Climate-Human Health Vulnerability: Identifying Relationships between Maximum Temperature and Heat-Related Illness across North Carolina, USA

Margaret Mae Kovach

A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Geography.

Chapel Hill
2015

Approved by:

Charles E. Konrad

Kirstin Dow

Erika Wise

Michael Emch

Conghe Song

ABSTRACT

MARGARET M. KOVACH: Climate-Human Health Vulnerability: Identifying Relationships between Maximum Temperature and Heat-Related Illness across North Carolina (Under the direction of Charles E. Konrad II)

Heat kills more people than any other weather-related event in the United States, resulting in hundreds of fatalities each year. In North Carolina, heat-related illness accounts for over 2,000 yearly emergency department admissions. In this study, data from the North Carolina Disease Event Tracking and Epidemiologic Collect Tool is used to identify spatiotemporal relationships between temperature and morbidity across six warm seasons (May-September) from 2007 through 2012. Spatiotemporal relationships are explored across different regions (e.g. coastal plain, rural) and demographics (e.g. gender, age) to determine the differential impact of heat stress on populations. Additionally, HRI incidence will be mapped across North Carolina and linked with land cover and socioeconomic data to determine which local characteristics correlate with an increase in a population's risk for HRI. This research reveals that most cases HRI occurs on days with climatologically normal temperatures (e.g. 31 to 35 ˚C); however, HRI rates increase substantially on days with abnormally high daily maximum temperatures (e.g. 35 to 37.8 ˚C). HRI ED visits decreased on days with extreme heat (e.g. greater than 37.8 ˚C), suggesting that populations are taking preventative measures during extreme heat, and therefore mitigating heat-related illness. Analyses also reveal the largest number of heat-related illnesses occur in rural locations, particularly in areas of the Coastal Plain where a large percentage of the population lives below the poverty line and engage in outdoor labor.

To my family.

ACKNOWLEDGEMENTS

I gratefully acknowledge the patient guidance, direction, and friendship of my advisor, Charles Konrad. His mentorship has had a positive impact on my professional and personal development and challenged me to become the academic I am today. I am grateful to my dissertation committee members: Erika Wise, Michael Emch, Conghe Song, and Kirstin Dow. I am grateful to Christopher Fuhrmann for his mentorship and support throughout my graduate program. I also acknowledge the North Carolina State Climate Office, the Southeastern Regional Climate Center, Carolinas Integrated Sciences and Assessments, National Science Foundation's Doctoral Dissertation Research Improvement Grant (Award Number: 1434202), and the Environmental Protection Agency's STAR Fellowship Assistance Agreement (no. F13D10708). Lastly, I am thankful to my many colleagues and friends too numerous to name.

This data was provided by NC DETECT is a statewide public health syndromic surveillance system, funded by the NC Division of Public Health (NC DPH) Federal Public Health Emergency Preparedness Grant and managed through collaboration between NC DPH and UNC-CH Department of Emergency Medicine's Carolina Center for Health Informatics. The NC DETECT Data Oversight Committee does not take responsibility for the scientific validity or accuracy of methodology, results, statistical analyses, or conclusions presented.

Outside academia, I am indebted to my parents whose countless scarifies and unconditional love have afforded me more opportunities than I deserve. I also have benefited from the love and friendship of my brothers, Paul, Robert, and Samuel, who remain and continue

to be my best friends. I am grateful for the support, love, and encouragement of Johnathan, my future husband.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
ACS	American Community Survey
AC	Air Conditioning
ED	Emergency department
GAM	Generalized Additive Model
GIS	Geographic Information System
HRI	Heat-related illness
HVI	Heat Vulnerability Index
NC	North Carolina
NC-DETECT	North Carolina Disease Event Tracking and Epidemiologic Collection Tool
NLCD	National Land Cover Database
NWS	National Weather Service
OLS	Ordinary Least Square Multivariate Linear Regression Model
VIF	Variance Inflation Factor
WWAMI	Washington, Wyoming, Alaska, Montana, and Idaho
ZCTA	ZIP code Tabulation Area
ZIP	Zone Improvement Plan

CHAPTER 1: INTRODUCTION

Environmental heat stress is associated with increased morbidity and mortality. Heat stress occurs when the thermoregulation system is overwhelmed and cannot shed sufficient heat through sweating, causing the body's core temperature to rise. In such instances, this heat stress can cause heat-related illness (HRI), which clinically manifests with symptoms, such as heat cramps, heat syncope, and heat exhaustion (Becker and Stewart 2011, Lugo-Amado et al. 2004). Signs of heat-related illness may include fatigue, thirst, tiredness, mental confusion, weakness, paleness, fainting, nausea, vomiting, and headache (Kilbourne et al. 1980). If left untreated, HRI can progress to heat stroke, a life threatening condition, with severe health effects such as, delirium, convulsions, or coma. Survivors of heat stroke experience neurologic impairment, which can persist long after recovery and often results in mortality within one year (Dematte et al. 1998).

Heat-related deaths are traditionally studied in the context of heat waves, where classic heat stroke and deaths from cardiovascular or respiratory diseases have been shown to rise. The major risk factors for heat-related mortality include age, socioeconomic factors, and lack of preventative behaviors (i.e. air conditioning, relocating to a cooling shelter). In the United States, one of the most studied heat waves occurred in Chicago in 1995 heat wave, where a five-day period of extreme heat event resulted in nearly 700 excess deaths (Johnson et al. 2012). These heat-related deaths were found to be most common among the poor or elderly and those who were socially isolated and required the assistance of visiting nurses, housekeepers, or outside programs (Whitman et al. 1997, Semenza et al. 1999, Naughton et al. 2002, Jones et al. 1982, Kilbourne et al. 1982). Living conditions, including the type of building, floor level, the presence of an air conditioning unit and the number of rooms, were also found to be important determinants of heat-related morality (Semenza et al. 1996). Other literature that examined heat waves in Chicago (1990), St. Louis (1980), and Kansas City (1980) have found similar results with greater mortality among the elderly, poor, social isolated non-whites, and city dwellers (Jones et al.1982, Naughton et al. 2002, Kilbourne et al. 1982).

Despite a well-establish relationship between heat and mortality, few studies have attempted to assess the impact of heat on *morbidity*. This gap in research is due to restrictions on the use and availability of hospital and emergency department data. These studies have contradictory results from heat-mortality studies. In London, for instance, United Kingdom hospital ED visits were compared to overall mortality rates. Results found that for the same high temperatures, ED visits did not increase, whereas mortality increased markedly (Kovats et al. 2004). Similarly, in the Chicago 1995 heat wave, overall mortality increased 147%, whereas ED visits increased by 11% (Semenza et al. 1999, Whitman et al. 1997). However, when examining ED visits specifically related to HRI, there are significant increases with temperature, even with modest temperature increases (Knowlton et al. 2009). Most of these HRI ED admissions occur in the elderly (i.e. 65 years and older), children, or for people with underlying medical conditions. These populations are generally considered more heat vulnerable, with thermoregulation systems that do not readily mitigate high temperatures (Jones et al. 1982, Semenza et al. 1999).

Variations in the relationship between temperature and HRI or deaths are complicated by a population's coping abilities and the timing of the heat onset. In the United States, there is not a universal temperature range where rates of heat-related morbidity and mortality rise significantly

(McGeehin and Mirabelli 2001).   Kalkstein and Davis (1989) found that the strongest relationships between temperature and mortality in the United States occur in regions where hot weather is uncommon and the weakest relationships occur in the hottest locations. These differences in the relationship between temperature and mortality can be attributed to regional acclimation (Kalkstein and Davis 1989). Similarly, Curriero et al. (2002) found that residents of northern cities (e.g. Chicago, IL Boston, MA) have lower minimum mortality temperatures than residents of southern cities (e.g. Miami, Tampa, FL). They also confirmed that residents of northern cities are at greater risk of dying from heat events due to a lack of regional acclimation. Research into acclimation demonstrates that initial physiological acclimation to hot environments can occur over a few days, but complete acclimation may take several years (Zeisberger et al. 1994).

The timing of extreme heat across summer months is also important. Heat waves or high temperatures occurring in the early summer or spring result in more deaths than the same high temperatures in the later summer months. This phenomenon is known as mortality displacement (formerly known as the harvesting effect) and occurs when the most vulnerable populations experience mortality earlier in the summer, while less vulnerable populations survive extreme heat either through behavioral or physiological adaptations (Basu and Samet 2002, Anderson and Bell 2011).

Heat-related deaths and illnesses are expected to increase in the future, as general circulation models of climate change project increases in temperatures and extreme heat events (Meehl & Tebaldi 2004). The potential for reducing future impacts is significant for several reasons.

1.) Heat-related illness is easily prevented through basic hydration or relocating to a cooler environment; thus basic warning and public health interventions can easily mitigate future heat-health effects.

2.) Meteorologists can accurately forecast the severity, duration, and intensity of heat several days prior to an extreme heat event. Therefore, identifying temperatures that cause HRI will allow for the activation of an early heat warning system or emergency response plan to mitigate future HRI. In other locations, heat warning systems (HWWS) have been applied and shown to decrease mortality (Ebi et al. 2004).

3.) High risk populations experience a disproportionate number of health impacts. Identifying these high risk populations in a given location will allow for targeted public health and resource allocation that can mitigate any negative health impacts. This motivates the need to identify vulnerable locations and populations as well as the temperatures that increase HRI.

The aim of this dissertation is to identify local to regional scale patterns of climate-health vulnerabilities and the temperatures that control these patterns. This will be carried out by identifying the spatiotemporal footprint of HRI and how it intersects with the spatial patterns of temperature. Specifically, this study will address the following questions:

1.) What is the spatial pattern of HRI across North Carolina and how does this pattern relate to socioeconomic, demographic, and land cover patterns?

2.) What is the spatial relationship between temperature and HRI, and how this relationship is modified among different demographics and regions (e.g. rural, mountains, etc.)?

3.) What is the intra-seasonal relationship between temperature and HRI across the warm months?

This study expands upon previous literature in several ways:

1.) It examines populations that have not been studied in the context of heat-health vulnerability (e.g. rural populations, farm workers). Previous research has focused mainly on metropolitan locations, where population density is the greatest and there is a heat island in which surface heat retention elevates nocturnal temperatures (McGeehin and Mirabelli 2001). This research, complements some recent research (e.g. Sheridan and Dolney 2003, Gabriel and Endlicher 2011), which suggests that rural populations experience greater rates of heat-health effects.

2.) It assesses regional differences in the heat morbidity and temperature relationship across the state of North Carolina. This approach addresses the need for more multi-location studies with consistent methodologies to make comparisons between temperature effects on locations and populations (Kalkstein and Greene 1997, Ye et al. 2012).

3.) It considers heat vulnerability through an examination of heat morbidity (i.e. HRI) rather than heat mortality. Because heat morbidity has received limited attention, these these findings open the door on that dimension of HRI.

4.) It will examine HRI in North Carolina, which is situated in the southeastern United States where there is a lack of heat-mortality and excess deaths from heat waves (Donaldson et al. 2003, Davis et al. 2003). Despite few heat-related deaths, North Carolina still experiences significant numbers of heat-related illness (Lippmann et al.

2013). The state also provides an excellent setting to study patterns of HRI due to its humid subtropical climate, large and rapidly growing population, and state of the art morbidity surveillance network (i.e. NC-DETECT).

Ultimately, results from this dissertation will provide new insights on the etiology of HRI in North Carolina and illustrate how geographic methods can be employed creatively to uncover significant climate-public health relationships.

CHAPTER 2: AREA-LEVEL RISK FACTORS FOR HRI

Every year, a large number of hospitalizations and deaths occur in association with exposure to heat (Basu and Samet 2002). This exposure is detrimental to a person's health when it overwhelms their ability to thermoregulate, increasing the likelihood of succumbing to heat stroke or exacerbating pre-existing health conditions (Kovats and Hajat 2008; Luber and McGeehin 2008). Most of these heat-health effects are concentrated in geographic areas where certain socioeconomic factors and physical exposure increase a population's vulnerability to heat-related morbidity or mortality. Adverse health effects from heat are preventable through basic hydration or relocating to a cooler environment; therefore, public health interventions are a key component in reducing these effects (Luber and McGeehin 2008). However, establishing which populations are at greatest risk is a complex issue involving a combination of environmental and social conditions.

Numerous studies have identified individual-specific risk factors for heat-related mortality, with age, income, and social isolation being the most important (Jones et al. 1982; Kilbourne et al. 1980; Naughton et al. 2002; Semenza et al. 1996, 1999). Certain living conditions, including the type of building, floor level, the presence of an air conditioning unit, and the number of rooms, are also important determinants of heat-related mortality (Semenza et al. 1996). Research assessing the impact of heat on *morbidity* is more limited, owing partly to the availability of hospitalization or emergency department (ED) data. Despite this limitation, increases in morbidities, such as heat-related illness (HRI), have been noted in heat waves in Chicago, IL in 1995 and St. Louis and Kansas City, MO in 1980 (Jones et al. 1982; Semenza et al. 1999). Most of these morbidities befall the elderly (65 years and older) and individuals with underlying medical conditions (Jones et al. 1982; Semenza et al. 1996, 1999; Knowlton et al. 2009).

The majority of heat-health research has been conducted in urban areas, which are generally warmer than surrounding rural areas due to the urban heat island effect (Dousset et al. 2011; Böhm 1998). Additionally, since urban areas display high population densities, the number of deaths and morbidities attributable to extreme heat can be very high (Luber and McGeehin 2008). Less research has been conducted in rural regions. Some examples include Gabriel and Endlicher (2011), who found higher mortality rates in urban locations compared to rural locations during extreme heat events in Germany. Similar results were noted in and around St. Louis and Kansas City, MO during the 1980 heat wave (Jones et al. 1982). In contrast, both Sheridan and Dolney (2003) and Henderson et al. (2013) found higher mortality rates in rural and suburban regions compared to urban regions in Ohio, USA and British Columbia, Canada, while Lippmann et al. (2013) found a similar pattern in North Carolina, USA using ED visit data for HRI.

Heat-health researchers have also attempted to address heat vulnerability at a local level by aggregating previous established area-level risk factors for heat mortality into heat vulnerability indexes. Often, these studies identify vulnerable locations, by examining the collocation of areas of greater physical exposure to extreme heat (e.g. urban surfaces) with locations displaying high social vulnerability (e.g. living below the poverty line, minorities) (Chow et al. 2012; Harlan et al. 2013; Johnson et al. 2012; Reid et al. 2009). Reid et al. (2009), provides a useful example of this approach. They incorporated several physical, socioeconomic, and environmental area–level factors at the metropolitan level through the creation of a heat vulnerability index (HVI). Using principal components analysis, their index reduces 10 variables into four representative factors including social and environmental vulnerability, social isolation, prevalence of air conditioning, and proportion of the population that are elderly or diabetics. Using the HVI, they contrast differences in vulnerability across different metropolitan regions of the United States, particularly downtown metropolitan areas, which have some of the highest HVI values.

The main limitation of these studies is that their results (i.e. identification of areas with high and low heat vulnerability) are not validated with actual counts of morbidity or mortality. Recent research has evaluated some of these indices, including the HVI, to assess whether they indeed demarcate areas of high heat vulnerability. Reid et al. (2012) assessed the utility of the HVI with hospitalization and mortality data and found that it correctly identified locations with an overall high health burden. However, the performance of the HVI varied when comparing the health burden on days with high temperatures across different locations. Harlan et al. (2013) evaluated the HVI in Phoenix, Arizona, United States and found that certain HVI factors, such as social and environmental vulnerability and elderly, accompanied with land surface temperatures, most accurately predicted heat mortality. Most recently, Maier et al. (2014) evaluated the HVI across the state of Georgia and found increases in all-cause mortality during extreme heat for counties with high HVI values.

Unlike the HVI approach, this research assessed the spatial variability of heat vulnerability using an ecological study design, where spatially explicit, area-level risk factors are associated with heat morbidity (i.e. HRI). I determine these area-level risk factors from fine-scaled spatial variations in the incidence of HRI using ED visit data, rather than from previously established individual-level risk factors. Additionally, I examine HRI incidence across rural and urban landscapes and populations. Thus, previously unexamined risk factors common to rural locations are included in the analysis (e.g. mobile homes, non-citizens, and labor requirements for agriculture production). By identifying the risk factors for HRI and the locations of vulnerable populations within North Carolina, more targeted public health interventions and strategies for resource allocation can be developed to help mitigate the health effects of heat.

Materials and Methods

Health Data

The incidence of HRI in North Carolina was determined using emergency department (ED) visit data from the North Carolina Disease Event Tracking and Epidemiologic Tool (NC DETECT), a statewide, public health surveillance system developed by the University of North Carolina and the North Carolina Division of Public Health (Lippmann et al. 2013). NC DETECT provides information on the age, sex, county of residence, and ZIP code of residence of the patient, as well as the date and time of the ED visit, and up to 11 diagnoses at discharge coded using the 9th revision of the International Classification of Disease (ICD-9-CM). It is estimated that NC-DETECT included ED visit data for 92% of the population in 2007 and 99.5% by 2008, allowing for statewide coverage of HRI incidence rates (Rhea et al. 2012). NC-DETECT does not include ED data from federally run military hospitals (Womach Army Hospital at Fort Bragg near Fayetteville and Naval Hospital at Camp Lejune near Jacksonville) or Indian Health Services hospital (Cherokee Indian Hospital) located on the Qualla Boundary. ED visits containing at least one heat-related code (ICD-9-CM code 992.xx) in any of the 11 diagnostic fields were used in this study to calculate the incidence of HRI. Due to the low number of HRI ED visits (i.e. $\leq$ 10 ED visits for HRI over the six year time period), the mountainous western quarter of the state, which rarely experiences temperatures above 35°C, was excluded from the analysis. The resulting dataset contains a total of 13,095 ED visits for HRI covering the warm season months (May-September) from 2007-2012.

Demographic and Socioeconomic Data

Information on the demographic and socioeconomic characteristics of North Carolina was gathered from the 2010 Census and the 2008-2012 American Community Survey (ACS) at the ZIP code level (i.e. ZIP code tabulation area, or ZCTA). Similar to the HVI (Reid et al. 2009), we gathered data on age, poverty, educational attainment, those living alone, and non-white population. Information on diabetes prevalence and air conditioning were not included, since these variables were not available at the ZIP code level. However, air conditioning is nearly ubiquitous in the southeastern U.S., with 97% of households owning either a window unit or central air system (U.S Energy Information Administration 2010). We also gathered data on non-citizens from the ACS. This variable is not included in the HVI but may capture potentially vulnerable populations in North Carolina, such as migrant farmworkers or immigrants who experience social isolation or lack of access to health care resources. Unlike Reid et al. (2009), I did not combine elderly and those living alone, and instead left them as discrete variables. All demographic and socioeconomic variables were expressed as a percentage of the total population for each ZCTA. Older houses and mobile homes tend to be less energy efficient (Harrison and Popke 2011), which in turn affects the ability to cool these structures during summer months. Therefore, to account for the potential effects of housing structure, we examined the median year that a house structure was built and the percentage of the population residing in a mobile home.

Land Cover and Agricultural Data

Land cover can influence the micro-climatic conditions, including temperature, evapotranspiration and surface run-off (Foley et al. 2005). Land cover data were obtained from the National Land Cover Database (NLCD) (U.S. Department of the Interior 2012). The NLCD provides a 30 X 30 m pixel raster of land cover data, which can be aggregated to varying spatial scales. Land cover classifications include developed land, different types of forest cover (i.e. mixed forest, deciduous forest, evergreen forest, mixed forest), and several classifications of agriculture. Similar to Reid et al. (2009), each NLCD pixel is assigned to a ZIP code in which its center is located. Percent land cover was calculated for ZIP codes, as the sum of the land area classification divided by the total area for the ZIP code. Percent land cover for different classifications was calculated for each year of available data (i.e. 2008-2012) and averaged to represent the entire study's time period (i.e. 2007-2012). The percentage of impervious surface area in each ZIP code was estimated by aggregating across all the developed land cover categories (i.e. open, low, medium, and high). Likewise, the percentage of green space in urban areas was estimated by aggregating across all forest cover types (i.e. mixed forest, deciduous forest, etc.).

The NLCD also provides land cover information for over 40 crop types from 2008 to 2012. Assessing heat vulnerability in rural populations that specialize in agriculture is especially important in North Carolina, which experiences the highest number of heat-related deaths among farm laborers in the U.S. (Luginbuhl 2008). Farm laborers acquire heat externally from the environment (e.g. solar radiation) but also generate much heat internally through metabolic processes resulting from strenuous muscular activity (May 2009). To estimate the amount of physical labor required for crop production, crop enterprise budgets (Greaser 1994) were acquired for each of the crop types identified in the NLCD found across North Carolina. Total labor costs were obtained from these budgets by averaging the hours of machinery labor and farm labor required per acre of crop production. These hourly labor estimates were obtained from crop enterprise budgets developed at Clemson University, North Carolina State University, Florida State University, and Mississippi State University. Labor requirements for different crops ranged from over 74 hours for fruit crops, including strawberries and peaches, to less than 1 hour for wheat or grass crops. Similar to other land cover variables, percent land cover for the different crop types were calculated from the NLCD data as the sum of the crop area classification divided by the total ZIP code land cover area. Within each ZIP code, the percent areal coverage of each crop type allowed for a weighted average of the hourly labor requirements for crop production. This resulted in a single hourly estimate of labor requirements for all the crops grown within each ZIP code.

Analysis

In order to identify a statistical relationship between ED visits and risk factors for HRI in North Carolina, spatial regressions were constructed for rural and urban populations using R software 3.0.1, specifically the spdep package (R Foundation for Statistical Computing, Bivard 2014). In contrast to previous heat-health research, which evaluated rural and urban differences at the county level, this study evaluates HRI at the ZIP code level. This provides a finer spatial scale of analysis that better captures Census-defined urban areas. Each patient's ZIP code address was used to assign the location of the ED visit. Using the 2010 Census for a comparison, ZIP codes with a population density of at least (less than) 150 people per km^2 were classified as urban (rural), since they encompassed the greatest number of Census defined locations (Figure 1).

In traditional multiple regression approaches, an *a priori* assumption is made that all data are collected from the same location. However, in practice, each location displays a unique relationship with the health data and risk factors in question. Spatial regression approaches, however, account for these spatial effects. These techniques have been employed in other public health studies (e.g. Drewenowski et al. 2007, Smiliey et al. 2010) to identify risk factors for separate health outcomes (i.e. obesity, tobacco, etc.) but, to date, have not been exploited for HRI outcomes.

ED visits for HRI were standardized by age and gender-specific population estimates from the 2010 Census at the ZIP code level. This standardization resulted in a crude incidence rate, with heat vulnerability being displayed as heat-related ED visits per 100,000 person-years. In order to perform a regression analysis, the HRI incidence rate was transformed to obtain a normal distribution. Potential transformations, including square root, log, and logistic transformations were tested. In this case, the log of HRI incidence followed the most normal distribution. To account for locations with zero ED visits for HRI, a coefficient of one was added to this transformation of log(HRI).

Similar to other spatial regression studies, (e.g. Drewnowski et al. 2007), I used a bivariate analysis to select variables for use in the spatial regression. Within the bivariate analysis, all 11 potential demographic, socioeconomic, and land cover risk factors were assessed to determine whether they have a statistically significant association with rates of HRI. Bivariate relationships were assessed with log linear regression models using a two tailed test, ($\alpha = 0.05$). In the urban areas, six risk factors were significant at the 95% confidence level, while all 11 risk factors in the rural areas were significant at the 95% confidence level (Table 1). Those risk factors found not to be statistically significant at the 95% confidence level were eliminated from the analysis.

	Rural			Urban		
Area Level Risk Factors	**R^2**	**R**	**p-value**	**R^2**	**R**	**p-value**
No High School Diploma	0.07	0.27	<0.001	0.13	0.36	<0.001
Mobile Home	0.13	0.35	<0.001	0.16	0.40	<0.001
Living below the Poverty Line	0.03	0.17	<0.001	0.11	0.33	<0.001
Median Year Structure Built	0.10	0.32	<0.001	0.03	0.17	<0.001
Non-Citizens	0.01	0.09	<0.01	0.04	0.20	<0.01
Minority	0.02	0.12	<0.001	0.01	0.10	0.68
Labor-Intensive Agriculture	0.03	0.18	<0.001	---	---	---
Forest Cover	---	---	---	0.02	0.16	<0.05
Developed Land	0.20	0.45	<0.001	0.00	0.01	0.89
Elderly	0.02	0.14	<0.001	0.02	0.13	0.09
Living Alone	0.01	0.12	<0.01	0.01	0.07	0.95

Table 1: Coefficient of determination and correlation coefficient for potential risk factors.

To address potential multicollinearity between risk factors, correlation matrices and variance inflation factors were calculated for all significant risk factors identified from the bivariate analysis. In the rural locations, four variables exhibited multicollinearity: *Median Year Structure Built* was highly correlated with the *Developed Land (*r = 0.70) and *No High School Diploma* was highly correlated with *Living below the Poverty Line* (r = 0.51). In these instances, the variables *Living below the Poverty Line* and *Median Year Structure Built* were removed from the analysis since both risk factors displayed the weakest relationship with HRI. Lastly, to ensure no additional multicollinearity existed among remaining variables, the variance inflation factor (VIF) was calculated. VIF quantifies how much the variance is inflated for each independent variable due to collinearity. A high VIF indicates that two or more collinear independent variables were included in the model. Typically, VIF values greater than 10 signify multicollinearity. In both rural and urban locations, the VIF for the remaining risk factors was less than 1.5, indicating no significant multicollinearity between them.

To confirm that spatial regression modeling was appropriate for this study, ordinary least square multivariate linear regression models (i.e. OLS) were constructed using the R statistical package to test for spatial autocorrelation of the residuals. In a regression analysis, spatially autocorrelated residuals violate the specification assumptions of OLS models. In this study, spatial autocorrelation was evaluated with Moran's *I,* which is roughly equal to zero when there is no spatial autocorrelation and increases to +/- 1 when there is greater spatial autocorrelation (Cliff and Ord, 1981, Anselin, 1998).

In the rural locations, bivariate predictors of the dependent variable, log(heat – related illness + 1) were all significant at the 95% confidence level. Within the OLS regression model only the coefficients for *Mobile Homes*, *Developed Land*, *Elderly*, *Non-citizen*, and *Labor Intensive Agriculture* were significant the 95% in confidence level. The coefficients for *Living Alone* and *No High School Diploma* were insignificant with the OLS and did not improve model performance (e.g. similar R^2 value and AIC value) (Table 2). In the urban locations, significant bivariate predictors of the dependent variable, log (heat – related illness + 1) included *No High School Diploma*, *Mobile Homes*, *Living below Poverty Line*, *Median Year Structure Built*, *Non-Citizen*, and *Forest Cover*. All of these variables were included in the OLS model and were significant at the 99% confidence level (Table 2). In both rural and urban OLS models, the regression residuals exhibited spatial autocorrelation at the 99% confidence level, verifying the need for spatial regression techniques to account for the spatial effects within the data.

Area-Level Factors	Coefficient	Standard Error	P-Value
Rural			
Mobile Homes	2.292	0.4701	0.0000
Developed Land	-0.030	0.045	0.0000
Non-Citizens	0.0002	00001	0.0509

Elderly	2.187	0.9223	0.0318
Labor-Intensive Agriculture	0.686	0.245	0.0053
R^2	0.25		
AIC	1660		
Urban			
No High School Diploma	3.201	1.095	0.0039
Mobile Home	2.994	0.6312	0.0000
Living below the Poverty Line	1.692	0.6025	0.0055
Median Year Structure Built	-0.001	0.0003	0.0028
Non-Citizen	-5.100	1.0959	0.0000
Forest Cover	-0.010	0.0028	0.0007
R^2	0.40		
AIC	2034		

Table 2: Ordinary least regression model output for rural and urban location

Spatial autocorrelation in the OLS residuals may be the result of autocorrelation of the dependent variable (i.e. spatial lag) or autocorrelation in the error term (i.e. due to spatially autocorrelated predictors that are not included in the model). The Lagrange Multiplier test identifies which form of spatial autocorrelation is present and what model type is best through the calculation of a Robust Lagrange Multiplier Index. Index values for both rural and urban locations indicate that the spatial error regression tends to be more significant (statistically significant: p-value <0.01) than the spatial lag regression model. Hence, the spatial error model is the more appropriate model specification for this data (Anselin 1988).

In the spatial error regression model, the spatial error term incorporates spatial dependence into the error term (Anselin and Bera 1998).

$$y = X\beta + \varepsilon \text{ with } \varepsilon = \gamma W + \varphi$$

where W is spatial weights matrix, is the vector error terms, ε are spatially lagged errors, and φ is a vector of independent random errors. γ is an autoregressive coefficient, which describes the extent to which the errors are correlated with each other, given the spatial weights matrix

(Anselin and Bera 1998). In order to apply the methods of spatial regression analysis, we needed to express the nearness of geographic units, using a spatial weights matrix (*W)* (GeoDa version 1.6.6, Tempe, AZ). The spatial weights matrices were assigned a first-order contiguity weights matrix (e.g. queen contiguity); where we considered ZIP codes that shared boundaries and vertices as contiguous (Anselin and Bera 1998, Aneslin et al. 2006).

Spatial error regression models were constructed for both rural and urban locations, using the same variables that were significant at the 95% confidence level in the OLS models. The results of the spatial error regression models are presented in Table 3. The residuals of both the urban and rural spatial error regression model exhibited no significant spatial autocorrelation. This finding further confirms that the spatial error regression model successfully incorporates the spatial effects.

Area-Level Factors	Coefficient	Standard Error	P-Value
Rural			
Mobile Homes	1.623	0.4895	0.0000
Developed Land	-0.0343	0.0047	0.0000
Non-Citizens	0.0002	0.0001	0.0500
Elderly	2.419	0.9025	0.0073
Labor-Intensive Agriculture	0.636	0.2883	0.0273
R^2	0.30		
AIC	1636		
Lambda	0.32		
Urban			
No High School Diploma	1.668	1.0845	0.1240
Mobile Home	2.475	0.5911	0.0000
Living below Poverty Line	2.070	0.6170	0.0009
Median Year Structure Built	-0.0009	0.0003	0.0031
Non-Citizen	-5.485	1.1151	0.0000
Forest Cover	-0.010	0.0028	0.0006
R^2	0.45		
AIC	345		
Lambda	0.36		

Table 3: Spatial error regression model output for rural and urban locations

Results

Figure 1 shows the incidence rate of heat-related ED visits by ZIP code across North Carolina for the warm season months (May-September) of 2007-2012. The majority of locations with high HRI incidence rates were located in the southern Coastal Plain or the southeastern region of North Carolina. The bottom 10% of ZIP codes with the lowest HRI incidence had less than 3.4 ED visits per 100,000 person-years. These locations were concentrated around metropolitan cities including, Raleigh, Durham, Greensboro, Charlotte, and Winston-Salem. The top 10% of ZIP codes with the highest HRI incidence had greater than 41.6 ED visits per person-years. These locations were concentrated in rural areas in the southern Coastal Plain of North Carolina, which experiences some of the warmest summer temperatures in North Carolina.

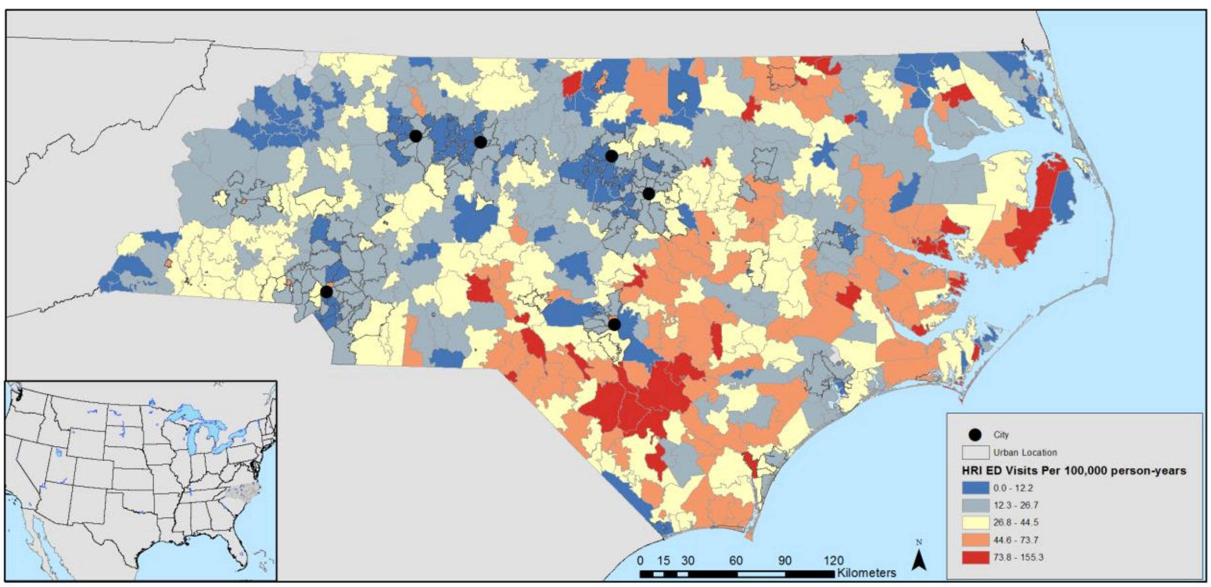

Figure 1: Map of study area featuring major cities and heat-related illness rates per 100,000 person-years. ZIP codes defined as urban using the 150 people per square kilometer definition are highlighted in black. Cities include Charlotte, Greensboro, Raleigh, Winston-Salem, Durham, and Fayetteville. Health data was collected from NC-DETECT.

Overall, urban locations had fewer total HRI ED visits (42 .7% of the total HRI ED visits) than rural ZIP locations (57.3% of total HRI ED visits). Accounting for age and gender specific populations, these differences are even further pronounced with 19.7 ED visits per 100,000 person-years in urban locations and 33.5 ED visits per 100,000 person-years in rural locations. Generally, rural locations displayed a greater *percentage of cropland, population living below the poverty line, mobile homes, elderly, and residents without a high school diploma* or *living alone.* Urban locations showed a greater *percentage of residents with a race other than white* and *percent developed land* (Table 4).

Characteristics of Rural/Urban Locations		**Living below the Poverty Line**	**No High School Diploma**	**Minority**	**Elderly**
Rural	Mean	17.6	13.1	29.2	15.5
	Standard Deviation	11.4	6	22	6.3
Urban	Mean	15.5	8	32.7	11.9
	Standard Deviation	9.7	5.2	20	6
Characteristics of Rural/Urban Locations		**Living Alone**	**Mobile Home**	**Developed Land**	**Cropland**
Rural	Mean	25.9	25.3	10.5	16
	Standard Deviation	9.2	12.9	14	13.2
Urban	Mean	28.5	6.3	25	5.3
	Standard Deviation	9.9	8.1	48.5	7.8

Table 4: Mean and Standard Deviation of Area-Level Risk Factors in Rural and Urban Locations

The rural spatial error regression model explained 30% of variance of HRI ED visits (Table 3). It reveals that rural locations with a greater percent of mobile homes, non-citizens, non-developed land, and more agricultural labor hours predict higher rates of HRI incidence. Increases in *elderly* (i.e. age greater than 65 years old) predicted the largest increase in HRI, with 10.23 ED visits per 100,000 person-years. Increases in *mobile homes* and *agricultural labor hours* predicted 4.07 and 0.89 ED visits per 100,000 person-years, respectively. Increases in the *percent developed land* predicted decreases in ED visits per 100,000 person-years (Table 3). Although *non-citizens* were significant in the rural model, it only predicted marginal increases in ED visits.

The urban spatial error regression model explained 45% of variance of HRI ED visits (Table 3). It reveals that urban locations with a greater percent of mobile homes, people with no high school diploma, and people living below the poverty line predict higher rates of HRI incidence. Whereas, urban locations with a greater percent of non-citizens, forested land cover, and newer median year structure built lower rates of HRI. Increases in *mobile homes, no high school diploma,* and *living below the poverty line* predicted increases in HRI incidence of 10.9, 4.3, and 6.9 ED visits per 100,000 person-years, respectively. Increases in *non-citizens, median year structure built, and forested land cover* predicted decreases in HRI incidence of -1.0, -0.0009, and -0.010 ED visits per 100,000 person-years, respectively.

Discussion

Rates of HRI across rural and urban regions of North Carolina were associated with socioeconomic, demographic, and environmental area-level risk factors at the ZIP code level. This study considered potential risk factors, such as living in poverty and low educational attainment that have been identified through previous research (e.g. Reid et al. 2009). Because of the inclusion of rural areas, un-examined risk factors relevant to these locations were also incorporated, including the number of mobile homes, non-citizens, and estimates of agricultural labor intensity. Spatial regression models were constructed separately for rural and urban locations, with each explaining 30% and 45% of the variance of HRI ED visits, respectively.

In urban areas, the best predictors of heat-related ED visits included percent of population lacking a high school diploma, living in mobile homes, living below the poverty line, median year structure built, percentage of forest cover, and percentage of non-citizens. Most of these risk factors are consistent with previous heat-health studies, which are focused on urban areas. Specifically, living in poverty and low educational attainment (i.e. no high school education) are well-established risk factors for heat-related mortality across many populations and regions (Kim and Joh 2006; Naughton et al. 2002; O'Neill et al. 2005). In our study, both of these risk factors predicted large increases in HRI ED visits in the urban locations (i.e. 6.9 and 4.3 ED visits per 100,000 person-years, respectively).

Forest cover and newer buildings have been identified as protective factors against adverse heat-health outcomes in urban environments (Vandentorren et al. 2006). Vegetation mitigates the urban heat island effect by reducing heat exposure, while older buildings often have deteriorating and insufficient insulation, which can affect the efficiency of air conditioning and increase heat exposure. However, our results only demonstrated a marginal decrease in predicted HRI with respect to these two variables.

This analysis also identified less-established risk factors in urban regions. The numbers of non-citizens in urban locations predicted decreases in HRI ED visits. This may result from stronger internal social network and subsequent social cohesion among this population (Chow et al. 2012). Also, large numbers of non-citizens have migrated to affluent urban areas where there are many jobs in the technology industry, such as Research Triangle Park near Raleigh.

Specifically, these immigrants are often of Asian descent and fulfill the growing demand for highly-skilled workers to fuel entrepreneurship and continued employment in the technology industry within these urban locations (Appold 2014). In addition, mobile homes predicted a large increase in the number of HRI ED visits within the spatial regression model. Mobile homes are an affordable housing option for low-income households in North Carolina and have not been studied in the context of heat-related morbidity or mortality (Rust 2007). Mobile homes are often energy inefficient, with little or no insulation in the walls, ceiling, floor, or doors (U.S Energy Information Administration 2010). Poor insulation limits the ability of air conditioning units to sufficiently cool the mobile home. This problem is compounded when residents cannot afford to run air conditioning for extended periods of time (Arman and Yarnal 2010).

In rural areas, the greatest risk factors for heat-related ED visits included elderly, labor-intensive agriculture, mobile homes, non-citizens, and developed land. Percent elderly (e.g. population greater than 65 years old) predicted the largest increases in HRI incidence. As noted in multiple heat-health studies, elderly have a biological predisposition towards heat stress causing them to be more sensitive to heat than younger populations (Basu 2009; Chow et al. 2012; Kovats and Hajat 2008; Vandentorren et al. 2006). In comparison to urban locations, rural elderly also tend to be of a lower socioeconomic status, which may further increase their vulnerability to HRI (Coburn and Bolda 2001). This difference in socioeconomic status may explain why older residents in urban locations do not predict HRI incidence.

By integrating hourly estimates of labor with land cover data, we developed a variable that quantifies the labor requirements of agriculture within each rural location. As expected, increases in hourly labor requirements predicted increases in ED visits for HRI. We hypothesize that farm workers are especially vulnerable in rural areas. Earlier research has demonstrated that

40% of North Carolina farm workers experience at least one HRI symptom while laboring in extreme heat (Mirabelli et al. 2010). In some cases, HRI cases can lead to death. A review of medical examiner records from 1977 to 2001 across the state identified nearly 50% of all occupational heat-related deaths also occurred within this group. These deaths often arose from physical labor in hot weather (Mirabelli and Richardson 2005). In addition, other research has highlighted that poor housing, lack of access to social networks and health care also make farmworkers particularly vulnerable to heat (Montz et al. 2011, Quandt et al. 2013). Investigation of the percentage of farm worker populations contributing to ED HRI visits relative to the proportion of labor-intensive agriculture would be an important direction for greater understanding of these patterns.

An additional risk factor for HRI in rural locations is the numbers of non-citizens. In contrast to urban locations, the number of non-citizens corresponded with increases in HRI ED visits in rural areas. While this may be related to the isolation experienced by some non-citzens (Chow et al. 2012; Harlan et al. 2013), many non-citizens in rural North Carolina perform agricultural labor (Carroll et al. 2011) and therefore are highly exposed to the heat and exertion heat stress from physical labor (May 2009).

Similar to urban locations, mobile homes predicted a large increase in heat-related ED visits in rural areas. Many mobile home owners cannot afford high energy bills that occur when attempting to cool poorly insulated mobile homes, particularly during the hot summer months. Harrison and Popke (2010) conducted interviews in rural North Carolina that provide evidence of unaffordable energy bills, some as high as $400 USD during the warmest months of the year.

In rural locations, the only risk factor that predicted decreases in HRI ED visits was the amount of developed land or impervious surfaces. This result contradicts previous heat-health research, which has mostly been carried out in urban locations, where effects of the urban heat island contribute to heat-related mortality or morbidity (Anderson and Bell 2011; Luber and McGeehin 2008). As reported earlier, rural areas in North Carolina experience significantly greater incidence rates of HRI ED visits, and underlying social vulnerabilities (e.g. poverty, low educational attainment) in rural areas are a greater concern for increased HRI.

It is important to discuss some limitations of this study. The counts and rates presented are likely underestimates of the true occurrence of HRI in North Carolina emergency departments, since data from NC-DETECT does not include ED visits for federally run hospitals (military and Indian Health Services) and other health clinics, such as urgent cares. Secondly, we analyzed data across ZIP code areas, which do not capture socioeconomic and demographic differences as effectively as census boundaries (Krieger et al. 2002). Thirdly, the use of single classes of rural and urban on the basis of population density does not allow for the capture of intervening areas in the urban-rural continuum (e.g. suburban, rural near urban areas etc.). Future analysis should incorporate gradations of urban and rural as well as proximity to urban areas. Lastly, we based our study on area-level measures, evaluating the risk factors at a population level rather than an individual level. Subsequently, we can only make suggestions of the causal pathways that alter individual health at the ZIP code level. Further research is needed to identify the effects of heat at an individual level.

Conclusion

This study relates socioeconomic, demographic, and land cover patterns to fine-scaled spatial variations of HRI for both urban and rural populations across the state of North Carolina. It addresses previous research gaps in several ways. First, this study identifies area-level risk factors for heat *morbidity* rather than heat mortality. Second, it demonstrates that rural populations are especially vulnerable to the heat. Over the six-year time period, rural locations presented greater rates of HRI compared to urban locations. Lastly, it incorporates several previously unexamined heat-health risk factors, including the number of mobile homes, non-citizens, and the labor-intensity of the agriculture, which were all associated with an increase in rural HRI. In urban locations, previously established risk factors for heat-related mortality, such as decreased vegetation, living in poverty, and low education attainment, were associated with increases in HRI. On the other hand, only one established risk factor, elderly, predicted an increase in HRI in rural locations of North Carolina. Future research should explore risk factors for HRI at the individual-level to confirm which populations and environments increase heat vulnerability. Ultimately, results from the present study highlight locations where targeted public health interventions, future research, and resource allocation can mitigate ED visits from HRI.

CHAPTER 3: RELATIONSHIPS BETWEEN HRI AND TEMPERATURE

Exposure to extreme heat is the most common cause of weather-related fatalities in the United States (NOAA 2007). This extreme heat exposure is detrimental to a person's health when it overwhelms their ability to thermoregulate, increasing the likelihood of succumbing to heat-related illnesses (Luber and McGeehin 2008). Heat-related illnesses (HRI) range from mild heat cramps to heat exhaustion, heat syncope and, in the most severe cases, heat stroke, which has a 50% mortality rate (Grogan and Hopkins 2002). Persons with chronic health conditions (e.g. cardiovascular disease, diabetes, or obesity) are more susceptible to the effects of heat, resulting in further increases in morbidity and mortality (Blum 1998). Understanding heat-related morbidity and mortality is of growing importance as climate change is anticipated to increase temperatures and the magnitude and frequency of extreme heat events.

The relationship between extreme temperatures, increased heat-related morbidity, and mortality is well established (Basu and Samet 2002). Most research evaluating temperature and human-health has investigated the exposure-response relationship of temperature and mortality in metropolitan locations (e.g. Chicago, IL, Boston, MA, Charlotte, NC, Tampa, FL.). These studies describe a non-linear relationship (a U, J, or V shaped curve), with the lowest mortality rates at moderate temperatures that rise progressively as temperatures increase or decrease (Curriero et al. 2003, Anderson and Bell 2009). The exposure-response relationship for temperature and mortality has been determined for multiple cities and reveals much spatial heterogeneity. This heterogeneity reflects the ability of local populations to adapt to extreme temperatures. Often, residents not acclimated to heat, such as populations in northern cities, are more heat-vulnerable, experiencing higher mortality at lower temperatures (Kalkstein and Davis 1989, Curriero et al. 2003). Variation in the temperature and mortality relationship also varies by race, education level, use of air conditioning, and population density (O'Neill et al. 2003, Kalkstein and Davis 1989). Overall, there is general agreement among the literature that within urban environments, the elderly, minorities, young, poor, and people with underlying medical conditions are the most vulnerable to heat-related mortality and morbidity (McGeehin and Mirbaelli 2001).

Consistent with the previous discussion on temperature and mortality, a number of studies (e.g. Baccini et al 2008, Kovats et al. 2004, Liang et al. 2008, Lin et al. 2009, Alessandrini et al. 2011) also find a V or J-shaped relationship between temperature and *morbidity*. The most common morbidities evaluated in these relationships include cardiovascular and respiratory diseases, such as stroke, acute myocardial infarction, acute coronary syndrome, and asthma (Ye *et al.* 2012, Buckley and Richardson 2012). Less research (e.g. Hartz et al. 2012, Golden et al. 2008, Ng et al. 2014) has evaluated the relationship between temperature and heat-related morbidities, such as heat stroke, heat exhaustion, fluid and electrolyte abnormalities, and acute renal failure. This limitation is due to the restricted availability of large-scale hospital admissions and emergency department visit surveillance systems. Recently, Hartz et al. (2013) and Ng et al. (2014) evaluated maximum temperature relative to heat-related 9-1-1 emergency dispatches in Chicago, IL, USA, Phoenix, AZ, USA, and cities across the Kato area of Japan and found that morbidity rates rise progressively as temperature increases in all locations. Other morbidity literature has focused on excess ED visit data or hospitalization during extreme heat events, demonstrating that the elderly (i.e. greater than 65 years old) are at particular risk for heat-related illnesses during such events (Knowlton et al. 2009). These heat-related health outcomes are a considerable burden in terms of reduced quality of life, higher cost of healthcare, and loss of economic productivity (Bambrick et al. 2008).

Unlike the majority of previous research, this study analyzed the association between the daily temperature and heat-related morbidity, rather than heat-related mortality, for six warm seasons (May – September) from 2007 to 2012. These relationships are evaluated across different regions (e.g. coastal plain, piedmont) and demographics (e.g. gender, age) within the state of North Carolina to determine the differential impact of heat stress across populations. In particular, we examine variations across rural populations, which are seldom addressed in the heat-health literature. North Carolina is an optimal location to conduct this research because of its large, diverse, and growing population, humid subtropical climate, topographic variability, and statewide surveillance emergency department network. Ultimately, results from this study will provide a better understanding of how temperature affects human morbidity and vulnerable populations, which is not only crucial to the medical community, but to policy makers and community leaders who develop mitigation and intervention strategies for extreme temperatures.

Methods

Data sources

The incidence of heat-related illness (HRI) in North Carolina was determined using emergency department (ED) visit data from the North Carolina Disease Event Tracking and Epidemiologic Collection Tool (NC DETECT), a statewide public health surveillance system developed by the University of North Carolina and the North Carolina Division of Public Health (Rhea et al. 2012; Lippmann et al. 2013). NC DETECT provides information on the age, sex, county of residence, and ZIP code of residence of the patient, as well as the date and time of the ED visit, and up to 11 diagnoses at discharge coded using the 9th revision of the International Classification of Disease (ICD-9-CM). NC DETECT provided ED visit data for 92% of the population in 2007 and 99% by 2008, allowing for statewide coverage of HRI incidence rates (Rhea et al., 2012). NC DETECT does not include ED data from federally operated military hospitals (Womach Army Hospital at Fort Bragg near Fayetteville and Naval Hospital at Camp Lejune near Jacksonville) or Indian Health Services hospital (Cherokee Indian Hospital) located on the Qualla Boundary. ED visits containing at least one heat-related code (ICD-9-CM code 992.xx) in any of the 11 diagnostic fields were used in this study to calculate the incidence of HRI. This code accounts for the effects of heat and light and includes diagnostic codes such as, heat stroke (992.0), heat syncope (992.1), heat cramps (992.2), heat exhaustion (992.3-992.5), heat fatigue (992.6), heat edema (992.7) and other specified and unspecified heat effects (992.8-992.9). The resulting dataset contains a total of 13, 364 ED visits for HRI covering the warm season months (May-September) from 2007-2012.

Age- and gender- specific estimates of the population included in this analysis were obtained from the United States Bureau of Census. The 2010 Census-based population estimates were used as denominators in the estimation of HRI ED visits per 100,000 person-years. Other socioeconomic, employment, and housing data were collected from the five-year estimates from the American Community Survey for 2008 to 2012 at the ZIP code level. These data were used to characterize ZIP code locations and regions. In order to obtain rates for different demographics, HRI ED visits were divided into 13 age categories (i.e. under 4, 10 to 14, 15 to 17, 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74, 75 to 84, and over 85), which correspond to the 2010 US Census demographic categories.

Daily maximum temperature observations were obtained from weather stations maintained by the National Weather Service and Federal Aviation Administration, the U.S. Forest Service, as well as stations in the North Carolina Environment and Climate Observing Network. In total, 169 weather stations were used across the following networks: the Automated Surface Observing System (ASOS), the Automated Weather Observing System (AWOS), the Remote Automatic Weather Station network (RAWS), and the North Carolina Environment and Climate Observing Network (EcoNet). The ZIP code of the patient's residential address was utilized to determine which weather station to assign to each ED admission. Specifically, the shortest distance was determined between the center of the patient's ZIP code area and the weather station based on the shortest Euclidean distance using the great circle distance formula:

$$D = R\cos^{-1}[\sin l_1 \sin l_2 + \cos l_1 \cos l_2 \cos(m_2 - m_1)]$$

where D is the distance (km) between the ED admission and the weather stations, R is the mean earth radius, *l*1 and *l*2 are the latitudes (rad) of the ED visit and weather station, respectively, and *m*1 and *m*2 are the longitudes (rad) of the ED visit and weather station, respectively (Cao, et al. 2004). Each ED visit was assigned a latitude and longitude based on the centroid of the patient's ZIP code address.

Initially, the daily maximum heat index was considered as a measure of heat stress for this study. The heat index was formulated by Steadman (1984) and later refined by the United States National Weather Service to take into account the combined effects of temperature and humidity on human thermal comfort. However, preliminary analyses revealed that the relationship between the number of HRI ED visits and daily maximum heat index was not as strong as the relationship identified with daily maximum temperature. Specifically, HRI shows a flatter, more dispersed distribution with respect to values of heat index (e.g. Figure 2). We hypothesize that there is greater spatial variability in heat index values due to microclimatic variations in humidity (e.g. effects of vegetation, bodies of water). Because the network of weather stations used in this study is too sparse to capture this variability, the relationship between HRI and maximum heat index is not as strong. In contrast, the maximum temperature displays more modest microclimatic variations, thus providing a more spatially robust measure of heat stress. Fahrenheit scale was used for data management and analysis. Celsius conversions were also presented in consideration of non-United States and scientific readers.

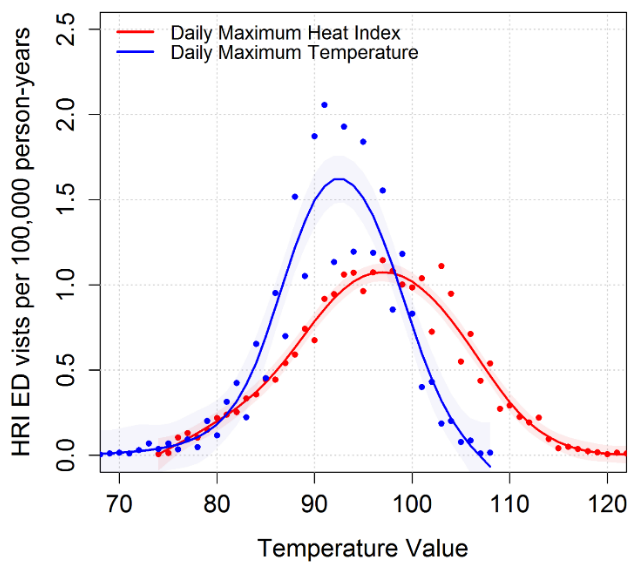

Figure 2: HRI ED visits per 100,000 person-years for maximum temperature and heat index versus heat-related illness.

Urban and rural character

There are large variations in the demographic and socioeconomic character across the state of North Carolina that may be tied to the incidence of HRI. Among other things, these differences relate to the urban and rural character of the landscape and the thermal environment in which people work (e.g. farm laborers who are exposed to heat versus office workers who spend much of their time inside in an air conditioned environment). The study area was therefore classified into four regions on the basis of the urban-rural character of the landscape and the Census-determined work commuting flows between areas (e.g. rural residents commuting to urban areas or remaining in rural areas) (Hartz et al. 2005). Regardless of whether a person lives in a rural or urban environment, large portions of their workday are spent at their place of occupation. In the case of HRI, specific occupational environments can promote (e.g. construction, agriculture) or reduce (e.g. office) heat exposure.

Rural-Urban Commuting Area (RUCA) codes were used to differentiate areas according to their economic integration (i.e. commuting patterns) with urban areas or other rural areas (WWAMI Rural Health Research Center 2004). RUCA codes were assigned to each United States ZIP code based on markers of population density, with values ranging from 1.0 (most urban) to 10.6 (most rural). In this study, ZIP codes were classified into one of four mutually exclusive RUCA groups (Table 5): 1) *Metropolitan*, defined as the most urban containing populations that reside and work in large urban environments; 2) *Rural metropolitan*, defined by a low population density, low values of impervious surface area, and large portions of its residents commuting and employed in nearby metropolitan locations; 3) *Rural town*, including larger towns and adjacent rural areas where few people commute into metropolitan locations; and 4) *Rural isolated*, the most rural category, including populations that reside in small towns and adjacent rural areas.

Location	RUCA code	Definition
Metropolitan	1.0	Census defined Urban Areas (e.g. Greater than 50,000 population)
Rural Metropolitan	2.0-3.0, 4.1, 5.1, 7.1, 8.1, 10.1	Locations with substantial commuter flows to Urban Areas (30% to 50%)
Rural Town	4.0, 4.2, 5.0, 5.2, 6.0, 6.1	Census defined (large) Urban Clusters (e.g. 10,000 to 25,000 population) with minimal

		commuter flows to Urban Areas (Less than 29%)
Rural Isolated	7.0, 7.2-7.4, 8.0, 8.2-8.4, 9.0-9.2,10.0,10.2-10.6	Census defined (small) Urban Clusters (e.g. 2,500 to 9,999 population) with commuter flows to Urban Clusters (Less than 50%) and minimal flows to Urban Areas (Less than 29%)

Table 5: Definition of Metropolitan, Rural Metropolitan, Large Rural City, and Rural and Isolated Town from Rural-Urban Commuting Codes (RUCA codes).

Statistical analysis

The objective of this study was to examine the relationship between the maximum temperature and HRI. Counts of HRI ED visits were standardized using age and gender specific 2010 Census estimates at the ZIP code level to provide crude incidence rates (i.e. HRI ED visits per 100,000 person-years). A generalized additive model (GAM) was used to describe the relationship between temperature and HRI. GAMs are commonly applied in time-series studies of air pollution and health data and more recently have been utilized in HRI and mortality studies (Li et al. 2012, Hondula et al. 2013). In this study, GAMs were calculated using a natural cubic spline (i.e. nonparametric smoothing function) to interpolate the non-linear relationship with temperature and HRI ED visits. Using daily maximum temperature observations for the warm season months (May-September) of 2007-2012, GAMs were constructed to model two aspects of the relationship between HRI and temperature: 1) the mean annual rate of HRI ED visits per 100,000 person-years *relative to* temperature. Because this measure takes into account the number of days in which a given temperature is observed annually, it reveals the cumulative effects of commonly occurring weather conditions. While rates of HRI may be relatively low on these days, their frequent occurrence yields high aggregate values over the course of the warm season. 2) The daily rate of HRI ED visits per 100,000 persons *with respect to* temperature. This provides a direct estimate of the rate of HRI expected on a day with a given maximum temperature.

Two summary statistics were developed from the GAM models and compared across different populations in the study area.

1) The threshold temperature, which represents the maximum temperature in which a significant elevation in HRI is observed. In studies of heat-related mortality, this defines the inflection point in the "U- or J- shaped" relationships between temperature and mortality. Applying similar methods, we defined the threshold temperature as the temperature in which HRI ED visits were statistically different from zero (at the 95% confidence level) and remain significant for higher temperatures (Davis et al. 2003, Gosling et al. 2014).

2.) Peak temperature, which is the daily maximum temperature in which the greatest rates of HRI ED visits occurred. All statistical analysis was conducted using R software 3.0.1 with the MGCV package (R Core Team 2013, Wood 2006, Wood 2011).

Results

Basic characteristics of HRI across North Carolina

Figure 3 illustrates the incidence rates of HRI ED visits by ZIP code across North Carolina for the warm season months (May-September) of 2007-2012. The highest HRI ED rates were observed in the rural locations of eastern North Carolina (i.e. Coastal Plain), while the lowest rates were largely concentrated in the western mountainous portion of North Carolina and the metropolitan areas around Charlotte, Greensboro, and Raleigh, NC. More than half of the HRI ED visits occurred when the maximum temperature was between 31.7˚C (89 ˚F) and 35.6˚C

(96 ˚F) (Figure 4a). Temperature of this magnitude are quite common across the eastern two-thirds of the state (e.g. approximately 10% to 15% of days within warm season) during the months of June through August (North Carolina State Climate Office 2014).

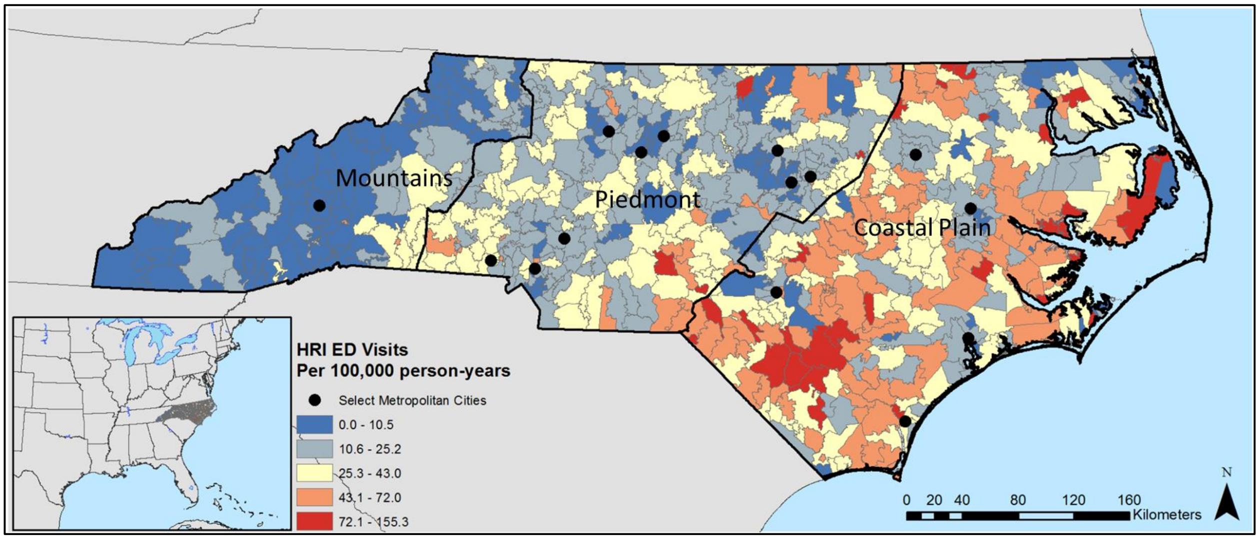

Figure 3: HRI ED visits per 100,000 person-years for May through September from 2007 to 2012. HRI ED visits are acquired through NC-DETECT. Map also includes regional locations and cities with metropolitan characteristics.

Figure 4b depicts the daily average rates of HRI ED visits across North Carolina with respect to temperature. HRI ED visits increase strongly at the threshold temperature of 30.6 ˚C (87 ˚F) and reach a peak at 38.3˚C (101 ˚F). Above this temperature, there is a very marked decline in HRI ED visits, with rates at 40.6˚C (105 ˚F) roughly half those observed at the peak temperature of 101 ˚F.

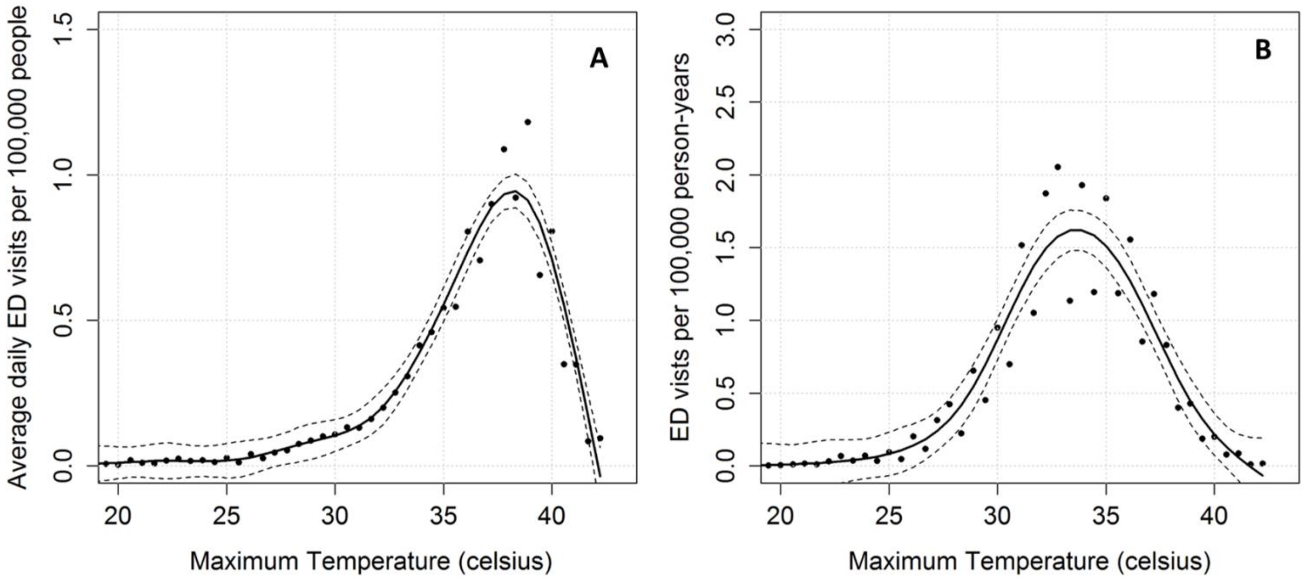

Figure 4: HRI versus maximum temperature across North Carolina for May - Sept 2007 to 2012 (a) Daily HRI ED visits per 100, 000 people with respect to maximum temperature; (b) HRI ED visits per 100,000 person-years relative to maximum temperature for North Carolina

Regional characteristics of HRI

HRI ED visits were significantly lower in the Mountains region compared to the Piedmont and Coastal Plain (Table 6). Owing to its higher elevation, most portions of the Mountains region rarely experience maximum temperatures above 35˚C (95 ˚F). Indeed, its threshold temperature of 26.7 ˚C (80˚F) for HRI was the lowest threshold temperature observed in this study. Additionally, the Mountain region displayed the lowest peak temperature (33.3˚C, 92 ˚F) across the three regions. The populous Piedmont region, on the other hand, experienced nearly double the number of HRI ED visits per 100,000 person-years and a threshold temperature that was 5 degrees Celsius higher than the Mountains region.

	ED visits per 100,000 person-years (HRI incidence Rates)	Threshold Temperature ˚C(˚F)	Peak Temperature ˚C(˚F)	Daily Maximum ED visits
Regional				
Mountains	11.6	26.7(80)	33.3(92)	0.35
Piedmont	20.3	31.7(89)	37.8(100)	0.62
Coastal Plain	34.7	31.1(88)	37.8(100)	1.53
Rural and Urban				
Metropolitan	18.8	32.2(90)	38.3(101)	0.62
Rural Metropolitan	26.7	32.2(90)	37.2(99)	1.00
Rural Town	37.7	30.6(87)	38.3(101)	1.24
Rural Isolated	38.6	31.7(89)	37.8 (100)	1.86
Age (years)				
Under 14	6.2	n/a	37.8(100)	0.19
15 to 17	34.8	31.7(89)	37.8(100)	1.06
18 to 44	35.6	31.1(88)	37.8(100)	1.32
45 to 64	25.8	31.7(89)	38.3(101)	1.01
65 and Older	23.9	31.7(89)	37.8(100)	0.71

Table 6: Regional and demographic characteristics of HRI including the crude incidence rates (i.e. HRI ED visits per 100,000 person-years), the threshold temperatures, peak temperatures, and maximum ED visits with respect to the peak temperature value.

The Coastal Plain exhibited significantly higher rates of HRI ED visits than the Piedmont and Mountains. The peak temperature for ED visits was 37.8˚C (100 ˚F), with significantly more ED visits (1.53 daily HRI ED visits) than the Piedmont (0.62 daily HRI ED visits) and Mountains (0.35 daily HRI ED visits) for peak temperatures. The threshold temperature was 31.7 ˚C (89 ˚F), which was lower than the Piedmont, suggesting the population's greater vulnerability to heat. All three regions exhibited a large decline in HRI ED visits after peak temperatures. This decline is especially precipitous across the Coastal Plain, even though the number of HRI ED visits remained higher than the other two regions (Figure 5). Due to the low incidence of

HRI in the mountain region, and a different relationship with HRI at lower maximum temperatures, the remainder of the analysis focused on the Piedmont and Coastal Plain.

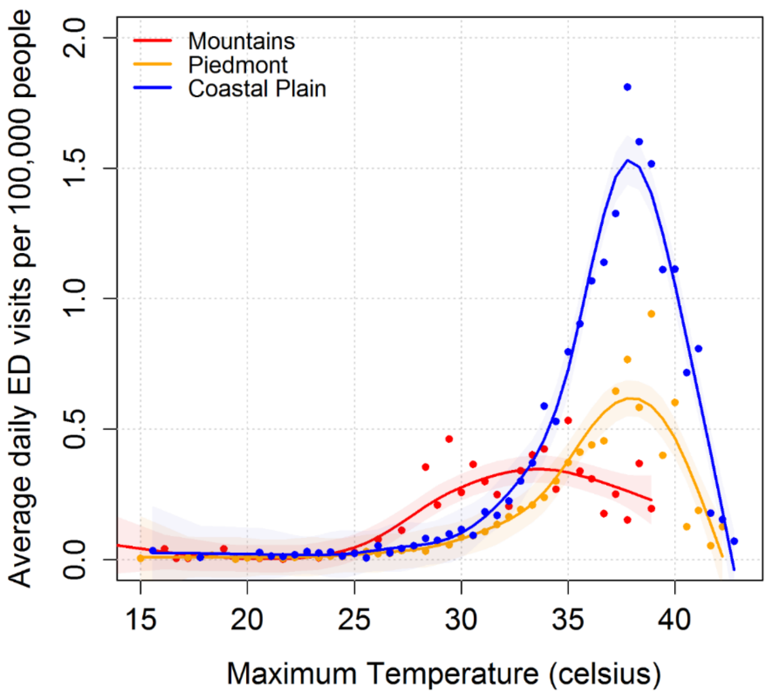

Figure 5: Daily HRI ED visits per 100, 000 people with respect to Maximum Temperature for different physiographic regions of North Carolina (i.e. Mountains, Piedmont, and Coastal Plain)

Rural and urban characteristics of HRI

In the assessment of the rural-urban characteristics of HRI, Table 6 reveals that incidence rates of HRI increased with the rurality of the region. Specifically, rural isolated populations displayed significantly higher HRI ED visit rates between temperatures of 31.7 ˚C (89 ˚F) and 40˚C (104 ˚F) compared to the other urban-rural categories. The differences across the four regions in the urban-to-rural continuum were greatest at higher temperatures (e.g. at the peak temperature). Threshold temperatures for the rural locations (i.e. rural isolated and rural town) were also lower compared to the more urban locations (i.e. metropolitan and rural metropolitan) (Figure 6).

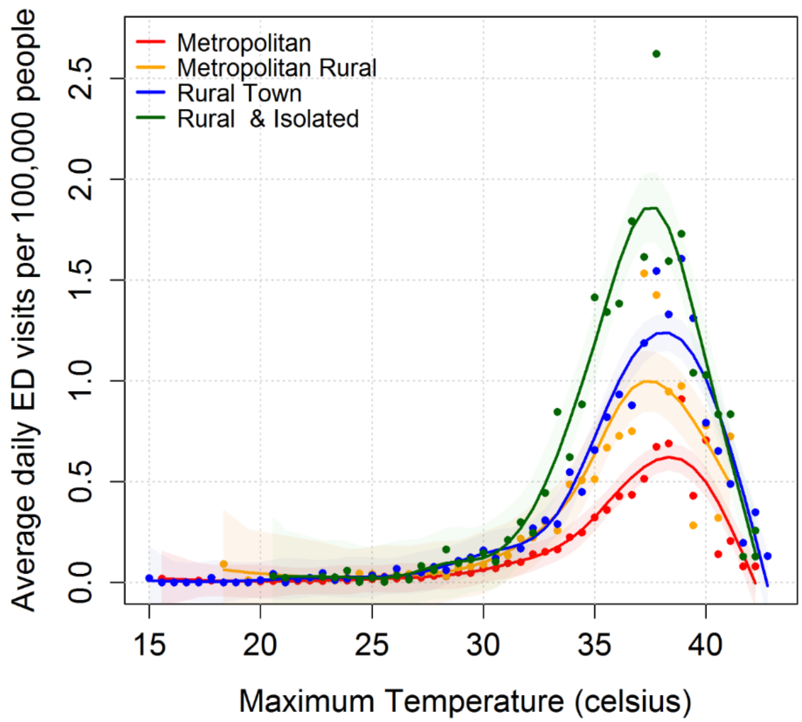

Figure 6: Daily HRI ED visits per 100,000 people with respect to maximum temperature for different rural-urban regions (i.e. metropolitan, metropolitan rural, rural town, and rural isolated)

Demographic characteristics of HRI

HRI ED visit data included demographic characteristics of the patient, allowing for the identification of age and gender differences between HRI and temperature. Figure 7 illustrates the incidence of HRI for each demographic age category within the rural and urban continuum. In rural locations (e.g. rural town and rural isolated), the highest HRI incidence rates were in the 15 to 64 age demographic. Urban locations experienced the highest HRI incidence rates in the 15 to 17 and 55 to 64 age demographic. The metropolitan-rural differences in HRI rates were most pronounced in the 18 to 34 age demographic.

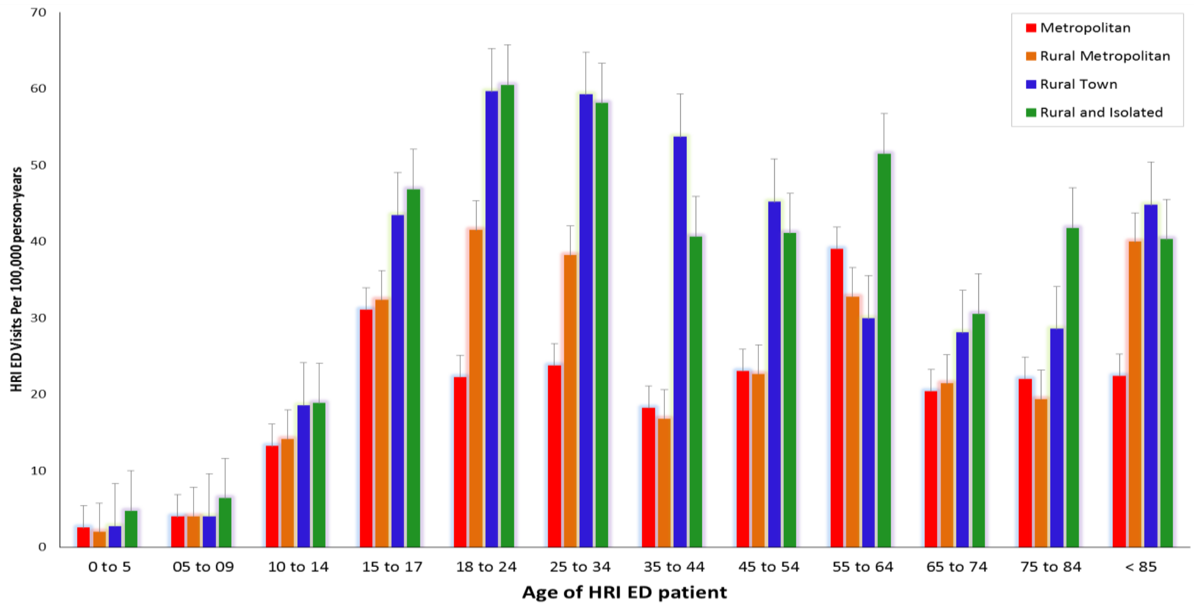

Figure 7: HRI ED visits per 100, 000 person-years (i.e. HRI incidences) for different age demographics across the rural-urban continuum

Figure 8 illustrates relationships between HRI by age group and maximum temperature. The relationships display generally parallel forms. Threshold temperatures were similar across age groups, but there were marked differences in the rates near the peak temperature, with those in the 18 to 44 age group nearly double HRI rates of the under 14 age group. Peak temperatures across the five groups are remarkably similar, though the peak for the 45 to 64 age group is slightly higher (38.3 ˚C, 101 ˚F) and the 15-17 age group slightly lower (37.2˚F, 99 ˚F). Due to small sample size, a robust threshold temperature could not be calculated for the under 14 age demographic (Table 6).

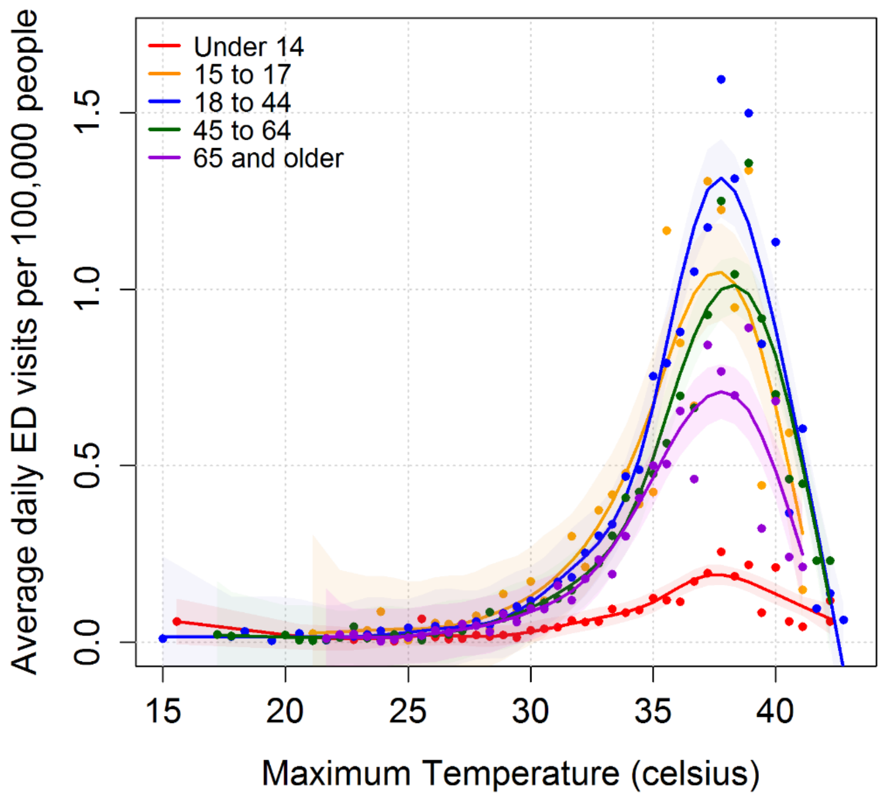

Figure 8: Daily HRI ED visits per 100, 000 people with respect to maximum temperature for different demographics

The rates of HRI ED visits for males were higher than for females across all age categories (Table 7). The gender differences between HRI rates were less pronounced for the younger patients (i.e. under 9 years) and older patients (i.e. 85 and older) than for the working age demographic (i.e. 25-44 years), where HRI rates were nearly four times greater for males (Table 7).

Age (years)	Female	Male
Under 4	2.5	2.7
5 to 9	3.1	5.6
10 to 14	12.8	16.9
15 to 17	23.3	45.8
18 to 24	16.6	49.7
25 to 34	13.5	55.9
35 to 44	12.9	47.8
45 to 54	13.5	45.0
55 to 64	23.5	55.2
65 to 74	13.0	34.7
75 to 84	16.6	36.3
85 and older	25.8	39.2

Table 7: Demographic characteristics of HRI incidence rates for males and females (incidence rates are reported as 100,000 person-years).

Discussion

This study investigated the association between the maximum temperature and heat-related morbidity in North Carolina across six warm seasons (e.g. May to September) from 2007 to 2012. The impact of temperature on human health has been studied extensively, however, most epidemiological studies have focused on the relationship between temperature and mortality in urban locations. Unlike previous studies, this study examined the relationship with heat *morbidity* rather than heat mortality. In addition, this relationship was investigated across an entire state, allowing for an examination of the differences between rural and urban populations.

Previous research reveals a U-or J-shaped curve with mortality peaks at the highest and lowest ends of the temperature spectrum. This study focused on the warm season and consequently, the higher end of the temperature spectrum. At the state level, results from this study indicated that the temperature and morbidity curves also followed a J-shape curve with HRI visits beginning to increase at a threshold temperature of 30.6˚C (87 ˚F). However, in our study the J-shape curve reached a maximum at 38.3˚C (101 ˚F), with the highest HRI rates occurring at this temperature. At extremely high temperatures (temperatures higher than 38.3˚C) HRI rates declined considerably. To our knowledge, this type of decline has not been reported in the research. Hartz (2013), for example, observed increased rates of heat-related 9-1-1 emergency dispatches at maximum temperatures above 38.3˚C (101 ˚F) in Chicago, Illinois, USA and Phoenix, Arizona USA. Also, Curriero et al. (2003) has observed linear or exponential increases in heat mortality at higher temperatures in other cities across the United States.

Noteworthy exceptions to the J-shape curve can be found when evaluating specific health outcomes. For instance, Xiang et al. (2014), evaluated associations between maximum temperature and work-related injuries and found a positive association with temperatures below 100 ˚F and a decline when temperatures exceeded this peak temperature. Xiang et al. (2014) suggested this decline was due to effective protective measures including hot weather policies, which advise the cessation of work when temperatures are extreme. In North Carolina, the decline in HRI at extremely hot temperatures could also be due to the implementation of similar protective measures. Air conditioning is prevalent, with 97% of households having either a window unit or central air system (U.S. Department of Energy 2010). Access to air conditioning significantly decreases heat stroke and heat mortality (Kilbourne et al. 1982, Kalkstein 1993). Therefore, coping measures for heat are nearly ubiquitous for the North Carolina population, allowing many residents to stay indoors and prevent HRI with air conditioning use. Additional coping mechanisms include a North Carolina High School Athletic Association mandate to suspend athletic practice at high temperatures and other recommendations by the North Carolina Department of Labor to mitigate occupational risk during extreme heat (North Carolina Department of Labor 2011, North Carolina High School Athletic Association 2014). Future HRI mitigation strategies should emphasize adaptive and coping measures at lower temperatures (i.e. 35 to 37.8 ˚C, 95 to 100 ˚F) to prevent HRI ED visits.

Regionally, the Mountains experienced significantly lower HRI ED visit rates than the Piedmont and Coastal Plain. The higher elevations (305 -2098 meters) of this region experience relatively cooler temperatures throughout the summer. The threshold temperature for the Mountain region (26.7˚C, 80˚F) was also lower than other regions, suggesting that its population is less acclimatized to heat. This result is consistent with Curriero et al. (2003) and Kalkstein and Davis (1987), who found regional differences in acclimatization, with cooler northern cities experiencing higher rates of heat mortality than southern cities.

The Coastal Plain displayed a lower temperature threshold (i.e. 31.1˚C, 88 ˚F) and greater rates of HRI ED visits than the Piedmont, suggesting that this population is more vulnerable to heat. The Coastal Plain is more rural than the Piedmont, with an economy primarily based on agriculture. According to estimates from the 2008 to 2014 American Community Survey, a greater percentage of the population is engaged in farming, forestry, and fishing occupations in the Coastal Plain (0.3%) as compared to the Piedmont (0.2%) and Mountains (0.1%). Farm laborers work outdoors, acquiring not only external heat from the environment but also internal heat through metabolic processes associated with the strenuous labor (May 2009). Mirabelli et al. (2010) found that 40% of farm workers in North Carolina experienced at least one HRI symptom while laboring in extreme heat from June through September in 2009. Many of these workers are migrant and seasonal farm laborers, and the greatest concentration of these workers reside in the Coastal Plain counties of Duplin, Sampson, and Wayne County (Montz et al. 2011). Migrant and seasonal farm laborers, are particularly heat vulnerable, as they not only experience HRI through strenuous activity in high temperatures, but also from dangerous hot indoor conditions within housing structures (Quandt et al. 2013).

To investigate the relationship between temperature and HRI across different regions within the urban-rural continuum of the study area, ZIP codes were categorized as Metropolitan, Rural Metropolitan, Rural Town, and Rural Isolated based on their population density and work commuting patterns. To date, few studies have examined the effect of temperature on rural populations. The lack of research likely relates to the well-established understanding among researchers that an urban environment is an important risk factor for heat-related morbidity and mortality, mainly due to the urban heat island effect (McGeehin and Mirabelli 2001). In North Carolina, however, we found that rural populations displayed significantly higher rates of HRI than the urban populations. Moreover, our results established that rates of HRI ED visits are greatest in isolated rural areas and rural towns relative to rural areas situated near larger cities, where many people commute to the city.

The Isolated and Rural locations experienced nearly a threefold increase in HRI at 37.8˚C (100 ˚F) compared to more urban regions. Additionally, rural locations (e.g. Rural Town and Isolated Rural) displayed a lower threshold temperature (e.g., 30.6 to 31.7 ˚C, 87 to 89 ˚F), compared to urban populations (32.2 ˚C, 90 ˚F). Several factors likely contribute to the heat vulnerability of rural residents. These factors may relate to the population's underlying social vulnerability, where a combination of environmental, demographic, and socioeconomic risk factors affect their capacity to cope with heat. One common factor that increases social vulnerability is poverty, a well-established risk factor for both heat morbidity and mortality (Anderson and Bell 2011). In the urban-rural continuum of regions, poverty levels increased from 15.2% (Metropolitan) to 20.1% (Rural Isolated), coincident with increasing rates of HRI. Other risk factors that influence social vulnerability include the proportion of the population with low educational attainment (i.e. no high school education) and older building structures (i.e. more energy inefficient) were also greater in rural locations (Table 8).

RUCA classification	Percent Mobile Homes	Percent of residents living below the poverty line	Percent of residents with no high school education	Population Density
Metropolitan	8	15.2	12.8	465
Metropolitan Rural	26	16	18.1	60
Rural Town	23	17.6	18.5	94
Rural Isolated	25	20.1	20.3	35
RUCA classification	**Median Year Structure Built**	**Percent Cropland**	**Percent Developed Land**	**Percent of residents within the farming, fishing, and forestry occupation**
Metropolitan	1982	9.9	43.7	0.096
Metropolitan Rural	1985	12.7	8.8	0.582
Rural Town	1979	19.4	13.5	0.583
Rural Isolated	1978	19.1	7.8	1.305

Table 8: Socioeconomic, housing, and land cover characteristics of rural and urban locations. Percent were calculated from a total population across each rural-urban ZIP code region (e.g. percent mobiles homes of total households).

HRI ED visits in the Rural Town and Rural Isolated regions were exceptionally high in the 18 to 44 male demographic, which corresponds to the working age population. This group, however, is more likely to engage in outdoor exertional activities associated with their occupation. In fact, these rural regions contain significantly more cropland and a greater proportion of the population engaging in agriculture (Table 8). As was observed in the Coastal Plain, farm laborers who engage in agriculture are predisposed to HRI due to outdoor exposure and strenuous labor. This occupational risk and added social vulnerability are a plausible explanation for the exceptional rates of HRI. Future research should explore patterns of HRI at the individual-level to understand the specific pathways (e.g. occupation, social vulnerability, etc.) that result in high HRI in rural communities.

Overall incidence rates of HRI were highest among the 15 to 64 age demographic, particularly the 18 to 44 age group. These results contradict previous research, which focused on excess morbidity and mortality during heat waves and found that the elderly, very young, and the debilitated (i.e. underlying medical conditions) were more likely to experience heat-health effects (e.g. Knowlton et al. 2009). In contrast, we found that these populations (i.e. young, elderly) experience significantly lower rates of HRI across North Carolina, even at the highest temperatures, which are typically experienced during heat wave events.

The average rates of HRI ED visits for males were three times greater than that for females. This pattern may be tied to the fact that men engage in more outdoor activities (e.g. yard work, home maintenance, outdoor occupations) than women. Research at the national level revealed similar differences between males and females, with exertional HRI ED visits resulting from activities such as, home maintenance, yard work, and sports like football, which are prone to high rates of HRI (Nelson et al. 2011). Interestingly, nearly half of exertional HRI ED visits nationally were in the under 19 age demographic, while in North Carolina, we found the highest rates within the male population were in the 15 to 54 demographic. Previous research in North

Carolina using ED triage notes found that cases of HRI were often occupational-related in the 19 to 45 demographic and exercise-related in the 15 to 17 demographic (Rhea et al. 2012). In this study, we found that much of the HRI in these demographics occurred when daily maximum temperatures ranged from 31.1 ˚C to 37.8 ˚C (88 ˚F to 100 ˚F). Therefore, future HRI preventative measures should target workplace and sports-related activities within this broad range of temperature, and not solely at the highest temperatures.

It is important to discuss the limitations of this study. First, in order to focus on spatial and demographic heterogeneity in the temperature-morbidity relationships, we did not investigate any potential delayed effects of temperature and only examined temperature on the same day as the ED visit. Secondly, maximum temperature observations were based on the ZIP code address of the patient. In an unknown number of cases, the place of heat exposure was at a location with a microclimate different from that found at the weather station in which the corresponding temperature observation was made. Lastly, the counts and rates of HRI presented here were likely underestimates of the true occurrence of HRI in North Carolina, either as a result of: 1) The under-diagnosis of HRI in which ED physicians fail to appropriately document its diagnosis and symptoms, 2) The non-reporting of HRI because the health care provider was not part of the NC DETECT network (e.g. federal military hospital, urgent care facility), or 3) People suffering from HRI that did not seek medical care. The under-diagnosis of HRI was likely more common in rural locations of HRI, particularly rural and isolated, where residents must travel longer distances to seek medical care at an ED.

Conclusion

This study analyzed the association between the daily maximum temperature and heat-related illness (HRI) for six warm seasons (May-September) from 2007 to 2012. These temperature and HRI relationships were evaluated across different regions (e.g. piedmont, coastal plain, rural isolated, etc.) and demographic groups (e.g. gender, age). Unlike previous research, this study analyzed the association between heat –related *morbidity* across a broad area that included both urban and rural populations. Results demonstrated that HRI incidence increases as rurality increases, particularly for the male, 15 to 44 age demographic. HRI incidence increased most significantly between temperatures of 30.6˚C (87 ˚F) to 38.3˚C (101˚F), though variations were noted across different regions and populations. Surprisingly, HRI incidence decreased at temperatures warmer than 38.3˚C (101˚F), suggesting that adaptive or coping measures were adopted when temperatures were excessively high. Overall these results suggest that a large portion of HRI in North Carolina is related to exertional activities. Future mitigation and intervention strategies for heat should target populations that engage in exertional activities, particularly at temperatures that are not exceptionally high (e.g. 31.1 ˚C to 37.8 ˚C, 88 ˚F to 100 ˚F).

CHAPTER 4: INTRA-SEASONAL RELATIONSHIPS OF HRI

There is increasing concern over the adverse health effects associated with hot weather. In the United States, heat kills more people annually than any other weather-related disaster, resulting in hundreds of fatalities each year (NOAA 2007). Prolonged exposure to high temperature can result in heat-related illnesses (HRI), such as heat syncope, heat exhaustion, head edema, heat cramps, and in the most severe cases, heat stroke, which has a very high mortality rate. The health effects from heat are likely to increase as temperatures are also projected to increase due to climate change. The adverse heat-health effects are easily mitigated through basic hydration, relocating to a cool environment, or the implementation of targeted public health intervention or heat-warning systems (Koppe 2004). Therefore, research is needed to identify susceptible population and *when* these populations are most vulnerable to adverse heat-health effects.

The relationship between extreme temperature and mortality has been evaluated across multiple metropolitan locations (e.g. Kalkstein and Davis 1989, Curriero et al. 2003), however, few studies have addressed the intra-seasonal trends of these relationships. Limited studies focus on extreme heat events or heat waves, and how the timing of these events influences mortality, particularly among susceptible individuals (Kaiser et al. 2007; Le Tertre et al. 2006; Anderson and Bell 2011; Baccini et al. 2008, Hajat et al. 2002). Results indicate that extreme heat events earlier in the warm season trigger higher mortality outcomes than similar heat events later in the summer season (Anderson and Bell 2011). High mortality rates early in the summer season were often attributed to a combination of the most susceptible individuals succumbing to the first heat wave (i.e. mortality displacement) and to a lack of heat acclimatization (Kilbourne 1980; Kalkstein and Smoyer 1993; Smoyer 1998). Susceptible populations include the elderly, infants, people with chronic diseases, and socially deprived groups (e.g. poverty, minority).

Consistent with most heat-health studies, research on intra-seasonal trends were also focused on heat mortality rather than heat-related *morbidly*. Recent research in the United States has examined heat-related morbidity through emergency 9-1-1 dispatches in Chicago, Illinois from 2003 to 2006 and Phoenix, Arizona from 2001 to 2006 (Hartz et al. 2013). In Phoenix, Arizona heat-related dispatches peaked in July, the month with the highest maximum temperatures and dew points, followed by August, which had the third highest average maximum temperatures (i.e. after June) and the second highest average dew point (i.e. after July) (Golden et al. 2008). Similarly, the maximum number of heat-related dispatches in Chicago, IL occurred in July, followed by August and then June (Hartz et al. 2012).

In the Kanto metropolitan area of Japan, heat-related dispatches also coincided with the highest temperatures. The month of August contained the most dispatches and highest temperatures, followed by July (i.e. second highest temperatures) and September. One key finding in Ng et al. (2014) was the increased risk for heat-related dispatches early in the warm season, particularly in June, when temperatures were typically below the heat watch warning thresholds.

The objective of this study is to evaluate intra-seasonal patterns of HRI across the North Carolina for six warm seasons from 2007 to 2012. The present study compliments previous research by Kovach et al. (2015) that evaluated the spatial patterns of HRI across different demographics (e.g. age) and regions (e.g. rural, urban, Coastal Plain). Unlike Kovach et al. (2015), which evaluated spatial patterns, this study focuses on intra-seasonal variations in HRI rates and how they vary across different demographics and regions of North Carolina. To our knowledge, this study provides the longest, continuous data set of HRI morbidity in the United States to date, and this allows for a more robust, in-depth investigation of how the timing of high temperatures influences rates of HRI.

Data and Methods

Study area

North Carolina is an optimal study location due to its large population (10^{th} most populous in the U.S.), varying climate, physiography, and topography (Mackun et al. 2011). While the urbanized areas of the state are growing rapidly, roughly one-third of its population still resides in rural areas, according to the 2010 Census. Given this diversity, analyses were performed across three separate physiographic regions (e.g. mountains, piedmont, and coastal plain) and four areas along an urban-rural continuum. Daily maximum temperature and minimum temperatures were highest in the month of July and lowest in the months of May (Table 9).

	Mountains	Piedmont	Coastal Plain
May			
Average Number of HRI ED visits	7.2	19.5	13.3
Maximum Temperature ˚C(˚F)	25.1(77.2)	29.2(84.5)	29.6(85.2)
Minimum Temperature ˚C(˚F)	12.7(54.8)	15.5(59.9)	16.7(62.0)
June			
Average Number of HRI ED visits	17.9	62.4	42.5
Maximum Temperature ˚C(˚F)	30.3(86.5)	33.3(92.0)	33.3(91.9)
Minimum Temperature ˚C(˚F)	16.9(62.5)	19.9(67.8)	21.2(70.2)
July			
Average Number of HRI ED visits	16.0	67.5	47.4
Maximum Temperature ˚C(˚F)	30.8(87.4)	34.1(93.3)	34.2(93.5)
Minimum Temperature ˚C(˚F)	18.2(64.8)	21.3(70.3)	22.4(72.3)
August			
Average Number of HRI ED visits	14.8	55.6	40.6
Maximum Temperature ˚C(˚F)	30.7(87.3)	33.8(92.8)	33.4(92.2)
Minimum Temperature ˚C(˚F)	17.9(64.2)	21.3(70.3)	22.3(72.1)
September			
Average Number of HRI ED visits	5.0	15.6	10.9
Maximum Temperature ˚C(˚F)	26.9(80.4)	29.8(85.7)	30.9(87.7)
Minimum Temperature ˚C(˚F)	13.9(57.0)	17.8(64.1)	19.2(66.5)

Table 9: 2007 to 2012 Monthly mean maximum, minimum and number of HRI ED visits for three physiographic regions of North Carolina

Health data

The incidence of heat-related illness (HRI) was determined using emergency department (ED) visit data from the North Carolina Disease Event Tracking and Epidemiologic Tool (NC DETECT), a statewide public health surveillance system developed by the University of North Carolina and the North Carolina Division of Public Health. ED visits containing at least one heat-related code (ICD-9-CM code 992.xx) in any of the 11 diagnostic fields were used to calculate the incidence of HRI. ED data are a valuable source of HRI information, as they are a common healthcare access point for patients experiencing HRI, which is sudden, acute, and debilitating illness.

Age and gender-specific estimates of the population included in this analysis were obtained from the United States Bureau of Census. The 2010 Census-based population estimates were used as population denominators in the estimation of HRI ED visits per 100,000 person-years.

Weather and Environmental data: Daily maximum temperature observations were obtained from 169 weather stations networks, including Automated Surface Observations Stations (ASOS), Automated Weather Observing System (AWOS), Remote Automatic Weather Stations (RAWS), and the North Carolina Environment and Climate Observing Network (EcoNet). These stations are maintained by the National Weather Service and Federal Aviation Administration, the United States Forest Service, and the North Carolina Environment and Climate Observing Network. The daily maximum temperature of the weather station closest to the patient's residential billing ZIP code was determined for each ED admission (see Kovach et al. (2015) for details).

Assessing heat vulnerability in rural populations that specialize in agriculture is especially important in North Carolina, which experiences the highest number of heat-related deaths among farm laborers in the United States (Luginbuhl 2008). To evaluate the intra-seasonal relationship for locations with agriculture, data from the National Land Cover Dataset (NLCD) were acquired. NLCD data provides land cover information for over 40 crop types from 2008 to 2012. Tobacco and sweet potatoes are two common cash crops in North Carolina that require strenuous labor for harvesting. To determine locations that specialize in these crops, geographic information system (GIS) was used to estimate their acreage within each ZIP code for the five years in which NLCD data were available (i.e. 2008 to 2012). These values were then divided by the ZIP code area to provide a percent coverage for each crop.

Rurality

There are large variations in the rural and urban character of the state. These differences affect the thermal environment in which people work (e.g. farm laborers who are exposed to heat versus office workers who spend much of their time inside in an air conditioned environment). To differentiate the rural and urban character of areas, Rural-Urban Commuting Areas were assigned to each ZIP code based on markers of population density and proximity to urban locations. In this study, ZIP codes were classified into one of four mutually exclusive RUCA categories (Table 11): 1) *Metropolitan* were identified as the most urban with populations that reside and work in urban locations where the population is greater than 50,000 people 2.) *Rural metropolitan* were defined by a low population density and large portions of its residents commuting into nearby metropolitan locations 3.) *Rural town* included larger towns and adjacent rural areas 4.) *Rural isolated*, the most rural category, included populations that resided in small towns and adjacent rural areas.

RUCA classification	RUCA code	Definition
Metropolitan	1	Census defined Urban Areas
Metropolitan Rural	2.0-3.0, 4.1, 5.1, 7.1, 8.1, 10.1	Locations with substantial commuter flows to Urban Areas (30% to 50%)
Rural Town	4.0, 4.2, 5.0, 5.2, 6.0, 6.1	Census defined (large) Urban Clusters (e.g. 10,000 to 25,000 population) with minimal commuter flows to Urban Areas (Less than 29%)
Rural Isolated	7.0, 7.2-7.4, 8.0, 8.2-8.4, 9.0-9.2,10.0,10.2-10.6	Census defined (small) Urban Clusters (e.g. 2,500 to 9,999 population) with commuter flows to Urban Clusters (Less than 50%) and minimal flows to Urban Areas (Less than 29%)

RUCA classification	Percent of residents within the farming, fishing, and forestry occupation	Percent of residents living below the poverty line	Percent of residents with no high school education
Metropolitan	0.096	15.2	12.8
Metropolitan Rural	0.582	16	18.1
Rural Town	0.583	17.6	18.5
Rural Isolated	1.305	20.1	20.3

Table 11: Definition and Characteristics of Rural and Urban Locations defined using the Rural Urban Community Area (RUCA) Codes. Percent of residents within the farming, fishing and forestry occupation, living below the poverty line, and residents with no highs school education were calculated using American Community Survey estimates from 2008 to 2012 and calculated based on total population within ZIP code.

Statistical analysis

A generalized additive model (GAM) was used to describe the relationship between temperature and HRI. GAMs are commonly applied in time series studies of air pollution and health data and more recently have been utilized in HRI and mortality studies (Li et al. 2012, Hondula et al. 2013). In this study, GAMs were calculated using a natural cubic spline (i.e. nonparametric smoothing function) to model the non-linear relationship with daily maximum temperature and HRI ED visits. GAMs were constructed to model the monthly (May – September) relationship between HRI and temperature. This model provides the daily rate of HRI ED visits per 100,000 persons *with respect to temperature* (i.e. number of temperature observations within month of interest). Thus, providing a direct estimate of the rate of HRI expected on a day with a given maximum temperature.

Three summary statistics were developed from the models and compared across different months, regions, and populations: 1) Monthly rate of HRI ED visits per 100,000 person-years (i.e. monthly HRI incidence rates) 2) Threshold temperature in which HRI ED visits increased to the point that they were statistically different from zero and remained significant for higher temperatures (Davis et al. 2003, Gosling et al. 2014). 3) Peak temperature, which is the daily maximum temperature in which the greatest rates of HRI ED visits occurred. Analyses were performed in R software 3.0.1 with the MGCV package (R Core Team 2013) at a 95% confidence level.

Results

Basic characteristics of HRI across North Carolina

Figure 9 illustrates the crude incidence rate of HRI ED visits across North Carolina for the warm season months (May-September) of 2007-2012. HRI ED rates were highest in the rural locations of eastern North Carolina (i.e. Coastal Plain), while the lowest HRI ED rates were largely concentrated in the western mountainous portion of the state and the metropolitan areas located within the Piedmont. The highest HRI ED visits were observed in July, June, and August. The month of July experienced the highest maximum and minimum temperatures values followed by August and June (Table 9).

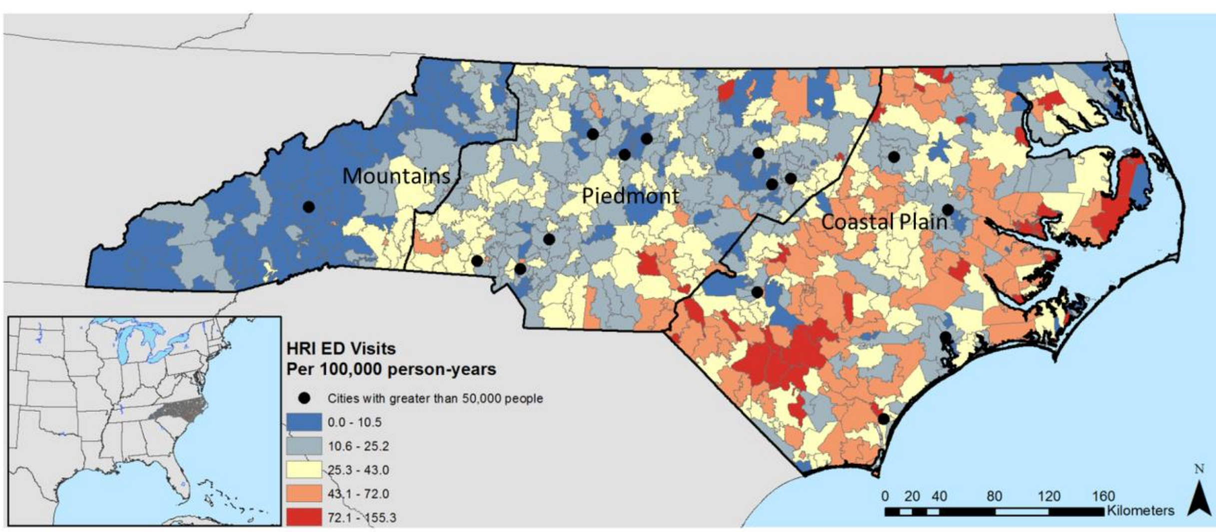

Figure 9: HRI ED visits per 100,000 person-years for May through September from 2007 to 2012.

Figure 10 depicts the monthly rates of HRI ED visits across North Carolina with respect to daily maximum temperature. HRI ED visits rates are the greatest in June and July and much lower in shoulder months of May and September. The form of the relationship is remarkably similar for the months of June and July, with a peak observed around 37.2 ˚C (99 ˚F) and a marked decline at the highest temperatures (Table 12). Although August displayed relatively lower rates of HRI, it showed the highest temperature threshold and peak temperature. Moreover, the decline of HRI ED visits at the very warmest temperatures was less pronounced (i.e. August displayed the highest rates of HRI at temperatures > 38.9 ˚C (102 ˚F). May displayed the lowest temperature threshold 26.7 ˚C (80 ˚F) and a much lower peak temperature 33.3 ˚C (92 ˚F) relative to June and July.

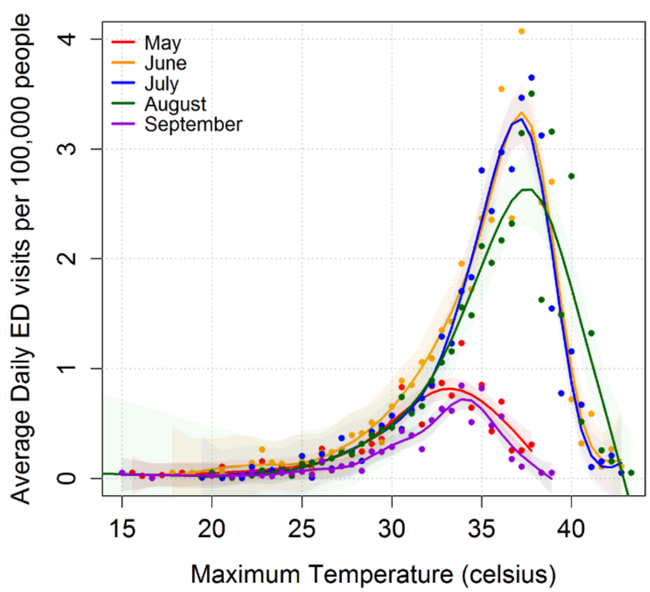

Figure 10: Daily heat-related illness emergency department visits per 100,000 people with respect to maximum temperature across the entire state of North Carolina. To account for monthly HRI with respect to temperature, the frequency of daily maximum temperatures was obtained for each month.

Regional characteristics of HRI

HRI ED visits were significantly lower in the Mountains region compared to the Piedmont and Coastal Plain. The threshold temperatures and peak temperatures in this region were the lowest across all months in the study (Table 12). Due to small samples, threshold and peak temperature values were not calculated for the months of May and September.

Month	Threshold Temperature ˚C(˚F)	Peak Temperature ˚C(˚F)	Daily Maximum HRI ED visits	Total HRI ED visits per 100,000 person-years
Entire State				
May	26.7 (80)	33.3 (92)	0.819	8.6
June	27.8 (82)	37.2 (99)	3.335	34.4
July	28.3 (83)	37.2 (99)	3.276	36.2
August	28.9 (84)	37.8 (100)	2.634	29.9
September	28.3 (83)	33.9 (93)	0.721	7.3
Mountains				
May	n/a	n/a	n/a	5.4
June	25.0 (77)	34.4 (94)	1.132	17.6
July	26.1 (79)	35.0 (95)	1.088	16.6
August	26.7 (80)	35.0 (95)	1.360	15.3
September	n/a	n/a	n/a	4.4
Piedmont				
May	27.8 (82)	32.2 (90)	0.760	7.6
June	28.9 (84)	36.7 (98)	2.439	30.4
July	30.0 (86)	36.7 (98)	2.638	31.0
August	30.6 (87)	37.8 (100)	2.294	25.2
September	27.8 (82)	32.8 (91)	0.413	6.1
Coastal Plain				
May	28.3(83)	34.4 (94)	1.403	11.9
June	29.4 (85)	37.2 (99)	5.799	49.6
July	30.6 (87)	37.8 (100)	5.966	54.9
August	30.0 (86)	37.2 (99)	4.200	45.5
September	31.1 (88)	34.4 (94)	1.491	10.9

Table 12: HRI incidence (i.e. Total HRI ED visits per 100,000 person-years), threshold temperature, Peak temperature, and corresponding maximum HRI ED visits (at peak

temperatures) values for the different physiographic regions (i.e. Mountains, Piedmont, and Coastal Plain) and the entire state of North Carolina.

Given the low incidence of HRI in the mountains, the remainder of the analyses focused on the Piedmont and Coastal Plain regions of North Carolina. The Coastal Plain displayed significantly higher rates of HRI visits than the Piedmont across all months (Figure 11). Near the peak temperature, the months of June and July experienced considerably higher rates of HRI than August, May, and September. The Coastal Plain showed a more marked drop than the Piedmont in HRI ED visits in the month of August relative to June and July.

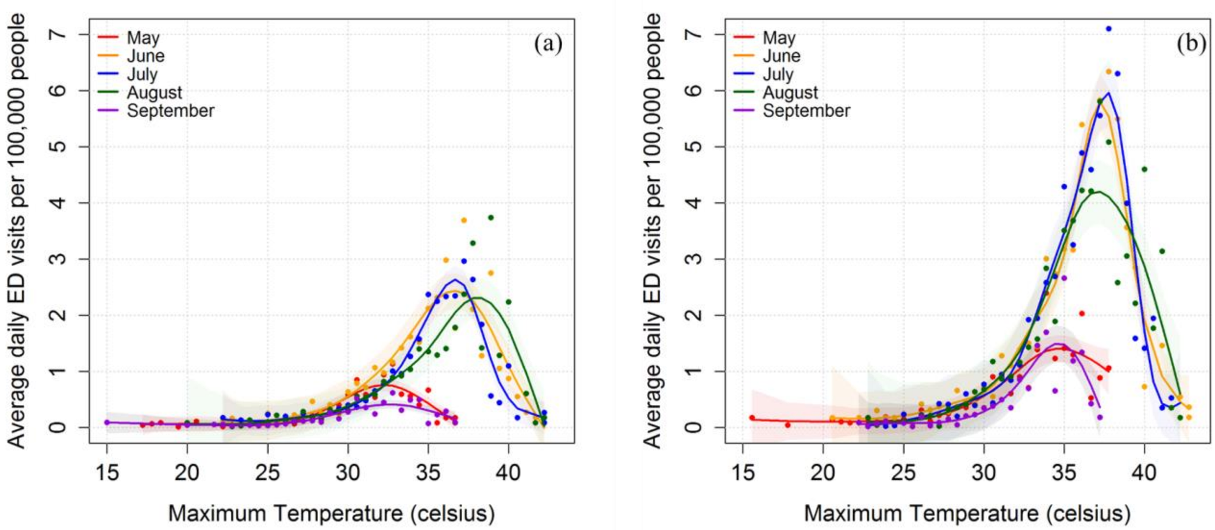

Figure 11: Daily heat-related illness emergency department visits per 100,000 people with respect to maximum temperature across the(a) the Piedmont (b) The Coastal Plain

Locations with a high percentage of sweet potatoes or tobacco crops were assessed to examine intra-seasonal trends in HRI. Crop locations were selected based on the natural grouping of the upper data distribution, which corresponded to the top 7% of ZIP codes for each crop type (i.e. sweet potato, tobacco). To assess, crop-type relationships comparisons were made with HRI rates in the Coastal Plain and/or Piedmont.

All locations with a high percentage of sweet potatoes were located in the Coastal Plain. Compared to Coastal Plain rates, HRI rates were greater for sweet potato locations in the months of June, July, August, and September (Table 13). September had exceptionally high HRI incidence rates, with the second highest September rates observed within the study.

Month	Sweet Potato	Coastal Plain	Tobacco	Average of Coastal Plain & Piedmont
May	11.6	11.9	9.2	10.6
June	51.0	49.6	45.0	43.8
July	59.3	54.9	53.1	47.7
August	49.7	45.5	42.5	39.4
September	13.2	10.9	11.7	9.4

Table 13: HRI incidence reported as HRI ED visits per 100,000 person-years for ZIP codes with a high percentage of sweet potato acreage and tobacco acreage. A weighted average was calculated for regional rates in the Piedmont (30%) and Coastal Plain (70%) as a comparison of HRI incidence for tobacco locations

Roughly two-thirds of locations containing a high percentage of tobacco were situated in the Coastal Plain, while the remaining third of locations were situated in the Piedmont. HRI incidence rates were greater for tobacco locations in the months of June, July, August, and September as compared to Coastal Plain and Piedmont HRI incidence rate (Table 13). Tobacco locations had considerably higher HRI incidence rates in the month of July with an additional 5.3 HRI ED visits per 100,000 person-years.

Demographic characteristics

Figure 12 illustrates the monthly rates of HRI ED visits across different demographics with respect to daily maximum temperature. The < 14 and >65 age demographic experienced the highest HRI ED incidence in June. In these age groups, June ED visits increased at the threshold temperature of 30 ˚C (86 ˚F) and 30.6 ˚C (87 ˚F) and reached a peak at 36.1 ˚C (97 ˚F) and 36.7

˚C (98 ˚F). Daily HRI ED visits at peak temperatures were also highest in June in the 45 to 64 age demographic. However, monthly HRI incidence rates for the demographic were slightly higher in July (Table 14).

Month	Threshold Temperature ˚C(˚F)	Peak Temperature ˚C(˚F)	Daily Maximum HRI ED visits	Total HRI ED visits per 100,000 person-years
Under 14				
May	28.3 (83)	36.1 (97)	0.352	4.6
June	30.0 (86)	36.1 (97)	0.697	10.5
July	31.7 (89)	38.3 (101)	0.613	7.7
August	31.7 (89)	37.2 (99)	0.436	7.3
September	29.4 (85)	33.9 (93)	0.306	4.3
15 to 17				
May	26.1 (79)	37.8 (100)	1.219	8.9
June	30.0 (86)	36.1 (97)	2.492	36.1
July	30.6 (87)	37.8 (100)	2.766	35.0
August	30.6 (87)	37.8 (100)	3.680	50.2
September	27.8 (82)	34.4 (94)	1.112	17.7
18 to 44				
May	26.1 (79)	33.9 (93)	0.947	10.1
June	27.8 (82)	37.2 (99)	3.803	41.6
July	28.9 (84)	37.2 (99)	4.287	45.9
August	30.0 (86)	37.2 (99)	3.306	36.9
September	28.3 (83)	34.4 (94)	0.769	7.6
45 to 64				
May	27.2 (81)	33.3 (92)	0.690	7.9
June	29.4 (85)	37.2 (99)	3.399	31.3
July	30.0 (86)	36.7 (98)	2.861	33.0
August	28.9 (84)	37.8 (100)	2.430	26.5
September	29.4 (85)	33.9 (93)	0.524	5.9
65 and Older				
May	27.2 (81)	33.3 (92)	0.782	7.4
June	30.6 (87)	36.7 (98)	2.928	28.4
July	28.9 (84)	36.7 (98)	2.085	29.4
August	29.4 (85)	37.2 (99)	1.481	20.6
September	28.3 (83)	36.1 (97)	0.414	5.4

Table 14: Total HRI ED visits per 100,000 person-years (i.e. HRI incidence), Threshold Temperature, Peak Temperature, and corresponding Maximum HRI ED visits (at Peak Temperatures) values for the different demographics age categories.

HRI incidence in the 15 to 17 age group was the highest in August and peaked at 37.8 ˚C (100˚F) with 3.7 HRI ED visits (Figure 12b). The September and August HRI incidence rates among this age group were also exceptionally high; the highest observed rates during these months for the entire study period.

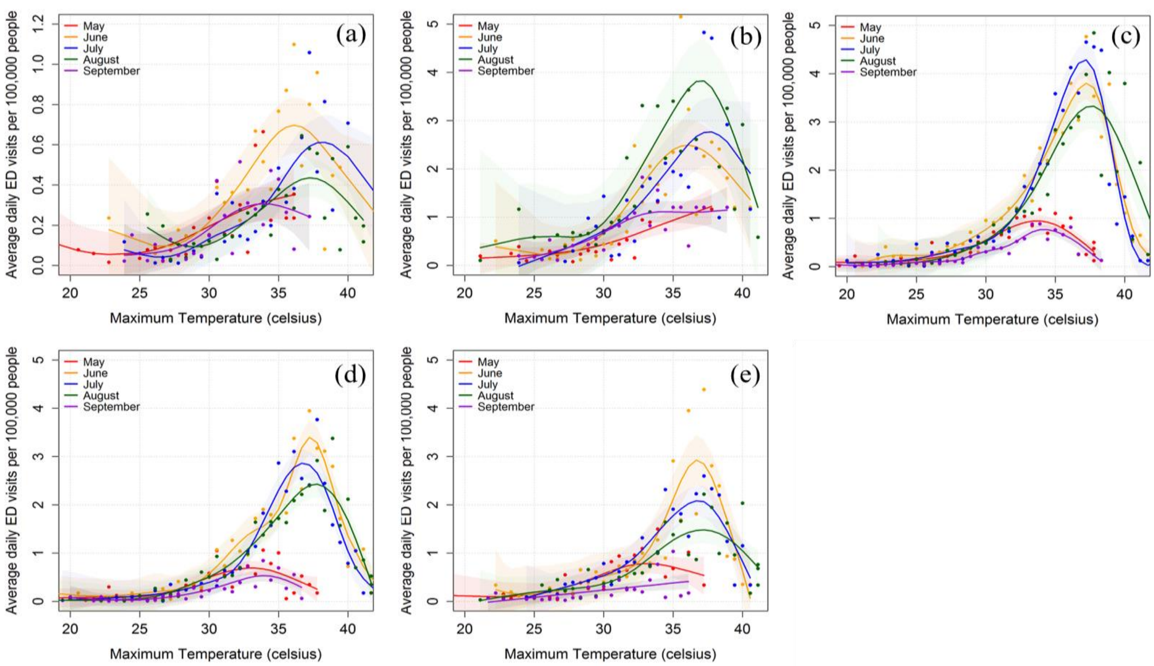

Figure 12: Daily heat-related illness emergency department visits per 100,000 people with respect to maximum temperature for the (a) Under 14 (b) 15 to 17 (c) 18 to 44 (d) 45 to 65 (e) 65 years and older age demographic

HRI incidence was exceptionally high in the months of June and July in the 18 to 44 year, the healthy, working age demographic (Figure 12c). In July and June, HRI ED visits increase strongly at the threshold temperatures and reach a peak at 37.2 ˚C (99 ˚F). At the highest temperatures, there is a very marked decline in June and July HRI ED visits. In contrast, August HRI ED visits exhibited a less pronounced decline at the highest temperatures.

Rural and urban characteristics

In the assessment of the rural-urban characteristics of HRI, rates of HRI ED visit rates increased with rurality, particularly during the months of June and July (Figure 13, Table 15). Metropolitan locations (i.e. most urban) displayed the lowest rates of HRI, which very similar relationships across the warmer months of June, July and August (Figure 13a), although the peak temperature for August was higher with a less pronounced decline at the highest temperatures.

Month	Threshold Temperature ˚C(˚F)	Peak Temperature ˚C(˚F)	Daily Maximum HRI ED visits	Total HRI ED visits per 100,000 person-years
Metropolitan				
May	n/a	34.4 (94)	0.645	7.2
June	30.0(86)	37.2 (99)	2.566	27.9
July	30.6(87)	37.2 (99)	2.410	28.9
August	31.1(88)	38.3 (101)	2.329	23.4
September	28.3 (83)	33.3 (92)	0.484	6.3
Rural Metropolitan				
May	28.9 (84)	32.8 (91)	1.074	9.7
June	29.4 (85)	36.7 (98)	3.227	39.2
July	32.2 (90)	36.7 (98)	4.529	41.0
August	30.0 (86)	36.7 (98)	3.007	36.6
September	29.4 (85)	33.3 (92)	0.838	6.6
Rural Town				
May	28.9 (84)	34.4 (94)	0.471	4.5
June	29.4 (85)	37.2 (99)	5.038	55.0
July	28.9 (84)	37.2 (99)	5.172	58.4
August	30.0 (86)	37.2 (99)	3.519	48.7
September	31.1 (88)	36.1 (97)	1.137	5.0
Rural and Isolated				
May	27.8 (82)	33.9 (93)	1.369	12.2
June	31.7 (89)	37.2 (99)	6.848	53.9
July	31.1 (88)	36.7 (98)	7.238	61.1
August	31.1 (88)	37.2 (99)	5.104	46.4
September	28.9 (84)	35.0 (95)	1.476	13.5

Table 15: Total HRI ED visits per 100,000 person-years (i.e. HRI incidence), threshold temperature, peak temperature, and corresponding maximum HRI ED visits (at peak temperatures) values for the different regions along the rural-urban continuum. Categories were determined using rural-urban continuum from RUCA codes.

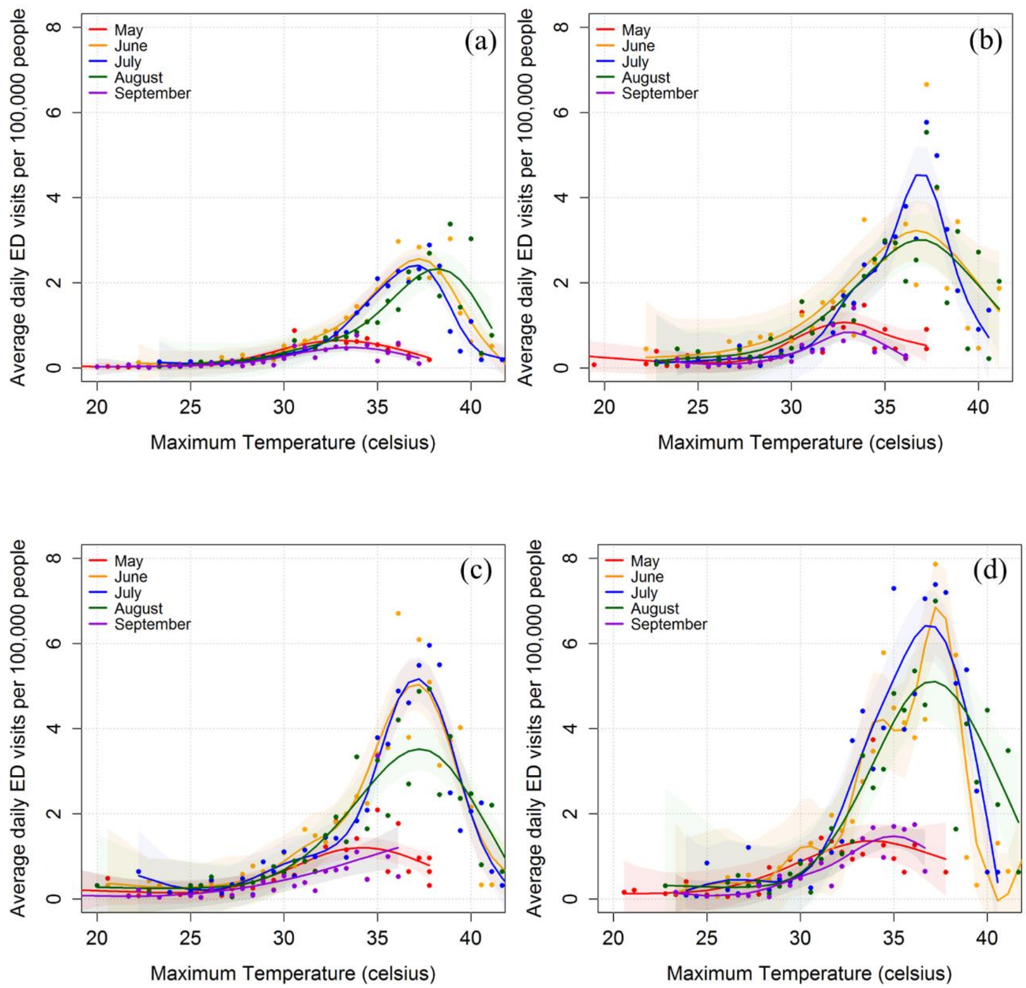

Figure 13: Daily heat-related illness emergency department visits per 100,000 people with respect to maximum temperature across the (a) Metropolitan (b) Rural Metropolitan (c) Rural Town (d) Rural Isolated locations

Rural metropolitan locations displayed a marked rise in HRI ED rates in July with a peak observed around 36.7 ˚C (98 ˚F) and a marked decline at the hottest temperatures. In addition, August and June exhibited a remarkably similar relationship between ED visits and maximum temperature (Figure 13b). Rural town locations, also displayed a similar relationship during the months of June and July, with a peak at 37.2 ˚C (99 ˚F) and a marked decline at the highest temperatures.

Rural Isolated locations had exceptionally high rates of HRI, particularly at peak temperatures during the months of June, July and August. HRI incidence rates were also exceptionally high in the month of May and September, relative to other locations in the rural-urban continuum. Moreover, the threshold temperature (27.8 ˚C, 82 ˚F) for the month of May was the lowest of all months relative to other locations in the rural and urban continuum.

Discussion

The objective of this study was to evaluate intra-seasonal patterns of HRI across the North Carolina for six warm seasons (May – September) from 2007 to 2012. The present study compliments previous research by Kovach et al. (2015) that evaluated the spatial patterns of HRI across different demographics (e.g. age) and regions (e.g. rural, urban, Coastal Plain). Unlike Kovach et al. (2015), this study focused on intra-seasonal variations in HRI rates across different demographics and regions of North Carolina.

Previous research has focused on the patterns of mortality around the timing of extreme heat events (i.e. heat waves). The aim of this study was to evaluate the intra-seasonal patterns of heat morbidity (i.e. HRI ED visits) and their relationship with daily maximum temperature. Similar to previous temperature-heat-health studies (e.g. Curriero et al. 2003, Hartz 2013, Kovats et al. 2004), the temperature - morbidity curves followed a J-shape, with a morbidity peak at the high end of the temperature spectrum. Temperature-morbidity curves displayed an inflection point at threshold temperatures that increased from 27.8˚C (82 ˚F) and 28.9 ˚C (84 ˚F) during June, July, and August, respectively, and peaked at approximately 37.2 ˚C (99 ˚F). During the shoulder months of September and May, on the other hand, the morbidity curves displayed a lower slope and temperature peak (e.g. 33.3 - 33.9 ˚C, 92 - 93 ˚F). All months exhibited a marked decline of HRI ED rates at the highest temperatures (i.e. beyond the peak temperature). This decline is likely due to coping measures, such as air conditioning. Roughly 97% of households own either a window unit or central air system in North Carolina (U.S. Department of Energy 2010).

Previous research (e.g. Hajat et al. 2002) has shown that hot days earlier in the warm season (e.g. June) produce a larger effect on all-cause mortality than hot days later in the warm season (e.g. August). In this study, the summer months (e.g. June, July, and August) produced the highest rates of HRI, especially at the warmest temperatures. Unexpectedly, significantly lower rates of HRI were found during May, the month in which one would expect there to be the least amount of acclimatization. There at least two possible reasons why the rates are lowest during May: 1) the lack of humidity during this month, which decreases heat index values, thereby increasing the human body's ability to thermoregulate. 2) At risk populations may not be as exposed during this month (e.g. fewer students engaged in high school athletics and smaller numbers of farm workers out in the fields).

The HRI highest rates were observed in June and July. The month of August exhibited decreases in HRI at high temperatures, compared to the months of June and July. This decrease was likely due to populations becoming acclimated by the end of summer. Acclimation occurs when populations who were exposed to early heat either physiologically or behaviorally adapt to heat and hence deal with it more effectively (Kalkstein and Davis 1989). Acclimatization was also a likely reason for the increase in threshold temperatures as the summer progressed (e.g. 26.7 ˚C in May to 28.9 ˚C in August).

Much intra-regional variation was observed between temperature and HRI across the study area. The cooler Mountain region experienced significantly less HRI than other regions. Additionally, HRI occurred at much lower temperatures, with threshold temperatures as low as 25 ˚C (77 ˚F) in the month of June and as high as 26.7 ˚C (80 ˚F) in the month of August. In the warmer regions of the Piedmont and the Coastal Plain, threshold temperatures were approximately 7 ˚F higher across the summer months, suggesting these populations are more acclimated to the heat. This finding is consistent with research across California, where locations with lower summer temperatures also experienced greater excess ED visits during heat wave events (Knowlton et al. 2009). To prevent future HRI, National Weather Service personal should account for the lack of acclimation in the mountain populations and adjust heat warnings and advisories to higher temperatures as the warm season progresses.

HRI ED visit rates were the greatest in the Coastal Plain. While this area typically experiences the highest temperatures and heat index values in the state, the population is more vulnerable than the more urbanized population of the Piedmont region. This may relate to the fact that a large portion of its residents are employed in outdoor occupations and therefore may not have the opportunity to adapt their outdoor behaviors to heat (Kovach et al. 2015). The Coastal Plain is also a major area for extensive agriculture and contains the greatest concentration of migrant and seasonal workers (Montz et al. 2011). HRI observed in the summer months also coincides with the harvesting season, thus heat exposure associated with harvesting may partially explain the high rates of HRI.

In both the Piedmont and Coastal Plain, August HRI ED visits were higher than other months at the hottest temperatures (i.e. 38.9 ˚C or 102 ˚F and higher). This pattern was particularly notable for the Piedmont and suggests that although populations are better coping with the extreme heat (as noted by the decline of HRI at the highest temperature), they are more exposed (e.g. engaging in outdoor activities).

Intra-seasonal temporal variations were most notable across different age groups. Both young (i.e. under 14 years) and older populations (i.e. 45 years and older) displayed the highest peak temperature HRI ED rates during June, the onset of summer. Similar results were noted in heat waves and mortality studies (i.e. Hajat et al. 2005, Anderson and Bell 2011), where susceptible individuals were more likely to experience high mortality at the onset of summer than later in the summer season (i.e. displacement effect). Although, HRI rates peaked in June, they remained elevated during the remainder of the summer, highlighting that these populations continued to be at risk throughout the summer season. This continued risk is of importance as these age groups, particularly the 65 and older, are more likely to be admitted to the hospital due to severe cases of HRI (Rhea et al. 2012).

Another interesting intra-seasonal pattern was revealed in the 15 to 17 age group, which was the only demographic group with the greatest HRI ED visits in the month of August. Rhea et al. (2012) examined HRI triage notes for approximately 25% ED visits in North Carolina and found that this age group were predominately related to heat exposure from organized sports, such as cross country and football. These organized sports begin in August with the onset of the fall athletic season. Similar to our results, HRI among high school athletes at the national level occurred most frequently during August and when practicing or playing football (Gilchrist 2010). Compared to other age groups, HRI ED visits were also the highest in the month of September, with the highest rates at lower maximum temperatures (i.e. 34.4 ˚C or 94 ˚F). Increased rates in September highlight that exertional HRI may occur throughout the fall sports season, even when summer heat is diminishing. In order to prevent HRI, heat mitigation strategies are needed for coaches to promote hydration or cooler indoor alternatives, especially when daily maximum temperatures range from 34.4 to 37.8 ˚C (94 to 100 ˚F).

The highest HRI among demographic categories was in the 18 to 44 age group, the healthy-working age demographic. Previous research in North Carolina highlighted that heat exposure among this age groups predominately resulted from outdoor occupational activities (i.e. farming, construction, etc.) (Rhea et al. 2012). In this age group, HRI was most elevated in the summer months of June-August, peaking at a temperature of 37.2 ˚C (99 ˚F). This research suggests that targeted public health interventions should be directed towards this demographic group in the summer months, particularly in June and July.

To investigate the intra-seasonal relationship between temperature and HRI across the urban-rural continuum, populations were categorized as Metropolitan, Rural Metropolitan, Rural Town, or Rural Isolated, based on their population density and work commuting patterns. To date, few studies examine the effect of temperature on rural populations and none examine the temporal effects of HRI on rural populations. Yet across North Carolina, rural populations displayed significantly higher rates of HRI than the urban populations. The intra-seasonal trends illustrate that as rurality increases (i.e. from metropolitan locations to isolated and rural locations), HRI rates increase in the months of July, June, and August. These months are the warmest of the year, with the highest maximum and minimum temperatures.

This relationship between rurality and HRI is likely related to the fact that a larger proportion of the population works in outdoor occupations and displays underlying social vulnerabilities (e.g. poverty, low educational attainment, etc.) (Table 11). Residents engaged in outdoor occupations can be exposed to the heat from the external environment and also internally through strenuous activity. As rurality increased, so did the percent of population engaged in outdoor occupations, such as farming, fishing or forestry occupations (Table 11).

To investigate if farm labor resulted in high HRI ED rates, two common cash crops that required strenuous labor were examined in detail, sweet potatoes and tobacco. Sweet potatoes are a labor-intensive crop (i.e. typical migrant worker is paid $50 to haul two tons of potatoes) (North Carolina Farmworker Institute 2013) that are harvested in late August through early November. In locations with sweet potato crops, HRI ED visits were exceptionally high during September, suggesting that migrant workers may be a vulnerable population. In the case of tobacco agriculture, the harvest is also labor-intensive, bringing approximately 558 million dollars to North Carolina a year on average. Harvesting begins in early July and can continue to September (North Carolina Department of Agriculture and Consumer Services, 2014). For locations with a high proportion of tobacco, HRI incidence was highest during the month of July and remained elevated into August, corresponding to harvesting time periods. These results suggest that labor-intensive agriculture influences intra-seasonal patterns of HRI. However, because these relationships were identified at the ZIP code level, they cannot be confirmed without further research at the individual-level that explicitly addresses farm laborer's heat exposure throughout the harvesting season.

The study incorporates some limitations that warrant further discussion. In particular, the use of counts and rates of HRI presented here were likely underestimates of the true occurrence of HRI. Underestimates can occur when people with HRI did not seek medical care or physicians failed to appropriately document HRI diagnosis and symptoms. Underestimates of HRI are more likely in isolated and rural locations where health-care access is limited. Secondly, this study is limited to generalizations about the cause of intra-seasonal trends. Future analysis should explore heat exposure at an individual-level to confirm why specific populations (i.e. isolated and rural, the 15 to 17 age group) experience greater rates of HRI.

Conclusions

The objective of this study was to evaluate intra-seasonal patterns of HRI across the North Carolina for six warm seasons (i.e. May – September) from 2007 to 2012. Unlike previous research, this study analyzed the association between intra-seasonal patterns of heat-morbidity, rather than heat-mortality. Results demonstrated that HRI incidence is highest in the months of July and June. Significant variations in the pattern were observed across different age groups. In particular, the young (i.e. younger than 14) and elderly (65 and older) experienced higher HRI rates in June with the onset of warmer summer temperatures. In contrast, the 15 to 17 age group experienced the highest rates in August, which corresponds with the beginning of the fall athletic season. The demographic with the highest rates of HRI, the 18 to 44 age group, experienced the most HRI in June and July. Similar patterns were observed for rural and isolated, whereas more urban locations had lower rates of in June and July. Additional research is needed to identify the intra-seasonal variations of HRI at the individual-level to confirm why vulnerable populations (i.e. migrant worker, high-school athletes) experience HRI in different warm season months. To mitigate future HRI, public health preparedness plans and heat advisories should be adjusted throughout the summer to account for the different populations at risk for HRI as the summer progresses (i.e. elderly in beginning of the summer, high school demographic at end of warm season). Additionally, heat advisories should account for the lack of acclimation at the beginning of summer and for populations who are not frequently exposed to high temperatures (i.e. mountainous populations).

CHAPTER 5: CONCLUSIONS

Temperature increases due to climate change will likely intensify heat-related morbidity and mortality. Adaptive and coping measures, including targeted public health interventions and heat-warnings systems are needed to prevent future and current heat-related health effects. The aim of this dissertation is to increase the understanding of the climatic, environmental, and population factors that affect patterns of heat-related illness (HRI). In doing so, this research identifies vulnerable populations and temperature ranges, where HRI is most common across North Carolina.

The principle objectives of our investigation were twofold:

1.) Identify area-level risk factors for HRI in both rural and urban populations.

2.) Ascertain the spatiotemporal relationship between temperature and HRI for different demographics and locations.

These objectives where guided by three specific research questions:

1.) What is the spatial pattern of HRI across North Carolina and how does this pattern relate to socioeconomic, demographic, and land cover patterns?

2.) What are the spatial relationships between temperature and HRI and how are these relationships modified for different demographics and regions (e.g. rural, mountains, etc.)?

3.) What are the intra-seasonal relationships between temperature and HRI across the warm months (i.e. May – September)?

Each of these questions were addressed in each chapter of the dissertation.

In the first chapter, area-level risk factors for HRI were evaluated across both rural and urban settings. Former research has addressed heat vulnerability at a local-level by aggregating previous established individual-level risk factors for heat mortality into heat vulnerability indexes. Often, these studies identify vulnerable locations by examining the collocation of areas of greater physical exposure to extreme heat (e.g. urban surfaces) with locations displaying high social vulnerability (e.g. living below the poverty line, minorities). Unlike this approach, the assessed spatial variability in heat vulnerability was investigated using an ecological study design, where spatially explicit, area-level risk factors are associated with heat morbidity. HRI was aggregated at the ZIP code-level into rural and urban populations based on population density. Area-level risk factors included previously established heat-health risk factors (e.g. poverty, minority) and unexamined area-level risk factors common to rural locations (e.g. mobile homes, agriculture). Due to high spatial autocorrelation, a spatial error regression model was applied to identify risk factors with a significant relationship with HRI.

In each environmental setting, different risk factors were associated with increased HRI. In urban environments, risk factors common to heat-mortality studies, such as reduced vegetation, low educational attainment, older median year structure built, and living below the poverty line were associated with increased HRI. However, in rural environments risk factors, such as mobile homes, un-developed land, non-citizens, elderly, and labor-intensive agriculture were associated with increased HRI. These differences highlight the variations in heat vulnerability for different populations and locations. To create successful preventative heat adaptation and mitigation plans, local knowledge of the unique risk factors for heat vulnerability is needed. Consequently, more research is needed to understand heat-related morbidity and mortality across the southeastern United States at a localized-scale.

Several unexamined risk factors (e.g. mobile homes, labor-intensive agriculture) were evaluated in this dissertation that had not been studied in the context of heat-related morbidity or mortality. Mobile homes were of particular interest as they predicted large increases HRI across both rural and urban locations, even after accounting for any potential multicollinearity with other risk factors (i.e. living below the poverty line). Mobile home are an affordable housing option for low-income households in North Carolina and are often energy inefficient, with little insulation in the walls, ceiling, or floors. Interviews in rural North Carolina have demonstrated that many mobile home owners cannot afford high energy bills in the summer, thus limiting their air conditioning use. In addition, some rural locations in North Carolina also have higher electricity costs also potentially influencing the unaffordability of air conditioning use. Additional research is needed at the individual-level (i.e. different spatial scale) to confirm heat exposure in these mobile homes and if mobile home owners are experiencing HRI.

In the second chapter, the relationship between HRI and maximum temperature was assessed across multiple regions (e.g. coastal plain, urban, etc.) and demographics (e.g. elderly, 15 to 17). HRI incidence increases as rurality increases, particularly for the male, 15 to 44 age demographic. These HRI ED visits increased from approximately 31.1˚C (88˚F) to 37.8 ˚C (100 ˚F), depending on the population being examined. Surprisingly, rates of HRI decreased at temperatures warmer than 37.8 ˚C (100 ˚F), suggesting that populations were more effectively coping to heat at these extremely hot temperatures. This decline was unprecedented, as all other US research has found significant increases in morbidity at extremely hot temperatures. These results suggest that heat warning systems in North Carolina should target rural populations that engage in exertional activities, particularly at temperatures that are not exceptionally high.

The National Weather Service (NWS) in Raleigh is tasked with issuing heat warnings across the eastern Piedmont and Coastal Plain of North Carolina. The NWS issues two-heat related products (Table 16): 1.) Excessive heat warnings, when heat poses a threat to life or property 2.) Heat advisory, when conditions are less extreme but still pose a potential threat if caution is not employed (NWS 2007). More than half of HRI in the state occurred at maximum temperatures between 31.7˚C (89 ˚F) and 35.6˚C (96 ˚F), climatologically normal summer conditions for North Carolina. These temperature fall outside NWS heat-related products and suggest that alternative methods are needed to mitigate the largest proportion of HRI ED visits. Preliminary research by Fuhrmann et al. (2014) also confirmed that the majority of HRI ED visits were occurring on days without a heat-related product forecast (Figure 14). This research points to the need for updated NWS heat-related products, which are currently not accounting for heat-health effects.

National Weather Service Heat-Related Products	Criteria
Heat Advisory	Issued when heat index is expected to reach between 105 - 109 ˚F for 2 or more hours or is expected to reach between 102 - 105 ˚F for three or more consecutive days
Excessive Heat Warning	Issued when the heat index is expected to reach 110 ˚F or higher for any duration

Table 16: National Weather Service Criteria for issuing either a heat advisory or excessive heat warning

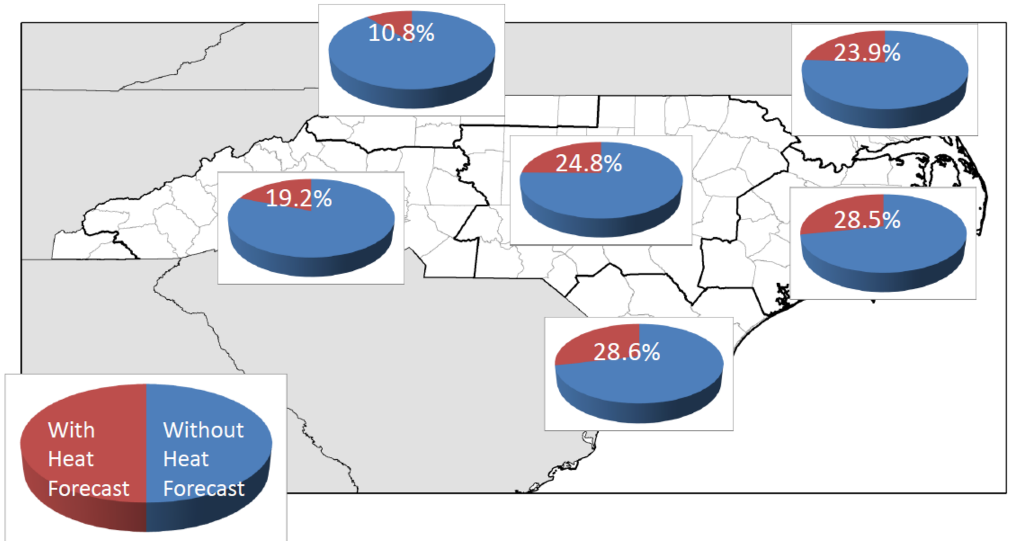

Figure 14: Percent of Heat-Related ED visits accompanied by a Heat Advisory or Warning by NWS Region (2007 to 2012) from Fuhrmann et al. 2014 at International Conference of Biometeorology

Most HRI ED visits are exertional-related with the highest incidence among the working age demographic (i.e. male, 18 to 44 years old) and in locations with a higher proportion of the population engaging in outdoor occupations (i.e. rural town and isolated rural). This vulnerability pattern is different than that observed with heat-related mortality, which is highest among infants, elderly, people with pre-existing illness, and low income groups. In addition, the morbidity studies in other regions of the United States have found similar patterns, with higher ED rates for HRI in the elderly and younger demographic (i.e. less than 4 years old) (Knowlton 2004). These differences in populations experiencing HRI suggest that the etiology of heat-morbidity is different for North Carolina. Rather than HRI resulting from exposure to high environmental temperatures and affecting vulnerable populations (i.e. elderly, very young), HRI results from exertional activities and affects younger individuals, such as athletes and manual laborers.

In the third chapter, the intra-seasonal patterns of HRI and maximum temperature were evaluated across North Carolina. Few studies have examined these patterns, except in the context of heat waves. This dissertation was unique in that the HRI morbidity was investigated using a continuous, long dataset that examined HRI across a broad area, allowing for a detailed investigation into the timing of high temperatures influence on HRI. Surprisingly, much lower rates of HRI at a given temperature were found during May, the month in which residents would be the least acclimated to high temperatures. HRI rates peaked during the summer months of June, July, and August. These monthly HRI rates were greatest across isolated rural locations and among the 18 to 44 age group, signifying that the rural, working age demographic are more likely to engage in outdoor activities that result in HRI in the summer heat. However, at the hottest temperatures (99 ˚F), however, this population saw marked declines in HRI, suggesting that they engaged in adaptive measures.

The threshold temperatures were found to increase as the warm season progressed, suggesting the occurrence of acclimatization. However, August HRI ED were higher than other months at extremely high temperatures (i.e. 38.9 ˚C or 102 ˚F and higher), highlighting that although populations are better coping with the extreme heat (e.g. decline of HRI at hot temperatures), they are more exposed (e.g. engaging in outdoor activities). Intra-seasonal temporal variations were most notable across different age groups. While the young and the older populations displayed the highest HRI at peak temperature during June, the onset of summer, the high school age demographic (i.e. 15 to 17 years old) experienced high HRI rates in August and into September. This peak coincides with organized sports beginning in August with the onset of the fall athletic season.

In order to prevent future HRI, various heat mitigation strategies need to be altered. In the early warm season, NWS heat products should account for the lack of acclimatization within the population by issuing heat advisories and warnings at lower temperatures. In addition, heat mitigation strategies should target particular vulnerable demographics, such as the elderly and young. These demographics are most vulnerable to heat at the beginning of the summer due to their inability to thermoregulate as efficiently as other demographics (McGeehin and Mirabelli 2001). During the late summer season, on the other hand, strategies should target exertional HRI that occurs among high school athletes and workers engaged in labor-intensive agriculture. Lastly, to mitigate the largest proportion of HRI, public health interventions are needed in June and July among the working age demographic who likely continue to work outdoors, perform home maintenance, and exercise on days with maximum temperatures ranging from 31.1˚C (88˚F) to 37.8 ˚C (100 ˚F).

This dissertation addressed several significant literature gaps. First, it demonstrated that heat vulnerability is also found among rural populations. Few studies have addressed rural populations due to small sample sizes, data restrictions, and a common understanding among researchers that urban populations are the most heat vulnerable. Previous research studies have highlighted that *rates* of heat mortality are highest in rural regions (i.e. Henderson et al. 2013, Sheridan and Dolney 2003), however, North Carolina is unique in that rural locations experience both increased *rates* and *absolute* numbers of HRI. In addition, when examining HRI rates across the rural-urban continuum, HRI rates increased with increasing rurality, highlighting that living in an urban area or commuting to an urban area was a protective factor for HRI. Moreover, this increase in HRI rates with increased rurality is likely underestimated, as rural populations may not seek medical care for HRI due to the limited access of emergency departments. This research highlights the need for more research in rural environments across regions outside of North Carolina and the southeastern United States.

This dissertation also addressed the need for more multi-locational studies of the temperature-morbidity relationships (Kalkstein and Greene 1997). Our results were surprising in that declines of HRI were observed at extremely high temperatures across a wide variety of populations and months in North Carolina. Declines of heat morbidity at the most extreme temperatures have not been identified in the United States and point to the need for more temperature-morbidity research. Ultimately, establishing the temperatures in which a population is at greatest risk for HRI is a complex issue involving a combination of environmental, social, and ecological variables.

This dissertation also addressed a literature gap regarding the effects of heat on agricultural workers. To our knowledge, no previous studies have documented the types of agricultural workers most at risk for HRI, nor have they identified when during the growing season agricultural workers are at risk (e.g. harvesting times). Identifying the types of agriculture that increase the risk of HRI is important. To assess these patterns, a measure of the labor-intensiveness of the agriculture was calculated by integrating land cover data and crop enterprise budgets to provide an estimate of the labor required for harvesting within each ZIP code. It was found that the labor intensity of the agriculture significantly predicted increases in HRI in rural environments. In addition, rural and isolated locations, where many of the labor-intensive crops are grown displayed exceptionally high rates of HRI among the working age demographic (i.e. 18 to 44 years old). To investigate harvesting times and potential HRI increases, HRI rates were evaluated for two labor-intensive cash crops, sweet potatoes and tobacco. Although HRI were higher during harvesting months, it is hard to infer a relationship without exposure or occupational information about the ED patient. Currently, ED visit information does provide insurance information, which can highlight occupational exposure with worker compensation insurance. This information will be utilized in future analyses to assess occupational HRI.

In order to more fully analyze heat exposure among agricultural workers and other residents of North Carolina, additional individual level data are needed to assess the degree to which exceptionally warm microclimates and strenuous activity contribute to adverse heat-health effects. Individual-level data would provide the necessary information to confirm the types of individuals most at risk for HRI (i.e. agricultural workers, high school athletes, etc.) allowing for more informative public health recommendations for interventions or warning systems. The health data used in this dissertation (i.e. NC-DETECT) included individual level data of the patient's age, gender, and insurance information. Although this dissertation examined the etiology of HRI through the individual-level data on the patient's age and gender, it did not utilize insurance information in the analysis. Future research will employ the patient's insurance information (i.e. no insurance, Medicare or Medicaid) to assess socioeconomic status and its influence on HRI across different demographics and locations.

It is hoped that the results of this dissertation will be applied in ways that contribute to a reduction heat-related morbidity across North Carolina. Specifically, relationships identified between temperature and heat-related illness are being integrated into a web-based heat-health vulnerability tool, which will generate predictions of the number of HRI ED visits based on National Weather Service forecasted temperatures. The tool will be used by emergency response personnel and public health officials to more effectively warn demographic groups that are especially vulnerable to HRI.

REFERENCES

Alessandrini, E., Sajani, S. Z., Scotto, F., Miglio, R., Marchesi, S., & Lauriola, P., (2011). Emergency ambulance dispatches and apparent temperature: A time series analysis in Emilia–Romagna, Italy. *Environmental research*. 111(8): 1192-1200.

Aman, D, Yarnal, B., (2010). Home sweet mobile home? Benefits and challenges of mobile home ownership in rural Pennsylvania. *Applied Geography*. 30(1): 84-95.

Anderson, G.B., Bell M.L., (2011). Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. *Environmental Health Perspectives*. 119(2): 210-218. doi:10.1289/ehp.1002313.

Anselin, L., (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical analysis*. 20(1): 1-17. doi:10.1111/j.1538-4632.1988.tb00159.x.

Anselin, L., Bera, A.K., (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Handbook of Applied Economic Statistics, (Ullah & D.E. Giles, ed). New York: CRC Press. 237-290.

Anselin, L., Ibnu ,S., Youngihn, K., (2006). GeoDa: An Introduction to Spatial Data Analysis. *Geographical Analysis*. 38 (1): 5-22.

Appold, S.J., (2014). Residential Segregation in North Carolina Metropolitan Areas and Municipalities. Available at SSRN: http://ssrn.com/abstract=2434369

Armstrong, B., (2006). Models for the relationship between ambient temperature and daily mortality. *Epidemiology*. 17(6): 624-631. doi:10.1097/01.ede.0000239732.50999.8f.

Baccini, M., Biggeri, A., Accetta, G., Kosatsky, T., Katsouyanni, K., Analitis, A, Anderson HR, Bisanti L, D'Ippoliti D, Danova J. et al., (2008). Heat effects on mortality in 15 European cities. *Epidemiology*. 19(5): 711-719.

Bambrick, H, Dear, K, Woodruff, R, Hanigan, I, McMichael A., (2008). The Impacts of Climate Change on Three Health Outcomes: Temperature-Related Mortality and Hospitalizations, Salmonellosis and Other Bacterial Gastroenteritis, and Population at Risk from Dengue. Garnaut Climate Change Review. Available: http://garnautreview.org.au/CA25734E0016A131/WebObj/03-AThreehealthoutcomes/$File/03-A%20Three%

Barnett, A.G., Tong, S., Clements, A.C., (2010). What measure of temperature is the best predictor of mortality? *Environmental Research*. 110(6): 604-611. doi:10.1016/j.envres.2010.05.006.

Basu, R, Samet, J. (2002). Relation between Elevated Ambient Temperature and Mortality: A Review of the Epidemiologic Evidence. *Epidemiologic Reviews*. 24(2):190-202. doi:10.1093/epirev/mxf007.

Basu, R., (2009). High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. *Environmental Health*. 8(1), 40. doi:10.1186/1476-069X-8-40.

Becker, J, A., Stewart, L, K. (2011). Heat-Related Illness. *American Family Physician*, 83(11): 1325–1330.

Bivard, R. (2014). spdep: Spatial dependence: weighting schemes, statistics and models. R package version 0.5-77. http://CRAN.R-project.org/package=spdep

Blum, L.N., Bresolin, L.B., Williams, M.A. (1998). Heat-related illness during extreme weather emergencies. *The Journal of the American Medical Association*. 279(19):1514. http://www.ncbi.nlm.nih.gov/pubmed/9605881.

Böhm, R., (1998). Urban bias in temperature time series–A case study for the city of Vienna, Austria. *Climate Change*. 38(1): 113-128.

Buckley, J. P., Richardson, D. B., (2012). Seasonal modification of the association between temperature and adult emergency department visits for asthma: a case-crossover study. *Environmental Health*. 11(55): 1-6.

Cao, C., Weinreb, M., Xu, H., (2004). Predicting Simultaneous Nadir Overpasses among Polar-Orbiting Meteorological Satellites for the Intersatellite Calibration of Radiometers. *Journal of Atmospheric and Oceanic Technology.* 21(4): 537-542.

Carroll, D., Georges, A., Russell, A., Russell, S., (2011). Changing characteristics of U.S. farm workers: 21 years of findings from the National Agricultural Workers Survey. Presentation at Immigration Reform and Agriculture Conference: Implications for Farmers, Farm Workers and Communities. Washington D.C.

Chow, W., Chuang, W., Gober, P., (2012). Vulnerability to Extreme Heat in Metropolitan Phoenix: Spatial, Temporal, and Demographic Dimensions. *Professional Geographer*. 64(2): 286-302. doi:10.1080/00330124.2011.600225.

Cliff, A.D., Ord, J.K., (1981). Spatial processes: models & applications Vol. 44. London: Pion.

Coburn, A.F., Bolda, E.J., (2001). Rural elders and long-term care. *Western Journal of Medicine.* 174(3): 209.

Curriero, F. C., Heiner, K. S., Samet, J. M., Zeger, S. L., Strug, L., Patz, J. A. (2002). Temperature and mortality in 11 cities of the eastern United States. *American Journal of Epidemiology*, 155(1): 80–7.

Davis, R. E., Knappenberger, P. C., Michaels, P. J., Novicoff, W. M. (2003). Changing Heat-Related Mortality in the United States. *Environmental Health Perspectives*. 111(14), 1712–1718. doi:10.1289/ehp.6336

Dematte, J. E., O'Mara, K., Buescher, J., Whitney, C. G., Forsythe, S., McNamee, T., Ndukwu, I. M. (1998). Near-fatal heat stroke during the 1995 heat wave in Chicago. *Annals of Internal Medicine*, 129(3): 173–181. doi:10.1059/0003-4819-129-3-199808010-00001

Donaldson, G. C., Keatinge, W. R., & Näyhä, S. (2003). Changes in summer temperature and heat-related mortality since 1971 in North Carolina, South Finland, and Southeast England. *Environmental Research*, 91(1): 1–7.

Dousset, B., Gourmelon, F., Laaidi, K., Zeghnoun, A., Giraudet, E., Bretin, P, Vandentorren, S. (2011). Satellite monitoring of summer heat waves in the Paris metropolitan area. *International Journal of Climatology*. 31(2): 313-323. doi:10.1002/joc.2222.

Drewnowski, A., Rehm, C., Solet, D., (2007). Disparities in obesity rates: analysis by ZIP code area. *Social Science and Medicine*. 65(12): 2458-2463. doi:10.1016/j.socscimed.2007.07.001.

Ebi, K. L., Teisberg, T. J., Kalkstein, L. S., Robinson, L., & Weiher, R. F. (2004). Heat Watch/Warning Systems save Lives: Estimated Costs and Benefits for Philadelphia 1995–98. *Bulletin of the American Meteorological Society*, 85(8): 1067–1073. doi:10.1175/BAMS-85-8-1067

Economic Research Service. Rural-urban commuting area codes. Washington (DC): U.S. Department of Agriculture. (2013). http://www.ers.usda.gov/data-products/rural-urbancommuting-area-codes.aspx. Accessed February 24, 2014.

Foley, J.A., Defries, R., Asner,G.P., Barford, C., Bonan, G., Carpenter, SR., Snyder, P.K., (2005). Review Global consequences of land use. *Science* 309(5734): 570-575

Fuhrmann, C., Konrad C., Kovach, M. (2014, October). Evaluation of the Effectiveness of National Weather Service Heat Forecasts in North Carolina. Paper presented at the meeting of 20th International Congress of Biometeorology

Gabriel, K., Endlicher, R., (2011). Urban and rural mortality rates during heat waves in Berlin and Brandenburg, Germany. *Environmental Pollution*. 159(8): 2044-2050. doi:10.1016/j.envpol.2011.01.016.

Gilchrist, J., Haileyesus, T., Murphy, M., Collins, C., McIlvain, N. (2010). Heat illness among high school athletes-United States, 2005-2009. *Morbidity and Mortality Weekly Report*, *59*(32): 1009-1013.

Golden, J. S., Hartz, D., Brazel, A., Luber, G., & Phelan, P. (2008). A biometeorology study of climate and heat-related morbidity in Phoenix from 2001 to 2006. *International Journal of Biometeorology*, *52*(6): 471–80. doi:10.1007/s00484-007-0142-3

Gosling S. N., Bryce E. K., Dixon P.G., et al. A Glossary for Biometeorology. (2014), *International Journal of Biometeorology*, 58(2): 277-308. doi:10.1007/s00484-013-0729-9.

Greaser, G.L., Harper, J.K., (1994). Enterprise budget analysis, Agricultural Alternatives, The Pennsylvania State University, College of Agricultural Sciences, Cooperative Extension.

Grogan, H., Hopkins, P. M. (2002). Heat stroke: Implications for critical care and anesthesia. *British Journal of Anesthesia*, 88(5): 700–707. doi:10.1093/bja/88.5.700

Hajat, S., Kovats, R. S., Atkinson, R. W., Haines, A., (2002). Impact of hot temperatures on death in London: a time series approach. *Journal of Epidemiology and Community Health*, 56: 367–372. doi:10.1136/jech.56.5.367

Harlan, S., Declet-Barreto, J., Stefanov, W., Petitti, D., (2013). Neighborhood effects on heat deaths: social and environmental predictors of vulnerability in Maricopa County, Arizona. *Environmental Health Perspectives*. 121(2): 197-204. doi:10.1289/ehp.1104625.

Harrison, C., Popke J., (2011). "Because you got to have heat": the networked assemblage of energy poverty in eastern North Carolina. *Annual of the Association of American Geographers*. 101(4): 949-961. doi:10.1080/00045608.2011.569659.

Hart, L.G., Larson E.H., Lishner D.M., (2005). Rural definitions for health policy and research. *American Journal of Public Health*. 95(7): 1149-1155. doi:10.2105/AJPH.2004.042432.

Hartz D.A., Golden JS, Sister C, Chuang W-C, Brazel AJ. (2012). Climate and heat-related emergencies in Chicago, Illinois (2003-2006). *International Journal of Biometeorology*. 56(1): 71-83. doi:10.1007/s00484-010-0398-x.

Hartz, D.A., Brazel, A. J., Golden, J. S. (2013). A comparative climate analysis of heat-related emergency 911 dispatches: Chicago, Illinois and Phoenix, Arizona USA 2003 to 2006. *International Journal of Biometeorology*, 57(5): 669–78. doi:10.1007/s00484-012-0593-z

Henderson, S.B., Wan, V., Kosatsky, T., (2013). Differences in heat-related mortality across four ecological regions with diverse urban, rural, and remote populations in British Columbia, Canada. *Health & Place* 23, 48–53. doi:10.1016/j.healthplace.2013.04.005

Hondula D.M., Davis R.E., Rocklöv J., Saha M. V., (2013) A time series approach for evaluating intra-city heat-related mortality. *Journal of Epidemiology and Community Health*. 67(8):707-712. doi:10.1136/jech-2012-202157.

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

Jones, T., Liang, P., Kilbourne, E., Griffin, M., Patriarca, P., Wassilak, S., Thacker, S., (1982). Morbidity and mortality associated with the July 1980 heat wave in St Louis and Kansas City, Mo. *The Journal of the American Medical Association*. 247(24): 3327-3331.

Kaiser, R., Le Tertre, A., Schwartz, J., Gotway, C. A., Daley, W. R., Rubin, C. H., (2007). The effect of the 1995 heat wave in Chicago on all-cause and cause-specific mortality. *American Journal of Public Health*, 97(1): 158–162. doi:10.2105/AJPH.2006.100081

Kalkstein, L. S., (1993). Direct impacts in cities. *The Lancet*, 342(8884): 1397-1399.

Kalkstein, L. S., Davis, R. E., (1989). Weather and human mortality: an evaluation of demographic and interregional responses in the United States. *Annals of the Association of American Geographers*, *79*(1): 44-64.

Kalkstein, L. S., Greene, J. S., (1997). An evaluation of climate/mortality relationships in large U.S. cities and the possible impacts of a climate change. *Environmental Health Perspectives*, 105(1): 84–93.

Kalkstein, L. S., Smoyer, K. E., (1993). The impact of climate change on human health: some international implications. *Experientia*, 49(11): 969–79.

Kilbourne, E. M., Choi, K., Jones, T. S., Thacker, S. B., (1982). Risk factors for heatstroke: a case-control study. *The Journal of the American Medical Association*, 247(24): 3332-3336.

Kilbourne, E. M., Choi, K., Jones, T. S., Thacker, S. B., Team, F. I., (1982). Risk Factors for Heatstroke. *The Journal of the American Medical Association*, 247(24): 3332 –3336. doi:10.1001/jama.1982.03320490030031

Kim, Y., Joh, S., (2006). A vulnerability study of the low-income elderly in the context of high temperature and mortality in Seoul, Korea. *Science of Total Environment*. 371(1): 82-88. doi:10.1016/j.scitotenv.2006.08.014.

Knowlton, K., Rotkin-Ellman, M., King, G., Margolis, H.G., Smith, D., Solomon, G., English, P., (2009). The 2006 California heat wave: impacts on hospitalizations and emergency department visits. *Environmental Health Perspectives*. 117(1): 61-67. doi:10.1289/ehp.11594.

Koppe, C, Kovats, R, Jendritzky, G, Menna, B., (2004). Health and global environmental change series, No. 2. World Health Organization Regional Office for Europe, Copenhagen.

Kovats, S, Hajat, S, Wilkinson, P., (2004). Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, U.K., *Occupational Environmental Medicine*. 61: 893-898.

Kovats, S., Hajat, S., (2008). Heat stress and public health: a critical review. *Annual Review Public Health*. 29:41-55. doi:10.1146/annurev.publhealth.29.020907.090843.

Krieger, N., Waterman, P, Chen, J.T, Soobader, M.J., Subramanian, S.V, Carson, R., (2010). Zip Code Caveat: Bias Due to Spatiotemporal Mismatches Between Zip Codes and US Census–Defined Geographic Areas—The Public Health Disparities Geocoding Project. *American Journal of Public Health*. 92(7):1100-1102. doi:10.2105/AJPH.92.7.1100.

Le Tertre, A., Lefranc, A., Eilstein, D., Declercq, C., Medina, S., Blanchard, M., Ledrans, M. (2006). Impact of the 2003 heatwave on all-cause mortality in 9 French cities. *Epidemiology* (Cambridge, Mass.), 17(1): 75–79. doi:10.1097/01.ede.0000187650.36636.1f

Li, B., Sain, S., Mearns, L. O., Anderson, H. A., Kovats, S., Ebi, K. L., Patz, J. A., (2012). The impact of extreme heat on morbidity in Milwaukee, Wisconsin. *Climatic change*, *110*(3-4): 959-976.

Liang,W.M., Liu W.P., Kuo H.W., (2009). Dirunal temperature range and emergency room admissions for chronic obstructive pulmonary disease in Taiwan. *International Journal of Biometeorology*. 53: 17-23.

Lin, S., Luo, M., Walker, R.J., Liu, X., Hwang, S.A., Chinery R. (2009). Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. *Epidemiology* 20: 738-746

Lippmann, S., Fuhrmann C., Waller A., Richardson D., (2013). Ambient temperature and emergency department visits for heat-related illness in North Carolina, 2007-2008. *Environmental Research.* 124:35-42. doi:10.1016/j.envres.2013.03.009.

Luber, G., McGeehin M., (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine*. 35(5):429-435. doi:10.1016/j.amepre.2008.08.021.

Luginbuhl, R.C., Jackson, L.L., Castillo, D.N., Loringer K.A., (2008). Heat-related deaths among crop workers-United States, 1992-2006. *The Journal of the American Medical Association*. 300(9): 1017-1018.

Lugo-Amador, N. M., Rothenhaus, T., & Moyer, P. (2004). Heat-related illness. *Emergency Medicine Clinics of North America*. 22(2): 315–327. doi:10.1016/j.emc.2004.01.004

Mackun, P.,Wilson, S., Fischetti, T.R., Goworowska, J., (2011). Population Distribution and Change: 2000 to 2010 (No. C2010BR-01), 2010 Census Briefs. U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau.

Maier, G., Grundstein, A., Jang, W., Li, C., Naeher, L.P., Shepherd, M., (2014). Assessing the Performance of a Vulnerability Index during Oppressive Heat across Georgia, United States. *Weather, Climate, and Society*. 6(2): 253-263.

May, J. (2009). Latino Farmworkers in the Eastern United States. (Quandt SA, Arcury TA, eds.). New York, NY: Springer New York.

McGeehin, M. A, Mirabelli, M., (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. *Environmental Health Perspectives*. 109 Suppl (May): 185–189.

Meehl, G. A, Tebaldi, C., (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science* (New York, N.Y.), 305(5686): 994–7. doi:10.1126/science.1098704

Mirabelli, M.C., Richardson, D.B., (2005). Heat-related fatalities in North Carolina. *American Journal of Public Health*. 95(4):635-637. doi:10.2105/AJPH.2004.042630.

Mirabelli, M. C., Quandt, S. A., Crain, R., Grzywacz, J. G., Robinson, E. N., Vallejos, Q. M., Arcury, T. A., (2010). Symptoms of heat illness among Latino farm workers in North Carolina. *American Journal of Preventive Medicine*. 39(5): 468-471.

Montz, B. E., Allen, T. R., Monitz, G. I., (2011). Systemic Trends in Disaster Vulnerability: Migrant and Seasonal Farm Workers in North Carolina. *Risk, Hazards & Crisis in Public Policy*. *2*(1): 1-17.

Naughton, M.P., Henderson, A., Mirabelli, M.C., Kaiser, R., Wilhelm, J.L., Kieszak, S.M., McGeehin, M.A. (2002). Heat-related mortality during a 1999 heat wave in Chicago. *American Journal of Preventive Medicine*. 22(4): 221-227.

Nelson, N.G., Collins, C.L., Comstock, R.D., McKenzie, L.B., (2011). Exertional heat-related injuries treated in emergency departments in the U.S., 1997-2006. *American Journal of Preventive Medicine*. 40(1): 54-60. doi:10.1016/j.amepre.2010.09.031.

Ng, C. F. S., Ueda, K., Ono, M., Nitta, H., Takami, A., (2014). Characterizing the effect of summer temperature on heatstroke-related emergency ambulance dispatches in the Kanto area of Japan. *International Journal of Biometeorology*, 58(5): 941–948. doi:10.1007/s00484-013-0677-4

NOAA (National Oceanic Atmospheric Administration). (2007). Heat wave: a major summer killer. Available at: http://www.weather.gov/om/heat/heat_wave.shtml. [Accessed 10 February 2015].

North Carolina Department of Agriculture and Consumer Services. (2014). North Carolina Agriculture Overview. Available at: http://www.ncagr.gov/stats/ [Accessed 14 March 2015].

North Carolina Department of Labor. (2011). A Guide to Preventing Heat Stress and Cold Stress. Available: http://www.nclabor.com/osha/etta/indguide/ig35.pdf [Accessed 11 March 2015].

North Carolina Farmworker Institute. (2013). Farmworkers' Impact on North Carolina. Available: http://www.ncfarmworkers.org/learn/introduction-to-farm-work/ [Accessed 15 March 2015].

North Carolina High School Athletic Association. (2014). 2014-2015 Heat and Humidity Guidelines from Handbook. Available at: http://www.nclabor.com/osha/etta/indguide/ig35.pdf [Accessed 11 March 2015].

North Carolina State Climate Office (2014). Overview of North Carolina. Available at: http://www.nc-climate.ncsu.edu/climate/ncclimate.html [Accessed 15 March 2015].

O'Neill, M.S., Carter, R., Kish, J.K., et al. (2009). Preventing heat-related morbidity and mortality: new approaches in a changing climate. *Maturitas*. 64(2):98-103. doi:10.1016/j.maturitas.2009.08.005.

O'Neill, M.S., Zanobetti, A., Schwartz, J. (2005). Disparities by race in heat-related mortality in four US cities: the role of air conditioning prevalence. *Journal of Urban Health*. 82(2):191-197. doi:10.1093/jurban/jti043.

Quandt, S.A., Wiggins, M.F., Chen, H., Bischoff, W.E., Arcury, T.A., (2013). Heat index in migrant farmworker housing: implications for rest and recovery from work-related heat stress. *American Journal of Public Health*. 103(8):e24-e26. doi:10.2105/AJPH.2012.301135.

R Development Core Team. R: a language and environment for statistical computing, (2012), R Foundation for Statistical Computing Vienna, http://www.R-project.org (accessed September 2014)

Reid, C.E., O'Neill, M.S., Gronlund, C.J., Brines, S.J., Diex-Roux, A.V., Brown, D.G., Schwartz, J.D., (2009). Mapping community determinants of heat vulnerability. *Environmental Health Perspectives*. 117(11):1730-1736. doi:10.1289/ehp.0900683.

Rhea, S., Ising, A., Fleischauer, A.T., Deyneka, L., Vaughan-Batten, H., Waller, A. (2012). Using near real-time morbidity data to identify heat-related illness prevention strategies in North Carolina. *Journal of Community Health*. 37(2):495-500. doi:10.1007/s10900-011-9469-0.

Rust, A. (2007). This is my home: The challenges and opportunities of manufactured housing. Durham, North Carolina. Carolina Academic Press

Semenza, J.C., McCullough, J.E., Flanders, W.D., McGeehin M.A., Lumpkin J.R., (1999). Excess hospital admissions during the July 1995 heat wave in Chicago. *American Journal of Preventive Medicine*. 16(4): 269-277.

Semenza, J.C., Rubin, C.H., Falter, K.H., Selanikio, J.D., Flanders, W.D., Howe, H.L., Wilhelm J.L., (1996). Heat-related deaths during the July 1995 heat wave in Chicago. *The New England Journal of Medicine.* 335(2):84-90.

Sheridan, S.C., Dolney, T.J., (2003). Heat, mortality, and level of urbanization: measuring vulnerability across Ohio, USA. *Climate Research*, 24(3):255-265.

Smiley, M.J., Diez Roux, A.V., Brines, S.J., Brown, D.G., Evenson, K.R., Rodriguez, D.A., (2010). A spatial analysis of health-related resources in three diverse metropolitan areas. *Health and Place.* 16(5):885-892. doi:10.1016/j.healthplace.2010.04.014.

Smoyer, K.E., (1998). Putting risk in its place: methodological considerations for investigating extreme event health risk. *Social Science & Medicine*, 47(11):1809–24.

Social Explorer; United States. Census Bureau; American Community Survey 2008-2012 Summary File: Technical Documentation [Accessed 10 February 2014]

Steadman, R. G., (1984). A universal scale of apparent temperature. *Journal of Climate and Applied Meteorology*. *23*(12): 1674-1687.

U.S. Census Bureau, Housing and Household Economic Statistics Division. 2010. American Housing Survey (AHS). Available: http://www.census.gov/hhes/www/housing/ahs/ahs.html [Accessed 6 August 2014].

U.S. Census Bureau, Housing and Household Economic Statistics Division. 2010. American Housing Survey (AHS). Available: http://www.census.gov/hhes/www/housing/ahs/ahs.html [Accessed 6 August 2014].

U.S. Department of the Interior. 2012. Multi-Resolution Land Characteristics Consortium: National Land Cover Database. Available: http://nassgeodata.gmu.edu/CropScape/NC [Accessed August 10 2014].

U.S. Energy Information Administration. 2010. Residential energy consumption survey 2009. Washington, DC: U.S. Energy Information Administration

U.S. Energy Information Administration. 2010. Residential energy consumption survey 2009. Washington, DC: U.S. Energy Information Administration

Uejio, C.K., Wilhelmi, O.V., Golden, J.S., Mills, D.M., Gulino, S.P., Samenow, J.P., (2011). Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health and Place*, 17(2): 498–507. doi:10.1016/j.healthplace.2010.12.005

Vandentorren, S., Bretin, P., Zeghnoun, A., Mandereau-Bruno, L., Croisier, A., Cochet, C., Ledrans, M., (2006). August 2003 heat wave in France: risk factors for death of elderly people living at home. *European Journal of Public Health*. 16(6):583-591. doi:10.1093/eurpub/ckl063.

Whitman, S., Good, G., Donoghue, E. R., Benbow, N., (1997). Mortality in Chicago Attributed to the July 1995 Heat Wave, *American Journal of Public Health*, 87(9): 1515-1518.

Wolf, J., Adger, W. N., Lorenzoni, I., Abrahamson, V., Raine, R., (2010). Social capital, individual responses to heat waves and climate change adaptation: An empirical study of two UK cities. *Global Environmental Change*, 20(1): 44–52. doi:10.1016/j.gloenvcha.2009.09.004

Wood, S.N., (2006) Generalized Additive Models: An Introduction with R. Chapman and Hall/CRC.

Wood, S.N., (2011) Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society*. 73(1):3-36

Washington, Wyoming, Alaska, Montana, and Idaho (WWAMI) Rural Health Research Center. Rural-urban commuting area codes (RUCAS). (2004). Available at: http://depts.washington.edu/uwrhrc/index.php [Accessed: 17 July 2014].

Xiang, J., Bi, P., Pisaniello, D., Hansen, A., Sullivan, T., (2014). Association between high temperature and work-related injuries in Adelaide, South Australia, 2001-2010. *Occupational and Environmental Medicine*. 71(4):246-252. doi:10.1136/oemed-2013-101584.

Ye, X., Wolff, R., Yu, W., Vaneckova, P., Pan, X., & Tong, S., (2012). Ambient temperature and morbidity: a review of epidemiological evidence. *Environmental Health Perspectives*. 120(1), 19–28. doi:10.1289/ehp.1003198

Zeisberger, E., Schönbaum, E., Lomax, P., (1994). Thermal balance in health and disease: recent basic research and clinical progress. Advanced Pharmacology Science. Birkhauser. Boston.