Catastrophe and Climate

Determining the Role of Anthropogenic Climate Change on Human Health Outcomes: A Case Study on Heat Related Illness Attribution

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Determining the Role of Climate Change on Human Health Outcomes: A Case Study on Heat Related Illness Attribution

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Executive Summary

This report is targeted to actuaries that are interested in identifying the adverse human health outcomes resulting from anthropogenic climate change. This is accomplished by providing a detailed framework to evaluate the impact of extreme heat on human health and identify the role that anthropogenic climate change has on extreme heat events. Although this document is designed around extreme heat, the concepts can be expanded to other climate-related events. As the primary focus of actuarial research is to promote human health and minimize the preventable economic burden, this document also provides recommendations to mitigate against excess heat related illness (HRI) due to extreme heat.

This report is focused on three objectives to understand the dynamics of HRI emergency room (ER) visits. The first objective is to understand the relationship between extreme temperature and HRI ER visits. The second objective is to construct a methodology to evaluate different heatwave definitions. The third objective is to attribute the excess HRI ER visits and health care expenditure towards ER visits that could be attributed to anthropogenic climate change. The study was based on the three physiographic divisions (Mountain, Coastal, and Piedmont) of North Carolina based on the variance of temperature across the state; however, due to limitations in data from the Mountain region, the results are only focused on two physiographic divisions (Coastal and Piedmont).

The HRI ER visits data was obtained from the North Carolina Disease Event Tracking and Epidemiologic Tool (NC DETECT), temperature data from Global Historical Climatology Network – Daily dataset and dew-point from PRISM dataset. Additionally, estimates of relative humidity and 6 most frequently used heat indices were derived from the literature. There were 28 heat wave definitions from the literature that were found to be sensitive to human health outcomes (mortality/morbidity). Heatwave definitions were used to divide the study period in heatwave and non-heatwave days to compare the sensitivity for excess HRI ER visits. To conduct the attribution analysis, historical natural simulations were obtained from the international CLIVAR climate of 20th Century Plus Detection and Attribution Project.

Twenty-eight heatwave definitions were evaluated to estimate the sensitivity towards HRI ER visits using a negative binomial model along with population as an offset term. An absolute threshold of daily maximum temperature greater than or equal to 95°F was most effective to identify extreme HRI ER visits compared to the other heatwave definitions included in the study. The results were slightly different from existing literature; we identified that using daily maximum temperature greater than the 95th percentile threshold for at least two consecutive days to be more effective for the region. But the available literature is based on comparatively larger geographic areas (group of states) and using all-cause mortality as the health outcomes. Our study results using HRI ER visits as the health outcome using a decentralized approach (focusing on climate divisions within a state) adds value to the existing literature. From the attribution analysis, we estimated that an excess of 25.19% of the cost related to HRI ER visits in Coastal and 27.32% Piedmont region could be attributed to anthropogenic climate change.

Section 1: Introduction

Climate change is already a threat to human health. Evidence has linked climate change to an increase in the frequency and intensity of some extreme weather events. Because of scientific advances in understanding the relationship between climate change and extremes, the conversation can now transition from identifying changes in historical trends of extreme events to determining the effect climate change has on a single extreme event. This new study area in climate science is called *extreme event attribution*. Understanding these relationships provides new opportunities to determine the current and future impacts of climate change on society and health delivery systems. The connection between extreme weather events and human health is already well established. With the advent of extreme event attribution, there is now an opportunity to identify the contribution that climate change has on human health and healthcare costs because of more intense and frequent extreme events in many parts of the world. This project aims to evaluate the relationship between extreme temperature and emergency room visits, while also estimating the health care cost associated with extreme temperature events. The goal of this report is to establish a framework for actuaries interested in evaluating the impacts of climate change on human health and determine additional costs.

1.1 CLIMATE CHANGE AND EXTREME TEMPERATURE

Changes in the Earth's climate since the early 19th Century is primarily the result of increases in anthropogenic greenhouse gases. As the concentration of these gases in the atmosphere continues to rise, the Earth's temperature is estimated to increase over time compared to the other natural drivers (volcanic, solar, and orbital). According to the recent Intergovernmental Panel on Climate Change special report, human-induced warming has reached approximately 1°C above pre-industrial levels and is projected to increase another 1.5°C by the end of the current Century (by 2100) (IPCC, 2018). Based on several lines of evidence, the report also concludes that there is high confidence that many regions will be exposed to more extreme weather, including more frequent and intense extreme temperature events (IPCC, 2018). For example, central and western North America are among the top regions in the world expected to

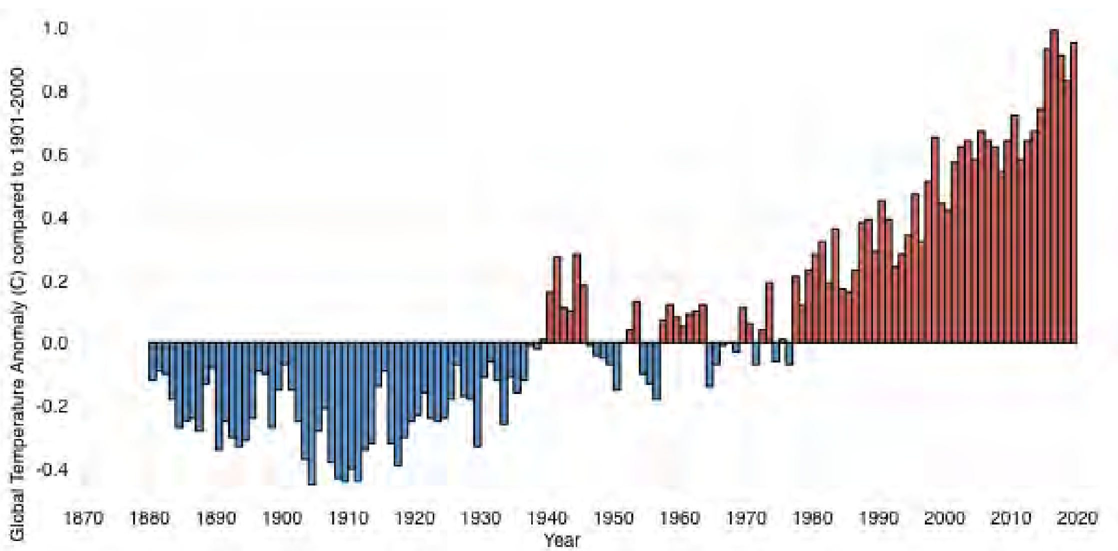


Figure 1. *The graph shows average annual global temperatures since 1880 compared to the long-term average (1901-2000). The zero line represents the long-term average temperature for the whole planet; blue and red bars show the difference above or below average for each year (Lindsey & Dahlman, 2002).*

experience higher warming rates and increased incidences of extreme heat (IPCC, 2018). Many areas around the world have already experienced increases in the frequency and intensity of extreme weather events over the last 50 to 100 years. In the United States, the frequency and duration of heatwaves significantly increased over last 50 years (1961 – 2018) (USGCRP, 2020). The U.S. Global Climate Change Research Program identified that a majority of the U.S. cities in the east coast region had statistically significant increase in the number of heatwaves, defined as two or more consecutive days with daily minimum temperature more than 85th percentile of historic summer period specific to the city (USGCRP, 2020). For the study conducted in this report, the focus was on changes in extreme temperature.

1.2 ATTRIBUTING HUMAN HEALTH OUTCOMES TO ANTHROPOGENIC CLIMATE CHANGE

In 2017, human-induced warming reached about 1.5 °C above the pre-industrial age. The past emissions are not the standalone factors to raise the global average temperature to 1.5 °C more than the pre-industrial level. Human-induced warming is a result of greenhouse gases (GHG) like carbon dioxide [Fig. 2], methane, chlorofluorocarbons, and nitrous oxide emissions. For the last few decades, there is an exponential rise in GHG that could worsen the warming trend (IPCC, 2018).

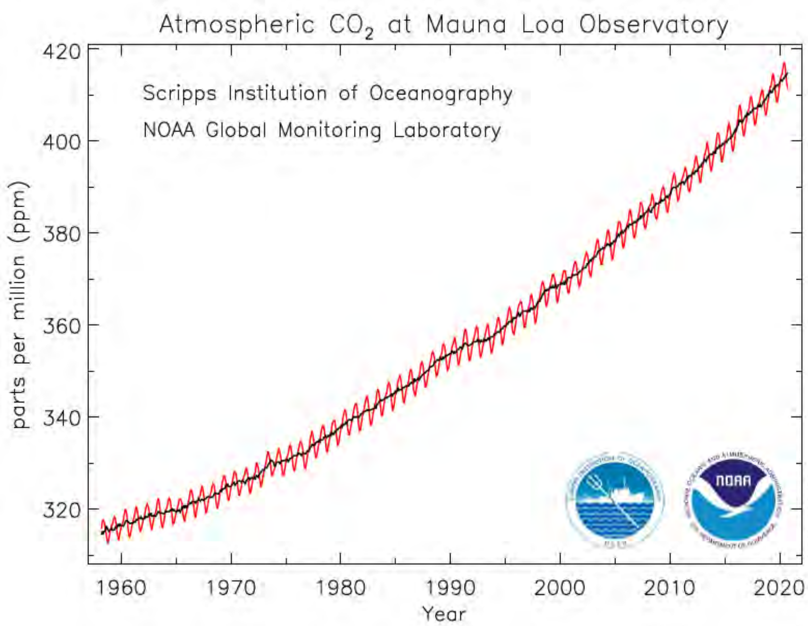


Figure 2. *The graphs show monthly mean carbon dioxide measured at Mauna Loa Observatory, Hawaii. The carbon dioxide data on Mauna Loa constitute the longest record of direct measurements of CO2 in the atmosphere. They were started by C. David Keeling of the Scripps Institution of Oceanography in March of 1958 at a facility of the National Oceanic and Atmospheric Administration (Keeling, 1976). NOAA started its own CO2 measurements in May of 1974, and they have run in parallel with those made by Scripps since then (Thoning, 1989) (NOAA, 2020).*

There are few studies based on probabilistic event attribution analysis to compare the difference between actual observed HRI mortality to the simulations based on natural scenario (Mitchell et al., 2016; Oudin et al., 2013). The impact of extreme temperature exposure on all-cause mortality was found to be doubled due to climate change (Oudin et al., 2013). As majority of literature on attribution analysis is focused on mortality, we focused our attention on morbidity using HRI ER visits as outcome.

1.2.A DETECTION AND ATTRIBUTION OF CLIMATE CHANGE

Determining the role that climate change has on extreme weather and climate events is an emerging scientific area of research, as indicated in the recent National Academy of Science report (National Academy of Sciences, 2016). Attribution analysis provides an opportunity to determine the role that climate change influences extreme weather events. This new and emerging field of extreme event attribution can assist other fields in identifying the impacts of climate change on their sectors (National Academy of Sciences, 2016).

Detection and attribution of climate change involves assessing the observed changes of the climate system through comparisons of climate models and/or observations using various statistical methods. Detection and attribution studies can determine if human-induced influence on climate variables (such as a temperature) varies from natural variability. Results from such studies can assist in decision making associated with climate policy and adaptation.

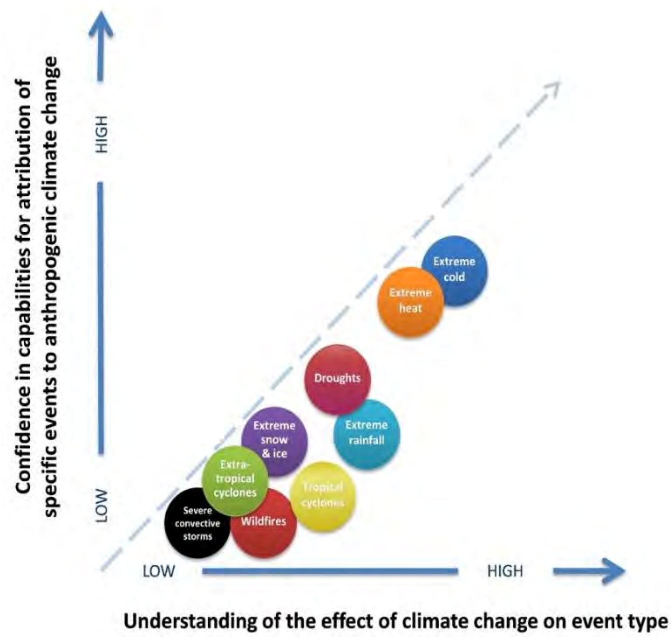


Figure 3. Diagram illustrates the evidence of anthropogenic climate change on various types of extreme weather and climate events. This work can assist in determining possible studies attribution and detection studies for actuarial work on impacts (National Academy of Sciences, 2016).

1.3 IMPACT OF EXTREME TEMPERATURE ON HUMAN HEALTH

A heatwave is an acute episode of consecutive days with temperatures exceeding a specific threshold (Mazdiyasni & AghaKouchak, 2015). In the United States, heatwaves are likely to result in more deaths than any other climate or weather-related disaster (NOAA, 2019). Heatwaves are expected to increase in intensity and frequency during the 21st century, and heatwave-related mortality is projected to increase in the United States (Anderson et al., 2018; Patz et al., 2014). About 30 percent of the current global population is exposed to extreme heat conditions, which is expected to increase to 50-75% by 2100 (Mora et al., 2017). The frequency of heatwaves was highest in the southeast region of the United States from 1979 to 2011 (Smith et al., 2013).

Human exposure to extreme heat often triggers a cascade of changes in the human body. The changes include depletion of water and electrolytes, abnormalities in cardiovascular, renal, hepatic, maternal, and coagulation functions (Atha, 2013). Additionally, it increases psychologic stress that could potentially trigger inflammatory responses (Danzl, 2018). Classic Heat-Related Illness (HRI) is an acute condition ranging from minor (edema, syncope, cramps, and exhaustion) to major (heat stroke) disorders (LoVecchio, 2016). Heat-related disorders could often be managed with public health mitigation plans or symptomatic care management and could lead to life-threatening conditions if untreated (LoVecchio, 2016; Nemer & Juarez, 2019). Furthermore, extreme heat, combined with different environmental drivers, could worsen the air quality that could increase the risk of adverse respiratory health outcomes (Nolte, 2018).

1.4 FACTORS INFLUENCE HUMAN HEAT EXPOSURE

There are multiple extrinsic and intrinsic factors associated with extreme heat exposure that could amplify heat-related morbidity and mortality. The extrinsic factors (e.g., urban housing) and intrinsic factors (e.g., individual's demographics, socioeconomic status, and pre-existing medical conditions) play a crucial role in exacerbating the vulnerability to HRI (Levy & Patz, 2015; McMichael et al., 2008). The majority of the world's population live in urban communities. Individuals living in urban communities are more vulnerable to HRI than those in rural communities, due to the urban heat island effect (UHI) and other societal factors. UHI is a common situation where the surface temperature in urban communities is higher than nearby rural regions (Zhao et al., 2014).

1.5 MORBIDITY AND MORTALITY IN THE U.S.

About 1.9 per 100,000 population per year were hospitalized due to heat-related illnesses. This was reported in 20 states of the United States during the summer seasons of 2001 - 2010 (Choudhary, 2014). About 658 deaths per year were reported due to excess heat exposure in the United States from 1999 – 2009. The mortality rate was higher in the elderly male population with peak death rate in July and August (David R. Fowler., 2013). In Florida, over eight years (2005-2012), 33.1 per 100,000 person-year emergency room visits, 5.9 per 100,000 person-year hospitalizations, and 0.2 per 100,000 person-year deaths related to non-occupational HRI were reported. This was higher than occupational related morbidity and mortality (Harduar Morano, Watkins & Kintziger, 2016).

The direct effect of extreme heat exposure triggering HRI is an underestimate of adverse health outcomes, as extreme heat exposure could exacerbate multiple pre-existing conditions. A classic example from California accounted for up to 6-fold increase in HRI ER visits and 10-fold increase in HRI related hospitalizations during the 2006 summer (Knowlton et al., 2009). There was a significant increase in HRI, acute renal failure, nephritis, cardiovascular, diabetic, and electrolytic imbalance in the central Coastal region. The region has a higher number of children and elderly population, known to be more susceptible to extreme heat (Knowlton et al., 2009). Additionally, the cardiac and respiratory health outcomes worsened with the comorbid condition of HRI (Schmeltz et al., 2016).

In North Carolina, there are a higher number of heat-related emergency department visits in the rural regions than the urban metropolitan cities during the warmest months (observed higher temperature during the calendar year relative to the annual average) from May through September. Increased mobile homes and socioeconomic status were associated with an increased risk of the HRI (Kovach et al., 2015). In North Carolina, heat-related emergency department visits were higher when the maximum daily temperature was between 87.8 to 100.4 °F (Sugg et al., 2016).

1.6 COST ASSOCIATED WITH HEAT-RELATED ILLNESS

During 2001-2010, the median length of HRI hospital stays during the summer months in the past decade has been two days (IQR 1 – 3 days), with a median total hospital expenditure per admission of $ 8,965 (IQR $ 5,017 - $ 17,047) [IQR stands for Interquartile Range]. From the National Inpatient Sample, about 48.9% of the patient hospitalizations were with Medicare/Medicaid as the primary payer and 27.9% with private or health maintenance organizations. Additionally, the U.S. southern region accounted for 54.4% of the HRI hospitalizations (Schmeltz et al., 2016).

Section 2: Methods

This study evaluated the relationship between extreme temperature and emergency department visits due to heat-related illness. A statistical model was trained to predict HRI ER visits, using the observed HRI ER visit data observed during the summer months from 2011-2016 (excluding 2013). Using the developed model, HRI ER visits were estimated based on the natural simulations (estimated daily temperature assuming that there is no climate change). Additionally, the cost percentage difference from the observed to the natural scenario was estimated (assuming that there is no climate change).

2.1 STUDY AREA

This study is focused on the three principal physiographic divisions in North Carolina: Coastal plains, Piedmont, and Mountain regions *(Climate of North Carolina).* The Coastal region includes 41 counties, the Piedmont region has 34 counties, and the Mountain region has 25 counties *[Figure 4].*

The average temperature across the climate regions varies by at least 20 °F (*Climate of North Carolina*). The temperature variance across the state is minimal during the summer compared to the winter season. The warmest temperature in North Carolina is recorded in the Coastal region during summer. Coastal region's daily maximum temperature would record up to 92 °F (Goldsboro) and up to 68 °F at the top of Mt. Mitchell (*Climate of North Carolina*). The historic average annual precipitation was found to be higher in the Mountain region. The Coastal region contains geographic areas with both drier and wetter areas, whereas the Piedmont region is drier. The Coastal and Piedmont regions have larger geographic areas categorized as urban compared to the Mountain region.

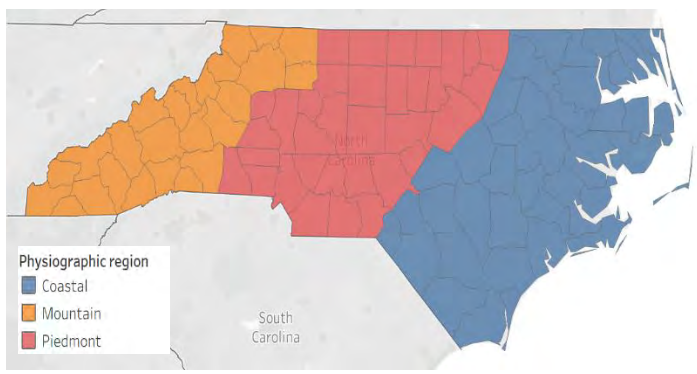


Figure 4. Physiographic divisions - North Carolina

2.2 CLIMATE DATA

Climate data were extracted from three different sources: 1- Global Historical Climatology Network – Daily (GHCN-D) dataset, 2-Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate data and 3-International CLIVAR Climate of the 20th Century Plus Detection and Attribution project. The exposure (temperature, relative humidity, and maximum apparent temperature) and outcome (heat-related illness emergency room visits) data was aggregated by three physiographic divisions in North Carolina.

The GHCN-D observations are based on ground observations (stations), and we extracted daily minimum, maximum, and mean temperatures for North Carolina from 2011 – 2016. The 28 heatwave definitions are based on the heatwave metric, the duration of the event and threshold intensity. They were adapted and modified from the literature. The heatwave definitions were based on heat metrics (maximum, minimum, and mean temperature), duration of events in two categories (event duration of 2 or more days / 3 or more days), and four percentile threshold values (90th, 95^{th,} 98th and 99th). The percentile threshold values are calculated using daily temperature values from 1895 – 2016 [Table 2].

Daily dewpoint temperatures were extracted from the PRISM database from 2011 – 2016 and calculated the relative humidity following the methodology explained by Alduchov and Eskridge (Alduchov et al.,1996). Maximum apparent temperature (MAT) was calculated from the dew point data and maximum daily temperature (Baccini, 2008). Additionally, the Steadman's heat index (Steadman_HI), National Weather Service (NWS) heat index, Thermal Distress Index (TDI), and Excess Heat Factor were computed for the study period.

For the purpose of the attribution analysis, historical natural simulations for the years 2011-2015 were obtained from the International CLIVAR Climate of the 20th Century Plus Detection and Attribution project (C20C +D&A) (Stone et al., 2019). The historical natural simulations are the runs with the anthropogenic drivers maintained at pre-industrial values. They simulate weather under boundary conditions that would have been expected in the absence of anthropogenic interference (Stone et al., 2019). The C20C and D&A project is designed to address concerns regarding the role of human interference in historical and current extreme weather. For the purpose of this project, we extracted maximum temperature and relative humidity from the Community Atmosphere Model (CAM5) outputs with the global average grid size of 580 km^2. Using the CAM5 gridded data, the aggregate daily maximum temperature and relative humidity data was computed by physiographic region in North Carolina.

2.3 HEALTH DATA

The data on heat-related illness emergency room (ER) visits was obtained from NC-DETECT, maintained by the North Carolina Division of Public Health (NC DPH). There are 124 hospitals in North Carolina participating in the NC-DETECT program ("Participating Hospitals," 2020). The dataset contains ER visit count by day from 2011 – 2016, during the summer season (May 01 – Sep 30). About 7.4% of Coastal records, 5.4% of records from Piedmont, and 36.6% of the Mountain region records were missing. The days with less than 5 ER visits were censored, so 34% (n=239) records from Coastal, 31% (n=220) from the Piedmont region were imputed to 3 ER visits. For the Mountain region, 49% (n=382) of the available data was suppressed, making Mountain data unreliable for training a statistical algorithm to estimate the ER visits. Due to large number (~85%) of missing and suppressed data, we excluded Mountain region from the analysis. The HRI ER cost data was obtained from the North Carolina DHHS, the cost value is the annual average medical expenditure spent towards HRI ER visits in 2019 based on Medicaid claims.

2.4 ANALYSIS

The working dataset contains information on daily timescale by physiographic region. The variables include a continuous measure of meteorological variables, multiple heat indices, and heatwave days recorded as a binary variable. The heatwave day classification based on different heatwave definitions is based on temperature/heat-index metric, percentile threshold value, and duration (listed in the appendix).

Descriptive statistics were conducted to compare the trend of ER visits between the two physiographic regions in North Carolina (Coastal and Piedmont). The annual rate of ER visits per day/100,000 population was calculated by region using population estimates from the 2010 Decennial Census. The analysis was conducted in three different steps

1. Epidemiologically evaluating the relationship between meteorological variables/heat-indices and HRI ER visits;

2. Evaluating the sensitivity of heatwave definitions towards estimate the HRI ER visits by region; and

3. Estimating the excess HRI ER visits and excess cost associated with anthropogenic climate change.

2.4.1 EPIDEMIOLOGIC EVALUATION

A Pearson correlation coefficient matrix was computed between variables to understand the association's magnitude and relationship between meteorological variables/heat-indices and HRI ER visits. The predictor variables and ER visits were non-linearly associated. The non-linear relationship between the top five variables highly correlated with HRI ER visits was evaluated using the Generalized Additive Model (GAM). The GAM model is one of the statistical methods to understand the non-linear relationship between continuous predictor variables and the outcome variable. The advantage with using GAM model approach is the relationship is based on the sum of smoothing functions of continuous predictor terms within the model.

2.4.2 HEATWAVE DEFINITION EVALUATION

As summarized in Table 2, 28 heatwave definitions were adapted from the literature identified to be sensitive for HRI morbidity/mortality. A majority of the studies that evaluated the heatwave definitions are based on a larger geographic area (combination of a few states as a group). In this study, the sensitivity of heatwave definitions were re-evaluated within the two subregions of North Carolina (Coastal and Piedmont). The analytic dataset contains a daily count of ER visits and a binary variable that describes if the day is a heatwave day according to each of the 28 heatwave definitions adopted in this study. To evaluate the sensitivity of heatwave definitions towards HRI ER visits, the negative binomial regression approach was used with the population as an offset term to account for population density. Additionally, based on the output from the negative binomial model, we ranked the sensitivity of heatwave definitions by region.

2.4.3 IMPACT OF ANTHROPOGENIC CLIMATE CHANGE ON HRI

The analyses in this report have been performed using two scenarios; (1) In the first analysis we used historical observed data and developed the model (section 2.4.1), (2) The second analysis is a repeat of first analysis with the historical natural data to exclude the human-induced role from our analysis. Using the statistical algorithm trained using the historical observed data (2.5.1), the ER visits were estimated per day by physiographic region in North Carolina. The excess HRI ER visits and the excess cost associated with HRI ER visits due to anthropogenic climate change was calculated. Comparing the two scenarios enables us to address the role that human-induced changes in our climate influences morbidity.

The total number of HRI ER visits during a heatwave day / non-heatwave day data was utilized to estimate the difference. Similarly, the number of HRI ER visits and the healthcare cost using the natural scenario simulation data was estimated using the GAM model. The difference between modeled and observed HRI ER visits was combined with the estimated healthcare cost associated with HRI ER visits based on actual observations to show the attribution of heatwaves due to anthropogenic climate change.

Section 3: Results

3.1 DESCRIPTIVE

The physiographic divisions are a group of counties with similar climate profiles but with different weather. The Coastal and Piedmont regions are significantly different in meteorological factors, population density, and population demographics. The Piedmont region contains a more significant number of cities, with a larger population size, than the Coastal region. Evaluating the relationship by physiographic region, even with the Mountain region excluded due to data withheld for privacy reasons, allows heatwaves and HRI ER visits to be better aligned. The summer of 2011 was the hottest in both the Coastal (maximum temperature (Tmax): 98.76°F) and the Piedmont regions (Tmax: 98.45°F). During the study period, July was the record hottest month in Coastal (Tmax: 98.76°F), and June was the hottest in the Piedmont (102.20°F) region. Whereas the annual rate of HRI ER visits was the highest during the summer of 2015 in Coastal (82.59 per 100,000) and Piedmont (45.69 per 100,000) [table.1]. In the Coastal region, the highest number of HRI ER visits (n=109) were observed on Jun 16, 2015 (Tuesday), the hottest day during the summer of 2015, with a record maximum temperature of 97.99 °F. Similarly, in the Piedmont region, the highest number of HRI ER visits (n=100) were observed on Jun 23, 2015 (Tuesday), with a recorded maximum temperature of 95.70°F. In both physiographic divisions in North Carolina, we observed 14 days starting from Jun 13 – Jun 27 in 2015 that exceeded a maximum daily temperature threshold of 90°F.

Table 1. The annual rate of HRI ER visits per 100,000

	2011	2012	2014	2015	2016
Coastal	57.71	50.05	35.46	82.59	54.52
Piedmont	39.12	33.66	19.00	45.69	45.22

*Rate = (observed HRI-ER visits / population) * 100,000*
Health data from year 2013 was not provided by the NC-DETECT

A similar pattern was observed anecdotally during the summer of 2012 and 2016, where the record highest number of ER visits were during the period where the daily maximum temperature exceed 90°F for a minimum of 10 consecutive days. We observed a higher rate of ER visits during the weekdays in both the physiographic regions in North Carolina. The rate of HRI ER visits was relatively higher during the weekdays while exposed to lower temperature compared to the weekends.

3.2 EPIDEMIOLOGIC RELATIONSHIP

To evaluate the relationship between extreme temperature and HRI ER visits, a stratified by physiographic divisions was conducted (Coastal and Piedmont).

3.2.1 COASTAL REGION

To evaluate the relationship, the correlation coefficient was calculated between all the meteorological/heat-indices (continuous) variables included in the study. Using a Pearson correlation coefficient matrix, the National Weather Service Heat Index (NWS HI) and daily maximum temperature were identified to be positively correlated with the rate of HRI ER visits (Figure 5-A). In Figure 5, the outcome of interest is the logarithmic rate of ER visits, with higher values representing stronger correlation with the independent variables included in the analysis. A non-linear pattern of association between

NWS_HI/maximum temperature and HRI ER visits was observed. To expand the analysis a non-linear regression approach was used in this study.

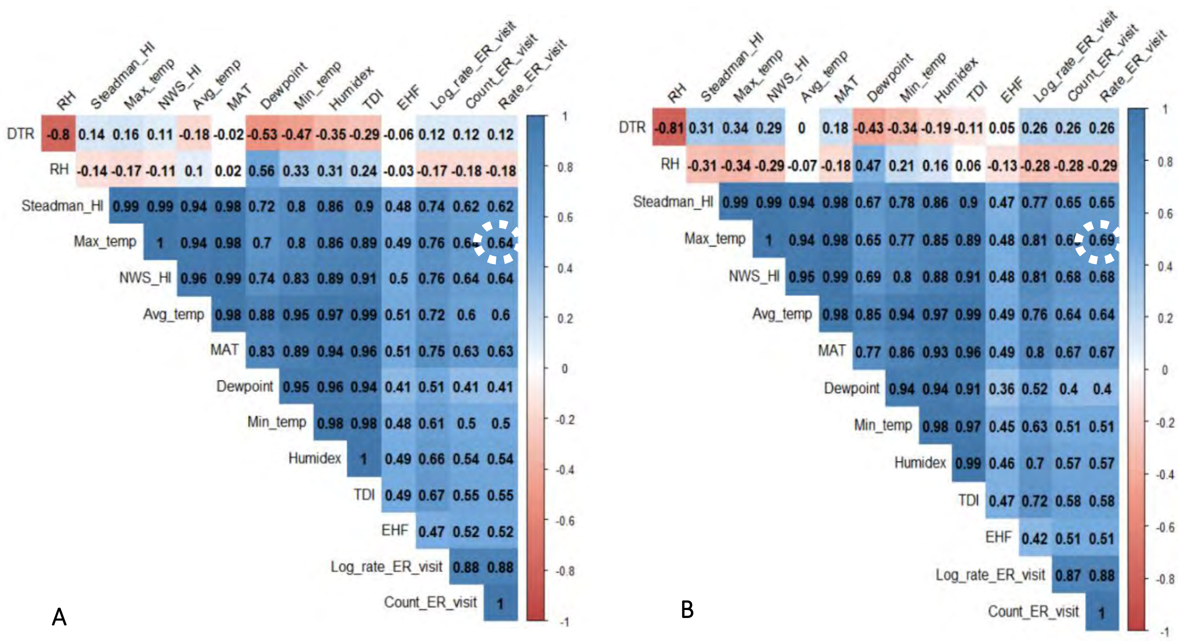


Figure 5. Association between meteorological variables/heat indices and HRI ER visits (A-Coastal & B-Piedmont). The above figure is a Pearson correlation coefficient matrix that allows us to understand the association between two continous variables. In this figure, we would like to highlight the correlation between daily maximum temperature and rate of HRI ER visits. The color bar represent the direction of association: red (negative association) and blue (positive association); darker colors represent stronger association. In this figure, we are interested to understand the association between the log rate of HRI ER visits and other indipendent variables included in the study.

To evaluate the non-linear association between NWS HI/maximum temperature and HRI ER visits, the GAM model with cubic regression splines and gamma distribution with log link feature was used. The performance of statistical models was compared using an ANOVA test and identified that the predictor variable maximum temperature has an optimum model fit to estimate the rate of HRI ER visits. A seasonal trend in HRI ER visits was observed. To decompose the trend, we used day of the week (DOW), month of the year, and year as covariates in the prediction model [Equation 1].

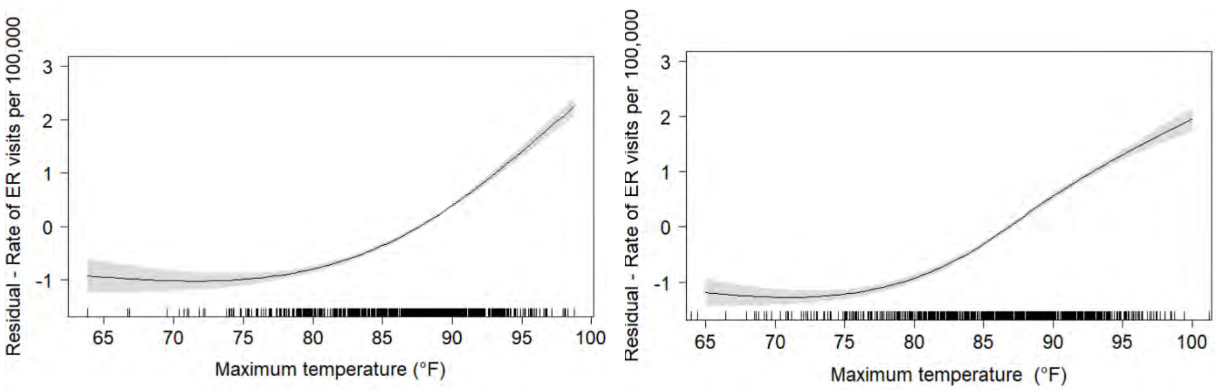
$$\log(\mathbb{E}[\text{Rate. ER visits}]) = \sum_{j=1}^{n} b_j\,(Tmax)\beta_j + \text{DOW} + \text{Month} + \text{Year} + \varepsilon \;\ldots(1)$$

In Equation 1, n is the number of splines, b represents the spline term, β represents coefficient specific to spline term and ε is the model error associated with the model. The model was built using three penalized cubic regression splines for daily maximum temperature variable (smoothing splines are optimized using Generalized Cross-Validation function), with an effective degree of freedom value of 1.99 demonstrating non-linear association. We optimized model performance using the GAM model diagnostic summary [Figure 6-A].

3.2.1 PIEDMONT REGION

Similar to the Coastal region, we estimated the Pearson correlation coefficient between meteorological variables/heat indices and HRI ER visits. The variables, NWS HI and daily maximum temperature were positively correlated with HRI ER visits [Figure 5-B].

A non-linear pattern between NWS HI/maximum temperature and HRI ER visits was observed. To evaluate the non-linear association between the NWS HI/maximum temperature and HRI ER visits, the GAM model with cubic regression splines was used. The performance of the statistical models was compared using the ANOVA test and identified that using daily maximum temperature as a predictor to estimate the rate of HRI ER visits has an optimal fit. To decompose the time-series trend, the day of the week (DOW), the month of the year and year were used as covariates in the prediction model [Equation 1].



A

B

Figure 6. Relationship between maximum temperature and HRI ER visits (A-Coastal & B-Piedmont). This is a plot generated using the GAM model to visually represent the relationship between daily maximum temperature and HRI ER visits. The x-axis reperesnt daily maximum temperature in Fahrenheit and the y-axis represent residual rate of ER visits (difference between actual and estimated) From this plot we could observe an exponential trend. The lines on the x-axis represents number of observations, which explains the width of the confidence intervals (less number of observations could result wider confidence intervals).

The model was built using four penalized cubic regression splines for the daily maximum temperature variable (smoothing splines are optimized using Generalized Cross-Validation function), with an effective degree of freedom value of 2.95 demonstrating non-linear association [Figure 6-B].

3.3 HEATWAVE SENSITIVITY ANALYSIS

To evaluate the sensitivity of heatwave definitions in North Carolina, 28 Heatwave definitions were adapted from peer-reviewed literature. The heatwave definitions were based on a meteorological variable, variable threshold, and duration. Additionally, relative and absolute heatwave definitions were included based on extreme, high, and moderate threshold values. [Equation 2]

$$\log(\#HRI\ ER\ visits) = \beta_0 + \beta_1 \left(\mathrm{HW_{day}}\right) + \ln(\text{population}) + \varepsilon \quad \ldots (2)$$

Table 2. Sensitivity analysis - Heatwave definitions by physiographic regions in North Carolina

Heatwave definition	Temperature metric	Threshold	Duration (days)	Type	Reference	Coastal threshold (°F)	Coastal IRR (95% CI)	Coastal rank	Piedmont threshold (°F)	Piedmont IRR (95% CI)	Piedmont rank
HI_01	Mean daily temperature	>99th	2+consecutive	Relativ	Smith et al	84.49	0.68 (0.50-0.94)	25	83.11	4.40 (3.31-6.00)	4
HI_02		>99th	3+consecutive	Relativ	Smith et al		0.66 (0.46-0.96)	26		3.98 (2.83-5.82)	9
HI_03		>98th	2+consecutive	Relativ	Anderson/Vaidyanathan	83.43	4.21 (3.50-5.10)	2	81.97	3.83 (3.15-4.70)	17
HI_04		>98th	3+consecutive	Relativ	Anderson/Vaidyanathan		3.92 (3.16-4.92)	11		3.92 (3.15-4.95)	11
HI_05		>95th	2+consecutive	Relativ	Anderson/Vaidyanathan	81.76	3.92 (3.44-4.50)	12	80.06	3.85 (3.40-4.37)	15
HI_06		>95th	3+consecutive	Relativ	Anderson/Vaidyanathan		3.99 (3.48-4.60)	9		3.91 (3.42-4.48)	12
HI_07		>90th	2+consecutive	Relativ	Anderson/Vaidyanathan	79.89	3.60 (3.25-	15	78.14	3.73 (3.37-4.13)	18
HI_08		>90th	3+consecutive	Relativ	Anderson/Vaidyanathan		3.60 (3.25-4.00)	16		3.72 (3.36-4.13)	19
HI_09	Maximum daily temperature	>99th	2+consecutive	Relativ	Smith et al	95.08	0.84 (0.59-1.25)	23	95.94	4.34 (3.07-6.38)	6
HI_10		>99th	3+consecutive	Relativ	Smith et al		0.45 (0.29-0.73)	28		3.90 (2.56-6.29)	13
HI_11		>98th	2+consecutive	Relativ	Anderson/Vaidyanathan	93.76	4.13 (3.26-5.31)	4	94.45	4.40 (3.45-5.73)	3
HI_12		>98th	3+consecutive	Relativ	Anderson/Vaidyanathan		4.06 (3.10-5.44)	7		4.62 (3.54-6.17)	1
HI_13		>95th	2+consecutive	Relativ	Anderson/Vaidyanathan	91.64	4.02 (3.51-4.63)	8	91.94	3.90 (3.39-4.50)	13
HI_14		>95th	3+consecutive	Relativ	Anderson/Vaidyanathan		4.09 (3.51-4.79)	5		3.94 (3.35-4.65)	10
HI_15		>90th	2+consecutive	Relativ	Anderson/Vaidyanathan	89.55	3.78 (3.41-4.19)	14	89.50	3.87 (3.48-4.30)	14
HI_16		>90th	3+consecutive	Relativ	Anderson/Vaidyanathan		3.79 (3.41-4.22)	13		3.84 (3.45-4.29)	16
HI_17		> 35°C	1day	Absolu	Smith et al	95.00	4.28 (3.21-5.87)	1	95.00	4.61 (3.56-6.09)	2
HI_18	Minimum daily temperature	>99th	2+consecutive	Relativ	Smith et al	74.96	0.72 (0.52-1.01)	24	71.35	2.91 (2.28-3.77)	21
HI_19		>99th	3+consecutive	Relativ	Smith et al		0.46 (0.32-0.68)	27		2.72 (2.02-3.74)	27
HI_20		>98th	2+consecutive	Relativ	Adapted/revised	74.05	3.60 (2.96-4.44)	17	70.52	2.73 (2.28-3.30)	26
HI_21		>98th	3+consecutive	Relativ	Adapted/revised		3.17 (2.53-4.03)	20		2.79 (2.28-3.46)	25
HI_22		>95th	2+consecutive	Relativ	Adapted/revised	72.63	3.33 (2.89-3.86)	19	69.15	2.83 (2.47-3.24)	24
HI_23		>95th	3+consecutive	Relativ	Adapted/revised		3.50 (3.01-4.09)	18		2.98 (2.59-3.44)	20
HI_24		>90th	2+consecutive	Relativ	Adapted/revised	70.96	2.95 (2.64-3.31)	22	67.51	2.89 (2.58-3.25)	22
HI_25		>90th	3+consecutive	Relativ	Adapted/revised		2.97 (2.65-3.34)	21		2.84 (2.52-3.20)	23
HI_26	Maximum daily apparent temperature	>95th	1 day	Absolu	Steadman	98.99	4.09 (3.20-5.31)	6	98.99	4.35 (3.24-6.02)	5
HI_27		>90th	1 day	Absolu	Steadman	97.16	4.18 (3.55-4.95)	3	97.16	4.15 (3.41-5.11)	7
HI_28		>85th	1 day	Absolu	Steadman	95.85	3.97 (3.49-4.54)	10	95.85	4.07 (3.52-4.73)	8

Model: Dependent variable = count of ER visits | Independent variable = Heatwave definition | Offset term = population

Interpretation: The incidence of HRI ER visits during a heatwave day (based on HI_01 to HI_28), increased by IRR times per day compared during the non-heatwave days

Heatwave definitions were tested by physiographic division in North Carolina. The analytic dataset includes the daily aggregate count of HRI ER visits (outcome variable) with the population as an offset term, and every day in the summer during the study period was classified as heatwave or non-heatwave day using multiple heatwave definitions (predictor variable). To understand the relative risk attributable to individual heatwave definition, the negative binomial regression approach was used [Equation 2] to estimate the incidence risk ratio along with a 95% confidence interval.

Using an absolute threshold was found to be highly sensitive (higher probability of HRI ER visits during heatwave days) to identify HRI ER visits in both Coastal and Piedmont regions compared with other heatwave definitions available in the literature [Table. 2]. The incidence risk ratio (probability of an individual visiting the ER due to HRI during a heatwave day) was 4.28 times higher (95% CI 3.21-5.87) in the Coastal region and 4.61 times higher (95% CI 3.56-6.09) in the Piedmont region during a heatwave day based on the definition with an absolute threshold where temperature maximum is greater or equal to 95°F in a day. Based on this observation, using the above-mentioned heatwave definition would effectively minimize the HRI ER visits during extremely heat vulnerable days in North Carolina [Figure 7].

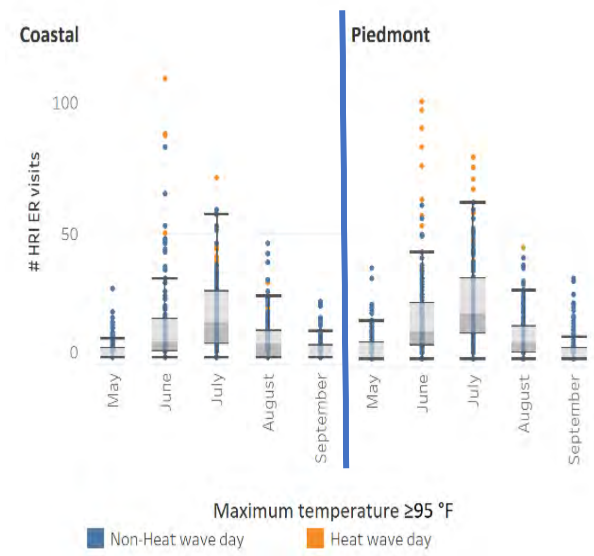


Figure. 7 Heatwave definition sensitivity

This box plot shows the distribution of HRI ER visits during the study period, by physiographic division in NC. Each dot represents HRI ER visits per day. The orange dots are a count of ER visits during a heatwave day (daily maximum temperature >= 95°F) and the blue dots represent a count of ER visits during non-heatwave days. In Figure 6, we highlight the finding from heatwave sensitivity analysis, that using heatwave definition using absolute threshold of daily maximum apparent temperature greater or equal to 95°F, could effectively minimize the extreme HRI ER visits.

3.4 IMPACT OF ANTHROPOGENIC CLIMATE CHANGE ON HRI

Figure 7 shows the maximum temperature probability distribution under the observed historical (Observed) and non-anthropogenic historical conditions (Natural). The plot shows that the probability of extreme hot days is higher in the actual observations than the natural simulations in both the Coastal and Piedmont regions [Figure 8]. Additionally, we estimated the rate of HRI ER visits during natural scenario by physiographic region in North Carolina for year 2011, 2012, 2014 and 2015 using the GAM model (equation 1), trained using the actual observations.

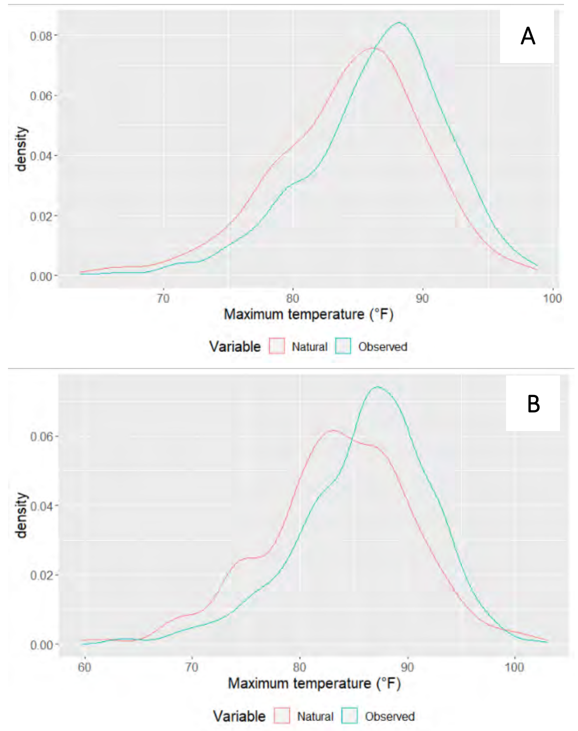


Figure. 8 Probability distribution of the daily maximum temperature for historically observed and non-anthropogenic (Natural) simulations for (a) costal and (b) Piedmont regions. (summers of 2011-2016)

A decrease in the pattern of HRI ER visits was observed during the natural scenario compared to the actual observed values [Figure 9]. Fewer HRI ER visits was consistent across the months during the study period. In the Coastal region during the summer of 2011 and 2015 there are a frequent number of days with a greater difference between the observed ER visits and ER visits estimated using natural simulations. In Piedmont the range of difference between observed and estimated ER visits using natural simulations was narrower compared to the Coastal region.

Using the heatwave definition from the sensitivity analysis, "daily temperature maximum greater or equal to 95°F in a day" would effectively detect the majority of the peaks in the rate of anomalies during the study period [Figure 9]. In the Coastal region, using the heatwave definition "temperature maximum greater or equal to 95°F threshold could reduce the HRI ER visit related expenditure by 11.43%. Similarly, in Piedmont region we could reduce an average of 15.81% of the healthcare cost spent towards HRI ER visits. Additionally, we estimated that an excess of 25.19% of the cost

Table 3. Healthcare cost by physiographic division

Region	Measure	Avg. Count	Avg. Cost	Percent difference	Avg. healthcare cost
Coastal	Observed	11.63	1239.40 (V1)		
	Estimated	8.70	927.15 (V2)		
				-25.19 (X1)	
Piedmont	Observed	14.20	1513.29 (V1)		
	Estimated	10.32	1099.80 (V2)		
				-27.32 (X2)	
North Carolina					= [(X1+ X2)/2] = [(25.19 + 27.32)/2] = 26.25

Observed – Actual ER visit count
Estimated – Calculated assuming non-anthropogenic climate change [Natural]

related to HRI ER visits in Coastal and 27.32% Piedmont region could be attributed to anthropogenic climate change (percentage difference calculation available in appendix) [Table 3.].

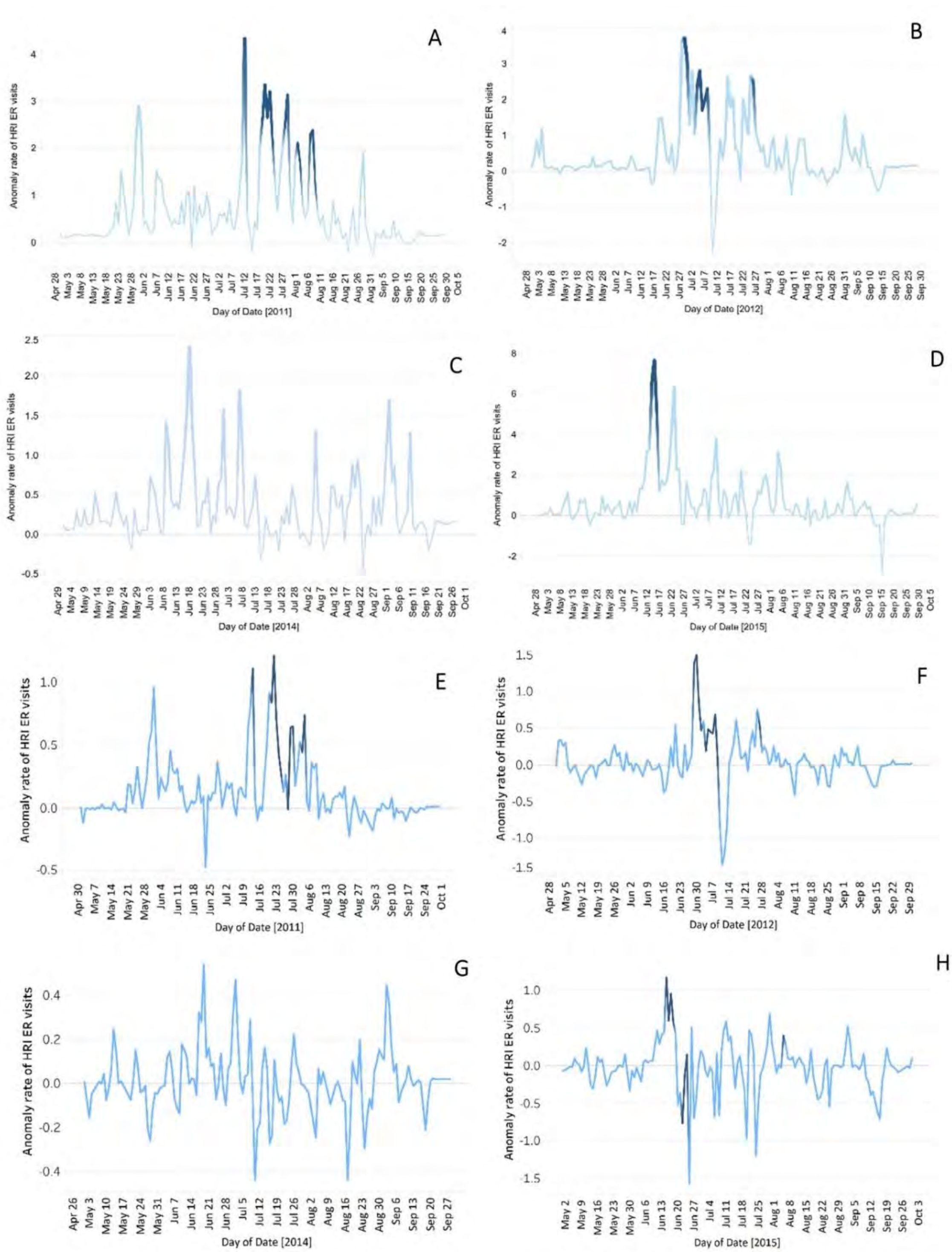


Figure. 9 HRI ER Anomaly – North Carolina [A,B,C,D – Coastal | E,F,G,H - Piedmont]; Anomaly = (observed rate HRI ER visits – Estimated ER visits using natural simulation)

Section 4: Conclusion

The purpose of this study was to demonstrate a methodology to understand the relationship between extreme heat exposure and heat related illness ER visits using North Carolina data as a template that could be used elsewhere. This study consisted of an evaluation of the epidemiologic relationship between extreme heat exposure and HRI ER visits, a sensitivity analysis on heatwave definitions available from the literature, and a climate attribution analysis (includes morbidity and cost analysis). The meteorological variable "daily maximum temperature" was determined to be best suited for estimating the HRI ER visits compared to other meteorological variables and heat indices evaluated in the study. The results also indicate that using the heatwave definition "daily temperature maximum greater or equal to 95 °F in a day" was more effective at identifying HRI ER visits during the summer season compared to existing early warning systems in the Coastal and Piedmont regions of North Carolina. The Mountain region was not included since daily ER visits below three for a hospital were suppressed, leaving insufficient data to draw conclusions.

The results from this report also show that human induced climate change likely caused a 26.25% increase in healthcare expenditure spent towards HRI ER visits in North Carolina [Table 3]. Actuaries can use the framework of this report to identify health impacts from heat events and determine excess burden that human-induced climate change has on health impacts and cost on their coverage areas. Similar work can be done for other fields to determine current costs of climate change on human health. This report, along with the GitHub repository, was created to help actuaries perform similar analysis for their work.

Section 5: Strength and Limitations

The study is based on a syndromic surveillance database that covers all the HRI ER visits (not a sample-based study) in North Carolina during the summers of the study period. We covered a longer timeframe (~5 years), containing daily observations, which aligns with the structure of the temperature data. We have used the physiographic divisions in North Carolina, instead of traditional geographic boundaries, which is significant while evaluating the relationship between temperature and health outcomes. We have tested the relationship with the lag temperature terms and did not identify significant relationships. To evaluate the relationship between exposure and outcome, we have used the generalized additive model, which is robust to evaluate non-linear relationships.

The major limitation of the study is the exposure assessment. The meteorological variables / heat indices are not personal measurements. Instead, we have used weather station ground observations as a proxy. The daily HRI ER visit data received from the NC DETECT syndromic surveillance database, contain censored information to protect the patient privacy according to the Health Insurance Portability and Accountability (HIPPA) regulation. The daily HRI ER daily visit data that contain less than five visits per day by physiographic region are censored. As a result of censoring, about 85% of the HRI ER visit data from the Mountain region was missing. Due to missing and censored data, we excluded the Mountain region for the analysis. Additionally, the health care cost was estimated using the average Medicaid HRI ER visit expenditure in 2019.

Section 6: Recommendations to reduce health outcomes from extreme heat

The following recommendations (6.1 and 6.2) come from the CDC

6.1 PUBLIC HEALTH ACTIONS

- Educating communities on heat health related illnesses (symptoms, when to consult a physician)
- Providing designated cooling shelters during the summer season
- Promoting community participatory events on planting tree in urban heat islands.

6.2 INDIVIDUAL

- Applying sunscreen at least 30 minutes prior to the exposure to sunlight.
- Drinking more fluids, despite of thirst or engagement in an activity.
- Avoid drinking alcoholic and high sugar beverages.

6.3 ADDITIONAL HEAT HEALTH RESOURCES

- CDC: https://www.cdc.gov/nceh/features/extremeheat/index.html
- https://nihhis.cpo.noaa.gov/
- https://www.weather.gov/rah/heat
- https://www.ready.gov/heat
- https://www.who.int/globalchange/publications/heat-and-health/en/

Section 7: Future direction

The methods and framework from this report are designed to assist actuaries to calculate the impacts of extreme weather and climate events on human health outcomes. This report provides actuaries a methodology to use attribution and detection analysis in identifying the excess health burden from historical climate change on extreme events. The concepts in this report are focused on extreme temperature due to the strongest evidence linking it to climate change. However, this framework could be adjusted for other extreme events. As extreme heat likely kills more people every year than any other climate or weather-related event, the research also provides a framework to define heatwave sensitivity for other locations outside the study area. This document also serves as a way to estimate excess morbidity that leads to medical resource burden and preventable healthcare costs. By following the methods in this report, actuaries could replicate this project to understand the costs of human-caused climate change on other health data sources. Additionally, actuaries could use similar frameworks to understand the impact of climate change on other health outcomes (motor vehicle crash, depression, maternal health outcomes, etc.) or evaluating other extreme events.

Section 8: Acknowledgements

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- Julia Lerche – NC Medicaid (Provided healthcare cost data)
- Daithi Stone – University of Wellington (Provided temperature – natural simulation data)
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- Adam Watts
- Sara Goldberg
- Emily Dougherty
- Rebecca Owen
- Julia Lerche

At the Society of Actuaries:

- Scott Lennox
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- Erika Schulty

Appendix:

The model summary for Coastal region include AIC : 189 ; R-sq (adj) : 78 ; deviance explained : 78.4% and GCV : 0.1843. Similarly, for Piedmont the diagnostics include AIC: -1779; R-sq (adj): 76.8; deviance explained: 80.8% and GCV: 0.1879.

To maintain research reproducibility, we documented the data frame properties and the R-code that we have used to generate the results. Additionally, any changes related to the analysis will be updated periodically. GitHub link: https://github.com/jagadeeshpuvvula/Heatwave-study

GAM model summary:

Coastal Region

```
Family: Gamma
Link function: log

Formula:
imp_rate ~ s(Max_temp, k = 3, bs = "cr") + dow + month +   year

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.69228    0.06937 -24.394  < 2e-16 ***
dow2         0.21116    0.06348   3.326 0.000926 ***
dow3         0.33835    0.06365   5.316 1.43e-07 ***
dow4         0.41368    0.06383   6.481 1.74e-10 ***
dow5         0.37877    0.06372   5.944 4.42e-09 ***
dow6         0.11606    0.06369   1.822 0.068860 .
dow7         0.32919    0.06412   5.134 3.70e-07 ***
month6       0.14727    0.05992   2.458 0.014229 *
month7       0.13571    0.06478   2.095 0.036529 *
month8      -0.07159    0.06009  -1.192 0.233865
month9      -0.12350    0.05835  -2.117 0.034655 *
year2012     0.13208    0.05432   2.432 0.015290 *
year2014     0.10086    0.05544   1.819 0.069328 .
year2015     0.51136    0.05341   9.575  < 2e-16 ***
year2016     0.40283    0.05358   7.518 1.74e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df     F p-value
s(Max_temp) 1.995      2 508.9  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R-sq.(adj) =   0.78   Deviance explained = 78.4%
GCV = 0.18653  Scale est. = 0.19875   n = 704
```

Piedmont Region

Family: Gamma
Link function: log
Formula: imp_rate ~ s(Max_temp, k = 4, bs = "cr") + dow + month + year

Parametric coefficients:

```
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.89360    0.06413 -29.529  < 2e-16 ***
dow2        0.16088    0.06056   2.656 0.008076 **
dow3        0.19780    0.05955   3.321 0.000942 ***
dow4        0.15663    0.05978   2.620 0.008978 **
dow5        0.15425    0.05955   2.590 0.009794 **
dow6        0.07769    0.05960   1.303 0.192864
dow7        0.37400    0.05962   6.273 6.19e-10 ***
month6      0.07053    0.05613   1.257 0.209339
month7      0.04138    0.05971   0.693 0.488528
month8     -0.29223    0.05575  -5.241 2.11e-07 ***
month9     -0.31797    0.05315  -5.982 3.51e-09 ***
year2012    0.03454    0.05097   0.678 0.498213
year2014   -0.15769    0.05234  -3.013 0.002684 **
year2015    0.24904    0.05018   4.963 8.72e-07 ***
year2016    0.24925    0.04976   5.009 6.94e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
              edf Ref.df     F p-value
s(Max_temp) 2.959  2.999 505.5  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.768   Deviance explained = 80.8%
GCV = 0.18792  Scale est. = 0.18291   n = 719
```

Avg. cost = Avg. count * 106.57 (cost value obtained from NC Medicaid)

Coastal cost difference calculation:
=((V2−V1)/|V1|)×100
=((927.15−1239.4)/|1239.40|)×100
=(−312.25/1239.4)×100
=−0.251936×100
=−25.1936%change
=25.19% decrease

Piedmont cost difference calculation:

$=((V2-V1)/|V1|)\times 100$

$=((1099.8-1513.29)/|1513.29|)\times 100$

$=(-413.49/1513.29)\times 100$

$=-0.273239\times 100$

$=-27.3239\%$change

$=27.32\%$ decrease

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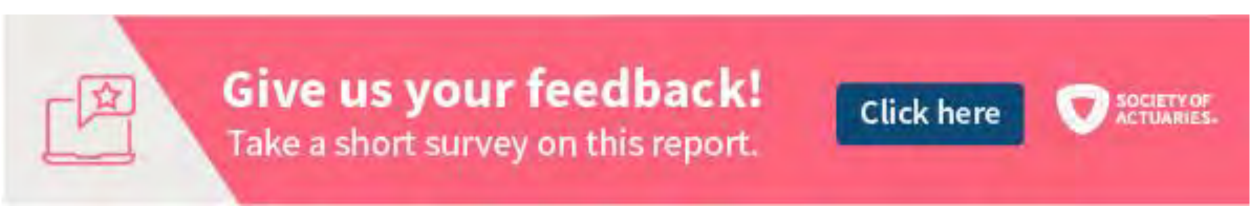
Feedback



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