8-2019

Heat Waves and Heat-Related Mortality in East Tennessee

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Heat Waves and Heat-Related Mortality in East Tennessee

A thesis

presented to

the faculty of the Department of Environmental Health

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Master of Science of Environmental Health

by

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August 2019

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Keywords: heat waves, climate change, mortality, East Tennessee

ABSTRACT

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Heat waves represent a public health challenge that requires multiple responses and warnings to protect vulnerable populations. Although studies have reported an increasing trend of heat wave occurrence in many areas of the world, no clear trend exists in East Tennessee. Using data from Parameter-elevated Relationships on Independent Slope Models (PRISM), CDC WONDER and the United States Census Bureau, the relationship between mortality rates and year was estimated during heat wave events between 1999 and 2010. Five heat wave definitions were tested. Overall, 2007 and 2010 stand out as the years with the highest number of heat wave days in East Tennessee. August could be described as the hottest month. Three of the heat wave definitions tested show increasing non-accidental mortality rates with year. The relative risk for cardiovascular mortality is elevated among females compared to males for one of the heat wave definitions (Relative Risk (RR) = 1.33, CI= 1.08-1.65).

DEDICATION

This work is dedicated to the loving memory of my late mum, Mrs. Esther Oluwafunmilayo Adesoba, whose life further motivated me to pursue a career in public health.

ACKNOWLEDGEMENTS

I sincerely appreciate the Chair of my thesis committee, Dr. Ying Li, who is also my academic mentor for her support and guidance throughout this phase of my academic pursuit.

I am grateful to Dr. Ken Silver for his interest in my work and his technical assistance.

The support of Dr. Andrew Joyner had a great impact on my geospatial data processing. I am grateful.

I thank the Chair of the Department of Environmental Health, Dr. Kurt Maier for supporting me with the development of my timelines and academic plan.

I appreciate the technical assistance provided by Dr. Zheng during the statistical data analysis.

I also appreciate Mr. Chuck Patton for his administrative support including liaison with the School of Graduate Studies.

This work would not have been successful without the support of my family. I express my profound gratitude to my darling wife, Adeola and son, Tijesunimi for their support, prayers, and understanding when I was busy with this work. I also thank my dad and my siblings for always encouraging me all the way.

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CHAPTER 1

INTRODUCTION

As unusually hot days occur globally more frequently over longer periods of time (Anderson and Bell 2011; Dong et al. 2016; Peng et al. 2011), it becomes increasingly important to conduct research to better understand the local peculiarities of this phenomenon, including who is most affected, how they are affected, and the extent to which they are affected. Heat waves result in morbidity (Chen et al. 2017; Ogbomo et al. 2017; Sun et al. 2014), including visits to emergency rooms (Guo et al. 2017; Knowlton et al. 2009; Mayner et al. 2010; Sun et al. 2014), and in some cases even mortality (Dong et al. 2016; Guo et al. 2017; Lee et al. 2016; Seposo et al. 2017; Zhang et al. 2016). Heat waves represent one of the possible outcomes of climate variability and change (Ebi et al. 2006; Peng et al. 2011). In the United States, climate change is projected to have a wide range of effects on extreme events, such as heat waves and flooding (Ebi et al. 2006). The release of greenhouse gases, most significantly, carbon dioxide (CO_2) is linked with the increased ambient temperature (Peng et al. 2011). Mortality from heat waves is projected to increase in the future (Peng et al. 2011). This study used weather data to estimate the number of heat waves that occurred between 1999 and 2010 and to examine possible trends. Mortality data were associated with heat wave occurrence, taking into account gender differences and county level differences.

Specific Research Objectives

The objectives of this study are:

1. To determine the extent to which East Tennessee experienced heat waves between 1999 and 2010 based on select definitions. Five heat wave definitions were developed

to determine if heat waves occurred based on each of the definitions within the period under review.

2. To determine mortality trends potentially associated with heat waves within the study period. Generalized Additive Models assessed variation of mortality with heat wave days, calculating relative risk by gender and county.

Literature Review

Definition of Heat Waves

Heat waves are events with a subjective and varied definition, and as such requires carefulness when defining, so that climate data are correctly interpreted during decision-making. Different authors have suggested how to best define this phenomenon in terms of its associated metrics: temperature, duration, intensity, and human susceptibility (Anderson and Bell, 2011; Chen et al. 2017; Dong et al. 2016; Guo et al. 2017; Lee et al. 2016; Ogbomo et al. 2017; Peng et al. 2011; Seposo et al. 2017; Sun et al. 2014; Zhang et al. 2016). It is, however, well-established that heat waves are a period of excessively hot weather (Anderson et al. 2011; Ebi et al. 2006).

In describing heat waves, two factors related to heat are critical: intensity and duration. These two factors are usually applied when testing the definitions of heat waves (Anderson et al. 2011; Chen et al. 2017; Dong et al. 2016; Ogbomo et al. 2017; Sun et al. 2014). As for intensity, a threshold above which temperature could be hazardous is first determined; different temperatures above this threshold are then matched with different durations and mortality to estimate the number of associated deaths. This threshold (intensity) could be absolute or relative (Robinson, 2001). It is reported that heat waves defined by higher temperature thresholds are correlated with higher heat-related mortality rates (Guo et al. 2017), but another study reports no precise relationship between heat wave metrics tested and mortality (Seposo et al. 2017). Guo et al. (2017) showed that the association between heat waves and mortality is acute and lasts between three and four days. Duration is significant because the added effects of heat can only be measured when heat is sustained for more than a day. In this case, the first day of a heat wave event is likened to any other hot day (Chen et al. 2017); but heat waves lasting one day have been previously tested in different studies (Hattis et al. 2012; Kent et al. 2014). Studies show that the mortality outcomes of heat waves increase as the duration increases (Seposo et al. 2017; Yin and Wang 2017).

The World Meteorological Organization (WMO) provides a unifying definition from which locally appropriate metrics for heat waves can be developed. WMO defines heat wave as "a marked unusually hot period of weather (based on the maximum, minimum, and daily temperature average) over a region persisting for at least two consecutive days during the hot period of the year, based on local climatological conditions with thermal conditions recorded above given thresholds" (WMO, 2015).

Heat Wave Vulnerability, Morbidity and Mortality

Vulnerability to the morbidity and mortality effects of heat waves varies with demography of the population (Dong et al. 2016; Tian et al. 2013), location of the study (Guo et al. 2017; Seposo et al. 2017; Xiao et al. 2017), heat wave definition used (Chen et al. 2017; Gasparrini et al. 2011; Guo et al. 2017), and individual adaptation strategies (Guo et al. 2017). These issues are explained below.

Heat wave vulnerability

Exposure (to heat) is a critical factor that affects heat wave vulnerability (Xiao et al. 2017), but exposure of a population to the same amount of heat may not produce the same response in every member of the population as reported in a previous study due to physiological differences and individual resilience (Toki et al. 2018). Higher intensity of heat exposure has been associated with higher adverse health effects (Xiao et al. 2017). The individual risk factors for effects of heat waves include age (Seposo et al. 2017; Tian et al. 2013; Xiao et al. 2017), gender (Seposo et al. 2017; Tian et al. 2013), socioeconomic status (Poumadère et al. 2015), remoteness (Xiao et al. 2017), race (Toki et al. 2018), and geographical locations (D'Ippoliti et al. 2010; Xiao et al. 2017). Generally, heat wave impact is not homogenous (D'Ippoliti et al. 2010); hence its effects on exposed populations are diverse.

Gender. The gender susceptibility of heat waves is as dynamic as heat waves themselves. Males and females are affected differently by heat waves. While some studies show that males are reported to have a higher vulnerability to heat-related all-cause death (Zhang et al. 2016), and cardiovascular deaths (Seposo et al. 2017), other studies show that women are at higher risk of all-cause mortality due to heat waves (D'Ippoliti et al. 2010), coronary heart disease mortality (Tian et al. 2013) and cardiovascular disease mortality (Yin and Wang, 2017). The diversity of the heat wave effects reported can be explained by the differences in the heat wave definition used, demographics and other peculiarities of the study population. An emergency room visit study showed that males had a higher susceptibility among the 15-64 age bracket, but women had a higher number of emergency room visits among those age 65 and above in the same population (Mayner et al. 2010). Another study shows that females are reported to have a higher rate of kidney failure than males during heat waves (Xiao et al. 2017). A possible reason for men's susceptibility to heat wave is that they work outside more than women during heat waves (Xiao et al. 2017). Another study found no significant difference by gender in the effects of heat waves (Anderson et al. 2013).

Age. Age is a factor that has been shown to affect heat wave vulnerability. Studies show that individuals of ages 4 years and younger (Knowlton et al. 2009), 14 years and younger (Tian et al. 2013; Rameezdeen and Elmualim, 2017), and the elderly above 60 years (Chen et al. 2017), and elderly above 65 years (Knowlton et al. 2009) have elevated morbidity and mortality risks resulting from heat wave impacts. One explanation for such susceptibility among the elderly is that thermal regulation becomes less efficient with older age (Yin and Wang, 2017). Young people are affected by heat waves because of the lower sweating capacity, which reduces their ability to disperse heat (Tian et al. 2013).

Location. Vulnerability and resilience levels differ from one community to the other (Rameezdeen and Elmualim, 2017). Previous studies show that populations in remote locations are more vulnerable than those in urban places due to poor access to health services (Rameezdeen and Elmualim, 2017). Other studies report that urban dwellers also experience the toll of heat wave events, which are often exacerbated by the "urban heat island" effect (Patz et al. 2005; Dong et al. 2016; Poumadère et al. 2015), making the urban setting several degrees warmer than the surrounding suburban and rural areas. The prevailing climatic conditions of an area determine to a notable extent how the people are affected by climate change. Heat waves tend to cause more mortality in temperate regions because of poor familiarity with excessive hot weather and poor preparedness (Ebi et al. 2004).

Socioeconomic Status (SES). SES is an important social determinant of health. It is also an influencer in heat wave morbidity and mortality because persons of low SES may not be able to afford heat wave adaptation measures such as air conditioning (Xiao et al. 2017). Low socioeconomic status contributes to higher mortality among populations with limited access to air conditioning equipment (Guo et al. 2017).

Heat Wave Morbidity and Mortality

The impact of heat waves can be divided into the main effects resulting from high temperatures, and a cumulative effect due to heat sustained over a period (Gasparrini and Armstrong 2011; Dong et al. 2016; Seposo et al. 2017; Toki et al. 2018). It is assumed that high daily temperature has an impact, which is independent of the added effect of sustained heat (Guo et al. 2017).

Some previous studies argue that the respiratory and cardiovascular systems are found to be the most sensitive and most affected by heat waves (D'Ippoliti et al. 2010; Dong et al. 2016; Seposo et al. 2017). Some other studies reported that the renal (Knowlton et al. 2009; Toki et al. 2018) and circulatory systems (Chen et al. 2017) were greatly affected by the phenomenon. Heat waves also influence the progression of infectious disease as sustained duration of heat exposure supports the growth of certain bacteria in the body (Chen et al. 2017). The cardiovascular system is affected by impaired cardiac and vasodilation functions (Dong et al. 2016).

Some studies report that the effect of heat exposure is immediate and acute (Knowlton et al. 2009; Sun et al. 2014; Chen et al. 2017; Guo et al. 2017; Toki et al. 2018). Other studies suggest that the cumulative effects of heat are more significant than the immediate effect (Dong et al. 2016; Lee et al. 2016). Another study described the added effect as small (Gasparrini and Armstrong 2011).

Heat Wave Adaptation and Mitigation

Communities respond to and cope with heat wave conditions differently, depending on their climatic peculiarities. These peculiarities determine socio-cultural practices adopted by community members to cope with the discomfort or outcomes of exposure to heat waves (Robinson 2001). Because of the acute nature of heat waves, helping a community, especially vulnerable populations, to develop appropriate interventions to cope with the event is critical to reducing heat-associated morbidity and mortality. Adaptation is critical for the wellbeing of low-income families and the elderly living alone (Barnett et al. 2013). This is relevant in urban heat islands where a large population is impacted. Adaptation can be achieved through protective job scheduling for outdoor workers (Lowe et al. 2011; Rameezdeen and Elmualim, 2017), urban greening (Barnett et al. 2013), adoption of heat repelling ceiling materials and behavioral adaptation options (Barnett et al. 2013). Air conditioning is a major intervention that mitigates the impact of heat waves on human health (Anderson and Bell 2011; Guo et al. 2017; Kalkstein et al. 2011; Lowe et al. 2011). It is recommended that the elderly and other vulnerable groups have access to air-conditioned homes or rooms when there is an increased likelihood of a heat wave event (Lowe et al. 2011).

Heat Wave Early Warning Systems

Early warning systems are believed to be effective in reducing heat-related morbidity and mortality (McGregor et al. 2015). They are designed to provide notification at the onset of a possible heat wave event, minimizing the impact on human health (Lowe et al. 2011; McGregor et al. 2015). Without a system to predict heat waves, there would be no efficient preparedness against this hazard. According to the WMO, an early warning system helps to provide meteorological information on the prospect of an imminent hot weather events that could potentially influence health (McGregor et al. 2015).

Heat wave early warning systems are a signaling system initiated when heat wave-related meteorological factors reach beyond a safe threshold. An early warning system helps to facilitate improved case management of heat-related illnesses and associated risk reduction (Tian et al. 2013). These systems should be relevant to the unique weather conditions of a location.

Responding to heat waves therefore requires understanding of local weather patterns, innovation for the development of indigenous or local approaches, and selection of the correct metrics using existing weather data. This will reduce confusion in interpreting warning and data use for decision-making. It should be noted that early warning metrics for a specific location may not be applied to other locations, i.e. it is localized (Sherbakov et al. 2018). Without a correct locally-relevant definition for heat waves, an early warning system will be ineffective. A cost-benefit analysis of heat wave early warning systems in some parts of Europe suggests that development of heat waves warning systems is a justifiable approach towards reducing heat-related death (Hunt et al. 2017). The effectiveness of heat waves warning system may be weakened by the release of inaccurate warnings (Lowe et al. 2011). Therefore, identifying accurate heat warning thresholds will help maintain the integrity of the system.

Heat Wave Study and Reasons for Non-Generalization

One characteristic of heat wave studies is the great caution required in generalizing both the definition and quantification. This makes it difficult to conduct a multi-level heat waves study using a unifying definition and quantification standard (Guo et al. 2017). For example, using a consistent definition and methodology for heat waves in a multi-country study, Guo et al. (2017) found that heat waves resulted in inconsistent mortality rates attributable to the varying local climatic conditions. A similar study found a contrary result (Anderson and Bell 2009). Another major reason for non-generalizability is the variation in the adaptation mechanisms available and adopted by local communities (Kinney et al. 2008). This results in differences in the impact of the same intensity and duration of heat. The absence or presence of susceptible subpopulations also influence the outcomes of exposure to heat waves (Guo et al. 2017, Kinney et al. 2008). These uncertainty and variability should be carefully considered when studying heat waves' impacts.

Implications of Research

Findings from this study will be useful for the development of early warning systems in East Tennessee in the future. In responding to the occurrence of heat waves, a warning system is needed to alert vulnerable populations including the elderly, children, outdoor workers, and persons with co-morbidities to move towards temperature-controlled cool locations or buildings to avoid the exacerbation of health conditions, sudden death and emergency room visits.

Justification for the Research

There are critical questions related to heat waves' impacts in East Tennessee that have not been answered such as "how often do heat waves occur in East Tennessee?" "Which county or counties (rural or urban) may be more affected by heat waves?" "Who is more affected?" Relevant data to answer these questions are lacking; hence, this study seeks to generate useful data and findings using available weather and epidemiological data. This study will advance scientific discussions on the occurrence of heat waves in East Tennessee and more specifically the impact of heat waves on the people of East Tennessee.

The hypothesis for this study is that heat-related mortality is higher in months with higher numbers of heat wave days compared to months with fewer heat wave days.

CHAPTER 2

MATERIALS AND METHODS

East Tennessee: Climatic Description

East Tennessee is one of three geographical divisions of Tennessee. The others are west and middle Tennessee. East Tennessee has 33 counties illustrated in figure 1 and a population of 2,327,544 according to the 2010 Census (United States Census Bureau, 2010). The Appalachian region, where East Tennessee is located is typically rural with disproportionately poor quality of healthcare (Griffith et al. 2011).

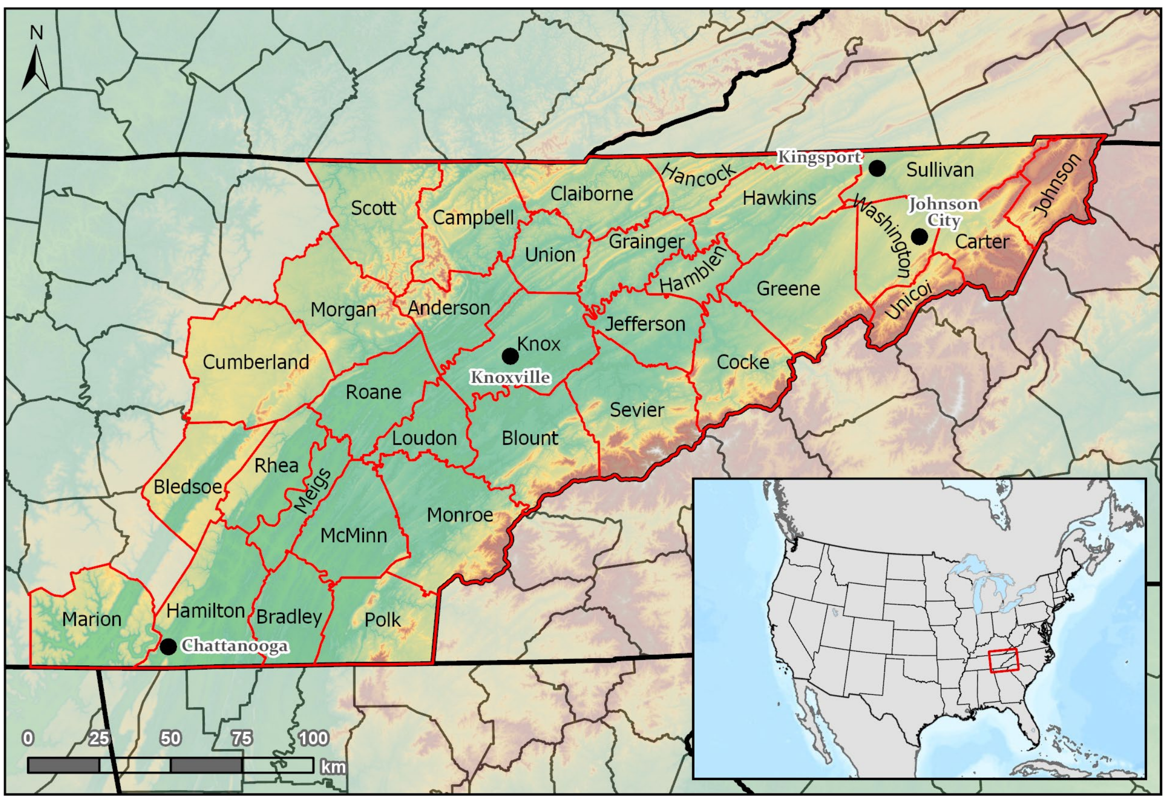


Figure 1: The 33 counties of East Tennessee

Located in the Southeast United States, Tennessee has topography characterized from east to west by the Appalachian Mountains, the Cumberland Plateau, rolling hills, and low-lying plains (Hodges et al. 2018). East Tennessee is mountainous and dominated by the ridge and valley system, with the popular Great Smoky Mountains National Park located in this region (Hodges et al. 2018). The oscillating topography of Tennessee underlies the varying temperature in different parts of the state, albeit the climate is generally temperate (NCEI, n.d.; Runkle et al. 2017). Temperatures are lower in the eastern part of Tennessee compared to other parts of the state, specifically in the Cumberland Plateau area and the Appalachian Mountains owing to their higher altitude, while higher temperatures are observed in the Great Valley of East Tennessee which has a lower altitude (Runkle et al. 2017). While the entire United States has warmed by about 1.5F, Tennessee has not experienced significant temperature rise because the area experienced a cooling sometime in the mid-20th century (Runkle et al. 2017).

Study Period

All data collected for this study covered May to September of year 1999 to 2010 (12 years). The select months are "hot months" (May to September), which are typically the period when elevated mortality risks associated with heat waves are likely to occur, and they have been used in past literature. (Anderson and Bell 2011; Tian et al. 2013; Kent et al. 2014).

Heat Wave Definitions

Five heat waves definitions were adopted from Kent et al (2014) as listed in Table 1.

Table 1: Heat wave names tested and their definitions (all definitions adopted from Kent et al. 2014; Original references presented in parentheses).

Heat waves abbreviation	Definition
HW1	Minimum daily temperature > 95th percentile for ≥ 2 consecutive days (Anderson and Bell 2011)
HW2	Mean daily temperature > 95th percentile for ≥ 2 consecutive days (Anderson and Bell 2011)
HW3	Maximum daily temperature > 95th percentile for ≥ 2 consecutive days (Anderson and Bell 2011)
HW4	Maximum daily temperature > 35°C (95°F) for ≥ 1 day (Tan et al. 2007)
HW5	Maximum daily apparent temperature > 95th percentile for ≥ 1 day (Hattis et al, 2012)

The denominator for the definitions was the five hot months (May-September) of years 1999 to 2010, the same approach given in Kent et al (2014).

HW5 used Apparent Temperature (AT) calculated as follows (Zanobetti and Schwartz, 2008):

$$AT = -2.653 + (0.994T_a) + 0.0153(T_d^2)$$

$$Where, T_a\ is\ air\ temperature\ and\ T_d\ is\ the\ dew\ point$$

Previous studies have used apparent temperature for heat-related mortality (Chen et al. 2017; Lee et al. 2016; Xiao et al. 2017; D'Ippoliti et al. 2010). Apparent temperature is believed to provide a reflection of human physiological response to heat much better than ambient temperature by combining humidity with ambient temperature (Zanobetti and Schwartz 2008).

<u>County Rurality Classification</u>

To examine the impact of a county's rurality level on the heat wave-mortality relationship, the 33 counties are classified into two groups: Urban v.s. rural based on the Index of Relative Rurality for Tennessee Counties (2010) developed by Tennessee Advisory Commission on Intergovernmental Relations (Reohrick-Patrick et al. 2016). As a result, 15 of the 33 counties are classified as "urban" and the remaining 18 as "rural." The urban counties include Anderson, Blount, Bradley, Carter, Hamblen, Hamilton, Hawkins, Jefferson, Knox, Loudon, Roane, Sevier, Sullivan, Unicoi and Washington; the rural counties include Bledsoe, Campbell, Claiborne, Cocke, Cumberland, Grainger, Greene, Hancock, Johnson, Marion, McMinn, Meigs, Monroe, Morgan, Polk, Rhea, Scott and Union.

<u>Mortality Data</u>

Mortality data, including underlying causes of death, were obtained from Centers for Disease Control and Prevention (CDC)'s WONDER database (https://wonder.cdc.gov/ucdicd10.html). The website provides an organization table to select the variables of interest including year, month, cause of death based on ICD-code 10, demographics, and location among others. For this study, two categories of cause of death were compared. ICD code A-R for all non-accidental causes of death (Anderson and Bell 2011; Kent et al. 2014; Peng et al. 2011), and ICD-Code I for Cardiovascular death (Yin and Wang 2017). The specific information collected includes sex, county, cause of death, month of death, and year of death. The data from the CDC WONDER database did not have monthly mortality rates. These were derived manually using the formula:

$$\frac{Number\ of\ deaths}{Population}\ X\ 100{,}000$$

Population Data

Population data were obtained from the United States Census Bureau's American Community Survey website https://www.census.gov/programs-surveys/acs/about.html. This website provides a path to the population database known as "American FactFinder" https://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t which has a large dataset including population data. The "American FactFinder" website allows for the customized selection of variables of interest such as geographical scope (state and county) and demographics (sex and age). Gender-specific population data for each county in East Tennessee were downloaded. The 2000 and 2010 census data were downloaded, and data for the years in-between were estimated by dividing the difference between 2000 and 2010 equally for each gender.

Meteorological Data

Daily minimum, maximum, and mean temperatures, and dew point temperature were derived from gridded data (4km by 4km spatial resolution) throughout East Tennessee from

Parameter elevation Regression Independent Slope Models (PRISM, http://prism.oregonstate.edu/normals/). The United States 30-year (1981-2010) normal maximum temperature raster files were downloaded from PRISM. Tennessee county shape files were extracted from the entire US administrative shape files- https://gadm.org/download_country_v3.html. The warmest locations in each county were identified using zonal statistical tool. These locations serve as reference for the entire county since we are interested in the impact of hot temperatures and because higher population centers generally occupy lower elevation areas that tend to be warmer (compared to higher elevation mountainous areas). Using the raster calculator tool, these locations in the form of pixels are converted to points whose geographical coordinates are then generated. An Excel file of these coordinates is then uploaded to PRISM to obtain the minimum, mean and maximum temperature of the warmest location in each county. Metrics which are not originally provided by PRISM such as the apparent temperature were calculated in MS Excel.

Study Design

A methodology used in previous related studies of heat waves and mortality is the Poisson generalized additive model (GAM) (Peng et al. 2011; Xuan et al. 2014, Sun et al. 2014; Chen et al. 2017; Zhang et al. 2016). It is suitable for non-linear regression models such as non-linear relationships between mortality and different predictors (Dominici et al. 2002), which is the situation of this study (time series data). Poisson is usually used in situations where probability *(p)* is small and population (n) is large (Pagano et al. 2000), which applies to the case of heat waves. Furthermore, because time series do not follow regression assumptions such as independence of data and normality of both outcome variable and predictors, the dependent variable is usually converted to a logarithmic format which then creates a model with both parametric and non-parametric functions (Dominic et al. 2002).

Data Analysis

MS Excel was used for the data preparation and cleaning while the statistical software used for the analysis and graphs in the study is R version 3.5.1.

Descriptive statistics were calculated to show a scatter plot of the relationship between each category of mortality and number of heat wave days for each definition of heat wave tested. Further descriptive statistics and plots included mortality variation by gender during heat waves from 1999-2010. Average daily temperature in each county for each heat waves definition was also analyzed.

The relationship between mortality and heat wave days was examined using an over-dispersed GAM (Chen et al. 2017; D'Ipolliti et al. 2010; Peng et al. 2011; Sun et al. 2014; Xuan et al. 2014). GAM, which is an extension of the generalized linear model, helps to study relationships between mortality and other independent variables that may not be linear (Moore et al. 2011). The basic model structure for this study is:

$$Y_t \sim Poisson(\mu_t)$$

Where Y_t is average mortality rate in month t.

To factor in the effects of heat wave days and other variables of interest for this study, three new terms were introduced, thereby leading to a final model:

$$\ln[\mathrm{E}(Y_t)] = \beta_0 + s(HW_t, k = 7) + GND + s(MNT_t, k = 3) + CNT + s(Year, k = 7)$$

Where $E(Y_t)$ is the expected mortality rate assumed to follow an over dispersed Poisson distribution (Gasparrini and Armstrong 2011; Zanobetti and Schwartz, 2008) in month *t*; β_0 is the model intercept; $s()$ is the spline function; GND is gender of the subjects; MNT represents month to adjust for long-term trends and seasonal patterns; CNT County classification i.e., rural or urban; HW_t is the number of heat wave days in month *t*; and $Year$ is year which ranges from 1999 to 2010; k is the number of knots, which is used to divide the curve into sections.

GAM is suitable for this analysis because the relationship between the mortality rates and number of heat wave days is typically non-linear. This model does not assume a linear relationship between the outcome variable (mortality rates) and predictors (number of heat wave days, gender, month, rurality level of a county and year). The model was run using the “gam” and “mgcv” packages in R version 3.5.1. Since the smooth functions of the predictors are unknown, mgcv helps to automatically generate the functions and is useful in the development of the graphs and plots (Wood 2017). Data already prepared in Excel files were imported into R using the file table in the lower right pane in the software opening page. Since GAM assumes the outcome variable has a Poisson distribution (count), the mortality rates estimated from Equation (1) were converted into integers.

Relative risk was calculated in R. A dummy variable was used to represent mortality as well as gender and rurality. A value of 1 means there was one or more deaths during heat waves in a particular month, and 0 means there were no deaths during heat waves in the month. This was done separately for gender where female has a value of 0 and male has a value of 1; and rurality where a rural county is given a value 0, and an urban county is given a value of 1.

CHAPTER 3

RESULTS

Descriptive Statistics of Number of Heat Wave Days per Year from 1999 to 2010

Using daily weather data in each county and the five heat wave definitions selected for this study, the trend of heat wave days over the period of study was assessed to see the direction of variation. Figure 2 shows the total number of heat wave days across the 33 counties in each year under the five definitions. The last year in the study period (2010) had the greatest number of heat wave days under all definitions except for HW3 and HW4. During the study period, there were some sharp rises in the heat wave days. For HW1, a sudden increase was seen in 2005 and a much bigger rise from 2009 to 2010. HW2 shows a sudden rise in the number of heat wave days in 2007, and again in 2009 to 2010. No (zero) heat wave days occurred in 2004 for HW2, HW3, HW4 and HW5. No heat wave days occurred in 2003 for HW3 and HW4. On average, 2004 has the lowest number of heat wave days considering all the definitions, followed by 2003 and 2009; while the highest number of heat wave days occurred in 2006, 2007, and 2010 respectively in increasing order as seen in Appendix B.

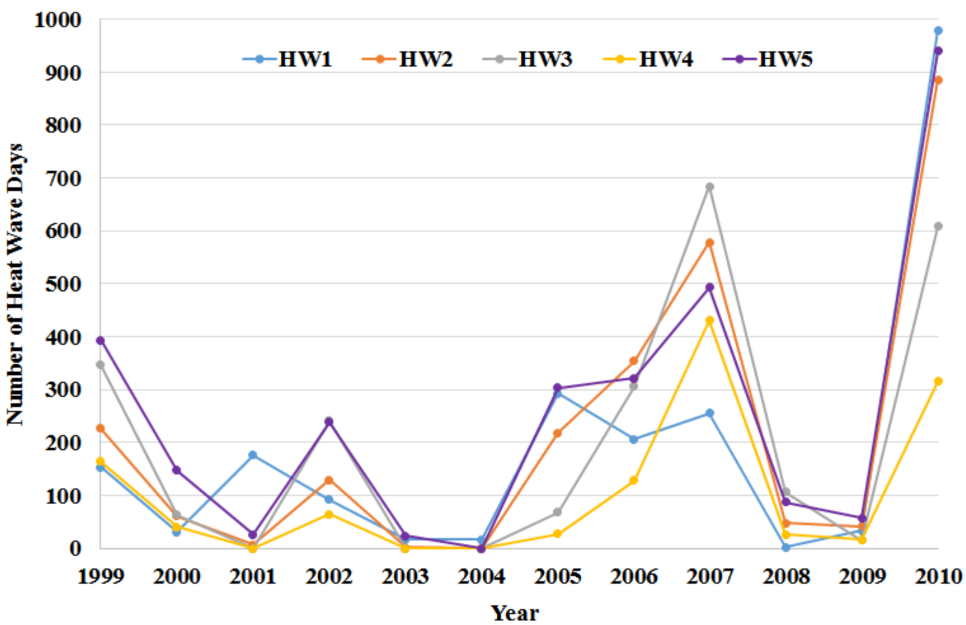


Figure 2: Total Number of heat wave days (aggregated across the 33 counties) in each year in the study period (1999 - 2010) for all definitions.

<u>Average Number of Heat Wave Days per Month</u>

The average number of heat wave days observed in each month is highest in August (Figure 3).

This indicates that heat waves are most frequent in August among the "hot months."

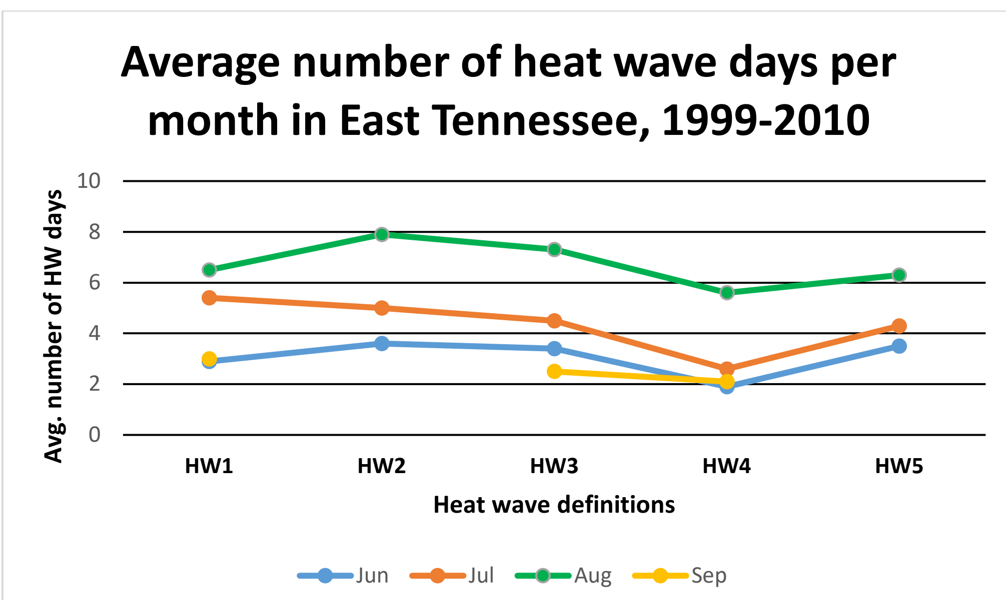


Figure 3: Average number of heat wave days per month.

Monthly temperature variation under different heat wave definitions

Towards understanding the trends and intensity of heat wave occurrence, average temperature was calculated for the heat wave days in a month across the 33 counties when heat waves occurred, for all five heat wave definitions (Figures 4-8). For each definition tested, the corresponding monthly mean temperature varied significantly but the month of August had the highest mean temperature for each of the definitions, and could be described as the hottest month when considering only heat wave periods. This is similar to the 'warmest day of the year' map produced by NOAA showing late July and early August being the warmest time of year in the region based on 1981-2010 temperature normals (https://www.ncdc.noaa.gov/file/us-warmest-day-year-mapjpg). For the five definitions, no heat wave days were observed in May in all 33 East TN counties. For HW1, HW2, and HW5, no heat wave day was observed in September.

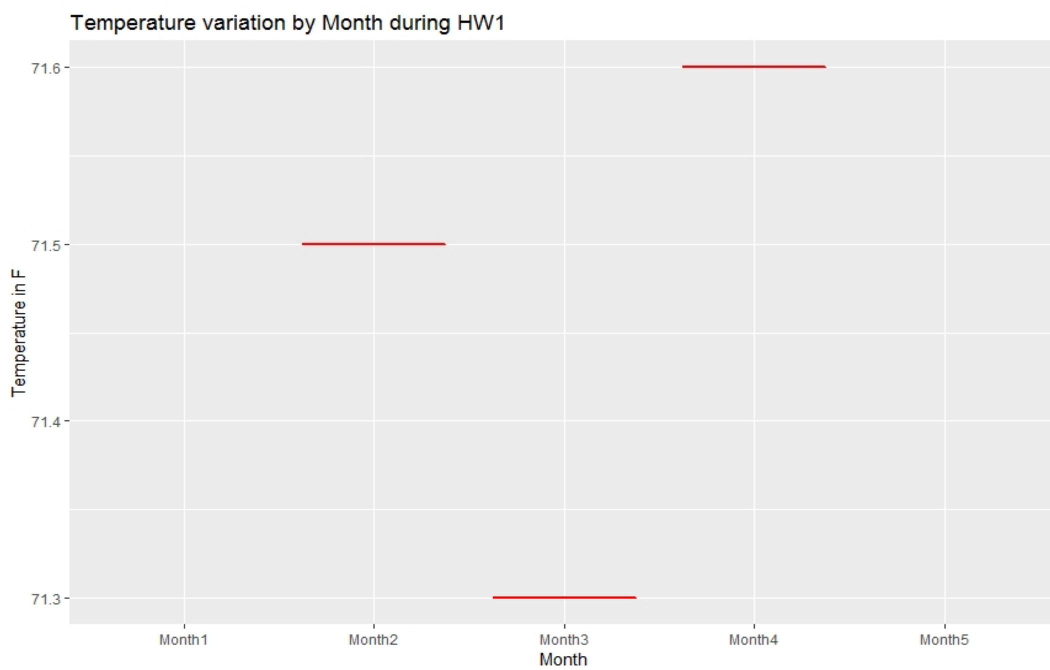


Figure 4:Average minimum daily temperature on heat wave days by Month from 1999 to 2010 using HW1. (Months are coded as follows: May= Month1, June=Month2, July=Month3, August=Month4, September=Month5)

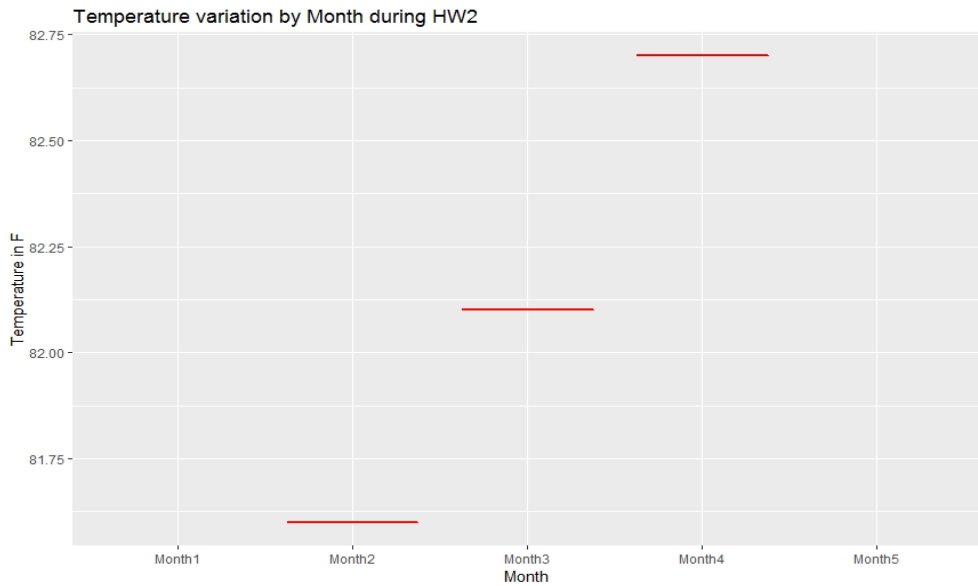


Figure 5: Average mean daily temperature on heat wave days by Month from 1999 to 2010 using HW2

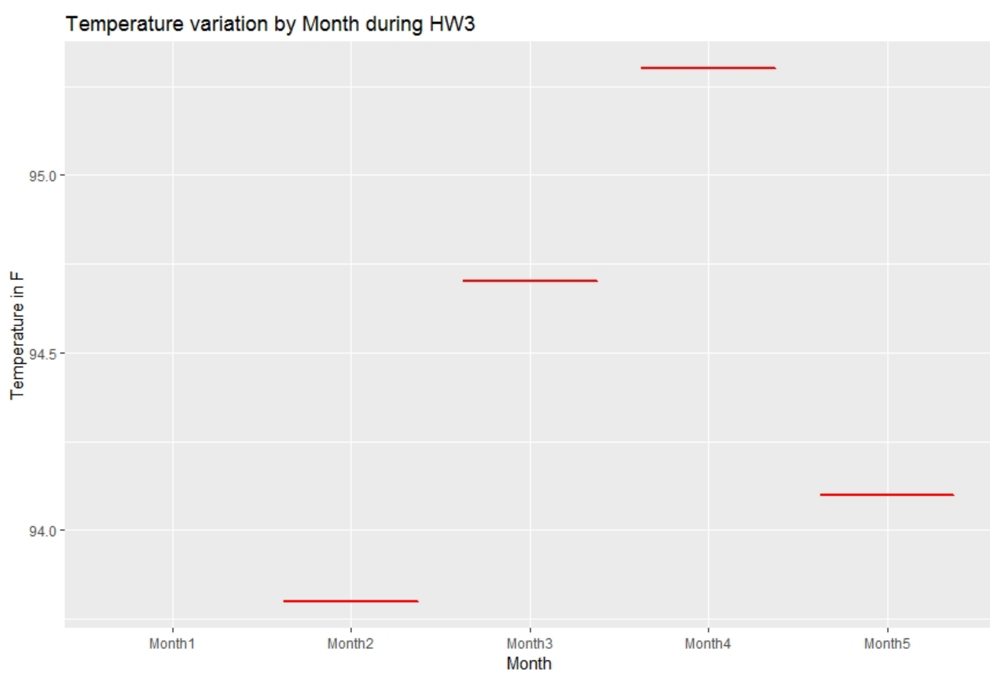


Figure 6: Average maximum daily temperature on heat wave days by Month from 1999 to 2010 using HW3

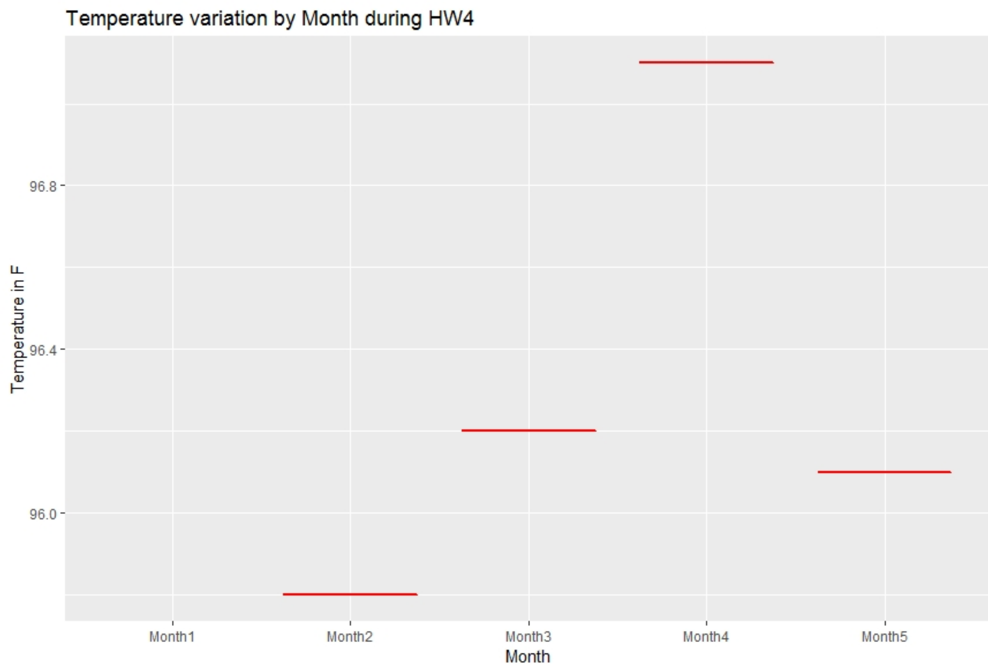


Figure 7: Average maximum daily temperature on heat wave days by Month from 1999 to 2010 using HW4

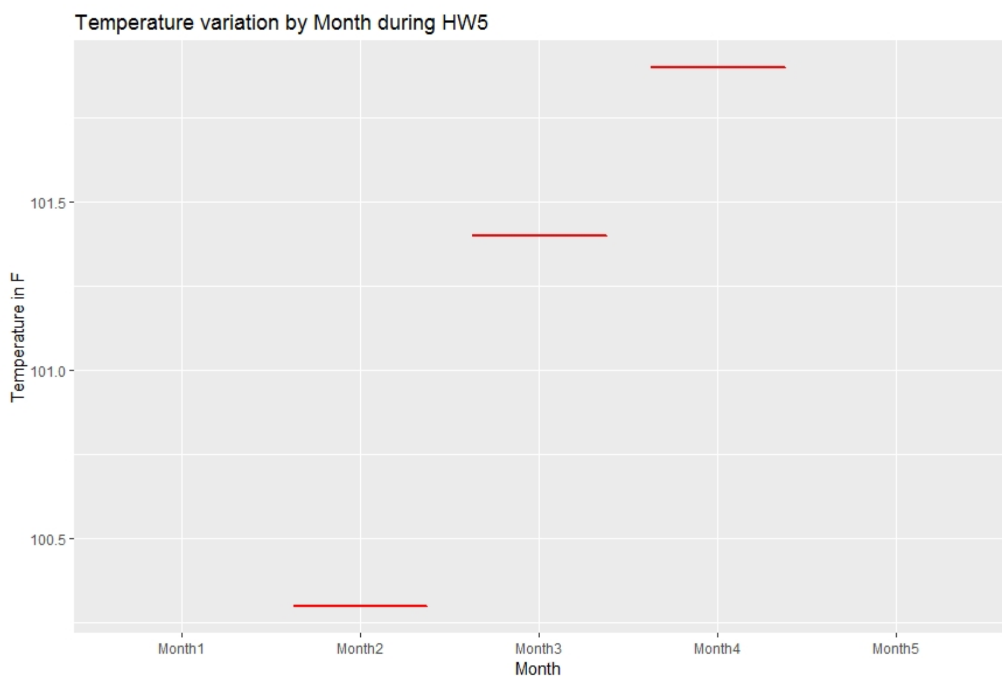


Figure 8: Average maximum daily apparent temperature on heat wave days by Month from 1999 to 2010 using HW5

<u>Variation of heat wave days with non-accidental and cardiovascular mortality rates between 1999 and 2010 in East Tennessee Counties</u>

A scatter plot of heat wave days and mortality was developed to visualize the relationship between monthly mortality rate and the number of heat wave days per month to assess the linearity. Time series data such as the one used for this study typically do not have a linear relationship with predictors, thereby making GAM an appropriate methodology for the test. The graphs are represented in Figures 9 to 13 for non-accidental mortality and Figures 14 to 18 for cardiovascular mortality. Each data point represents the mortality rate in a county.

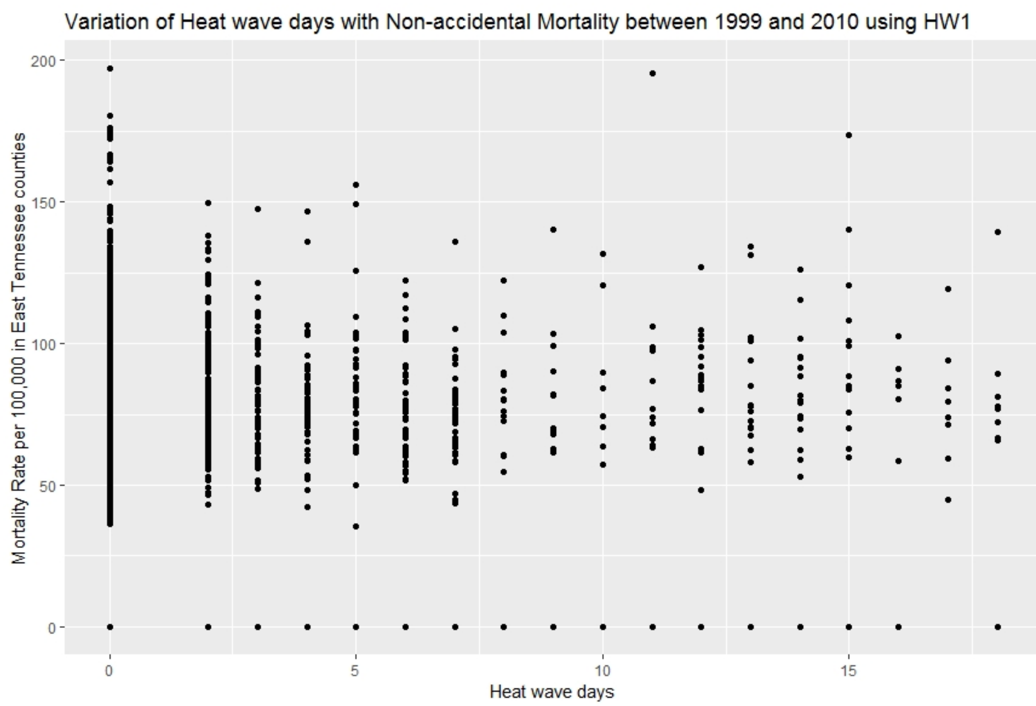


Figure 9: Variation of heat wave days with non-accidental mortality using HW1

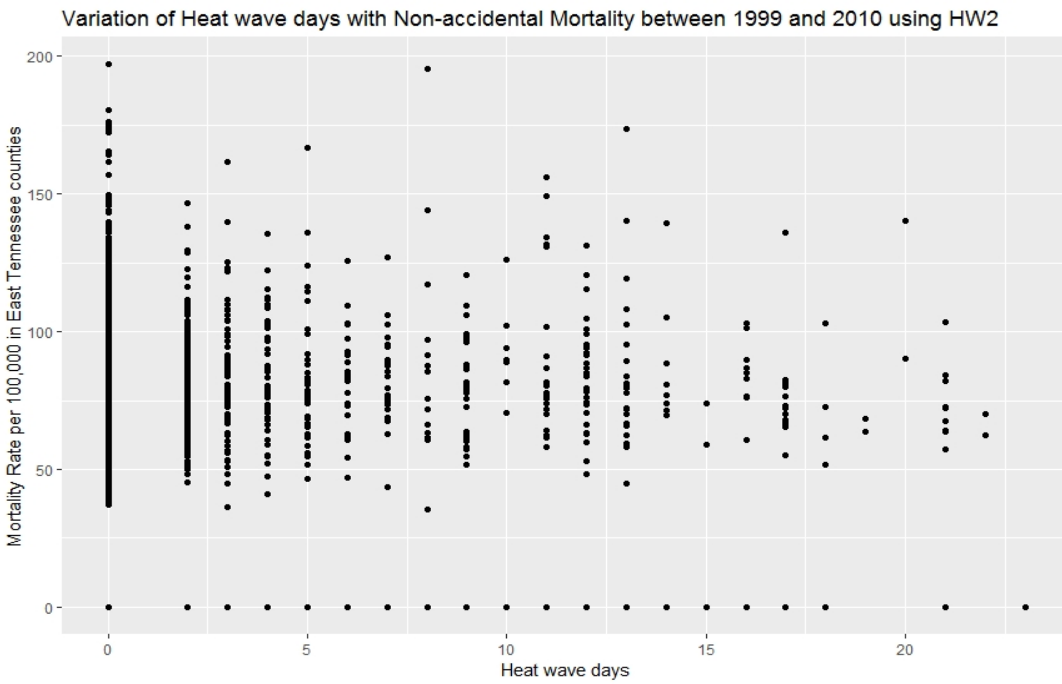


Figure 10: Variation of heat wave days with non-accidental mortality using HW2

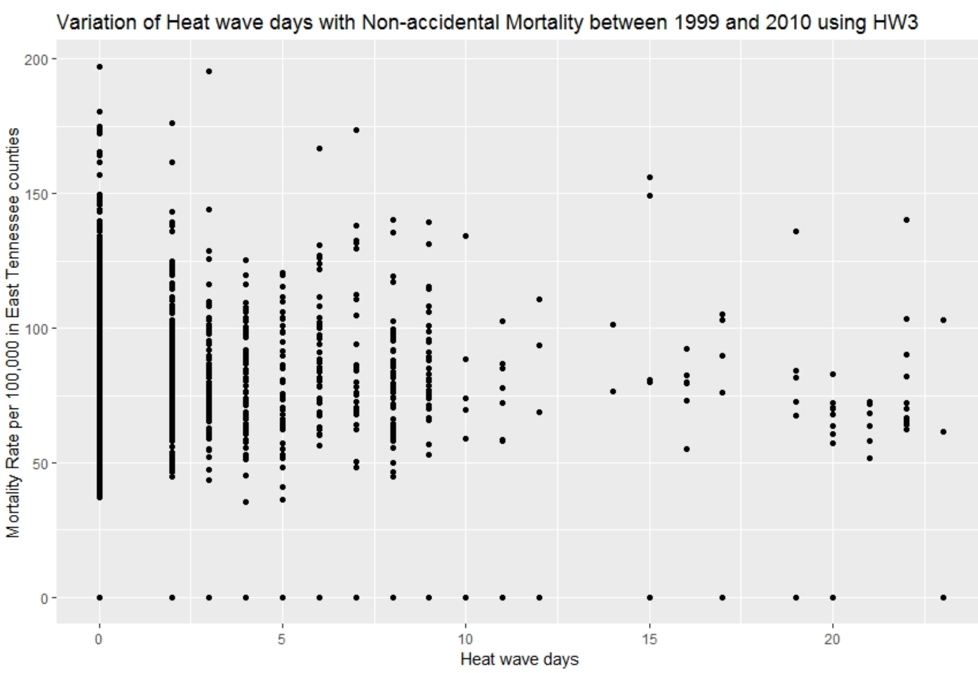


Figure 11: Variation of heat wave days with non-accidental mortality using HW3

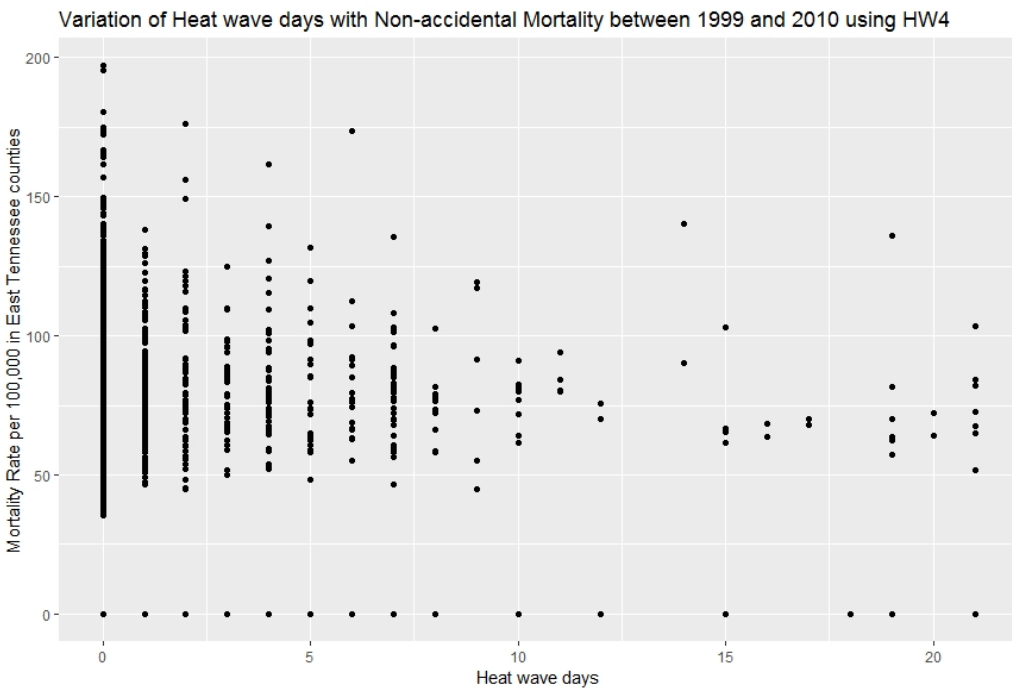


Figure 12: Variation of heat wave days with non-accidental mortality using HW4

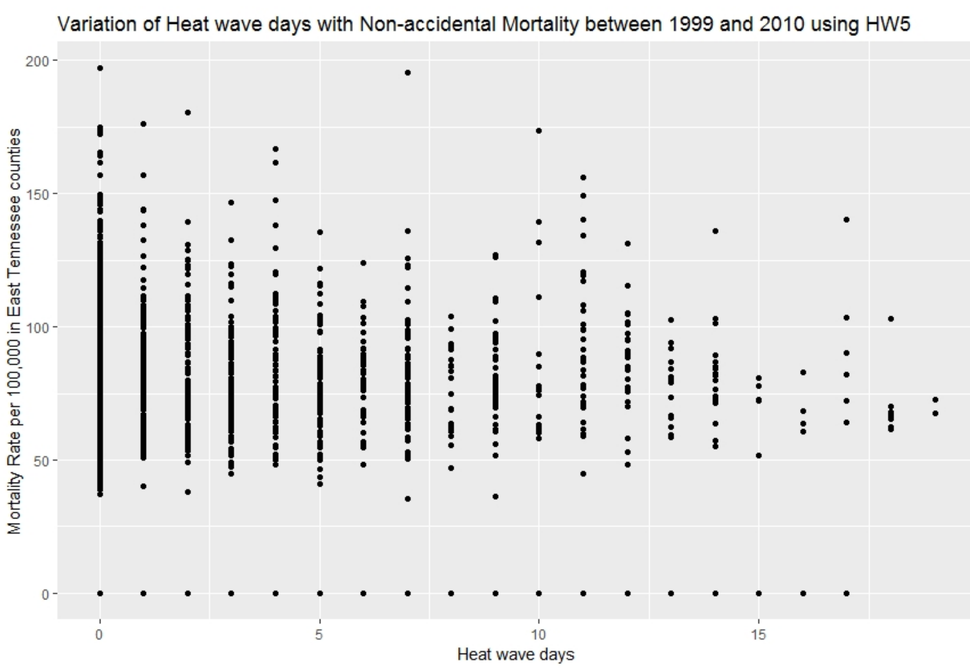


Figure 13: Variation of heat wave days with non-accidental mortality using HW5

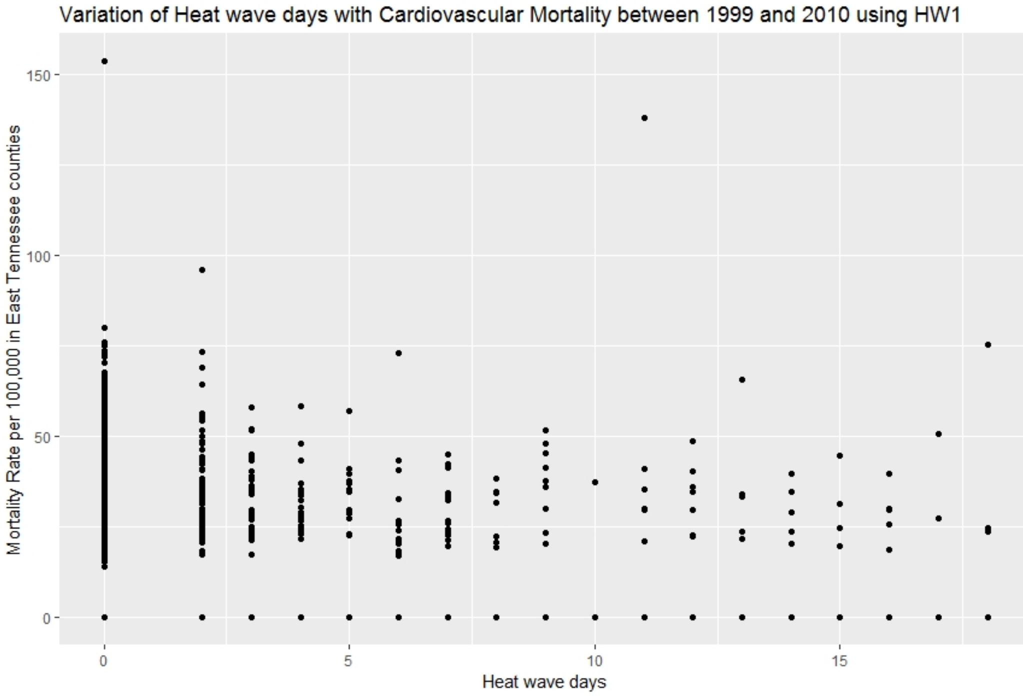


Figure 14: Variation of heat wave days with cardiovascular mortality using HW1

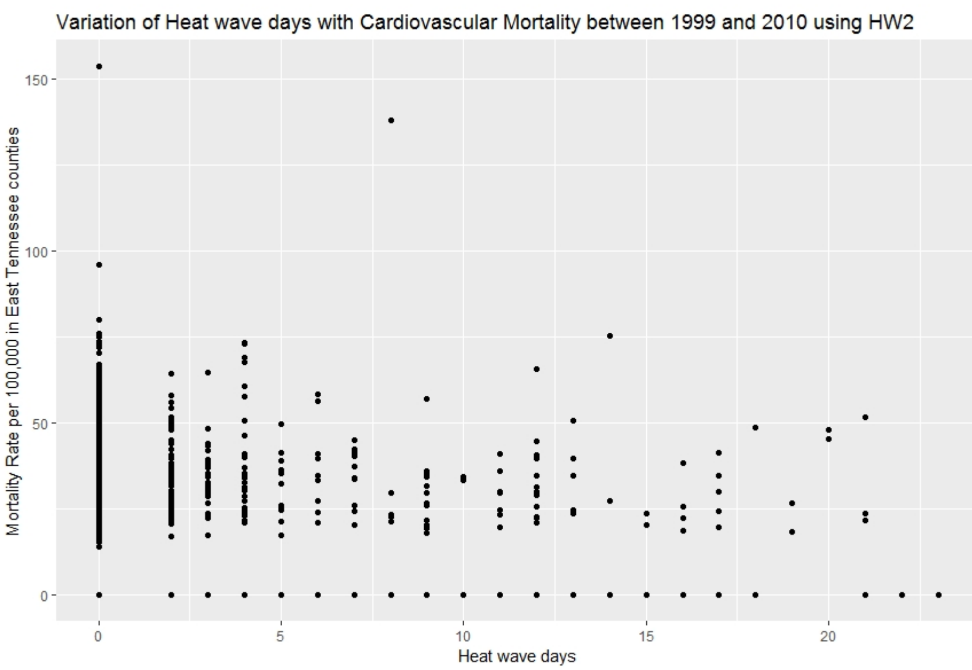


Figure 15: Variation of heat wave days with cardiovascular mortality using HW2

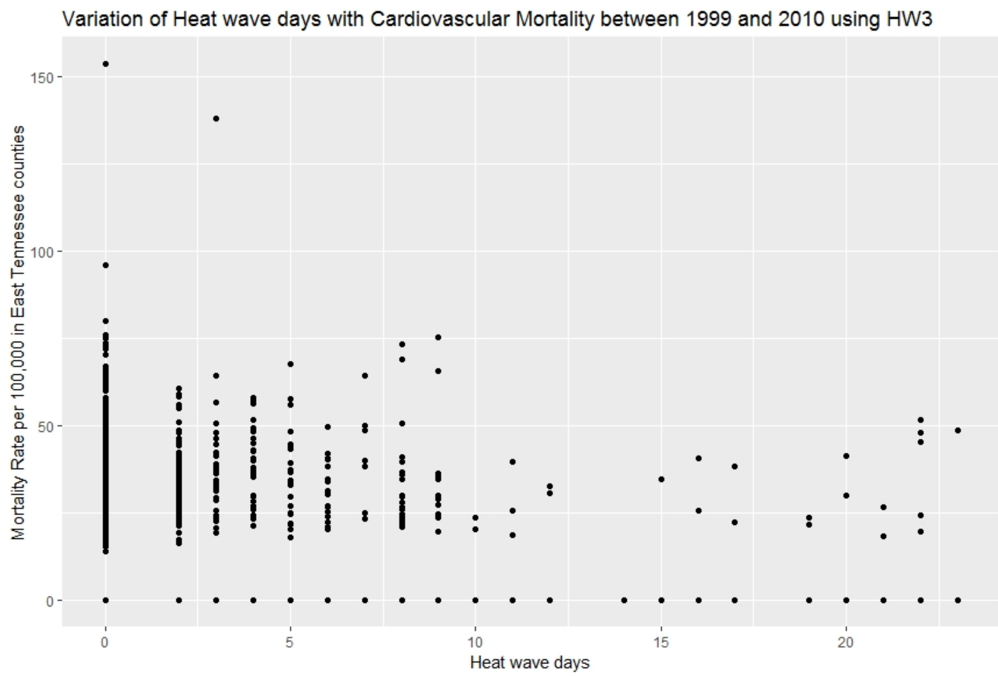


Figure 16: Variation of heat wave days with cardiovascular mortality using HW3

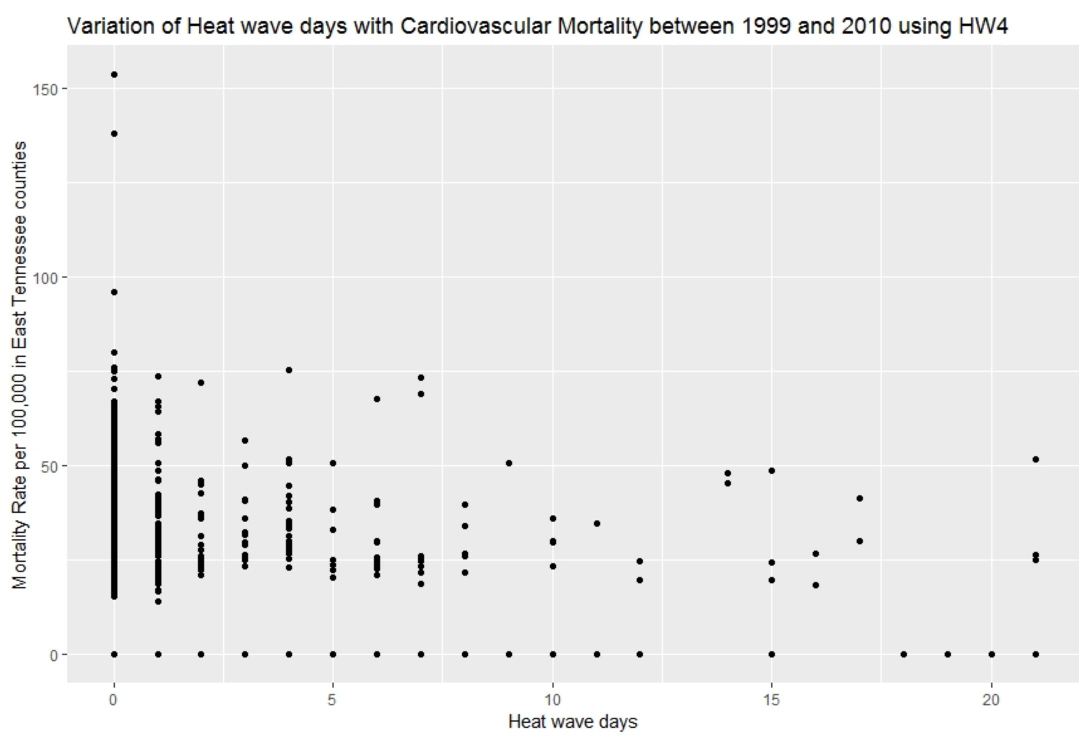


Figure 17: Variation of heat wave days with cardiovascular mortality using HW4

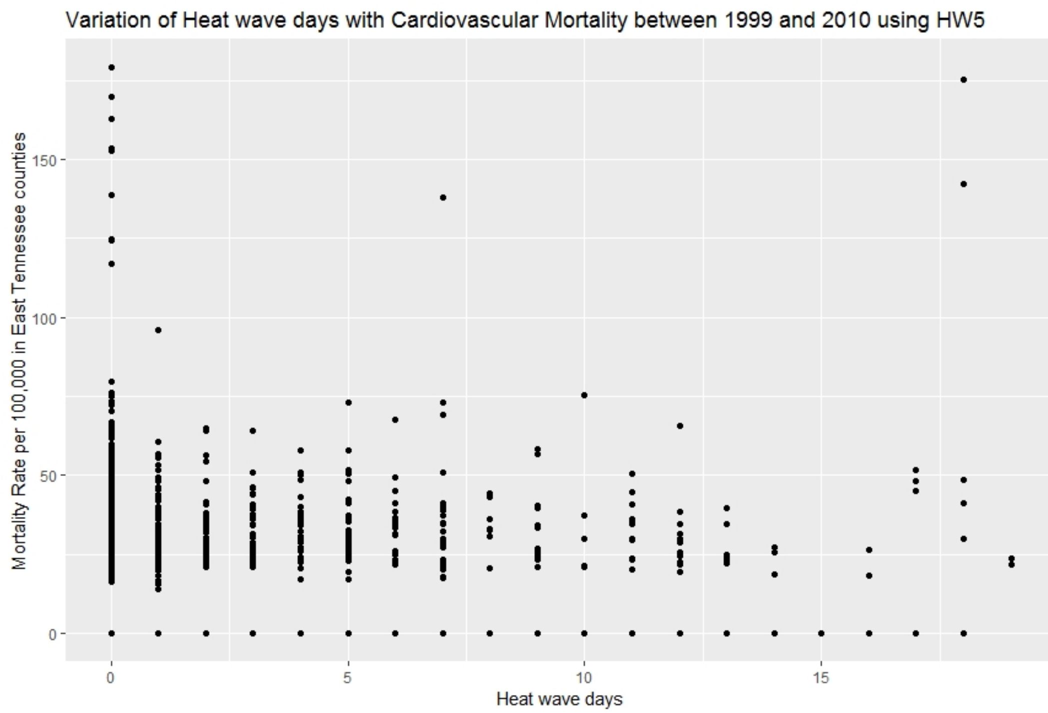


Figure 18: Variation of heat wave days with cardiovascular mortality using HW5

<u>Mortality trend by gender</u>

As part of the question "Who is more affected?" mortality rates on heat wave days were compared between gender: male and female. This is particularly necessary to understand if there is a gender difference in mortality rates during the months with heat wave days.

There were gender differences in non-accidental mortality rates on heat wave days from 1999 to 2010 with respect to each definition. No gender was consistently higher than the other for the entire 12-year period (Figure 19). In all, the annual average non-accidental mortality rate is slightly higher among females (60.8 per 100,000) compared to males (57.9 per 100,000) during heat wave days (Appendix C) but higher among males (60.1 per 100,000) compared to females (57.6 per 100,000) during non-heat wave days (Appendix F).

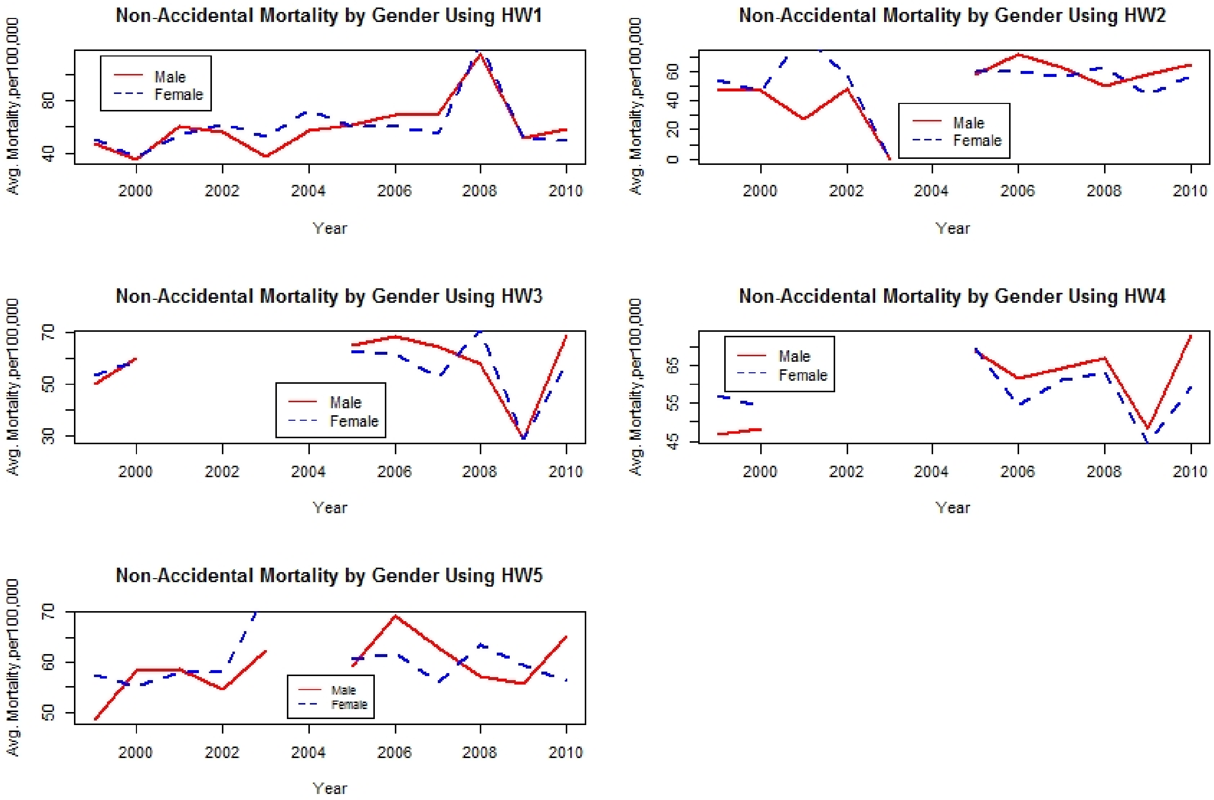


Figure 19. Non-accidental mortality rates by gender from 1999-2010

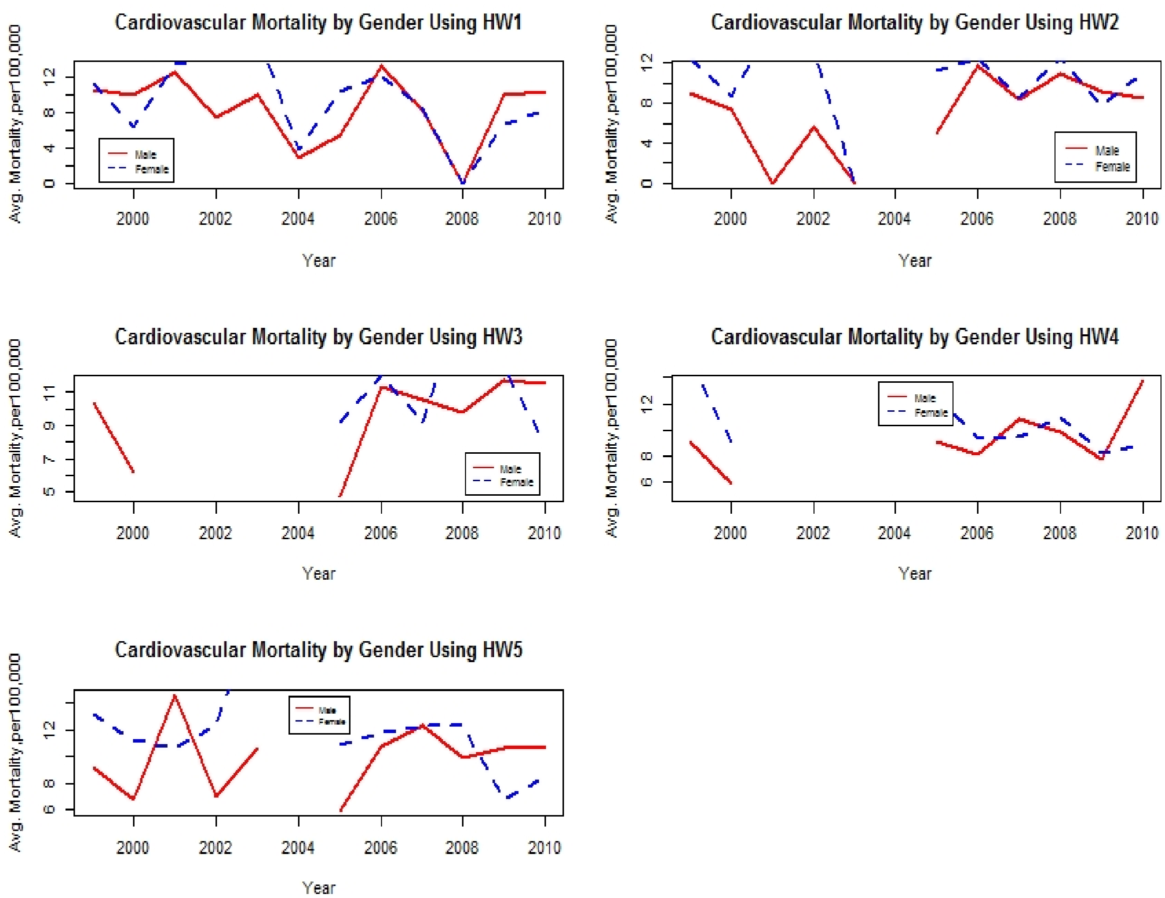


Figure 20: Cardiovascular mortality rates by gender from 1999-2010

Gender differences were more profound in cardiovascular mortality than non-accidental mortality (Figure 20). No gender was consistently higher than the other for the 12-year period. Cardiovascular mortality was higher among females in 1999 but higher among males in 2010 for almost all the definitions. The average mortality rates are slightly higher among females (10.4 per 100,000) than males (8.2 per 100,000) during heat wave days (Appendix D) and still higher among them (11.1 per 100,000 versus 9.8 per 100,000) during non-heat wave days (Appendix G).

Average county temperature for each definition from 1999-2010

One of the broad intents of this study is to identify which county was the most affected by heat waves. Mean temperatures of all counties for each heat wave definition were compared (Figure 21-25). For each definition, Hamilton County is noticeably the warmest among all the counties. Hancock County, one of the least populous rural counties in Tennessee, also had significantly higher maximum daily apparent temperature than the other counties under HW5 (Figure 25). For HW4, the average maximum daily temperature was similar for all counties, ranging from 95.5 to 97.3 ˚ Fahrenheit. Johnson and Unicoi counties markedly have the lowest value for each heat wave metric tested for all heat wave definitions except for HW4. The actual values of these data points can be found in Appendix A.

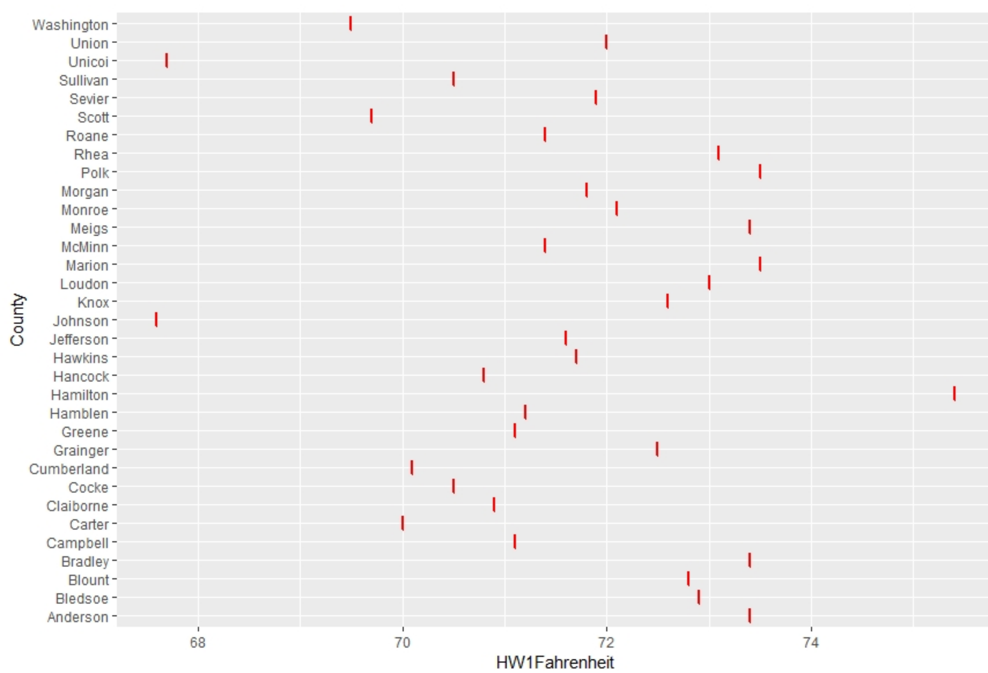


Figure 21: Average daily minimum temperature by county on heat wave days between 1999 and 2010 for HW1

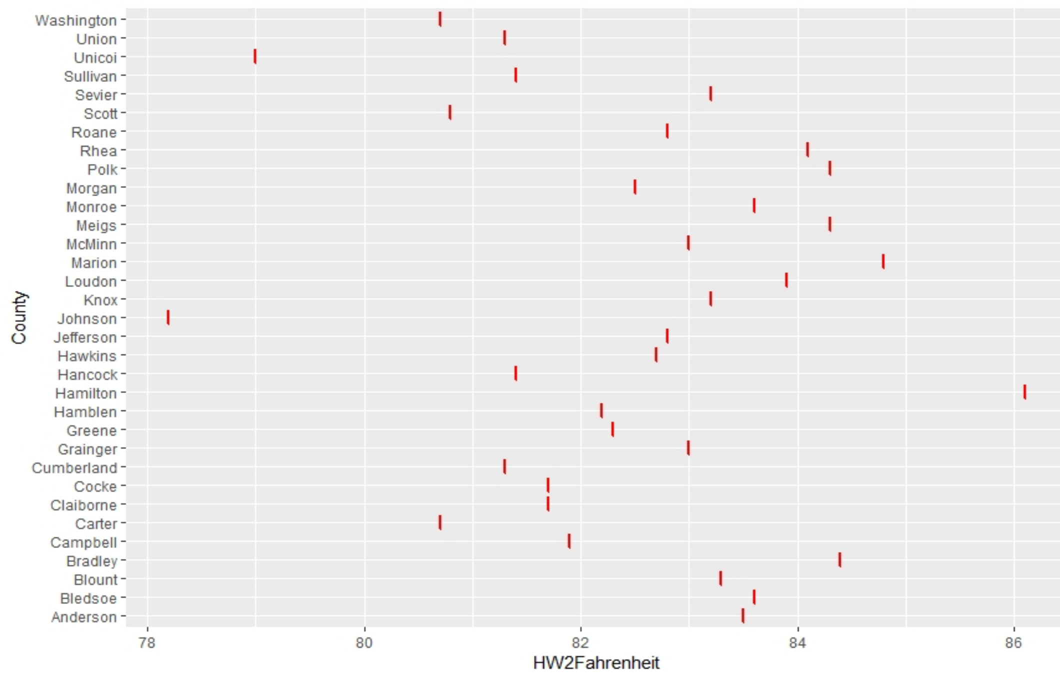


Figure 22: Average daily mean temperature by county on heat wave days between 1999 and 2010 for HW2

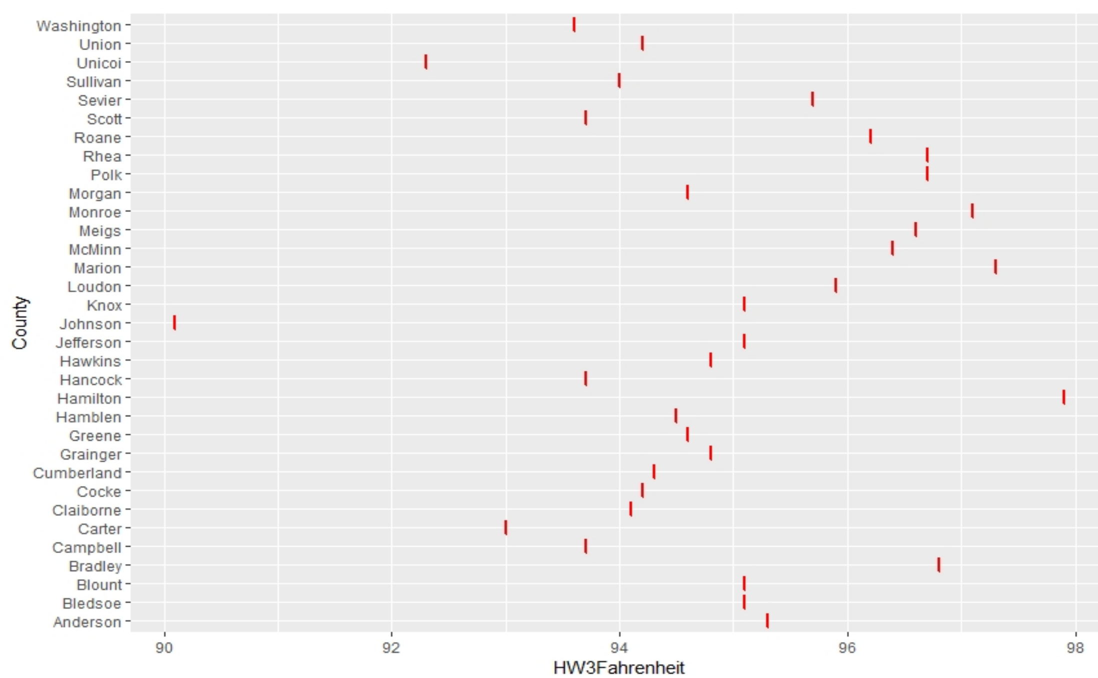


Figure 23: Average daily maximum temperature by county on heat wave days between 1999 and 2010 for HW3

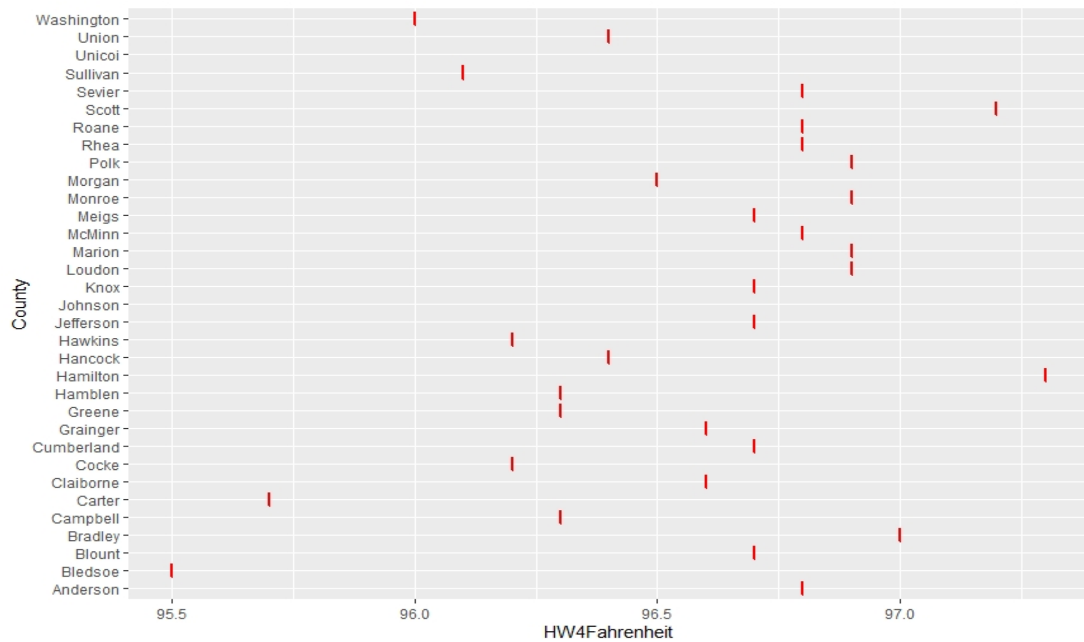


Figure 24:.Average maximum daily temperature by county on heat wave days between 1999 and 2010 for HW4 (no data shown for Johnson county since there was no heat wave days in the county under this definition).

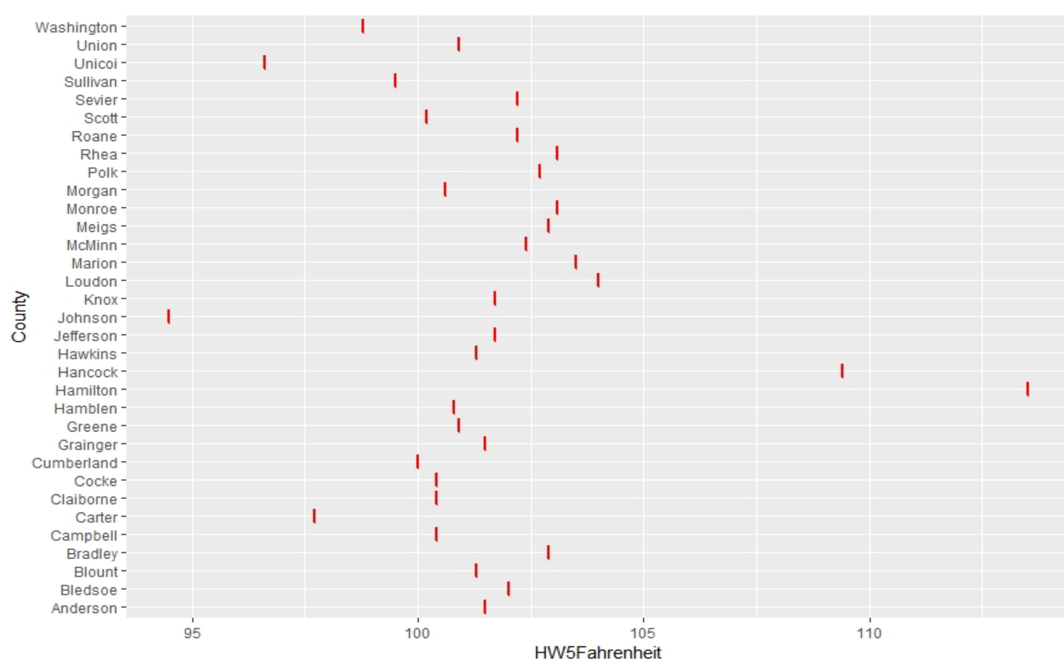


Figure 25: Average maximum daily apparent temperature by county on heat wave days between 1999 and 2010 for HW5

Regression Analysis

A Poisson GAM was used to study the relationship between mortality rate and heat wave days. For each of the five heat wave definitions and mortality outcome categories (non-accidental or cardiovascular), two models were developed. One is strictly between the two primary variables (mortality rates and the number of monthly heat wave days without adjusting for confounders); and the second model is still between the two primary variables, but accounted for confounders. These confounders are month, rurality level of a county, gender, and year. The purpose of running two models is to see if the addition of confounders will cause a significant change in the initial relationship between the two primary variables.

In interpreting the GAM results (figures 26-33), solid line in each graph represents the predicted values of the outcome variable as a function of the predictors or independent variables. The grey band that buffers the solid line shows the margin of error from the predicted values. Furthermore, the figures demonstrate the partial contributions of each covariate to the possibility of occurrence of the outcome variable, i.e., non-accidental and cardiovascular mortality (Hothorn and Everitt 2014). For this study the errors are quite small as depicted by the space between the solid line and two dotted lines in each figure.

Non-accidental mortality rate and number of monthly heat wave days unadjusted for confounders: The unadjusted models of the relationship between non-accidental mortality rates and monthly heat wave days using the five heat wave definitions are presented in Figure 26. The y-axis of each graph is the function of the respective mortality rate and x-axis is number of monthly heat wave days represented as "HWDays." Only HW1 indicates a seemingly clear trend of heat related mortality rate with increasing monthly heat wave days. The relationship between mortality and monthly heat wave days is significant with a *p* value less than 0.05 (Table

2) for all definitions tested. For HW1, months with total heat wave days numbering more than eleven days have substantially higher mortality rates compared with those with heat waves of less than five days. It is noteworthy that some inflection was observed between months that record five heat wave days and those with ten heat wave days.

With respect to the unadjusted model for HW2, the non-accidental mortality rate was approximately stable until the monthly heat wave days increased beyond 16 days. A surge in mortality rate was observed, followed by a plummeting till the monthly heat wave days increased to 23.

The unadjusted model for HW3 shows an oscillating pattern of relationship between monthly heat wave days and non-accidental mortality rates, with highest mortality rates recorded in months with 16, 7 and 23 heat wave days in that order. Months with heat wave days totaling 11 and 19 days have lower mortality rates.

Non-accidental mortality rates did not show a gently increasing trend in months with 1 to 14 heat wave days in the unadjusted model with respect to HW4, but there is a significant dip in the non-accidental mortality rate observed in months with 17 heat wave days.

For HW5, months with 18 to 19 heat wave days had the highest non-accidental mortality rates probability while months with 16 heat wave days had the lowest mortality rates probability.

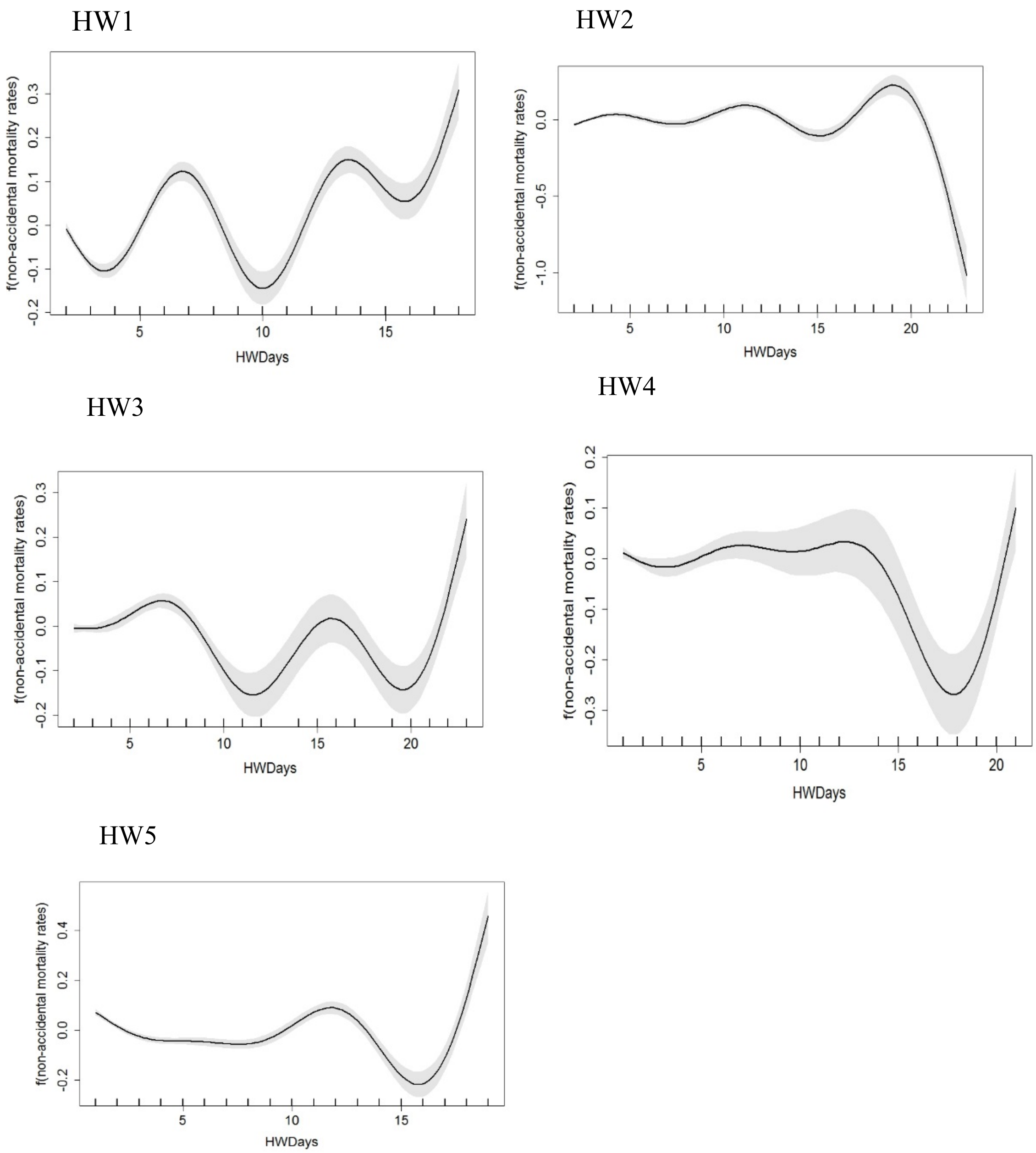


Figure 26: Non-accidental mortality rate and number of monthly heat wave days unadjusted for confounders

Cardiovascular mortality and number of heat wave days unadjusted for confounders: Cardiovascular mortality rates did not show a noticeable trend with the number of heat wave days in the unadjusted model for HW1 (Figure 27). For HW2, cardiovascular mortality rates were much more stable in months that have 2 to 15 days of heat wave days for HW2; the highest mortality rate was in months with 17 to 20 heat wave days. Cardiovascular mortality rate is highest in months with 22 heat wave days and lowest in months with 16 heat wave days for HW3 (Figure 27). With respect to HW4, the highest cardiovascular mortality rates are observed in months with 14 heat wave days and lowest rates were in months with heat wave days totaling 19 days. In HW5, cardiovascular mortality rates produce a downward trend as the number of heat wave days increase from 1 to 15 days, and afterwards the trend increases.

The unadjusted model shows that for all the heat wave definitions, heat wave days are significantly associated with mortality rates (Table 2).

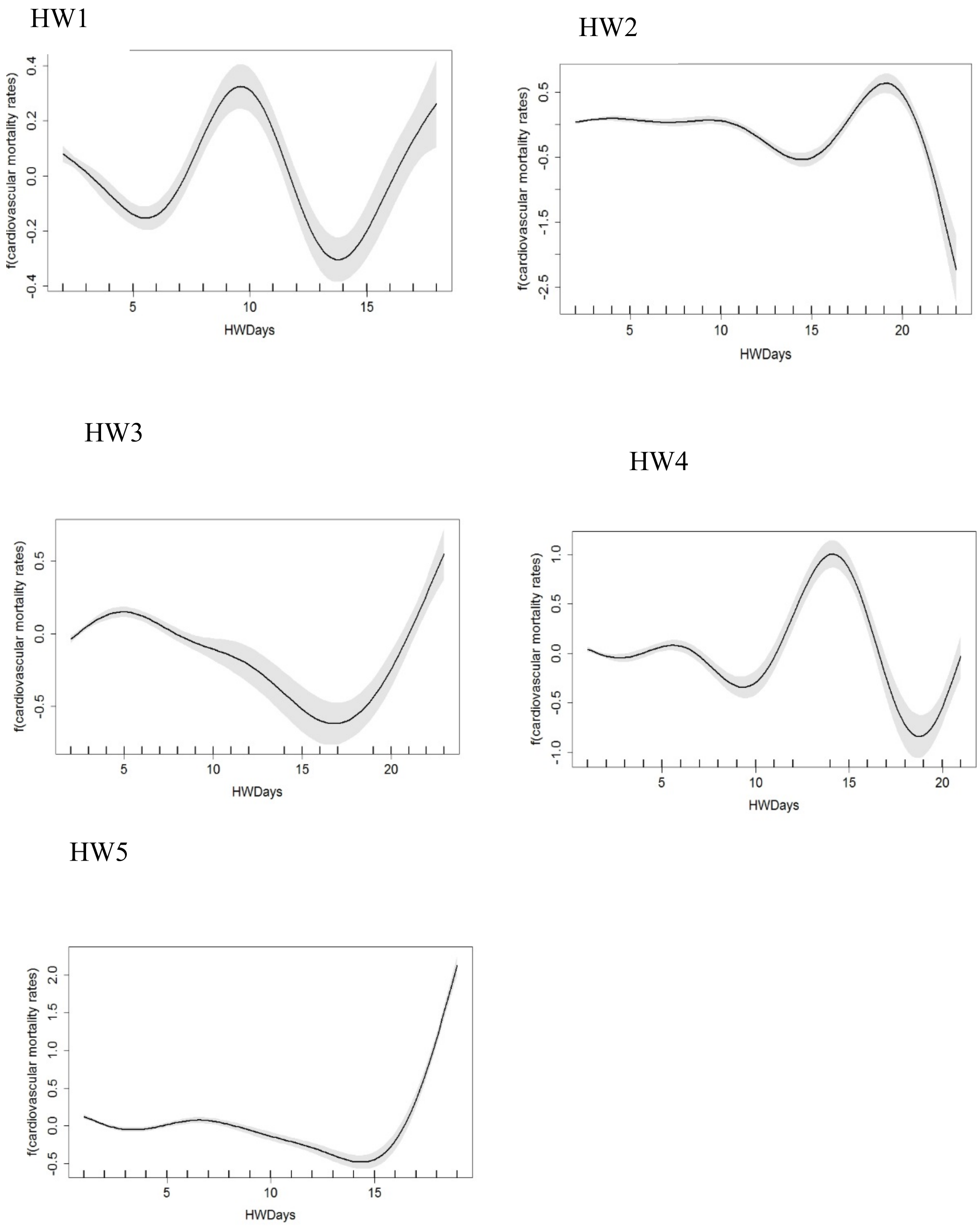


Figure 27: Cardiovascular mortality and number of heat wave days unadjusted for confounders

Non-accidental mortality and number of heat wave days adjusted for confounders: After adjusting for confounders including county, gender, year and month, the relationship between the number of heat wave days and mortality rates remains apparently the same for unadjusted HW1 as shown in Figure 28, with a significant *p*-value (<0.05) as seen in Table 3. Also, the trends of non-accidental mortality rate plotted against heat waves for HW2 and HW3 are not so much different from the unadjusted model. HW4 adjusted model shows that non-accidental mortality rates reduced gently as the number of monthly heat wave days increased from 1 to 14 days but plunged as the heat wave days increased from 14 to 18 days (Figure 28). For HW5, the adjusted model shows that non-accidental mortality rates decrease as the number of heat wave days increase from 1 to 15 days.

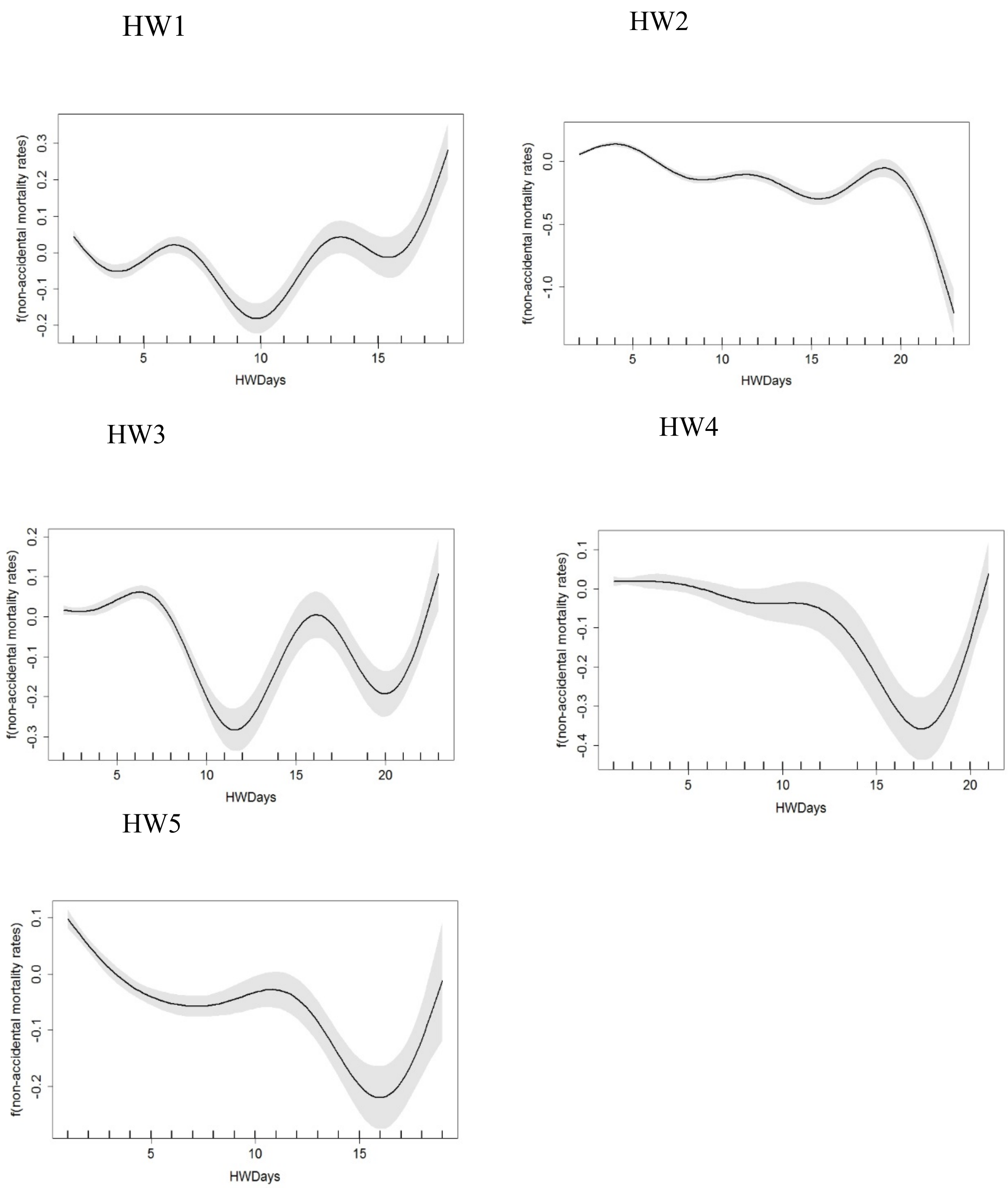


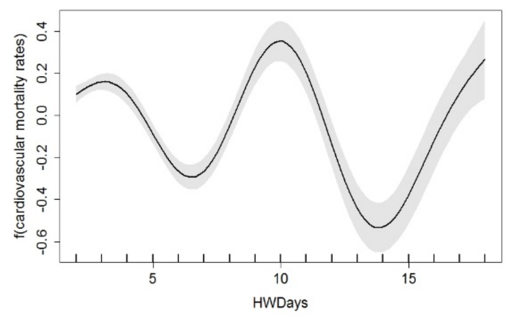
Figure 28: Non-accidental mortality and number of heat wave days adjusted for confounders

Cardiovascular mortality and number of heat wave days adjusted for confounders

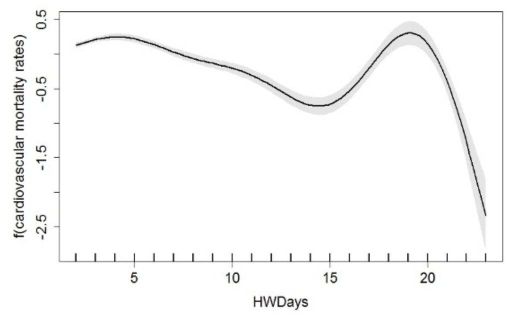
After adjusting for confounders, the number of monthly heat wave days remains significantly associated with cardiovascular mortality rates for all heat wave definitions with

p<0.05 (Table 3). After adjusting for confounders, the relationship between heat wave days and cardiovascular mortality remains nearly unchanged (Figure 29) for HW2. The adjusted model shows that the relationship between cardiovascular mortality rate and the number of heat wave days is similar to the unadjusted for HW3, HW4 and HW5

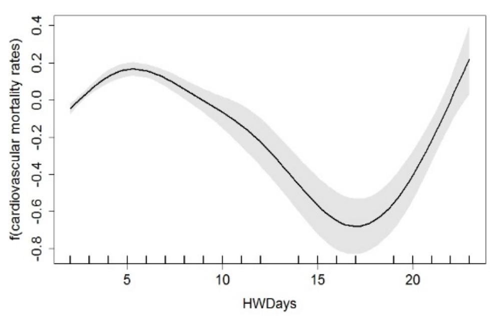
HW1



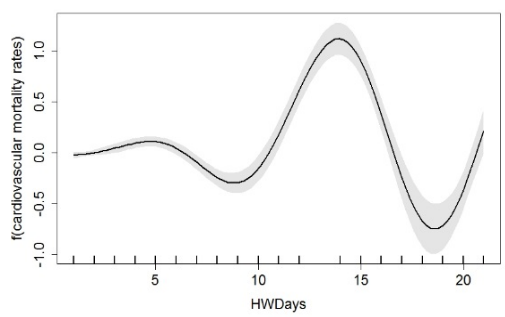
HW2



HW3



HW4



HW5

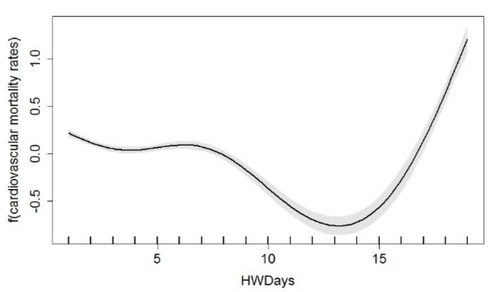


Figure 29: Cardiovascular mortality and number of heat wave days adjusted for confounders

Non-accidental mortality rate and Year adjusted for confounders: Non-accidental mortality rates increase markedly from 1999 to 2007, and thereafter take a nosedive for HW1 (Figure 30). For HW2, non-accidental mortality rate was somewhat flat from 1999 to 2003 but increased sharply from 2004 and peaked in 2007 followed by a gentle tapering. The graph for HW3 indicates that the non-accidental mortality rate increased from 1999 to 2010 in a wave-like manner while the number of non-accidental mortality rate increased somewhat steadily from 2002 to 2010 in HW4. For HW5, years 2006 and 2008 show highest and lowest non-accidental mortality rates respectively (Figure 30).

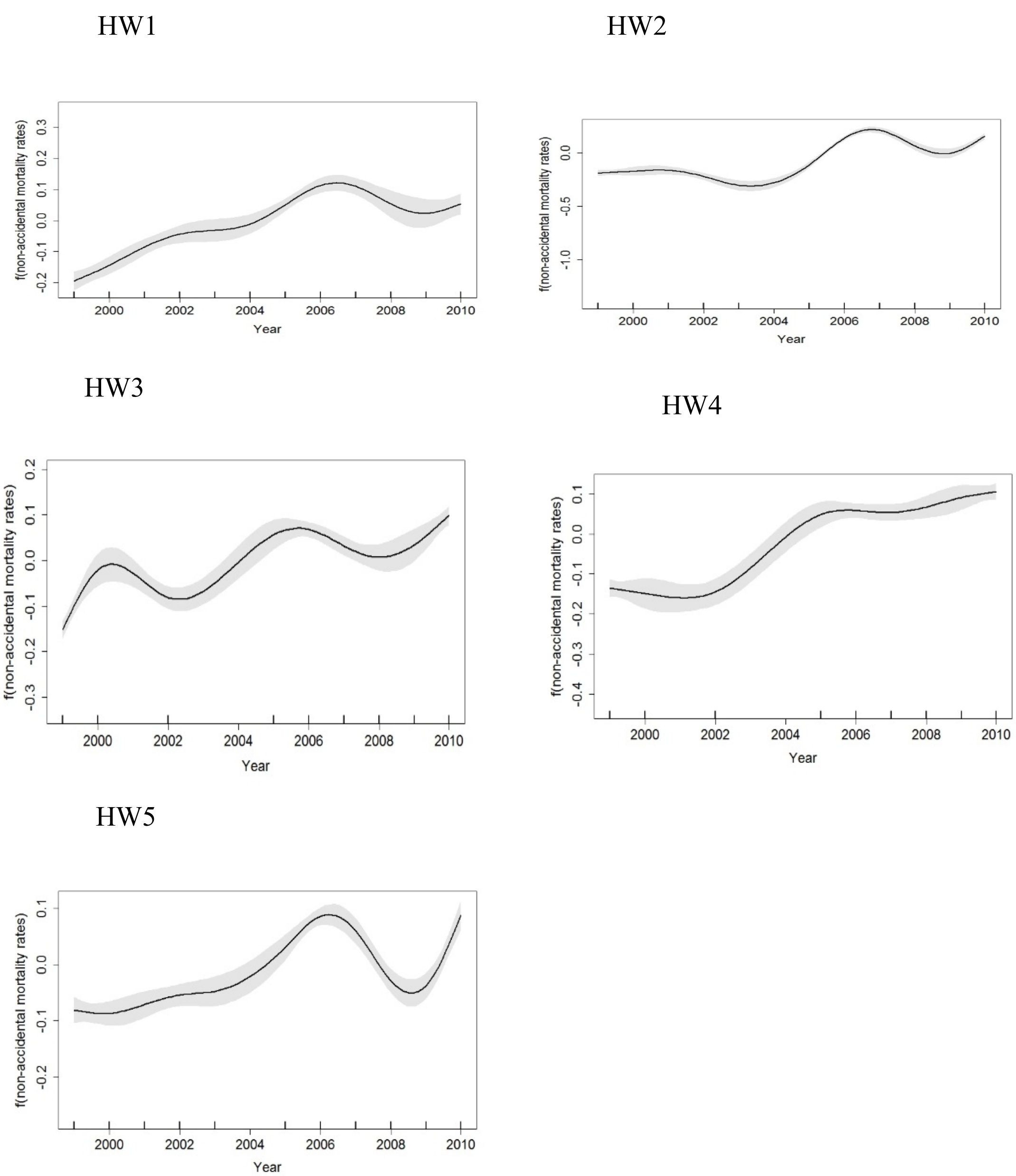


Figure 30: Non-accidental mortality rate and Year adjusted for confounders

Cardiovascular mortality rate and Year adjusted for confounders

The GAM result between cardiovascular mortality rates and year has considerable inflections but 2006 to 2007 has the highest mortality rate for HW1 (Figure 31); a noticeably higher mortality was observed in 2007 with HW2. For HW3, the highest cardiovascular mortality rate was observed in 2007 and the lowest is 2004. Three major peaks- in 1999, 2005 and 2009 are observed with HW4. For HW5, the wavy trend of mortality rates with year has peaks in 1999, 2002, 2007 and 2010.

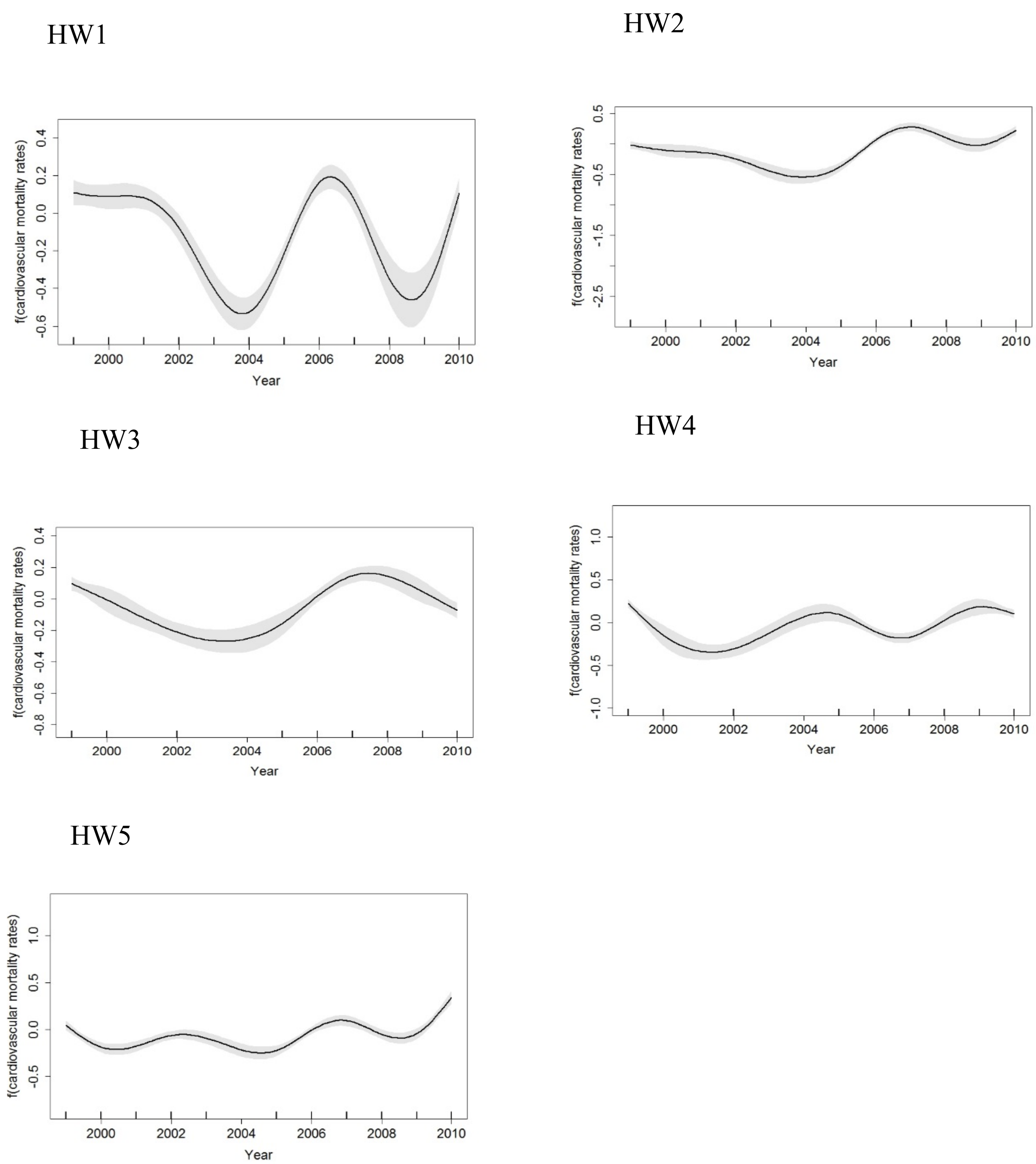
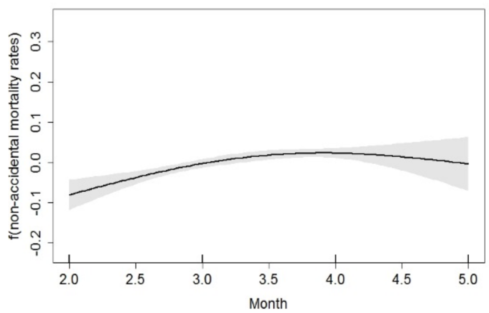


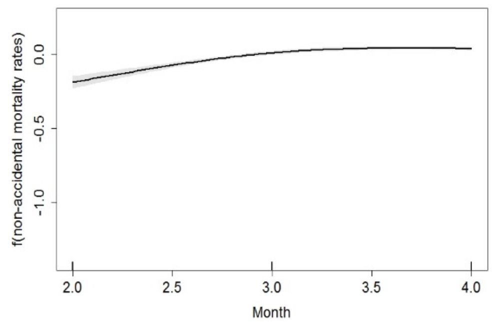
Figure 31: Cardiovascular mortality rate and Year adjusted for confounders

Non-accidental mortality and Month adjusted for confounders: For HW1, the monthly variation of non-accidental mortality rates shows an increase from June to August with the least error observed in July (Figure 32). It can also be seen that the margin of error is slimmest from July to August for this definition. The monthly non-accidental mortality showed an increasing trend from June to August for HW2 with no heat wave day observed in May and September. For HW3, monthly mortality variation has an arc-shape with August having the highest non-accidental mortality rate. August has the highest mortality rate for HW4 and HW5.

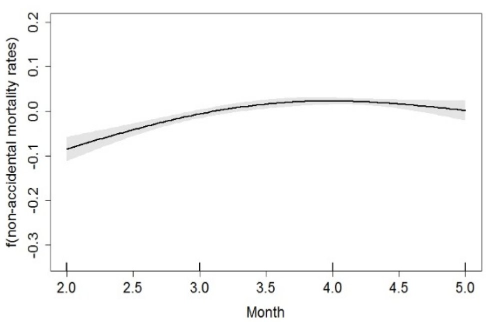
HW1



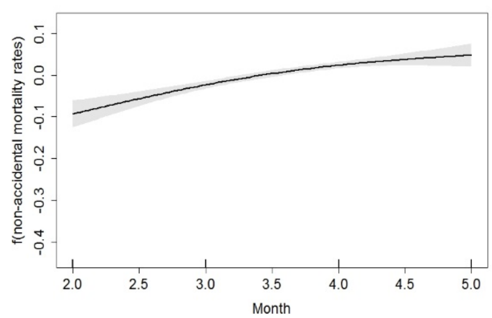
HW2



HW3



HW4



HW5

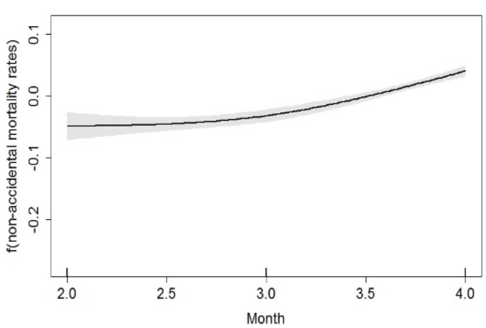


Figure 32: Non-accidental mortality and Month adjusted for confounders

Cardiovascular mortality rates and Month adjusted for confounders: Monthly cardiovascular mortality rates show the highest possibility of occurrence between July and August for all the heat wave definitions tested HW1 (Figure 33).

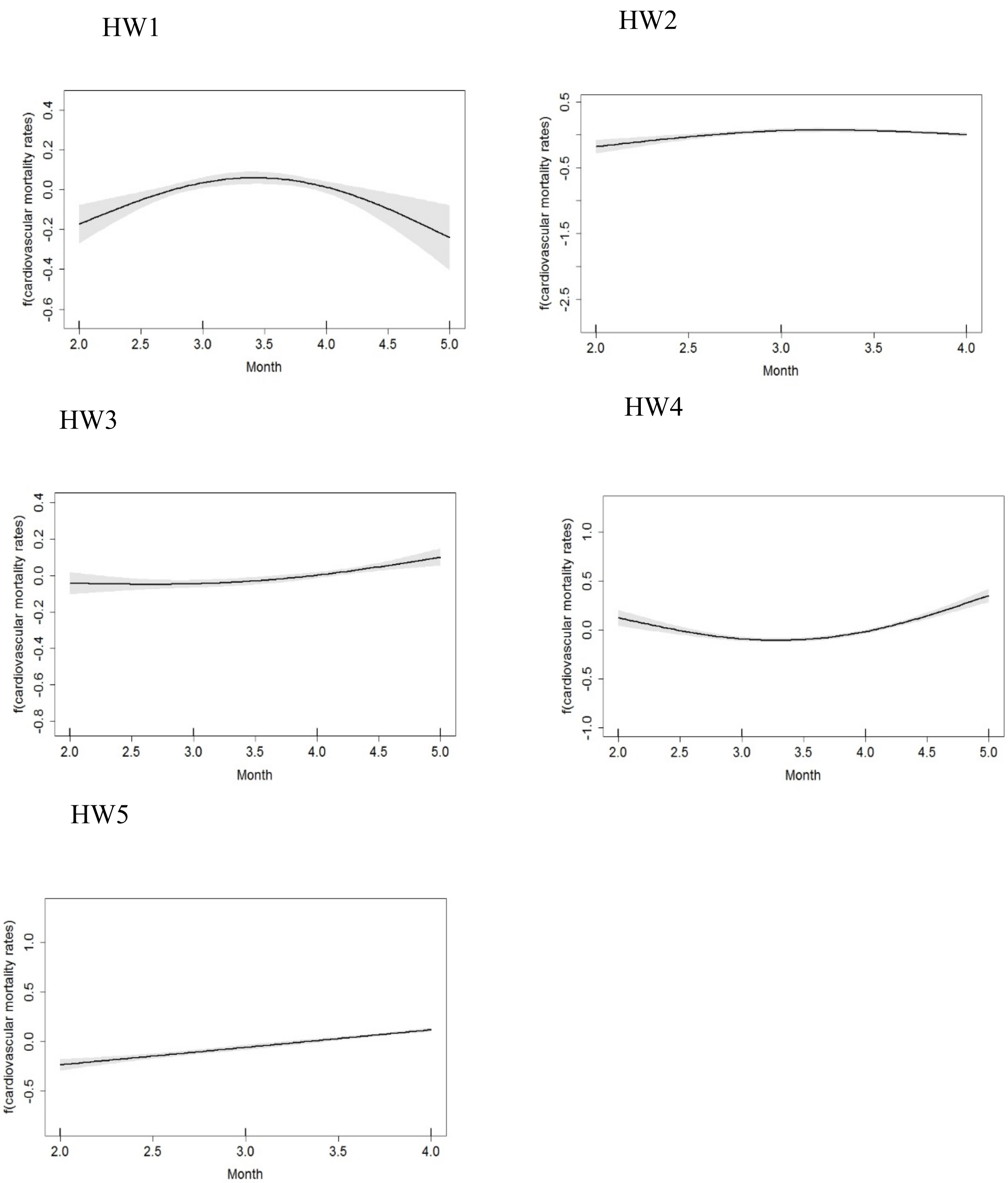


Figure 33: Cardiovascular mortality rates and month adjusted for confounders

Table 2: GAM results for unadjusted Models

HW Definition	Mortality	Chi. Sq	p-value	R.sq. (adj)	Deviance explained
HW1	Non-accidental	348	<2e-16	0.00705	0.954%
	Cardiovascular	135.7	<2e-16	-0.00172	0.665%
HW2	Non-accidental	163.4	<2e-16	-0.00148	0.495%
	Cardiovascular	162.5	<2e-16	6.67e-05	0.907%
HW3	Non-accidental	99.19	<2e-16	-0.00315	0.261%
	Cardiovascular	158.2	<2e-16	0.000242	0.721%
HW4	Non-accidental	53.05	2.28e-09	-0.00644	0.223%
	Cardiovascular	238.3	<2e-16	0.00384	1.36%
HW5	Non-accidental	274.1	<2e-16	0.00278	0.54%
	Cardiovascular	1274	<2e-16	0.0144	2.77%

Table 3: GAM results for adjusted models

Non-Accidental mortality using HW1								
	Estimate	Std. Error	Z-value	Pr(> |z|)	Chi. Sq	P-value	R-sq. Adj	Deviance Explained
County	0.493327	0.009588	51.450	< 2e-16	-	-		
Gender	0.067103	0.009265	7.243	4.4e-13	-	-		
s(HWDays)	-	-	-	-	172.04	< 2e-16		
s(Year)	-	-	-	-	300.07	< 2e-16	0.123	9.83%
s(Month)	-	-	-	-	20.14	3.12e-05		
Cardiovascular mortality using HW1								
County	1.34363	0.02662	50.47	< 2e-16	-	-		
Gender	-0.08184	0.02236	-3.66	0.000252	-	-		
s(HWDays)	-	-	-	-	255.38	< 2e-16		
s(Year)	-	-	-	-	176.21	< 2e-16	0.134	16.6%
s(Month)	-	-	-	-	16.01	0.000535		
Non-Accidental mortality using HW2								
County	0.505540	0.009361	54.008	< 2e-16	-	-		
Gender	0.026069	0.009210	2.831	0.00465				
s(HWDays)	-	-	-	-	334.03	<2e-16		
s(Year)	-	-	-	-	515.09	<2e-16		
							0.126	10.2%
	Estimate	Std. Error	Z-value	Pr(> |z|)	Chi. Sq	P-value	R-sq. Adj	Deviance Explained

s(Month)	-	-	-	-	80.14	<2e-16		
Cardiovascular mortality using HW2								
County	1.26040	0.02530	49.824	<2e-16	-	-		
Gender	-0.19584	0.02242	-8.736	<2e-16	-	-		
s(HWDays)	-	-	-	-	202.5	< 2e-16		
s(Year)	-	-	-	-	142.5	< 2e-16		
s(Month)	-	-	-	-	23.3	1.48e-05	0.113	15.6%
Non-Accidental mortality using HW3								
County	0.489871	0.008706	56.266	< 2e-16	-	-		
Gender	0.045845	0.008595	5.334	9.6e-08	-	-		
s(HWDays)	-	-	-	-	182.29	< 2e-16		
s(Year)	-	-	-	-	348.84	< 2e-16		
s(Month)	-	-	-	-	37.21	5.01e-09	0.121	9.5%
Cardiovascular mortality using HW3								
County	1.28426	0.02375	54.064	< 2e-16	-	-		
Gender	-0.15867	0.02071	-7.662	1.83e-14	-	-		
s(HWDays)	-	-	-	-	157.13	< 2e-16		
s(Year)	-	-	-	-	104.40	< 2e-16		
s(Month)	-	-	-	-	15.55	0.000222	0.124	16%
Non-Accidental mortality using HW 4								
County	0.463020	0.010484	44.164	<2e-16	-	-		
Gender	0.019849	0.010373	1.914	0.0557	-	-		
s(HWdays)	-	-	-	-	86.74	< 2e-16		
s(Year)	-	-	-	-	325.50	< 2e-16	0.122	9.63%
s(Month)	-	-	-	-	44.96	1.53e-09		
Cardiovascular mortality using HW4								
County	1.33323	0.02860	46.614	< 2e-16	-	-		
Gender	-0.11672	0.02498	-4.673	2.97e-06	-	-		
s(HWDays)	-	-	-	-	225.0	<2e-16		
s(Year)	-	-	-	-	163.2	<2e-16		
s(Month)	-	-	-	-	114.2	<2e-16	0.144	18.6%
Non-Accidental mortality using HW5								
County	0.467810	0.007686	60.867	<2e-16	-	-		
Gender	0.008841	0.007539	1.173	0.241	-	-		
s(HWDays)	-	-	-	-	208.11	<2e-16		
s(Year)	-	-	-	-	224.37	<2e-16	0.116	8.66%
	Estimate	Std. Error	Z-value	Pr(> |z|)	Chi. Sq	P-value	R-sq. Adj	Deviance Explained
s(Month)	-	-	-	-	82.14	<2e-16		
Cardiovascular mortality using HW5								
County	1.28894	0.02118	60.86	<2e-16	-	-		
Gender	-0.19884	0.01810	-10.98	<2e-16	-	-		
s(HWDays)	-	-	-	-	585.0	<2e-16		
s(Year)	-	-	-	-	139.7	<2e-16		
s(Month)	-	-	-	-	126.7	<2e-16	0.134	17.6%

The unadjusted models in the GAM produced low values of "Deviance Explained," an equivalent of r-square which explains the proportion of the variability of the outcome explained by the model (Vittinghoff et al. 2012). Expectedly, the deviance explained was higher for adjusted models (i.e., when confounders were included in the model) compared to the unadjusted model for all definitions.

For non-accidental mortality using the HW1 scenario, the GAM for unadjusted model shows a significant relationship between non-accidental mortality rate and the number of heat wave days. The deviance explained for the model increased from 0.954% for the unadjusted (Table 2) to 9.83% for adjusted model as seen in Tables 3. For HW2, the non-accidental and cardiovascular mortality rates are both significantly related to the number of heat wave days for the respective unadjusted models. The adjusted models for both mortality types show a significant relationship with confounders (heat wave days, year, and county). The deviance explained value increased from 0.495% for the unadjusted (Table 2) to 10.2% for the adjusted non-accidental mortality and from 0.907% (unadjusted) to 15.6% (adjusted) for cardiovascular mortality. For HW3, the deviance explained increased from 0.261% (unadjusted model) to 9.5% (adjusted model) for non-accidental mortality and from 0.721% (unadjusted) to 16% (adjusted) for cardiovascular mortality, while for HW4, the deviance explained the unadjusted model for non-accidental mortality rates and cardiovascular mortality was 0.223% and 1.36%, respectively, which increased to 9.63% and 18.6% for the adjusted models. HW5 had deviance explained of 0.54% and 2.77% for the unadjusted non-accidental and cardiovascular mortality models, respectively, and 8.66% and 17.6% for the adjusted models (Table 3).

Relative Risk

Relative risk for mortality was examined with reference to gender and rurality.

Gender relative risk: The relative risk for non-accidental and cardiovascular mortality among females and males was calculated using each of the heat wave scenarios and the corresponding non-heat wave days. For each heat wave scenario, the period under study was grouped into heat wave days and non-heat wave days, and the corresponding relative risk was calculated for each group. As summarized in Table 4 below, the relative risk of non-accidental mortality on heat wave days is slightly higher among females and males for HW2, HW4, and HW5 and lesser among females in HW 1 and HW3, although none of these is statistically significant. Furthermore, non-accidental mortality is lower among females in all heat wave definitions tested, but not statistically significant in any of them.

Table 4: Relative risk between females and male for different heat wave definitions

	Non-Accidental mortality			Cardiovascular mortality		
On Heat waves days						
HW Definition	**RR**	***P***	**95%CI**	**RR**	***P***	**95%CI**
HW1	0.98	0.718	0.90-1.08	1.33	0.008	1.08-1.65
HW2	1.01	0.88	0.92-1.10	1.22	0.079	0.98-1.51
HW3	0.99	0.825	0.91-1.07	1.16	0.147	0.95-1.42
HW4	1.02	0.652	0.93-1.12	1.11	0.385	0.88-1.41
HW5	1.01	0.846	0.94-1.08	1.21	0.031	1.02-1.45
Non heat wave days						
HW1	0.99	0.599	0.95-1.03	1.23	0.008	1.05-1.43
HW2	0.98	0.426	0.94-1.03	1.14	0.013	1.03-1.27
HW3	0.99	0.547	0.94-1.03	1.16	0.008	1.04-1.29
HW4	0.98	0.379	0.94-1.02	1.17	0.004	1.05-1.30
HW5	0.98	0.378	0.93-1.03	1.13	0.031	1.01-1.27

On heat wave days, cardiovascular mortality was higher among females for all definitions but statistically significant only for HW1 (1.33, 1.08-1.65) and HW5 (1.21, 1.02-1.45). On non-heat wave days, cardiovascular mortality was higher among females than males significantly for all definitions.

Rural-Urban Risk: Relative risks for both non-accidental and cardiovascular mortality rates in rural counties was compared with urban counties. Tennessee rural and urban counties have been previously determined by Roehrich-Patrick and Moreo (2016). Counties classified as rural include Bledsoe, Campbell, Claiborne, Cocke, Cumberland, Grainger, Greene, Hancock, Johnson, Marion, McMinn, Meigs, Monroe, Morgan, Polk, Rhea, Scott, and Union; urban counties include Anderson, Blount, Bradley, Carter, Hamblen, Hamilton, Hawkins, Jefferson, Knox, Loudon, Roane, Sevier, Sullivan, Unicoi, and Washington. It should be noted that Hamilton and Knox Counties are actually categorized as metropolitan counties by Roehrich-Patrick and Moreo (2016), but were categorized as urban for the purpose of this study. For all heat wave definitions, both non-accidental and cardiovascular mortality rates were higher among urban counties than rural counties. This is consistent with the well-studied phenomenon "Urban Heat Island", which states that the health effect of heat risk is exacerbated in urban areas (Heaviside et al. 2017). Non-accidental mortality relative risk was higher on heat wave days than non-heat wave days only for HW1, HW2, and HW3. Also cardiovascular mortality rates were higher on heat wave days than non-heat wave days only for HW4.

Table 5: Relative risk between Urban and Rural populations for different heat wave definitions

	Non-Accidental mortality			Cardiovascular mortality		
On heat wave days						
HW Definition	**RR**	***P***	**95%CI**	**RR**	***P***	**95%CI**
HW1	1.93	<0.001	1.75-2.13	5.67	<0.001	4.16-7.74
HW2	1.96	<0.001	1.79-2.16	5.34	<0.001	3.99-7.14
HW3	1.89	<0.001	1.73-2.06	5.44	<0.001	4.12-7.18
HW4	1.86	<0.001	1.69-2.05	6.08	<0.001	4.35-8.51
HW5	1.86	<0.001	1.72-2.00	5.56	<0.001	4.34-7.12
Without heat wave days						
HW1	1.86	<0.001	1.77-1.94	5.89	<0.001	5.05-6.87
HW2	1.85	<0.001	1.76-1.93	5.99	<0.001	5.12-7.00
HW3	1.86	<0.001	1.78-1.96	5.98	<0.001	5.10-7.01
HW4	1.87	<0.001	1.79-1.96	5.80	<0.001	4.99-6.75
HW5	1.87	<0.001	1.78-1.97	5.97	<0.001	5.06-7.05

CHAPTER 4

DISCUSSION AND RECOMMENDATION

Tennessee State Climate Summaries indicate that the state generally is not currently experiencing severe climate change impact as it relates to temperature rise (Runkle et al. 2017). Heat wave occurrence did not show any particular trend from year to year. However, the analysis shows that the number of heat wave days recorded in 2010 is higher than 1999 for all definitions of heat waves tested by this study. Between these temporal ends is a series of inflections, with some years having a higher number of heat wave days above what is recorded in 1999 and 2010.

The relationship between mortality rate and heat wave days indicates non-linearity which is typical of time series data. This necessitates the use of a statistical model that allows such relationships. This study used a Generalized Additive Model (GAM) which has been used in previous related studies (Chen et al. 2017; D'Ipolliti et al. 2010) because it is useful for studying variables with non-linear relationships.

Number of heat wave days: The GAM results showed that the non-accidental mortality rates steadily increased in months that have a cumulative of at least 16 days of heat wave days compared to those with less than five heat wave days based on the HW1 scenario. This suggests that mortality increases with the number of heat wave days. Conversely, there was a dip in non-accidental mortality rates in months with a cumulative of ten heat wave days. The wavering patterns of non-accidental mortality rates with the number of monthly heat wave days for all other definitions do not give a clear explanation of a relationship between the two variables both before and after adjusting for confounders. The increase or decrease in non-accidental mortality and cardiovascular mortality rates cannot be directly linked to the cumulative number of heat wave days because the unit of measurement is month which obscures information on how consecutive the heat wave days are in each month. As reported in a previous study, the lag effects of heat waves cannot be determined by this study because the scale of mortality rate measurement is month (Xuan et al. 2014). For all the heat wave definitions tested, adjustment for confounders did not change the statistical significance of the relationship between non-accidental mortality and the number of heat wave days.

Year: All non-accidental mortality rate curves show a somewhat increasing trend with year, in spite of their wavy patterns. HW1 and HW5 had decreased non-accidental mortality rates in 2008 to 2009 but later increased in 2010. The outcome is not the same for cardiovascular mortality rates which are noticeably inconsistent with year across all definitions. For the HW1 scenario, non-accidental mortality rates on heat wave days increased between 1999 and 2006 while cardiovascular mortality rates tended to decrease from 1999 to 2004. HW2 produced a slightly elevated non-accidental mortality rates in the second half of the study period -years 2005-2010 compared to the first half (1999 to 2004). Although the cardiovascular mortality rate for HW2 has gentle inflections, it is almost uniform between 1999 and 2010, but with a major elevation in 2007. The second half of the twelve year period of HW3 has a higher non-accidental mortality rate than the first half. Non-accidental mortality rate increased noticeably from 2000 to 2010 using HW4. The cardiovascular mortality rate has a similar, but less noticeable trend with the HW4 scenario. For HW5, a consistent increase in the non-accidental mortality rate is only observable from 2001 to 2006, but the cardiovascular mortality rate is almost even with a wavering pattern. Over all, the second half of the period under study has elevated mortality compared to the first half for all heat wave scenarios except for HW1. The highest non-accidental mortality rates were observed in 2010 for HW2 and HW5. This corresponds to the results obtained in Figure 2 which indicate that 2010 had the highest number of heat wave days for these two definitions. The highest cardiovascular mortality rates for HW3 were observed in 2007, the year with the second highest number of heat wave days (Figure 2).

Month: The likelihood for non-accidental mortality increased from June to September but the least error or highest accuracy was observed in the space of time between July and August for the HW1 scenario. The likelihood for an increased cardiovascular mortality rate is highest also between July and August in HW1 and for non-accidental mortality rate in HW2 and HW3. The highest likelihood for non-accidental and cardiovascular mortality rates are observed in August for HW5. August shows the highest likelihood for non-accidental mortality for HW4. September demonstrates the highest likelihood for cardiovascular and non-accidental mortality in HW4. Likelihood for cardiovascular mortality rates was lowest in the transition period between July and August for the HW3 and HW4 scenarios. The descriptive statistics confirm that August is the hottest month among the five. It therefore follows that the month of August as well as the later part of July may have increased ambient temperature and likelihood of heat-related mortality as seen in most of the definitions tested.

Gender: From the GAM model (Table 3), the statistical significance of gender with mortality rates during heat waves was determined. At a 95% confidence level, gender is significantly associated with non-accidental mortality and cardiovascular mortality rates for all heat wave scenarios except HW4 non-accidental mortality and HW5 non-accidental mortality rates. In absence of heat waves, women have less risk than men of non-accidental mortality but the relative risk values were not significant at 95% confidence level. Cardiovascular mortality rates were significantly higher ($p< 0.05$) in females than males in the absence of heat waves. HW1 produced the highest and most significant risk of cardiovascular mortality among females than males with and without heat waves. Heat wave increased the probability for both non-accidental and cardiovascular mortality among females for most of the definitions.

Rurality: Relative risk calculation shows that with or without heat waves, both non-accidental and cardiovascular mortality were higher in urban counties than rural counties. Heat waves elevated the relative risk for non-accidental mortality among urban counties for HW1, HW2 and HW3 but not in HW4 and HW5, with HW2 producing the greatest elevated non-accidental mortality relative risk for urban counties. HW4 produced the highest cardiovascular mortality risk difference between heat wave days and non-heat wave days as risk was elevated during heat wave days. It has been shown that the southwestern and midwestern parts of the United States are likely to be the most affected areas during climate change due to the poorer and more rural populations (Runkle et al. 2017). Also, as the southeastern part of the US invests in urbanization, it may experience some new climate vulnerabilities such as urban heat islands (Carter et al. 2018).

The significant relationship between non-accidental mortality rates and the confounders mean that mortality rates differ between male and females, rural and urban counties, number of heat wave days, from year to year and from month to month. The cardiovascular mortality rate for HW1 was also significantly associated with all the confounders. The deviance explained rose from 0.665% for the unadjusted model to 16.6% for the adjusted model, indicating that the confounders are important in explaining the relationship between mortality and heat wave days.

Recommendation

This study lays a foundation for further research into heat-related mortality in East Tennessee. It is advisable for residents of East Tennessee to be mindful of outdoor activities in

August as high temperatures are typically experienced in this month and also both non-accidental and cardiovascular mortality are highest in this month and the period of transitioning from July to August. While this study cannot identify the county most affected by heat waves, urban counties appear to have a higher risk of non-accidental and cardiovascular mortality during heat waves scenarios and non-heat wave periods, but other research indicates a more nuanced interpretation of geography-based risk (Runkle et al. 2017). Elevated non-accidental and cardiovascular risks were also observed during heat wave events.

Gender-sensitive approaches should also be considered in raising awareness and formulating policies that will protect community members from exposure to heat waves in East Tennessee since non-accidental mortality risk increased among females during heat waves. Further research is required to understand those factors that underlie the elevated cardiovascular mortality risk in urban counties (HW4) found by this study.

Limitations

1. The unit of data collected is month and hence it is be difficult to account for how lag in heat waves specifically impacted mortality. For each month, cumulative heat wave days are obtained and used for the analysis which may obscure the consecutiveness of the heat wave days.
2. Although useful for this study in comparing large groups of people, ecological designs are generally weak in that they provide less information about individuals.
3. The use of urban and rural may not accurately capture the affected populations since for example, urban counties may still have some rural areas within them. More specific-location data such as addresses or zip codes would have made the findings more precise.

4. This study did not take age strata into account. Therefore, the most affected age stratum in each gender group cannot be identified from the study.

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APPENDICES

Appendix A

Summary of average temperature on heatwave days by definition in each county from 1999-2010

S/N	County	Lat	Long	HW1	HW2	HW3	HW4	HW5
1	Anderson	36.08	-84.13	73.40	83.50	95.30	96.80	101.50
2	Bledsoe	35.46	-85.29	72.90	83.60	95.10	95.50	102.00
3	Blount	35.54	-84.08	72.80	83.30	95.10	96.70	101.30
4	Bradley	35.00	-84.88	73.40	84.40	96.80	97.00	102.90
5	Campbell	36.38	-83.96	71.10	81.90	93.70	96.30	100.40
6	Carter	36.33	-82.29	70.00	80.70	93.00	95.70	97.70
7	Claiborne	36.38	-83.58	70.90	81.70	94.10	96.60	100.40
8	Cocke	36.00	-83.25	70.50	81.70	94.20	96.20	100.40
9	Cumberland	35.83	-84.79	70.10	81.30	94.30	96.70	100.00
10	Grainger	36.08	-83.67	72.50	83.00	94.80	96.60	101.50
11	Greene	36.17	-83.17	71.10	82.30	94.60	96.30	100.90
12	Hamblen	36.17	-83.21	71.20	82.20	94.50	96.30	100.80
13	Hamilton	35.00	-85.21	75.40	86.10	97.90	97.30	113.50
14	Hancock	36.42	-83.38	70.80	81.40	93.70	96.40	109.40
15	Hawkins	36.29	-83.25	71.70	82.70	94.80	96.20	101.30
16	Jefferson	35.96	-83.50	71.60	82.80	95.10	96.70	101.70
17	Johnson	36.33	-82.00	67.60	78.20	90.10	0.00	94.50
18	Knox	35.96	-83.71	72.60	83.20	95.10	96.70	101.70
19	Loudon	35.67	-84.25	73.00	83.90	95.90	96.90	104.00
20	Marion	35.04	-85.63	73.50	84.80	97.30	96.90	103.50
21	McMinn	35.38	-84.42	71.40	83.00	96.40	96.80	102.40
22	Meigs	35.42	-85.00	73.40	84.30	96.60	96.70	102.90
23	Monroe	35.38	-84.29	72.10	83.60	97.10	96.90	103.10
24	Morgan	36.04	-84.38	71.80	82.50	94.60	96.50	100.60
25	Polk	35.00	-84.75	73.50	84.30	96.70	96.90	102.70
26	Rhea	35.46	-84.96	73.10	84.10	96.70	96.80	103.10
27	Roane	35.75	-84.71	71.40	82.80	96.20	96.80	102.20
28	Scott	36.54	-84.67	69.70	80.80	93.70	97.20	100.20
29	Sevier	35.92	-83.58	71.90	83.20	95.70	96.80	102.20
30	Sullivan	36.54	-82.58	70.50	81.40	94.00	96.10	99.50
31	Unicoi	36.13	-82.42	67.70	79.00	92.30	96.80	96.60
32	Union	36.17	-83.75	72.00	81.30	94.20	96.40	100.90
33	Washington	36.21	-82.63	69.50	80.70	93.60	96.00	98.78

Appendix B

Numbers of heat wave days per year from 1999-2010 using different heat wave definitions

Year	HW1	HW2	HW3	HW4	HW5	Average
1999	154	227	347	164	394	257.2
2000	31	61	64	41	148	69
2001	177	7	0	0	26	42
2002	92	130	241	65	239	153.4
2003	17	2	0	0	24	8.6
2004	17	0	0	0	0	3.4
2005	293	218	68	28	304	182.2
2006	207	354	306	128	322	263.4
2007	256	579	684	431	493	488.6
2008	2	48	107	26	88	54.2
2009	34	42	15	17	57	33
2010	979	886	608	316	940	745.8
Total	**2259**	**2554**	**2440**	**1216**	**3035**	

Appendix C

Non-Accidental Mortality Rates (per 100,000) during heat wave (M: Male; F: Female)

	HW1		HW2		HW3		HW4		HW5			
Year	M	F	M	F	M	F	M	F	M	F	Average M	Average F
1999	46.7	50.3	47.7	54.3	50.0	53.2	46.7	57.1	48.5	57.3	47.9	54.4
2000	35.6	37.3	46.8	46.8	59.9	58.8	48.4	54.0	58.3	55.0	49.8	50.4
2001	60.7	53.4	27.6	84.3	N/A	N/A	N/A	N/A	58.5	58.1	48.9	65.3
2002	55.6	62.0	48.4	56.7	51.5	57.3	45.5	56.6	54.6	57.9	51.1	58.1
2003	37.7	52.3	0.0	0.0	N/A	N/A	N/A	N/A	62.4	73.7	33.4	42.0
2004	57.1	72.7	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	57.1	72.7
2005	61.4	60.1	57.6	60.2	65.0	62.8	68.7	69.3	59.2	60.5	62.4	62.6
2006	69.0	60.7	71.4	60.3	68.6	61.8	61.6	54.5	69.3	61.6	68.0	59.8
2007	70.1	54.9	63.3	55.6	64.7	53.0	64.1	61.2	62.8	56.1	65.0	56.2
2008	114.5	122.9	49.5	62.5	94.1	119.1	114.1	132.8	111.7	96.2	96.8	106.7
2009	51.4	52.0	58.4	44.3	28.9	29.3	48.3	44.5	55.8	59.5	48.5	45.9
2010	58.2	49.1	65.0	57.0	68.9	58.4	72.9	59.2	65.2	56.4	66.0	56.0
	Average of Yearly Average										**57.9**	**60.8**

Appendix D

Cardiovascular Mortality Rates (per 100,000) during heat waves (M: Male; F: Female)

	HW1		HW2		HW3		HW4		HW5			
Year	M	F	M	F	M	F	M	F	M	F	Average M	Average F
1999	10.6	11.2	9	12.5	10.3	13.1	9.1	15.2	9.2	13.2	9.6	13.0
2000	9.9	6.4	7.4	8.7	6.2	12.4	5.9	9.1	6.8	11.3	7.2	9.6
2001	12.5	13.4	0	16	N/A	N/A	N/A	N/A	14.7	10.7	9.1	13.4
2002	7.5	14.4	5.6	13.4	5.1	11.7	4.9	10.4	7	12.3	6.0	12.4
2003	10	17.1	0	0	N/A	N/A	N/A	N/A	10.7	21.3	6.9	12.8
2004	2.9	3.7	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2.9	3.7
2005	5.4	10.3	5	11.2	4.7	9.2	9.1	12.7	5.9	10.9	6.0	10.9
2006	13.2	12.2	11.7	12.5	11.3	12	8.1	9.4	10.8	11.9	11.0	11.6
2007	8.2	8.3	8.4	8.6	10.5	9.2	10.8	9.5	12.4	12.3	10.1	9.6
2008	0	0	10.9	12.6	9.8	16.4	9.9	11	9.9	12.3	8.1	10.5
2009	10	6.7	9.2	7.7	11.7	12.4	7.8	8.3	10.7	6.7	9.9	8.4
2010	10.4	8.2	8.5	11.1	11.5	7.9	13.8	8.9	10.8	8.4	11.0	8.9
	Average of Yearly Average										**8.2**	**10.4**

Appendix E

Average number of heat wave days per month for 1999-2010

	HW1	HW2	HW3	HW4	HW5
May	N/A	N/A	N/A	N/A	N/A
Jun	2.9	3.6	3.4	1.9	3.5
Jul	5.4	5	4.5	2.6	4.3
Aug	6.5	7.9	7.3	5.6	6.3
Sep	3	N/A	2.5	2.1	N/A

Appendix F

Non-Accidental Mortality Rates during non-heat wave days

	HW1		HW2		HW3		HW4		HW5			
Year	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1999	54.9	57.1	55.3	55.6	57.3	55.4	56.1	54.0	55.5	53.7	55.8	55.2
2000	59.6	57.3	59.7	57.3	57.2	55.0	58.7	55.8	57.2	56.0	58.5	56.3
2001	56.7	54.2	58.5	53.4	58.0	54.0	58.0	54.0	57.9	53.4	57.8	53.8
2002	56.6	56.4	58.9	57.7	58.8	57.5	59.0	57.7	57.6	57.1	58.2	57.3
2003	58.2	59.9	57.8	60.0	57.4	59.6	57.4	59.6	56.8	57.9	57.5	59.4
2004	62.1	56.4	61.8	57.2	61.8	57.2	61.8	57.2	61.8	57.2	61.9	57.0
2005	62.8	57.9	64.0	57.5	61.0	57.6	60.7	57.0	63.4	57.1	62.4	57.4
2006	62.3	60.2	60.9	59.9	62.2	58.7	66.1	61.8	60.9	58.6	62.5	59.8
2007	56.2	56.9	56.7	57.0	54.0	59.0	56.1	55.3	56.8	56.9	56.0	57.0
2008	60.7	60.5	62.5	60.7	61.9	58.4	60.1	60.6	63.4	59.5	61.7	59.9
2009	68.4	62.0	67.8	62.9	68.0	62.0	67.7	61.8	69.0	61.5	68.2	62.0
2010	63.9	58.2	63.4	55.7	58.2	53.8	58.2	54.5	63.0	56.6	61.3	55.8
											60.1	**57.6**

Appendix G

Cardiovascular Mortality Rates during non- heat wave days

	HW1		HW2		HW3		HW4		HW5			
Year	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1999	9.6	13.1	10.4	12.6	9.5	12.1	10.3	11.0	10.4	12.1	10.0	12.2
2000	8.9	12.4	9.3	12.6	9.5	11.8	9.3	12.3	10.2	12.3	9.4	12.3
2001	12.1	14.4	12.5	14.0	12.3	14.1	12.3	14.1	11.9	14.5	12.2	14.2
2002	8.1	12.9	8.7	13.1	9.4	13.8	8.7	13.8	8.6	13.8	8.7	13.5
2003	9.4	14.7	9.5	14.9	9.5	14.8	9.5	14.8	9.3	14.0	9.4	14.6
2004	9.5	11.2	9.1	10.8	9.1	10.8	9.1	10.8	9.1	10.8	9.2	10.9
2005	8.6	10.4	8.5	10.0	7.8	10.6	7.0	10.1	8.2	10.0	8.0	10.2
2006	9.4	9.2	9.6	8.4	9.8	8.5	11.3	10.2	10.1	8.2	10.0	8.9
2007	9.3	9.0	9.2	8.9	8.2	8.6	8.5	8.6	13.0	12.9	9.6	9.6
2008	10.6	10.5	10.5	10.2	10.7	9.0	10.6	10.3	10.9	9.3	10.7	9.9
2009	8.1	7.6	8.1	7.5	8.2	7.4	8.3	7.5	7.8	7.6	8.1	7.5
2010	13.2	9.0	12.5	8.6	11.9	9.5	10.2	8.3	13.0	8.8	12.2	8.8
											9.8	**11.1**

Appendix H

R Codes

Codes for descriptive statistics:

```
> install.packages("pastecs")
> library(pastecs)
> Mortstat<-cbind(Gamna1$Gender,Gamna1$HWDays,Gamna1$Rate)
> stat.desc(Mortstat)
```

Graphs

```
> par(mar=c(5,4,4,8)+0.1)
> plot(NonAccByGender$Year,NonAccByGender$MHW5,type="l",col="red",lwd=
"2",ylab="Average Male Non-Accidental Mortality",xlab="Year")
> par(new=TRUE)
> plot(NonAccByGender$Year,NonAccByGender$FHW5,yaxt="n",xaxt="n",ylab
= "",xlab="",col="blue",type="l",lwd="2",lty=2)
> axis(side=4)
> mtext("Average Female Non-Accidental Mortality",side=4,line =3)
> title(main = "Average Yearly Male and Female Non-Accidental Mortalit
y during Heat Wave Months- HW5")
> legend("topleft",inset=.05,legend=c("Male","Female"),col = c("red","
blue"),lty=1:2)
```

Convert to decimal palces

```
Gamna2$RateR<-round(Gamna2$Rate) #This converts Rate to zero decimal pl
aces with a new name - RateR
```

Average Non-Accidental and Cardiovascular Mortality during HW Months

```
> par(mar=c(5,4,4,8)+0.1)
> plot(AvgMort$Year,AvgMort$NARHW5,type="l",col="red",lwd="2",ylab="Av
erage Non-Accidental Mortality",xlab="Year")
> par(new=TRUE)
> plot(AvgMort$Year,AvgMort$CARHW5,yaxt="n",xaxt="n",ylab = "",xlab="
",col="blue",type="l",lwd="2",lty=2)
> axis(side=4)
> mtext("Average Cardiovascular Mortality",side=4,line =3)
> title(main = "Average Non-Accidental and Cardiovascular Mortality du
ring Heat Wave Months Using HW5")
> legend("top",inset=.04,legend=c("Non-Acc","Cardiovasc"),col = c("red
","blue"),lty=1:2)
```

To Create more than one graph on a single page

```
> par(mfrow=c(2,2))--#2/2rows of graphs
```

```
> plot(AvgMort$Year,AvgMort$NARHW1,type="l",col="red",lwd="2",ylab="Average Non-Accidental Mortality",xlab="Year")
> title(main ="Average Mortality")
> plot(AvgMort$Year,AvgMort$NARHW2,type="l",col="red",lwd="2",ylab="Average Non-Accidental Mortality",xlab="Year")
> title(main ="Average Mortality")
```

Create two graphs with single y-axis

```
> plot(NonAccByGender$Year,NonAccByGender$MHW4,type = "l",col="red",lwd="2",ylab = "Avg. Mortality,per100,000",xlab = "Year")
> points(NonAccByGender$Year,NonAccByGender$FHW4,type = "l",col="blue",lwd="2",lty=2)
> title(main = "Non-Accidental Mortality by Gender Using HW4")
> legend("bottom",inset = 0.05,legend = c("Male","Female"),col=c("red","blue"),lty=1:2)
> legend("topleft",inset = 0.05,legend = c("Male","Female"),col=c("red","blue"),lty=1:2)
> ggplot
```

Graphs comparing temp with each county using categorical variable for county (Using ggplot2)

```
> install.packages("ggplot2")
> install.packages("Lock5Data")
> library(ggplot2)
> library(Lock5Data)
> str(Avghwt)
> ggplot(Avghwt,aes(x=County,y= HW5Fahrenheit))+ geom_boxplot(position = "dodge",col="red")+ coord_flip()

Boxplot for Monthly variation of HW temperatures
> ggplot(Mthvar,aes(x=Month,y=HW2))+geom_boxplot(col="red")+ ylab("Mean Temperature for HW2 in F")


Scatterplot for heat wave distribution by counties
> ggplot(ALLCombinedSPSS,aes(x=County,y=HWDays))+geom_boxplot(position="dodge",col="blue")+coord_flip()

Mortality rate distribution by county for HW definitions
Non Acc:
> qplot(Cmbndnahw5$HWDays,Cmbndnahw5$Rate,geom = "point")+ylab("Mortality Rate per 100,000")+xlab("Heat wave days")+ggtitle("Variation of Heat wave days with Non-accidental Mortality between 1999 and 2010 using HW5")
Cardio:
> qplot(Cmbndcahw5$HWDays,Cmbndcahw5$Rate,geom = "point")+ylab("Mortality Rate per 100,000")+xlab("Heat wave days")+ggtitle("Variation of He
```

```
at wave days with Cardiovascular Mortality between 1999 and 2010 using
 HW5")
```

Plot GAM

```
> install.packages("gam")
> library(gam)
> install.packages("mgcv")
> library(mgcv)
> HW1GAMCA<-gam(RateR~s(HWDays,k=7),data=Gamca1,family = poisson(link = "log
")) #fit the unadjusted model
> HW1GAMCA<-gam(RateR~s(HWDays,k=7)+s(Year,k=7)+s(Month,k=3)+County+Gender,da
ta=Gamca1,family = poisson(link = "log")) #fit the adjusted model
> summary(HW1GAMCA)
> plot(HW1GAMCA,se=TRUE)
> gam.check(HW1GAMCA) #To see diagnostics including number of knows (k), resi
duals and fitted graphs.
>vis.gam(HW1GAMCA) #To visualize graphs.
```

Diagnostics

```
      > mod<-lm(Cmbndcahw1$Rate~Cmbndcahw1$HWDays) #Plot linear model
      > summary(mod) #See the model summary
      > abline(mod) #See the regression line in graphs
      > plot(mod) #See the plots to check for linearity, homoscedaticity, nor
mality.
```

Relative Risk

```
> install.packages("epiR")
> library(epiR)
> epi.2by2(Tab1,method="cohort.count",conf.level = 0.95)
```

VITA

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