

VULNERABILITY INDEX FOR HEAT-RELATED MORTALITY IN GEORGIA, U.S.

ABSTRACT

Background: Heat is a natural hazard, and heat-related mortality is a matter of great public health concern. Exposure to extreme heat has been associated with both increased mortality and morbidity, especially for vulnerable populations. **Methods:** Collect vulnerability, atmospheric, air quality and mortality data. Quantify vulnerability index on a county level for the entire state of Georgia. Summary statistics for maximum daily temperature, minimum daily temperature, and daily number of death in summer season (May-September) Georgia, during 1995–2004. Use multiple Poisson regression to model the effect of the vulnerability index on deaths during extreme heat days. **Results:** Days that met or exceeded the 95th percentile threshold of summer maximum temperature showed greater increases in mortality than days that did not reach this threshold. Counties with the higher vulnerability levels had higher mortality on oppressive heat days compared to days that were not. **Conclusion:** Counties that have higher vulnerability levels have greater mortality increase for oppressive heat days versus non-oppressive heat days, compared to counties with lower vulnerability levels.

INDEX WORDS: Heat mortality, Vulnerability, Georgia

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1. Introduction

Heat is a natural hazard, and much is known about the effects of high temperatures on the human body. Heat-related mortality is a matter of great public health concern. Exposure to extreme heat has been associated with both increased mortality and morbidity. Several factors may increase the number of people that are exposed to extreme heat. Lots of studies showed that excessive ambient heat exposures result in significant mortality to vulnerable populations (Applegate et al. 1981; Wainwright et al. 1999). Particular population subgroups are at increased risk of heat-related mortality, including the elder people (Medina-Ramon et al. 2006), people who live alone (Naughton et al. 2002; Semenza et al. 1996), people of lower income (Kaiser et al. 2001), people of lower socioeconomic status (Rey et al. 2009), people of races other than white (O'Neill et al. 2003; Schwartz 2005), people with less education (Medina-Ramon et al. 2006; O'Neill et al. 2003), people with poor housing (Vandentorren et al. 2006), people without access to cooling devices such as air conditioning (Chestnut et al. 1998; Curriero et al. 2002), and people with preexisting health conditions such as cardiovascular disease, diabetes, renal disease, and pulmonary conditions (Schwartz 2005; Stafoggia et al. 2006, 2008).

In this study, the overarching objectives are to (1) Summary statistics for maximum daily temperature, minimum daily temperature, and daily number of death in summer season (May-September) Georgia, during 1995–2004, (2) quantify vulnerability index on county level for the entire state of Georgia, and (3) determine if a greater number of deaths occur during oppressive heat day than non-oppressive heat day, investigate the vulnerability index and mortality hypothesis where vulnerability modifies the relationship of oppressive heat days and mortality; that is, higher vulnerability levels will show greater mortality increase for oppressive heat days versus non-oppressive heat days, compared to counties with lower vulnerability levels.

2. Background

2.1 Heat wave and Climate Change

Heat is a natural hazard, and much is known about the effects of high temperatures on the human body. Extreme hot weather conditions are projected to increase in frequency, severity, and duration in many parts of the world because of climate change (Meehl et al. 2004). Over the 20th century, the average annual temperature in the United States increased by 1°F (NAST 2000). Annual average temperatures for the region in the 2050s have been projected to rise by 2.5°F to 6.5°F, with summer temperature increases of 2.7°F to 7.6°F (Rosenzweig et al. 2001). The Intergovernmental Panel on Climate Change (2007) reported that climate change is likely to lead to more intense and frequent extreme weather events. With climate change, hotter climates are expected to result in higher mean summer temperatures and fluctuations will likely result in more frequent and intense heat waves (Patz et al. 2005). Moreover, even a small shift in the mean temperature will entail a non-linear large increase in the frequency of extreme weather events, such as heat waves (Meehl et al. 2007). Global warming could determine physical environment alterations, social-economic disruptions, and adverse health consequences for human health on a large scale (Stern et al. 2007).

A study used an air mass-based synoptic procedure to evaluate historical weather–mortality relationships, data from 44 large U.S. cities were analyzed for air masses identified in each city, and for each air mass the weather–mortality relationship was estimated (Kalkstein et al. 1997).

Urban areas, can be particularly vulnerable to heat because of high concentrations of

susceptible people (Hajat et al. 2007), the urban heat island effect (Smargiassi et al. 2009), and the interaction between air pollution and heat (Ren et al. 2006). Urban heat islands are created when human-made surfaces in cities made of concrete, asphalt, metal, and stone absorb incident sunlight during the day, which is re-radiated as heat, especially at night. Several studies have shown that under clear skies and light wind conditions, cities are typically hotter than surrounding rural environments by up to 10°C (Shepherd et al. 2004; Bornstein et al. 2006). Studies have shown that the albedo, or reflectivity, of an urban area is one of the most important determinants of the magnitude of the heat island (Kolokotroni et al. 2008). Urban surfaces which have low albedos and absorb much of the incoming solar radiation will remain warm in comparison to surrounding areas even with the absence of the sun (Taha et al. 1997). This, along with few trees and grass to provide cooling, produces an overall effect of urban areas tending to have higher surface temperatures than surrounding rural areas (Bornstein et al. 2006). There is also an interaction effect between heat and air pollution. A positive association between temperatures >90°F and ground-level ozone production had been found (Patz 2000).

As a state located in the southeastern United States, Georgia is often affected by extreme heat, hot and humid summers are typical. The highest temperature ever recorded is 112 °F . For major Georgia Cities, the average maximum temperature in July is 91 °F in Athens, 88 °F in Atlanta, 92 °F in Augusta, 92 °F in Savannah, and 93 °F in Macon.

2.2 Heat related mortality

Heat exposure's physiological effects range from symptoms such as dizziness, weakness, fatigue to multi-organ failure, coma and death (Wexler. 2002), in the case of heat stroke, heat

exhaustion, heat syncope, or heat cramps (Keatinge et al. 2000). The initial human physiologic response to heat exposure is increasing surface blood circulation, thereby promoting heat loss through radiation, convection, perspiration, and increased rates of evaporative cooling (Knochel 1989). Under extreme or chronic heat stress, the body loses its ability to maintain temperature balance and death may occur. The most common cause of death attributable to heat is heat stroke, it has a substantial case-mortality ratio, and progression to death can be very rapid (within hours). In survivors, the permanent damage to organ systems can cause severe functional impairment and increase the risk of early mortality (Wallace et al. 2007). Other causes of death observed to increase following heat exposure include heart disease, diabetes, stroke, and respiratory diseases (Ellis, 1972).

Studies have shown that the total impact of a heat wave event will be dependent on a number of factors including heat wave intensity, duration, timing in season, location and magnitude (Hajat and Kosatky 2010; Hoffmann et al. 2008), population experience of heat wave events, and public health responses (Koppe et al. 2003). One study showed that duration sometimes modified heat wave mortality effects (Kalkstein et al. 1993). Heat waves earlier in the summer can be more hazardous to health than those later in the summer (Anderson and Bell 2011). Another study found greater mortality effects for longer heat waves (Diaz et al. 2002).

The association between heat and mortality has been reported since the early 20th century. A study reported excess deaths associated with elevated ambient temperature exposure in 86 U.S. cities from 1925 to 1937 (Gover 1938). In recent years, several devastating heat waves have caused large health consequences all across the world. For example, in a 1980 heat wave, there were 1,700 deaths in the United States (CDC, 1995); the 1987 heat wave in Athens caused more than 2000 deaths (Katsouyanni et al. 1998); the 1995 heat wave in which maximum

temperatures in Chicago, Illinois, ranged from 93 to 104°F, caused around 700 deaths, most of which were directly attributed to heat (Semenza et al. 1996), the number of deaths reported increased by 85%, and the number of hospital admissions increased by 11% compared with numbers recorded during the same period in the preceding year (Semenza et al. 1999); the 2003 heat wave in Europe is estimated to have caused 15,000 excess deaths in France (Fouillet et al., 2006), and overall 70,000 deaths in all European countries (Robine et al. 2003); and the heat wave in California 2006 resulted in an increase in morbidity which included 16,166 excess emergency department visits and 1,182 excess hospitalizations state-wide (Knowlton et al. 2009).

High temperatures had significant impacts on deaths from all causes, chronic bronchitis, pneumonia, ischemic heart disease, and cerebrovascular disease in England and Wales (Langford et al. 1995). Studies have examined hot temperatures in relation to total non-accidental deaths and cause-specific deaths (Stafoggia et al. 2006). The city- or region-specific temperature–mortality relationship is often V-, U-, or J-shaped, with increases in mortality at temperatures above the hot threshold (Hajat and Kosatky 2010). One study found a U-shaped temperature–mortality relationship in developing countries, with strong evidence of increased deaths on hot days (McMichael et al. 2008). Another study found an increase in mortality associated with elevated average temperature in Seoul, Beijing, Tokyo and Taipei in Asia (Chung et al. 2009).

2.3 Vulnerability

Vulnerability to heat-related mortality is marked by a variety of characteristics, including being elderly, living alone (Naughton et al. 2002; Semenza et al. 1996), socially isolated (Rey et al. 2009), non-white race (O’Neill et al. 2003; Schwartz 2005), being less educated (Medina-

Ramon et al. 2006; O'Neill et al. 2003), outdoor laborers, lacking access to cooling devices such as air conditioning (Gouveia et al. 2003; Curriero et al. 2002), and with preexisting health conditions (Schwartz 2005; Stafoggia et al. 2006, 2008).

The elderly and young children are regarded as populations that are especially vulnerable to the effects of heat and heat waves (Koppe et al. 2003), they may not be able to thermo regulate efficiently because of their impaired adaptation abilities, higher surface-area-to-mass ratio, higher sweating thresholds, thus increasing the risk of life-threatening consequences when their body temperatures rise (Lifschultz et al. 1998). When body heat production is greater than necessary to maintain a normal body temperature, blood flow from the body core to the skin increases, and heat is transferred more rapidly to the external environment. As a result, blood pressure may increase initially, and heart and respiratory rates increase (Bouchama et al. 2002).

The risk for heat-related mortality increases sharply with age, as those 85 years of age or older are most at risk (CDC 1995). In the United States, an average of 274 people died due to heat-related causes each year, with the highest death rates occurring in persons at least 65 years of age (CDC. 2001). In California an increase in the daily mean apparent temperature of 10°F led to an increase in non-accidental mortality among the elderly (Basu et al. 2008). In 15 European cities, the relative risk of heat-related mortality was elevated for the 65–74 year old populations across countries (Bacchini et al. 2008). Research shows that temperatures increasing were associated with an increase in all-cause and cardiovascular mortality in the 75 year old and above population in Moscow, Russia (Revich et al. 2008). In Sydney, Australia, a study show there is a significant increase in mortality on extremely hot days for populations aged above 65 years old (Vaneckova et al. 2010). In Shanghai, China, for the above 65 years old population, the

number of deaths increased when the average temperature increased above a threshold (Huang et al. 2010).

Numerous socioeconomic factors found to be significant predictors of vulnerability to heat include: African-American ethnic group (Kaiser et al. 2007), low level of education (O'Neill et al. 2003), lower income (Borrell et al. 2006), unemployment, and heavy physical labor (Vandentorren et al. 2006). Recent epidemiologic studies reported non-Whites to be at greater risk than Whites in the US (Schwartz et al. 2005). Research on the 1995 heat wave in Chicago indicates that heat related mortality among African Americans was 50% higher than among whites (Whitman et al. 1997). Also, populations of lower socioeconomic status may not have access to air-conditioned places because of the cost of air-conditioning (Semenza et al. 1996).

Housing characteristics and behaviors specific to the elderly, including living alone, living in urban areas (Jones et al. 1982), living on the top floor of apartment buildings, lacking air conditioning, and keeping windows and doors closed for safety reasons, may increase mortality risk from heat exposure (Semenza et al. 1996). Study in St. Louis and Kansas City showed that alcoholism, living on higher floors of multistory buildings, and using major tranquilizers increased risk (Kilbourne et al. 1982). Another study showed that living alone and not leaving home daily increased risk (Senebza et al, 1996).

Several studies indicate that the heat-related mortality rates are higher in the urban area than in surrounding areas. One reason is the elevation in heat-related deaths in urban areas to the high population density (Buechley et al. 1972). The other suggested that urban areas retain heat throughout the night time more efficiently than the rural areas (Clarke, 1972). During a heat wave in St. Louis, higher mortality rates were recorded in the business and urban core areas than

in rural areas of the city (Smoyer 1998). Furthermore, populations of more deprived cities are at higher risk, even after adjusting for latitude (Curriero et al. 2002); and accordingly people in economically underprivileged neighborhoods within a city are usually more vulnerable to heat (O'Neill et al. 2003).

Cities in the U.S. with higher air conditioning prevalence tend to have lower heat-related mortality (Chestnut et al. 1998). Populations with lower socioeconomic status still have no or limited access to air conditioning. During the 1995 Chicago heat wave, the risk of dying during the heat wave was 70% lower among individuals with air conditioners than among individuals without air conditioners (Semenza et al. 1996).

Extreme heat can have a deleterious effect on the health of persons who are already sick from other causes. Heat may affect these frail individuals differently depending on the disease they already have. People with chronic diseases of the heart or lungs may be more susceptible to the effects of high ambient temperatures (McGeehin et al. 2001). A study showed that there is an association between elevated temperatures and short-term increases in cardiovascular related hospital admissions for 12 U.S. cities (Schwartz et al. 2004). People with diabetes, chronic mental disorders, or other preexisting medical conditions are at greater risk from heat exposure (Kovats and Hajat 2008). People having a mental illness increased risk of heat-related mortality (Kaiser et al. 2001). People confined to bed or unable to care for themselves are at increased risk due to less fluid intake during heat waves (Semenza et al. 1996).

3 Materials and Methods

3.1 Data Collection

3.1.1 Mortality Data

Georgia is a state located in the southeastern United States, which has 159 counties, it is the 24th most extensive and the 9th most populous of the 50 United States. Atlanta is the state's capital and its most populous city. The United States Census Bureau estimates that the population of Georgia was 9,815,210 on July 1, 2011 (United States Census Bureau 2011). The majority of Georgia is primarily a humid subtropical climate. Hot and humid summers are typical, except at the highest elevations.

We selected mortality data from all 159 counties in Georgia. The study period ranged from May to September, 1995 through 2004, since heat mortality is most likely to occur. County-level mortality data for Georgia, from 1995-2004 were drawn from the National Center for Health Statistics (NCHS).

Heat-related mortality will be examined during the summer months (May – September) when heat stress is most likely to occur. We used total mortality without exclude accidental death, since for small populations in rural counties; it is hard to stratify the death cause with few deaths per day. Also it is hard to acquire the cause of death and sometimes death may be caused by several factors included or related to heat.

3.1.2 Meteorological Data

The Maximum and minimum daily temperature obtained from the National Climatic Data Center (NCDC 2011). We used the 90th and 95th maximum and minimum temperature percentiles of the entire five month period and used the 90th and 95th maximum and minimum temperature percentiles of each month each year for every county in this study, and use these two values as a threshold indicating oppressive weather conditions. In all, there are eight measures

which are summer 90th percentile max, summer 95th percentile max, summer 90th percentile min, summer 95th percentile min, monthly 90th percentile max, monthly 95th percentile max, monthly 90th percentile min, and monthly 95th percentile min. We considered days over these percentiles as extremely hot days, and target the increase in mortality associated with extreme heat. In general, there are two basic ways of setting the temperature threshold: either by using a criterion whereby the trigger temperature is the result of the relationship between temperature and some health indicator, generally mortality; or, by using a statistical–meteorological criterion, in such cases, once the series of daily temperatures in recent years is known, excessive heat days are defined as those which exceed a given percentile (Pascal et al., 2006). Using these percentiles, rather than a cut-off value at a given temperature, the fact can be taken into account that individuals adapt to their local weather conditions (Medina-Ramon et al. 2007). In fact, heat mortality is higher in cooler climates than in warmer climates since the people are less acclimated to high temperatures (Kalkstein et al. 1997).

A second measurement is the air mass, a measure of outdoor air conditions. These data were obtained from Athens, Atlanta, Augusta, Columbus, Macon, and Savannah, Chattanooga, Jacksonville, and Tallahassee stations. We use the Spatial Synoptic Classification (SSC; Sheridan 2003; Sheridan 2011) in this study. For a given station, the SSC classifies each day into 1 of 7 weather types, or a transition between weather types. We use two subdivisions of the Moist Tropical weather type in this study, Moist Tropical Plus (MT+) and Moist Tropical Double Plus (MT++). Counties that were reported MT+ or MT++ air mass types on a particular day were considered as very warm, humid and were counted as having oppressive heat for that day. Conversely, counties that were grouped with a station that reported any other type of air mass or transition on a particular day were counted as not having oppressive heat for that day.

3.1.3 Air Quality Data

Many studies have demonstrated the effects of air pollutants have a clear correlation with the number of daily deaths and hospitalizations as a result of respiratory and cardiovascular diseases (Pope et al. 2002). Air pollution is a complex mixture of gaseous, volatile, semi-volatile and particulate matter and its exact composition varies widely. Indeed the composition in a single location will vary depending on the meteorological conditions, time of the day, day of the week, industrial activity and traffic density.

This study used the Air Quality Index (AQI) available from the U.S. Environmental Protection Agency (EPA). The AQI is an index for reporting air quality designed specifically for determining how clean or polluted the air is by monitoring 5 major air pollutants regulated by the Clean Air Act (Air Now 2012). AQI values range from 0 to 500, and are separated into 6 categories with “levels of health concern” and associated color code. The colors are displayed cartographically on the publicly available website AIRNOW. The AQI calculates ground-level ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen oxide, each of which have the potential to cause adverse health effects within hours or days after exposure (Air Now 2012). Many rural areas lack data on air quality, so we haven’t get air quality data for every county in Georgia.

Table 3.1.1 Air Quality Index and Levels of Health Concern

AQI Value	Levels of Health Concern	Colors
0-50	Good	Green
51-100	Moderate	Yellow
101-150	Unhealthy for Sensitive Groups	Orange
151-200	Unhealthy	Red
201-300	Very Unhealthy	Purple
301-500	Hazardous	Maroon

3.1.4 Vulnerability data

In this study, vulnerability data constructed uses eight vulnerability variables which are a combination of demographic, health, and land cover data. For demographic category, there are six variables which are percent population below poverty line, percent population greater or equal than 25 years of age with less than a high school diploma, percent population of a race other than white, percent population living alone, percent population greater or equal to 65 years of age, percent population greater or equal to 65 years of age and living alone. These variables were gathered from the Censtats data made available by the U.S. Census Bureau (USCB 2011) for the year 2000 on the county level for the state of Georgia. For health category, we use percent population ever diagnosed with diabetes, which gathered from the Behavioral Risk Factor Surveillance System (BRFSS) of Center for Disease Control and Prevention (CDC), which is a telephone survey conducted monthly by state on behavioral risk factors and preventative health practices for the year 2000 by county level for the state of Georgia. And for land cover category, we use percent of county with land use/land cover described as urban; this data downloaded from the Georgia GIS Clearinghouse and displayed cartographically using ArcGIS software from Natural resource Spatial Analysis Lab at the University of Georgia. This dataset includes the following land cover types: Beaches/Dunes/Mud, Quarries/Strip Mines/Rock Outcrops, Open water, Low Intensity Urban, High Intensity Urban, Clear cut/Sparse, Deciduous Forest, Evergreen Forest, Mixed, Forest, Row Crops/Pasture, Forested Wetland (salt water), Forested Wetland (freshwater), and Non-forested Wetland (NRSAL 2011). The Low Intensity Urban and High Intensity Urban types were added together to form one urban class, while all other land cover types are considered non-urban.

3.2 Data analysis

First, we calculated summary statistics for maximum daily temperature, minimum daily temperature, daily number of death, and vulnerability index for every county in summer season (May-September), during 1995-2004.

Second, we used the Poisson Model for each county to estimate the present-day mortality risk in the summer season (May-September) comparing extreme hot days with non-oppressive days, and if counties with greater vulnerability respond with greater increases in mortality than counties with lower vulnerability. And then the results were combined into a random effects model.

To ascertain the days which would have been classified as an oppressive heat day, we selected those days that met the condition of simultaneously exceeding the summer 95th percentile maximum temperatures for each county, based on this, we then defined this binary variable where 1 represents as oppressive days and 0 as non-oppressive days.

We let Y_{it} denote the total number of deaths on day t in county i , and assuming that Y_{it} follows a Poisson distribution with mean μ_{it} .

$$Y_{it} \sim \text{Poisson}(\mu_{it})$$

For county i in day t ,

$$\ln(\mu_{it}) = \beta_{0i} + \beta_{1x_{it}} + \beta_{2v_i} + \beta_{3x_{it}} \cdot v_i + ns(\text{year}, df)$$

μ_{it} represents the mean of daily number of deaths over the whole period for each county. β_{0i} is a random intercept term, β_1 is the slope of the oppressive heat indicator, and it is the estimated regression coefficient associated with oppressive heat. x_{it} is the indicator of oppressive days in i county on day t , known as s95max, which is a binary term where 1 represents as oppressive days and 0 as non-oppressive days. β_2 is the slope of the vulnerability index value, which is the estimated regression coefficient associated with the vulnerability index value, and v_i is the vulnerability index value. β_3 , is the interaction effect estimates of both the oppressive indicator value and the vulnerability index value. ns ($year$, $df=3$) is a natural cubic spline function of time year with $df=3$ to control for unidentified possible confounders and over dispersion. The vulnerability index values were rescaled from the original range of outcomes (6 to 15) down to a range of values more compatible with this modeling approach (0 to 9), i.e. each county's vulnerability index value was reduced by 6 for modeling purposes.

We will use this model to examine if oppressively hot days, as $s95max=1$, respond with greater mortality than days that were not oppressively hot, as $s95max=0$, and if counties with greater vulnerability, respond with greater increases in mortality on oppressive days than counties with lower vulnerability values.

Analyses were first conducted separately for each county, and the cumulative effects were combined using random effects model. Because there was no heterogeneity of effect by county level, we present the results obtained after pooling the data and analyzing them jointly. We used a quasi-Poisson function that allows for over-dispersion in daily deaths for pooled regression.

Altogether, this model utilizes multiple Poisson regression to analyze mortality in Georgia, with mortality as the response variable and the vulnerability index and oppressive heat as the predictor variables. The coefficients of the predictors in this model are used to describe the natural log of the relative risk (RR), which is the ratio of death occurring in oppressive heat days and the difference in the relative risk of mortality experienced on oppressive days versus non-oppressive days whether be greater in counties with greater vulnerability index values than counties with lesser vulnerability index values or not.

To examine the heat effect on mortality, we evaluated the relative risk of all mortality associated with high temperature (> 95th percentile of summer temperature). We evaluated the model fit using deviance for quasi-Poisson. Our initial results showed that summer 95th percentile temperature was a better predictor. We use $df=3$ per year for time to control for season.

All the analyses were performed using R software (version 2.15.0).

4. Results

4.1 Summarize statistics

During summer season (May-September) in the period 1995-2004, the maximum average daily temperature was 89.37°F (range 55.00–98.53°F), the minimum average daily temperature was 71.88°F (range 38.00–79.37°F).. The minimum number of death for each day and each county is 0, the maximum number of death for each day and each county is 43, and the

mean of the number of death is 1.013, the standard deviation of the number of death is 2.53 (Table 4.1.1).

The mean of the daily number of death for each county during summer season (May-September) 1995-2004 ranges from 0 (Ben Hill County) to 21.47 (Fulton County). The mean of daily death of most rural counties are less than 1, but for larger counties, this number is more than 10 (De Kalb 12.24, Fulton 21.47). Analysis the variance of each county's daily death number using anova method showed that quite a lot county means are different from overall mean (F-value=7746.6, p-value<0.0001).

Table 4.1.1 Summary statistics for maximum daily temperature, minimum daily temperature, and daily number of death in summer season (May-September) Georgia, during 1995–2004

Variables	Mean	Min	Median	Max	SD*
Max Daily Temperature (°F)	88.96	55.00	90.01	110.20	6.63
Min Daily Temperature (°F)	71.47	38.00	73.48	87.00	6.86
No. of Daily Death	1.01	0.00	0.00	43.00	2.53

* SD is the standard deviation from the mean

The mean of the daily maximum temperature for each county during summer season (May-September) 1995-2004 ranges from 86.09°F (Douglas County) to 91.71 (Decatur County). Analysis the variance of each county's daily maximum temperature using anova method showed that a lot county means are different from overall mean (F-value=115.63, p-value<0.0001).

A heat vulnerability index was developed from eight variables which are demographic, health, and land use variables. The variable "race other than white" had the greatest range among counties (1.71 – 78.70); and the variable "urban" also has a large range (2.44 – 60.62). These two variables observed much greater standard deviations from the mean compared to the other variables (race other than white 16.95, urban 9.53). However, the range of "live along" (7.75-13.96) and "diabetes" were quite small (5.01-12.80), the standard deviations of these two variables were much smaller (live alone 1.71, diabetes 1.43), having much less variation among different counties. Counties had an average of 29.29% for "population with less than a high school degree", with range from 7.6% to 43.80% and 28% for "population age more than 65 that live alone", with range from 18.82% to 38.66% (Table 4.1.2).

Table 4.1.2 Summary statistics for the eight vulnerability index variables in Georgia, during 1995–2004

Variables	Mean	Min	Median	Max	SD*
Below Poverty	16.11	3.81	16.40	28.60	5.37
Less than a high school degree	29.29	7.60	30.30	43.80	7.54
Race other than white	32.40	1.71	32.00	78.70	16.95
Live alone	8.52	7.75	8.72	13.96	1.71
Age \geq 65	12.04	1.80	12.17	25.85	3.36
Age \geq 65 and live alone	28.03	18.82	28.31	38.66	3.88
Diabetes	9.12	5.01	9.00	12.80	1.43
Urban	9.36	2.44	6.07	60.62	9.53

* SD is the standard deviation from the mean

First, a spearman’s rank correlation was used to identify the level of association among the eight variables. It shows a great amount of association among many of the variables (Table 4.1.3). Below poverty is highly positive associated with variables which are having less than a high school diploma, being a race other than white, being 65 years of age or older and living alone, and having diabetes. Having less than a high school diploma is highly positive associated with being 65 years of age or older, and is highly negative associated with urban. Being a race other than white is highly positive associated with having diabetes. The association between living alone and being 65 years of age or older is the highest among these variables. Being 65 years of age or older is also highly positive associated with diabetes. The only variable that

showed any negative association with other variables was percent urban land cover, which was negatively correlated with all other variables.

A principal component analysis was used for data reduction because of the strong associations among the input variables. Three Factors which represent social isolation/prevalence of elderly/poor health (diabetes), poverty/proportion of people of a race other than white, and education/land use explain 82% of the variability. A value of 1 represented the least vulnerable score for that factor in the respective county while a value of 6 represented the highest value of vulnerability.

Table 4.1.3 Spearman’s correlation values for vulnerability variables for all counties in Georgia during 1995-2004 (n=159).

	Poverty	Less than high school diploma	Race other than white	Live alone	Age ≥ 65	Age ≥ 65 and live alone	Diabetes	Urban
Below Poverty	1.0000							
Less than high school diploma	0.6622	1.0000						
Race other than white	0.6823	0.2754	1.0000					
Live alone	0.5427	0.3304	0.4088	1.0000				
Age ≥ 65	0.4600	0.4916	0.1733	0.7430	1.0000			
Age ≥ 65 and live alone	0.7131	0.5814	0.4066	0.5621	0.3747	1.0000		
Diabetes	0.6474	0.4705	0.6107	0.6366	0.6923	0.4314	1.0000	
Urban	-0.5666	-0.5547	-0.3399	-0.2801	-0.4107	-0.4191	-0.5342	1.0000

These three factors were combined into a total vulnerability index value score between 3 (low vulnerability) and 18 (high vulnerability), for each county level range from 6 (Chattahoochee County) to 15 (Clay, Taliaferro County). The mean of Vulnerability Index is 10.42. Baker, Bibb, Brooks, Chatham, Clarke, Clay, Clayton, Cobb, Crisp, Decatur, Early, Fannin, Fulton, Glynn, Greene, Gwinnett, Hancock, Hart, Jefferson, Jenkins, Muscogee, Rabun, Randolph, Richmond, Screven, Stephens, Stewart, Talbot, Taliaferro, Taylor, Terrell, Thomas, Troup, Union, Warren, Wilkes counties have high vulnerability index which is greater than 12. Most of these counties are located in the large cities; some of these located in the east-central Georgia and southwestern Georgia. The high values for these counties mostly contributed to Factor 1.

Table 4.1.4 Summary statistics for vulnerability index in summer season (May-September) Georgia, during 1995–2004

Variables	Mean	Min	Median	Max	SD*
Vulnerability Index	10.42	6.00	10.00	15.00	1.74

* SD is the standard deviation from the mean

4.2 Statistic Model

During the summer season (May- September) from 1995 to 2004 in 159 counties of Georgia, we used the 95th maximum temperature percentiles of the entire five month period each year for every county in this study, and use this variable as a threshold indicating oppressive heat weather conditions. We rescaled vulnerability index value from an original range of 6-15 to 0-9. Then, each of the nine oppressive heat indicators was tested to see whether it indicated increased mortality by using the statistic model in section 3.2.

The slope of 95th percentile summertime maximum temperature is -0.035, the slope of vulnerability index is 0.105, the slope of interaction term of 95th percentile summertime maximum temperature and vulnerability index is 0.012. The interaction term showed a statistically significant effect (P-value=0.0049). For oppressive heat days (the 95th percentile summertime maximum temperature =1), the slope of vulnerability index = 0.105+0.012 = 0.117, $\exp(0.117)=1.124$ is the risk increase in daily number of death for 1 unit increase in vulnerability index. In other words, 12.4% increase in mortality for 1 vulnerability index increase on oppressive heat days. For non-oppressive heat days, (the 95th percentile summertime maximum temperature =0), the slope of vulnerability index = 0.105, $\exp(0.105)=1.111$ is the risk increase in mortality for 1 unit increase in vulnerability index. In other words, 11.1% increase in mortality for 1 vulnerability index increase on non-oppressive heat days.

The slope of 95th percentile summertime maximum temperature = (-0.035+ 0.012* vulnerability index). For vulnerability index > 3, the slope of 95th percentile summertime maximum temperature is positive which corresponds to increasing in mortality. For example, if vulnerability index =12, the slope of 95th percentile summertime maximum temperature = 0.0344. This corresponds to 3.5% increase ($\exp(0.034) = 1.035$) in mortality due to oppressive heat days compare to non-oppressive heat days.

The relative risks for oppressive and non-oppressive days indicate that the mortality increases in both conditions as vulnerability increases. However, the risk of mortality does not increase at the same rate. On oppressive days, the risk increases at a greater rate than on non-oppressive days as the vulnerability index increases. This signifies that summertime 95th percentile maximum temperature is an adequate indicator of increased risk of mortality.

The results of the model indicate a lesser effect with low values on the vulnerability index, but a greater effect with high vulnerability index values (Table 4.2.1). For instance, an vulnerability index value of 6 indicated a slightly negative association with mortality; meaning that counties with the lowest vulnerability index value showed greater mortality on days that were not oppressively hot than on days that were considered oppressively hot. However, this relationship was not statistically significant. Greater values on the vulnerability index value show a positive association with mortality, starting at an HVI value of 7, the relative risk becomes greater than one, starting at an HVI value of 9, the relative risk for oppressive heat days become higher than non-oppressive heat days, signifying that the number of mortalities on oppressive days is greater than the number of mortalities on non-oppressive days. As values on the vulnerability index value increase, the proportion of deaths on oppressive days to deaths on non-oppressive day's increases as well. This models shows that greater HVI values indicate greater relative risks. In other words, counties with greater vulnerability, respond with greater increases of mortality rates on days that are oppressive than counties with less vulnerability.

Table 4.2.1 Output from the statistic model for vulnerability index values and 95th percentile summertime maximum temperature

Vulnerability Index	Oppressive days		Non-oppressive days	
	ERC*	RR**	ERC*	RR**
6	-0.035	0.966	0	1
7	0.082	1.085	0.105	1.111
8	0.199	1.220	0.210	1.234
9	0.316	1.372	0.315	1.370
10	0.433	1.542	0.420	1.522
11	0.550	1.733	0.525	1.690
12	0.667	1.948	0.630	1.878
13	0.784	2.190	0.735	2.085
14	0.901	2.462	0.840	2.316
15	1.018	2.768	0.945	2.573

* ERC is the estimated regression coefficient

** RR is the relative risk for daily number of death

5. Discussion and Conclusion

An increase in the frequency, duration and intensity of oppressive heat days is one of the most certain impacts of global climate change, and therefore, it is important to characterize the heat-related health risks.

In this study, we examined the effects of heat and vulnerability index on mortality in summer season (May-September), Georgia, during 1995–2004. In general, we found that the temperature-mortality relationships were non-linear for all mortality type. Extreme hot temperatures had negative impacts on health; vulnerability index had positive impacts on mortality, the greater the vulnerability index, the more number of daily deaths.

We summary statistics for maximum daily temperature, minimum daily temperature, and daily number of death in summer season (May-September) Georgia, during 1995–2004. The vulnerability index value was mapped, which included a range of 10 levels across the state. Highest vulnerabilities were found in the metro Atlanta area around Fulton County and the southwestern part of the state around Clay Count, although islands of high vulnerability can be seen in Taliaferro, Bibb, Richmond, and Chatham counties. The lowest areas of vulnerability were found encircling the high vulnerability counties of metro Atlanta, as well as the southeastern part of the state near the Atlantic coast. Lee and Chattahoochee Counties had low vulnerabilities despite being in the Southwest. And then we use multiple Poisson regression to model the effect of the vulnerability index on deaths during extreme heat days. When coupled with mortality data, the vulnerability index value was modeled as an effect modifier of oppressive heat. The oppressive heat indicator and vulnerability index values were used as predictor variables and mortality data were used as the response variable. Vulnerability index

values of 6 actually showed more mortality on non-oppressive days than oppressive days. This interesting result may be explained by chance because of the lack of statistical significance. Starting with a vulnerability index value of 9, the relative risk for oppressive heat days is higher than non-oppressive heat days, signifying greater mortality on days with oppressive heat than days without oppressive heat. As the vulnerability index value increased, so did the relative risk, meaning the ratio of mortality on oppressive days to non-oppressive days increased. Thus, populations in high vulnerability counties were much more susceptible to heat-related mortality on oppressive heat days.

The strengths of our study include the large number of population, which allowed the exploration of a large number of deaths. This allowed the detection in a single population of many conditions that have been only reported occasionally. Some rural counties had small numbers of deaths, and therefore less precision.

Several limitations of this study must also be acknowledged. We only focused on one state, so the results might not be generalizable to other areas. However, the approaches applied in this study can be used in further research in other areas.

We only use all-cause mortality with no stratifications for cause of death or demographic variables for the deceased. Since there are few deaths per day in small populations in many rural counties would make any stratification difficult, even during exceptional hot days, very few deaths are directly attributed to heat and the majority is instead ascribed to other causes, such as cardiovascular and respiratory diseases (Ostro et al. 2009).

One limitation of the present study was the exclusion of air quality data for use as a confounding factor in the relationship between heat and mortality. Many rural areas lack data on

air quality and therefore a comprehensive study could not be completed. However, future work might include an analysis of a subset of counties with air quality data such as ground level ozone and small particulate matter.

Additionally, we didn't acquire air conditioning data. Air conditioning data are only available in major metropolitan regions from the American Housing Survey. This issue led Reid et al. (2009) to limit their study to only large cities, leaving rural areas unexamined. Some studies showed a clear inverse relationship between air conditioning and heat mortality (Davis et al. 2003). However, the importance of including air conditioning data may vary in studies of different region. Air conditioning prevalence of some kind (including both central and separate units) in Atlanta was at 93.8% in 1996 and 97% in 2004 (American Housing Survey 1997; 2005). Air conditioning data would likely improve this study, but based on the results by Reid et al. (2009), and the nearly saturated air conditioning levels in the South, that not all areas with low air conditioning prevalence also had high overall vulnerability, and concluded that air conditioning was not driving the vulnerability index, the absence of it should not discredit the forthcoming analysis/results.

In conclusion, the results of this study demonstrate counties that have higher vulnerability levels have greater mortality increase for oppressive heat days versus non-oppressive heat days, compared to counties with lower vulnerability levels. This finding may have implications for future studies of heat-related health effects.

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APPENDIX:

R code:

```
mort <- read.csv( file.choose(), header=F)
names(mort) = c("date","year","month","day","county", "tmpd.max", "tmpd.min", "death",
"vuln", "AQI", "station", "airmass","s90max", "s90min","m90max", "m90min","s95max",
"s95min","m95max", "m95min", "population")
id <-mort$county
tmpd.max <-mort$tmpd.max
tmpd.max <- as.numeric(levels(tmpd.max)[tmpd.max])
tmpd.min <-mort$tmpd.min
tmpd.min <- as.numeric(levels(tmpd.min)[tmpd.min])
death <-mort$death
death <- as.numeric(levels(death)[death])
vuln <- mort$vuln
vuln <- as.numeric(levels(vuln)[vuln])-6
airmass <- mort$airmass
year <-mort$year
year <-as.numeric(levels(year)[year])
population <-as.numeric(mort$population)
s95max <-mort$s95max
s95min <-mort$s95min
m95max <-mort$m95max
m95min <-mort$m95min
tmpd.max.trend <- filter(tmpd.max, rep(1/153,153), sides=2)
tmpd.max.mean <- tmpd.max - tmpd.max.trend
tmpd.min.trend <- filter(tmpd.min, rep(1/153,153), sides=2)
tmpd.min.mean <- tmpd.min - tmpd.min.trend
airmass2 <-rep(0, length(airmass))
airmass2[airmass=="MT+"] <-1
airmass2[airmass=="MT++"] <-1
s95max <- as.numeric(s95max)-2
```

```

m95max <- as.numeric(m95max)-2
s95min <- as.numeric(s95min)-2
m95min <- as.numeric(m95min)-2
miss <-
is.na(id)|is.na(tmpd.max)|is.na(tmpd.min)|is.na(death)|is.na(vuln)|is.na(airmass2)|is.na(year)|is.na
(population)|is.na(s95max)|is.na(s95min)|is.na(m95max)|is.na(m95min)
id <-id[!miss]
tmpd.max <-tmpd.max[!miss]
tmpd.min <-tmpd.min[!miss]
death <- death[!miss]
vuln <- vuln[!miss]
airmass2 <- airmass2[!miss]
year <- year[!miss]
population <- population[!miss]
s95max <- s95max[!miss]
s95min <- s95min[!miss]
m95max <- m95max[!miss]
m95min <- m95min[!miss]
library(lme4)
lm.unpooled.contrast.from.grand.mean <- lm (death ~ id)
anova(lm.unpooled.contrast.from.grand.mean)
sum(coef(summary(lm.unpooled.contrast.from.grand.mean))[,4]<0.05/159)
tapply(death,list(id),mean)
summary(tmpd.max)
summary(tmpd.min)
tapply(tmpd.max,list(id),mean)
summary(vuln)
tapply(vuln,list(id),mean)
M1 <- lmer(death ~s95max +vuln +s95max*vuln + ns( year,3) + (1|id)), family=poisson)
summary(M1)
display(M1)

```

```
glm.0 <- glm(death ~ vuln, family=quasipoisson, offset=log(population))
summary(glm.0)
pdf("glm.0.pdf")
plot(glm(death~vuln, family=quasipoisson, offset=log(population)))
abline(glm.0)
dev.off()
```