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Relationships between heat alerts, extreme heat days, and heat related mortality within the contiguous United States over the last decade

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A gap of knowledge lies within the hazard of extreme heat within the United States and the public's response and perception of their own vulnerability. Even with constant communication from meteorologist at the National Weather Service and within the broadcast industry, there are still ongoing issues which include the possibility that ambient air temperature from fixed sites do not accurately reflect what the general population is experiencing, that the thresholds for excessive heat warnings are not appropriate, and that the most vulnerable individuals do not have the knowledge, and/or ability to protect themselves when extreme heat does occur. Assessment of the spatial pattens of heat alerts across the United States, mortality risks associated with extreme heat, and days above alert thresholds between 2010 to 2021 will be utilized to exhibit cities and regions where thresholds could be inappropriate and to reveal the most vulnerable between regions within this period.

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CHAPTER I

INTRODUCTION AND BACKGROUND

In the Unites States, there have been more deaths traced back to heat than to any other weather phenomenon over the past 30 years (National Weather Service, 2021). However, there is a gap in knowledge of the danger and health impacts of heat and the population's perception and response to it. National Weather Service forecasters, broadcasters, emergency managers, and health officials are constantly pressing information out to the public when warnings do occur within their specific viewing areas. Communication is evolving with stronger warning language and sense of urgency, but additional issues include the possibility that the thresholds for excessive heat warnings are not appropriate, that ambient air temperature from fixed sites do not accurately reflect what the general population is experiencing, and that the most vulnerable individuals do not have the knowledge, resources, and/or ability to protect themselves from extreme heat. By looking at the frequencies of heat advisories and warnings in different regions across the U.S. and comparing them to the frequencies of heat-related deaths and extreme heat index values, the effectiveness of heat alerts can be assessed.

Heat advisories, watches, and warnings provided by National Weather Service (NWS) Weather Forecast Offices (WFOs) are not only issued in response to daytime high temperatures and humidity. Multiple factors like the time of year, power outages, dry heat, large outdoor gatherings, and nighttime temperatures are also considered (Hawkins et al., 2017). As a result, it is imperative that forecasters understand the intricacies of not just the weather but also the county warning area. Since these factors vary from one region to the next, the criteria required to officially issue a warning or advisory should be flexible. Through the Hazards Simplification Project, the NWS has adjusted its approach to clearly and effectively informing the public, including allowing individual WFOs to set their own criteria for heat warnings and watches (Hawkins et al., 2017). Indeed, each WFO has the jurisdiction to assign their own heat alert criteria to better account for local variations in weather conditions and population vulnerability. The local criteria can also be modified. For example, WFOs in the New England region lowered their heat advisory criteria in 2017 in response to a study conducted by the Northeast Regional Heat Collaborative, which found that the heat index thresholds used did not capture most of the heat-related emergency department visits and deaths in the region. They found that lower thresholds were needed to account for the relative lack of physiological adaptation and inadequate infrastructure to mitigate the effects of extreme heat (NWS, 2017). Ultimately, these WFOs changed their heat advisory criteria from a heat index of 95ºF to 99 °F for 2 consecutive days or 100ºF to 104ºF for any duration, to a heat index of 95ºF to 104ºF for 2 or more consecutive hours.

Most of the Unties States currently still uses maximum daytime air temperature and heat index for their criteria thresholds, along with the additional factors previously mentioned, but the western half of the country has taken a shift into a new forecasting tool called ‘Heat Risk’. This prototype forecasting procedure uses colors and numbers to identify the corresponding level of heat risk. It also pinpoints groups who could have a higher risk within the specific levels. Significance above normal temperature, time of year, duration of heat event, and if temperatures are at levels that elevate the risk of heat illness are all considered to produce levels/categories (NWS HeatRisk Prototype; ‘Overview’, ‘What’s In HeatRisk?). HeatRisk began in 2013 with the

California Office of Emergency Services collaborating with the NWS's western regional headquarters about producing a different heat alert tool. Because of the mountainous terrain, valleys and coastal area of California, advisory and warning thresholds across the state were not consistent. By using the 'HeatRisk' prototype, one tool could be used for the entire state. The tool has been available since 2014 to the Western United States. The usage continues to increase to other surrounding areas of the western part of the Unites States. Much of the state of Colorado now obtains heat alerts issued with this tool which began in 2019 when the NWS WFO in Boulder, Grand Junction and Pueblo all decided to adopt it (Hawryluk, 2022). The 'HeatRisk' tool is expected to expand its usage and availability nationally within 2023 (NWS HeatRisk Prototype; 'Overview').

While accurate forecasts are important, the public must also understand how to use this information to mitigate adverse health effects. Resources are available through the Centers for Disease Control and Prevention and the National Oceanographic and Atmospheric Administration that include guidance on heat mitigation strategies such as avoiding alcohol, wearing lightweight clothing, and drinking regularly even when not thirsty (Hajat et al., 2010). Heat-related health effects are entirely preventable if accurate and timely forecasts and appropriate resources reach vulnerable individuals. Through the Hazards Simplification Project, the NWS has adjusted its approach to clearly and effectively informing the public, including allowing individual WFOs to set their own criteria for heat warnings and watches (Hawkins et al., 2017). Risk perception naturally changes in the summer months, with some people believing they are more prepared and immune, which then leads to ignoring and not acting in response to heat warnings (Sheridan, 2010). Within heat warning systems (HWS), guidance on effective communication is not always straightforward, and each WFO must communicate in ways that target their geographical region and motivate individuals to change behaviors (Toloo et al., 2013).

The issuance of heat warnings, watches or advisories can be in response to heat waves. Heat waves are weather events associated with temperature extremes that often lead to significant public health and socioeconomic impacts (Robinson, 2001). There are no formal criteria for defining a heat wave, though most studies and organizations use relative or absolute temperature thresholds over a specific period. Likewise with heat watches and warnings, the NWS has national standards but enables individual offices to produce unique thresholds based on local variability and climate (Robinson, 2001). Excess mortality resulting from heat waves can be substantial. In August of 2003, much of Europe experienced nine consecutive days with maximum temperatures 11 to 12º F higher than the seasonal average. In France alone, this heat wave resulted in 14,729 excess deaths, which corresponds to an excess mortality of 55% (Fouillet et al., 2006). In the United States, one of the most historic heat waves occurred across the Midwest region in July 1995, which claimed at least 700 excess deaths in the city of Chicago (Semenza et al., 1996).

The impacts from heat waves are generally related to their intensity and duration. For example, Anderson and Bell (2011) found that for every 1ºF increase in heat wave intensity, mortality increased by 2.49%. Mortality also increased by 0.38% for every 1-day increase in heat wave duration. In terms of heat-related morbidity, Abasilim and Friedman (2021) found that cases of heat stroke in Illinois between 2013 and 2019 were four times higher during heat waves compared to non-heat wave days. It is expected that heat waves will become more frequent and longer lasting in the future, resulting in even greater excess mortality unless adaptation and mitigation strategies are implemented (Habeeb et al., 2015). The success of these strategies will be due in large part to the effectiveness of heat forecasts and warnings and the ability to communicate this information to vulnerable populations.

Understanding the geographical variation in public perception of heat risks is critical to assess ways to increase public awareness during dangerous heat waves. Though some may perceive the South as a region of lower awareness of heat risk due to an already warm climate ("we're used to it"), a study by Howe et al. (2019) found that the southern U.S. actually has the highest heat risk perception, meaning individuals in this region believe they are likely to experience a heat wave, that the heat wave would affect them, their family and community, and worry about the negative effects it would bring. Beyond a person's location, other factors such as age and race can affect one's vulnerability and perception of heat waves. For example, Howe et al. (2019) found that communities with citizens over 65 years old exhibited lower heat-risk perception despite being one of the more vulnerable populations. In contrast, populations with higher African American, Hispanic, and Latino citizens tend to have a higher heat-risk perception (Howe et al., 2019). Social indices, indicating higher or lower vulnerability levels, can be combined with climate indices to indicate areas where heat mitigation strategies and resources should be targeted. Such information could be incorporated into projections of both population and heat wave characteristics to assess future public health risks from extreme heat. Such a study was conducted in Quebec, Canada and found increased risk from extreme heat resulting from future changes in demographics and heat waves (Vescovi, 2005).

Past studies have documented an apparent disconnect between the awareness of the heat hazard, perception of risk, and resulting behavioral modification. Sheridan (2006) surveyed residents in four cities in North America and found that most respondents were aware of a heat wave taking place but did not perceive themselves to be vulnerable and therefore did not make any behavioral adjustments. Moreover, the public struggled to differentiate between a formal heat warning and a common understanding that it would simply be “hot outside.” And, while they showed awareness of the need to stay hydrated and/or stay inside, they showed little awareness of the risk associated with overexertion. It was recommended that the local media receive additional training on the heat hazard to increase awareness of the factors that make people vulnerable, including poverty, lack of education, excessive outdoor labor (Sheridan 2006).

Variations in perception to heat may also be reflected in the patterns of heat-related mortality over time. In recent decades, there has been a general decline in heat-related mortality in the U.S., which is likely due to the increase of higher education, evolution of heat warning systems, and the ubiquity of air conditioning (AC) (Sheridan et al. 2021). An examination of four U.S. cities (Chicago, Detroit, Minneapolis, and Pittsburgh) from 1980-1985 found that the rate of heat-related mortality was 42% lower among individuals with a central AC unit compared to those without one (O’Neill et al., 2014). Lack of AC is an important contributor to heat-related health effects and was also recognized during the 1995 heat wave in Chicago. Many of those who died had medical conditions and were socially isolated and did not have access to AC (Semenza et al., 1996). Mobility, affordability of electricity, social contracts, and personal security all impacted whether people in Chicago had the means to cool their home, whether through AC or opening windows to improve air flow (Klinenberg, 2015). When considering external factors that affect vulnerability, such as social or environmental vulnerability, social isolation, being elderly and/or being diabetic, the lack of AC exhibits the greatest spatial variation across the U.S. Also, regions with the highest AC prevalence tended to have the lowest vulnerability values (Reid et al., 2009).

While many parts of the U.S. have exhibited a decline in heat-related mortality over time, there are some locations where the decline has been slower or even reversed (Sheridan et al., 2021). Historically, the Northeast and Northwest regions have experienced the greatest proportion of heat-related deaths in the U.S. However, over the last few decades, where heat-related deaths have been proportionally higher in the Southeast (Bobb et al. 2014). These patterns suggest that gaps remain in our understanding of public awareness, perception, and adaptive capacity.

Urban populations are particularly vulnerable to heat due in large part to the urban heat island (UHI), which is defined by the occurrence of higher temperatures in cities compared to surrounding rural areas. This occurs due to the lower albedo of urban materials, which absorb more incoming solar radiation, and their higher heat capacity, which slows the rate at which they emit this energy. Tall buildings can also prevent the escape of radiation, particularly at night when the UHI is most pronounced. In addition, the lack of vegetation and water relative to surrounding rural areas results in more solar radiation being used to heat the urban surface, resulting in greater daytime warming (Santamouris, 2001). Reducing the UHI by increasing the amount of vegetation ("urban greening") and incorporating cooling design strategies should improve thermal comfort and air quality in cities and help reduce vulnerability to extreme heat (Kleerekoper et al., 2012).

In a warming climate, the likelihood of experiencing extreme heat is expected to increase, but the amount of increase (relative to climatologically normal conditions) and the impacts on human health will vary geographically. To assess future impacts, changes in climate and population characteristics, including acclimatization (Howe et al. 2019), will both have to be taken into consideration. When these factors are combined, the Northeast and East Coast are projected to experience the greatest impacts and vulnerability to extreme heat (Jones et al., 2015; Howe et al. 2019). Additional resources will be needed in these areas to improve public knowledge and perception through reliable heat warning systems (Abasilim & Friedman, 2021). To reduce risk from extreme heat, such systems should help fill the gaps in knowledge of the danger of heat (i.e. perception), its impact on human health (i.e. vulnerability), and increasing frequency of extreme heat (i.e. exposure) (Howe et el., 2019). These systems should also account for changes in risk, even among populations that may already have greater awareness, perception, and acclimatization to extreme heat. One example is in the Southeast U.S., where extreme heat is more common and perception to heat is higher than in the Northeast U.S. But just because communities in the Southeast are more accustomed to extreme heat does not mean they will not be impacted in the future. The frequency of warm nights in the region, where temperatures do not drop below 75ºF, has doubled over the past half century. Not only does this affect the comfort and health of people, but it also negatively affects agriculture and other socio-economic systems (USGCRP 2018).

Though extreme heat has become more frequent, the U.S. population seems to be adapting, as reflected in the general decline in heat-related mortality over the past several decades. Therefore, projected *increases* in mortality and other impacts associated with extreme heat in the future imply that climate change is not the sole factor. Instead, a combination of factors related to population characteristics (e.g. a large elderly population), hazard communication (e.g. heat warnings), risk perception (e.g. behavioral changes), and adaptive capacity (e.g. heat mitigation plans), in addition to climate change, are driving current projections of future risk from extreme heat (Hondula et al., 2015).

Assessing risk to extreme heat has traditionally been done at the scale of populations and across relatively broad geographic areas. More recently, advancements in sensor technology have allowed researchers to examine various elements of risk (e.g. exposure, vulnerability, perception) at the individual level. Taken together, these elements can be used to evaluate an individual's thermal comfort, which is a measure of their experience and level of satisfaction with their surrounding thermal environment. Because thermal comfort is assessed at the individual level, it exhibits considerable variability in space and time, as well as from one individual to the next. As a result, there is no universal metric for thermal comfort, as it depends on highly variable and dynamic factors such as clothing, activity, posture, and location (Djongyang et al., 2010). Strategies to improve thermal comfort at the individual (e.g. pedestrian) level include increased green space and shade availability (Taleghani, 2018).

Unfortunately, most heat mitigation strategies and warning systems are unable to adequately account for individual-level variations in thermal comfort. Instead, measures of heat risk that account for exposure, vulnerability, and adaptive capacity are found at much broader spatial (and sometimes temporal) scales. This "mis-match" in scales between individual-level heat risk and operational heat warning systems can manifest in different ways. One of the more notable examples is the misclassification of heat exposure, which can occur when individual exposure is assumed to be the same as the ambient air temperature obtained from weather stations at fixed sites, such as airports (Lee et al., 2016). Personal heat exposure varies from person to person and from location to location. The temperature and relative humidity at an airport located in a rural area next to a body of water will be very different than the same variables taken while walking through a populated area downtown. Variations in exposure to sunlight and shade also occur on scales that fixed site weather stations cannot adequately or routinely resolve. In addition to measuring the ambient thermal environment, assessments of personal heat exposure must also account for behavioral and social factors, as well as aspects of the built environment (see Figure 1 in Kuras et al., 2017).

Exposure misclassification creates challenges for heat-health studies, such as identifying meteorological thresholds associated with excess mortality and morbidity. The only record of weather data is from a fixed site, but because most individuals are not near that site or in similar conditions, such as shading, topography etc., the specific weather variables that are assessed could be much different. Another challenge is with outdoor activities involving athletic events and outdoor occupations. In addition to the severity and duration of exposure, the level of exertion and other human energy budget components contribute to an individual's thermal comfort, which is not accurately captured by most operational heat metrics. Within competitions, hot outdoor conditions can heavily influence performance and even lead to injury (Ji et al., 2022). The question remains whether the fixed site weather station observations accurately represent conditions at the individual level. One of the solutions to this issue is utilizing temperature data from satellites to see more accurate effects that lead to morality (Lee et al., 2016).

Heat mitigation strategies go beyond the construction and planning of outdoor spaces. Athletes who exercise and/or perform in the heat also must be cautious and have alternate plans. The rapid rise of body core temperature due to increased metabolic heat production commonly results in decreased performance and exercise capacity. Aerobic fitness, pre-exercise cooling and fluid ingestion are the most effective heat mitigation strategies for athletes who plan to participate in competitions in warmer climates or seasons (Alhadad, 2019).

The primary method of communicating the risk of extreme heat in the U.S. is through heat alerts issued by the NWS, namely Heat Advisories and Excessive Heat Warnings. Sheridan (2007) found that communication of heat alerts resulted in greater risk perception, though it was not clear from the surveys whether the alerts themselves were effective at altering behaviors or taking adaptive action. More recent studies have found that heat warnings as a communication tool can not only increase risk perception but encourage adaptive behavior (Hass et al. 2021). Therefore, this thesis project will explore the spatial and temporal patterns of NWS Heat Advisories and Excessive Heat Warnings (referred to collectively as heat alerts) across the contiguous U.S., as well as examine how these patterns relate to the observed frequency of extreme heat index values, and the frequency of heat-related deaths. The results of this work will provide insight into the efficacy of current NWS heat alert products in different parts of the country.

CHAPTER II

DATA AND METHODS

Archived heat alert products issued by the NWS (i.e. Heat Advisories and Excessive Heat Warnings) from 2010 through 2021 were retrieved from the Iowa Environmental Mesonet (IEM; Iowa State University, 2001). This period was chosen because it overlaps with available mortality data retrieved from Sheridan et al which was examined from 2010 to 2018. The NWS also issues Excessive Heat Watches; however. these products were not examined as they are issued in advance of a warning (typically 24 to 72 hours) and would result in an exaggerated count of heat alerts. Heat alert products for each calendar year are contained within zipped folders on the IEM website. Within these folders are shapefiles that contain information for all products (i.e., tornado warnings and watches, severe thunderstorm warnings and watches, flood watches and warning, etc.) issued by each NWS forecast office for that year, including the date and time the product was issued and expired, as well as the area it covers. All shapefiles from 2010 to 2021 that contained all alerts by the NWS were imported into ArcGIS where the attribute table was opened. This table contains all individual alerts and their supplement data (i.e., when alerts were issued, or expired, what office issued the alert, the computed area of the event, etc.) associated with the files used in this study. The “select by attribute” tool was used to retrieve all heat advisories and excessive heat warnings issued by all NWS forecast offices in the contiguous U.S. for the years 2010 through 2021 (Figure 2.1). These alerts were listed under the ‘PHENOM’ column, which lists 2-character identification given by the NWS of the Valid Time Event Code

(VTEC) type. The mesonet has a list containing all 2-character identifiers and their respected event linked within their ‘Frequently Asked Questions’ (FAQ) page. Excessive heat warnings are listed as ‘EH’ and heat advisories as ‘HT’.

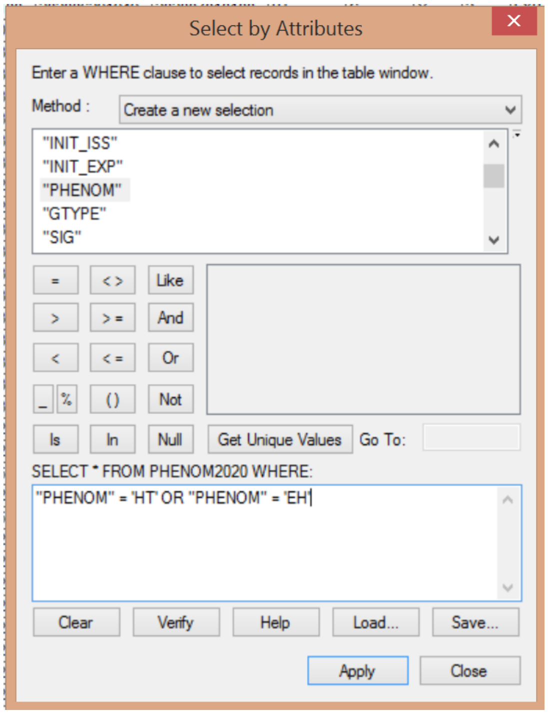

Figure 1.1 Select by Attribute tool displayed within GIS.

After heat alerts were separated from the original dataset, and then converted into two datasets, one for advisory and one for warning, the datasets were converted to specific points, implementing the ‘feature to points’ tool (Figure 2.2). The tool produced the points by utilizing the central point of the input feature given. It this case the input features were shapefiles that contained all warning or advisories between 2010 to 2021 placed on the map based on their ‘area_KM2’ column, which is the IEM’s computed area for the event. The IEM generates computed areas by an ArcGIS geoprocessing tool named ‘Albers’, which is commonly and best used for land masses that extend east to west in the midlatitudes (Albers; ArcGIS Pro). By changing the shapefiles to dots placed on top of a U.S. County map, a count of heat alerts by county could be acquired (Figure 2.3)

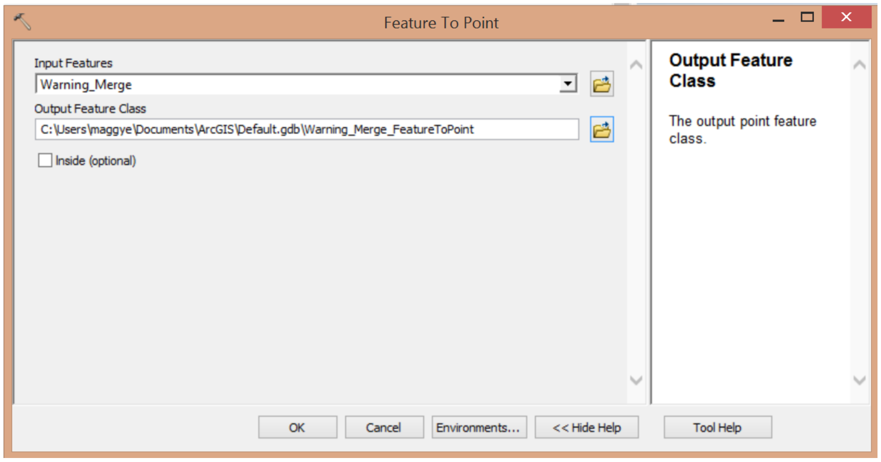

Figure 2.1 Feature To Point tool displayed within GIS.

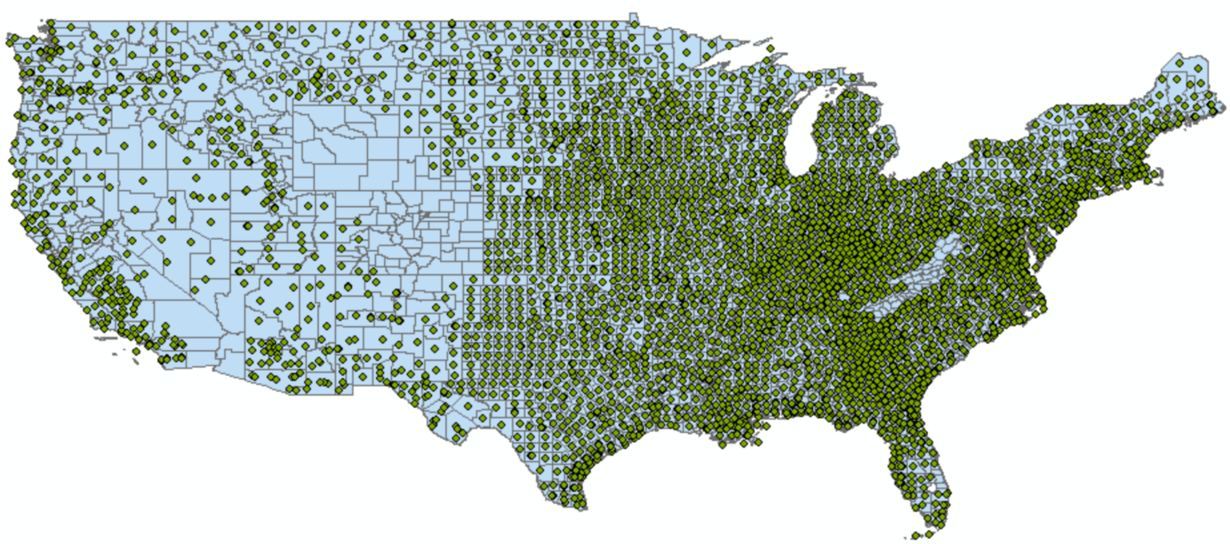

Figure 2.2 Each heat alert product within respected county.

The years were then merged creating one dataset for warnings and another for advisories. The ‘spatial join’ feature was then used to join the points to the map of counties for the contiguous U.S. and to create a count of heat alerts based on the counties (Figure 2.4).

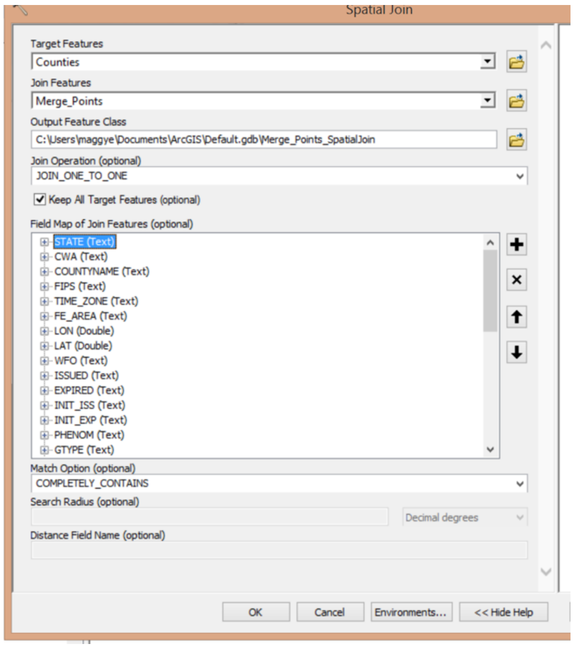

Figure 2.3 Spatial Join feature displayed within GIS.

Matching rows of the ‘Join Features’, which are the heat alerts, to the ‘Target Field’, the counties, based on their spatial locations allowed for a ‘join count’ column. Located within the datasets, this column indicates how many points fell within that county. Using this same column, the spatial patterns were able to be made visible (Figure 2.5).

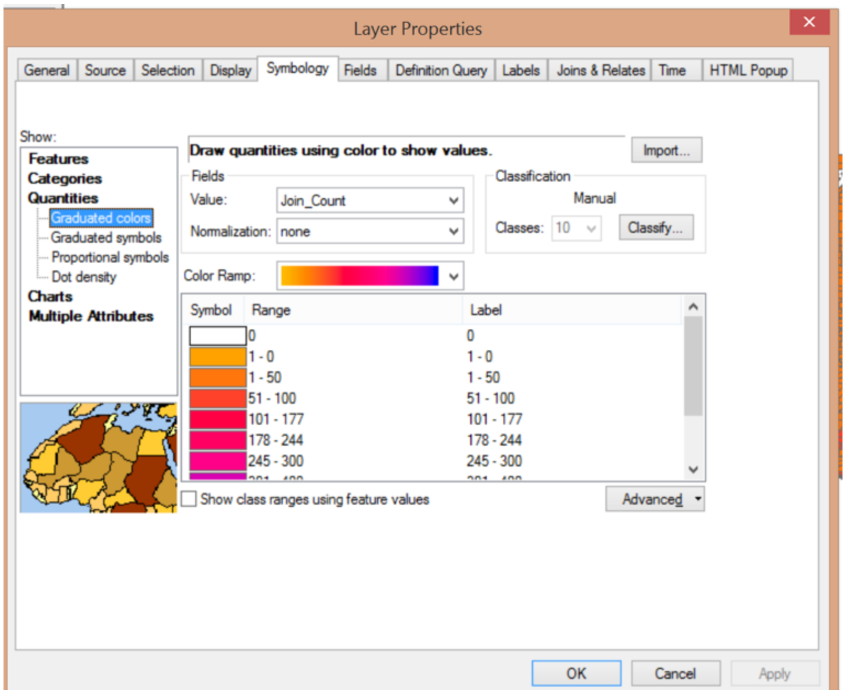

Figure 2.4 Layer properties tab displayed within GIS.

The previous steps were then used to joins the points to the National Weather Service public forecast zones (Figure 2.6). The majority of forecast zones align with the counties, but certain regions have relatively larger counties, mainly the Western U.S., and diverse topography. To make their alerts accurate in terms of issuing alerts to precise locations and populations who will be impacted, these regions have counties that are dispersed into numerous zones. Spatial patterns in the frequency of heat alerts were illustrated by summing the annual counts of alerts by type across the entire study period and mapping them at the county and forecast zone levels. Furthermore, a flow chart was made to convey this process within GIS, see figure 2.7 below.

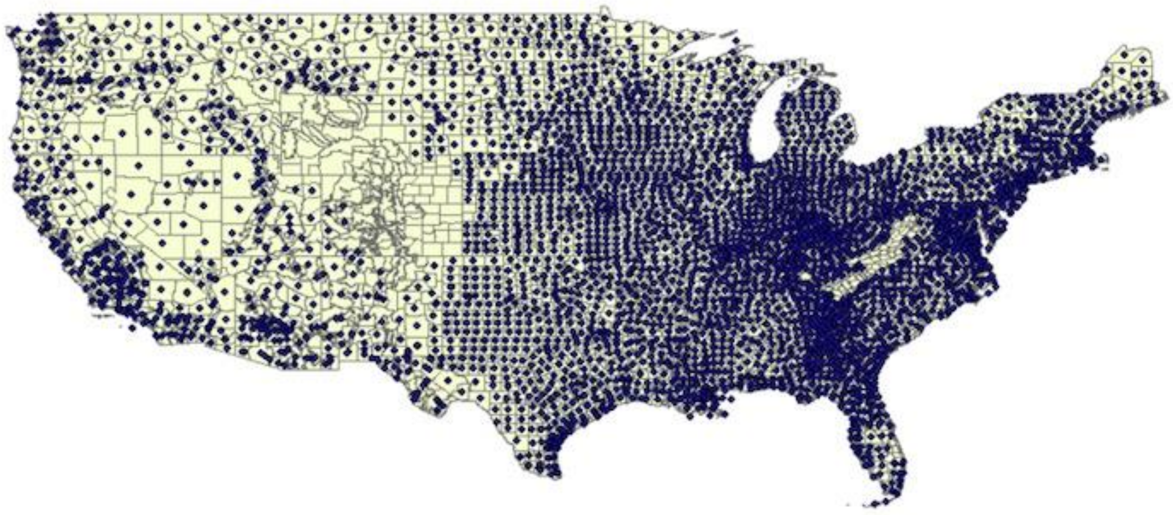

Figure 2.5 Each heat alert product within respected zone.

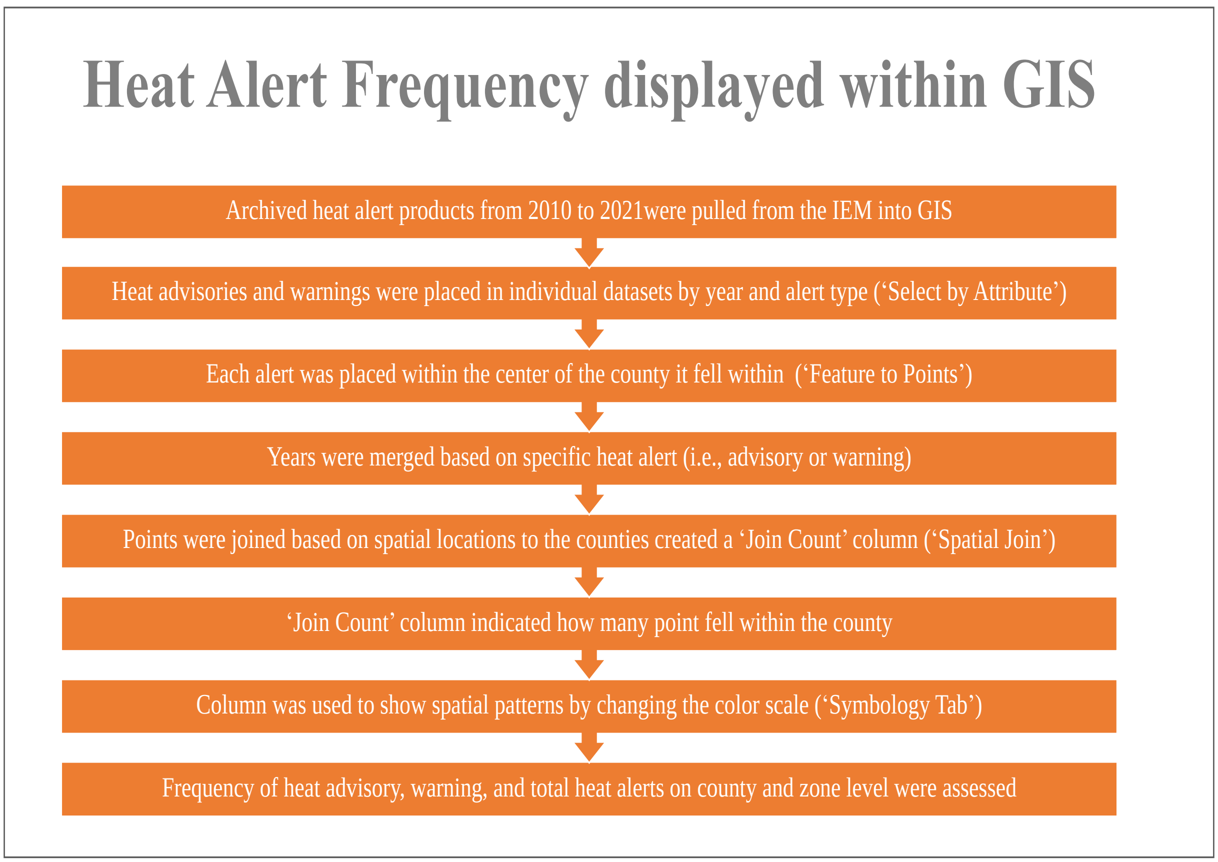

Figure 2.6 Flow chart communicating the process of displaying heat alert frequency with GIS.

To determine how the patterns of heat alert products relate to the frequency of heat-related deaths, mortality estimates for 107 metropolitan areas (cities) in the contiguous U.S. from 2010 to 2018 were obtained from Sheridan et al. (2021) (Figure 2.8). Each city had a population of at least 500,000 based on data from the 2018 U.S. Census. The estimated heat-related mortality for each city was calculated from death records across all counties within the city's Census-defined metropolitan statistical area (MSA). Mortality estimates in Sheridan et al. (2021) were provided for all genders and ages, as well as specific subsets. These include middle-aged (45-64) male, middle-aged female, elderly (65+) male, and elderly female. For purposes of this study in comparing mortality to heat alerts, all subsets were assessed. The heat-related mortality estimates were given as relative risk ratios, which represent the relative change in mortality on EHE (Extreme Heat Event) days compared to non-EHE days. EHE days were defined within Sheridan et al. as a day where the EHF (excess heat factor) exceeds the 85th percentile of all positive EHF values for the location over the climatological period. The EHF is an index based on a 3 day averaged daily mean apparent temperature (Nairn and Fawcett, 2015). To obtain this change, the relative risks of mortality were calculated on EHE days for each metropolitan area, each age and gender subset, and 9-year period they assessed. The risks were calculated in R using a distributed-lag nonlinear model to evaluate the change in mortality on EHE days relative to non EHE days. Because there is a delayed response concerning heat to mortality, the relative risks were assessed over a 10-day period following an EHE day (Sheridan et al., 2021). The selection of this metric was primarily due to the bounds being comparable to the frequency of heat alert products. All other metrics had bounds in which their lowest limit was below zero. Because each location's heat frequency can never be negative, this metric's limits coincided over the others given. While other city-level mortality estimates are available in the peer-reviewed literature (e.g. Gasparrini et al. 2015), the Sheridan et al. estimates are used because 1) they overlap spatially and temporally with the NWS heat alert products examined and 2) are calculated from a relative upper-tail metric (95th percentile apparent temperature) that is better aligned with the local NWS thresholds.

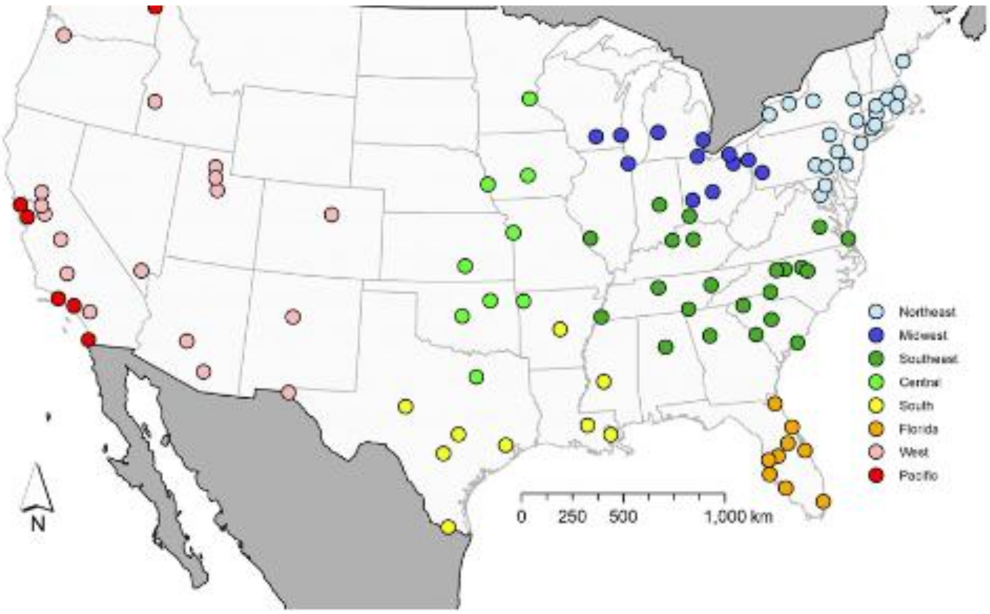

Figure 2.7 Figure I from Sheridan et al. 2021 indicating each MSA within their defined area.

To assess how the frequency of heat alerts and heat-related mortality relate to the observed frequency of extreme heat index values, hourly air temperature and dew point temperature for each city over the full study period (2010-2021) were obtained from a representative weather station using the Applied Climate Information System (ACIS), a web-based data management system maintained by NOAA's Northeast Regional Climate Center (http://climod.nrcc.cornell.edu/climod/hourly/). If there were days with missing data of any kind (i.e., temperature, dewpoint, hour), those entire days were taken out of the dataset in R. By the removal of these days, it was certain that the maximum heat index of each day was assessed. With the remaining data, hourly heat index values were calculated from the air temperature and dew point observations using the “weathermetrics” package in R, which includes the equations that are used operationally by the NWS (Anderson et al. 2016). From each city’s hourly dataset, the maximum heat index value was obtained for each calendar day; these values were used to determine how many days met or exceeded the threshold at which a heat warning would be issued by the local NWS office. Specifically, the thresholds for Excessive Heat Warnings were obtained from Figure 3 from Hawkins et al. (2017). Warning criteria that were noted as “locally defined” in Hawkins et al. were determined by contacting those NWS offices to obtain their specific thresholds or obtained from regional NWS websites. Advisory criteria were obtained through the websites of each NWS office or regional headquarters (Appendix, Table 1). The values were represented by 1, which were days over the threshold or 0, days below the threshold. The bootstrap method was then used obtain the mean frequency of days at or exceeding heat alert thresholds for each city. The dataset was bootstrapped in R and resampled 5000 times. The resample number is based on vector size, which was 3000 to 4200 per city, between 250 to 350 per year after days with missing data were subtracted. Afterwards, confidence intervals were produced using the ‘boot.ci’ function. The mean frequency of the number of days above thresholds were then able to be observed using the 95 percent confidence intervals. The median values of each confidence interval for each city were pulled into an independent dataset to discern the correlation between the heat-related mortality estimates and counts of heat alerts previously described. This interval was pulled for all days above or equal to heat alert threshold criteria.

Regional mean number of days above advisory thresholds were able to be assessed based on the counts of days above or equal to their specific advisory level for city in that region. Regions used were defined by Sheridan et at. where the 107 cities were divided into 8 regions: Northeast, Midwest, Central, Southeast, South, Florida, West, and Pacific (Figure 2.8). The aggregating of cities into regional clusters were determined by analyzing temporal variability with EHE days across the U.S. This allowed for grouping by the 107 metropolitan areas by known heat event experiences that haven taken place with the time period assessed (Sheridan et al., 2021). Once the values were calculated of day above or below specific thresholds, 1 being above and 0 being below, the counts above for each city within a region were added up using the 'sum' function. After all were obtained, they were put into an independent dataset, using the 'c' function, and bootstrapped in R to be resampled 10,000 times. The resample number is based on vector size, which was between 22 to 6 cities per region. The result was the mean number of days above or equal to advisory thresholds for each region. 95 percent confidence intervals were then made using the 'boot.ci' function and each region was shown by independent boxplots, using the 'boxplot' function. This was done for each region that was previously explained, and defined by Sheridan et al. The null hypothesis would be that each of the cities have the same frequency of the number of days above their specific threshold and the alternative would be that the means would not be equal.

Specific cities from a few regions of the U.S. were chosen based on results of their number of days above advisory thresholds in context with the 95 percent confidence intervals from their corresponding region, spatial patterns across the United States of heat alert products, and the relationship between heat related mortality and heat alert frequency for the 107 cities examined by Sheridan et al. (2021). These specific cities illustrated an off-diagonal relationship between mortality and heat alerts, meaning they obtained a high number of heat alerts but a low amount of mortality or vice versa. Cities chosen also were also within the mean, upper, or lower bounds of their regional 95 percent confidence intervals. They were selected to examine their mean number of days from 2010 to 2021 above their specific advisory thresholds relative to other cities within their region. Once again, the days over or under the specific thresholds were calculated and then bootstrapped in R and resampled 5000 times. Confidence intervals were then produced. These cities were contrasted on a box and whisker plot to present confidence intervals of the frequency of the mean number of days above or equal to advisory thresholds between each city. In doing this, locations will be assessed based on the frequency of heat alerts relative to the climatological frequency of extreme heat days. The null hypothesis would be that each of the cities have the same mean frequency of days above their specific threshold and the alternative would be that the means would not be equal.

By using Excel, each mortality subset estimates from the 107 cities evaluated were linked with their corresponding county counts of the total heat alert products, and mean frequency of the number of days that fell above or equal to heat alert criteria thresholds. After linked, Spearman rank correlations were conducted between the frequency of heat alert products, mortality, and frequency of days equal or greater than thresholds. The Spearman correlation was chosen over Pearson because the datasets are continuous and the relationship between them is non-linear. First, the rank of each city was found based on each group previously described by using the 'RANK.AVG' function. Then the Spearman rank correlation coefficient between the frequency of alerts and mortality, and the frequency of alerts and the number of days equal to or greater than alert thresholds were determined by using the 'CORREL' function and selecting the specific columns. These relationships were then plotted on a scatter diagram with heat related mortality or mean number of days on the x axis and heat alert frequency on the y axis. This was done for all 107 metropolitan areas and by regions defined by Sheridan et al. The regional correlations were illustrated on bar graphs showing regional variations in the correlation of heat alerts and threshold counts with each mortality subset, as well as the regional correlations between alert frequency and threshold counts. While the correlation coefficients provide a general assessment of the strength and direction of the association between variables, the scatter plots allow for the identification of specific cities and regions that do not follow the general association. For example, there may be cities with a high frequency of heat alerts but low heat-related mortality, or cities with a low frequency of heat alerts despite a high count of extreme heat days. These “off-diagonal” relationships may indicate more complex or nuanced associations between the issuance of heat alert products and resulting health effects.

CHAPTER III

RESULTS

During this study heat product frequency was first assessed on the county level (Figure 3.1 and 3.2). Cities within certain states in the Southwest, like Arizona and California, who have sizeable counties began to show an inaccurate representation when comparing across the entirety of the U.S. In Figure 3.2, this region had an Excessive Heat Warning count for Maricopa County, Arizona, where Phoenix is located, over 700. It accumulated to that amount because their WFO does not issue heat alerts on the county level but by specific forecast zones. There are multiple forecast zones within the jurisdiction of Maricopa County, making heats alert products massively expand in size over only one day of extreme heat. In response, figures 3.3 and 3.4 were produced to show a more representative view of the frequency of heat alert products across all 48 states by utilizing NWS forecast zones. For a majority of the U.S. results were consistent across the county and zonal level but for the Southwest region this allowed for a better representation of heat products given during this time frame.

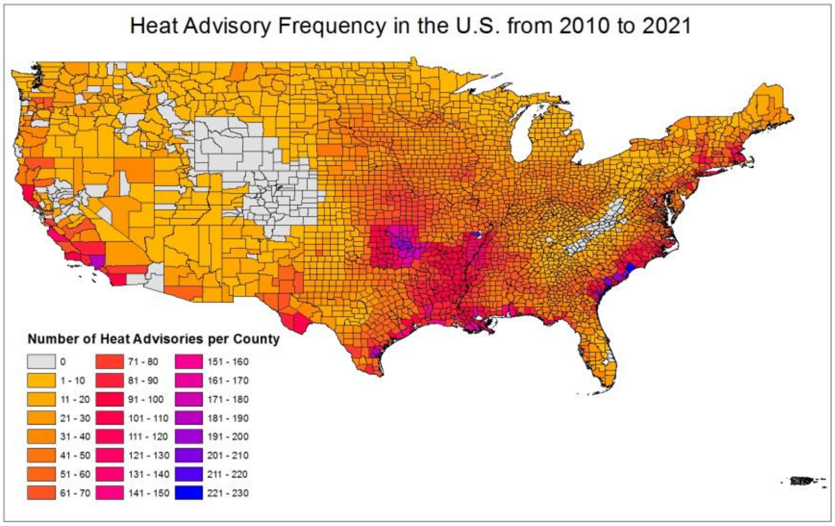

Figure 3.1 Heat Advisory frequency shown on the county level across the United States from 2010 to 2021.

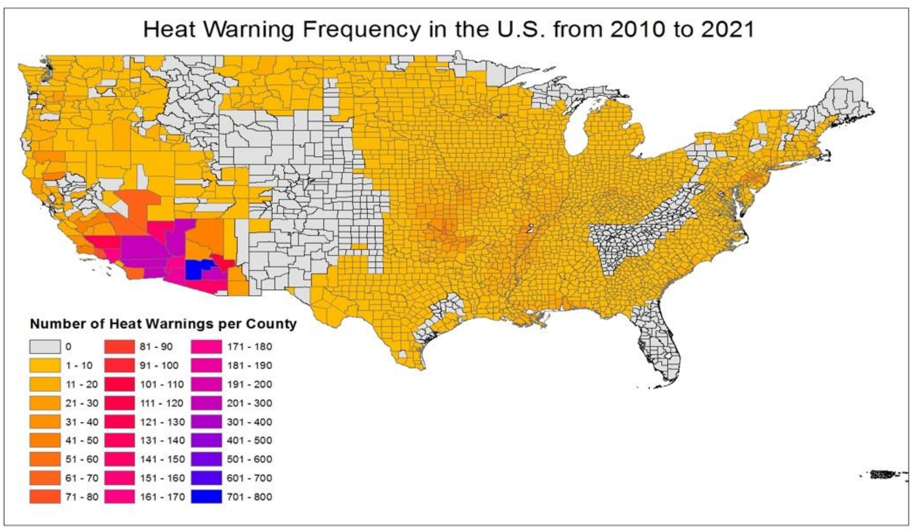

Figure 3.2 Excessive Heat Warning frequency shown on the county level across the United States from 2010 to 2021.

Regions of the United States had diverse frequency between Excessive Heat Warnings and Advisories. An example being the West, specifically southern California, southern Nevada, and Arizona. Forecast zone 003 in Arizona, which contains a vast portion of Mohave County, had an Excessive Heat Warning count of 94 between 2010 to 2021 (Figure 3.4). While the advisory count was 0 (Figure 3.3). Numerous surrounding forecast zones had a similar outcome, while this specific one was the most extreme case. When speaking to a forecaster from the Phoenix WFO, the point was confirmed that the greater issuance of warnings was due to this criterion being exceeded more often. If WFOs are consistently reaching above the advisory criteria and into warning criteria, a solution would be to raise advisory and warning criteria into the necessary bounds that advisories would also be issued. By only issuing warnings, the public can become numb to the warning language and in turn does not take the necessary precautions.

On the contrary, the rest of the United States, especially the Southeast and along the Carolinas and Georgia coastline, exhibited a higher frequency of advisories rather than warnings. Counties like Bolivar in Northwest Mississippi had over 100 advisories issued but had less than 50 warnings in the same time period. Louisiana compared to surrounding states had a greater portion and consistency of advisories across the entirety of the state.

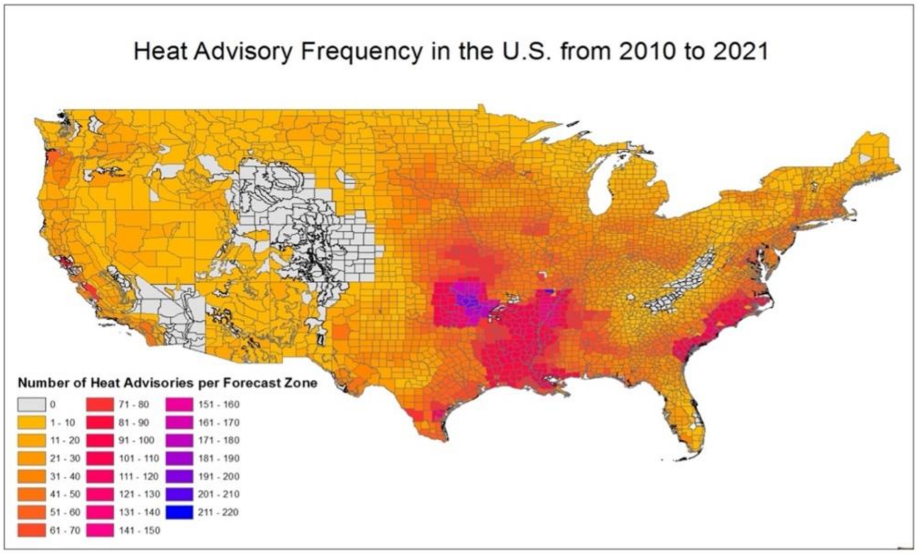

Figure 3.3 Heat Advisory frequency shown by NWS forecast zone across the United States from 2010 to 2021.

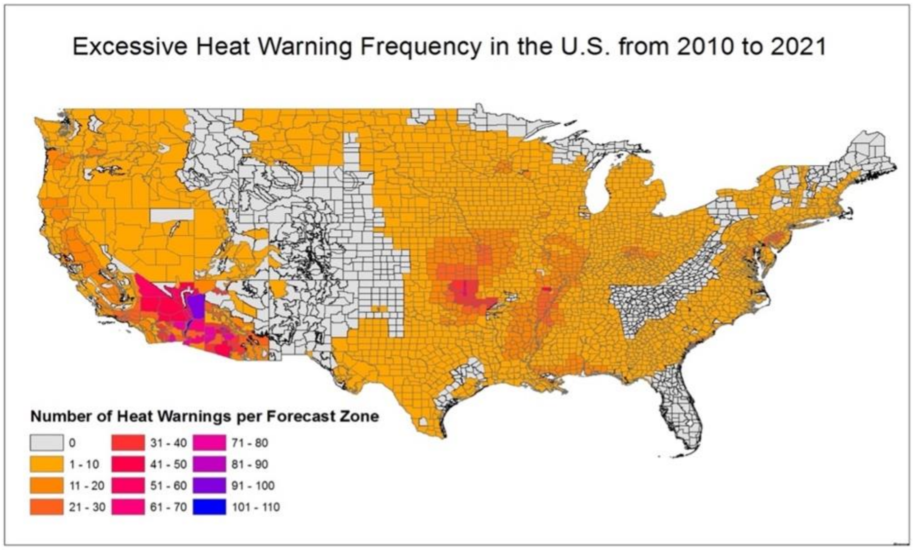

Figure 3.4 Excessive Heat Warning frequency shown by NWS forecast zone across the United States from 2010 to 2021.

Two main ‘hot-spot’ regions of the United States are evidently pictured in Figures 3.5 to 3.6 – The Mid-South (Arkansas, Louisiana, Mississippi, and Oklahoma) and the West (Southern California southern Nevada and Arizona). These two areas have the greatest number of warnings and advisories compared to the other regions of the United States. Eastern Oklahoma compared to its surrounding states had a greater number of heat alerts over the period assessed. This specific area also happens to be covered by a different WFO, Tulsa, than the rest of the state, Norman. Forecaster bias between the central to eastern portions of the state could explain this due to alerts coming from two different WFO but the reason for alerts dipping off into western Oklahoma is due to advisory criteria going up from 105ºF to 110ºF. Oklahoma remained with the general trend with the rest of the Mid-South, which was a higher frequency of Heat Advisories than Excessive Heat Warnings but again, obtained a higher count over the specific area especially when it came to warnings.

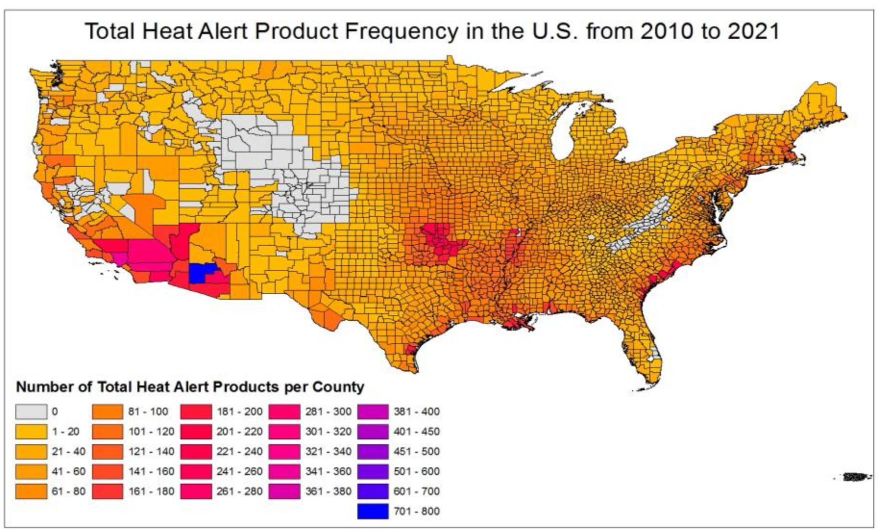

Figure 3.5 Total Heat Alert Product frequency shown by counties across the United States from 2010 to 2021.

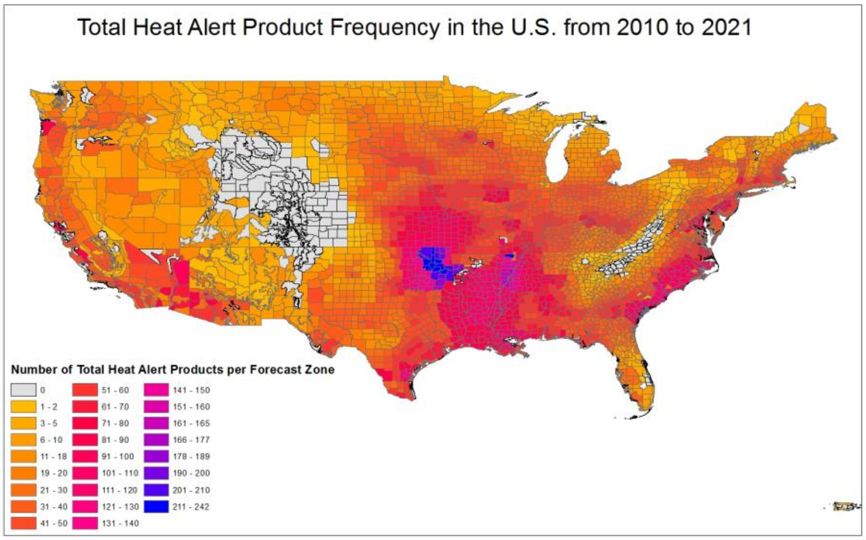

Figure 3.6 Total Heat Alert Product frequency shown by NWS forecast zone across the United States from 2010 to 2021.

There are also regions that have relatively low to 0 alerts, including portions of the Appalachian Mountains, intermountain west, and the state of Florida. For the mountainous areas, they experience cooler temperatures than the areas around them which in turn causes them to see less alerts. The state of Florida, even with the higher temperatures within the summer months and higher average temperature overall, has lower amounts of total alerts in comparison to other Southern and Southeastern states. This is due to the state having higher thresholds in comparison to other parts of the county, with the advisory thresholds being 108ºF and the warning being 113ºF. Higher thresholds within Florida are in part due to the prevailing climate but could also be connected to lower risk perception due to acclimatization. Floridian cities compared to overall 107 cities studied had the highest alert thresholds for the state as a whole. Specific location within different states like McAllen, Texas, located on the southern tip of

Texas, and Augusta Georgia, on the western edge of Georgia, had the highest individual advisory thresholds being 110ºF and warning up to 115ºF.

Mean number of days above or equal to advisory thresholds were evaluated by the 8 regions (Figure 2.8 & Figure 3.7). Multiple regions median fell within another's interval meaning that they are statically similar, including the Northeast and Southeast, Central and South, South and West, and the Midwest and Southeast. Central, South, and West regions had the highest mean number of days above or equal to their specific thresholds. The central region had the highest median, with 115.2 days equal or above the advisory threshold. This stays on trend with total heat alerts issued with the same regions also experiencing the highest amount of product frequency (Figure 3.5 & 3.6). Pacific had the lowest with a mean of only 3.

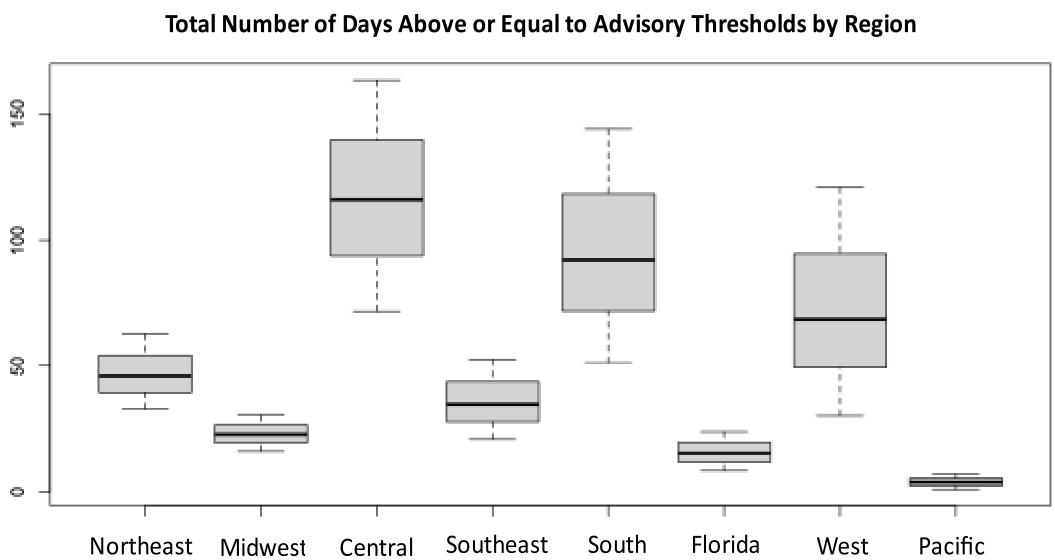

Figure 3.7 Confidence intervals for the total number of days above or equal to advisory criteria between 2010 to 2021 clustered by regions define by Sheridan et al. (2021)

6 cities from each region were pulled to compare frequencies above or equal to advisory thresholds. Cities were chosen that had the highest and lowest counts and cities that approached closer to the median value within their specific region. By evaluating frequencies, further conclusions could be made for the particular rank of each region. Within the Northeast only two cities had medians that fell within each other's intervals, Hartford Connecticut, and Lancaster, Pennsylvania (Figure 3.8). We can't reject the null hypothesis within these 2 cities that their mean frequencies are equal and that this result is statistically significant, meaning it is unlikely due to mere chance. The additional 4 cities' frequencies were all higher than the 2 previously mentioned. Poughkeepsie, New York and Worchester, Massachusetts had the highest frequencies. Poughkeepsie's higher placement within these 6 cities could in part be due to have a lower threshold, 95ºF for advisory and 105ºF for waning. Albany, New York also obtains these same thresholds.

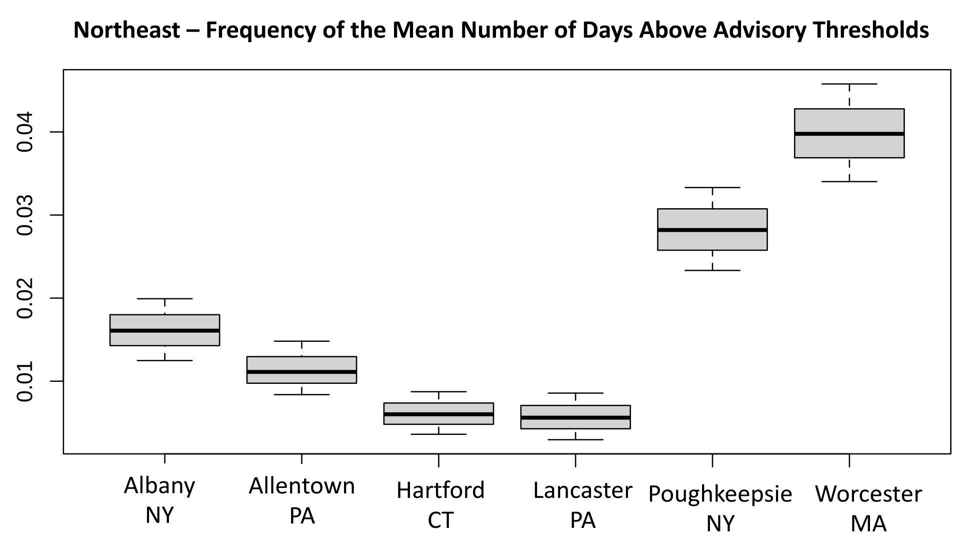

Figure 3.8 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Northeastern cities examined by Sheridan et al. (2021)

The Midwestern cities of Cleveland, Ohio, Youngstown, Ohio and Chicago, Illinois, had medians that fell within each other's intervals and Dayton and Toledo, Ohio as well (Figure 3.9). We can't reject the null hypothesis within these 2 cities in the Midwest that their mean frequencies are equal and that this result is statistically significant. Dayton and Toledo also obtained the highest frequency values with both medians reaching above .010. The frequency values represent the percentage of days that fell above or equal to advisory thresholds from the time period as a whole therefore they will be relatively low as most days are not above heat alerts thresholds. The Midwest had the highest number of cities falling within each other intervals although out of the 6 cities chosen, 4 were out of the state of Ohio, and only 2 sets of those cities' medians fell within each other's intervals. All Ohio cities have the same thresholds, and the cities of Toledo, Cleveland, and Youngstown are all under the same WFO of Cleveland. This could suggest a need for modification to local criteria due to the difference in frequencies being due to meteorological conditions.

Midwest – Frequency of the Number of Days Above or Equal to Advisory Thresholds

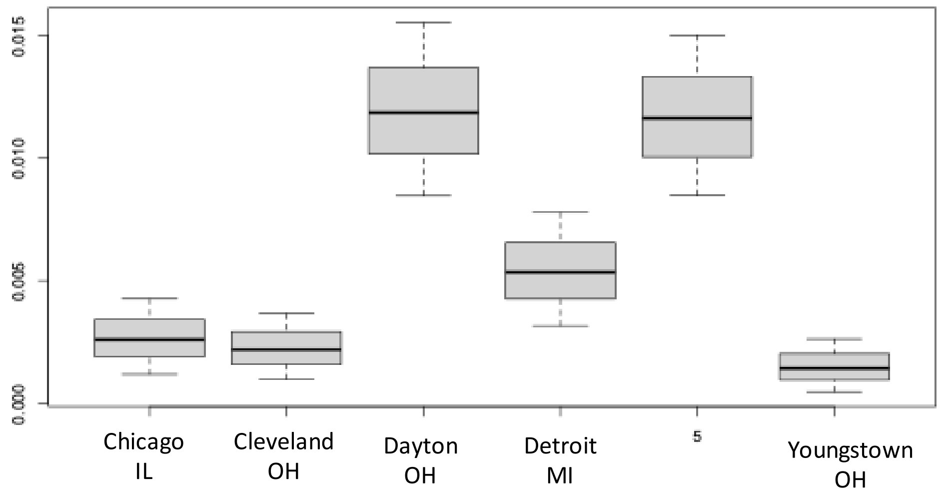

Figure 3.9 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Midwestern cities examined by Sheridan et al. (2021)

Within the Central region (Figure 3.10), Tulsa, Oklahoma had the highest frequency with a median of .055, and Dallas, Texas next at .050. The lowest within this region was Fayetteville, Arkansas with a median frequency not even reaching .01. Kansas City, Missouri and Oklahoma City, Oklahoma medians fell within each other's intervals meaning they are statistically similar. Dallas, Texas and Tulsa, Oklahoma also had medians within the intervals of the other and additionally are statically similar. The Central region had the second greatest spread of frequencies with medians stretching from .055 to below .01. Tulsa within the plains of Oklahoma versus Fayetteville, Arkansas being located within the Ozarks, even though they are only 113 miles from one another, obtain the same alert thresholds and are even within the same WFO, see this large frequency difference could be due to their contrasting topography or the need for criteria within this specific area to be reassessed.

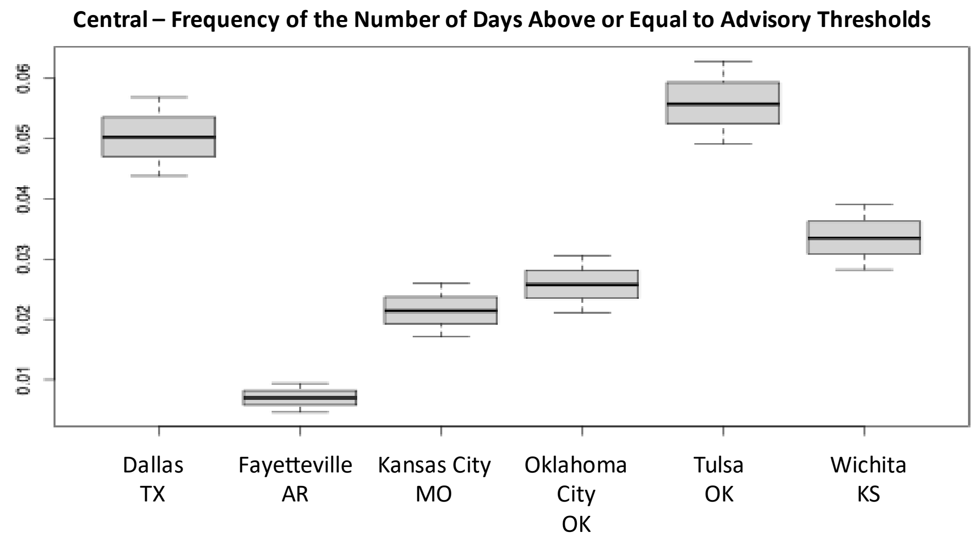

Figure 3.10 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Central cities examined by Sheridan et al. (2010)

Augusta, Georgia, and Winston-Salem, North Carolina acquired the lowest frequencies with the Southeast (Figure 3.11). These 2 cities along with Greensboro, North Carolina had medians fall within each other's intervals, so we can't reject the null hypothesis that the means are equal and statistically similar, meaning the result is unlikely due to mere chance. Memphis, Tennessee reached far beyond the other frequencies within this region with a value of .040. The Southeast did not rank high within its mean days above thresholds compared to other regions due to a larger count of cities who had low to relatively low alerts. Cities within this region were located east of the Mississippi river reaching cities into Kentucky and one in Ohio, with the Southern region obtaining the cities west of the river. This allowed the region to capture the lower frequencies and mean days within cities in proximity to the Appalachian Mountains, like Winston-Salem. It also acquired cities within the Columbia, South Carolina WFO (i.e., Augusta, Georgia, Columbia, South Carolina, Charleston, South Carolina) that have higher advisory and warning criteria than their surrounding areas.

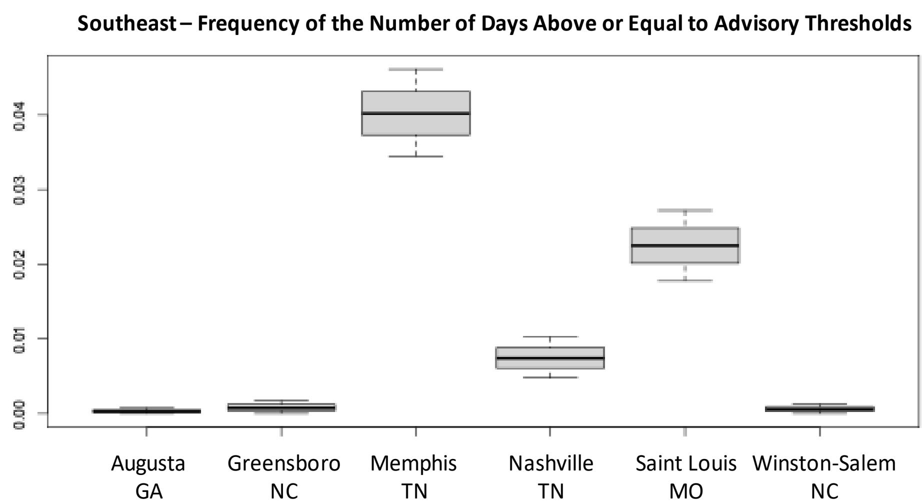

Figure 3.11 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Southeastern cities examined by Sheridan et al. (2021)

The Southern region had two cities, Little Rock, Arkansas and McAllen, Texas that obtained medians that fell within the others' interval meaning they are statistically similar (Figure 3.12). These 2 cities also acquired the highest frequencies with McAllen, Texas being at the top within with Little Rock, Arkansas following it, both with frequency values above .05. McAllen also obtained this while having the highest thresholds out of all Southern regional cities. The Southern region reached the 3rd highest mean overall due to only having 9 cities out of the 107 contained within this region and 3 of those falling having median frequency values above .03.

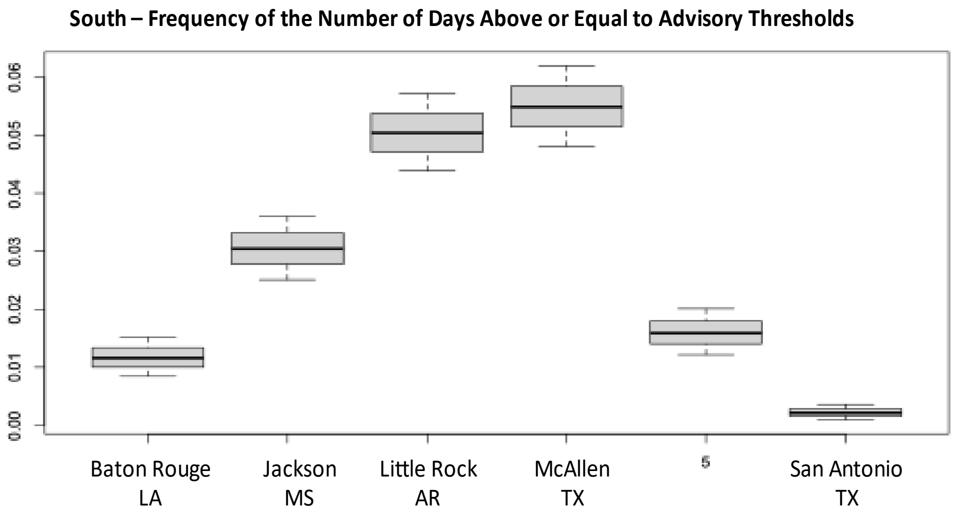

Figure 3.12 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Southern cities examined by Sheridan et al. (2021)

The state of Florida's spread of frequencies were minor compared to the other 7 regions (Figure 3.13). With this compact spread it also collected the statically similar cities. These included Jacksonville and Sarasota, Ft Myers and Jacksonville, Ft Myers and Miami, and lastly Orlando and Miami. The frequencies within this region were low with Daytona Beach securing the highest frequency at a value of .009. The lowest frequency was Orlando which was the only inland city out of the 6 chosen. Lower frequencies and mean number of days within Floridan cities could be the result of higher thresholds due to higher average temperatures throughout the year, 108ºF for advisories and 113ºF for warnings.

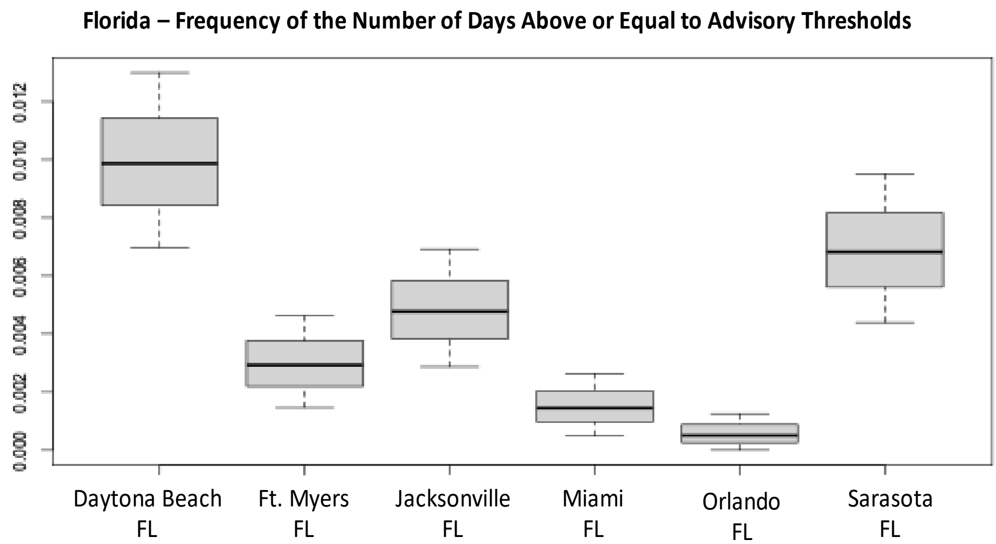

Figure 3.13 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Florida cities examined by Sheridan et al. (2021)

El Paso, Texas and Provo, Utah obtained the lowest frequencies within the Western region (Figure 3.14). These 2 cities and Bakersfield and Fresno, California had medians that fell within the other's intervals. With that, we can't reject the null hypothesis that the means are equal and statistically similar. Phoenix, Arizona, with a mean of .091, obtained the highest frequency within the Western region and the highest frequency overall. Results were consistent with total heat products on the county level, where Maricopa County also received the highest total. This region had the greatest spread of frequencies across all regions from medians of near 0 to .091. Cities of the mountainous West (i.e., Provo, Utah) and pacific coastline (i.e. Seattle, Washington) who had lower frequencies were also included within this region along with hot Southwestern cities (i.e., Phoenix, Arizona, and Las Vegas, Nevada) who had some of the highest frequencies overall, which created this large spread.

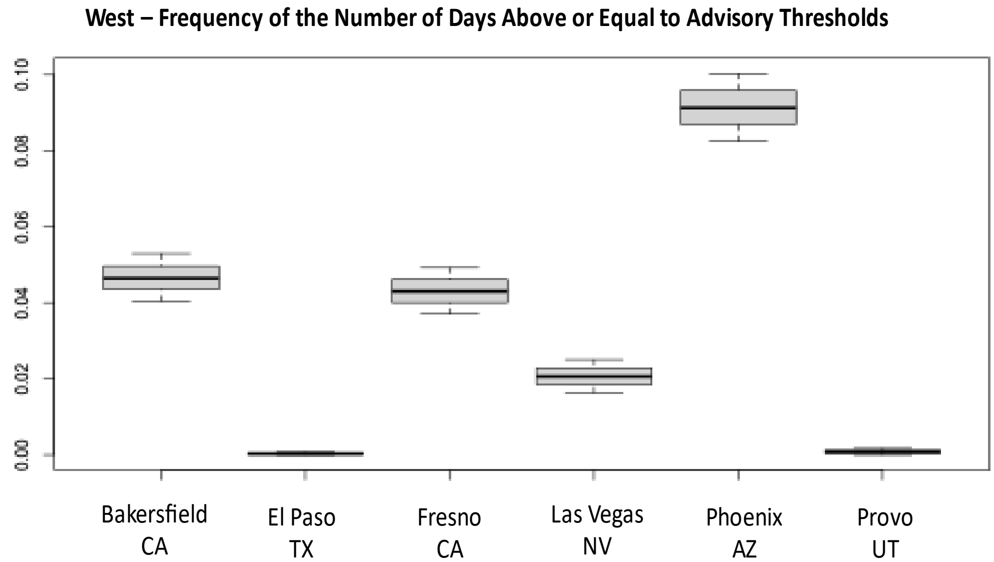

Figure 3.14 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for certain Western cities examined by Sheridan et al. (2021)

Pacific region frequencies were lowest, even under the Florida region, with the highest mean not even reaching .003 (Figure 3.9). Spread of frequencies was only the most concise with the lowest median value being 0 and the highest previously mentioned, below .024. This median was Los Angeles, California with a value of .024 with Spokane, Washington receiving the next highest at .001. Spokane and Los Angeles, Spokane and San Jose, California, and lastly Oxnard, San Diego, and San Francisco, all located in California, obtained median values that fell within each other's intervals, meaning we can't reject the null hypothesis that these cities' means are equal and that their mean are statistically similar. There were only 6 cities included within this region with almost all falling along the coast/bay area of California, with Spokane, Washington being the lone one on the eastern fridge of Washington. Low frequencies for the coastal cities mentioned have multiple factors that play into their conditions, with the main one being prevailing winds off the coast transport cooler air into the region. Proximity to water also causes temperatures to not vary much from day to night and summer to winter, which is an additional reason for the compact spread of frequencies.

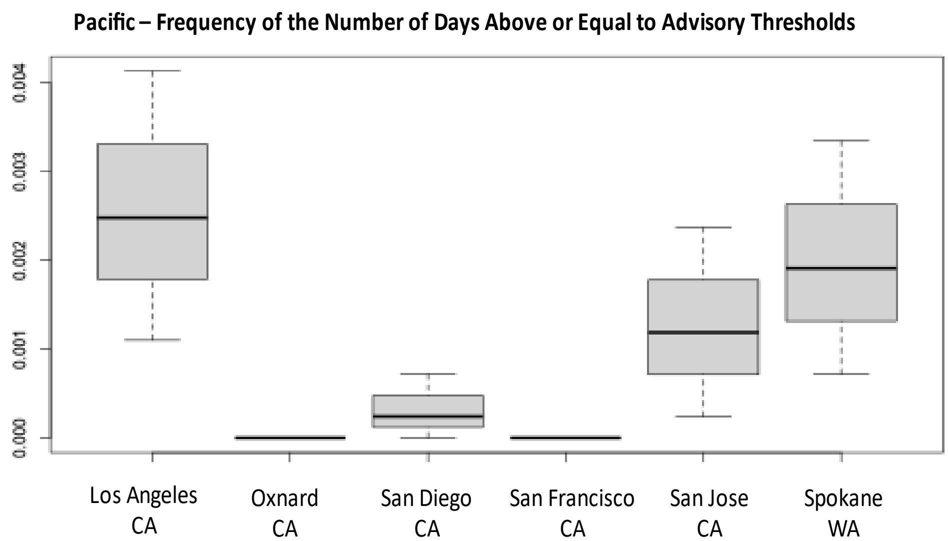

Figure 3.15 Confidence intervals for the frequency of days above or equal to advisory criteria between 2010 to 2021 for all Pacific cities examined by Sheridan et al. (2021)

Correlations were assessed for the continental U.S., using all 107 metropolitan areas, between total heat alerts by county to each mortality subset (Figure 3.16). This was additional accomplished regionally using the regions once again defined by Sheridan et al (Figure 3.17). For the U.S., the highest positive correlation was within men 65 and older, with a value of .198, then next highest subset, and only other one with a positive correlation, was the All Mortality subset with a much smaller value of .058. These results indicates that across the U.S. when alerts are frequent, men who are 65 and older observe higher mortality rates, as well as all mortality going up. Possible low assessment within these subsets of individual view of the severity of their risk to heat perception (i.e., risk perception) could be factor, as well as shortcoming within communication to this group across the U.S. when alerts are issued.

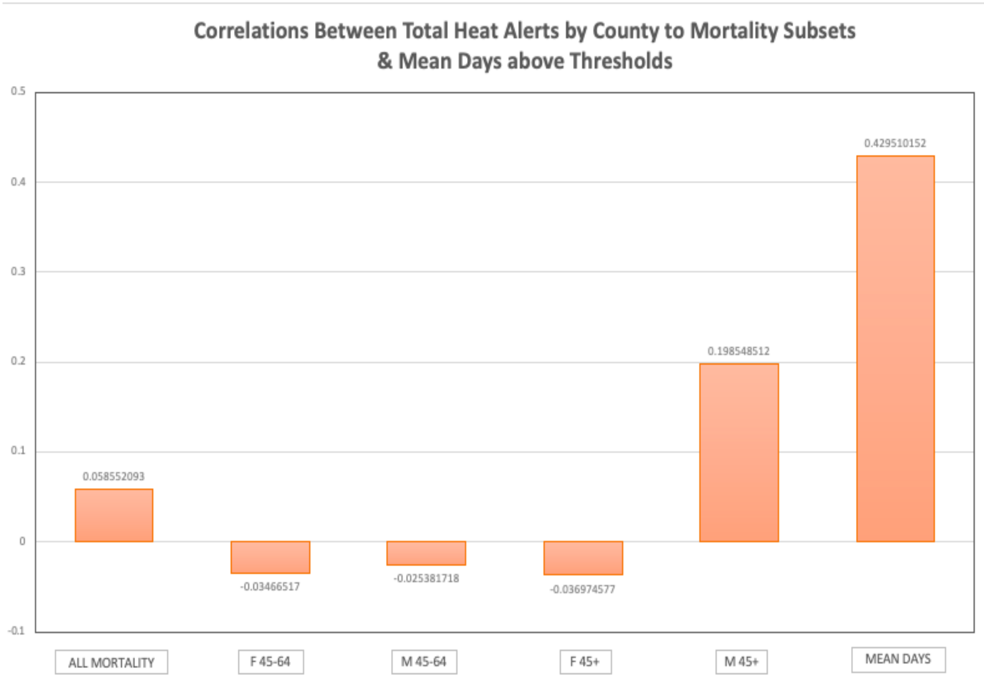

Figure 3.16 Spearman rank correlations between total heat alerts by county to subset mortality estimates for the 107 cities in Sheridan et al. (2021) and median frequency of days above or equal to alert thresholds.

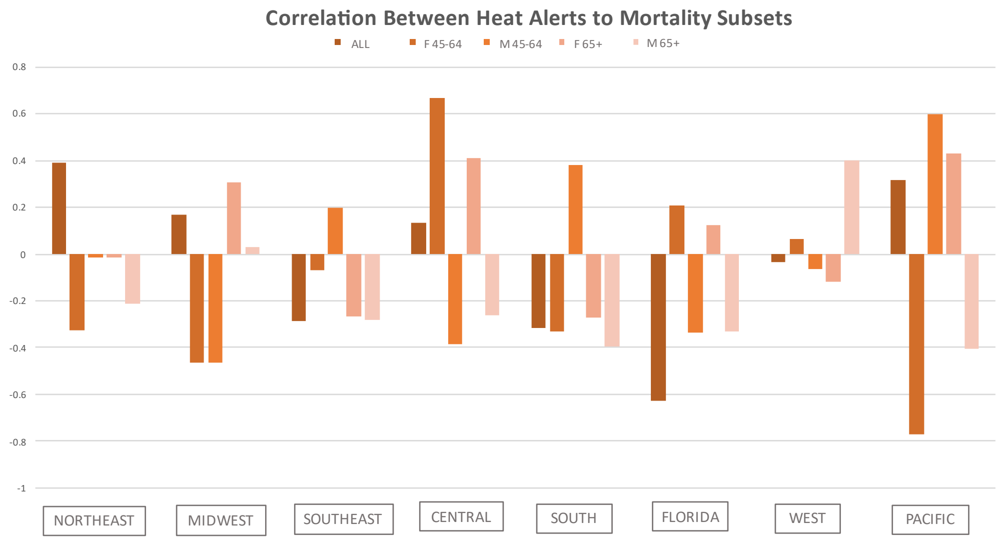

Figure 3.17 Spearman rank correlations between heat alerts on the county level to subset mortality estimates aggregated by region for the 107 cities in Sheridan et al. (2021) between 2010 to 2021 (4,384 days total).

Positive correlations were also found regionally, with the All Mortality being the highest overall within the Northeast, with a correlation of .388. Within the Midwest and Central regions, the highest positive correlations were Females 65 and older, as well as obtaining positive correlations with the All Mortality subset. The Midwest also had positive correlation with Men 65 and older. Men 45 to 64 was the only positive correlation found with the Southeast and Southern regions, with a value of .195 for the Southeast and .382 for the South. Florida's positive correlations fell within both females' subsets, 45 to 64 and 65 and older. Their highest correlation was with Females 45 to 64, with a value of .209. Out West positive correlations were the highest within Men 65 and older, with a value of .399, and the only other positive correlation was minimal with a value of .062 in Females 45 to 64. Pacific cities had a strong positive correlation with Men 65 and older, with the correlation reaching .600. Their next highest was Females 65 and older, and then the All Mortality subset. Higher positive correlations found within each region convey which age and gender group displays higher rates of mortality as heat alerts become more frequent for that specific region. Indications of risk perceptions being low within these specific groups in each region could be the reason for the positive correlations and/or lack of communication within the most vulnerable groups of each region.

Across the continental U.S. negative correlations between each gender and age group assessed were within Females and Males 45 to 64, and within Females 65 and older (Figure 3.16). All negative correlations were relatively low with Females over 65 being the most substantial with a value of -.036. With the U.S. when alert frequencies rise these subsets see lower mortality rates. This could be the result of effective alerts or when assessed on individual city levels of alerts issued on the county level, an unnecessary amount when taken into account with population vulnerability and overall mortality rates. Within the Western and Pacific regions in particular, certain cities like Phoenix, Arizona and Los Angeles, California, have a substantial number of total heat alerts in comparison to their All Mortality subset (Figure 3.18). These cities had a congruent frequency of days above their thresholds (Figure 3.14 & 3.15) in comparison to their alerts issued but again had a lesser than value of mortality. This off diagonal relationship could represent a lower population vulnerability to extreme heat, higher risk perception and in turn could be a need for alert thresholds to be altered. Cities were also assessed using alerts issued by zone to show additional cities with off diagonal relationships other than Western cities who have substantial larger counties than the rest of the U.S (Figure 3.19). Central, and Southeastern cities also displayed a larger number of heat alerts in comparison to their coinciding mortality values. Tulsa, Oklahoma and Memphis, Tennessee were the two cities who showed the greatest off relationship. Their frequencies above thresholds were also elevated, both being the highest within their regions (Figure 3.10 & 3.11). Again, their mortality values fell short, around average compared to all 107 cities. This results as well could represent a lower population vulnerability to extreme heat, higher risk perception and in turn could be a need for alert thresholds to be altered.

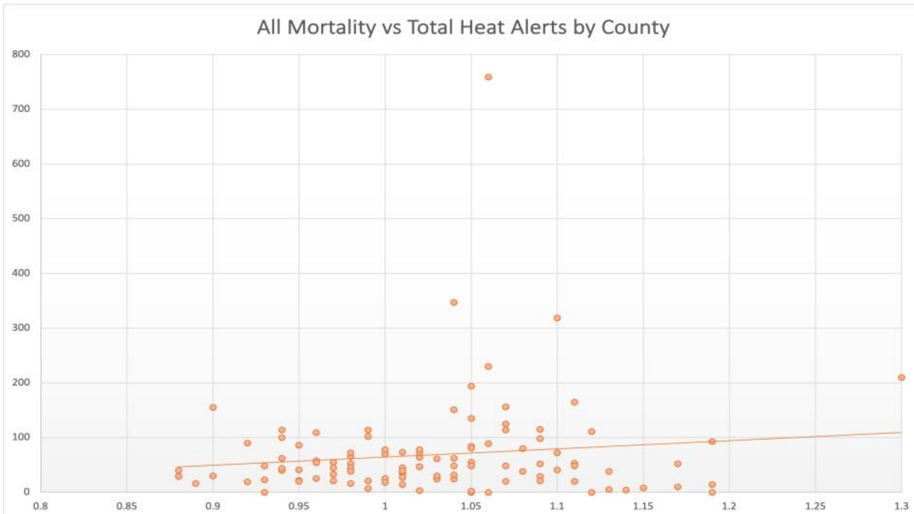

Figure 3.18 Plot indicating the relationship between Heat Related Mortality (x-axis) and Heat Alert Frequency by county (y-axis) for the 107 cities examined by Sheridan et al. (2021) between 2010 to 2021 (4,384 days total).

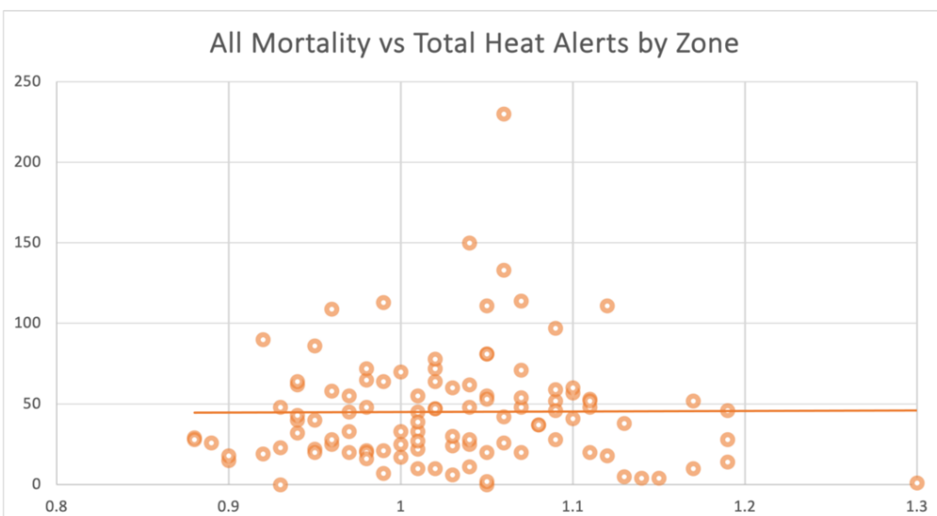

Figure 3.19 Plot indicating the relationship between Heat Related Mortality (x-axis) and Heat Alert Frequency by forecast zone (y-axis) for the 107 cities examined by Sheridan et al. (2021) between 2010 to 2021 (4,384 days total).

Negative correlations regionally were found in a greater extent with the Northeast although all values were minimal (Figure 3.17). Each gender and age subset were negative, other than All Mortality, with Females 45 to 64 being the highest with a value of -.326. The Midwest also had its highest correlations within this same subset, and Males 45 to 64, with a tie of -.462. Central region's negative correlations were within both Males subsets, 45 to 64 and 65 and older. All Mortality was the highest negative correlation within the Southeast with Females 45 to 64, and Females and Males 65 and older all also obtaining negative correlations. Females 45 to 64, and 65 and older, Males 65 and older and the All Mortality subset all had negative correlations with the Southern region. The highest of those being within Men 65 and older, with a value of -.395. Florida had negative correlations within both Males subsets, as well as the All Mortality subset. The All Mortality subset within this region doubled the other negative correlations within the region with a value of -.627. Within the Western region All Mortality, Males 45 to 64, and Females 65 and older all received negative correlations. All correlations were minor with the highest -.118 within Females 65 and older. The Pacific region had a high negative correlation with Females 45 to 64 with a value of -.771. Men 65 and older also obtained a negative correlation within this region with a value of -.405. Within most regions with the U.S. the subsets who had negative correlations derived lower mortality rates when seeing a higher heat alert frequency. Although within the Pacific region, this is not the case but the opposite. As this region of the U.S. obtained little to no heat alerts the negative correlations convey lower alert frequency with higher mortality rates within those subsets. Additionally, this could be the result of alert thresholds being high given population vulnerability.

The correlations between threshold exceedance and total heat alerts products were also assessed across the continental U.S. with the same 107 cities (Figure 3.16). Specifically, this was the median frequency of days above specific threshold and total heat alerts by county. The correlation was moderately positive with a value of .4295, which suggest that the frequency of heat alerts is consistent with what expectations given the background climate.

Positive correlations were also found regionally between thresholds exceedance and total alerts given (Figure 3.20). The Southeast, Central, South, Florida, West and Pacific all had positive correlations with the Southeast obtaining the highest with a value of .735. Within all these regions it can be concluded that when receiving alerts more frequently they also experience a higher mean number of days above alerts thresholds.

The sole negative correlation was acquired by the Northeast with a smaller value of -.090. This indicated a small scale of higher alerts versus a lower count of days above thresholds. In the Northeast this could mean office issue an excessive number of alerts or have a strict and robust heat mitigation plan due to being in a location with population who has higher vulnerability to heat. This result is in congruence with the All Mortality subset for this region being the highest positive correlation compared to the additional 7 regions, showing a higher mortality risk within the population as a whole as the frequency of alerts goes up.

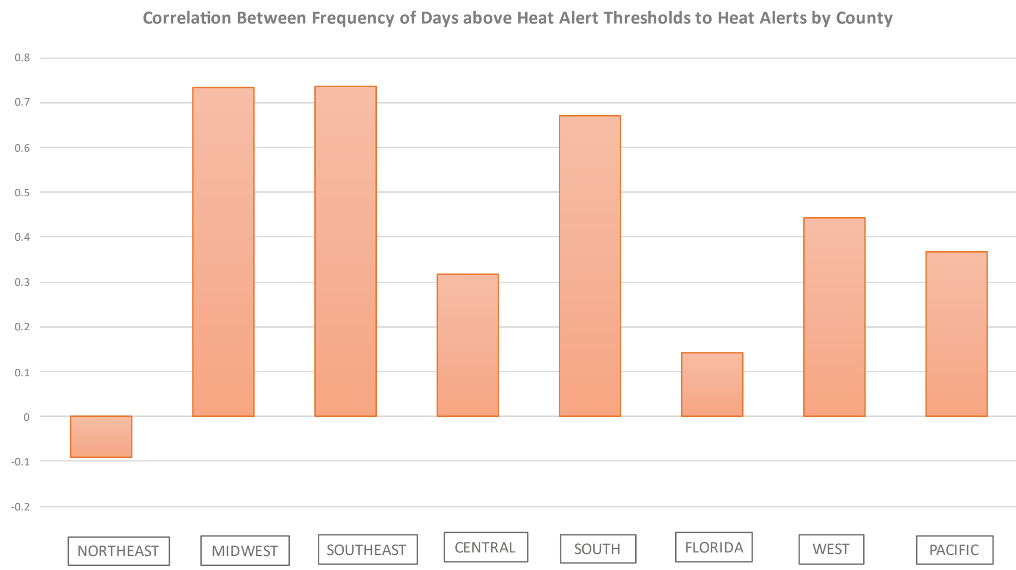

Figure 3.20 Spearman rank correlations aggregated by regions between total heat alerts by county and median frequency of days above or equal to alerts thresholds.

CHAPTER IV

DISCUSSION AND CONCLUSIONS

Spatial patterns of heat alerts across the United State were shown on the county level then with NWS forecast zones. While counts for alerts were used from the county-based map, due to mortality estimates being on the county level and the need for consistency across the lower 48, mortality and patterns within Western counties with forecast zones would reveal a better representation of this area. The sole study of this area with mortality could also reveal any differences within mortality estimates, and alerts being issued once the Western region began to issue and communicate alerts based on the ‘HeatRisk’ tool in place of heat index criteria for each WFO.

Expected days and frequencies above thresholds for specific cities and regions were based on past hourly weather data from a fixed site closest to each city. While the heat products do show an accurate representation of the minimum products being used, it does not guarantee that all were covered during the 11-year timeframe. Because heat products can be issued based on more than just heat index, no assumptions can be made that the days studied and listed were the only days with heat products. Because of the low amount of heat product days, a speculation would be would other specific indices and outside factors that each office considers when issuing heat alerts.

Vulnerable populations and risk perceptions influence communication and thresholds of heat alerts across the U.S. Evaluating the vulnerability discussed within age and gender subsets within each region of the U.S., further research could be accomplished on how these results influence geographic variations and communication in risk perception. Communication could be assessed from the specific population who exhibited higher positive correlations with mortality to alerts and the WFO perspective of methods and tools of communicating alerts to the general population and the most vulnerable. This could be accomplished by survey with demographic questions as well as heat alert perception. Analyzing census data and social vulnerability indices for certain forecast zones to determine risk factors for heat related mortality and alert frequency would also help give additional details for each region.

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APPENDIX A

ADVISORY AND WARNING CRITERION FOR THE 107 CITIES ASSESSED

Table A.1 107 Metropolitan Cities from Sheridan et al. with Advisory and Warning Criteria.

Cities	Advisory	Warning
Akron OH	100	105
Albany NY	95	105
Albuquerque NM	100	105
Allentown PA	100	105
Atlanta GA	105	110
Augusta GA	110	115
Austin TX	108	113
Bakersfield CA	100	105
Baltimore MD	105	110
Baton Rouge LA	108	113
Birmingham AL	105	110
Boise ID	105	110
Boston MA	100	105
Bridgeport CT	100	105
Buffalo NY	100	105
Charleston SC	110	115
Charlotte NC	105	110
Chattanooga TN	105	110
Chicago IL	105	110
Cincinnati OH	100	105
Cleveland OH	100	105
Columbia SC	110	115
Columbus OH	100	105
Dallas TX	105	110
Dayton OH	100	105
Daytona Beach FL	108	113
Denver CO	95	100
Des Moines IA	105	110
Detroit MI	100	105
Durham NC	105	110
El Paso TX	105	110
Fayetteville AR	105	110
Fresno CA	100	105
Ft. Myers FL	108	113
Grand Rapids MI	100	105
Greensboro NC	105	110
Greenville SC	105	110
Harrisburg PA	100	105

Table A.1. (continued)

Hartford CT	100	105
Honolulu HI	105	110
Houston TX	108	113
Indianapolis IN	105	110
Jackson MS	105	110
Jacksonville FL	108	113
Kansas City MO	105	110
Knoxville TN	105	110
Lakeland FL	108	113
Lancaster PA	100	105
Las Vegas NV	105	110
Lexington KY	105	110
Little Rock AR	105	110
Los Angeles CA	100	105
Louisville KY	105	110
Madison WI	100	105
McAllen TX	110	115
Melbourne FL	108	113
Memphis TN	105	110
Miami FL	108	113
Milwaukee WI	100	105
Minneapolis MN	100	105
Modesto CA	100	105
Nashville TN	105	110
New Haven CT	100	105
New Orleans LA	108	113
New York NY	100	105
Ogden UT	105	110
Oklahoma City OK	105	110
Omaha NE	100	105
Orlando FL	108	113
Oxnard CA	100	105
Philadelphia PA	100	105
Phoenix AZ	105	110
Pittsburgh PA	100	105
Portland ME	95	105
Portland OR	105	110
Poughkeepsie NY	95	105
Providence RI	100	105
Provo UT	100	105

Table A.1. (continued)

Raleigh NC	105	110
Richmond VA	105	110
Riverside CA	100	105
Rochester NY	95	105
Sacramento CA	100	105
Saint Louis MO	105	110
Salt Lake City UT	100	105
San Angelo TX	105	110
San Antonio TX	108	113
San Diego CA	100	105
San Francisco CA	100	105
San Jose CA	100	105
Sarasota FL	108	113
Scranton PA	100	105
Seattle WA	100	105
Spokane WA	100	105
Springfield MA	100	105
Stockton CA	100	105
Syracuse NY	95	105
Tampa FL	108	113
Toledo OH	100	105
Tucson AZ	105	110
Tulsa OK	105	110
Virginia Beach VA	105	110
Washington DC	105	110
Wichita KS	105	110
Winston- Salem NC	105	110
Worcester MA	100	105
Youngstown OH	100	105