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A Mixed-Methods Approach to Assessing Factors Contributing to Heat Exposure at the Neighborhood- and Individual-Levels in Knoxville, Tennessee

Alisa Lynn Hass

University of Tennessee, ahass@vols.utk.edu

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To the Graduate Council:

I am submitting herewith a dissertation written by Alisa Lynn Hass entitled "A Mixed-Methods Approach to Assessing Factors Contributing to Heat Exposure at the Neighborhood- and Individual-Levels in Knoxville, Tennessee." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

Kelsey Ellis, Major Professor

We have read this dissertation and recommend its acceptance:

Sally Horn, Jiangang Chen, Isabel Munoz

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)
A Mixed-Methods Approach to Assessing Factors Contributing to Heat Exposure at the Neighborhood- and Individual-Levels in Knoxville, Tennessee

A Dissertation Presented for the
Doctor of Philosophy
Degree
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Alisa Lynn Hass
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Abstract

Urban areas are warmer than rural areas because urban landscapes disrupt the movement of energy, wind, and water, effectively trapping more heat near the surface. Urban resident heat exposure is a growing concern as climate change is expected to exacerbate urban heat. Exposure to excessive heat can result in heat-health effects, such as heat stroke, and comorbidities, such as heart attacks. Understanding who is exposed to heat can pinpoint where adaption resources are most needed. The purpose of this research was to use a comprehensive approach to assess how residents of Knoxville, Tennessee, vary in their exposure to, perceptions of, and adaptation to heat exposure. To do this, I 1) evaluated neighborhood-level weather data to quantify microclimate variability, 2) assessed lifestyle surveys and individually collected temperature and humidity data to evaluate who is most exposed to dangerous levels of heat and why, and 3) analyzed mixed-methods surveys to understand how urban residents describe, perceive, and adapt to heat.

Urban neighborhoods had different microclimates; specifically, areas with greater vegetation reported higher heat indices. Participant heat exposure, as measured by heat index, was not well-represented by airport conditions, with participants usually being less exposed than the airport weather station, especially during the daytime and during a heatwave. Because ambient heat indices are highest during the day, it is likely that participants employed effective adaption actions to avoid heat during a heatwave, reducing their individual exposure. Some participants, however, were more exposed at night and during non-heatwave conditions, likely indicating that buildings retained heat or less adaptive actions were taken during these times despite participants being exposed to dangerous levels of heat. The heat adaption actions that participants took to reduce their vulnerability to heat-health effects were related to their income,
educational background, perception of heat danger, and previous heat-health issues. Participants were less likely to take adaptation actions if they did not feel that they were at risk for heat-health issues or were unable to alter their schedules. This work contributes to a small research base that assesses neighborhood- and individual-level heat exposure to understand heat inequality in an urban area.
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Chapter 1

Introduction
1.1 Introduction

Urbanized areas in the southeastern United States have grown rapidly since the mid-1900s and are predicted to continue their quick population growth (Ingram et al. 2013). Urban areas, which can be defined as those with 50,000 people or more (USCB 2017), provide a multitude of advantages to residents. Some advantages of urban areas include access to healthcare, higher quality jobs, education, and increased mobility from public transportation (Antrop 2004). Urban areas provide entertainment, advancement of technology, and cultural diversity (Antrop 2004; Von Oort and Lambooy 2013). People occupy less land in an urban area because of multilevel dwellings. However, such a large number of people living in one area causes a resource sink. The need to supply urban areas with energy, paper products, food, and other necessities, places a high demand on rural areas (Borucke et al. 2013). This demand results in fragmentation of the landscape, overuse of croplands and pastures, increased fishing, and so forth (Borucke et al. 2013).

Another disadvantage of urban areas is that residents are subject to warmer temperatures because of the existence of urban heat islands (UHI), where urban areas are warmer than rural areas. The existence of a UHI is determined by comparing urban temperatures with rural temperatures. The classic UHI signal consists of the highest temperatures in the area with the most impervious surfaces, highest population and building density, and the highest anthropogenic actions. Specifically, the UHI exists because of radiation trapping, rainfall partitioning, less evapotranspiration, anthropogenic heat sources, disrupted wind patterns, increased pollution, and other characteristics of urban areas that cause heat to be trapped near the surface (Aida 1982; Shukla and Mintz 1982; Oke 1987; Taha 1997; Oleson et al. 2015).
1.1.1 Urban heat variability in a city

Most early UHI research focused on the temperature difference between the city and its surrounding area (Clarke 1972; Oke 1982, 1987). Often, ambient urban temperatures are collected from weather stations near airports (Oke 1982; Ripley et al. 1996; Unger et al. 2001; Huang et al. 2011; Mallick and Rahman 2012; Mohsin and Gough 2012; Kuras et al. 2015). Recent research has identified variability of the UHI signal within a single city. Differences in UHI strength have been found at the city (Lo et al. 1997; Yu and Hien 2006; Mallick and Rahman 2012), neighborhood (Harlan et al. 2006; Luber and McGeehin 2008; Ellis et al. 2017), census block (Huang et al. 2011; Chow et al. 2012; Harlan et al. 2013), and zip code (Hondula et al. 2012; Harlan et al. 2013; Hondula et al. 2013) levels.

The spatial variability of UHI intensity is related to land-cover characteristics within a city, specifically characteristics such as building density and tree cover (Ellis et al. 2017). Analyses that incorporate remotely sensed thermal data, population density inferred from a national census, and land-cover measurements taken in the field have shown that areas with less vegetation, a greater population density, and more buildings have a greater UHI intensity (Mallick and Rahman 2012). Networks of meteorological observation sites, such as portable temperature sensors (Sullivan and Collins 2009) and weather stations (Basara et al. 2010; Giannopoulou et al. 2014; Ellis et al. 2017), have also been used throughout cities to investigate how land cover affects UHI. Similar to studies that use remotely sensed thermal data, these studies indicate that areas with greater imperviousness and less vegetation observe a greater UHI intensity than areas with more vegetation and less impervious surfaces (Sullivan and Collins 2009; Basara et al. 2010; Ellis et al. 2017). In Knoxville, Tennessee, Ellis et al. (2017) deployed a network of weather stations and concluded that land-use patterns have a more consistent influence on temperature than distance from the urban core, that tree cover helps to minimize
daytime heating in urban neighborhoods, and that urban neighborhoods cool more at night than the city center. Urban areas cool slower than rural areas, likely because of the great ability of urban areas to store and retain heat, and less evaporative cooling from increased runoff and decreased vegetation (Sullivan and Collins 2009).

1.1.2 Thermal Comfort and Humidity

Water vapor content in the atmosphere affects the thermal comfort of urban residents. Sweat evaporation decreases when there is a high amount of moisture in the air, reducing a person’s ability to thermoregulate (Malchaire et al. 2000). The subjective measure of atmospheric comfort within an area is called thermal comfort, and includes both relative humidity and temperature (Giannopoulou et al. 2014). Studies incorporating thermal indices have been used to determine how urban residents experience high temperatures and humidity (Harlan et al. 2006; Hajat et al. 2010; Hondula et al. 2012; Ketterer and Matzarakis 2014). Using thermal indices to describe the UHI shows more variability in UHI intensity than when using temperature alone (Ketterer and Matzarakis 2014). These studies show that relative humidity affects human thermal comfort in urban settings, especially during hot weather (Harlan et al. 2006; Giannopoulou et al. 2014; Ketterer and Matzarakis 2014).

The heat index is a thermal index that accounts for the amount of heat an individual experiences based on the combined effect of temperature and humidity (National Weather Service 2019). High heat indices are often used as the basis for issuing heat advisories and warnings (Hajat et al. 2010; National Weather Service 2019). A greater risk of heat-related mortality occurs in areas where apparent temperature, a combination of temperature, wind, and humidity, is highest (Hondula et al. 2012). Humidity is especially dangerous to persons who have a lessened
ability to thermoregulate, such as the elderly and children, and for those with less access to heat adaption resources (Kenney and Hodgson 1987; Harlan et al. 2006).

Areas with low thermal comfort tend to be those with less vegetation, greater building density, higher minority populations, and lower income (Harlan et al. 2006). This is important because lower-income urban residents have less means to adapt to high temperatures and humidity and are more vulnerable to heat effects (Harlan et al. 2006). Research on thermal comfort emphasizes understanding the patterns of extreme heat and humidity, not only for the health of urban residents, but also to determine where adaption efforts can be emphasized. Connections between socioeconomic and demographic characteristics and thermal comfort, as documented by Harlan et al. (2006), need to be further incorporated with land surface cover to ensure a better understanding of what elements in urban neighborhoods contribute to or reduce high temperatures and humidity. This will inform proper neighborhood adaption and education measures.

While the city center is usually the area of greatest temperature, it often has a lower humidity and heat index than surrounding areas because there is less vegetation and more impervious surfaces that cause runoff (Clarke 1972). A lower heat index in the city center potentially leads to lower heat stress on populations in urban areas (Harlan et al. 2006). This counters the traditional idea that those living in the inner city are most at risk for heat exposure. Conversely, shading provided by vegetation can serve to mitigate extreme heat. The shading provided by trees blocks some direct radiation, reducing heat exposure (Heisler 1974; Mayer and Hoppe 1987; Middel et al. 2016). Thus, the effects of trees and greenspaces likely increase thermal comfort.
1.1.3 Heat-Health Effects and Inequality

Increased heat exposure associated with the UHI may affect the health of urban residents. Heat-health effects in an urban area are a concern for climatologists as climate change is expected to cause higher average temperatures and more intense and frequent heat waves in the southeastern United States (Ingram et al. 2013; U.S. Global Change Research Program 2018). Increasing temperatures, especially over long periods, can place humans at risk for significant health problems (Ingram et al. 2013). Heat waves in urban areas tend to cause an increase in heat-health effects. This is especially true in locations where individuals are not used to high temperatures and humidity (Kalkstein and Greene 1997; Luber and McGeehin 2008; O’Neill and Ebi 2009; Wilhelmi and Hayden 2010; Fischer et al. 2012; Ingram et al. 2013). Despite acclimatization to high temperatures, the southern United States has a high rate of heat-related deaths because of frequent exposure to extreme heat and an aging population (Berko et al. 2014).

The effects of varying UHI intensity on heat-health has been studied by incorporating personal data with landcover and meteorological observations. For these studies, human health and socioeconomic data are often gathered from mortality records (Hondula et al. 2012; Harlan et al. 2013; Hondula et al. 2013) or a countrywide census (Mallick and Rahman 2012; Harlan et al. 2013). These data are then integrated with meteorological observations collected from one or more weather stations (Hondula et al. 2012, 2013; Ellis et al. 2017) or remotely sensed thermal data (Lo et al. 1997; Chen et al. 2006; Huang et al. 2011; Mallick and Rahman 2012; Harlan et al. 2013). Areas with a higher socioeconomic status often have more vegetation, less pavement, and less compacted structures, leading to an overall cooler climate (Taha 1997; Oleson et al. 2015). Areas with a higher population of the elderly, minorities, those with a low socioeconomic status, and those who live in areas of high building densities experience greater UHI intensity (Huang et al. 2011; Hondula et al. 2012; Harlan et al. 2013; Hondula et al. 2013; Ellis et al. 2017). Higher-
intensity UHI areas have greater incidences of heat-related mortality because of increased heat exposure (Harlan et al. 2013; Hondula et al. 2013). Those who live in a higher-intensity UHI area are potentially more vulnerable to heat-health effects as they often lack resources to adapt to greater heat exposure (Harlan et al. 2013).

Heat inequality is a pertinent issue because heat exposure varies within an urban area. Marginalized groups, such as low-income individuals and the elderly, experience more frequent heat-related morbidity and mortality than non-marginalized groups (Harlan et al. 2006; Mitchell and Chakraborty 2018). Those living on a warmer upper floor of a multi-story building (Tamerius et al. 2013) may be more exposed to high temperatures. Likewise, those living in an unsafe neighborhood may be more exposed to high temperatures because they are less willing to open windows for increased air circulation (Blum et al. 1998; Uejio et al. 2011).

1.1.4 Individually Experienced Temperatures

Emerging research on individual heat exposure reveals variability within urban populations. Wearable temperature sensors designed to measure conditions near an individual are used to understand variability in individual heat exposure (Kuras et al. 2015; Sugg et al. 2018; Uejio et al. 2018). Using small temperature sensors (iButtons) worn by urban residents, Kuras et al. (2015) found that individual behaviors like work, school, and exercise; socioeconomic and demographic characteristics; and access to heat adaption resources are more successful in determining heat exposure than neighborhood, census block, or city-wide ambient studies. Individuals are exposed to a variable level of heat throughout the day because they move between indoors and outdoors (Nguyen et al. 2014). Other factors, such as housing condition and daily activities, can affect the amount of heat individuals are exposed to even when indoors (Brasche and Bischof 2005). Similarly, occupational studies using iButtons show that ambient outdoor
temperatures do not necessarily represent the conditions that individual urban workers experience (Sugg et al. 2018; Uejio et al. 2018). Understanding individual heat exposure variability is important to determine who is most affected during heat events and what mitigation and adaption resources would best serve these populations (Kuras et al. 2015).

1.1.5 Urban Resident Perceptions and Behaviors in Response to Extreme Heat

The actions an individual takes to adapt to heat varies based on their access to resources and their perception of heat danger. Access to heat adaption resources, such as air conditioning and shade, varies within a population. Often, lower-income and minority groups lack access to these resources and are at a greater risk for heat exposure (O’Neill et al. 2005; Smargiassi et al. 2008; Reid et al. 2012). Others do not think that they are at risk for heat-related illnesses and thus do not take measures to protect themselves (Kalkstein and Sheridan 2007; Abrahamson et al. 2008; Semenza et al. 2008).

Quantitative, readily downloadable data, including meteorological, mortality, and remote sensing data, are traditionally used to understand heat exposure and effects. Surveys, focus groups, and similar means of obtaining information from urban residents provide additional insight into individual experiences, perceptions, and behaviors. Studies using these methods to assess resident perceptions of heat warnings conclude that most residents are aware of heat warnings because of extensive media reporting but are unsure of the differences between a heat warning and a hot day (Sheridan 2007). In fact, very few residents take action to adapt to heat exposure because they do not think they are at risk for heat-related illnesses, signaling a need for heat education (Kalkstein and Sheridan 2007; Sheridan 2007; Abrahamson et al. 2008; Semenza et al. 2008). For example, despite studies showing that the elderly are often more at risk, many do not consider themselves vulnerable to heat-related illness and only use “common sense
behaviors,” such as keeping the house cool with shades and drinking more water, to avoid becoming ill (Abrahamson et al. 2008).

The socioeconomic status of a resident may affect what actions they take to adapt to hot weather. A resident with low socioeconomic status is more likely to perceive high heat as a risk and take adaption actions (Kalkstein and Sheridan 2007; Mason et al. 2017). However, this same population is less likely to have access to adaption resources (Kalkstein and Sheridan 2007). Mason et al. (2017) found that residents in lower socioeconomic neighborhoods in Knoxville are more concerned about hot days than those in neighborhoods with a higher socioeconomic status. These residents cite the high expense of air conditioning and weatherization, health, needing to stay inside to avoid heat exposure, and checking on others as the basis for their concerns (Mason et al. 2017). Transportation, specifically walking to and sitting at a bus stop to get to work, was also a concern in lower-income neighborhoods, as this exposed residents to heat and caused health problems (Mason et al. 2017). While many urban residents associate trees, green spaces, and parks with a more beautiful neighborhood, residents in lower-income neighborhoods cited the need for trees for shade and heat mitigation (Mason et al. 2017). Mason et al. (2018) additionally found that residents with poorer health or less social cohesion were more likely to experience heat-health effects in the summer.

1.2 Study Area

This research was conducted within the city of Knoxville, Tennessee. Knoxville is a mid-sized town located in a valley between the Cumberland Plateau to the west and the foothills of the Appalachian Mountains to the east. The metropolitan area contained approximately 837,571 people in 2014 and experienced a moderate growth rate of about 20,000 people during
the previous four years (USCB 2015). Knoxville covers 158.6 km² and has a mean population density of 2,905 persons per km² (USCB 2018).

As a city located in the southeastern United States, Knoxville has a humid subtropical climate. Knoxville has warm, humid summers, averaging 34 days above a maximum temperature of 32.2 °C (90 °F; National Weather Service 2015). This area is at risk for several types of meteorological hazards, including severe storms and tornadoes, winter storms, and heatwaves.

The southeastern United States, and Knoxville in particular, is an ideal place to study extreme heat events. The warm and humid summers typical for this area are expected to increase in the future (Ahrens and Samson 2010; Ingram et al. 2013). Average temperatures in the region have increased 1.1 °C since 1970 (Ingram et al. 2013). An even greater warming of regional average temperatures of 1.2 °C by 2050 is expected with mid-range emission scenarios (U.S. Global Change Research Program 2018). In addition to mean temperature increasing during all seasons, also increasing are the intensity, frequency, and length of heat events (U.S. Global Change Research Program 2018); nighttime temperatures (Ahrens and Samson 2010); and the amount of humidity, which will create a higher heat index (Ahrens and Samson 2010).

This study of Knoxville, Tennessee, serves as a case study of the experiences and perceptions of urban residents in a mid-sized city in the southeastern United States. This area has seen and will continue to see an increase in population (Ingram et al. 2013), exposing more people to extreme weather events. The United Nations (2015) reported that nearly 83% of the populations in more-developed regions will live in urban areas by 2030. Thus, a large percentage of the population will be vulnerable to the effects of an increase in heat events that may be caused by climate change and exacerbated by the UHI. Large cities of more than 5 million people only account for 8.4% of the worldwide population. Cities with populations less than 5 million in the more-developed world, like Knoxville, are expected to see the greatest increase in population by
2030 (United Nations 2015), making them an important place to study how urban climates affect residents.

1.3 The Dissertation

The goal of this dissertation was to determine how residents of Knoxville, Tennessee, vary in their exposure to, perceptions of, and adaptation to high temperatures and humidity. To achieve this goal, this dissertation is driven by three primary research objectives:

1. To assess how the environmental conditions relevant to thermal comfort vary across and within four urban neighborhoods in Knoxville, Tennessee.
2. To evaluate how and why individually experienced heat index (IEHI) observations vary within Knoxville, Tennessee.
3. To assess the perceptions of heat exposure and heat-health vulnerability during heat events in Knoxville, Tennessee.
4. To understand the factors that affect whether or not Knoxville, Tennessee, residents employ heat-adaption behaviors during extreme heat events.

1.3.1 Organization of Dissertation

This dissertation is organized into five chapters. Chapter 1 has provided an introduction to urban heat variability, how this variability affects urban populations, and the need for the research presented in this dissertation. Chapters 2–4 consist of three manuscripts, which are published or prepared for submission to peer review journals.

Chapter 2 addresses my first research objective by analyzing the heat index collected from 10 weather stations during a warm season in Knoxville, Tennessee. The heat index data
were used to produce a high-resolution record of heat index variability across an urban area. A study by Ellis et al. (2017) provides theoretical basis for this research by providing evidence of the existence of a UHI in Knoxville and UHI variability at the neighborhood-level. The data gathered by the weather stations used in the Ellis et al. (2017) research are also used for portions of this research.

Chapter 3 addresses my second, third, and fourth research objectives. In this chapter, I present an analysis of IEHI and lifestyle survey data collected from 38 Knoxville, Tennessee, residents. These data provide valuable insight into how residents of an urban area are differentially exposed to heat, and how their exposure varies from traditionally reported ambient conditions. Further, this chapter provides an integrated analysis into how exposure affects participant perception of heat and the adaption actions they employ.

Chapter 4 also addresses my third and fourth research objectives. In this chapter, I present a mixed-methods analysis of a lifestyle survey from 86 respondents in Knoxville, Tennessee. The results address how respondents describe heat, how they perceive their vulnerability to heat danger, the health effects they experience during heat events, and the actions they do or do not take to adapt to heat. This research expands upon the limited qualitative research used in climatology by using hierarchical coding methods.

Chapter 5 provides a summary of the main conclusions from this dissertation, a discussion of the applications of this research, and suggestions for future research.
1.4 References


Chapter 2

A version of this chapter was originally published by Alisa L. Hass, Kelsey N. Ellis, Lisa Reyes Mason, Jon M. Hathaway, and David A. Howe.


My use of “we” in this chapter includes my co-authors, Kelsey N. Ellis, Lisa Reyes Mason, Jon M. Hathaway, and David A. Howe. I served as first author, and my work on this project included experimental design, data collection and analysis, and writing the manuscript. Kelsey Ellis’ work on this project included experimental design, data collection and analysis, and editing the manuscript. Lisa Reyes Mason provided the socioeconomic analysis for the study neighborhoods. Kelsey Ellis, Lisa Reyes Mason, and Jon Hathaway obtained equipment and set up and managed the microclimate observation network. David Howe gathered and processed data and completed the impervious/tree canopy analysis.

2.1 Abstract

Daily weather conditions for an entire city are usually represented by a single weather station, often located at a nearby airport. This resolution of atmospheric data fails to recognize the microscale climate variability associated with land use decisions within urban neighborhoods. This study uses heat index, a measure of the combined effects of temperature and humidity, to assess the variability of heat exposure from ten weather stations across four urban neighborhoods and two reference locations (downtown and in a nearby nature center) in Knoxville, Tennessee, USA. Results suggest that trees may negate a portion of excess urban heat, but are also associated with greater humidity. As a result, the heat index of locations with more trees is
significantly higher than downtown and areas with fewer trees. Trees may also reduce heat stress by shading individuals from incoming radiation, though this is not considered in this study. Greater amounts of impervious surfaces correspond with reduced evapotranspiration and greater runoff, leading to a higher temperature, but lower relative humidity. Heat index and relative humidity were found to significantly vary between locations with different tree cover and neighborhood characteristics for the full study period as well as for the top 10% of heat index days. This work demonstrates the need for high-resolution climate data and the use of additional measures beyond temperature to understand urban neighborhood exposure to extreme heat and expresses the importance of considering vulnerability differences among residents when analyzing neighborhood-scale impacts.

Keywords: urban heat island, heat exposure, microclimate, impervious surface, canopy

2.2 Introduction

Heatwaves, such as one recently experienced in Karachi, Pakistan, in 2015 where more than 1000 people succumbed to heat-related deaths (Imtiaz and Ur-Rehman 2015), are becoming more frequent and intense with changing climate (Davis et al. 2003; Bell et al. 2008; Luber and McGeehin 2008; Ingram et al. 2013). For those who live in highly populated areas, there is a higher risk of experiencing a more extreme heat wave than for those who live in surrounding areas because of the Urban Heat Island (UHI) effect (Clarke 1972; Oke 1973).

2.2.1 The Urban Heat Island

The UHI is a well-studied phenomena where densely populated areas observe higher temperatures than more sparsely populated areas, especially at night (Clarke 1972; Oke 1973,
This phenomena exists primarily because of decreased albedo and increased heat capacity of urban materials (Oke 1987); decreased evapotranspiration because of a lack of vegetation and high levels of rainfall partitioning to runoff; the geometry of the built environment causing radiation trapping and wind disturbance (Oke 1987); and an increase in heating from anthropogenic activities (Aida 1982; Shukla and Mintz 1982; Taha et al. 1988; Taha 1997; Oleson et al. 2015). Further, the UHI is expected to intensify with changing climate. UHI intensification may create an increase in days with high heat stress, potentially compounding the effects of the UHI on urban populations.

Within a city, differences in UHI intensity have been observed between urban neighborhoods. Neighborhood characteristics, such as density of housing and amount of vegetation, can affect the temperature in each neighborhood (Harlan et al. 2006; Luber and McGeehin 2008; Ellis et al. 2017). Neighborhood UHI variability is also related to the socioeconomic characteristics of an area. Lower income areas are more likely to have higher population densities, less green space, and less access to heat mitigation resources like tree planting (Harlan et al. 2006; Jenerette et al. 2007; Tan et al. 2010; Wilhelmi and Hayden 2010; Huang et al. 2011; Uejio et al. 2011; Harlan et al. 2013).

2.2.2 Assessing UHI and Thermal Comfort

The representative proxy for determining the existence and intensity of UHI is often temperature collected from one or more in-situ weather stations, such as those near airports (Oke 1982; Ripley et al. 1996; Unger et al. 2001; Huang et al. 2011; Mallick and Rahman 2012; Mohsin and Gough 2012). Meso-scale studies of UHI, covering cities, states, and even whole countries (Grimmond et al. 2010), have been undertaken using simulations (Georgescu et al. 2013), modeling (Oleson et al. 2015), remote sensing (Chen et al. 2006; Dousset et al. 2011;
Huang et al. 2011; Chow et al. 2012), census data (Huang et al. 2011; Chow et al. 2012), and preexisting city-wide weather station data (Davis et al. 2003). These studies often produce an understanding of UHI over a large spatial area that can provide comparison data between cities, and help to understand climate changes through time (Davis et al. 2003; Dousset et al. 2011).

To assess patterns of UHI intensity within a city and, in turn, determine the best way to mitigate excessive heat within an urban location, small-scale, high-resolution data must be collected and analyzed. Local-scale UHI studies involving neighborhood-level data given by numerous weather stations (Sullivan and Collins 2009) or remotely sensed data (Lo et al. 1997; Laaidi et al. 2012; Mallick and Rahman 2012) provide information about the difference in weather conditions experienced by those within a single city. These studies are often based on the proportion of green space, building density and configuration, and quantity of impervious surfaces within neighborhoods. Results from such studies suggest that inner cities typically experience a higher temperature and suburbs exhibit a lower temperature (Harlan et al. 2006; Hondula et al. 2012, 2013). This fine-scale research reveals relationships between increased UHI strength and neighborhoods that are more densely populated, have lower socioeconomic status, and high have concentrations of racial and ethnic minorities (Harlan et al. 2006; Huang et al. 2011; Harlan et al. 2013). Given this information, microscale research can be conducted to determine how small-scale factors, such as living conditions, building types, and access to resources, will impact a specific individual.

Humidity also affects which urban residents are exposed to the highest UHI intensity as the effect of high temperatures on humans is increased with increased moisture in the air (Burt et al. 1982). High moisture content decreases a person’s ability to evaporate sweat off their skin, and thus decreases the effectiveness of the body’s natural cooling system (Malchaire et al. 2000). Often, inner cities have a lower humidity than surrounding areas as there is less vegetation and a
large amount of rainfall partitioned to runoff due to impervious surfaces, resulting in a slightly lower heat index (Clarke 1972) and potentially lower heat stress on humans (Harlan et al. 2006). However, these areas lack the shading provided by trees. Trees affect the human energy budget, which takes into account metabolism, net radiation, latent heat flux from respiration and sweat, and convective heat transfer, among other factors, during times of high temperatures by blocking some direct radiation (Heisler 1974; Mayer and Hoppe 1987).

To assess the variation in humidity throughout an urban area, thermal indices are calculated for the combined effect of temperature and humidity and used to determine the “feels like” outdoor temperature (National Weather Service 2015). These indices are used to issue heat warnings to the public when necessary (Hajat et al. 2010). Thermal indices, such as heat index and Humidex, have also been used to determine how the influence of humidity on high temperatures is experienced at a finer scale (Steadman and Steadman 1979; Giannopoulou et al. 2014). Studies have concluded that relative humidity will impact human thermal comfort during times of warm conditions in urban settings (Giannopoulou et al. 2014; Ketterer and Matzarakis 2014). Additionally, UHI intensity and variability throughout an urban area were greater when using thermal indices instead of temperature (Ketterer and Matzarakis 2014).

2.2.3 Urban Health

The UHI may affect the health of those living in an urban area. Heat-related illnesses and deaths tend to increase in urban areas during heatwaves, especially in areas that are unaccustomed to high temperatures like the upper mid-west, USA (Kalkstein and Greene 1997; Luber and McGeehin 2008; O’Neill and Ebi 2009; Wilhelmi and Hayden 2010; Fischer et al. 2012; Ingram et al. 2013). Despite acclimatization to potential extreme weather such as heatwaves, the overall increased exposure to extreme heat in the southern United States, coupled with an aging
population, results in an overall higher rate of heat-related deaths (Berko et al. 2014). Access to heat adaption resources, such as central air conditioning, often varies with race and other socioeconomic characteristics, placing certain groups at a greater risk for heat-health effects (O’Neill et al. 2005; Smargiassi et al. 2008; Reid et al. 2012).

Indirectly, high temperatures may make health issues, such as asthma, air pollution, and allergens, worse in populations more readily exposed to high heat (Ingram et al. 2013; Gubernot et al. 2014; Oleson et al. 2015). Some inter-city population-level studies have shown that humidity does not affect health as much as temperature; however sample size might mask the significance of humidity (Barnett et al. 2010). Additionally, humidity can result in more severe consequences at the neighborhood level, especially where there is an increased population of those with a lessened ability to thermoregulate, such as the elderly (Kenney and Hodgson 1987). The combined effect of UHI, a lack of resources, and less coping ability may place these populations at a greater risk of suffering heat-related stress, illness, and mortality. With the expected changing of climate towards more frequent and intense heatwaves, these vulnerable populations and those that are not acclimated to high heat will become more at risk for heat illness and stress (O’Neill and Ebi 2009).

2.2.4 Assessing the Role of Urban Neighborhood Characteristics in Knoxville, Tennessee on Heat Index

The purpose of this project is to investigate how environmental conditions relevant to human heat stress vary across and within four urban neighborhoods in a mid-sized city using heat index, a measure of the combined effect of temperature and humidity. This work utilizes neighborhood-scale data to determine how the daily 1500 LDT heat index (HI) varies within and between four diverse urban neighborhoods in Knoxville, Tennessee, USA, as well as at reference
locations in downtown Knoxville and at Ijams Nature Center. Within each neighborhood, we compare the HI of two different locations with varying levels of tree cover and impervious surfaces, and then make comparisons between neighborhoods. We additionally analyze the top 10% of HI values to determine if there is greater HI variability at 1500 LDT during the warmest days of the study period. This work expands upon UHI research by using strategically located weather stations to estimate the variability of combined exposure of the effect of humidity on temperatures during the warm season across surface and socioeconomic characteristics.

2.3 Materials and Methods

2.3.1 Site Descriptions and Data Collection

Data were collected from 10 identical weather stations for a period of one year in Knoxville, Tennessee, USA. The City of Knoxville, the third largest in the state, had an estimated population of 184,281 people on 1 July 2014 (United States Census Bureau 2015a). The Knoxville Metropolitan Statistical Area, which encompasses the entirety of the study location, contained an estimated 837,571 people on 1 July 2014, with an increase of about 20,000 people within the prior four years (United States Census Bureau 2015b). In 2010, it was estimated that Knoxville covers 158.6 km² with an average population density of 2,905 persons per km² (United States Census Bureau 2015a).

Knoxville is located in eastern Tennessee, in a valley between the Cumberland Plateau to the west and the foothills of The Great Smoky Mountains National Park to the east. Knoxville experiences a climate categorized as humid subtropical, with warm summers exemplified by an average maximum temperature of 31.2 °C in July and cool winters exemplified with an average maximum temperature of 8.5 °C in January (National Weather Service 2015b). As the National
Weather Service classifies heat indices above 26.7 °C and 40% humidity as hazardous (National Weather Service 2015a) we chose the warmest five months of the year (May, June, July, August, September) for the purposes of this study as they hold the highest potential for cautionary levels (or above) during a normal year.

Weather stations were positioned in four urban neighborhoods, downtown Knoxville, and Ijams Nature Center (Figure 2.1). Each of the four neighborhoods (Burlington, Lonsdale, Vestal, and West Hills) contained one station in a minimally vegetated (MV) location (very little vegetation) and one station in a highly vegetated (HV) location (more dense vegetative cover). These specific urban neighborhoods were chosen as they are all within the Knoxville city limits, they provided a geographic coverage of the city from all cardinal directions, and they allowed for the exploration of different socioeconomic characteristics. Site selection was undertaken carefully to ensure similar elevations in each neighborhood location as well as to avoid localized weather influences, such as cold air drainage. Locating weather stations in both MV and HV areas of each urban neighborhood allows examination of how heat exposure may vary in a small area and can help provide an understanding of how vegetation can impact relative humidity, and therefore HI, in each neighborhood.

The four neighborhoods were chosen to reflect a range of socioeconomic characteristics (Table 2.1). Lonsdale has the highest population density and lowest mean income, and West Hills has the lowest population density and the highest mean income (United States Census Bureau 2015c). By race and ethnicity, the populations in West Hills and Vestal are predominantly white. In Burlington, most residents are African American. In Lonsdale, residents are more racially and ethnically diverse, including white, African American, and Hispanic households (United States Census Bureau 2015c).
Figure 2.1. Locations of minimally vegetated (MV) and highly vegetated (HV) weather stations within each neighborhood, and reference weather stations downtown and in Ijams Nature Center. Shading indicates the amount of imperviousness.
Table 2.1. Population density, approximate mean income, and general qualitative description of four Knoxville, Tennessee neighborhoods examined in this study (United States Census Bureau 2015c).

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Population Density (People/sq km)</th>
<th>Approximate Mean Income (USD)</th>
<th>Qualitative Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lonsdale</td>
<td>5941</td>
<td>22,950</td>
<td>Medium density housing with parks and open space</td>
</tr>
<tr>
<td>Burlington</td>
<td>4971</td>
<td>29,447</td>
<td>Medium density housing with parks and open space</td>
</tr>
<tr>
<td>Vestal</td>
<td>3322</td>
<td>24,456</td>
<td>Medium density housing with parks, open space, and shopping centers</td>
</tr>
<tr>
<td>West Hills</td>
<td>2052</td>
<td>42,147</td>
<td>Medium density housing with parks, open space, and a large amount of shopping centers and highway access</td>
</tr>
</tbody>
</table>
The weather stations located in the reference locations (one each in downtown Knoxville and Ijams Nature Center) serve as a comparison to typical UHI patterns seen in urban areas, with higher temperatures and lower humidity being experienced in downtown locations than in vegetated and sparsely developed areas. These locations also serve to compare the traditional UHI temperature patterns across the city to the patterns of HI.

The temperature and relative humidity were measured in five-minute increments at each weather station. The stations consist of Onset Smart Sensors attached to a Cantex Junction Box (20 × 20 × 10 cm). The sensors are connected to a HOBO Micro Station Data Logger (H21-002). Temperature measurements by the Onset 12-bit T/RH Smart Sensor (S-THB-M002) have an accuracy of ±0.21 °C, and a resolution of 0.02 °C. Relative humidity measurements have a range of 0%–100%, with an accuracy of ±2.5% and a resolution of 0.1%. The manufacturer establishes accuracy for the weather stations based on testing of the components prior to shipment. Additionally, before deployment, the weather stations were tested to ensure consistent readings across all units. The sensors are installed approximately 2.25 m above ground inside of a white, vented enclosure. Ideally, data would be collected at a lower height, but this height was chosen to minimize vandalism.

2.3.2 Data

The stations began collecting data on 2 July 2014. This study analyzed data from 2 July 2014 through 30 September 2014 and 1 May 2015 through 1 July 2015. The data set covered a full warm season in Knoxville. Because of an act of vandalism at the Lonsdale MV location, data were not available for this location from 15–21 August 2014. Additionally, data sensor malfunctions resulted in data unavailability from 1–5 May at the Lonsdale MV station, 1–4 May 2015 at the West Hills HV station, and 1–5 May 2015 at the Burlington HV station.
Daily temperature (T) and relative humidity (RH) were parsed from each station’s data at 1500 LDT daily. The 1500 LDT observation was chosen since the hottest time of day typically occurs around this time because of a delay in insolation reaching and warming the surface (National Climate Data Center 2015). Additionally, hourly T distributions at the reference locations for the study period indicate the highest daily T is typically between 1500 LDT and 1600 LDT (Figure 2.2). Choosing the hottest time of the day targets the HI during maximum heating for each day during the warm season. This was confirmed with preliminary unadjusted hourly HI distributions at our reference locations for the time period studied, with the maximum HI occurring at both locations between 1400 LDT and 1500 LDT though HI showed a larger overall variation than T. Keeping a consistent observation time allows for snapshot comparisons across the city at the approximate time of maximum heat loading. Changes in this daily pattern because of synoptic forcing were not considered in this study.

2.3.3 Data Processing

2.3.3.1 Calculation of Imperviousness and Tree Cover

We quantified the amount of impervious surface and tree cover within 100 m of each weather station. The 100-m radius was chosen because land cover has greatest influence on air temperature at radii less than 500 m, with the effects diminishing at larger distances (Lindén 2011; Lindén et al. 2015). Stewart and Oke (2010) suggest a 100–200-m circle of influence for their “local climate zones.” Similarly, Gallo et al. (1996) and Li and Roth (2009) found that 100-m radii were the ideal spatial resolution for visualizing land use effects on diurnal temperature range and UHI intensity, respectively. GIS data for impervious cover in Knox County were obtained from KGIS (kgis.org), a Geographic Information System collaboration between the city
Figure 2.2. Hourly T distributions for Downtown (a) and Ijams (b) during the study period.
of Knoxville, Knox County, and Knoxville Utilities. The 1-m solution raster was processed with ArcMap 10.2. Every impervious cell is represented by a value of 1 and every other cell is represented by a value of 0. The percentage of impervious cover for a given area was calculated by dividing the total number of impervious cells by the total area.

Tree cover within the 100-m radius of each weather station was estimated using i-Tree Canopy, an online analysis tool by the USDA Forest Service. I-Tree Canopy uses aerial images available in Google Maps to produce an estimate of tree cover. Project boundaries (the 100-m radius of each weather station) were loaded from ArcMap 10.2 for each area. Random sample points were generated by i-Tree Canopy and classified by the user as either “tree” or “non-tree”. For the classification of an entire city, i-Tree suggests using between 500 and 1000 survey points; 300 survey points were classified within each of the 100-m radii. These analyses were completed three times and the average result was used.

2.3.3.2 Calculation of HI

HI was calculated from daily 1500 LDT T and RH data using the NOAA Rothfusz equation (National Weather Service 2015a; Rothfusz 1990), which is based on T readings in °F, as follows:

\[
HI = -42.379 + 2.04901523T + 10.14333127R - 0.224755417TR - 6.83783 \times 10^{-3}T^2 - 5.481717 \\
\times 10^{-2}R^2 + 1.22874 \times 10^{-3}T^2R + 8.5282 \times 10^{-4}TR^2 - 1.99 \times 10^{-6}T^2R^2
\]

For days when T was between 80–87 °F and RH was greater than 85%, the below adjustment was added to the Rothfusz regression equation (National Weather Service 2015a):
The Rothfusz regression equation is not suitable to use when the HI is below 80 °F (National Weather Service 2015a). For all days in which the Rothfusz regression equation yielded a HI of less than 80 °F, the following equation was used to recalculate the HI (National Weather Service 2015a):

\[
HI = 0.5 \times (T + 61.0 + [(T - 68.0) \times 1.2] + (RH \times 0.094))
\]

The results of the above equation were averaged with \(T\) to obtain the final HI for days with HI below 80 °F (National Weather Service 2015a). All \(T\) and HI data were converted from Fahrenheit to Celsius prior to statistical analysis.

2.3.3.3 Statistical Analysis

\(T, RH,\) and HI were used to estimate heat and humidity variability across study neighborhoods during the warm season. First, HI, \(T,\) and RH were compared between HV and MV locations within each of the four urban neighborhoods. Second, HI was compared across neighborhoods (averaged HV and MV station data) and the reference locations (downtown Knoxville and Ijams). Paired-sample t-tests were used for both of these analyses, except in the case of missing data where independent t-tests were used. We address the multiple comparison problem, where using a large number of independent t-tests could increase the number of tests deemed significant by chance, by verifying our t-test results through two-way analysis of variance (ANOVA) tests. Two-way ANOVA tests were used to determine if significance existed between

\[
Adjustment = \frac{RH - 85}{10} \times \frac{87 - T}{5}
\]
locations during the top 10% of HI values for each station. A two-way ANOVA tests the separate influence of each independent variable, and also analyzes the interaction between the two variables. ANOVA was also specifically used to determine the combined effects of neighborhood and tree cover. Three two-way ANOVAs were performed for each dependent variable (T, RH, HI) to assess the independent and combined influence of neighborhood and tree cover.

2.4 Results and Discussion

2.4.1 Descriptive Statistics

Station characteristics (location, elevation, etc.) are listed in Table 2.2, along with average T, RH, and HI during the study period. Sample size is provided and is based on the number of days available for testing after station malfunction and vandalism data were removed. Mean T and mean RH show the typical UHI pattern of warm and dry conditions in the downtown reference location and cool and humid conditions in the Ijams Nature Center reference location. Mean HI was highest downtown and at Ijams; lowest mean HI was in the HV locations of the four urban neighborhoods. The locations with the highest variation in HI during the warm season include Ijams and the HV station in West Hills (in order, respectively).

2.4.2 Imperviousness and Tree Cover

Percent of imperviousness and tree canopy at each weather station (Table 2.3, also visualized in Figure 2.1) were estimated to demonstrate the appropriateness of station location. Within each individual neighborhood, the MV location showed a higher level of imperviousness than the corresponding HV location. The greatest amount of neighborhood imperviousness is
Table 2.2. Station information, including neighborhood name and station designation, elevation (m), location (° latitude and longitude), and sample size (number of days recorded). Also shown for each station is the 1500 LDT mean $T$ (°C), mean RH (%), mean HI (°C), maximum HI (°C), minimum HI (°C), and the standard deviation of the HI (°C).

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Lonsdale</th>
<th>West Hills</th>
<th>Vestal</th>
<th>Burlington</th>
<th>Downtown</th>
<th>Ijams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station</td>
<td>MV</td>
<td>HV</td>
<td>MV</td>
<td>HV</td>
<td>MV</td>
<td>HV</td>
</tr>
<tr>
<td>Designation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>290.8</td>
<td>293.7</td>
<td>316.4</td>
<td>312.2</td>
<td>288.5</td>
<td>280.4</td>
</tr>
<tr>
<td>Latitude</td>
<td>35.980</td>
<td>35.984</td>
<td>35.936</td>
<td>35.937</td>
<td>35.922</td>
<td>35.929</td>
</tr>
<tr>
<td>Longitude</td>
<td>-83.962</td>
<td>-83.957</td>
<td>-84.043</td>
<td>-84.030</td>
<td>-83.922</td>
<td>-83.916</td>
</tr>
<tr>
<td>$T$</td>
<td>28.73</td>
<td>28.38</td>
<td>28.16</td>
<td>27.74</td>
<td>28.94</td>
<td>28.56</td>
</tr>
<tr>
<td>RH</td>
<td>53.61</td>
<td>55.61</td>
<td>58.14</td>
<td>63.00</td>
<td>55.68</td>
<td>57.31</td>
</tr>
<tr>
<td>HI</td>
<td>29.94</td>
<td>29.79</td>
<td>29.81</td>
<td>29.61</td>
<td>30.63</td>
<td>30.42</td>
</tr>
<tr>
<td>Max HI</td>
<td>37.98</td>
<td>39.24</td>
<td>39.3</td>
<td>39.82</td>
<td>41.17</td>
<td>40.52</td>
</tr>
<tr>
<td>Min HI</td>
<td>16.32</td>
<td>16.60</td>
<td>18.48</td>
<td>18.01</td>
<td>16.78</td>
<td>19.60</td>
</tr>
<tr>
<td>HI St Dev</td>
<td>4.12</td>
<td>4.18</td>
<td>4.38</td>
<td>4.70</td>
<td>4.40</td>
<td>4.46</td>
</tr>
</tbody>
</table>
Table 2.3. Percent impervious land cover and tree cover within a 100-m radius of each station.

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Station Designation</th>
<th>Imperviousness</th>
<th>Tree Cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lonsdale</td>
<td>MV</td>
<td>48.8</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>HV</td>
<td>32.3</td>
<td>28.2</td>
</tr>
<tr>
<td>West Hills</td>
<td>MV</td>
<td>23.1</td>
<td>33.0</td>
</tr>
<tr>
<td></td>
<td>HV</td>
<td>20.1</td>
<td>60.1</td>
</tr>
<tr>
<td>Vestal</td>
<td>MV</td>
<td>41.7</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>HV</td>
<td>16.9</td>
<td>51.3</td>
</tr>
<tr>
<td>Burlington</td>
<td>MV</td>
<td>25.6</td>
<td>27.0</td>
</tr>
<tr>
<td></td>
<td>HV</td>
<td>18.0</td>
<td>47.2</td>
</tr>
<tr>
<td>Downtown</td>
<td>–</td>
<td>84.0</td>
<td>4.6</td>
</tr>
<tr>
<td>Ijams</td>
<td>–</td>
<td>3.6</td>
<td>78.8</td>
</tr>
</tbody>
</table>
48.8% at the Lonsdale MV station. Likewise, the HV station has a higher level of tree cover than the corresponding MV station for each neighborhood, as desired per the experimental plan. The greatest amount of tree cover is 60.1% at West Hills. The downtown station had the highest level of impervious surfaces (84%) and the lowest amount of tree cover (4.6%). The station located within Ijams Nature Center had the highest amount of tree cover (78.8%) and lowest amount of impervious land cover (3.6%). Standard error for these calculations never exceeded 3% using 300 survey points.

The amount of impervious surfaces and tree cover can affect both the T and RH of an area, which in turn can affect the HI. Greater imperviousness corresponds with reduced evapotranspiration and greater rainfall lost to runoff, leading to a higher T and lower RH (Oke 1987). Increased tree cover reduces T by shading the area from incoming solar radiation and increasing evapotranspiration, leading to a higher RH (Oke 1987; Taha 1997; Pielke 2001; Scheitlin and Dixon 2010).

These physical relationships are represented in the data collected here, with the warmest locations occurring at the stations with the greatest amount of impervious surfaces (the MV locations of Lonsdale, West Hills, Vestal, and Burlington; Table 2.2). The locations with the highest RH were those with the greatest amount of tree cover (the HV stations of Lonsdale, West Hills, Vestal, and Burlington). The reference locations additionally follow the maxim of high T and low RH occurring in areas with high amounts of impervious surfaces and low tree cover (downtown Knoxville) and low T with high RH occurring in areas with low amounts of impervious surfaces and high tree cover (Ijams Nature Center).
2.4.3 Inter-Neighborhood Variability

T-tests were used to determine if there were significant differences between the mean HI of the neighborhoods (combined HV and MV station data) and reference locations. Vestal and West Hills showed a significantly higher mean HI than the other neighborhoods but were not significantly different from each other (Table 2.4). Downtown reported a higher HI than all four urban neighborhoods, but this difference is not significant when compared to West Hills (0.48 °C lower) and Vestal (0.59 °C lower). Ijams Nature Center exhibited a significantly higher HI than all other locations, including the neighborhoods and downtown location.

While the T and RH data follow the traditional UHI pattern (Oke 1987), the HI data highlight the importance of examining combined the effects of T and RH. The comparison between the two reference locations (downtown and Ijams) gave somewhat unexpected results, with the HI being significantly higher at Ijams Nature Center. Typically, downtown locations have higher temperatures because of the UHI effect (Oke 1987; Bornstein 1968), which would seemingly correspond to greater heat exposure. However, the consistently higher RH at the Ijams Nature Center more than compensates for the lower daytime T, causing a greater HI. The higher RH at Ijams is likely because the greater vegetative cover leads to increased evapotranspiration and slows air movement, decreasing air mixing (Oke 1987; Pielke 2001; Voogt 2002). Air mixing is likely different at Ijams than downtown. In the latter, air tunneling and redirection may result in increased mixing of wet and dry air layers, whereas less wind at Ijams might result in less mixing of surface humidity (Oke 1987). Although testing this explanation is beyond the study scope, it is a possible area for future research.

Ijams Nature Center also had a significantly higher HI than all of the neighborhoods, likely because of the reasons discussed above. Meanwhile, the downtown location had a higher HI than three of the neighborhoods (statistically significant in Lonsdale and Burlington, p<0.05),
Table 2.4. Comparison of 1500 LDT HI (°C) between combined data (HV and MV) for each neighborhood and reference locations (Downtown and Ijams). Mean differences are shown. Bolded numbers indicate significant results ($p<0.05$). Negative numbers indicate the column neighborhood is lower than the row neighborhood mean.

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Downtown</th>
<th>Ijams</th>
<th>Lonsdale</th>
<th>West Hills</th>
<th>Vestal</th>
<th>Burlington</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown</td>
<td>–</td>
<td>0.34</td>
<td>−1.25</td>
<td>−0.48</td>
<td>−0.59</td>
<td>−1.52</td>
</tr>
<tr>
<td>Ijams</td>
<td>−0.34</td>
<td>–</td>
<td>−1.60</td>
<td>−0.83</td>
<td>−0.82</td>
<td>−1.86</td>
</tr>
<tr>
<td>Lonsdale</td>
<td>1.25</td>
<td>1.60</td>
<td>–</td>
<td>0.82</td>
<td>0.77</td>
<td>−0.27</td>
</tr>
<tr>
<td>West Hills</td>
<td>0.48</td>
<td>0.83</td>
<td>−0.82</td>
<td>–</td>
<td>−0.11</td>
<td>−1.03</td>
</tr>
<tr>
<td>Vestal</td>
<td>0.59</td>
<td>0.82</td>
<td>−0.77</td>
<td>0.11</td>
<td>–</td>
<td>−0.92</td>
</tr>
<tr>
<td>Burlington</td>
<td>1.52</td>
<td>1.86</td>
<td>0.27</td>
<td>1.03</td>
<td>0.92</td>
<td>–</td>
</tr>
</tbody>
</table>
likely because of decreased albedo, decreased evapotranspiration, and increased anthropogenic heat sources contributing to the UHI (Taha 1997; Harlan et al. 2006; Mallick and Rahman 2012). Thus, extremely developed or under-developed land can exhibit higher HIs for different reasons, depending on the conditions.

The amount of trees and lack of impervious surfaces in West Hills likely corresponded to the high HI experienced here, but to a lesser degree than Ijams. The cause of the high HI in Vestal is less clear. Vestal has the greatest differences in the impervious surface and tree cover amounts between stations of all neighborhoods, but a significant difference in HI between stations. Perhaps the Vestal locations are each experiencing high HI values for different reasons, the MV station because of increased absorption and daytime heating, and the HV station because of greater humidity. Within-neighborhood differences are discussed in detail in the next section.

Within a city, the UHI strengthens with increased population and building density and often decreases with income (Harlan et al. 2006). Given the physical and socioeconomic characteristics of each neighborhood, Lonsdale would be expected to show the highest HI because of an increased population density and a lower mean income. Conversely, West Hills would be expected to show the lowest HI because of a lower population density and a higher mean income. West Hills (both MV and HV stations) also has greater tree cover and less imperviousness than most locations, independent of being the HV or MV station. Yet, these results suggest that, in terms of HI, West Hills’ residents may experience more heat exposure during the warm season. While neighborhood-scale climate data may imply West Hills residents are more exposed to heat, social data would likely suggest that Lonsdale residents have less resources available for coping with extreme conditions. A recent qualitative study in the same four neighborhoods found that Lonsdale, Burlington, and Vestal interviewees expressed greater concerns about extreme heat, its impacts, and household coping ability than participants from
West Hills (Mason et al. 2017). Future pairing of physical data, socioeconomic characteristics, and personal experiences of neighborhood residents could expand on these initial insights.

2.4.4 Intra-Neighborhood Variability

T-tests were used to determine how HI, T, and RH vary between MV and HV locations within each urban neighborhood to highlight smaller-scale differences (Table 2.5). All four urban neighborhoods showed similar T and RH tendencies. A significantly lower T was recorded by HV locations than MV locations by as little as 0.061 °C at West Hills and as much as 1.136 °C at Burlington. A significantly higher RH was recorded at HV stations than MV locations by as much as 4.317% at West Hills. Burlington, Lonsdale, and West Hills all reported a lower HI at the HV location; however, Burlington is the only neighborhood that showed significant difference (mean HI was 1.467 °C lower at the HV location). West Hills exhibited a significant HI of 1.657 °C higher at the HV station than at the MV location.

Lonsdale, Vestal, and Burlington showed a reduced HI at the sites with less imperviousness and more tree cover; however, a significantly higher HI was experienced at the West Hills HV station (Figure 2.3). While T is significantly lower at the HV location than at the MV location, the amount of variation (0.061 °C) is small whereas the much higher RH at the HV location might help us understand what is happening. The West Hills stations have a relatively similar impervious-surface level but a vastly different tree-cover level. The increased vegetation at the HV location is likely causing a higher RH because of increased evapotranspiration from the plants, which in turn leads to a higher HI at the HV location.

While the MV station within the four urban neighborhoods represents what is expected to be the highest temperatures and least humid locations, there is a likely a wide range of variability
Table 2.5. Comparison of daily maximum HI (°C), T (°C), and RH (%) between MV and HV locations within each neighborhood. Mean differences are shown. Bolded numbers indicate significant results ($p<0.05$). Negative numbers indicate the HV location has a lower mean than the MV location in each neighborhood.

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>HI</th>
<th>T</th>
<th>RH Humidity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lonsdale</td>
<td>-0.021</td>
<td>-0.235</td>
<td>2.409</td>
</tr>
<tr>
<td>West Hills</td>
<td>1.657</td>
<td>-0.061</td>
<td>4.317</td>
</tr>
<tr>
<td>Vestal</td>
<td>-0.208</td>
<td>-0.386</td>
<td>1.631</td>
</tr>
<tr>
<td>Burlington</td>
<td>-1.467</td>
<td>-1.136</td>
<td>3.171</td>
</tr>
</tbody>
</table>
Figure 2.3. HI data range for each station location. Bold horizontal lines indicate median value, boxes represent the upper and lower quartiles of each data set, upper and lower whiskers represent the maximum and minimum values respectively, and open circles represent outliers less than 3/2 times of lower quartile.
between the two extremes for each neighborhood. Shading from the tree cover and the amount of impervious surface will vary throughout each neighborhood. Additionally, although all MV stations have greater impervious surfaces and less tree cover, that does not mean that they are devoid of vegetative effects.

Vegetation types and age (Skelhorn et al. 2014), neighborhood parks and greenways, building height and density, roadway density, and traffic (Hart and Sailor 2009) can all have a large effect on the strength of the UHI for various places within each neighborhood. Parks and greenways represent a prominent method for UHI mitigation and increasing thermal comfort in urban neighborhoods. Increased vegetation results in less energy used for cooling, decreased air pollution, and may potentially reduce greenhouse gasses (Jenerette et al. 2011). However, this specific method of mitigation has associated costs. Aside from the initial costs of purchasing and planting vegetation, upkeep in the form of irrigation from a public water supply, removing dead vegetation, and replanting can result in high long term costs (Jenerette et al. 2011). Tree planting programs, while effective, are expensive and often distributed to higher-income areas of cities (Jenerette et al. 2011). In locations like urban Phoenix, for example, where water can be scarce, temperatures can be higher by several degrees in areas with lower income because there is less tree cover (Wilhelmi and Hayden 2010).

Additional attempts to alleviate the heat produced and trapped in urban areas have included technologies such as cool-roofs (Luber and McGeehin 2008; Georgescu et al. 2013) and changes to architecture and city planning (Taha et al. 1988; Luber and McGeehin 2008; Grimmond et al. 2010; Middel et al. 2014). However, all of the factors that affect UHI intensity and the human perception of heat will vary by location (Davis et al. 2003; Luber and McGeehin 2008; Ingram et al. 2013). As emphasized by our study of intra-neighborhood variability in impervious surfaces and vegetation cover, a one-size-fits-all prescription to mediate the effects of
the UHI may be ineffective and unrealistic, but may assist in urban neighborhood heat reduction if used appropriately (Georgescu et al. 2013).

2.4.5 Interacting Effects of Neighborhood and Tree Cover

Three two-way ANOVAs were used to determine how neighborhood and tree cover affected T, RH, and HI (Table 2.6). Tree cover was the only significant variable, and neighborhood was not a significant contributor to T. It is somewhat surprising that neighborhood was not significant; however, as shown in Table 2.4, there is significant variability between HV and MV stations in each neighborhood, pointing to tree cover as the main contribution. The lack of a significant interaction between neighborhood and tree cover, as well as no clear neighborhood signal, suggests that more immediate tree cover has a larger influence on T than larger-scale neighborhood characteristics.

The RH ANOVA results (Table 2.7) show that tree cover was once again significant, as was neighborhood. The interaction between the two was insignificant. Therefore, tree cover and neighborhood were significant contributors to RH, but the role of tree cover did not change based on the neighborhood. The HI ANOVA results (Table 2.8) are similar to the RH ANOVA, with both neighborhood and tree cover being significant, but not the interaction between the two.

These results suggest that the large-scale attributes of imperviousness and tree canopy around the city can affect each location to a greater extent than previously thought. Alternatively, or perhaps in addition to the large-scale effect, the effect of imperviousness in some locations, such as West Hills, might be more localized than the 100-m radii studied here. The spatial effect of imperviousness and canopy cover on localized weather conditions is a question that cannot be answered through this study and is subject to further research (Shashua-Bar and Hoffman 2000; Yu and Hien 2006). Convective mixing in each location might additionally reduce the localized
Table 2.6. Two-way ANOVA for mean T at 1500 LDT for the entire warm season based on neighborhood classification and tree density, including mean-square error (MS), F value, and significance. Bold variables are significant \((p<0.05)\).

<table>
<thead>
<tr>
<th>Variables</th>
<th>MS</th>
<th>F-Value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighborhood</td>
<td>21.94</td>
<td>2.210</td>
<td>0.066</td>
</tr>
<tr>
<td>Tree Cover</td>
<td>88.49</td>
<td>8.913</td>
<td><strong>0.002</strong></td>
</tr>
<tr>
<td>Neighborhood * Tree</td>
<td>14.69</td>
<td>1.480</td>
<td>0.228</td>
</tr>
</tbody>
</table>
Table 2.7. Two-way ANOVA for mean RH at 1500 LDT for the warm season based on neighborhood classification and tree density, including mean-square error (MS), F value, and significance. Bold variables are significant ($p<0.05$).

<table>
<thead>
<tr>
<th>Variables</th>
<th>MS</th>
<th>$F$-Value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighborhood</td>
<td>1659.1</td>
<td>9.876</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td>Tree Cover</td>
<td>1165.2</td>
<td>6.937</td>
<td>0.009</td>
</tr>
<tr>
<td>Neighborhood * Tree</td>
<td>48.6</td>
<td>0.289</td>
<td>0.749</td>
</tr>
</tbody>
</table>
Table 2.8. Two-way ANOVA for mean HI at 1500 LDT for the entire warm season based on neighborhood classification and tree density, including mean-square error (MS), F value, and significance. Bold variables are significant ($p<0.05$).

<table>
<thead>
<tr>
<th>Variables</th>
<th>MS</th>
<th>$F$-Value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighborhood</td>
<td>109.75</td>
<td>5.777</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td>Tree Cover</td>
<td>84.41</td>
<td>4.443</td>
<td>0.035</td>
</tr>
<tr>
<td>Neighborhood * Tree</td>
<td>41.39</td>
<td>2.179</td>
<td>0.114</td>
</tr>
</tbody>
</table>
cooling effect of radiation blocking and increased humidity from evapotranspiration provided by vegetation, resulting in a more uniform temperature throughout the urban neighborhoods (Oke 1987; Yu and Hien 2006).

2.4.6 Extreme Heat Variability

A two-way ANOVA was used to determine how neighborhood and tree cover impacted HI during the top 10% of the highest HI values from each neighborhood (Table 2.9). Both neighborhood and tree cover were significant contributing factors for cross-site differences in HI on the days ranked in the top 10% of HI values in the study area. There was no significant interaction between neighborhood and tree cover found during the highest HI values. The top 10% of HI values have a similar significance pattern to all of our data combined (Table 2.8), with neighborhood and tree cover contributing to both observed HI across the study period as well as for the top 10% of HI values, but with no interacting effects of neighborhood and tree cover. While neighborhood and tree cover were both significant contributors to HI, it is likely that this contribution is consistent across all neighborhoods.

2.5 Conclusions

While temperature is often the focus of UHI studies, this work addresses the need to include humidity to better understand local heat exposure. By comparing locations with different amounts of imperviousness and tree cover, it is clear that there are competing factors that influence the HI of an area. A location with more impervious surfaces and little vegetation will likely experience a greater maximum temperature. Meanwhile, a location with expansive tree cover and vegetated surfaces will likely have higher humidity.
Table 2.9. Two-way ANOVA for top 10% of HI values at 1500 LDT based on neighborhood classification and tree density, including mean-square error (MS), F value, and significance. Bold variables are significant ($p<0.05$).

<table>
<thead>
<tr>
<th>Variables</th>
<th>MS</th>
<th>F-Value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighborhood</td>
<td>109.75</td>
<td>5.777</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Tree Cover</td>
<td>84.41</td>
<td>4.443</td>
<td>0.035</td>
</tr>
<tr>
<td>Neighborhood * Tree</td>
<td>41.39</td>
<td>2.179</td>
<td>0.114</td>
</tr>
</tbody>
</table>
This work emphasizes the importance of using smaller-scale data, such as at the neighborhood level, to determine which neighborhoods and corresponding socioeconomic groups have the greatest exposure to HI within a medium-sized city. Studies conducted in larger cities, such as Phoenix, have shown that predominately white neighborhoods with a higher mean income experience less heat stress (Harlan et al. 2006). However, of the four Knoxville neighborhoods studied here, the neighborhood with the greatest HI exposure is the wealthiest and is predominantly white. This may seem somewhat encouraging for the other neighborhoods; however, it is likely that the lack of resources to cope with HI will counteract any difference in exposure. Discernment of risk and vulnerability to heat exposure will require these results to be paired with quantitative and qualitative data collected directly from urban residents in diverse neighborhoods. Quantifying how HI variability affects urban residents on a neighborhood-level is a timely and critical issue and can help inform heat mitigation efforts for other similar-sized cities. Mitigation efforts might include heat advisory warning systems and neighborhood heat exposure education for both awareness of heat exposure consequences and personal mitigation.

It is important to note other factors that contribute to spatial patterns of UHI intensity that were not addressed in this study. We used HI with the assumption that this index would give a better understanding of the level of the influence of humidity on temperature in different urban settings. Given this, we did not consider individually experienced temperatures or the human energy budget as our data did not allow for this scale of analysis. Radiative effects that are influenced by shading from vegetation, such as blocking of solar radiation, will influence the human energy budget by reducing the radiative heat exchange between the environment and the person by as much as 30% (La Gennusa et al. 2005). Increased wind speed can also account for cooling of the individual and can somewhat offset the effects of short- and long-wave radiation.
fluxes and temperature on the human energy budget (Oke 1995; Thorsson et al. 2007; Herrmann and Matzarakis 2012).

Additionally, while neighborhood-level data show a much more complex relationship between urban neighborhoods and the UHI than previously considered, access to resources such as air conditioners, residential building height and structure, the amount of time spent indoors versus outdoors, and the resiliency and vulnerability of people living in each neighborhood were not considered. These factors could affect how residents experience heat during the warm season in Knoxville. Further research, including resident interviews and individual or household surveys, could help to shed light on these factors and further inform heat mitigation and land cover management.
2.6 Acknowledgements

This work was funded by the Institute for a Secure and Sustainable Environment at the University of Tennessee, Knoxville. Knoxville Utilities Board, Ijams Nature Center, and Knoxville’s Community Development Corporation provided access to utility poles and property for weather station placement. We appreciate Laurel Christian’s assistance in assembling, deploying, and maintaining the weather stations. We thank David Massey and Jackie Clay of the Office of Neighborhoods, and Stan Johnson of SEEED, for help identifying study neighborhoods. We also thank committee members, Sally Horn, Solange Munoz, and Jiangang Chen, and three reviewers for the International Journal of Environmental Research and Public Health for their valuable comments and suggestions to improve this manuscript.
2.7 References


Chapter 3

Using wearable sensors to assess how a heatwave affects individual heat exposure, perceptions, and adaption methods
This chapter is being prepared for submission to a journal. My use of “we” in this chapter includes my co-author, Kelsey N. Ellis. I served as first author, and my work included experimental design, data collection and analysis, and writing the manuscript. Kelsey Ellis contributed to the experimental design, data analysis, and editing of this manuscript.

3.1 Abstract

Urban areas are typically warmer than nearby rural areas, especially during hot weather. This increases heat exposure, morbidity, and mortality rates of urban residents. Heat adaption methods can improve public safety during heat events, but the availability and usage of these resources varies based on socioeconomic and demographic characteristics, as well as personal perception of warmth. Heat events are often studied using city- and neighborhood-level meteorological and socioeconomic data, which do not reflect individual exposure or access to and use of heat adaption resources. We collected lifestyle surveys and individually experienced temperature and humidity data for 38 Knoxville, Tennessee, residents during a heatwave and a period of climatically normal summer conditions. Participants were less exposed to heat during the daytime than airport conditions suggest, indicating successful use of heat adaption methods, such as staying indoors. Some participants were warmer at night and during the non-heatwave period. Heat inequality is especially problematic at night, with older, less educated, and lower-income individuals being more exposed to heat. Even when exposed to dangerous heat levels, participants were less likely to take adaption actions to protect themselves from heat-health effects during the non-heatwave period and at night because they do not perceive themselves as being at risk or have the resources to do so. These findings signal the need for improved heat
education, as future climate projections indicate an increase not only in heatwaves but also mean temperature and humidity during the warm season, and especially warmer temperatures at night.

*Keywords: individually experienced heat index, heat exposure, heat perception*

### 3.2 Introduction

Higher average temperatures and warmer and more frequent heatwaves are expected to occur as Earth’s climate continues to change (Habeeb et al. 2015; U.S. Global Change Research Program 2018). The southeastern United States, specifically, has observed an increase in daily maximum and minimum temperatures, relative humidity, and the frequency and intensity of extreme heat events (Peterson et al. 2013; U.S. Global Change Research Program 2018). These conditions place humans at risk for significant health problems (Bobb et al. 2014; Mora et al. 2017). Previous studies have shown that high ambient temperatures (Basu 2009), especially increased daily minimum temperatures in the summer (Clarke 1972; Karl and Knight 1997; Chestnut et al. 1998), have corresponded to increased heat-related illnesses and mortality. Vulnerable individuals, such as the elderly, children, and those not acclimated to a hot climate, are at greater risk of heat illness and stress (O’Neill and Ebi 2009).

Urban residents are often exposed to warmer temperatures than rural residents because a city is usually warmer than surrounding areas; this characteristic of a city is referred to as the urban heat island (Oke 1982). During a heatwave, heat-related mortality and morbidity are greatest in urban areas (Kalkstein and Greene 1997; Luber and McGeehin 2008; Fischer et al. 2012; Davis et al. 2016). Urban populations in the southeastern United States have grown rapidly since the mid-1900s and this growth is expected to continue, placing increasingly more individuals at risk of heat exposure (Ingram et al. 2013).
One specific characteristic of the urban heat island is higher minimum temperatures at night. Urban structures inhibit overnight cooling by “trapping” outgoing longwave energy near the surface, and by increasing surface friction, resulting in slower winds and a lack of air mixing (Clarke 1972; Chestnut et al. 1998). Warmth is a factor inside large buildings that store heat more efficiently, resulting in increased personal exposure to high temperatures at night (Clarke 1972). Individual actions can reinforce this overnight exposure because people may have less options for heat adaption methods, such as going to a cooler location, at night (Harlan et al. 2006; Kuras et al. 2015).

In addition to temperature, humidity is another atmospheric variable that can affect the thermal comfort and health of its residents (Harlan et al. 2006; Giannopoulou et al. 2014; Heaton et al. 2014; Ketterer and Matzarakis 2014). Thermal comfort, a subjective measure that expresses atmospheric comfort within the environment, has been estimated using mean relative humidity and ambient temperature (Giannopoulou et al. 2014). Individuals are more affected by high temperatures when moisture content is greater because sweat evaporation is less efficient in environments with greater relative humidity (Burt et al. 1982; Becker and Stewart 2011). Greater risks of heat-related illness and mortality exist where temperature, humidity, and wind speed, are highest (Hondula et al. 2012). Thus, the heat index (HI), which combines temperature and relative humidity to calculate a “feels-like temperature,” has been used as the basis for determining the level of heat that poses a risk to humans (Hajat et al. 2010; National Weather Service 2017a).

Individual exposure to uncomfortable or dangerous levels of heat varies greatly across an urban area, causing heat inequality. Lower-income areas and those with higher minority populations usually have less vegetation and greater building density, which typically correspond with low thermal comfort (Harlan et al. 2006; Uejio et al. 2011). Similar patterns have been seen
in urban neighborhoods in Knoxville, Tennessee. Neighborhoods with lower mean income and higher population density experience warmer temperatures. However, these neighborhoods sometimes have slightly lower heat indices because the lack of green space and subsequent lack of evapotranspiration results in lower relative humidity (Hass et al. 2016; Ellis et al. 2017). These neighborhood-level studies confirmed that ambient heat varies between Knoxville’s urban neighborhoods with differing socioeconomic and physical characteristics, but they do not provide information on how individuals are exposed to heat in their daily lives.

Variability in individual heat exposure is not captured in neighborhood- or city-level data analyses. Urban residents are exposed differently because they often fluctuate between being indoors and outdoors (Nguyen et al. 2014; Bernhard et al. 2015), and have different housing conditions and daily schedules (Brasche and Bischof 2005). By collecting data on the meteorological conditions experienced by individuals throughout a day, researchers have begun providing a more detailed understanding of the conditions and health risks to which urban residents are exposed (Kuras et al. 2017). For example, by analyzing temperature data from small, wearable sensors, researchers have shown that individual activities like work, school, and exercise; socioeconomic and demographic characteristics; and access to heat adaption resources alter the heat exposure patterns that have been recorded in neighborhood or city-wide ambient studies (Bernhard et al. 2015; Kuras et al. 2015; Sugg et al. 2018; Uejio et al. 2018). Quantifying individual temperature variability is important to determine who is most affected during heat events and what mitigation and adaption resources would best serve these populations (Kuras et al. 2015, 2017; Uejio et al. 2018). Helping individuals understand their personal risk for heat exposure can result in them taking greater adaption actions against heat (Thompson et al. 2018).

An individual’s use of adaption resources during hot weather varies based on their location, perception, and access. Obtaining insight into the individual experiences, perceptions,
and behaviors of residents during heat events requires surveys, interviews, or focus groups. Some studies have found that few residents take action to adapt to heat exposure because they do not think they are at risk for heat-related illnesses, signaling a need for heat education (Kalkstein and Sheridan 2007; Abrahamson et al. 2008; Semenza et al. 2008). Despite studies showing that the elderly are often more at risk, many do not consider themselves vulnerable to heat-related illness (Abrahamson et al. 2008). Elderly individuals often only use “common sense behaviors,” such as using shades on windows and drinking more water, to avoid becoming ill (Abrahamson et al. 2008).

The socioeconomic status of a resident may affect how they perceive their risk to excessive heat and what actions they take to adapt to hot weather. Specifically, studies have shown that individuals with low socioeconomic status were more likely to perceive high heat as a risk and to take adaption actions (Kalkstein and Sheridan 2007; Mason et al. 2017). Residents in lower socioeconomic neighborhoods in Knoxville, Tennessee, for example, were more concerned about hot days than those in neighborhoods with a higher socioeconomic status (Mason et al. 2017). Lower-income residents are also less likely to have access to adaption resources and are more vulnerable to heat-health effects (Harlan et al. 2006; Kalkstein and Sheridan 2007). In Knoxville, residents of lower socioeconomic neighborhoods cited the high expense of air conditioning and weatherization, health, needing to stay inside to avoid heat exposure, and checking on neighbors and the elderly as the basis for their concerns (Mason et al. 2017). Likewise, residents in high-crime neighborhoods have been less likely to employ heat adaption methods like opening windows for cross ventilation (Uejio et al. 2011). The combined effects of warmer temperatures and less access to heat adaption resources result in marginalized groups, such as low-income and elderly people, more frequently experiencing heat-related health effects.
than non-marginalized groups (Harlan et al. 2006; Uejio et al. 2011; Rosenthal et al. 2014; Hondula et al. 2015).

This work uses individual temperature and humidity data and surveys to assess which socioeconomic and demographic characteristics affect heat exposure, perceptions, and adaption during heatwave and normal climate conditions in Knoxville, Tennessee. Specifically, we aim to answer four questions: 1) does participant exposure to high temperatures and humidity (herein referred to as heat) differ between heatwave (HW) and non-heatwave (NHW) periods, between day and night, and from ambient conditions at a nearby airport; 2) what factors affect the amount of time that participants spend above the heat advisory threshold; 3) what factors affect participants’ perception of heat exposure; and 4) what factors affect the adaption actions participants take during hot weather?

The significance of this work is using a new methodology in applied climatology, personable wearable sensors, to understand the characteristics and variables that are important contributors to exposing individuals to heat, and what motivates those individuals to take adaption actions. We are one of the first to incorporate HI in the context of individual heat exposure, with only one study published to our knowledge (Uejio et al. 2018).

3.3.1 Study location

This study was conducted in Knoxville, Tennessee. Knoxville is a mid-sized city in eastern Tennessee, with an estimated population of 186,239 in 2016 (USCB 2018a). The Knoxville Metropolitan Statistical Area (KMSA), which includes the entire location of this study, had an estimated population of 868,546 in 2016 (USCB 2018b). The population of the KMSA increased by approximately 31,000 between 2010–2016. In 2010, KMSA was estimated to cover 158.6 km², with a population density of approximately 2,905 persons/km² (USCB 2018b). Race
and ethnicity estimates for Knoxville’s 2016 population are approximately 77% white, 13% Black or African American, 6% Asian, and 18% Hispanic or Latino (USCB 2018a).

Knoxville is in a valley, flanked to the east by the Great Smoky Mountains National Park and to the west by the Cumberland Plateau. Knoxville experiences a humid subtropical climate, with average high temperatures in the warmest month (July) of 28.3 °C and average high temperatures in the coldest month (January) of 11.1 °C (NWS 2018).

3.3.2 Recruitment and study participants

We recruited study participants between May and July 2017. Recruitment efforts consisted of contacting community leaders to circulate information to Knoxville residents; holding informational meetings at businesses, neighborhood meetings, university classes, and apartment complexes; and minimally using snowball sampling. During informational meetings we provided participants material on study procedures and incentives. Participants reviewed and signed an informed consent form and completed a short survey detailing their socioeconomic and demographic information (Appendix A). In total, 45 participants were recruited, with data from 38 participants ultimately being used in the analyses. All study participants resided within the KMSA.

Participants ranged in age from 18–65+, with 78.9% of the participant population between 18–49 years old (Table 3.1). Female participants comprised of 63.2% of the participant population. Race and ethnicity of participants were similar to the Knoxville averages with 84.2% participants being white and 10.5% participants being Black or African American.
Table 3.1. Socioeconomic and demographic characteristics of study participants.

<table>
<thead>
<tr>
<th></th>
<th>Count</th>
<th>Percent</th>
</tr>
</thead>
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</tr>
<tr>
<td><strong>Race/Ethnicity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>1</td>
<td>2.6</td>
</tr>
<tr>
<td>Black or African American</td>
<td>4</td>
<td>10.5</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1</td>
<td>2.6</td>
</tr>
<tr>
<td>White</td>
<td>32</td>
<td>84.2</td>
</tr>
<tr>
<td><strong>Annual Household Income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under $20,000</td>
<td>4</td>
<td>10.5</td>
</tr>
<tr>
<td>$20,000–$40,000</td>
<td>5</td>
<td>13.2</td>
</tr>
<tr>
<td>$40,000–$60,000</td>
<td>6</td>
<td>15.8</td>
</tr>
<tr>
<td>$60,000–$80,000</td>
<td>8</td>
<td>20.1</td>
</tr>
<tr>
<td>$80,000–$100,000</td>
<td>6</td>
<td>15.8</td>
</tr>
<tr>
<td>Over $100,000</td>
<td>5</td>
<td>13.2</td>
</tr>
<tr>
<td>Prefer not to answer</td>
<td>4</td>
<td>10.5</td>
</tr>
<tr>
<td><strong>Highest Level of Education Completed</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school diploma or equivalent</td>
<td>2</td>
<td>5.6</td>
</tr>
<tr>
<td>Some college, no degree</td>
<td>7</td>
<td>18.4</td>
</tr>
<tr>
<td>Associate’s Degree</td>
<td>1</td>
<td>2.6</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>8</td>
<td>21.1</td>
</tr>
<tr>
<td>Master’s Degree</td>
<td>13</td>
<td>34.2</td>
</tr>
<tr>
<td>Doctoral or Professional Degree</td>
<td>7</td>
<td>18.4</td>
</tr>
<tr>
<td><strong>Employment Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed full-time</td>
<td>19</td>
<td>50.0</td>
</tr>
<tr>
<td>Employed part-time</td>
<td>14</td>
<td>36.8</td>
</tr>
<tr>
<td>Retired</td>
<td>3</td>
<td>7.9</td>
</tr>
<tr>
<td>Unemployed</td>
<td>2</td>
<td>5.3</td>
</tr>
<tr>
<td><strong>Student Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not a student</td>
<td>23</td>
<td>60.5</td>
</tr>
<tr>
<td>Part-time student</td>
<td>1</td>
<td>2.6</td>
</tr>
<tr>
<td>Full-time student</td>
<td>14</td>
<td>36.8</td>
</tr>
</tbody>
</table>
3.3.3 Equipment and data collection

We gathered data observed by McGhee Tyson airport from the National Climate Data Center (NCDC 2017) to compare airport temperatures to individual temperatures (Table 3.2). We used two data collection periods to assess exposure during different levels of heat. The first of these periods was a HW period. We defined a HW using criteria from the National Weather Service (NWS), which issues three types of heat alerts: excessive heat warning, excessive heat watch, and heat advisory (NWS 2017b). Excessive heat watches alert the public that a heat event is coming but the exact time and intensity have not yet been determined (NWS 2017b). Heat advisories and excessive heat warnings are issued 12 hours in advance of heat conditions that are considered dangerous, with a heat advisory having a lower threshold than an excessive heat warning (NWS 2017b). The criteria given for a heat advisory by the NWS is two or more days of an expected HI of 39.4 °C or greater and a night time temperature remaining above 23.9 °C (NWS 2017b). For this study, we defined a HW as two or more consecutive days forecasted to exceed the heat advisory thresholds given by the NWS.

Because official heat advisories are only issued 12 hours in advance (NWS 2017b), we relied on Excessive Heat Outlooks issued by the NWS and personal communication with the NWS Weather Forecasting Office in Morristown, Tennessee, to determine the best period for HW data collection. The HW data collection began at 0800 LDT on 20 July 2017 and ended at 0800 LDT on 24 July 2017.

We collected our second set of data during conditions near or below average temperatures. We defined our NHW as being at or below the normal daily high temperature. As with the HW collection period, we used forecasts from the NWS and personal communication with NWS Morristown to determine the best period for NHW data collection period. This data collection period was also scheduled to align with the same days of the week (Thursday through
Table 3.2. Maximum and minimum temperature, HI, sky cover, and precipitation during the HW and NHW study periods (NCDC 2017).

<table>
<thead>
<tr>
<th>Day</th>
<th>Maximum Temperature (°C)</th>
<th>Minimum Temperature (°C)</th>
<th>Maximum HI (°C)</th>
<th>Minimum HI (°C)</th>
<th>AM Sky Cover</th>
<th>PM Sky Cover</th>
<th>AM Precipitation (mm)</th>
<th>PM Precipitation (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Heatwave</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thursday, 20 July</td>
<td>32.8</td>
<td>21.7</td>
<td>33</td>
<td>22</td>
<td>Clear</td>
<td>Scattered clouds</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Friday, 21 July</td>
<td>34.4</td>
<td>22.2</td>
<td>34</td>
<td>22</td>
<td>Clear</td>
<td>Clear</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Saturday, 22 July</td>
<td>35.6</td>
<td>23.3</td>
<td>36</td>
<td>23</td>
<td>Clear</td>
<td>Clear</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sunday, 23 July</td>
<td>30.6</td>
<td>21.0</td>
<td>31</td>
<td>21</td>
<td>Few clouds</td>
<td>Clear</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Monday, 24 July</td>
<td>31.7</td>
<td>21.7</td>
<td>32</td>
<td>22</td>
<td>Few clouds</td>
<td>Clear</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td><strong>Non-heatwave</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thursday, 27 July</td>
<td>31.1</td>
<td>24.4</td>
<td>31</td>
<td>24</td>
<td>Few clouds</td>
<td>Few clouds</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Friday, 28 July</td>
<td>24.4</td>
<td>21.7</td>
<td>24</td>
<td>22</td>
<td>Few clouds</td>
<td>Overcast</td>
<td>0</td>
<td>0.58</td>
</tr>
<tr>
<td>Saturday, 29 July</td>
<td>28.3</td>
<td>19.4</td>
<td>28</td>
<td>19</td>
<td>Scattered clouds</td>
<td>Few clouds</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sunday, 30 July</td>
<td>28.9</td>
<td>17.2</td>
<td>29</td>
<td>17</td>
<td>Clear</td>
<td>Clear</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Monday, 31 July</td>
<td>30.0</td>
<td>17.8</td>
<td>30</td>
<td>18</td>
<td>Clear</td>
<td>Clear</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>
Monday) as the HW period to avoid bias that may occur from participants having different work and/or activity schedules throughout the week. The NHW data collection began at 0800 LDT on 27 July 2017 and ended at 0800 LDT on 31 July 2017.

We collected data using Hygrochron iButtons (DS1923-F#). These small (16.25 mm x 0.51 mm) wearable sensors have a temperature accuracy of ±0.5 °C between -10 °C to +65 °C and relative humidity accuracy of ±5% (Embedded Data Systems 2017). iButtons were individually calibrated in a NIST-traceable chamber by Embedded Data Systems prior to purchase (Meyer et al. 2008; Embedded Data Systems 2017). Our pilot studies investigating 1-minute, 3-minute, and 5-minute sampling intervals showed that relative humidity did not vary significantly between sampling intervals, though temperature did vary significantly between each sampling interval. We chose to collect data at a 5-minute temperature and humidity sampling rate given the results of the pilot study, to reduce excessive or redundant data, and to ensure the capture of data at a scale appropriate to heat-health variables (Kuras et al. 2017). Kuras et al. (2015), one of the pioneering iButton studies, also used a 5-minute sampling rate. All of the analyses for this work are based on these 5-minute observations. Prior to equipment distribution, the iButtons were calibrated to a main computer’s clock to ensure accuracy in collection times, that each iButton was collecting data properly, and that each iButton was cleared of previous data.

Approximately 24–48 hours prior to each data collection period, we contacted participants to determine equipment drop-off locations and times. Each participant received an iButton mounted on a fob and two options (a lanyard and a clip) for wearing the iButton, and activity logs. As pilot studies showed no significant differences between wearing iButtons on a belt loop or around the neck on a lanyard, participants were given a choice in which location they wore them. We asked participants to fill out an activity log for each day of data collection.
Activity logs were modeled after Uejio et al. (2018). Participants noted in the logs if and when they went to work, adaption actions they took during the day (0800–1800 LDT) and at night (1800–0800 LDT), and details on equipment issues, including times the iButton was not worn. Participants selected adaption actions from a list that included: stayed indoors, used air conditioners, minimized outdoor work, drank more fluids, wore light clothing, wore a hat, reduced activities, went to a location with air conditioning, sought shade, changed routine, scheduled heavy work during the cooler part of the day, and did nothing different (after Uejio et al. 2018). They could also select “other” and write in adaption activities that were not listed.

In their activity logs, participants also noted their perceived heat exposure by selecting their thermal comfort from five possible categories (cold, neither hot nor cold, warm, hot, very hot) as a response to the questions: “How hot or cold were you during the day (8:00 am–6:00 pm)?” and “How hot or cold were you during the night (6:00 pm–8:00 am)?” These five categories were reconfigured to three categories for analysis. The new perception categories included comfortable (cold, neither cold nor hot), warm, and hot (hot, very hot). We completed this reconfiguration because it made logical sense while also ensuring that all categories had enough observations for comparison.

We contacted participants via text, e-mail, or phone each morning to remind them to wear their iButtons and fill out the activity log for that day. We collected iButtons and activity logs at the end of each data collection period and participants were provided with a $15 VISA gift card as incentive for participating. Participants who did not wear their iButtons for more than 10% of the data collection periods (n=3), were non-responsive to communication for equipment drop off (n=2), lost their equipment (n=1), or were only available to collect data during one of the data collection periods (n=1) were removed from the study. This resulted in data from 38 total participants being used for analysis.
3.3.4 Data and Statistical Analyses

We downloaded data from each iButton after the HW and NHW data collection periods. We took several steps to ensure data quality. First, data were manually inspected for outlier data that could signal sensor malfunction. Next, data were cross checked with participant activity logs to remove data during periods where participants reported not wearing their iButton. Last, we trimmed the data to include only the appropriate study period. As the Thursday and Monday data collection for both the HW and NHW periods were not full 24-hour periods and the weather was cooler than heat advisory conditions during the HW collection period, Thursday and Monday data were removed from the study. We removed Sunday data for both collection periods because of lack of participant compliance during the NHW collection period. The final HW study period included Friday, 21 July 2017 and Saturday, 22 July 2017. The final NHW study period included Friday, 28 July 2017 and Saturday, 29 July 2017.

Our socioeconomic and demographic data categories were reconfigured to ensure we had enough observations for comparison. The new age categories were under 40 and over 40. The new annual household income categories were under $60,000 and over $60,000. The new education categories were Associate’s degree or less and Bachelor’s degree or higher. The employment status categories were reconfigured into employed full time and employed part-time or less (including part-time, retired, and unemployed). The new student status categories were not a student and student (including part-time and full-time). We reconfigured the time spent in the southeastern United States into two categories, including over 10 years and under 10 years. Finally, the housing type category was reconfigured into single family house and other (including apartment, condo, townhouse, or duplex). Race or ethnicity was not included in statistical analyses as the sample size for categories other than “white” were too small. All “prefer not to answer” responses were removed from the study.
We assessed individually experienced heat index (IEHI) values to determine the exposure to heat. We used the Weather Metrics package in the R Statistical Suite (Anderson et al. 2016) to calculate IEHI from the 5-minute temperature and relative humidity data. We calculated the number of 5-minute IEHI observations at or above heat advisory threshold (obs≥HAT) during the HW and NHW, and day and night. Heat advisory threshold was based on the criteria given by the NWS of daytime HI of 39.4 °C or greater and a night time temperature remaining above 23.9 °C (NWS 2017). Time of day was subset into daytime (0800–1800 LDT) and nighttime (1800–0800 LDT), which corresponded to the times provided in the activity log where participants described how warm they felt at night and during the day. Specific methods used to address each research question are presented below.

1) Does participant exposure to heat differ between HW and NHW periods, between day and night, and from ambient conditions at a nearby airport?

We used paired-sample t-tests to determine if there were significant differences in 1) average airport HI and average IEHI during the HW and NHW periods, 2) average airport HI and average IEHI during the day and night, and 3) individual differences in IEHI between the HW and NHW data collection periods. In cases where there were an unequal number of data points between HW and NHW data collection periods for a specific participant, such as when a participant did not wear an iButton for part of the collection period, independent t-tests were used. We used the Bonferonni correction to adjust the p-value for multiple comparisons when testing for individual differences.
2) What factors affect the amount of time that participants spend above the heat advisory threshold?

We used Kruskal-Wallis tests to determine if significant differences in the number of obs≥HAT occurred between 1) HW and NHW periods, 2) day and night, and 3) participants with different socioeconomic and demographic characteristics. Negative binomial regression was used to model how the number of obs≥HAT were affected by the binary heatwave variable (HW or NHW), and time of day.

3) What factors affect participants’ perception of heat exposure?

We used Kruskal-Wallis tests to examine whether the number of obs≥HAT, the binary heatwave variable, and time of day influenced participant perception of heat exposure. We used Chi-squared tests to determine the associations between socioeconomic/demographic characteristics and heat perception. The modified perception categories discussed above were used for analyses involving participant perception.

4) What factors affect the adaption actions participants take during hot weather?

We used Chi-squared tests to determine the associations between adaption actions and 1) socioeconomic/demographic characteristics, and 2) HW and NHW periods. We used Kruskal-Wallis tests to examine whether the number of obs≥HAT influenced the adaption actions that participants took. These tests were preformed using 1) all study data combined, 2) HW data only, and 3) NHW data only.
3.3.5 Study Limitations

This study relies on a relatively small sample size of 38 participants, which resulted in limited socioeconomic and demographic categories for statistical analyses. Recruitment was limited for several reasons. First, many individuals were concerned about GPS tracking. To ease their concerns, we showed participants the pilot data that were downloaded from the equipment, which included only date, time, temperature, and humidity readings. Second, the data collection periods only allowed for short notice to participants. The nature of forecasting only allowed us to give 24- to 48-hour notice to participants that we would start collecting data. As such, some individuals chose not to participate in the entire study as they were unsure if they would be available for data collection. One individual participated during the HW period but not the NHW period because they were traveling.

Based on the nature of participatory research, participant noncompliance can result in data errors. Each participant was provided with written and verbal instructions on how to wear their sensor. In pilot studies, we found that sensors worn on shoes often had a higher relative humidity, likely resulting from evapotranspiration from ground vegetation or evaporation from moisture on concrete. To reduce error in humidity readings, participants were asked not to wear their sensor clipped to their shoes. Likewise, errors in humidity readings could occur if the sensors detected body sweat through the participant’s clothing (Kuras et al. 2017). Participants were instructed to wear their sensor outside of their clothing, reducing the effect of body sweat on relative humidity data (Dumas et al. 2016). Temperature outliers could potentially occur when participants were in direct sunlight (Kuras et al. 2017), near heat sources such as an oven, or in front of air conditioning outputs such as car air vents. The data were checked to ensure suspected outlier data points were removed. We also checked the data against participant activity logs and removed data where the participant reported leaving their sensor in the sun while swimming and
in the car while at work or school. Additionally, each participant was given the same sensor to use for both study periods to ensure consistency. While participants were asked to log any time where they were not wearing their sensor, it is possible that participants may not have provided this information, resulting in data that did not accurately reflect their exposure to environmental conditions.

As this data collection period was based on forecasting, it did not satisfy the NWS’ criteria for a heat advisory during the HW data collection period but was still well above average temperatures. The minimum ambient HIs recorded at the airport were the same on Friday, 21 July, a HW day, and Friday, 28 July, a NHW day. However, the range in ambient temperatures were much greater during the HW study period than during the NHW study period, likely because of cloud cover during the NHW period. Cloud cover may have reduced the range of HI recorded at the airport. Additionally, the cloud cover and minimal amount of rain on the first day of the NHW study period may have affected participant actions, potentially introducing bias into our adaption action data.

3.4 Results

3.4.1 Does participant exposure to heat differ between HW and NHW periods, between day and night, and from ambient conditions at a nearby airport?

The mean IEHI experienced by participants during the HW period (25.9 °C) was slightly higher than during the NHW period (25.3 °C). The range of IEHI was also greater during the HW period (6.7 °C) than the NHW period (6.0 °C). The median IEHI during the daytime (27.2 °C) was higher than during the nighttime (25.1 °C). The ranges of IEHI during the day (8.3 °C) and at night (8.5 °C) were relatively similar. Except during the morning hours (0200–
0900 LDT), the average IEHI during the HW period was higher than during the NHW period (Figure 3.1). The maximum average IEHI for all participants during the HW (NHW) period was 28.5 °C (27.6 °C). The minimum average IEHI for all participants during the HW (NHW) period was 23.3 °C (23.2 °C).

During the HW period, airport HI measurements did not accurately reflect the conditions that participants experienced (Figure 3.2, Table 3.3). The average ambient HI recorded at the airport was significantly greater than the average IEHI for all participants. During the HW period, mean airport measurements were significantly greater than mean IEHI during the daytime. During the NHW period, mean airport HI did not vary significantly from the conditions participants experienced during the day; however, at night, mean IEHI was significantly greater than the mean HI recorded at the airport.

Paired sample t-tests indicated that, of 38 participants, 23 experienced significantly greater mean IEHI during the HW period than during the NHW period, with 15 participants experiencing a 5.0–14.9 °C greater mean IEHI during the HW period than the NHW period (Figure 3.3, after Kuras et al. 2015). One participant experienced HI 16.7 °C warmer than their personal study-wide average, though this could have been a result of equipment or data collection errors (see Section 3.3.5 Study Limitations). Five participants experienced significantly higher mean IEHI during the NHW period, with the majority experiencing a higher IEHI within the 0.1–4.9 °C range. Ten participants did not experience significantly different mean IEHI between the HW and NHW periods.
Figure 3.1. Average IEHI (°C) during the HW period (red line) and NHW period (blue line).
Figure 3.2. Average hourly IEHI for all participants (black dashed line) and average hourly airport HI (black solid line) for the HW study period (A) and NHW study period (B). The orange line indicates the average maximum daily temperature (31.1 °C). The blue line indicates the average minimum daily temperature (20.6 °C).
Table 3.3. Difference in means between average airport HI and average IEHI for all participants. Bold values are significant ($p<0.05$). Positive values indicate that the average airport HI was higher than the average IEHI whereas negative values indicate that the average IEHI was higher than average airport HI.

<table>
<thead>
<tr>
<th>Study Period</th>
<th>Difference in Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW</td>
<td>4.779</td>
</tr>
<tr>
<td>NHW</td>
<td>-0.413</td>
</tr>
<tr>
<td><strong>HW: Day (8:00am–6:00pm)</strong></td>
<td><strong>8.360</strong></td>
</tr>
<tr>
<td>HW: Night (6:00pm–8:00am)</td>
<td>1.749</td>
</tr>
<tr>
<td>NHW: Day (8:00am–6:00pm)</td>
<td>0.335</td>
</tr>
<tr>
<td>NHW: Night (6:00pm–8:00am)</td>
<td>-1.047</td>
</tr>
</tbody>
</table>
Figure 3.3. Participant variation in IEHI. Bars below zero indicate that the participant experienced a higher average IEHI (°C) during the NHW period. Bars above zero indicate that the participant experienced a higher average IEHI (°C) during the HW period. Black (grey) bars indicate that the participant experienced significantly (insignificantly) different IEHI between the HW and NHW periods.
3.4.2 What factors affect the amount of time that participants spend above the heat advisory threshold?

When assessing the difference in medians, our Kruskal-Wallis tests indicated that the time of day significantly influences the number of obs≥HAT, but the binary heatwave variable does not (Table 3.4). There were no significant interacting effects between the binary heatwave variable and time of day in the Kruskal-Wallis test. The results of the negative binomial regression, which tests for the difference in means, supported our Kruskal-Wallis findings, with the time of day significantly ($p<0.001$) influencing the number of obs≥HAT. Negative binomial regression results indicated that participants experienced 5.19 times more obs≥HAT at night than during the day. However, our negative binomial regression results are inconsistent with our Kruskal-Wallis results for the binary heatwave variable. When testing for the difference in means (negative binomial regression), the binary heatwave variable significantly ($p<0.001$) influenced the number of obs≥HAT participants experiences, with 0.71 times less obs≥HAT during the NHW period than during HW period. Kruskal-Wallis results also indicated that the number of obs≥HAT varied significantly between age groups, income levels, employment status, and housing types at night during the both the HW and NHW study periods (Table 3.5). The number of obs≥HAT participants experienced during the daytime did not vary significantly between these groups or when testing all HW data against all NHW data.

3.4.3 What factors influence participants’ perception of heat exposure?

Time of day and the binary heatwave variable both influenced the perception of how warm a participant felt. Chi-squared test results indicated that socioeconomic and demographic characteristics were not related to perception during the day, but income was significantly related
Table 3.4. Kruskal-Wallis results for testing the number of obs≥HAT based on the binary heatwave variable and time of day. Significance codes are as follows: * 0.05, ** 0.01, *** 0.001 or less.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kruskal-Wallis Chi-squared</th>
<th>Degrees of Freedom</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary Heatwave Variable</td>
<td>2.2315</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Time of Day</td>
<td>118.97</td>
<td>1</td>
<td>***</td>
</tr>
</tbody>
</table>
Table 3.5. Kruskal-Wallis results for testing the number of obs≥HAT at night based on socioeconomic and demographic data. Significance codes are as follows: * 0.05, ** 0.01, *** 0.001 or less.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kruskal-Wallis Chi-squared</th>
<th>Degrees of Freedom</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>11.306</td>
<td>5</td>
<td>*</td>
</tr>
<tr>
<td>Gender</td>
<td>1.451</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>28.528</td>
<td>5</td>
<td>**</td>
</tr>
<tr>
<td>Education</td>
<td>29.805</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Student Status</td>
<td>4.659</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Employment Status</td>
<td>7.738</td>
<td>3</td>
<td>*</td>
</tr>
<tr>
<td>Time Spent in the SEUS</td>
<td>2.762</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Housing Type</td>
<td>13.902</td>
<td>4</td>
<td>***</td>
</tr>
<tr>
<td>Proper Insulation</td>
<td>1.050</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>
at night. During the HW and NHW periods the opposite variables are significant. During the HW period, age, gender, income, and housing insulation were significantly associated with perception of how warm participants reported feeling (Table 3.6). During the NHW period, education was significantly associated with participants’ perception of how warm they felt.

3.4.4 What factors affect the adaption actions participants take during hot weather?

Chi-squared tests indicated that income, education, employment type, and time spent in the southeastern United States were significantly associated with the actions reported by participants (Table 3.7). These socioeconomic and demographic characteristics were significantly related to at least three of the actions tested. Staying indoors was significantly related to all socioeconomic and demographic characteristics except the amount of time spent in the southeastern United States.

The binary heatwave variable was significantly associated with participants having taken the following actions: stayed indoors, used air condition, minimized outdoor work, drank fluids, wore light clothing, wore a hat, reduced activity, went to a location with air condition, or did nothing different (Table 3.8). The frequency of all adaption actions reported by participants increased during the HW period and decreased during the NHW period, except “did nothing different.”

3.5 Discussion and Conclusions

This study contributes to a growing research base that suggests an individual’s socioeconomic and demographic characteristics, perception of heat, and adaption actions are important to understanding heat exposure (Kuras et al. 2015; Sugg et al. 2018; Uejio et al. 2018).
Table 3.6. Chi-squared results for testing the association between perceived heat exposure and socioeconomic characteristics. The Chi-squared statistic ($X^2$), degrees of freedom (df), and significance codes (* 0.05, ** 0.01, *** 0.001 or less) are provided.

<table>
<thead>
<tr>
<th>Socioeconomic / Demographic Characteristic</th>
<th>Perception (comfortable, warm, hot)</th>
<th>During HW</th>
<th>During NHW</th>
<th>During the Night</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$X^2$</td>
<td>Df</td>
<td>Significance</td>
<td>$X^2$</td>
</tr>
<tr>
<td>Age</td>
<td>6.827</td>
<td>2</td>
<td>*</td>
<td>0.227</td>
</tr>
<tr>
<td>Gender</td>
<td>6.827</td>
<td>2</td>
<td>*</td>
<td>3.772</td>
</tr>
<tr>
<td>Income</td>
<td>5.544</td>
<td>2</td>
<td>*</td>
<td>1.519</td>
</tr>
<tr>
<td>Education</td>
<td>2.377</td>
<td>4</td>
<td></td>
<td>19.253</td>
</tr>
<tr>
<td>Housing Insulation</td>
<td>11.525</td>
<td>4</td>
<td>*</td>
<td>6.809</td>
</tr>
</tbody>
</table>
Table 3.7. Chi-squared tests for testing for the association between action taken and socioeconomic and demographic characteristics. The Chi-squared value ($X^2$) and significance codes (* 0.05, ** 0.01, *** 0.001 or less) are provided.

<table>
<thead>
<tr>
<th>Socioeconomic / Demographic Characteristic</th>
<th>Stayed Indoors</th>
<th>Used AC</th>
<th>Minimized Outdoor Work</th>
<th>Drank Fluids</th>
<th>Wore Light Clothing</th>
<th>Wore Hat</th>
<th>Reduced Activity</th>
<th>Went to Location with AC</th>
<th>Scheduled Heavy Work During Cool Times</th>
<th>Did Nothing Different</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>12.166***</td>
<td>0.020</td>
<td>2.464</td>
<td>1.535</td>
<td>4.419*</td>
<td>0.620</td>
<td>0.234</td>
<td>0.009</td>
<td>0.355</td>
<td>2.068</td>
</tr>
<tr>
<td>Gender</td>
<td>6.927**</td>
<td>0.391</td>
<td>1.414</td>
<td>5.221*</td>
<td>1.653</td>
<td>11.720***</td>
<td>3.557</td>
<td>0.320</td>
<td>20.618***</td>
<td>1.631</td>
</tr>
<tr>
<td>Income</td>
<td>14.062***</td>
<td>5.469*</td>
<td>1.830</td>
<td>0.746</td>
<td>4.295*</td>
<td>1.035</td>
<td>1.376</td>
<td>1.080</td>
<td>1.056</td>
<td>8.112**</td>
</tr>
<tr>
<td>Education</td>
<td>17.906***</td>
<td>4.704</td>
<td>12.541**</td>
<td>10.744**</td>
<td>0.313</td>
<td>3.149</td>
<td>30.069***</td>
<td>34.714***</td>
<td>23.928***</td>
<td>3.010</td>
</tr>
<tr>
<td>Student Status</td>
<td>12.689***</td>
<td>1.752</td>
<td>0.011</td>
<td>0.590</td>
<td>0.539</td>
<td>0.027</td>
<td>1.353</td>
<td>0.009</td>
<td>17.799***</td>
<td>2.663</td>
</tr>
<tr>
<td>Employment</td>
<td>5.278**</td>
<td>1.425</td>
<td>12.546***</td>
<td>3.390</td>
<td>0.053</td>
<td>0.371</td>
<td>0.995</td>
<td>2.990</td>
<td>9.604***</td>
<td>2.252</td>
</tr>
<tr>
<td>Time in the SE US</td>
<td>0.236</td>
<td>0.105</td>
<td>10.627**</td>
<td>18.933***</td>
<td>1.271</td>
<td>7.628**</td>
<td>4.387*</td>
<td>0.976</td>
<td>0.191</td>
<td>3.708</td>
</tr>
<tr>
<td>Housing Type</td>
<td>10.064***</td>
<td>1.986</td>
<td>1.745</td>
<td>3.973</td>
<td>16.344***</td>
<td>0.644</td>
<td>1.868</td>
<td>1.628</td>
<td>1.152</td>
<td>3.724</td>
</tr>
</tbody>
</table>
Table 3.8. The frequency of adaption actions taken by participants and Chi-squared tests to determine if there was an association between actions taken during different heatwave conditions. The Chi-squared statistic ($X^2$), degrees of freedom (df), and significance codes (* 0.05, ** 0.01, *** 0.001 or less) are provided.

<table>
<thead>
<tr>
<th>Adaption Action Taken</th>
<th>Stayed Indoors</th>
<th>Used AC</th>
<th>Minimized Outdoor Work</th>
<th>Drank Fluids</th>
<th>Wore Light Clothing</th>
<th>Wore a Hat</th>
<th>Reduced Activity</th>
<th>Went to Location with AC</th>
<th>Did Nothing Different</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of participants who reported action during HW (2 days)</td>
<td>46</td>
<td>60</td>
<td>28</td>
<td>46</td>
<td>38</td>
<td>16</td>
<td>15</td>
<td>20</td>
<td>8</td>
</tr>
<tr>
<td>Number of participants who reported action during NHW (2 days)</td>
<td>28</td>
<td>37</td>
<td>7</td>
<td>24</td>
<td>29</td>
<td>10</td>
<td>6</td>
<td>10</td>
<td>19</td>
</tr>
<tr>
<td>df</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Significance</td>
<td>***</td>
<td>**</td>
<td>**</td>
<td>***</td>
<td>***</td>
<td>**</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
</tbody>
</table>
The results of this study indicate that exposure to heat during both heatwaves and normal conditions varies across participants in an urban area. Traditional means for measuring the temperature of an area is to record hourly observations at nearby airports. We found that ambient airport measurements do not accurately reflect the exposure patterns of participants during a heat event, because many participants lessened their heat exposure through effective heat adaption actions.

Individual heat-exposure patterns did not always follow the traditional idea that individuals are more exposed to heat during a heatwave. Nearly 40% of participants were either warmer during the NHW period or did not experience significantly different IEHI between HW and NHW conditions. These patterns were also cited by Kuras et al. (2015). Kuras et al. (2015) explains that one of their participants did not see a significant difference in exposure during their HW and reference study periods because they chose to stay at home in air conditioning during a heatwave. Likewise, one of our participants indicated on their activity log during the HW period that they chose to stay home from work and classes to avoid walking in the heat in the middle of the day. Other participants from our study indicated that they did not work outdoors at their job and generally reduced activity during the hottest parts of the day during the HW period, thus lowering their exposure to heat. Studies on occupational exposure (e.g., Uejio et al. 2018) also found that those who were able to work indoors during at least some of their work time were less exposed to heat, though this is not a possibility for all outdoor workers.

Overall, participants in our study were more likely to take adaption actions during the HW period than the NHW period. Whether they were exposed to HW or NHW conditions affected participant perception of warmth, likely leading to more adaption actions taken during the HW period. These factors may explain why some participants experienced overall higher IEHIs during normal conditions. For example, one participant noted that they turn off their air
conditioning during typical summer weather. This could result in warmer conditions inside their home on a climatically normal day, as compared to when they used air conditioning during a heatwave, exposing them to increased heat. As daily temperature and humidity increase with climate change (U.S. Global Change Research Program 2018), residents in the southeastern United States will need to take adaption actions throughout the warm season, not just during heatwaves, to avoid heat-related illnesses.

Our participants were more exposed to conditions over heat advisory threshold at night than during the day. This is partly because the heat advisory threshold is lower at night compared to during the day, with nighttime heat advisory criteria requiring that temperatures stay above 23.9 °C (NWS 2019). Robinson (2000) found that the thresholds for a heatwave correctly identified the heat-health effects individuals experience during excessive heat. However, these criteria may need to be revisited and refined as nighttime temperatures are increasing across the southeastern United States (Peterson et al. 2013; U.S. Global Change Research Program 2018). When nighttime temperatures do not cool off, individuals are more likely to experience heat-health effects as they are not as able to recover from their daytime heat exposure (Fischer and Schär 2010). Our results suggest that individuals are taking less adaption actions at night, which could amplify their heat-health effects.

The heat advisory thresholds also do not account for acclimatization and other personal characteristics. Fischer and Schär (2010) found that the thresholds for heat-health effects varied greatly among individuals, with socioeconomic and demographic characteristics contributing to these varied heat-health thresholds. Income, employment type, and housing type were significantly related to our participant’s heat exposure, especially at night, supporting the results from similar research (e.g., Harlan et al. 2006; Dousset et al. 2011; Kovach et al. 2015). Varying heat-health thresholds highlight the importance of urban residents employing heat adaption
methods to avoid heat-related illnesses. Neighborhood-level mitigation methods, such as planting additional trees or shrubs, have not been shown to reduce ambient temperature, especially at night (Jenerette et al. 2016), indicating that individual and household adaptation might be more effective to reducing heat exposure.

Personal heat adaption methods are not equally available across an urban area (Harlan et al. 2006; Uejio et al. 2011), which may affect whether an urban resident has access to or ability to use specific methods. Having the financial means and knowledge of heat adaption and mitigation methods are important to reducing overall and nighttime ambient temperatures individuals are exposed to and thus decreasing the risk for heat-related illnesses. In this study, income and educational attainment significantly influenced the actions that participants took to adapt to heat. Income specifically related to the use of air conditioning, even though all participants in the study had access to air conditioning in their residences. If we were able to recruit Knoxville residents without access to functioning residential air conditioning, their exposure would likely differ from our sample, especially since knowledge of and access to public cooling facilities varies by location (Fraser et al. 2017). Education was related to an individual’s decision to stay inside during heat, drink fluids, reduce activity, and other adaption actions, which likely indicates the access to knowledge on heat adaption methods. Other studies (e.g., Semenza et al. 2008, Reid et al. 2009) have also cited the connection between educational attainment and the risk for heat exposure, with lower education attainment being linked to higher heat-related illness and mortality.

Other societal factors not discussed in this study, such as social cohesion, neighborhood stability, community and household resources, educational opportunities, and community risk mitigation programs, are all important factors when understanding exposure to heat and related health risks (Harlan et al. 2006; Wilhelmi and Hayden 2010; Uejio et al. 2011). Additional
studies incorporating these themes with exposure data are needed to better understand the adaptive capacity of urban populations.
3.6 Acknowledgments

This work was funded by a University of Tennessee, Knoxville Thomas Graduate Fellowship. We thank Emma Reed and Sarah Greene for their assistance in the pilot studies for this research. We appreciate the community members who graciously participated in this research. We also thank committee members, Sally Horn, Solange Munoz, and Jiangang Chen, for their valuable comments and suggestions to improve this manuscript.
3.7 References


Chapter 4

Motivation for heat adaption: How perception and exposure affect individual behaviors during hot weather in Knoxville, Tennessee
This chapter is being prepared for submission to a journal. My use of “we” in this chapter includes my co-author, Kelsey N. Ellis. I served as first author, and my work included experimental design, data collection and analysis, and writing the manuscript. Kelsey Ellis contributed to the experimental design, data analysis, and editing of this manuscript.

4.1 Abstract

Heat is the deadliest meteorological hazard; however, those who are exposed to heat often do not feel they are in danger of heat-health effects and do not take the necessary precautions to avoid heat exposure. Socioeconomic factors, such as the high cost of running air conditioning, might prevent people from taking adaption measures. We use a mixed-methods survey (n=86) collected from residents of urban Knoxville, Tennessee, to determine how respondents describe and interpret their personal vulnerability during hot weather. Thematic analyses reveal that many respondents describe uncomfortably hot weather based on its consequences, such as health effects and the need to change normal behavior, which misaligns with traditional heat-communication measures using specific weather conditions. Only 55% of those who perceived excessive heat as dangerous cited health as a reason why they were concerned about heat. Respondents who have experienced health issues during hot weather were more likely to perceive heat as dangerous and take actions to reduce heat exposure and heat-health effects. Social cohesion was not a chief concern for our respondents, even though it has been connected to reducing time-delayed heat-health effects. These results support the use of thematic analyses, a relatively underutilized tool, in climatology research to increase understanding of public perception of meteorological hazards. We recommend a multi-faceted approach to addressing heat vulnerability. This could include increasing access to heat adaption...
methods, increasing social cohesion, changing the perception of heat-related dangers through community education, and refining heat risk communication.

*Keywords: heat, heat perception, heat adaptation*

### 4.2 Introduction

Excessive heat is increasing in many places as a result of global climate change. Average annual temperatures have increased by 0.7 °C over the last 30 years in the contiguous United States, and they are expected to continue to increase by at least 1.2 °C by 2050 (U.S. Global Change Research Program 2018). In the southeastern United States, heatwaves are likely to become more frequent and intense, hot days are expected to become warmer, and the warm season is expected to be longer (U.S. Global Change Research Program 2018), exposing individuals in these areas to excessive heat and heat-related illnesses.

People are differentially exposed to heat. Urban areas change the way that wind, water and energy move through the area, trapping more heat near the surface (Oke 1982). This results in a phenomenon called the Urban Heat Island, which exposes urban residents to higher temperatures than rural residents (Oke 1982). Heat exposure also varies within an urban area. For example, a location with a greater building density is likely to be warmer than one with a lower building density (Jenerette et al. 2016; Ellis et al. 2017). Meanwhile, an area with more vegetation, and thus higher amounts of evapotranspiration, is likely to have a higher heat index, the combined effect of temperature and humidity, than an area with less vegetation (Hass et al. 2016). At an even smaller scale, an individual living or working in an upper floor of a building may be more exposed to heat that rises and persists in the upper floors of a building (Blum et al. 1998). Additionally, those who work outside or in buildings without air conditioning or efficient
air flow are more exposed to heat than those who work in a temperature-regulated environment (Sugg et al. 2018; Uejio et al. 2018).

Heat is the deadliest metrological hazard (NWS 2017). Health effects of heat exposure include heatstroke, heat exhaustion, muscle cramps, and dehydration (Semenza et al. 1999; Centers for Disease Control and Prevention 2017). Those with pre-existing health issues can experience heat-related comorbidities, such as cardiovascular and respiratory difficulties and mental health disorders (Blum et al. 1998; Centers for Disease Control and Prevention 2017). Heat exposure (Hass 2019) and heat-related illnesses (Sugg et al. 2016) are more likely on days that are at or near average temperature as individuals are more likely to take actions to reduce heat-health risks during extreme heat events. Those not acclimatized to heat or with a reduced ability to thermoregulate, such as children and the elderly, are more at risk for heat-related illnesses (Blum et al. 1998; O’Neill and Ebi 2009), whereas those who report good health are less likely to experience heat-related illnesses (Mason et al. 2018). Likewise, individuals with higher income and more social cohesion are less likely to report heat-related illnesses (Mason et al. 2018).

People can use heat adaption methods to reduce exposure to high temperatures and humidity and minimize health risks. Examples of these adaption methods include using air conditioning, going to a cooler location, wearing lightweight clothing, and staying hydrated. Many factors affect the heat adaption actions that individuals take. Those living in unsafe areas are less likely to open their windows because of fear of crime (Blum et al. 1998; Uejio et al. 2011). Other residents may not have access to or be willing to use air conditioning, citing the high cost of running and repairing units (Blum et al. 1998; Mason et al. 2017). Still others are not aware of what actions to take to avoid heat exposure, are not aware of heat events, or are unsure
whether they are at risk for heat-related illnesses (Kalkstein and Sheridan 2007; Abrahamson et al. 2008).

Heat-related education and personal perception of the dangers of heat also affect the heat adaption actions taken. Individuals often do not perceive extreme heat as a hazard. Many individuals who live in a warm climate feel they are sufficiently acclimatized to heat so it is no longer a concern (Kalkstein and Sheridan 2007). When individuals do not consider themselves at risk for heat-related illnesses, they are less likely to take measures to protect themselves (Kalkstein and Sheridan 2007; Semenza et al. 2008). Despite being more prone to heat-related illnesses, the elderly often do not see themselves at risk and take “common sense” actions during heat events, such as using fans (Abrahamson et al. 2008), which can be an ineffective means for cooling and for reducing heat-health issues (Sheridan 2007). At the same time, having been negatively affected by a heat event, or knowing someone else who has, tends to increase in an individual’s risk perception (Perry and Lindell 1997) and increase their use of adaption methods.

Public opinions on heat risk and adaption actions have been studied using surveys in several cities in the United States (Kalkstein and Sheridan 2007; Sheridan 2007). Sheridan (2007) noted that, while most of the participants in his study were aware of a heat event, they were less aware of what adaption actions they should take. Only half of those surveyed changed their behavior because of the heat. The most common adaption actions taken by participants were avoiding the outdoors and using air conditioning (Sheridan 2007). In Phoenix, Arizona, individuals were more likely to feel they are at risk to excessive heat if an excessive heat warning is issued (Kalkstein and Sheridan 2007). Socioeconomic characteristics, such as race, income, and age, played a role in whether individuals took adaption actions when they were aware of an excessive heat warning (Kalkstein and Sheridan 2007).
Using a mixed-methods survey for such studies expands the range of information usually obtained from exclusively qualitative or quantitative surveys (Bryman 2006; DeLyser and Sui 2014). Social measures, power relations, and perception cannot be easily measured through quantitative surveys (Elwood 2009). In quantitative surveys, responses are required to fit into specific, researcher-defined categories. Perception studies focusing on climate (Abrahamson et al. 2008; Semenza et al. 2008) and heat (Sheridan 2007) that use mixed-methods interviews and phone surveys have provided more elaborate responses on social structures, such as what barriers exist for adaptation to hazards, as well as perceptions of hazards from participants. These studies demonstrate the potential for mixed-method surveys to obtain data that is deeper in information, though perhaps less extensive in study size, than quantitative surveys (McGuirk and O’Neill 2010).

We use a survey containing a mix of open-ended and single- and multi-select questions to assess how residents of Knoxville, Tennessee, describe, experience, perceive, and adapt to heat. Specifically, we aim to answer four questions: 1) how do respondents describe uncomfortably hot weather; 2) how do respondents perceive heat danger; 3) what health effects do respondents typically experience during hot weather; and 4) how do respondents adapt to hot weather? The significance of this work is to expand upon the limited research using combined qualitative and quantitative analyses to understand how heat affects urban residents’ health and what motivates them to take adaptation actions during heat events.

4.3 Methods

We distributed a community survey between June and November 2017 in Knoxville, Tennessee. Knoxville is a mid-sized city in the southeast United States. The estimated
population of the metropolitan area is 868,546 (USCB 2018). The city is located in a valley between Great Smoky Mountains to the east and the Cumberland Plateau to the west. Knoxville has a humid subtropical climate. The city’s residents are at risk to several types of meteorological hazards, including severe convective weather, winter precipitation, flooding, and heatwaves.

The survey was distributed both electronically and in hardcopy. It consisted of qualitative and quantitative questions aimed to determine the respondents’ demographic and socioeconomic characteristics, housing information, use of heat adaption and mitigation methods, understanding of meteorological hazards and heat-health effects during past heat events, and social cohesion (Appendix C).

To recruit participants, we generally targeted three neighborhoods in Knoxville, including West Hills, Vestal, and Burlington. These neighborhoods were chosen because they consist of a range of incomes, offer a diverse population, and have varying population densities (Hass et al. 2016). They have also been shown to experience different heat indices, with higher-income and lower-density neighborhoods experiencing higher heat indices because of increased vegetation (Hass et al. 2016). We did not include “neighborhood” as a predictive variable in our study because specific neighborhood boundaries in Knoxville were, at the time of data collection, not clearly defined by the city. We recruited participants over the age of 18 by 1) attending two neighborhood association meetings in June 2017 and one community group meeting in November 2017, 2) going door to door in the neighborhoods, 3) approaching people in neighborhood parks, and 4) minimally using snowball and convenience sampling.

In total, 86 surveys were collected. Respondents at meetings were given a choice between taking the survey electronically on their own time or filling out a paper survey at the meeting. All other participants were asked to fill out a paper survey. Submission of the
electronic survey implied informed consent, whereas those who filled out a paper survey signed a detached informed consent form. All study procedures were approved by the University of Tennessee, Knoxville Institutional Review Board.

Participants and all others who were eligible to take the survey were able to enter a raffle to win one of twenty $20 VISA gift cards. Raffle entries were not connected to the completed surveys to ensure anonymity. Names were randomly drawn using a random-number generator and raffle winners were contacted and mailed their gift cards.

We entered the survey data into Microsoft Excel and inspected them for inconsistencies or lack of responses. Responses of “prefer not to answer” were removed, as needed. Descriptive statistics were used to delineate socioeconomic and demographic categorical answers—those where respondents had several options to choose from (Table 4.1). Respondents ranged in age from 18–65 and over, with 87.2% of respondents being 18–59. Approximately 69.0% of respondents identified as female. The majority (64.0%) of respondents identified as white, 24.4% of respondents identified as Black or African American, and 9.4% identified as either Asian or Hispanic. Approximately 49.0% of respondents had earned a higher education degree and worked full-time.

Categories were collapsed to ensure there were enough samples in each category to preform statistical analyses, specifically the need for an expected value of five or more for the Chi-squared tests. The new age categories were 18–29, 30–49, and over 50. The new annual household income categories were under $20,000, $20,000–$40,000, and over $40,000. The new categories for the highest level of education completed were high school graduate/GED or less, some college to Associate’s degree, and Bachelor’s or higher. The new employment categories were full-time, part-time, and other (including retired, homemaker, and unemployed). Student status was recategorized as not a student and student (including part-time and full-time). We
Table 4.1. Demographic and socioeconomic characteristics of survey respondents.

<table>
<thead>
<tr>
<th></th>
<th>Count</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>24.4</td>
</tr>
<tr>
<td>30–39</td>
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<td>33.7</td>
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<tr>
<td>40–49</td>
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</tr>
<tr>
<td>60–65</td>
<td>6</td>
<td>7.0</td>
</tr>
<tr>
<td>Over 65</td>
<td>5</td>
<td>5.8</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>27</td>
<td>31.4</td>
</tr>
<tr>
<td>Female</td>
<td>59</td>
<td>68.6</td>
</tr>
<tr>
<td><strong>Race/Ethnicity</strong></td>
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<td></td>
</tr>
<tr>
<td>Asian</td>
<td>4</td>
<td>4.7</td>
</tr>
<tr>
<td>Black or African American</td>
<td>21</td>
<td>24.4</td>
</tr>
<tr>
<td>Hispanic</td>
<td>4</td>
<td>4.7</td>
</tr>
<tr>
<td>White</td>
<td>55</td>
<td>64.0</td>
</tr>
<tr>
<td>Prefer not to answer</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td><strong>Annual Household Income</strong></td>
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<tr>
<td>Under $20,000</td>
<td>22</td>
<td>25.6</td>
</tr>
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<td>$20,000–$40,000</td>
<td>23</td>
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<td>$60,000–$80,000</td>
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<td>10.5</td>
</tr>
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<td>$80,000–$100,000</td>
<td>5</td>
<td>5.8</td>
</tr>
<tr>
<td>Over $100,000</td>
<td>5</td>
<td>5.8</td>
</tr>
<tr>
<td>Prefer not to answer</td>
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<td>4.7</td>
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<tr>
<td><strong>Highest Level of Education Completed</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than high school</td>
<td>2</td>
<td>2.3</td>
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<tr>
<td>High school diploma or equivalent</td>
<td>15</td>
<td>17.4</td>
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<tr>
<td>Post secondary, non-degree award</td>
<td>6</td>
<td>7.0</td>
</tr>
<tr>
<td>Some college, no degree</td>
<td>21</td>
<td>24.4</td>
</tr>
<tr>
<td>Associate’s Degree</td>
<td>5</td>
<td>5.8</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>25</td>
<td>29.1</td>
</tr>
<tr>
<td>Master’s Degree</td>
<td>10</td>
<td>11.6</td>
</tr>
<tr>
<td>Doctoral or Professional Degree</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td><strong>Employment Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed full-time</td>
<td>42</td>
<td>48.8</td>
</tr>
<tr>
<td>Employed part-time</td>
<td>25</td>
<td>29.1</td>
</tr>
<tr>
<td>Homemaker or stay at home parent</td>
<td>6</td>
<td>7.0</td>
</tr>
<tr>
<td>Retired</td>
<td>9</td>
<td>10.5</td>
</tr>
<tr>
<td>Unemployed</td>
<td>4</td>
<td>4.7</td>
</tr>
<tr>
<td><strong>Student Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not a student</td>
<td>66</td>
<td>76.7</td>
</tr>
<tr>
<td>Part-time student</td>
<td>8</td>
<td>9.3</td>
</tr>
<tr>
<td>Full-time student</td>
<td>12</td>
<td>14.0</td>
</tr>
</tbody>
</table>
recategorized acclimatization to create two categories: more than 10 years of residency in the southeastern U.S. and 10 or fewer years of residency in the southeastern U.S. The new social cohesion categories were cohesive (including survey responses of somewhat confident and very confident that they had social support) and not cohesive (including survey responses of not too confident and not confident at all that they had social support). Finally, self-reported health status was recategorized as excellent, good (including very good and good), and fair to poor.

We used hierarchical coding to analyze the open-ended survey responses. Each response was categorized into primary themes and then further into secondary themes (Miles et al. 2014). Some responses were included in multiple primary and secondary themes, as they contained information that could potentially contribute to the data analysis in more than one context (Miles et al. 2014). For example, for the question, “Why do you feel that hot days and heatwaves are dangerous to you?” a participant responded:

“I work outside often, and I have read about how prolonged exposure to extreme heat can lead to kidney problems through repeated dehydration.”

This was placed under both the “exposure (outside/work)” and “health” primary themes. This response was further assigned a secondary code of “dehydration.” Some of the themes that resulted from our thematic data analysis were applied to our dataset as categories to enable us to preform statistical analysis for information that was provided in a qualitative format.

We used multiple logistic regression to determine whether socioeconomic and demographic characteristics affected how respondents described hot days. Multiple logistic regression was also used to determine if the amount of time spent in the southeastern United States (acclimatization) affects respondents’ descriptions of hot days. We used Chi-squared to
test the associations between individual characteristics/perceptions and 1) reported heat-health effects and 2) reported heat adaption behaviors.

4.3.1 Study Limitations

Sampling urban neighborhoods can introduce potential problems because there is no efficient and practical way to collect information on all behaviors and perspectives in a large group of people (Arcury and Quandt 1999; Campbell et al. 2010). This was considered during data analysis. Snowball sampling was used with care to avoid overrepresentation of specific personalities or groups (Arcury and Quandt 1999). To account for these limitations, we used purposive sampling instead of random, representative, convenience, or stratified sampling procedures (Tongco 2007). Purposive sampling allows for efficient data collection while maintaining a low level of bias (Tongco 2007).

This study is based on a small sample size. This is partly because we physically went out to collect data, instead of using phone, email, or mail to distribute the surveys. The small sample size is also reflective of our decision to use a mixed-methods approach including qualitative data analysis, which allows us to delve deeper into our participants’ responses, rather than casting a wide net as seen in other studies using quantitative data. However, a smaller sample size could result in fewer significant results during statistical analyses.

We collected data from June through November, which may result in a seasonal bias in the survey responses (Miles et al. 2014; World Health Organization 2019). For example, respondents that took the survey during the warm season might be more concerned about heat-related issues than someone who took the survey during the late fall, when the weather was cooling down.
4.4 Results and Discussion

4.4.1 How do respondents describe uncomfortably hot weather?

Respondents were asked, “How do you describe uncomfortably hot weather?” and their open-ended answers were placed into five primary themes (Table 4.2). Of the five major themes, the most common was for respondents to describe uncomfortably hot weather in terms of specific weather conditions. To a lesser degree, participants also described uncomfortably hot weather as times when they needed to alter their normal behaviors and activities, when they were generally uncomfortable, and when they experienced health effects, such as breathing difficulties and sweating. Approximately 10% of participants reported that they were generally indifferent to heat. According to our multiple logistic regression analyses, citing being indifferent to heat was not significantly ($p<0.05$) affected by 1) socioeconomic characteristics, 2) demographic characteristics, 3) self-reported health status, or 4) acclimatization to heat.

We looked further into our most commonly assigned theme, which was defining heat using specific weather conditions. Of the 45 responses that fit into this category, describing uncomfortably hot weather as temperatures above 90 °F (n=13) or humid (n=14) was most common. Six respondents described uncomfortably hot weather as temperatures between 80 and 89 °F. Thirteen respondents answered in a way that we described as “other.” Examples of responses from the “other” category include “Sub Saharan Africa hot,” “Searing oven,” “Heat waves,” and “Late summer.” According to our multiple logistic regression analyses, describing uncomfortably hot weather as a specific weather condition was not significantly ($p<0.05$) affected by 1) socioeconomic characteristics, 2) demographic characteristics, 3) self-reported health status, or 4) acclimatization to heat. Little research has been published on how the public describes hot weather. Currently, the National Weather Service defines excessive heat based on specific heat
Table 4.2. Examples of open-ended responses to the survey question, “How do you describe uncomfortably hot weather?” (n=86). As some responses fit into multiple themes, the total number and percentage of responses described below is greater than 86 samples and 100%.

<table>
<thead>
<tr>
<th>Specific weather conditions</th>
<th>Change in activities and normal behavior</th>
<th>General discomfort</th>
<th>Health effects</th>
<th>Indifference to heat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total number and percent of responses</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=45</td>
<td>n=16</td>
<td>n=11</td>
<td>n=9</td>
<td>n=9</td>
</tr>
<tr>
<td>52.3%</td>
<td>18.6%</td>
<td>12.8%</td>
<td>10.5%</td>
<td>10.5%</td>
</tr>
<tr>
<td><strong>Example responses</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“Anything above 95°.”</td>
<td>“It makes me feel like I can not [sic] move or act like normal people anymore.”</td>
<td>“Uncomfortable in pants.”</td>
<td>“Dizzy, sweating.”</td>
<td>“I’m rarely uncomfortable in heat.”</td>
</tr>
<tr>
<td>“Muggy – like breathing through a wet washcloth.”</td>
<td>“If I need to turn on extra fans.”</td>
<td>“Miserable.”</td>
<td>“Suffocating.”</td>
<td>“Undesirable but tolerable.”</td>
</tr>
<tr>
<td>“More than 90°F and 90% humidity.”</td>
<td>“When it’s too hot to hike, etc.”</td>
<td>“Awful.”</td>
<td>“Anytime it is hard to breathe.”</td>
<td>“I am more comfortable when it is hot.”</td>
</tr>
<tr>
<td>“Oppressive.”</td>
<td>“Uncomfortable is when you have to turn on the AC.”</td>
<td>“Unbearable.”</td>
<td>“Humid and energy draining.”</td>
<td>“It doesn’t bother me too much.”</td>
</tr>
<tr>
<td>“Summer – July/August.”</td>
<td>“Too hot to have the baby out.”</td>
<td>“Ugh!!!.”</td>
<td>“When you get heat exhaustion.”</td>
<td>“I am used to hot.”</td>
</tr>
</tbody>
</table>
indices and temperatures (National Weather Service 2019). While some respondents described hot weather based on specific temperatures and humidity levels, others equated hot weather to health effects, changes they needed to make to their normal activities, or general discomfort. Warning the public of excessive heat by using specific terminology, such as temperature, humidity, and heat index, may not be an effective way of communicating to those that do not use these terms to define dangerously hot weather. When specifically looking at ways to improve heat education, understanding how to describe heat to the public in a meaningful way is important to convey the importance of heat-related risks and helping the public understand how to recognize excessive heat conditions.

Only one respondent mentioned heat-related advisories as a way of defining uncomfortably hot weather by saying:

“If the meteorologist tells me to be careful.”

Other studies found that heat warnings, when heavily covered by the media, are an effective way of warning individuals of the risk of heat exposure (Sheridan 2007). However, Kalkstein and Sheridan (2007) found that apathy to heat exposure was partly because of lack of media coverage. Nearly 11% of our respondents were apathetic to uncomfortably hot days and many reported that their lack of concern was because they were acclimatized to excessive heat, although this relationship was not statistically significant, which is likely a result of our small sample size.

4.4.2 How do respondents perceive heat danger?

We asked respondents, “Which weather event do you feel is the biggest threat to you?” Respondents could choose from 1) drought, 2) extreme cold, 3) extreme heat, 4) flooding, 5) hail,
6) ice storms and snow, 7) severe storms, 8) tornadoes, 9) all of the above, or 10) none. Only one respondent indicated that no meteorological hazards are dangerous to them. Overwhelmingly, respondents felt that severe storms and tornadoes (44.2%) and cold-related hazards (34.9%) were most dangerous. Only 14.0% of respondents indicated that they felt extreme heat was the biggest threat to them. Excessive heat is the deadliest meteorological hazard; however, heat events do not have the “awe factor” of other hazards, such as tornadoes and ice storms, and thus might be perceived as less dangerous (Sandman 1994; Kalkstein and Sheridan 2007). Likewise, heat events are more common in our study area than cold events, which may produce feelings of apathy as respondents may see excessive heat as a common event without much risk.

We asked respondents the single-select question, “How dangerous do you think hot days and heatwaves are to you?” If respondents indicated that they felt that extreme heat was a little, somewhat, or very dangerous to them (n=75), they were asked the open-ended question, “Why do you feel hot days and heatwaves are dangerous to you?” Analyses of their answers resulted in six themes, the most common being health, exposure, and general danger (Table 4.3). The themes of age, general discomfort, and social cohesion only included 6.0%, 8.6%, and 2.8% of responses, respectively, and are not discussed here. Exposure was cited as a reason why hot days and heatwaves are dangerous, with sub-themes including being outside during hot weather (50.0% of respondents who cited exposure) and being exposed while at work (37.5% of respondents who cited exposure). Multiple logistic regression results suggest that socioeconomic and demographic characteristics, self-reported health status, and acclimatization to heat did not have a statistically significant \( p<0.05 \) effect on respondents’ reasoning for why they felt hot days and heatwaves were dangerous to them, which could be a result of our small sample size.

Common sub-themes of health dangers cited by respondents were dehydration (35.9% of respondents who cited health as why heat is dangerous), heat stroke and exhaustion (20.5%),
Table 4.3. Examples of open-ended responses to the survey question, “Why do you feel hot days and heatwaves are dangerous to you?” (n=70). Themes that included less than 10% of responses are not included here.

<table>
<thead>
<tr>
<th>Total number and percent of responses</th>
<th>Health</th>
<th>Exposure (Outside/Work)</th>
<th>General Danger</th>
</tr>
</thead>
<tbody>
<tr>
<td>n=39 55.7%</td>
<td>n=16 22.9%</td>
<td>n=8 11.4%</td>
<td></td>
</tr>
<tr>
<td>Example responses</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“It’s easy to get dehydrated.”</td>
<td>“I am exposed to them [heatwaves] more often than any other weather activity.”</td>
<td>“They are dangerous, but I take measures to protect myself.”</td>
<td></td>
</tr>
<tr>
<td>“Risk for heat exhaustion.”</td>
<td>“I walk to work.”</td>
<td>“Extreme weather is dangerous to everyone if proper precautions, etc. are not taken.”</td>
<td></td>
</tr>
<tr>
<td>“I have heart problems and have trouble breathing when hot.”</td>
<td>“Too hot to work.”</td>
<td>“Heat is dangerous to everyone.”</td>
<td></td>
</tr>
<tr>
<td>“…I get migraines from the heat occasionally.”</td>
<td>“I enjoy running and hiking so I am outdoors a lot.”</td>
<td>“Heatwaves make normal activities dangerous.”</td>
<td></td>
</tr>
<tr>
<td>“I work outside often, and I have read about how prolonged exposure to extreme heat can lead to kidney problems through repeated dehydration.”</td>
<td>“Makes it hard to be outside.”</td>
<td>“Not as dangerous as cold but extreme weather is a risk.”</td>
<td></td>
</tr>
</tbody>
</table>
respiratory issues (20.5%), and general health dangers (33.3%). Examples of general health dangers included, “can be deadly,” “without adequate elements such as shade and water, hot days can pose a serious health risk to anyone,” and “you can overheat.”

Only one respondent noted mental health issues resulting from heat events:

“I find that my mental health is affected by having to find shelter from the heat. Being outside for extended periods during the hottest part of the year can lead to feeling physically ill from exhaustion/dehydration, and being confined inside to escape the heat becomes mentally draining.”

Mason et al. (2018), however, found that more than 55% of Knoxville residents in lower- to moderate-income neighborhoods experienced mental health effects from summer heat. We did not specifically provide “mental health effects” as an option for the categorical response options to the question of, “What health effects do you typically experience during hot weather?” (see section 4.4.3). These differing results suggest that the mental health effects of heat may not be well known by the public and they may not connect the ideas of heat exposure and mental health if unprompted. This could be in part because heat-related illnesses are not well reported by the media (Sandman 1994).

In a previous study, increased social cohesion, or the amount of social support an individual feels that they have, resulted in a decreased report of physical or mental impacts from summer heat (Mason et al. 2018). Only two of our respondents reported lack of social cohesion as a reason why they feel excessive heat is dangerous to them by both saying, “I live alone.” This theme was more prominent in the Mason et al. (2018) study. Increasing the social cohesion of a neighborhood by developing systems to check on one another during heat and other
dangerous weather events is one potential way to reduce delayed heat-health impacts for some individuals (Browning et al. 2006; Mason et al. 2018), yet our research shows that for many others social cohesion is not a primary concern and the effects of social cohesion may vary by neighborhood, socioeconomic, and health characteristics.

Nearly 23% of respondents cited exposure while outside and/or while at work as a reason why they feel excessive heat is dangerous. Occupational studies using personal temperature sensors indicated that higher temperatures, exposure to direct sunlight, and exposure to heat from machinery led to outdoor workers being exposed to excessive heat (Sugg et al. 2018; Uejio et al. 2018). Options for reducing heat-related illnesses at work include periodically moving to temperature-regulated locations to reduce exposure, staying hydrated, seeking shade, reducing physical exertion, and allowing time to acclimatize to excessive heat (Sugg et al. 2018; Uejio et al. 2018; Hosokawa et al. 2019). While the Occupational Safety and Health Administration, the National Institute for Occupational Safety and Health, and other agencies recommend specific ways in which employers should address employee heat exposure (Hosokawa et al. 2019), our study shows that occupational heat exposure is still a concern in Knoxville. Studies assessing employee exposure to high temperatures and humidity in specific work environments could help employers ensure they are reducing their employees’ risk for heat-related illnesses.

4.4.3. What health effects do respondents typically experience during hot weather?

We asked respondents, “What health effects do you typically experience on hot days?” The options respondents were able to choose from included 1) sweating, 2) headache, 3) dehydration, 4) nausea, 5) confusion, 6) muscle cramps, 7) no effects, and/or 8) other symptoms (open ended). Sweating, dehydration, headaches, and muscle cramps were most reported as being experienced by respondents on hot days (Table 4.4). Only one respondent
Table 4.4. Percent of respondents that reported health effects and Chi-squared results for the associations between reported heat-health effects and personal characteristics and perceptions (n=85). The Chi-squared value (X²) and significance codes (* 0.05, ** 0.01, *** 0.001 or less) are provided. Italicized numbers are the difference between observed and expected values for each significant result. Negative numbers indicate that there were less observations than expected.

<table>
<thead>
<tr>
<th>Percent of respondents that reported health effect(s)</th>
<th>Sweating</th>
<th>Dehydration</th>
<th>Headaches</th>
<th>Muscle Cramps</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=83</td>
<td>n=55</td>
<td>n=20</td>
<td>n=20</td>
</tr>
<tr>
<td>Work</td>
<td>96.5%</td>
<td>64.0%</td>
<td>23.3%</td>
<td>23.3%</td>
</tr>
<tr>
<td>Full-time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.909</td>
<td>3.622</td>
<td>4.174</td>
<td>16.442***</td>
</tr>
<tr>
<td>Part-time</td>
<td></td>
<td></td>
<td></td>
<td>-3.8</td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td></td>
<td>-2.8</td>
</tr>
<tr>
<td>Social cohesion</td>
<td></td>
<td></td>
<td></td>
<td>6.5</td>
</tr>
<tr>
<td>Cohesive</td>
<td>0.882</td>
<td>2.823</td>
<td>10.070*</td>
<td>1.858</td>
</tr>
<tr>
<td>Not cohesive</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-1.6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whether or not respondents felt heat was dangerous</td>
<td>8.089**</td>
<td>7.362***</td>
<td>3.822</td>
<td>3.822</td>
</tr>
<tr>
<td>Yes</td>
<td>10.6</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>-8.6</td>
<td>-4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cited “health” as why heat is dangerous</td>
<td>3.822</td>
<td>4.514*</td>
<td>4.578*</td>
<td>1.236</td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td>4.7</td>
<td>4.2</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td></td>
<td>-4.7</td>
<td>-4.2</td>
<td></td>
</tr>
</tbody>
</table>
reported having no health effects on hot days. No respondents reported that they experienced nausea or confusion.

The respondent’s work status was only associated with experiencing muscle cramps. Fewer full- and part-time workers experienced muscle cramps than expected. Conversely, more participants in our “other” work category experienced muscle cramps than expected, likely because this category includes those more prone to heat-related illnesses, such as retired individuals at an advanced age. Work status did not affect the other variables, showing that headaches, dehydration, and sweating affect a larger and broader population.

Social cohesion was only associated with headaches and, as shown by p-value and a small difference in observed versus expected values, it is not a notable finding. Thus, social cohesion, in this study, did not prove to be highly related to the health effects that we tested. This is likely because our respondents did not connect their social cohesion with heat-health concerns or do not feel that they are at risk for heat-health issues. Browning et al. (2006) found that structural characteristics and social trust affects the social cohesion of a neighborhood. We collected many of our surveys in a door-to-door manner and in community meetings and thus collected in spaces where there were increased structural characteristics, such as sidewalks and gathering areas, and greater social trust, such as in areas generally considered safe or within groups of individuals that were invested in their neighborhoods. This data collection pattern could have created a bias towards collecting information in areas with greater social cohesion.

Perceptions of heat and heat-health danger were each significantly related to two of the health effects, with those who think heat is dangerous and a health concern reporting more health effects than expected. An individual’s perception of their risk for heat-related illnesses plays a significant role in whether respondents reported health effects during excessive heat. These perceptions may come from previous exposure to excessive levels of heat (Perry and Lindell
Respondents may be more sensitive to heat-health risks if they or someone they know has experienced the hazard before (Perry and Lindell 1997), and thus might be more likely to recognize or connect health effects to the hazard.

4.4.4 How do respondents adapt to hot weather?

When asked, “What behaviors or actions do you normally take during hot days and heatwaves?” the most common reported behaviors were using air conditioning (86.0%), making an extra effort to stay hydrated (80.2%), using fans (50.0%), avoiding overexertion (47.7%), seeking a cooler location (46.5%), avoiding being outside (45.3%), changing clothing (34.9%), and using water features, such as splash pads and pools (22.1%). Those that were found to be significantly associated to any of the personal characteristics or perception variables are listed in Table 4.5.

Using water features was significantly more common for those who have been in the southeastern United States less than 10 years, those in excellent or good health, and those who are students. Those who are not acclimatized to the weather are likely using water features more because it is a common-sense heat adaption method. Students, on the other hand, might use water features because it is cost efficient, with pools being generally available to students for free through their school or publicly for a minimal cost.

Seeking a cooler location was more common for respondents who perceived heat as dangerous and for those who cited heat-health concerns. Of the heat adaption behaviors that respondents chose from, seeking a cooler location was one of the most accessible and inexpensive options. This is also a common-sense behavior. Those with health concerns are likely using this adaption method to reduce their exposure and thus reduce the likelihood that they will experience heat-health effects.
Table 4.5. Percent of respondents that reported behaviors and Chi-squared results for the associations between reported behaviors and personal characteristics and perceptions. The Chi-squared value ($X^2$) and significance codes (* 0.05, ** 0.01, *** 0.001 or less) are provided. Italicized numbers are the difference between observed and expected values for each category. Negative numbers indicate that there were less observations than expected.

<table>
<thead>
<tr>
<th>Number and percent of respondents that reported behavior</th>
<th>Using fans</th>
<th>Avoiding over exertion</th>
<th>Seeking cooler location</th>
<th>Avoiding being outside</th>
<th>Use water features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student</td>
<td>n=43</td>
<td>n=41</td>
<td>n=40</td>
<td>n=39</td>
<td>n=19</td>
</tr>
<tr>
<td>Yes</td>
<td>50.0%</td>
<td>47.7%</td>
<td>46.5%</td>
<td>45.3%</td>
<td>22.1%</td>
</tr>
<tr>
<td>No</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acclimatization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 10 yr</td>
<td>0.059</td>
<td>1.424</td>
<td>1.736</td>
<td>2.818</td>
<td>5.295*</td>
</tr>
<tr>
<td>More than 10 yr</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.9</td>
</tr>
<tr>
<td>Health</td>
<td>0.731</td>
<td>1.715</td>
<td>0.587</td>
<td>3.705</td>
<td>7.440*</td>
</tr>
<tr>
<td>Excellent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.8</td>
</tr>
<tr>
<td>Good</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.3</td>
</tr>
<tr>
<td>Fair to poor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-4.1</td>
</tr>
<tr>
<td>Whether or not respondents felt heat was dangerous</td>
<td>4.715*</td>
<td>0.822</td>
<td>7.583**</td>
<td>6.328*</td>
<td>0.100</td>
</tr>
<tr>
<td>Yes</td>
<td>2.5</td>
<td>5.2</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>-2.5</td>
<td>-5.1</td>
<td>-1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cited “health” as why heat is dangerous</td>
<td>2.606</td>
<td>10.26**</td>
<td>10.968***</td>
<td>0.411</td>
<td>1.492</td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Respondents who did not alter their normal schedule on hot days were asked in an open-ended question, “Why do you not change or move daily activities on hot days?” (Table 4.6). There were three main themes for why they do not change their activities on hot days: 1) they are acclimatized to or well prepared for heat, 2) they cannot alter their schedule because of work or other factors, and 3) they do not normally spend time outside and are thus not exposed to changes in temperature.

The perception of a lack of heat danger and heat-health danger had the most effects on respondents not taking adaption actions. This pattern was also reported by Sheridan (2007), Abrahamson et al. (2008), and Toloo et al. (2013). Some individuals feel “pride” that they can handle uncomfortably hot weather (Sheridan 2007). Others simply do not see themselves at risk (Sheridan 2007; Abrahamson et al. 2008). These perceptions can result in an individual not taking adaption actions to reduce exposure and thus potentially exposing themselves to heat-health risks. One opportunity to improve risk perception is to have media outlets inform their audience on which populations are vulnerable to heat-health risks during heat advisories and warnings (Sheridan 2007).

Nearly one in 10 respondents cannot or feel that they are unable to take adaption actions and are at a higher risk for heat-related illnesses. Individuals who cannot alter their routine and feel they are acclimatized or “used to” heat would benefit from advanced heat-health education provided by the National Weather Service, city governments, or other outreach personnel. These educational opportunities should include the development of individual action plans could help those who simply do not want to alter their routines or feel that there are no other options but to keep with business as usual.
Table 4.6. Examples of open-ended responses to the survey question, “Why do you not change or move daily activities on hot days?” (n=29).

<table>
<thead>
<tr>
<th>Total number and percent of responses</th>
<th>Acclimatized to heat or well prepared</th>
<th>Cannot alter schedule</th>
<th>Does not normally spend time outside</th>
</tr>
</thead>
<tbody>
<tr>
<td>n=11 37.9%</td>
<td>n=9 31.3%</td>
<td>n=7 24.1%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Example responses</th>
<th>“Am easily acclimated to extreme heat/cold.”</th>
<th>“I walk a short distance to my job.”</th>
<th>“I do not spend a lot of time outside.”</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“Used to heat.”</td>
<td>“It would disturb my routine.”</td>
<td>“Because I don’t have to be outdoors.”</td>
</tr>
<tr>
<td></td>
<td>“I feel safe as long as I prepare.”</td>
<td>“Some activities cannot be avoided.”</td>
<td>“I don’t go outside.”</td>
</tr>
</tbody>
</table>
4.5 Conclusions

We used a mixed-methods survey to assess how respondents in Knoxville, Tennessee, describe, experience, perceive, and adapt to hot weather. Our results indicate that a multi-faceted approach to reducing heat vulnerability is needed as individuals within an urban area have varying concerns. We specifically suggest increasing access to heat adaption methods, strengthening social cohesion, refining heat risk communication, and changing the perception of heat-related dangers through community education. However, these suggestions for systemic changes will take resources, including time and financial support. Our results support first focusing on individual-level heat adaption methods, such as using air conditioning, seeking a cooler location, and using water features.

Currently, many individuals do not perceive heat as a danger. Changing this perception is imperative as the warm season is expected to become warmer and longer, and heatwaves are expected to become more frequent and intense. Likewise, our results found there is a discordance between traditional heat communication methods and the needs of residents, which may affect how individuals perceive heat danger. One example of these misaligned communication methods is that many of our respondents defined heat primarily based on changes they needed to make to their normal routine. Those who describe heat in ways other than quantitative temperature and humidity measurements may not understand their risk for exposure when being presented with only specific weather conditions. A second example is that our results suggest that, while the majority of survey respondents feel that excessive heat is at least somewhat dangerous to them, less respondents feel heat is a health risk. We recommend that the media inform their audience of heat-related risks by using specific weather conditions to outline heat danger, and by emphasizing health risks, vulnerable populations, and how people might need to change their normal routine to
avoid heat exposure. While some National Weather Service offices have begun distributing infographics on social media to inform the public of excessive heat risk and heat-adaptive actions, this information does not typically contain information on the populations most at risk for heat-related illnesses. These infographics are also not usually distributed during normal climate conditions, when some individuals are more exposed to heat as they are taking less adaptive actions (Hass 2019). Heat education provided by the media, the National Weather Service and similar agencies, city governments, and other outreach professionals is also needed to change the public’s perception of heat. These educational opportunities should include information on health risks, vulnerable populations, heat awareness, and adaption options to increase the prevalence of heat adaption activities. Heat education should also include individual action plans to ensure that the public is prepared for excessive heat before it occurs. We also suggest further research to understand how the public defines heat to bolster media coverage and strengthen heat education efforts.

Whether respondents experience health issues during excessive heat plays a notable role on their perception of heat danger and if they take heat adaption actions to avoid exposure. Those who perceive that heat is dangerous are more likely to recognize heat-related dangers and health risks and take actions to reduce heat exposure. Those who do not feel that they are at risk for heat-health issues are less likely to take adaption actions. This is important as it shows that perception is a critical decision-making component in deciding which adaption actions to take.

Social cohesion was not a primary concern to our respondents; however, it is an important aspect in reducing vulnerability to heat-health effects. We suggest programs to strengthen social cohesion in vulnerable neighborhoods to reduce time-delayed heat-health effects. Increasing social trust and building more extensive neighborhood structures, such as sidewalks, are two methods of growing social cohesion in a neighborhood.
This research adds to the small research base that uses qualitative analyses in climatology research. Our mixed-methods approach allowed for the statistical analyses necessary to gain insight into broad concepts, such as whether respondents felt heat was dangerous, while the qualitative thematic coding shed light on deeper ideas, such as why they felt heat was dangerous, supporting the need for education on why heat is dangerous. While more significant patterns might emerge from statistical analyses of a larger sample size, small-scale studies and qualitative research allows for respondents to provide information outside of set boundaries and expand our knowledge base beyond what has been previously studied and in ways we may not have hypothesized. For example, when asking respondents why they did not change their behavior to avoid heat exposure, some simply felt that they were not able to change their routine because, for instance, their transportation to work is walking or they do not feel comfortable changing their routine. These ideas would not have been accessible using single- or multi-select questions. Future survey-related climatology research should aim to include some open-ended response questions to gain insight into ideas and themes that researchers may not currently be aware of.
4.6 Acknowledgments

This work was funded by a University of Tennessee, Knoxville Thomas Graduate Fellowship. We thank Erica Massengill for her assistance in collecting surveys. We appreciate the community members who graciously participated in this research. We thank Micheline Van Riemsdijk for her guidance in qualitative methods and developing the survey. We also thank committee members, Sally Horn, Solange Munoz, and Jiangang Chen, for their valuable comments and suggestions to improve this research and manuscript.
4.7 References


Chapter 5

Conclusions
5.1 Summary of Research

The goal of this research was to determine how residents of Knoxville, Tennessee, vary in their exposure to, perceptions of, and adaption to high temperatures and humidity. To achieve this goal, we used a comprehensive approach, including collecting and analyzing data from 1) weather stations in urban neighborhoods and reference locations, 2) a weather station at a nearby airport, 3) personal weather sensors, and 4) surveys.

To determine how heat indices in urban neighborhoods vary during a warm season, we collected temperature and humidity data in four neighborhoods with differing socioeconomic, demographic, and population-density characteristics. These neighborhoods included West Hills, Vestal, Lonsdale, and Burlington. Two weather stations were deployed in each neighborhood, one each in a highly vegetated location and one each in a minimally vegetated location. We also collected data from one weather station in downtown Knoxville, which served as the representative proxy for weather in the urban core, and one weather station in Ijams Nature Center, which served as the representative proxy for weather in a rural area. Temperature and humidity data were converted to heat index values to assess the “feels like” temperature, which may more closely predict heat-health effects than actual temperature. We used statistics to assess how heat index varied within and between neighborhoods, whether there were significant differences between locations during the top 10% of heat index values, and to determine whether land cover and neighborhood characteristics, such as population density, influenced heat index values at each location.

We assessed personal heat exposure, actions, and perceptions for 38 Knoxville residents by collecting and analyzing lifestyle surveys and individual temperature and humidity data during heatwave and normal climate conditions. Temperature and humidity data were collected using
wearable sensors, a new technology in applied climatology. These data were converted into heat index values to determine the “feels like” temperature to which each individual was exposed. Participants’ individual heat indices were compared to ambient conditions at a nearby airport to determine whether the traditionally reported conditions from nearby airports were a reliable measure of the conditions to which individuals were exposed. We analyzed differences in participant heat exposure during a heatwave and climatically normal conditions, and between daytime and nighttime using statistical methods. We also assessed participant perception of heat exposure and the factors that affected the adaption actions that participants took during hot weather.

Finally, we used a mixed-methods community survey to determine how 86 Knoxville, Tennessee, residents describe and interpret their personal risk during heatwaves and how their perceptions affect the heat adaption methods they use. We analyzed open-ended survey responses, such as the reasons respondents cited for perceiving heat as a danger to them, using thematic analyses, which is an underutilized method in heat exposure research. We used statistical tests to assess associations between the answers to our closed-ended questions on personal characteristics, heat-health effects, and heat adaption behaviors, and the qualitative themes that described heat perception and the reasons respondents did or did not take heat adaption actions.

5.2 Major Conclusions

5.2.1 Variability of neighborhood heat index values

In Knoxville, tree cover affects how heat is felt throughout an urban area. Our results suggest that areas with more vegetation have a higher heat index because vegetation increases
evapotranspiration and thus increases relative humidity. These results counter the traditional urban heat island pattern of higher temperatures being observed in areas with more impervious surfaces and highlight the importance of including relative humidity in urban climate studies. Incorporating relative humidity by using the heat index variable provides a more accurate assessment of the conditions to which urban residents may be exposed.

Tree cover is related to the socioeconomic and population-density characteristics of an urban neighborhood. We found that neighborhoods with higher average income and lower population densities exhibit a higher heat index because of increased vegetation. However, individuals in higher-income neighborhoods likely have more resources to adapt to or mitigate heat than individuals in neighborhoods with low or average income, potentially negating the variation in exposure. Thus, heat exposure is likely more of a concern for individuals living in lower socioeconomic neighborhoods who often have less access to adaption resources. Additionally, the relationship between vegetation and heat exposure is complicated because, despite a higher heat index, shading from vegetation can increase thermal comfort and decrease the demand for energy used for cooling buildings.

5.2.2 Variability of personal heat exposure, perceptions, and adaption actions

Our results suggest that ambient airport conditions are not reflective of residents’ heat exposure during a heatwave, with individuals being less exposed to heat during the daytime than airport conditions suggest. We found that nighttime heat exposure is a major issue, with participants often experiencing heat indices greater than the National Weather Service criteria for a heat advisory at night. Increased nighttime exposure above the heat advisory threshold likely occurs because the temperature required to meet the heat advisory criteria is lower at night than during the day. However, this increased exposure remains a concern as individuals are more
likely to experience heat-health effects if they are not able to physically cool down and recover from daytime heat exposure. Heat advisory thresholds also do not account for personal characteristics, such as age, that may make an individual more vulnerable to heat-health effects.

The use of heat adaption methods can reduce vulnerability to heat-health effects. Those who perceive that they are in danger from heat exposure are more likely to use heat adaption methods, reducing their risk for heat-health effects. Likewise, education and income are significantly related to the use of heat adaption methods and reduced heat exposure. Education likely increases the knowledge of the danger heat poses and income often increases access to adaption methods. Efforts such as heat education and increased access to adaption methods are needed to reduce the risk of heat-health effects for those that are less educated or have a lower income.

5.2.3 Variability in the factors that affect the way individuals describe, perceive, and adapt to heat

When we asked residents how to describe heat, many individuals did so according to their need to change their normal behavior or based on other consequences, such as feeling uncomfortable or experiencing health effects. Describing heat based on a change in behaviors or consequences counters traditional heat risk communication methods that use specific weather conditions to define heat risk. These traditional communication methods may not be effective across an entire population and may result in a misunderstanding of an individuals’ risk for heat exposure and heat-health effects.

Our results show that many individuals do not perceive themselves as being vulnerable to heat-health effects because they are acclimatized to heat or are otherwise healthy. Heat danger perception may play a critical role in heat vulnerability, especially as heatwaves and hot days...
become more frequent and intense, because it affects whether an individual takes adaption actions. Those who do not perceive that they are at risk for heat-related illnesses or are unable to alter their schedule are less likely to take adaption actions and are more vulnerable to heat-health issues. Individuals that experience heat-health issues are more likely to feel that heat is dangerous and take heat adaption actions, likely reducing their vulnerability to heat-health issues. Heat-related education is needed to ensure individuals exposed to excessive heat understand whether they are part of a vulnerable population and are aware of the actions they can take to reduce their vulnerability.

5.3 Future Research

This research emphasized the importance of using relative humidity in research related to the thermal comfort of urban areas. The inclusion of relative humidity in neighborhood heat assessments altered the pattern of the urban heat island and provided surprising results that higher income and less population-dense neighborhoods observed higher ambient heat indices. Additional research in other regions, as well as different sized cities, is needed to determine if this effect is consistent across space, or if it is a function of a smaller city. A better understanding of how ambient heat is observed throughout an urban area is key to determining where more education and resources are needed to prepare a community for heat-related risks.

Our analysis of temperature and humidity data from personal sensors adds to a small but growing research base working to understand how individual characteristics and behaviors affect heat exposure. This research is only the second of such studies to include relative humidity, which has been shown to worsen heat-health effects. Studies that include more individuals over a longer time are necessary to clarify which populations are most exposed to heat and the factors
that contribute to exposure. We recommend more specialized studies that assess how individuals are exposed to heat during specific circumstances, such as college football games or while waiting at a transportation terminal.

We used qualitative research methods to assess how individuals describe, experience, and react to extreme heat. Qualitative research has only been minimally used in heat exposure studies; however, these methods allowed us to parse out information that would not have been available through single- or multi-select questions alone. Further, our results show that preparing a community for heat safety is a complicated matter. Some individuals need more refined communication, others need better access to heat adaption resources, some require improved heat education that includes individual action plans, and still others need to build stronger social cohesion. Research that dives deeper into the nuances of individual heat adaption and mitigation needs is needed to better prepare communities for heat-related concerns.
Appendices
Appendix A: iButton Survey

Individually Experienced Temperatures in Knoxville

Demographic Data
1. What neighborhood do you live in?

2. What is your age?
   a. 18–29
   b. 30–39
   c. 40–49
   d. 50–59
   e. 60–65
   f. Over 65

3. Are you male or female?
   a. Male
   b. Female

4. What is your racial or ethnic background?
   a. White
   b. Hispanic
   c. Black or African American
   d. Native American
   e. Asian
   f. Other
   g. Prefer not to answer

5. What is your approximate annual income for your entire household?
   a. Under $20,000
   b. $20,000–$40,000
   c. $40,000–$60,000
   d. $80,000–$100,000
   e. Over $100,000
   f. Prefer not to answer
6. What is the highest level of education that you have achieved?
   a. Less than high school
   b. High school diploma or equivalent
   c. Some college, no degree
   d. Post-secondary non-degree award
   e. Associate’s Degree
   f. Bachelor’s Degree
   g. Master’s Degree
   h. Doctoral or Professional Degree

7. Are you currently enrolled as a part-time or full-time student?
   a. Yes, part time student
   b. Yes, full time student
   c. No

8. What is your current employment status?
   a. Employed full-time (skip to question 8a)
   b. Employed part-time (skip to question 8a)
   c. Retired (skip to question 9)
   d. Unemployed (skip to question 9)
   e. Homemaker or stay at home parent (skip to question 9)

8a. Do you typically work (circle all that apply):
    ___ At home
    ___ At a fixed job site
    ___ At a mobile job site
    ___ Outside
    Other _____________________

   Proceed to question 9.

Housing

9. What state(s) and/or countries have you previously lived in for at least one year (please do not use abbreviations)?

10. In total, how long have you resided in the Southeastern United States?
    a. Less than 1 year
    b. 1–5 years
    c. 5–10 years
    d. 10 or more years
11. What type of housing do you live in?
   a. Single family house
   b. Duplex
   c. Apartment
   d. Condo
   e. Townhouse
   f. Mobile home
   g. Other _______________________

12. Do you feel that your housing is well insulated with tightly sealed windows and doors?
   a. Yes
   b. No
   c. Unsure

13. Do you have and use a working air conditioner in your residence?
   a. Yes
   b. No
Appendix B: Activity Log

**Activity Log**
Assessing heat in Knoxville, Tennessee

*Please do not wear the sensor underneath clothing (for example, in your pocket) or while swimming, bathing, or sleeping.*

**Day 1: Day of week__________________________ Date________________________**

1. Did you wear your iButton today? [ ] Yes [ ] No

2. Where was your iButton when you were not wearing it?
________________________________________________________________________

3. Did you work today? [ ] Yes [ ] No
   a. If Yes, what time did you arrive at work today? _________ [ ] am [ ] pm
   b. If Yes, what time did you leave work today? _________ [ ] am [ ] pm

4. At any point today, did you take any actions to reduce your exposure to high temperatures? (Check all that apply)
   [ ] Stayed indoors
   [ ] Used an air-conditioner
   [ ] Minimized outdoor work
   [ ] Drank plenty of water or non-alcoholic beverages
   [ ] Wore light, loose-fitting clothing
   [ ] Wore a hat
   [ ] Reduced activity
   [ ] Went to an air-conditioned place to cool-off
   [ ] Sought out shade
   [ ] Changed your daily routine
   [ ] Scheduled heavy work during the coolest parts of day
   [ ] Other (specify)

5. How hot or cold were you during the day (8:00 am – 6:00 pm)?
   [ ] Cold
   [ ] Neither cold nor hot
   [ ] Warm
   [ ] Hot
   [ ] Very hot
   [ ] Refused

6. How hot or cold were you during the night (6:00 pm – 8:00 am)?
   [ ] Cold
   [ ] Neither cold nor hot
   [ ] Warm
   [ ] Hot
   [ ] Very hot
   [ ] Refused

Comments: _______________________________________________________________________

Thank you for taking the time to complete this survey.
Appendix C: Community Survey

Behaviors of Knoxville Residents During Hot Weather

Demographic Data
1. What neighborhood do you live in?

2. What is your age?
   a. 18–29
   b. 30–39
   c. 40–49
   d. 50–59
   e. 60–65
   f. Over 65

3. Are you male or female?
   a. Male
   b. Female

4. What is your racial or ethnic background?
   a. White
   b. Hispanic
   c. Black or African American
   d. Native American
   e. Asian
   f. Other
   g. Prefer not to answer

5. What is your approximate annual income for your entire household?
   a. Under $20,000
   b. $20,000–$40,000
   c. $40,000–$60,000
   d. $60,000–$80,000
   e. $80,000–$100,000
   f. Over $100,000
   g. Prefer not to answer
6. What is the highest level of education that you have achieved?
   a. Less than high school
   b. High school diploma or equivalent
   c. Some college, no degree
   d. Post-secondary non-degree award
   e. Associate’s Degree
   f. Bachelor’s Degree
   g. Master’s Degree
   h. Doctoral or Professional Degree

7. Are you currently enrolled as a part-time or full-time student?
   a. Yes, part time student
   b. Yes, full time student
   c. No

8. What is your current employment status?
   a. Employed full-time (skip to question 8a)
   b. Employed part-time (skip to question 8a)
   c. Retired (skip to question 9)
   d. Unemployed (skip to question 9)
   e. Homemaker or stay at home parent (skip to question 9)

8a. Do you typically work (circle all that apply):
    At home
    At a fixed job site
    At a mobile job site
    Outside
    Other _____________________

   Proceed to question 9.

Housing
9. What state(s) and/or countries have you previously lived in for at least one year (please
do not use abbreviations)?

10. In total, how long have you resided in the Southeastern United States?
    a. Less than 1 year
    b. 1–5 years
    c. 5–10 years
    d. 10 or more years
11. What type of housing do you live in?
   a. Single family house
   b. Duplex
   c. Apartment
   d. Condo
   e. Townhouse
   f. Mobile home
   g. Other _______________________

12. Do you feel that your housing is well insulated with tightly sealed windows and doors?
   a. Yes
   b. No
   c. Unsure

13. Do you own or rent your home?
   a. Own (skip to question 13a)
   b. Rent (skip to question 13b)
   c. Other (skip to question 14)

13a. As a homeowner, what measures do you or your Home Owners Association take to reduce the amount of heat in or around your home?

   Proceed to question 14.

13b. As a renter, what measures do you or the owners of your rental property take to reduce the intensity of heat around your rental property?

   Proceed to question 14.

General Health

14. Considering your age, how would you describe your general health?
   a. Excellent
   b. Very good
   c. Good
   d. Fair
   e. Poor
   f.
Weather Threats and Behaviors

15. Which weather event do you feel is the biggest threat to you?
   a. Severe storms
   b. Tornados
   c. Ice storms and snow
   d. Extreme cold
   e. Extreme heat
   f. Drought
   g. Flooding
   h. Other ________________________

16. Why do you feel that this weather event is the biggest threat to you?

17. How do you describe uncomfortably hot weather?

18. How dangerous do you think hot days and heatwaves are to you?
   a. Very (skip to question 18a)
   b. Somewhat (skip to question 18a)
   c. A little (skip to question 18a)
   d. Not at all (skip to question 18b)

   18a. Why do you feel that hot days and heatwaves are dangerous to you?

   Proceed to question 19.

   18b. Why do you feel that hot days and heatwaves are not dangerous to you?

   Proceed to question 19.
19. What health effects do you typically experience during hot days (circle all that apply)?

- Sweating
- Headache
- Dehydration
- Nausea
- Confusion
- Muscle cramps
- I do not experience any health effects on hot days
- Other ________________________

20. What behaviors or actions do you normally take during hot days and heatwaves (circle all that apply)?

- Avoid being outside
- Staying hydrated
- Drink less alcohol
- Use air conditioning
- Use fans
- Use pools, waterparks, or splash pads
- Change clothing
- Avoid overexertion
- Check on neighbors and elderly
- Seek cooler location
- I do not modify my behavior
- Other ________________________

21. If you see a cooler location, which of the following do you normally use (circle all that apply)?

- Shade
- Friend’s or relative’s house
- Shopping mall
- Movie theater
- Pool, waterpark, or splash pad
- Civic building
- Restaurant/bars
- I do not seek a cooler location
- Other ________________________

22. How much time do you normally spend outside on a normal day?

a. Less than one hour
b. 1–3 hours
c. 3–5 hours
d. 5–10 hours
e. 10–15 hours
f. 15 or more hours
23. How much time do you normally spend outside on a hot day?
   a. Less than one hour
   b. 1–3 hours
   c. 3–5 hours
   d. 5–10 hours
   e. 10–15 hours
   f. 15 or more hours

24. During hot days and heatwaves, do you normally change or move your daily activities (such as exercise, yard work, walking the dog, and so on) to a different time of day?
   a. Yes (skip to question 24a)
   b. No (skip to question 24c)

24a. When do you normally spend time outdoors (circle all that apply)?
   Early morning (before 9:00am)
   Late morning (9:00am- noon)
   Early afternoon (noon-3:00pm)
   Late afternoon (3:00pm-5:00pm)
   Evening or night (after 5:00pm)

24b. How do you change your normal outdoor activities on hot days (circle all that apply)?
   Avoid outdoor activities
   Change when I spend time outdoors
   Other ________________

   Proceed to question 25.

24c. Why do you not change or move daily activities on hot days?

   Proceed to question 25.

Access to Heat Relief

25. Do you have and use a working air conditioner in your residence?
   a. Yes (skip to question 25a)
   b. No (skip to question 26)
25a. What are the reasons that you do not have or use an air conditioner in your residence (circle all that apply)?
   - Air conditioner is broken
   - Too expensive to buy
   - Too expensive to run
   - Residence stays cool without air conditioning
   - Do not like air conditioning
   - Other _____________________

   Proceed to question 26.

26. How confident do you feel that you have 1 or more local friend(s) and/or family member(s) that would help you if you developed heat stroke or other heat-related illness?

   a. Very confident
   b. Somewhat confident
   c. Not too confident
   d. Not confident at all
Vita

Alisa L. Hass earned a Bachelor of Science in Geography, with concentrations in environmental management/analysis and geographic information science from the University of Wisconsin-Oshkosh in 2007. She went on to earn a Master of Science in Geography with concentrations in paleoenvironmental reconstruction and geographic information science from the University of Tennessee, Knoxville in 2008. After completing her Master’s degree, she worked at a photogrammetry company, Aero-Metric, Inc., as a proposal coordinator before returning to academia. Alisa served as a lecturer at the University of Wisconsin-Platteville for three years and the Science Outreach Coordinator at the University of Wisconsin-Whitewater for two years before continuing her education in the Ph.D. program in the Department of Geography at the University of Tennessee, Knoxville. Alisa was awarded a Thomas Graduate Research Fellowship and an award for Outstanding Graduate Teaching Associate. She completed her Ph.D. in Geography in May 2019. Alisa will continue her career in academia as an assistant professor in the Department of Geosciences at Middle Tennessee State University.