracting the number of mortalities which occur within a single census boundary to match the social and environmental variables (Johnson et al. 2012; Stanforth 2011).

6 Principal Component Analysis Findings

To completely understand the intricacies of a principal component analysis can require some studying, as it can be quite complex. However, the project's results can be discussed in generic terms for simplicity purposes in this chapter. A principal component analysis identifies relationships between variables by identifying clusters or patterns (UCLA 2015). Imagine each independent variable value is plotted along the x-axis of a graph, while the dependent is plotted against the y-axis. The statistical analysis identifies clusters within the graph and reclassifies those attributes as new principal components, which are a composite of the input census and environmental variables in this example. The use of principal components allows for the reduction of variables from the analysis that do not contribute to the analysis, or demonstrate the same information, to reduce dimensions (number of inputs) and therefore simplify the dataset. Only components that explain at least the same amount of variation within the data as any original variable are considered to be a principal component (Kaiser 1960). Statistical nomenclature identifies these as having an eigenvalue greater than 1, and is classified as a Kaiser Criteria. Each input variable can then be identified by how much they contribute to each principal component to identify how important they are to the overall analysis (StatSoft 2015). Variables heavily loaded in the principal components are identified as important, and should be considered in future vulnerability models. Such variables add predictive value for identifying local risk.

6.1 Chicago Heat Wave

With this basic understanding of a principal component analysis, we can demonstrate population impacts during extreme heat events. The data shown in Table 1 represent a sample of the principal component results available from the study of the 1995 Chicago, IL heat wave. In addition to U.S. Census socioeconomic variables, the three previously discussed environmental variables collected by the Landsat 5 Thematic Mapper on July 1, 1995, were included in the PCA analysis, examples of these variable can be viewed in Fig. 1 (USGS, Census). The statistical output illustrates four principal components, which cumulatively explain over 79 % of the data's variability. It can also be thought that the four variables explained 79 % as much as the full list of variables, but has removed variable noise which contributed to some of the remaining 21 %. Of those principal components, the variables which contributed most to these results can be identified. In general, variables that best represent heat mortality (the dependent variable), are the population's age, educational attainment, and income. Race is often cited as being essential for predicting population vulnerability (Cutter et al. 2003); this study shows race can range anywhere between the first and fourth components, depending on the classification, suggesting it may not be as important in this type of analysis for all designations or

Table 1 PCA result sample set for the EHVI analysis. Only variables with large (0.8 or higher) positive or negative component loading are considered highly important to the analysis

Component	Eigenvalue	% Variance explained
1	8.88	46.71
2	2.64	13.9
3	2.24	11.82
4	1.33	6.98
		Cumulative = 79.41 %

	Component loading			
Variable	1	2	3	4
Age 65 and older, female	0.94	0.09	0.21	0.18
Age 65 and older, male	0.93	0.10	0.23	0.18
Age 65 and older: female socially isolated	0.93	0.11	0.15	0.10
White race population	0.90	0.28	0.15	−0.07
Age 65 and older: male socially isolated	0.86	0.19	0.12	0.14
Mean family income	0.85	0.27	0.24	0.23
Per capita income	0.84	0.29	0.20	0.18
Mean household income	0.83	0.26	0.25	0.26
Adult population without: high school diploma	0.83	0.30	0.27	0.24
Asian race population	0.64	0.18	−0.07	−0.39
Age 65 and older. group living	0.49	−0.01	0.10	−0.32
Hispanic race population	0.31	0.91	0.15	−0.02
Adult population with: high school diploma	0.11	0.61	0.06	0.36
NDBI	0.25	0.16	0.90	−0.02
NDVI	−0.36	−0.15	−0.89	0.04
Black race population	0.40	0.03	0.33	0.67
Land surface temperature	0.10	0.10	−0.13	0.94

locations (Stanforth 2011; Johnson et al. 2013). Environmental variables rank lower within the component loading. This was unexpected, as previous studies have found a positive relationship between UHI and heat mortalities, but is believed to be due to the larger resolution of satellite imagery compared to the census boundaries (Johnson and Wilson 2009; Johnson et al. 2009, 2012; Stanforth 2011).

Discussion on the component loadings can either support previous research, and endorse the variables use in future analysis, or can disagree and merit further investigation. Age, education, and financial situation all contain strong placement within the component matrix within this and previous studies (Cutter et al. 2003; Ebi et al. 2003; Harlan et al. 2006; Johnson et al. 2009; Reid et al. 2009; Stanforth 2011). Therefore, these sociodemographic variables are supported for continued use in vulnerability studies. Race was not as significant in our analysis. Since this is contrary to previous studies, additional analysis should be conducted to see whether the low ranking in this study is site specific to the Chicago region in 1995, or due to a confounding error in other studies (Cutter et al. 2003; O'Neill et al. 2005; Stanforth 2011; Davis 1997; Whitman et al. 1997; Schwartz 2005). Confounding variables are important to identify, because if two variables are confounded (similar to one another), individually they do not add any additional information to the analysis. Since confounding variables do not contribute additional info, they may only increase the quantity of variable noise, or might be 'piggy backing' off its correlated partner. For example, if the highest educated individuals in a population also always maintain the highest income, it would be redundant to include both income and education; race may be acting in this way with another variable.

Environmental variables were not very predictive during our analysis, as they were located in the 3rd component, and land surface temperature in the 4th. It had been anticipated these variables would have a stronger relationship with the mortality rate due to previous research associating urban heat proximity to areas of high health impact (Johnson and Wilson 2009; Johnson et al. 2009). The low impact may be explained by an aggregation bias since the environmental variables had less range difference and had moderate resolutions (30–120 m thermal) compared to the census variables (Stanforth 2011). Additional analysis should be conducted on the environmental variables when improved remote sensing data is available to further identify their impact on the analysis.

Although the variables in Table 1 can demonstrate which variables have a greater impact on mortality risk, they do not directly provide information as to where the population living in higher risk is geographically located. Some statistical analysis tools provide a vulnerability output for each political boundary based on the independent variable values it contains. Areas with high rates of elderly, uneducated, and poor populations will be assigned a higher risk value. These can be mapped in a choropleth (themed color) map to visually demonstrate and spatially compare areas of low or high risk (Stanforth 2011; Johnson et al. 2012, 2013). The map allows for the identification of landmarks or locations in the city experiencing a greater number of heat health impacts. A public health or emergency management worker could use such a map to work on mitigation practices to reduce or eliminate negative health impacts. The data does not suggest that mortalities will only occur in high-risk neighborhoods, but can be used to identify populations that require the most or more urgent assistance.

Cities are also frequently changing through population migration and building practices. Additionally, no two cities are alike, they all have distinct demographic characteristics. Therefore, no two cities will exhibit the same vulnerability patterns in regards to their variables or spatial arraignment. It is also expected that patterns of vulnerability will change over time within a single geographic (Johnson et al. 2013). Therefore, this level of analysis must be dynamic and updated through time

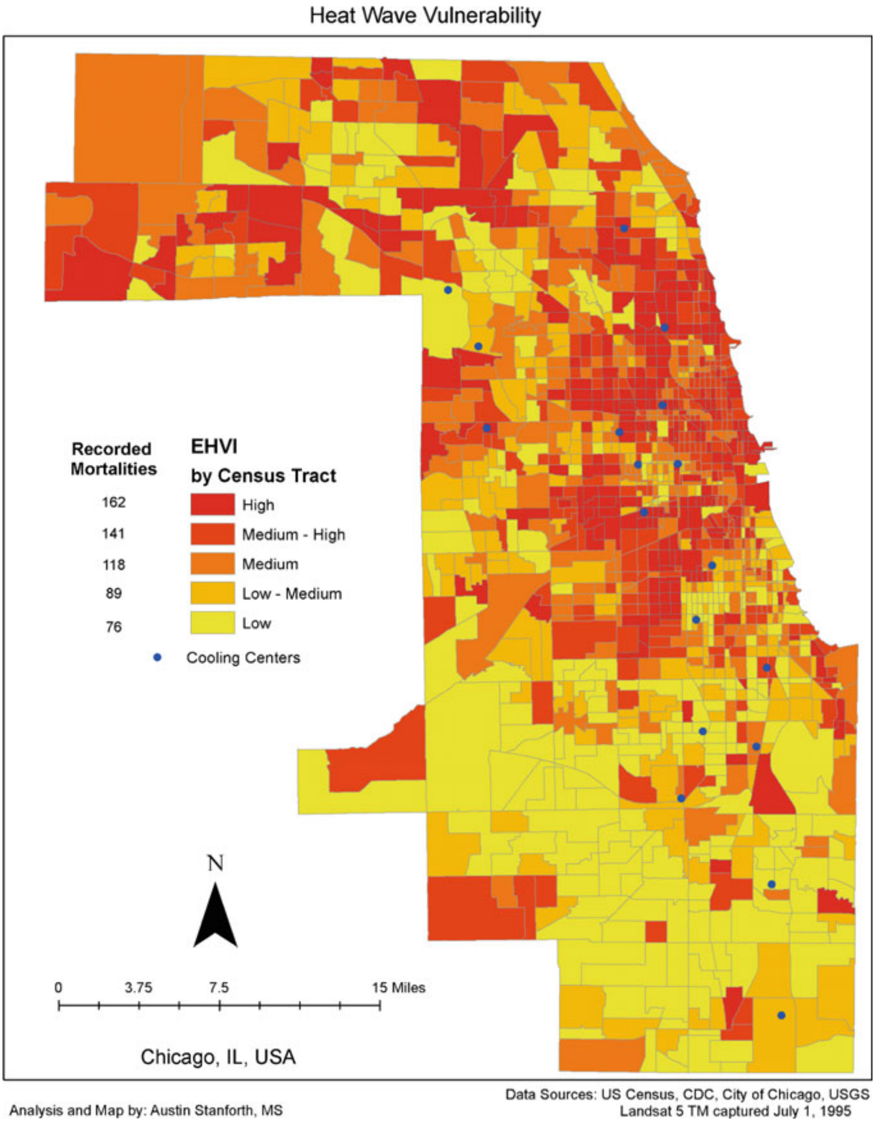

Fig. 2 Extreme heat vulnerability index (EHVI) demonstration for the city of Chicago, IL. Data used for the analysis includes 1990 Census variables and a Landsat 5 TM image acquired July 1, 1995. Note the locations of the cooling centers. Which facilities should public health officials ensure are open during a heat wave?

and across geographical regions. This further demonstrates why a standardized, or national, model for either weather risk or vulnerability will not identify the true nature of the oppressive event. Figure 2 provides an example of the choropleth style map created by the EHVI. It identifies higher risk environments where mitigation practices should be prioritized. The high risk classification is supported by the count of mortalities occurring within each risk rank. High risk boundaries contained a higher rate of mortality than the lower risk boundaries. This style of map can be used to plan mitigation practices and identify local resources, such as proximal cooling centers.

7 Data Hindrance

Most scientists will be able to find a complication or shortcoming within any dataset. Heat vulnerability modeling is no different. One of the most common problems with heat vulnerability research has been the classification of impacted populations, or the dependent variable. Until the heat waves of the middle 1990s, there was no standardized criteria for coroners to identify heat mortalities (Shen et al. 1998; Changnon et al. 1996). This recent standardization has provided only a short window of documented historical cases for study; even now the criteria remains relatively lax (Centers for Disease Control 2002; Donoghue et al. 1997).

Proper identification of heat mortality is very time sensitive because the coroner needs to document body temperature shortly after death. This is often difficult to obtain, as many individuals may have been deceased for many days before their 'lack of presence' is noticed and officials are notified. Therefore, researchers tend to include other mortality classifications when pre-existing conditions which could have been exasperated by heat, such as cardiovascular issues, are listed as a contributing mortality factor (Shen et al. 1998). This inclusive method has provided a better baseline dataset for analysis, but has not been found to overestimate the impact of heat waves on mortality rates (Shen et al. 1998; Schwartz 2005; Bohnert et al. 2010; Iniguez et al. 2010).

The independent variables used for analysis also have shortcomings. Both U.S. Census and satellite data have temporal and spatial resolution limitations. Historical U.S. Census data can be obtained through their website, www.census.gov. Previously, the census had been collected once every ten years, which could cause problems in identifying the local population between collection years. As previously mentioned, the U.S. Census was formally converted to the American Community Survey in 2010. This new survey-derived dataset is designed to provide more temporally relevant data, by sampling a portion of populated areas each year and interpolating the remaining population. This new method will never conduct a full census, which weakens its continued ability to document future population demographics. Since it is the best dataset currently available, all future research will have to acknowledge the potential errors associated with using a sample-derived dataset.

7.1 Satellite Data

Satellite data has similar temporal and resolution limitations. For satellite remote sensing a balance must be made between the spatial (the smallest measurement, or pixel, the instrument can collect data) and temporal (how often an area is recorded) resolutions of a sensor (Jensen 2007). An example of this dilemma might occur when documenting a landscape with a camera. When collecting a wide or panoramic image, the background becomes unfocused but the wide angle allows for the collection of many quick images of the scene. If however, you zoom into a specific area to improve the image detail, you cannot capture as much area in a single shot; rather you must reposition the camera and take additional photos to cover the same amount of area as the wide view shot. This is an oversimplification of what happens with remotes sensing, but should illustrate the balance between collecting detail and big-picture view resolutions. Collecting a high spatial resolution (zoomed) image will collect more detail, but will not cover as large of an area. A wider view does not have the same level of detail, but collects a larger feature area and allows for more rapid collection of images at the same spot. Satellites which collect higher spatial resolution, such as the Landsat with a 30 m resolution, are focused to collect more spatial data and are only able to collect data in the areas once every 16 days.

A satellite with improved temporal resolution, such as the MODerate Resolution Imaging Spectroradiometer (MODIS), collects imagery over the entire Earth each day but has very low spatial resolution. The MODIS's 'zoomed out' image has a spatial resolution between 250 m and 1 km (USGS). This suggests that MODIS may not provide enough detail for highly heterogeneous urban environmental modeling, but can document more homogenous features (forests, agriculture) daily. These limitations must also be considered due to weather, as satellites are notoriously impacted by clouds. With the Landsat's 16 day revisit window, it can be difficult to collect data during a period of interest; if cloud cover is present, it could be a month or more until between the acquisition of useful image data is available over a specific area.

With the limitations of satellite data used to identify the thermal influence on populations, the question could be raised—why not simply stick with meteorological data? The reason is meteorological data has even lower spatial resolution than MODIS. Common weather forecast maps, distributed by local broadcast affiliates, provide temperatures at County boundaries that are on average 230,000 km^2 (U.S. Census 2015). The National Digital Forecast Database is a National Weather Service gridded forecast product, and has a resolution of 5 km (https://www.nws.noaa.gov.ndfd/). These resolutions are not capable of recording the disparities of environmental impact between or within urban neighborhoods. These meteorological tools also do not consider the UHI, as most weather stations are located near municipal airports far away from the urban centers. Since the UHI can increase local temperatures, one can assume the UHI could cause heat wave conditions within specific neighborhoods before meteorological data could identify any risk. Therefore meteorological data cannot provide information to advance the analysis of urban vulnerability modeling.

8 Mitigation Practices—How to Use Vulnerability Models to Improve Health

The usefulness of a vulnerability tool depends upon whether individuals are willing to implement mitigation plans to alleviate the stressors. For instance, knowing seat belts save lives would be frivolous knowledge if car manufacturers failed to install them in vehicles. Similarly, vulnerability models that identify local health stressors are only useful if used to improve mitigation plans. How can a community mitigate high UHI? An urban tree planting organization could use UHI and vulnerability model maps to prioritize planting locations within areas of high UHI to increase vegetation cover, reduce high land surface temperature, and reduce the local thermal risk. If the high risk area has more socioeconomic risk, employment or educational programs could provide more financial security to the area, thereby reducing individual socioeconomic risk.

Models like the EHVI could allow city managers to assess their current mitigation practices. The EHVI map can help assess whether the city's cooling centers are located in areas where they are needed. Sensible urban planning priorities could be established to provide additional centers in areas where current facilities do not cater to the population's need. Maps are also a simple and versatile tools for those with little training. Proactive citizens can read the simple EHVI risk map and identify neighborhoods with a high rate of elderly and shut-in neighbors; during high risk weather they could organize volunteers to aid high risk residents and ensure they are safe. Hospitals can also use this information to assess staffing needs. Hospitals located near highly vulnerable neighborhoods could schedule extra employees and strategically place first responders in high-risk areas to improve their efficiency. Medical facilities located in low-risk areas, however, may not need to schedule as many extra employees during a heat wave; this could reduce the hospital's operating budget.

9 EHVI Mitigation Examples—Practiced and Theoretical

9.1 Cooling Center Assessment

The EHVI, and similar vulnerability models, allows Emergency Management personal to assess their mitigation practices in a way weather forecast models cannot. A simple example of the sophistication of these models for mitigation planning is the previously mentioned assessment of cooling centers within a city. City managers can locate their cooling centers on the EHVI map to see which of

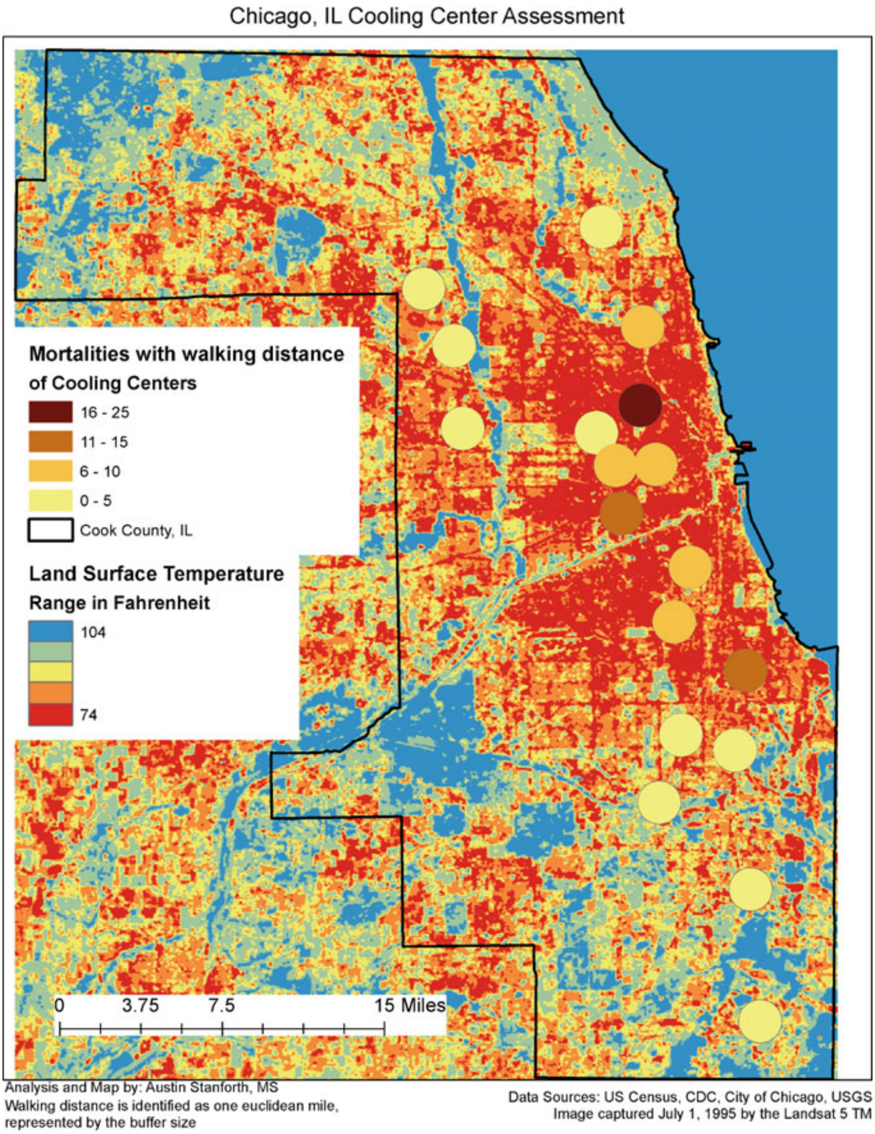

Fig. 3 Cooling center utilization—identifies the locations and quantity of mortalities that occurred within walking distance of each center superimposed on a land surface temperature map

their centers are located within high risk areas; they can also identify new 'best practice' locations to build future centers. Incorporating UHI maps can help management assess whether they should open centers before meteorological forecasts indicate a heat wave. It can also help them identify which centers will require the most staffing. Figure 3 shows one type of assessment for Chicago, IL. First, the map's LST background could identify priority order for the order of opening cooling centers during an imminent heat wave. After the heat wave has passed, it can assist in identifying whether the centers were used appropriately. Figure 3 shows a buffer identifying the quantity of heat mortalities that occurred within walking distance of the center during the 1995 heat wave. One center demonstrates having between 16 and 25 mortalities within one mile of the center. Two additional centers had 11–15 mortalities. This knowledge would allow a manager to investigate why this happened. Was the center not opened appropriately so people could gain access to it? Were the mortalities representative of people who have lower mobility and unable to make it to the cooling center? Or does this cooling center's primary purpose deter marginalized populations from visiting, such as can be the case when a police station is used as a cooling center? Depending on the answers to these questions, the manager can move forward to make their city safer during future heat waves.

9.2 Climate Region Considerations

The advantage of using a model like the EHVI, is that it is a local model. It utilizes local population data, local climate implication, and does not try to compare distinct populations or cultures. As previously discussed, standardized national warnings do not create adequate risk models due to the vastly different climate regions of this country (Hajat et al. 2010). Local populations have various cultural and biological adaptations to heat, depending on where they reside. Local collaborators on the project informed us that some form of air conditioning utility is required in building codes for Phoenix, AZ, due to the frequent high temperatures reached in their arid environment (personal communication 2010). Midwestern states, like Chicago, IL, or Philadelphia, PA, had a much lower prevalence of including cooling utilities in their building practices until after the 1995 heat wave. Philadelphia commonly builds brick and mortar homes, which can increase the urban heat island and even increase internal residential temperatures, similar to a brick oven. Philadelphia collaborates were quick to explain that their residential building practices have been designed to withstand cold winter winds rather than summer's heat (personal communications 2010). As suggested here, these cultural differences show up within building practices, through building codes, and the cultural adaptations of residents' daily lives throughout the world. This make a regional, standardized warning system impractical.

Phoenix is a arid climate, dry and hot all year, while Chicago's summer climate is more mild and humid when heat waves are most problematic. These climate differences can drive different societal habits between the two cities. While Phoenix residents will need to be very cautious about their hydration and fluid intake while they are outside, Chicago residents have the opportunity to cool their core body temperatures by visiting the shores of nearby Lake Michigan, if they have transportation. The response of populations, due to their local climate, is also prevalent in their attitudes toward the weather and mitigation practices. The authors conducted an unpublished telephone survey to identify any patterns in response to residents' impressions of extreme heat events. During this survey, Phoenix residents frequently dismissed the notion of severe or extreme heat. To paraphrase numerous study participants, they disregarded the notion because, "It's always hot". These indifferent attitudes can also stem from acclimation of the climate, since they are acclimated they don't worry about it. However, population sub-groups can have different responses from their neighbors, such as could be the case with 'winter bird' or retired populations who recently moved to the area.

Elderly populations are notorious for not using air conditioning (Davis 1997). Some studies suggest this is in response to fixed financial status, but there are reports of elderly populations who do not feel they need air conditioning because they did not use it when they were young (Naughton et al. 2002). May elderly people may not know, realize, or consider the implications of their aging bodies, which may have a reduced thermoregulatory ability, and assume they are as resilient as they were in their youth. Philadelphia has several service opportunities designed to aid elderly populations, one being the Corporation for Aging (http://www.pcacares.org/). Collaborators from the city identified numerous volunteer opportunities with the center, including an annual "fan drive." Although the use of fans can prove disadvantageous during heat waves, as they reduces sweat's ability to assist in thermoregulation, it does provide an opportunity for the EHVI map to aid volunteers in identifying areas in greater need of assistance (Davis 1997). Similarly, a pastor in Indianapolis, IN expressed interest in using the local EHVI map to guide their youth volunteers to identify high-risk neighborhoods with elderly populations. These youth visited these elderly residents to ensure they had the resources necessary to survive the heat wave.

Other volunteer activities could similarly improve resilience within neighborhoods. Keep Indianapolis Beautiful (KIB) is an organization which manages volunteers to plant trees. The organization's leaders were interested in identifying the best locations, or areas of highest need, to plant trees within the city. Implementing the EHVI and LST maps for Indianapolis, IN allowed the organizers to identify specific neighborhoods that would receive the greatest benefit from tree plantings. Similar organizations could pair up with city officials to identify abandoned lots or spaces where new parks, cooling centers, or urban farming plots could be established. These practices would reduce local heat impacts and improve both air and water quality. Urban farms could improve socioeconomic status and generally improve the quality of life for local residents.

These last two vegetation planning examples are geared towards Midwestern communities, or any environment with a higher precipitation record. Desert environments, like Phoenix, may not benefit as much from tree plantings without the infrastructure to keep them adequately watered. Municipality officials in Phoenix could instead use the EHVI maps to plan new cooling centers or drinking fountains. Additional drinking fountains in high-risk neighborhoods could allow residents to maintain proper hydration while they are outside. Small local municipality pools or 'wading fountains' could similarly be opened when temperatures reach extreme levels. Phoenix could also consider mobile cooling centers practices similar to what has been tested in both Philadelphia and Indianapolis. Municipal buses not in service can be used as mobile cooling centers. These buses could be driven to neighborhoods with higher risk and parked with the air conditioning running. Local residents are able to get on and off the bus to cool down without fee. Vulnerability maps can help identify neighborhoods which may be in more need of the mobile facility, and help assess which neighborhoods could receive the greatest benefit from their presence.

9.3 Residences

People commonly associate their residence with a level of protection from dangerous or oppressive events. However, there are many reasons why a home cannot always provide the protection people assume it should. Low income property value residences can have less insulation, are often older, built in more dense configurations, and lack air conditioning. These characteristics can compound summer temperatures and the UHI, making them dangerous (Davis 1997; Changnon et al. 1996). Many people with lower financial resources have less access to protective environments near their home. Individuals living in poverty, or elderly populations living on a fixed income, have fewer resources to visit air conditioned establishments, such as movie theaters which require an entrance fee, during periods of extreme heat. Patrons must pay to sit in a restaurant, enter a movie theater or museums, and shopping centers or malls similarly elicit purchases for the use of their facilities. Swimming pools may similarly require a membership to gain access. All these options would also require some sort of transportation to reach (Changnon et al. 1996). The condition, or presence, of sidewalks can also inhibit individuals from walking or biking to a protective environment, should they lack an automobile. Lack of transportation and infrastructure maintenance further demonstrates how lower socioeconomic or marginalized populations can have difficulty relocating to safer environments, as these neighborhoods often receive the least upkeep.

Many government-sponsored cooling centers do not charge an entrance fee and can appear like a remedy to solving an extreme heat situation. However, the challenge is that many people who need cooling centers may have limited transportation options or may not feel safe visiting some of these facilities. In many large cities, cooling centers often serve dual purposes. Chicago, IL has been known to advertise their police stations as a cooling center during periods of inclement heat. This type of a cooling center may turn-away many people who could potentially benefit. Freely walking into a police station could be very uncomfortable for people who have criminal records, have witnessed the marginalization of populations they associate with, or whose immigration status is debatable (personal communication 2010). The utilization and/or under-utilization of available resources therefore often depends on the sub-culture of a city. Furthermore, the repair of streets/sidewalks, construction of cooling centers or parks, and general expenditures on mitigation policy are heavily politicized and the value will often be expected to return to local taxpayers or to those supporting the politician. It can be assumed that higher income neighborhoods will have better resource maintenance than the low-income neighborhoods which need the maintenance. Funding allocation is commonly observed with school district distribution of funds. Implementation of an EHVI or similar vulnerability model not only allows for a better argument for distributing funds to areas that need it, but they could potentially be used to provide documentation for FEMA natural disaster grant funding to reduce risk in highly vulnerable areas.

It should also be noted that some individuals do not actively seek out ways to reduce their heat risk, due to a level of concern for their personal safety. This may sound counterintuitive, but it can be common to find closed and locked windows in neighborhoods with higher crime rates during heat waves. Without air conditioning, buildings sealed to reduce theft are also sealed to eliminate air circulation. The operation of kitchen appliances or any number of electronic devices (TVs, computers, fans) give off heat during operation, thereby increasing the ambient temperature within the sealed residence (Changnon et al. 1996). High crime rates will most often drive people to keep their windows and doors locked at night. This causes residents to miss the benefits of cooler night temperatures when diurnal thermoregulation is most important. This is particularly relevant to shut-ins, or those living in isolation who eliminate interaction with the outside world, as it further increases their risk (Naughton et al. 2002).

10 Concluding Remarks

This chapter demonstrates some of the advantages of studying vulnerability to extreme heat at a smaller, more localized scale. Improved understanding and mitigation plans can be made through the use of location-specific weather, environment, and social attributes that help explain why certain populations are at an increased risk. This chapter explored how small scale analysis and modeling for extreme heat vulnerability is advantageous due to the availability of U.S. census and environmental indicators of risk. It was also demonstrated how local cultural attributes or conditions affect responses to risk. National criteria for 'extreme heat' thresholds do not work due to climate differences across the nation and due to cultural responses to local weather acclimation. Low resolution meteorological and physical vulnerability models are not able to account for within city variations of thermal impact due to the effects of the Urban Heat Island. Similarly, national or similarly large models cannot provide the details necessary to assess or improve local mitigation practices. Additionally, local environmental conditions caused by UHIs can cause heat wave conditions before meteorological measurements indicate any risk.

Since variations in socioeconomic status can cause populations to be less resilient than their more financially resilience neighbors, spatially specific vulnerability models must be considered to identify the populations at greatest risk. With numerous mitigation practices available, both economic and environmental, it stands to reason that identifying the best practice mitigation plans would provide for a more complete and efficient reduction in vulnerability. Extreme heat warning systems should therefore focus on micro scale analyses in order to incorporate local variations in the social and environmental variables to reduce health risks by improving location-specific mitigation practices and strategies.

11 Preventative Practices to Reduce Heat Impacts on Community Health

This chapter strives to discuss heat mitigation practices by providing real world examples of risk mitigation. The following is a summation of key points that have been previously addressed to emphasize their significance.

11.1 Heat Mitigation Is Multidisciplinary

Proximity to heat sources is important when identifying the risk of local populations. This can be measured through both meteorological equipment and measurements of the urban heat island. A combination of the two variables will provide a better metric. However, only looking at the heat sources will not identify the population's risk of being affected by the heat. To understand the full risk of a neighborhood, an understanding of the population's ability to withstand or recover from the exposure to heat must also be known. Resilience to heat can be a factor of an individual's physical attributes (good health) and socioeconomic status. An individual with the financial ability to utilize home air conditioning or visit air conditioned establishments, will probably experience less health risks during a heat wave. Knowing the general health resilience and socioeconomic demographics of neighborhoods will be useful when selecting which cooling centers or aid facilities to open during inclement weather. This can allow centers located close to high risk populations to be identified and opened during heat waves. Including factors of both physical and social environments will allow for the creation of improved mitigation practices.

11.2 Heat Waves Are a Local Phenomena

Previously, heat waves were forecasted by a national standardized criteria. As has been discussed previously in this chapter, this is inadequate due to the numerous diverse climates found within the continental United States. The climate conditions between the cool and wet Pacific Northwest states is vastly different from the hot and dry desert conditions of the Southwest. Therefore a standardized criteria for identifying heat waves is inadequate. Heat wave criteria need to be updated for local climate patters and the populations who have acclimated to them. This would likely improve public acceptance of heat wave warnings, improve their knowledge about dangerous weather patterns, and reduce hazardous weather warning message fatigue.

11.3 Heat Wave Vulnerability Evolves with the Population and Location

Population and city characteristics change through time. Population demographics are dynamic, due to both immigration/migration and birth/death patterns changing with medical advances. Cities are also dynamic, as building practices and housing values change. The values of homes or neighborhoods can fluctuate depending on the current, local economic status. Emergency management representatives therefore need to realize that mitigation practices and modeling must also be dynamic to compensate for urban change. Many of these changes will not occur suddenly, except in the case of a disaster, but the option to monitor and update their process should be considered at least annually. Therefore officials should assess their mitigation practices frequently. Assessments can be conducted through epidemiological-style studies to identify whether their mitigation strategies have been effective in previous heat waves. This would allow officials to further improve their mitigation plans before another heat wave occurs.

11.4 Mitigation Is a Local Problem and Requires Local Response

Similar to the discussion of heat waves being a local phenomenon, mitigation needs to be addressed at a local scale. There are many practices that could be used within collaborating communities, such as eliminating entrance fees for community pools or organizing volunteers to visit high risk elderly neighbors during heat events. Longer term mitigation practices, however, require a very local approach. Frequent rain patterns in the Midwest allow for tree planting initiatives to reduce the urban heat island and alleviate thermal stress. This same mitigation plan may be cost prohibitive in arid climates, as trees would require additional attention and water resources to survive. A desert environment may benefit more by making drinking fountains or covered shelters more accessible.

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