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Developing and Testing a Simple Approach for Projecting Temperature Trends to Facilitate Public Health Preparedness

By

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Master of Public Health

Environmental Health

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By

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B.S.
University of Michigan
2008

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Abstract

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By Shivangi Khargonekar

Extreme heat events (EHEs) are expected to intensify in North America in the 21st century, posing challenges outside current public health capacity. Adaptation will likely be required to minimize health impacts. Most adaptation to date has been in response to extreme weather events, e.g., the response to the European heat wave of 2003. The US has not experienced a similarly dramatic EHE and likely has a significant preparedness deficit. Scenario-driven table-top exercises are one way to facilitate preparedness, but these require credible projections of climatic shifts. Downscaled projections are computationally expensive, unavailable for most localities, and most public health agencies cannot make their own. Given the advent of warming trends in many locales, our objective is to determine whether it is appropriate to use historical weather data to project future temperature trends. Such an approach is relatively straightforward, intuitive, inexpensive, scalable, and generalizable compared with downscaled projections. To test this proposition, we used a dataset of historical weather for selected major US cities to identify appropriate indicators for projection, test multiple methods for extrapolating historical trends, project findings forward by climate region and city, and compare findings with available downscaled projections. Average daily temperature, average daily maximum temperature, and maximum of the daily maximum temperature in June-July-August (JJA) from 1950-2010 were selected as indicators. Stepwise autoregressive methods were used to generate polynomial projections of the indicators. The projections most consistent with historical data occurred with the indicators of central tendency and showed mostly positive trends (e.g., average daily temperatures in JJA in the Southeast are projected to increase by 5.6°F by 2035, and 10.0°F by 2055). Negative trends for extremes (maximum of the daily maximum temperature in JJA) resulted for three regions. The trends were determined to be a function of the extrapolation method and greater variability in historical data for these regions. Available downscaled regional projections were in concordance with our findings that much of the US will experience warming in the future. We conclude that this approach has promise but may systematically underestimate the magnitude of likely future temperature changes in regions with variable historical temperature trends.

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Introduction

Background

Extreme weather, particularly heat, causes significant morbidity and mortality in the US and many other developed countries. Human exposure to extreme heat can result in detrimental health outcomes, including dehydration and heat stroke, as well as exacerbate a range of underlying illnesses [1]. Heat is the leading weather-related cause of mortality in the US [2], and there are over 60,000 emergency department visits for heat illness in the US every year [3]. Extreme heat events (EHEs) are thus one of several significant threats associated with climate change in the developed world.

The US, like other Northern Hemisphere mid-latitude regions, has experienced warming and increasing weather variability in the summer months [4], trends consistent with anthropogenic climate forcing and in alignment with expectations of how climate change will affect weather in North America [5]. These shifts are expected to lead to a greater frequency of climate extremes. Climate extremes have been defined as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" [6]. EHEs are one such extreme. The Fourth Intergovernmental Panel on Climate Change (IPCC) Assessment report concluded that in the twenty-first century, it is very likely (i.e., a probability greater than 90%) that EHEs will intensify in magnitude and duration [6]. Some of these expected trends are already manifest. For instance, a study conducted by Alexander et al. concluded that the lowest and highest daily minimum and maximum temperatures in the later part of the 20th century increased in many regions around the world [7].

Future EHEs are likely to be increasingly frequent and severe. Diffenbaugh et al. explored the nature of future EHEs from the perspective that previous temperature extremes may become less severe than future minimum temperatures, and with increasing confidence observed that many regions of the world may experience increasing intensity of extreme heat as captured by global climate models [8]. Furthermore, Li et al. used a global circulation climate model to project temperature trends, and found that monthly average temperatures will increase in the 2059–2070 time period, especially in the summer months [9]. In addition, the global average temperature is predicted to further increase by between 1° and 3° Celsius by the year 2100 according to the IPCC [5].

The aforementioned studies and findings, among others, provide evidence for the potential for a shift in temperature, consistent with anthropogenic climate change. Shifts in average temperatures will likely result in a non-linear large increase in the frequency of extreme weather events, such as EHEs [10]. In the US, regions including the Northeast and Midwest are likely to experience the greatest number of illnesses and deaths as a result of to the predicted EHE intensification [11]. Consequently, extreme heat related mortality and morbidity within vulnerable populations - the elderly, children, those ill with chronic diseases, and individuals engaged in outdoor labor - are expected to increase, in the absence of adaptation, in a warming climate [1].

The European heat wave of 2003 vividly underscores the great need for public health preparedness for shifting EHE severity, particularly for rare, severe events that occur relatively infrequently but are becoming more likely as a result of climate change.

This particular heat wave was the result of climate variability on top of an already shifted temperature distribution. In the historical record, such an event had an annual probability of approximately 1 in 1,000 (this probability is often referred to as a "1-in-1000 year" event). Given anthropogenic climate change, however, the probability of such an event at the time was shifted and the new probability in the anthropogenically forced climate was approximately 1 in 250 [12]. This heat wave was associated with an excess mortality of approximately 35,000 people [13]. This large death toll resulted in part from lack of public health preparedness for such an event [14-16].

In light of this unprecedented EHE, the Third IPCC Assessment indicated that treatment of extreme weather events is "clearly inadequate" [17]. While no formal assessment of heat wave preparedness in the US has been conducted recently, presumably this concern includes the US as well. Preparedness and response measures that were implemented in Europe following this incident have reduced the health impact and the burden of illness of subsequent similar events [18]. For example, increased access to cooling centers and air conditioning prevalence, as well as heat health warning systems, have been implemented since 2003 [19]. Studies of a 2006 European heat wave suggest that these measures were effective and resulted in the avoidance of an expected 4,400 excess deaths during the 2006 event [20].

As exemplified by the response to the 2003 heat wave, most climate change adaptation (CCA) to date has been in response to extreme weather events [21]. It appears that local public health authorities are not yet shifting preparedness activities to account for the shifting temperature distribution [22]. Shifts in temperature may become greater in the future in the absence of aggressive mitigation strategies and efforts. Thus, preparedness for EHEs going forward needs to be based on expectations of these climate shifts occurring at a local level [21].

CCA to EHEs can take a wide range of forms, many of which originate and are administered and promoted locally. Some prevention messaging is aimed at changing individual behaviors, including use of air conditioning, taking frequent showers, and wearing lightweight clothing [11]. Local level action for prevention and adaptation can involve planting trees, heat health warning systems, media announcements, public education, and opening of cooling centers, among others [19, 23].

As heat wave response plans are complicated, often requiring coordinated efforts that typically include multiple partners, planned adaptation at the local level can be also facilitated using scenario-based approaches [24]. For example, reliable information and knowledge regarding likely hazard scenarios can support better preparation for heat-related emergency situations with regards to planning for response capacity and placement of emergency resources and personnel [20]. Furthermore, understanding the areas that will allow for an effective public health response is critical. Some of the key areas of response that have been identified include heat response plans, the use of remote sensing and GIS methodologies, and effective communications strategies [25]. In addition, it is imperative that early warning systems are in place to prepare for EHEs. Studies have shown that early warning systems implemented in Philadelphia and Chicago following severe heat waves that occurred in those cities have saved lives and costs [26].

Another widely accepted method for scenario-based planning and preparedness is the use of tabletop exercises to gather teams of individuals for identifying gaps in preparedness. These teams will ultimately need to work together in a real event. The

Homeland Security Exercise and Evaluation Program (HSEEP), for instance, is an exercise-based program accessible on-line that provides tools and resources for improving capacity, capability, and performance for a wide range of scenarios and events, including EHEs [27]. In the case of EHE preparedness, tabletop exercises bringing together key players, such as emergency responders, city managers, health care delivery personnel, urban planners, and utility managers may be very effective at identifying areas in which preparedness efforts are likely to fall short, as well as finding weaknesses in protective systems.

Prevention requires a range of actions at different levels, from health system preparedness coordinated with meteorological early warning systems, to timely public and medical advice and improvements to housing and urban planning [12]. Moreover, preparedness planning should be robust compared with the range of possible climate futures that emergency responders may face. As the US has not yet experienced an event such as the European heat wave, preparedness efforts have generally not incorporated the increasing potential for a very severe event in the US [22].

Significance

Preparedness for extreme heat is a climate change adaptation priority for public health. To facilitate this process through activities such as table-top exercises, there is a need for credible, locally-relevant projections of likely climatic shifts, along with robust preparedness planning compared with the range of possible climate futures that emergency responders may face. Projections of temperature trends could be helpful in emergency preparedness planning. Reliable climate projections for numerous regions of the world are now increasingly available due to more advanced climate modeling capabilities [28]. Such projections are often obtained through downscaling of Generalized Circulation Models (GCMs), which have relatively low-resolution outputs, to scales that are more locally relevant.

GCM projections are credible because they are generated from well-established physical climate models, they can simulate important aspects of the current climate, and they are able to replicate previous climatic trends [28]. These downscaled projections are computationally intensive, however, and are not available for a wide range of locales. Moreover, the public health sector does not house the relevant expertise to secure and interpret these downscaled projections [22], and frequently must request them from their state climatologists (in the case of state and local public health agencies) or from universities or federal agencies that have access to GCMs. As a result, most local public health planners do not have easy access to locally relevant projections. This is a barrier to public health preparedness for EHEs [29], particularly in regions that have yet to experience dramatic EHEs outside public health's historic coping range.

Extreme value theory (EVT) is a statistical method that can be used to predict EHEs. However, there are few data available to make such assessments, specifically regarding changes in the frequency or intensity of EHEs; increasing rarity of an event makes it more difficult to determine long-term climate changes [6]. Furthermore, while there have been significant efforts to model EHEs, such as the European Statistical and Regional Dynamic downscaling of Extremes for European regions (STARDEX) and Modeling the Impacts of Climate Extremes (MICE), clarity regarding impact of climate change on EHEs remains hindered by the lack of very long data series and difficulties of existing climate models to efficiently represent these events [30]. Parey et al., among others, have conducted studies on predicting EHEs using EVT in a stationary context for fixed periods in the future based on available simulations [31]. Often, these extreme value statistics are extrapolations for estimating return values and return periods, and do so by fitting the data to the tails of probability distribution functions [32].

Further evaluation using EVT for characterizing the likely severity and frequency of rare future EHEs as a result of climate change would be useful. Since changes in extremes can be linked to changes in the mean, variance, or shape of probability distributions, or all of these [6], EVT could be used to provide further insight into the relationship between measures of central tendency and extremes, as well as creating reliable predictions of return periods for EHEs in the future [31]. Such an exercise, however, would require examination of historical temperature trends, evaluation of appropriate indicators to use, and consideration of how to project future trends.

Goals and Objectives

The rationale for this study is that local public health agencies need to enhance their preparation for severe EHEs as a result of climate change. This effort is impeded by lack of easily available, reliable information regarding local climate shifts. Our aim is thus to explore a possible approach to filling this preparedness gap by considering whether it is possible to use available historical data and straightforward methods for characterizing and projecting historical temperature trends to generate locally-specific projections of temperature trends in the near-term. One common maxim in climate science is that "stationarity is dead," i.e., that we can no longer assume that static historical trends will prevail [33, 34]. Recent trends, however, may still provide a reliable guide to near- and mid-term climate shifts. The complexity and unavailability of downscaled GCM output is a barrier to public health adaptation to climate change [29].

Projections based on freely-available recent historical data would have several advantages over downscaled model outputs: ready availability, low cost, consistency with local historical data, and intuitive connections between historical data and likely future trends. They would also allow local public health agencies, which are voicing increasing concern over CCA needs and the lack of resources for these activities, to channel this concern into quickly generating relevant projections and pursuing preparedness activities, rather than securing and learning how to manipulate downscaled climate data. Furthermore, the climatic projections generated from this study would be especially intrinsic to emergency preparedness planning, as they could be used to generate predictions of the frequency and magnitude of future EHEs using EVT.

Our study aims to address this barrier by developing and testing a straightforward approach to generating local projections for near-term temperature shifts using historical data. Our goal is to develop such an approach and evaluate its efficacy based on several predetermined *a priori* criteria and in comparison with available downscaled regional projections. Accordingly, the study has several objectives:

1. To evaluate several possible temperature indicators to assess what measure(s) are most highly correlated with measures of extremes;
2. To determine what type of curvilinear function best fits historical temperature trends for the chosen indicators;
3. To project future temperatures by climate region and city using the derived curvilinear functions;

4. To apply *a priori* criteria, e.g. whether projected trend lines for temperature maxima cross those for average temperatures, to projection results to determine their face validity; and
5. To compare projection results with available downscaled regional projections to assess the degree of con- or discordance with more computationally intensive methods for generating downscaled projections.

Questions remain, however, regarding feasibility, generalizability, and validity of this approach. Consequently, our study objectives pertain both to development of appropriate methods for using EVT for predicting EHEs, and to evaluation of their overall performance compared with more data-intensive downscaled climate projections, where available. Ultimately, the goal of this study is to determine whether it is appropriate to use readily available historical data to project temperature trends for the near to mid-term. If these projections are valid and reliable, they will be useful for local preparedness planning surrounding EHEs.

Methods

Study Design

To address the need for EHE preparedness, we developed and tested a relatively low-cost, straightforward, more intuitive approach for generating projections that can easily be replicated by local public health authorities with freely available data. This approach involved using a freely available dataset of historical weather for major US cities to identify appropriate indicators of temperature trends (including those for central tendency and extremes), test multiple methods for extrapolating historical trends, project findings forward by climate region and city, and compare findings with available downscaled climate model projections to evaluate the degree of agreement.

Study Setting

The study setting was the contiguous lower 48 states of the United States from 1950 to 2010. Specifically, we used historical daily temperature and humidity data from 1950-2010 for 87 major US cities and 9 NOAA climate regions. Projections of extrapolated temperature trends were made for these cities and regions through 2055.

Site Selection

The current top 100 most populous cities in the US, based on population size, were identified from the 2010 US Census Bureau for our study sample. This list was cross-referenced to ensure that it included cities from the lower 48 states; if not, capital cities from states not represented were added to the list. Cities were then selected as final sites to be used in the study sample if they had historical data spanning the time period of 1/1/1950 to 12/31/2010. The cities were further categorized by the 9 US National Oceanic and Atmospheric Administration (NOAA) climate regions (Figure 1) [35] and the 9 US Census regions (Figure 2) [36]; this enabled regional climatic trend derivation. Note that cities representative of Alaska and Hawaii were not included in our sample because they were not included in the NOAA climate regions.

Data Sources and Management

Daily weather data for this sample (T_{max}, T_{min}, and T_{avg}, humidity, and precipitation) from 1950 to 2010 was captured from the National Climatic Data Center

(NCDC) weather database. Specifically, archived temperatures (in degrees Fahrenheit) and dew points between 1/1/1950 until 9/1/2011 from about 200 weather stations were extracted using tools provided on-line by the NCDC from the Integrated Surface Hourly datasets [37]. Most weather stations used were located at airports or air bases. Multiple readings from a single hour were combined to generate a single average for that hour. The 24-hourly averages were combined to produce the final daily temperature maximums, minimums, and averages. Daily relative humidity averages were calculated from the temperatures and dew points using a standard formula [38].

Some cities lacked data for the time period from 1965-1973. During this time period, many weather stations only collected data every third hour throughout the day due to budgetary cut-backs. In this case, the available measures were used as reported. As a result, from the initial 100 cities in our sample, 87 cities had complete datasets (i.e., daily data from at least 1/1/1950-12/31/2010). A subset of daily weather data for June-July-and-August (JJA) from 1950-2010 for each of the 87 cities was created, containing at least 22,428 observations; it was assumed that the summer months would include the most relevant data of temperature extremes for the study.

Data Analysis and Outcomes

Indicators

An exploratory factor analysis was performed of seasonal weather variables to identify which of these are most highly correlated with measures of extreme summer temperatures (e.g. temperature of the warmest JJA day of the corresponding year). A literature review to identify seasonal weather variables was conducted on PubMed and

Google Scholar (Google, Mountain View, CA). Specific search terms included: *climate change, temperature indicators, temperature variables, climate variables, temperature projections, temperature trends, extreme heat events,* and *extreme value theory*. Based on the results of this search, forty seasonal weather variables were identified and considered for the analysis, which included measures of counts (e.g., number of days above a maximum threshold temperature), measures of central tendency (e.g., average summer daily maximum temperatures during JJA), and measures of extremes (e.g., maximum summer daily maximum temperatures during JJA).

Bivariate correlation analyses were then conducted for all of the seasonal weather variables; for each NOAA climate region, correlation matrices were generated containing Pearson correlation coefficients, as well as descriptive statistics of the variables, including mean and standard deviation. The magnitude of the correlations between the variables, and evidence of consistent high correlations, were two criteria used to identify potential indicators to be used for the study sample. These indicators would act as our dependent variables for extreme temperature, and were assumed to be most highly correlated with truly extreme heat events.

Descriptive statistics (i.e., mean, median, minimum, maximum, range, and standard deviation) of the three indicators for all regions were examined by decade from 1950-2010 to determine if there was any significant decadal variation among these values or variation among regions. These findings would enable assessment of the reliability of the time period the historical data spanned for projecting trends.

Three relevant factors for the 87 cities and the nine NOAA US climate regions from 1950 to 2010 were chosen and used for extrapolation of trends. For determining indicator values for an entire region, an average was taken of the indicator values for all cities in the region. This established mean indicator values for regional trend derivation.

Projections

A comparison of two curvilinear functions (i.e., linear and polynomial) was conducted to determine which was best for extrapolation of trends. Thus, R^2 values of historical data were used to assess goodness-of-fit for the trend lines to the historical data. Using the most appropriate curvilinear function, temperature trends were extrapolated based on the historical data from 1950-2010, and were projected forward through 2060 to generate point estimates of the three temperature indicators of EHEs. Specifically, a stepwise autoregressive method was used which combined a quadratic time trend regression with an autoregressive model in order to capture short-term fluctuations that were assumed to occur in daily temperature data. The stepwise regression procedure allows for the selection of appropriate autoregressive parameters for the model; the parameters are only used at lags during which they are statistically significant. This method also fits a quadratic time trend regression for the entire data series and places equal weights on all observations in the data set [39].

The projections of the three indicators based on historical data from 1950-2010 for the 87 cities and nine climate regions in the sample were then compared for positive or negative trends. Deviations in temperature projections in 2035 and 2055 compared to temperature normal (the average baseline temperatures for 1950-2010) for all three indicators for each region were also assessed. Maps of the US and its climate regions with these data were created to visualize the deviations using ArcGis 10 (Redlands, CA).

Confidence intervals surrounding the projected trend lines for each indicator of five regions exhibiting positive and negative trend lines were calculated to further assess reliability of the projections extrapolated from the 1950-2010 historical data (Figures 39-41). To assess for sensitivity to multi-year trends in historical data, trend lines were also derived for subsets of the historical sample subsets (i.e., 1950-2010, 1960-2010, 1970-2010, and 1980-2010) for regions with unanticipated results (Figures 42-44).

All data management and analyses were performed using SAS 9.3 (SAS Institute, Cary, NC) and Microsoft Excel 2010 (Microsoft Corporation, Redmond, WA).

Comparisons

A comparison was conducted to evaluate consistency with expectations for regional changes based on downscaled projections. A literature review using PubMed and Google Scholar (Google, Mountain View, CA) was conducted to identify existing downscaled GCM temperature projection trends in New York, NY, Sacramento, CA, and the US to assess any concordance or discordance with our study's approach and results for both cities and regions. Search terms included: *New York, California, United States, climate change, climate regions, temperature trends, projections,* and *extreme heat events.*

Results

Study Sample

Of the 100 most populous US cities identified, a total of 87 cities met the inclusion criteria. These cities and their respective NOAA climate regions were compiled for the study sample (Table 1). A total of 1,980,131 temperature observations were in the sample. Most of the cities in our sample had a dataset including 22,524 observations (1/1/1950-9/1/2011), while a few others had slightly less data; however, all cities in our sample had enough data to conduct analyses using a consistent time period of historical data from 1/1/1950-12/31/2010.

Indicators

When assessing indicators, we were interested in identifying which were the best indicators of extremes. Three out of the 40 seasonal variables (Table 2) that were evaluated were determined to be highly correlated with EHEs, including: mean of the daily summer average temperatures during JJA for each year ("Mean_Tavg"), mean of the daily summer maximum temperatures during JJA for each year ("Mean_Tmax"), and maximum of the daily summer maximum temperatures during JJA for each year ("Max_Tmax"). The indicators of central tendency contained consistently higher Pearson correlation coefficients closer to 1 compared to other indicators considered, such as those of count (e.g., number of days above a threshold temperature).

Max_Tmax was selected to be an indicator of EHEs to include a measure of extremes, even though it did not maintain consistently high Pearson correlation coefficients (Table 3). Specifically, Max_Tmax had correlation coefficients ranging from -0.27 to 0.91 across all regions.

Variability of Historical Data

Most regions had similar and fairly low standard deviation values (in degrees Fahrenheit) for the three indicators across each decade of the historical data (1950-2010), except the West (region 5) Standard deviation values ranged from 2.3 to 4.4 for the Northeast (region 1), 2.2 to 4.5 for the Southeast (region 2), 2.4 to 4.1 for the South (region 3), 4.7 to 6.2 for the Southwest (region 4), 3.3 to 6.4 for the Northwest (region 6), 2.8 to 4.7 for the West North Central (region 7), 3.4 to 4.6 for the East North Central (region 8), and 3.0 to 4.6 for the Central climate region (region 9). The West, however, had much higher standard deviation values, ranging from 9.0 to 12.2. The range between the minimum and maximum values (in degrees Fahrenheit) for each indicator in the West was also much higher than the other regions (ranged from 30.7 to 38.0). Finally, as expected, across all regions, values of other descriptive statistics (i.e., mean, median, minimum, maximum) for Max_Tmax were highest, followed by Mean_Tmax, and Mean_Tavg.

There is thus evidence of historical variability over time among and within regions (Table 4). The spread of data given by the descriptive statistics for each indicator can also be visualized in the boxplots for the Northeast and West climate regions (Figures 3-5). The boxplots show the mean, median, minimum, maximum, and interquartile range (i.e., the difference of the upper and lower quartiles, or the middle 50% of the data) for each climate region over time. It is evident that the West displays a larger interquartile range and a larger overall range of temperatures compared to the Northeast, indicating that there is historical variability between regions for all three temperature indicators. Furthermore, it is apparent that there is some decadal variability within the regions, as the mean, median, interquartile range, and overall range (difference between the maximum and minimum temperatures), seem to moderately fluctuate over time for all three temperature indicators. This is especially apparent for the West, reflective of its variable historical data.

Projections

Both polynomial and linear functions were fit to the historical data. Based on R^2 values, the polynomial functions had a stronger goodness-of-fit for the historical data compared to linear functions (Figures 6-14), though R^2 values for both linear and polynomial functions were relatively low. Based on our *a priori* criteria, we selected polynomial projections with quadratic trend lines of temperature based on historical data to extrapolate for regions and cities using a stepwise autoregressive method. Results for these extrapolations are presented in Figures 21-29.

The Northeast, Southeast, South, Southwest, Northwest, and Central climate regions (regions 1, 2, 3, 4, 6, and 9, respectively) all showed positive trends for all three indicators. Some Regions had projected trends that sloped more positively than others (confirmed by their quadratic functions), including the Southeast, South, and Central climate regions (regions 2, 3, and 9, respectively). The West (region 5) showed negative trends for all three indicators. The West North Central and East North Central regions (regions 7 and 8, respectively) showed slight negative trends for the indicators involving maximum temperature (Max_Tmax and Mean_Tmax), but a positive trend for Mean_Tavg based on point estimates at 2035 and 2055, as well as overall trends for projected data (Table 5). None of the projected quadratic curves for any indicator crossed, with projected temperatures being highest for Max_Tmax, followed by Mean_Tmax, and Mean_Tavg (Figures 30-38).

Projections at 2035 and 2055 of all three temperature indicators were assessed in regards to regional levels of deviation (both positively and negatively) from the temperature normal (average temperature of the indicators from 1950-2010). The West, West North Central, and East North Central climate regions deviated negatively in differing amounts for all three indicators, while the Southeast, South, and Central regions deviated more positively from the temperature normal (Table 6, Figures 15-20).

Given the negative projections in the Western climate region, we used this region to test for sensitivity to variability in the historical data by generating derivations using subsets of the historical data to generate projections, as described in the Methods section. Subsets of data including 1950-2010 and 1960-2010 generated negative trends for all three indicators for the region. Historical data from 1970-2010 generated negative trends in Mean_Tavg and Mean_Tmax, but a positive trend for Max_Tmax. Finally, historical data from 1980-2010 generated positive trends for all three indicators (Figures 42-44). The positive trends generated from more recent data for this region (1980-2010) appeared to be much more positively sloped for all three indicators compared to any positive trends generated from the entire historical dataset or any subset of it. In addition, the trend generated for this region for Max_Tmax was much more positively trended compared to the other two indicators for this region, based on historical data from 1980-2010.

Comparisons with Downscaled GCM Outputs

There are limited published downscaled GCM outputs for the US as a whole and no published studies providing outputs that were directly comparable with our results for the entire sample. We were only able to find downscaled GCM outputs reflecting seasonal and annual global temperatures for “warm days” and “warm nights” during the

20^{th} century (1901-2003) from a study by Alexander et al. (2006) [40]. The study concluded that the Northern Hemisphere mid-latitudes showed significant shifts in temperatures reflecting warming over the area, based on stations with nearly complete data from 1901 to 2003. In addition, the US was found to have significant temperature increases for “warm nights” in JJA by 0-6°F for most of the country from 1979-2003. Moreover, a significant increase in annual nighttime temperatures was observed for regions in the northern hemisphere (including the US) from 1979-2003 compared to the earlier historical data of the 20^{th} century. The aforementioned findings suggest continued trends of warming for these regions in the future (Figure 48). Only a small portion of the country (visually appeared to be some part of the West North Central climate region) had negative temperature projections associated with extremes; however, these were claimed to be of lesser magnitude and insignificant by the study’s authors compared to the significant positive temperature projections. Their study results were consistent with our overall projections of warming for most of the US. However, our negative trended projections for the West, West North Central, and East North Central, are not in concordance with their findings.

To compare more localized projections, we found existing projected temperature data and GCM outputs available in the literature for New York, NY and Sacramento, CA. In 2009, the New York City Panel on Climate Change published their findings on climate change scenarios, and future temperature trends based on 16 downscaled GCM outputs and 3 climate scenarios (Figure 46) [41]. They analyzed extreme heat events using threshold indicators of temperature maxima, including: the number of days with maximum temperatures greater than 90°F or greater than 100°F based on historical data from 1971-2000. Their projections included maximum temperatures in New York City increasing by 1.5 to 3°F by the 2020s, 3 to 5°F by the 2050s, and 4 to 7.5°F by the 2080s. Their findings are similar to ours in the near-term, as our projections have New York City average maximum temperatures increasing by 2.6°F by the 2020s; however, we projected an increase of 9.3°F by the 2050s which is more extreme compared to their projections (Tables 7-8, Figures 45-46).

In 2012, a study by Mastrandrea and Luers [42] was published with projections of various climate extremes, including temperature, for the state of California. Specific summer temperature projections for mid-century were generated for Sacramento, CA using baseline data from 1971-2000. The authors of this study found that the average annual temperature of the state is projected to increase by 1.8 to 5.4°F, under either the A2 (higher emissions) or B1 (lower emissions) scenario. The projections are more extreme for the end of the century under the A2 scenario, with temperatures expected to rise by 4.5 to 9°F. The study also concluded that by mid-century, Sacramento summer temperatures are projected to increase by 5.4 to 10.8°F for the A2 scenario, and 2.7 to 7.2°F for the B1 scenario (Table 10). However, our study projects opposite trends, with average daily summer temperatures in JJA for Sacramento expected to decrease by 1.2°F by mid-century (2050); this negative projection is based on the city's temperature normal of 72.2°F, calculated from historical data for average daily summer temperatures in JJA from 1950-2010 (Tables 9-10, Figure 47).

Discussion

It was determined that two temperature indicators, both of central tendency, were most highly correlated with measures of extremes. This finding is in concordance with what is in the literature regarding EHEs and temperature indicators: changes in extremes can be linked to changes in the mean [6]. A measure of extremes, maximum of the daily maximum temperature in JJA, was also included in our analyses to assess any resulting trends that may be more pronounced in the future for temperature maxima. Polynomial functions were found to fit the historical temperature trends better than linear functions for these chosen indicators, and were used to project future temperatures by climate region and city. Projected trend lines for temperature maxima never crossed those for average temperatures, demonstrating that recent historical trends in all projected indicators follow similar trajectories. Most of the projections were positive, suggesting a trend of warming for much of the country for all three temperature indicators.

Certain findings were surprising, particularly the negative projection results for three of nine regions. However, the reliability of these trends was less certain given the greater variability and lower R^2 values in the historical data for these regions. Moreover, in the West, there is a much wider range of temperatures in the data compared to other regional locales, and this relatively wide range may have resulted in less reliable trends. For the regions with negative projections based on data from 1950-2010, positive projections resulted when using a more recent subset of historical data (e.g., 1980-2010), which supports the idea that these regions may be more sensitive to the local historical data variability and trends. This prompts the question of what is the most appropriate historical baseline to use for projecting future temperature trends, and whether a more recent data series that shows more pronounced warming trends, is most appropriate.

Using more recent data may result in more uniformly positive trends across all regions, though confidence intervals are likely to be larger as there is less data available to generate extrapolations.

Overall, the results of our method generated projections that were largely in accordance with available downscaled regional projections, with future warming to occur across most of the US. However, several regions and cities with negative projections were discordant with what is available in the current literature. As noted above, these projections were recognized as being less precise, most likely due to our method and the use of historical data for these regions which were more variable than other regions. That the method we developed produced projections that were not in accordance with GCM outputs suggests that our approach may be prone to over- or underestimating future temperature trends. In some regions, this method may not be reliable and the more computationally intensive GCM outputs may be required for public health activities requiring precise estimates of future warming likely from climate change.

Indicators

It was evident that the indicators of central tendency in temperature distributions were more highly correlated to with extreme values (our proxy for EHEs) than indicators based on counts of days with temperatures above predefined thresholds. This is consistent with the findings of prior studies that changes in climate extremes are associated with changes in mean [6]. This result may also be artifactual, as two continuous variables within a distribution are more likely to demonstrate correlation than a continuous variable and a discrete one. The maximum of the daily maximum temperature in JJA (Max_Tmax), which was the selected indicator of extremes for EHEs, resulted in more extreme temperature projections (i.e., the slopes of the quadratic curves were higher) regardless of whether projections were positively or negatively trended. The mean of the daily average temperature in JJA and the mean of the daily maximum temperature in JJA produced less extreme projections. These findings suggest that indicators of central tendency may be more reliable for projecting future temperature trends; however, it is possible that there could be a separate trend in extremes that could be more pronounced in the future.

Variability of Historical Data

The descriptive statistics provided evidence of variability within each decade for the climate regions, which generally neither increase nor decrease over time, suggesting short-term fluctuations of historical data. The highest standard deviations resulted in the West (region 5), indicating that this region's observed data is highly variable compared to other climate regions. When examining local projections within this region, Las Vegas, NV, had much higher temperatures than the other cities and these data points extended the region's data range much further than in other regions. Las Vegas was also the only city with positively trended higher temperature results for all three temperature indicators. Oakland, CA was also found to have positively projected trends for average daily maximum temperature in JJA and maximum of the daily maximum temperature in JJA. Finally, Fresno, CA and Sacramento, CA had positively projected trends for maximum of the daily maximum temperature in JJA. Otherwise, all other cities in this region had negatively trended projections with lower temperatures for all three indicators (Table 9). Thus, it is important to recognize that the negative projection for this region may be a result of the variability of data present among the cities in the region. Slightly higher variability was also apparent in the West North Central and East North Central climate regions (regions 7 and 8, respectively). It is possible that the variable historical data of these regions may be a cause for decreased precision and reliability of their projected temperatures; the decrease in precision is reflected in their 95% confidence intervals which were larger than other regions' with positive projected trends, such as the Southeast (region 2). Furthermore, statistics such as the maximum, minimum, and mean, for Max_Tmax (the maximum of the daily maximum temperature in JJA) had values that were higher than for the other two indicators which were measures of central tendency; this further supports our earlier conjecture that the measure of extreme produces more extreme temperature estimates than the measures of central tendency.

Projections

We used an observational historical dataset from 1950-2010 to study past, present, and future daily temperature trends across major cities and regions of the US through 2060. Polynomial functions were chosen over linear functions to extrapolate trends, as these functions were able to account for short-term fluctuations in the historical data and were assumed to be better for approximating the curvilinear historical data trends. Projected trends for regions and cities within our study sample suggested that most of the US will experience increasing temperature trends, but regional projections were more variable. The West North Central and East North Central climate region projections suggested that temperature maxima would decrease but average temperatures would rise. Ultimately these two trends are incompatible, though the trendlines did not cross for the study period we projected. As historical temperature maxima are more variable, these findings again suggest that projections based on highly variable data are likely less reliable than projections based on historical data with relatively little variability.

Projected temperature trends for all three indicators in the West were negative, despite recent historical warming trends in this region. The projected negative trends were surprising and prompted close examination of these projections to assess the reliability of historical data generating these trends and the validity of the projections themselves. This led to several conclusions. First, we again see that projections based on highly variable data (e.g. on historical Max_Tmax) produce more extreme projections, even for negative trends. Thus the trends for maxima may be less reliable because they are based on fewer data points than those of central tendency. Second, since projected trends of temperature maxima for the West, West North Central, and East North Central became positive when using a subset of historical data (1980-2010), we conclude that more recent data in which warming trends are more pronounced may be more reliable for projecting short-term to medium-term trends for all three indicators, though the confidence intervals around such projections will be wider than for projections based on a longer time series. Third, we conclude that this method produces estimates with wide confidence intervals past mid-century, indicative of less precision and greater uncertainty in later years (closer to 2060). This finding is even more pronounced for the West compared to the Northeast, Southeast, West North Central, and East North Central climate regions, suggesting that the projections for the West are less reliable than for other regions.

Comparisons

When comparing our projections with downscaled GCM outputs of future trends for “warm nights” across the globe including the US, most of our regions had similar projections of positive trending (Figure 48) [40]. The comparison was not based on consistent measurements. The study by Alexander, et al. (2006) used annual temperatures for their global projections, whereas we focused on summer temperatures in JJA. However, the GCM outputs supported the positive trends seen in most of our regional projections. Their statistically insignificant findings of negative trends of lower magnitudes in the northern hemisphere mid-latitudes may support the idea that some of our negative projections for the West, West North Central, and East North Central may also be insignificant, given that the projections become positively trended based on more recent historical data compared to using the entire historical dataset (1950-2010).

For comparing local maximum temperature projections for New York City, projections were similar in terms of general positive trending in the near and medium-term. However, the comparison was not consistent; our projections were seasonal and based on a conservative approach, while their projections were annual and based on combined data from 16 GCM outputs and three climate scenarios. Moreover, they projected specific ranges of increases in temperature maxima based on threshold indicators, which we compared to our measure of average maximum temperature, a measure of central tendency. Nevertheless, projections of temperature increases from baseline temperature normal were similar in the 2020s, which suggests that our projections are consistent in the near-term. While the projections for increases in temperature maxima by the 2050s differed, the comparisons were not based on consistent indicators of temperature, nor on similar periods of time for baseline data. Overall, the evident trend of warming in New York City is apparent in their findings and in ours, although the rate of increase of projected warming in their study is lower than ours, leading to progressively larger differences in projected trends further into the future.

Our projections for Sacramento, CA differed from the findings from the Mastrandrea and Luers (2012) study. Their study projected positive trends for summer temperatures by mid-century, whereas our study projected negative trends. Again, the comparison is not exact. Firstly, it is unclear from the study what months were used to project the summer temperature increases. Secondly, their study used different baseline data from 1971-2000, and our projections were based on 1950-2010. Since Sacramento, CA is in the West climate region (region 5), we may extrapolate that this city may also show positive trends based on more recent historical data, just as the region did when using data from 1980-2010 for projecting average summer daily temperatures in JJA.

Study Strengths and Limitations

It is notable that our study took a relatively conservative approach, as compared to downscaled climate models, for generating temperature projections; it did not take into consideration the accumulation of atmospheric carbon dioxide, which is expected to result in accelerating warming over time. Despite this, the downscaled GCM projections for New York City were of a smaller magnitude than those we generated, particularly for the mid-century. For Sacramento, our method produced negative projections compared to existing downscaled positive projections based on the A2 and B1 emissions scenarios. Additionally, in other regions across the country, the changes projected using our methods are considerably smaller than expected based on GCM outputs. Thus, our study method appears to result in a wider range of projections than GCMs and to be much more sensitive to local historical data variability and trends.

Concerns regarding both internal and external validity of our study are evident. Different levels of data variability by region over time were apparent; this variability overwhelmed other trends in some regions. This detracted from the internal validity of our study. In addition, some climate regions had many data points while others had relatively few, due to the cities in our study sample (i.e., our sample contained more cities that were categorized in the Northeast climate region). This suggests that the findings from our study are more valid for regions with more data, implicating the external validity of our study.

The approach we developed is based on freely available historical data and is easily replicable and low-cost. Our decision to use a stepwise autoregressive method to produce polynomial projections took into account significant short-term fluctuations and variability in the historical data. Comparisons to GCM outputs supported the positive direction of most of our regional projections, confirming warming trends across the US. For the regions that had negative projections based on the entire dataset, it is clear that using a more recent subset of data gave way to projections that were positively sloped. Thus, projections for these regions using only more recent data subset may increase the validity of these projections. Overall, our method appears to be appropriate for facilitating public health preparedness for most US climate regions, with projections reflecting warming trends for much of the country. However, our approach may systematically under- or overestimate the magnitude of likely future temperature changes in regions with variable historical temperature trends.

Conclusion

Currently only geographically coarse temperature projections are widely available, and these projections are limited in their ability to capture local climatic phenomena and climate extremes [43] and are thus too general to facilitate public health preparedness. To address this issue, either new methods for generating local projections will need to be developed, or downscaled GCM outputs will need to be made much more widely available in order to facilitate public health preparedness for EHEs. We have developed a low cost, generalizable approach for generating temperature projections using historical data that performed relatively well in a majority of US climate regions. Increases in both average and maximum temperature were projected for most climate regions, suggesting future warming across much of the US and consistent with existing available downscaled GCM outputs. The method's universal validity is in question, however, as projections for some regions resulted in negative trends. These projections become positive if a more recent historical baseline is used, suggesting that the overall method is sensitive to the range and variability of historical data.

Our approach may be used to facilitate public health preparedness for EHEs, particularly for regions with relatively little historical variability, keeping in mind that it has the potential for over- or underestimation of future temperature trends. Future studies may wish to only use more recent data to project temperature trends in the future, especially for the medium- to long-term. Additionally, one may wish to pursue projections using threshold indicators of EHEs. While our results showed that these factors did not have high correlation coefficients, indicating they are not the best indicators of EHEs, it is worth noting that other studies have utilized threshold variables as they enable analyses of multiple heat waves in a given time period [44]. Further, our study assessed seasonal summer temperatures, which was defined using data from only JJA. The same approach may be used while considering data from additional months, such as May-September. This may account for additional temperature extremes which may not have been included in our dataset. Finally, all available downscaled GCM outputs should be used for facilitating preparedness of EHEs, though currently these outputs are rare. Future efforts should be made to provide the public health community with such downscaled outputs and the skills required to apply the outputs to activities that will increase public health preparedness for EHEs.

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Tables and Figures

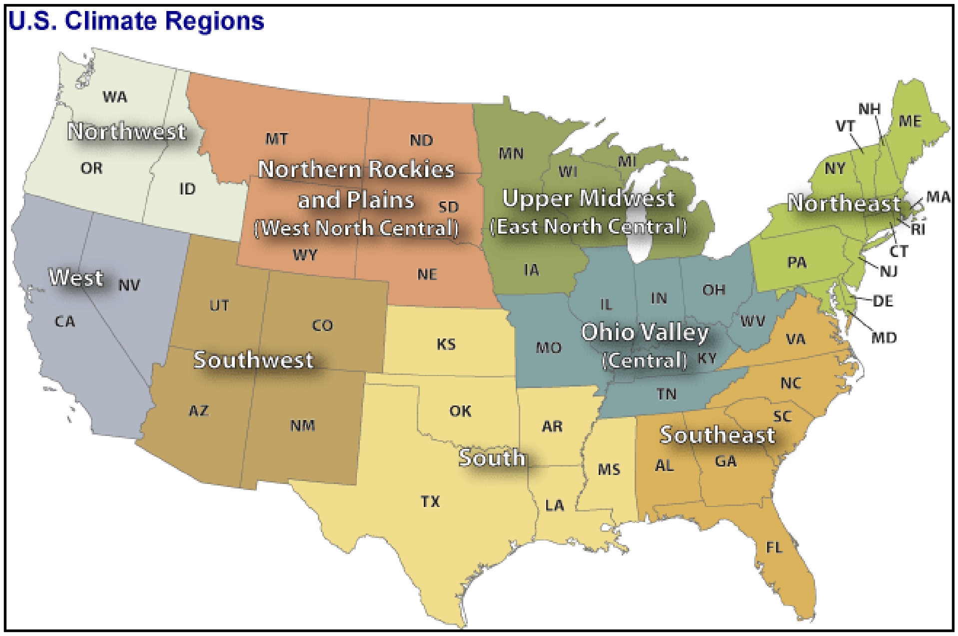

Figure 1: NOAA US Climate Regions.

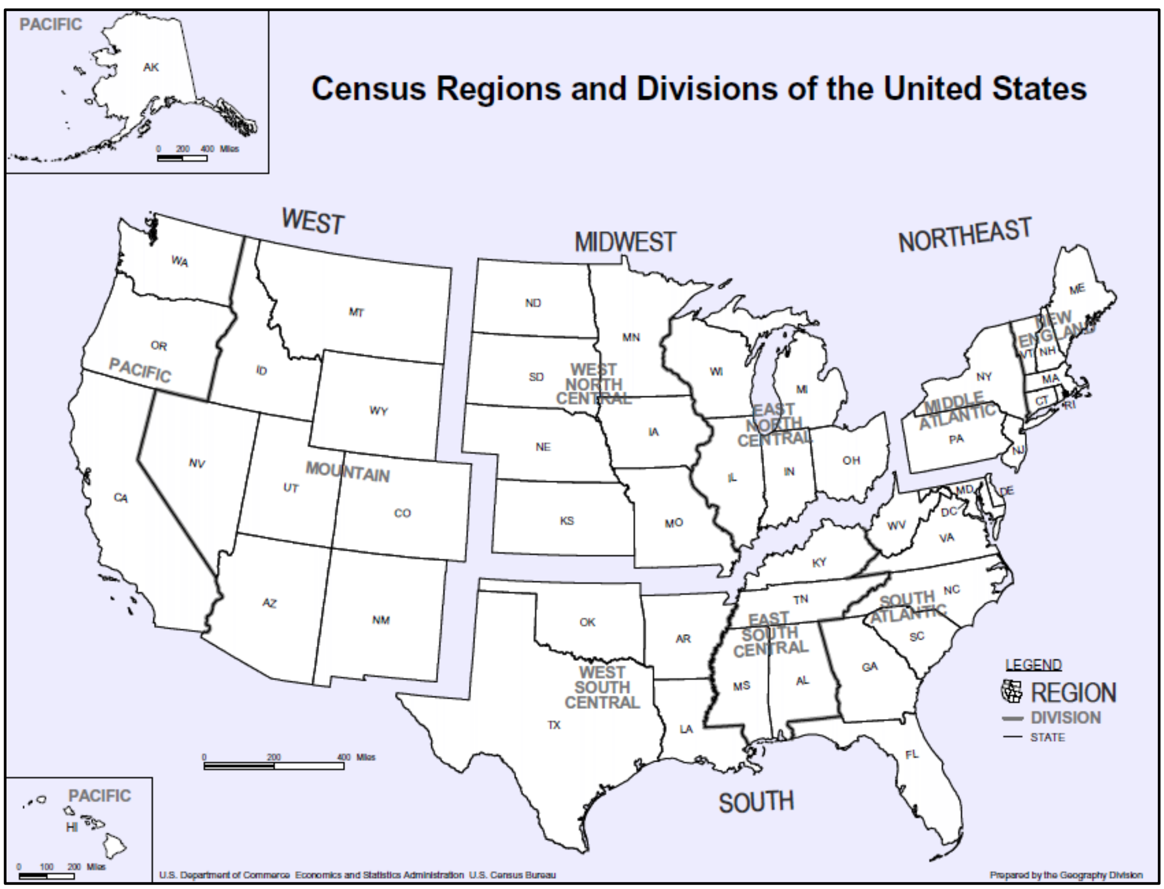

Figure 2: US Census Regions.

City	State	Number of Observations	NOAA Climate Region	NOAA Climate Region Code
Akron	Ohio	22524	Central	9
Albuquerque	New Mexico	22524	Southwest	4
Atlanta	Georgia	22524	Southeast	2
Bakersfield	California	22524	West	5
Baltimore	Maryland	22524	Northeast	1
Billings	Montana	22524	Central	9
Birmingham	Alabama	22524	Southeast	2
Charleston	West Virginia	22524	Central	9
Charlotte	North Carolina	22524	Southeast	2
Cheyenne	Wyoming	22524	West North Central	7
Chicago	Illinois	22524	Central	9
Colorado Springs	Colorado	22524	Southwest	4
Columbia	South Carolina	22524	Southeast	2
Concord	Massachusetts	22524	Northeast	1
Corpus Christi	Texas	22524	South	3
Denver	Colorado	22524	Southwest	4
Duluth	Minnesota	22524	East North Central	8
El Paso	Texas	22524	South	3
Fort Wayne	Indiana	22524	Central	9
Fresno	California	22524	West	5
Greensboro	North Carolina	22524	Southeast	2
Honolulu	Hawaii	22524	N/A	N/A
Houston	Texas	22524	South	3
Indianapolis	Indiana	22524	Central	9
Jacksonville	Florida	22524	Southeast	2
Kansas City	Missouri	22524	Central	9
Las Vegas	Nevada	22524	West	5
Long Beach	California	22524	West	5
Louisville	Kentucky	22524	Central	9
Lubbock	Texas	22524	South	3
Madison	Wisconsin	22524	East North Central	8
Memphis	Tennessee	22524	Central	9
Miami	Florida	22524	Southeast	2
Milwaukee	Wisconsin	22524	East North Central	8
Minneapolis	Minnesota	22524	East North Central	8
Nashville	Tennessee	22524	Central	9
New York	New York	22524	Northeast	1

Newark	New Jersey	22524	Northeast	1
Norfolk	Virginia	22524	Southeast	2
Oklahoma City	Oklahoma	22524	South	3
Philadelphia	Pennsylvania	22524	Northeast	1
Phoenix	Arizona	22524	Southwest	4
Portland	Oregon	22524	Northwest	6
Providence	Rhode Island	22524	Northeast	1
Raliegh	North Carolina	22524	Southeast	2
Richmond	Virginia	22524	Southeast	2
Rochester	New York	22524	Northeast	1
Salt Lake City	Utah	22524	Southwest	4
San Antonio	Texas	22524	South	3
San Diego	California	22524	West	5
San Francisco	California	22524	West	5
Seattle	Washington	22524	Northwest	6
Shreveport	Louisiana	22524	South	3
Sioux Falls	South Dakota	22524	West North Central	7
Spokane	Washington	22524	Northwest	6
St. Louis	Missouri	22524	Central	9
Tampa	Florida	22524	Southeast	2
Tulsa	Oklahoma	22524	South	3
Washington	District of Columbia	22524	N/A	N/A
Wichita	Kansas	22524	South	3
Austin	Texas	22523	South	3
Baton Rouge	Louisiana	22523	South	3
Boise	Idaho	22523	Northwest	6
Boston	Massachussetts	22523	Northeast	1
Buffalo	New York	22523	Northeast	1
Columbus	Ohio	22523	Central	9
Dallas	Texas	22523	South	3
Des Moines	Iowa	22523	East North Central	8
Jackson	Mississippi	22523	South	3
Little Rock	Arkansas	22523	South	3
Montgomery	Alabama	22523	Southeast	2
Fargo	North Dakota	22522	West North Central	7
Tucson	Arizona	22522	Southwest	4
Detroit	Michigan	22521	East North Central	8
Lexington	Kentucky	22521	Central	9
New Orleans	Louisiana	22521	South	3
Cincinnati	Ohio	22520	Central	9
Cleveland	Ohio	22519	Central	9

Burlington	Vermont	22515	Northeast	1
Oakland	California	22506	West	5
Pittsburgh	Pennsylvania	22505	Northeast	1
Toledo	Ohio	22503	Central	9
Sacramento	California	22489	West	5
Bridgeport	Connecticut	22487	Northeast	1
Fayetteville	North Carolina	22453	Southeast	2
Wilmington	Delaware	22136	Northeast	1
Omaha	Nebraska	21854	West North Central	7

Table 1: List of cities in study sample.

Variable Name	Variable Definition
mean_tavg	Mean of daily average temperature
mean_tdiff	Mean of the difference between daily maximum temperature and daily minimum temperature
mean_tmax	Mean of daily maximum temperature
mean_tmin	Mean of daily minimum temperature
med_tavg	Median of average daily temperature
med_tdiff	Median of the difference between daily maximum temperature and daily minimum temperature
med_tmax	Median of daily maximum temperature
med_tmin	Median of daily minimum temperature
max_tmax	Maximum of daily maximum temperature
mean_3dtmax	3-day rolling average of maximum temperature
Days_Tmaxabove85f	Number of days where maximum temperature is above 85 degrees F
Days_Tmaxabove90f	Number of days where maximum temperature is above 90 degrees F
Days_Tmaxabove95f	Number of days where maximum temperature is above 95 degrees F
Days_Tmaxabove100f	Number of days where maximum temperature is above 100 degrees F
Days_Tmaxabove105f	Number of days where maximum temperature is above 105 degrees F
Days_tmax50_80_1SD	Number of days the maximum temperature is above 1 standard deviation measured from 1950-1980
Days_tmax80_10_1SD	Number of days the maximum temperature is above 1 standard deviation measured from 1980-2010
Days_tmax50_80_2SD	Number of days the maximum temperature is above 2 standard deviations measured from 1950-1980
Days_tmax80_10_2SD	Number of days the maximum temperature is above 2 standard deviations measured from 1980-2010
Days_tmax50_80_3SD	Number of days the maximum temperature is above 3 standard deviations measured from 1950-1980
Days_tmax80_10_3SD	Number of days the maximum temperature is above 3 standard deviations measured from 1980-2010

Days_tmax50_80_pctl99	Number of days the maximum temperature is above the 99th percentile measured from 1950-1980
Days_tmax50_80_pctl95	Number of days the maximum temperature is above the 95th percentile measured from 1950-1980
Days_tmax80_10_pctl99	Number of days the maximum temperature is above the 99th percentile measured from 1980-2010
Days_tmax80_10_pctl95	Number of days the maximum temperature is above the 95th percentile measured from 1980-2010
mean_HI_tmax	Mean of heat index of daily maximum temperature
mean_HUM_tmax	Mean of humidex of daily maximum temperature
mean_HUM_tmin	Mean of humidex of daily minimum temperature
mean_HUM_tavg	Mean of humidex of daily average temperature
mean_HUM_diff	Mean of humidex of the difference between daily maximum temperature and daily minimum temperature
mean_AT_tmax	Mean of the apparent temperature of daily maximum temperature
mean_AT_tmin	Mean of the apparent temperature of daily minimum temperature
mean_AT_tavg	Mean of the apparent temperature of daily average temperature
mean_AT_diff	Mean of the apparent temperature of the difference between daily maximum temperature and daily minimum temperature
Days_HImaxabove90	Number of days where humidex is above 90 degrees F
Days_HImaxabove105	Number of days where humidex is above 105 degrees F
Days_HImaxabove130	Number of days where humidex is above 130 degrees F
Days_ATmaxabove80	Number of days where maximum apparent temperature is above 80 degrees F
Days_ATmaxabove90	Number of days where maximum apparent temperature is above 80 degrees F
Days_ATmaxabove95	Number of days where maximum apparent temperature is above 80 degrees F

Table 2: Names and definitions of potential indicators of EHEs.

Region	Variable	mean_t avg	mean_t diff	mean_t max	mean_t min	med_t avg	med_t diff	med_t max	med_t min	max_t max
1	**mean_tavg**	1.00	-0.25	0.93	0.96	0.99	-0.20	0.91	0.96	0.49
	mean_tmax	0.93	0.05	1.00	0.82	0.92	0.09	0.98	0.83	0.59
	max_tmax	0.49	0.33	0.59	0.40	0.48	0.37	0.57	0.41	1.00
2	**mean_tavg**	1.00	-0.16	0.83	0.92	0.99	-0.17	0.80	0.90	0.22
	mean_tmax	0.83	0.35	1.00	0.60	0.83	0.34	0.98	0.59	0.56
	max_tmax	0.22	0.66	0.56	-0.03	0.22	0.66	0.56	-0.01	1.00
3	**mean_tavg**	1.00	0.01	0.84	0.85	0.98	0.01	0.80	0.84	0.40
	mean_tmax	0.84	0.50	1.00	0.48	0.84	0.50	0.98	0.48	0.70
	max_tmax	0.40	0.70	0.70	0.03	0.41	0.68	0.67	0.04	1.00
4	**mean_tavg**	1.00	-0.32	0.85	0.93	0.98	-0.37	0.80	0.91	0.63
	mean_tmax	0.85	0.17	1.00	0.63	0.86	0.11	0.98	0.61	0.80
	max_tmax	0.63	0.26	0.80	0.43	0.65	0.21	0.79	0.41	1.00
5	**mean_tavg**	1.00	0.61	0.98	0.87	1.00	0.61	0.98	0.85	0.86
	mean_tmax	0.98	0.70	1.00	0.79	0.97	0.70	0.99	0.78	0.90
	max_tmax	0.86	0.75	0.90	0.60	0.85	0.75	0.88	0.58	1.00
6	**mean_tavg**	1.00	0.86	0.98	0.69	0.98	0.86	0.97	0.67	0.82
	mean_tmax	0.98	0.93	1.00	0.59	0.97	0.92	0.99	0.57	0.82
	max_tmax	0.82	0.72	0.82	0.59	0.77	0.71	0.77	0.53	1.00
7	**mean_tavg**	1.00	-0.54	0.94	0.98	0.98	-0.58	0.89	0.97	0.73
	mean_tmax	0.94	-0.26	1.00	0.87	0.94	-0.31	0.96	0.85	0.76
	max_tmax	0.73	-0.19	0.76	0.68	0.71	-0.23	0.70	0.67	1.00
8	**mean_tavg**	1.00	-0.06	0.95	0.95	0.98	-0.06	0.94	0.93	0.74
	mean_tmax	0.95	0.20	1.00	0.82	0.93	0.19	0.98	0.81	0.78
	max_tmax	0.74	0.14	0.78	0.66	0.71	0.12	0.75	0.64	1.00

9	**mean_tavg**	1.00	-0.13	0.91	0.96	0.99	-0.15	0.87	0.95	0.54
	mean_tmax	0.91	0.21	1.00	0.80	0.91	0.18	0.98	0.78	0.74
	max_tmax	0.54	0.44	0.74	0.40	0.54	0.41	0.75	0.39	1.00

Table 3: Sample of correlation values across temperature variables for the three selected indicators of EHEs by NOAA climate region.

Region 1 (Northeast)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	71.4	2.8	76.3	65.8	71.7	10.5
	1960-69	70.6	2.9	76.9	64.6	70.4	12.3
	1970-79	71.4	2.7	77.3	65.6	71.3	11.7
	1980-89	71.7	3.1	77.3	65.3	71.8	12.0
	1990-99	72.3	3.2	78.4	65.4	72.2	13.0
	2000-09	71.9	3.1	77.4	66.0	71.6	11.5
Mean_Tmax	**1950-59**	81.3	2.7	86.6	75.5	81.4	11.1
	1960-69	80.3	2.7	87.3	74.0	79.8	13.3
	1970-79	80.7	2.3	85.8	74.9	80.5	11.0
	1980-89	81.1	3.0	88.1	75.5	80.8	12.6
	1990-99	81.7	3.1	88.3	74.2	81.6	14.1
	2000-09	80.8	3.0	87.1	74.2	80.6	13.0
Max_Tmax	**1950-59**	95.3	3.6	102.0	88.0	95.0	14.0
	1960-69	93.8	3.4	104.0	88.0	93.0	16.0
	1970-79	94.1	3.4	104.0	86.0	94.0	18.0
	1980-89	94.9	3.4	104.0	86.0	95.0	18.0
	1990-99	95.2	4.4	105.0	87.0	96.0	18.0
	2000-09	94.4	3.8	103.0	87.0	95.0	16.0
Region 2 (Southeast)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	78.7	2.2	82.9	73.5	78.8	9.4
	1960-69	77.3	2.5	82.5	72.5	77.2	10.0
	1970-79	77.6	2.4	82.5	72.9	77.1	9.7
	1980-89	78.8	2.2	83.7	73.7	78.7	10.0
	1990-99	79.0	2.3	84.4	73.7	79.0	10.7
	2000-09	78.9	2.2	83.7	74.3	78.8	9.3
Mean_Tmax	**1950-59**	88.9	2.3	95.2	83.4	89.0	11.8
	1960-69	86.7	2.3	91.9	81.2	86.8	10.8
	1970-79	87.1	2.2	92.2	82.6	87.2	9.6
	1980-89	88.6	2.3	93.6	82.8	88.8	10.9
	1990-99	88.6	2.5	93.9	82.6	89.0	11.4
	2000-09	88.2	2.4	94.6	82.9	88.5	11.7
Max_Tmax	**1950-59**	98.4	3.2	106.0	92.0	98.0	14.0
	1960-69	96.0	2.8	106.0	89.0	96.0	17.0
	1970-79	96.0	3.0	105.0	90.0	96.0	15.0
	1980-89	98.3	3.4	106.0	90.0	98.0	16.0
	1990-99	98.1	3.0	106.0	93.0	98.0	13.0
	2000-09	97.3	4.5	129.0	90.0	97.0	39.0
Region 3 (South)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	81.8	2.7	88.0	73.3	81.8	14.7
	1960-69	80.8	2.6	87.8	74.2	80.6	13.5
	1970-79	80.5	2.4	91.6	75.4	80.2	16.1
	1980-89	81.5	2.5	89.3	75.5	81.3	13.7
	1990-99	81.6	2.6	88.4	74.4	81.6	14.0

	2000-09	81.9	2.6	91.4	75.1	81.7	16.3
Mean_Tmax	**1950-59**	92.6	3.2	99.9	84.0	92.3	15.8
	1960-69	91.4	2.9	100.5	85.9	91.1	14.6
	1970-79	91.1	2.4	99.9	86.2	90.7	13.7
	1980-89	92.4	2.9	101.5	86.4	91.9	15.1
	1990-99	92.4	2.8	100.6	86.0	92.3	14.6
	2000-09	92.5	3.0	104.8	86.5	92.1	18.3
Max_Tmax	**1950-59**	101.5	4.1	113.0	94.0	102.0	19.0
	1960-69	100.5	3.8	109.0	92.0	100.0	17.0
	1970-79	100.1	3.9	111.0	93.0	99.0	18.0
	1980-89	101.8	4.1	112.0	94.0	102.0	18.0
	1990-99	101.7	4.1	114.0	93.0	102.0	21.0
	2000-09	101.8	3.7	109.0	93.0	102.0	16.0
Region 4 (Southwest)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	74.4	5.2	85.6	65.5	73.8	20.1
	1960-69	73.3	5.3	85.0	64.9	73.2	20.1
	1970-79	75.2	5.5	86.5	67.2	75.0	19.3
	1980-89	76.3	5.7	87.2	65.7	75.7	21.5
	1990-99	76.1	6.2	90.1	65.2	75.8	24.9
	2000-09	77.1	5.8	87.4	64.4	77.2	23.0
Mean_Tmax	**1950-59**	87.3	5.5	98.7	78.4	86.3	20.3
	1960-69	86.2	5.6	98.2	76.4	84.9	21.8
	1970-79	88.0	5.3	99.4	77.6	87.8	21.8
	1980-89	89.1	5.5	102.0	78.3	88.5	23.7
	1990-99	88.9	6.0	104.8	79.0	88.3	25.7
	2000-09	89.4	5.3	100.4	77.0	88.9	23.3
Max_Tmax	**1950-59**	98.6	5.0	110.0	89.0	98.5	21.0
	1960-69	97.6	4.8	109.0	88.0	97.0	21.0
	1970-79	99.3	4.8	110.0	90.0	98.8	20.0
	1980-89	99.9	4.7	113.0	93.0	99.0	20.0
	1990-99	100.9	5.4	116.0	91.5	100.0	24.5
	2000-09	100.4	4.9	113.0	91.0	99.0	22.0
Region 5 (West)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	71.8	9.0	89.7	57.5	70.4	32.2
	1960-69	72.4	9.2	90.0	58.7	71.1	31.3
	1970-79	73.2	9.4	90.2	59.5	71.3	30.7
	1980-89	73.5	9.1	91.3	59.3	72.0	31.9
	1990-99	73.4	9.1	93.1	59.8	72.3	33.3
	2000-09	73.8	9.9	92.8	60.8	72.0	32.0
Mean_Tmax	**1950-59**	84.5	11.6	102.8	67.2	85.6	35.6
	1960-69	84.4	11.9	103.5	67.7	84.7	35.9
	1970-79	85.1	12.2	103.6	67.2	86.0	36.3
	1980-89	85.7	11.8	104.4	68.6	86.1	35.8
	1990-99	85.1	11.6	105.3	67.8	86.0	37.5
	2000-09	85.4	12.2	104.1	69.9	86.6	34.2
Max_Tmax	**1950-59**	99.3	9.6	115.0	81.0	102.0	34.0

Indicator	Decade	Mean (°F)	SD (°F)	Max (°F)	Min (°F)	Median (°F)	Range (°F)
	1960-69	98.8	10.2	115.0	81.0	102.0	34.0
	1970-79	100.4	10.1	115.0	80.0	103.0	35.0
	1980-89	100.3	9.2	116.0	82.0	104.0	34.0
	1990-99	100.3	9.8	115.0	81.0	104.0	34.0
	2000-09	100.2	9.9	117.0	79.0	103.5	38.0
Region 6 (Northwest)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	65.7	4.0	72.1	58.4	65.7	13.7
	1960-69	66.6	3.8	75.8	60.5	65.9	15.3
	1970-79	67.1	3.5	74.2	61.2	66.7	12.9
	1980-89	66.7	3.3	73.8	60.4	66.4	13.4
	1990-99	67.1	3.7	75.1	60.8	66.5	14.3
	2000-09	68.3	4.3	77.0	60.8	67.3	16.2
Mean_Tmax	**1950-59**	79.0	5.6	88.3	68.1	79.0	20.2
	1960-69	79.9	5.3	91.6	70.7	79.0	20.9
	1970-79	80.4	5.0	89.6	71.9	80.3	17.6
	1980-89	80.5	5.1	91.0	70.6	80.5	20.4
	1990-99	80.7	5.3	91.8	71.1	80.2	20.7
	2000-09	81.8	5.8	92.6	71.1	81.2	21.5
Max_Tmax	**1950-59**	95.7	6.4	106.0	80.0	97.0	26.0
	1960-69	97.5	6.3	109.0	84.0	98.0	25.0
	1970-79	97.9	5.2	107.0	85.0	99.5	22.0
	1980-89	97.7	5.2	106.0	85.0	99.0	21.0
	1990-99	98.0	5.2	108.0	86.0	99.0	22.0
	2000-09	99.5	5.5	109.0	87.0	100.0	22.0
Region 7 (West North Central)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	70.2	4.2	78.0	61.9	69.3	16.1
	1960-69	69.7	3.6	76.3	62.7	69.6	13.6
	1970-79	70.1	4.0	76.9	63.4	69.8	13.5
	1980-89	70.3	3.8	76.8	63.9	70.6	12.9
	1990-99	69.5	3.7	76.4	62.7	69.5	13.7
	2000-09	70.6	3.6	77.6	63.0	70.2	14.6
Mean_Tmax	**1950-59**	82.7	3.6	89.5	75.0	82.2	14.5
	1960-69	82.2	2.8	87.7	76.3	82.1	11.4
	1970-79	82.9	3.6	89.9	77.0	81.9	12.9
	1980-89	83.0	3.5	90.2	76.9	83.3	13.3
	1990-99	81.4	3.1	88.6	75.0	81.2	13.6
	2000-09	82.5	3.2	89.1	76.0	82.6	13.1
Max_Tmax	**1950-59**	97.7	4.6	107.0	89.0	98.0	18.0
	1960-69	96.7	3.6	106.0	90.0	97.5	16.0
	1970-79	97.7	4.6	107.0	89.0	97.5	18.0
	1980-89	98.7	4.7	109.0	90.0	100.0	19.0
	1990-99	95.5	4.5	109.0	90.0	95.0	19.0
	2000-09	96.6	3.9	105.0	89.5	97.0	15.5
Region 8 (East North Central)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**

Mean_Tavg	**1950-59**	69.6	3.9	75.8	59.6	70.5	16.2
	1960-69	68.6	3.6	73.5	59.8	69.4	13.7
	1970-79	69.5	3.8	75.8	60.6	70.2	15.1
	1980-89	70.0	4.0	78.7	60.2	70.3	18.4
	1990-99	69.6	3.7	75.3	59.0	70.2	16.3
	2000-09	70.2	3.8	75.8	60.1	70.7	15.7
Mean_Tmax	**1950-59**	80.4	3.9	87.1	70.6	80.6	16.4
	1960-69	79.1	3.5	84.2	70.9	79.4	13.3
	1970-79	80.3	3.9	88.0	71.7	80.9	16.3
	1980-89	80.8	4.1	90.2	71.2	80.9	19.0
	1990-99	79.4	3.6	85.4	69.6	80.2	15.8
	2000-09	79.9	3.6	85.9	70.8	80.2	15.0
Max_Tmax	**1950-59**	94.7	4.1	105.0	87.0	95.0	18.0
	1960-69	93.7	3.4	100.0	86.0	94.0	14.0
	1970-79	95.0	3.9	103.0	86.0	95.0	17.0
	1980-89	95.7	4.6	107.0	84.0	95.0	23.0
	1990-99	94.1	4.1	103.0	84.0	94.0	19.0
	2000-09	93.8	3.7	101.0	86.0	94.0	15.0
Region 9 (Central)							
Indicator	**Decade**	**Mean (°F)**	**SD (°F)**	**Max (°F)**	**Min (°F)**	**Median (°F)**	**Range (°F)**
Mean_Tavg	**1950-59**	74.0	3.8	83.9	65.2	73.7	18.8
	1960-69	72.8	3.3	80.7	66.5	72.4	14.2
	1970-79	73.2	3.3	82.6	65.9	72.7	16.6
	1980-89	74.3	3.8	85.5	67.7	73.9	17.8
	1990-99	73.9	3.6	82.5	63.0	73.9	19.5
	2000-09	74.1	3.6	83.7	67.2	73.6	16.5
Mean_Tmax	**1950-59**	85.1	3.8	95.6	77.8	84.9	17.8
	1960-69	83.4	3.0	90.5	77.8	83.1	12.6
	1970-79	83.5	3.1	92.0	76.4	83.1	15.6
	1980-89	84.9	3.8	95.4	77.3	84.6	18.1
	1990-99	84.2	3.4	91.9	76.4	84.4	15.5
	2000-09	84.1	3.6	93.5	76.6	83.9	16.9
Max_Tmax	**1950-59**	97.2	4.3	113.0	89.0	97.0	24.0
	1960-69	95.2	3.7	105.0	88.0	95.0	17.0
	1970-79	94.9	3.3	106.0	87.0	95.0	19.0
	1980-89	97.0	4.4	108.5	90.0	96.0	18.5
	1990-99	96.3	3.4	105.0	87.0	96.0	18.0
	2000-09	95.4	4.6	106.0	85.0	95.0	21.0

Table 4: Values of descriptive statistics for three temperature indicators for each region by decade.

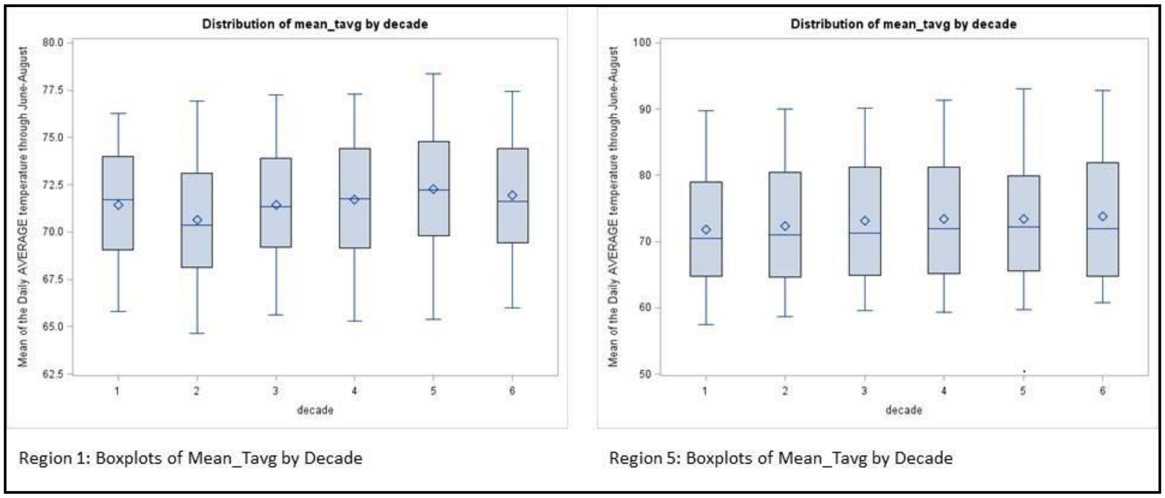

Figure 3: Boxplots by decade for Mean_Tavg for the Northeast (region 1) and West (region 5). Decade 1=1950-59, 2=1960-69, 3=1970-79, 4=1980-89, 5=1990-99, 6=2000-09

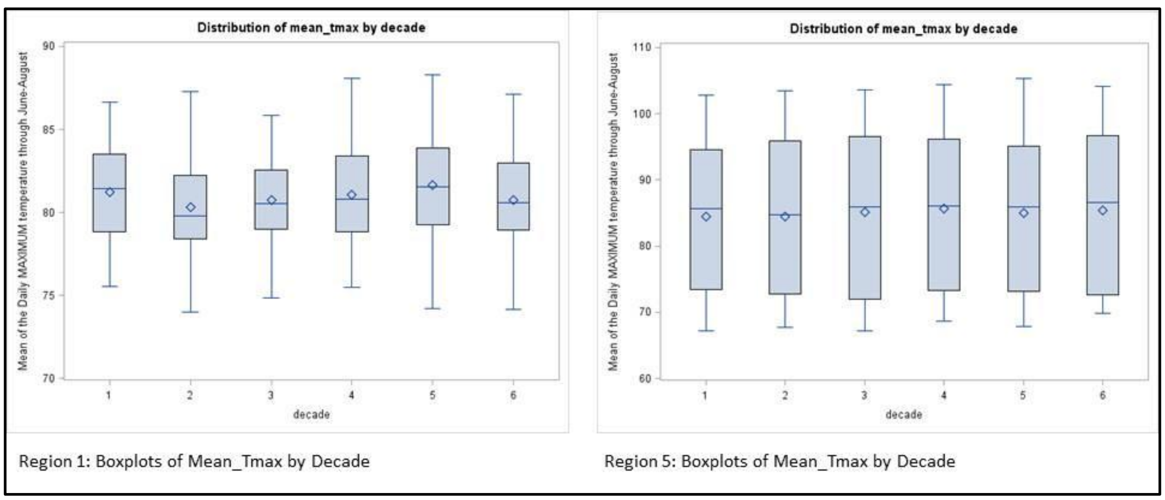

Figure 4: Boxplots by decade for Mean_Tmax for the Northeast (region 1) and West (region 5). Decade 1=1950-59, 2=1960-69, 3=1970-79, 4=1980-89, 5=1990-99, 6=2000-09

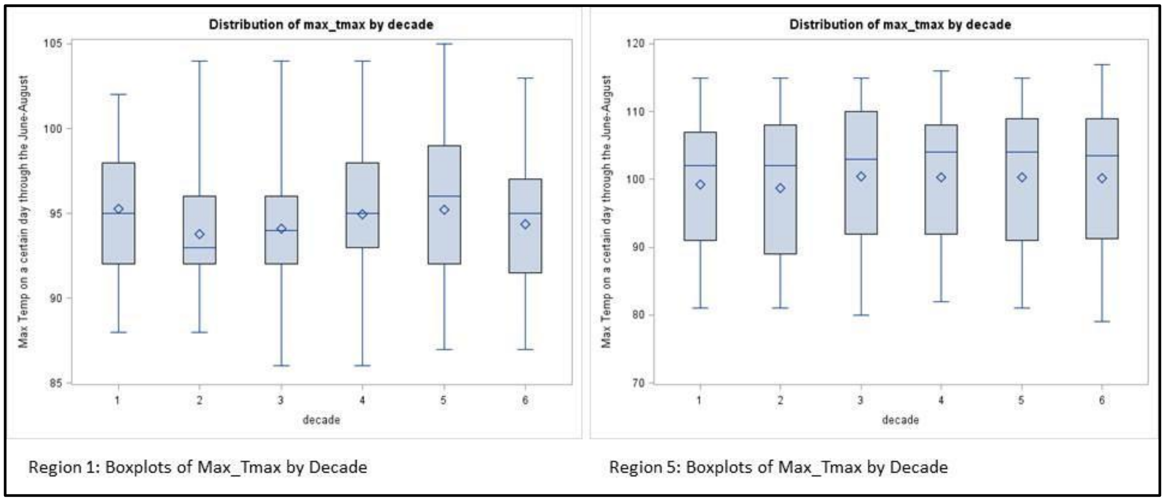

Figure 5: Boxplots by decade for Max_Tmax for the Northeast (region 1) and West (region 5). Decade 1=1950-59, 2=1960-69, 3=1970-79, 4=1980-89, 5=1990-99, 6=2000-09

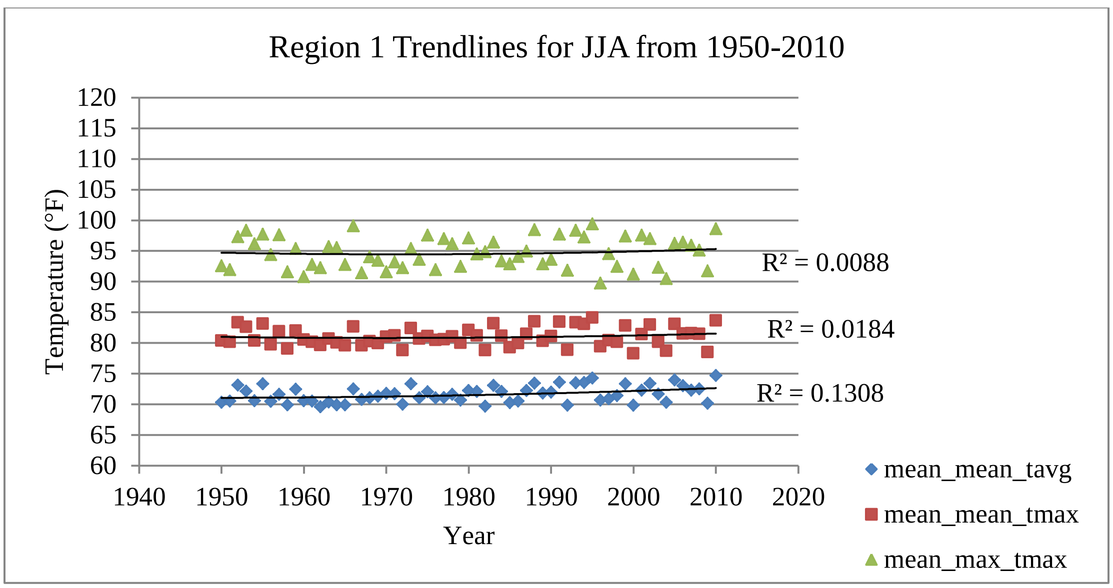

Figure 6: Region 1 historical data trend lines for all three indicators for JJA from 1950-2010.

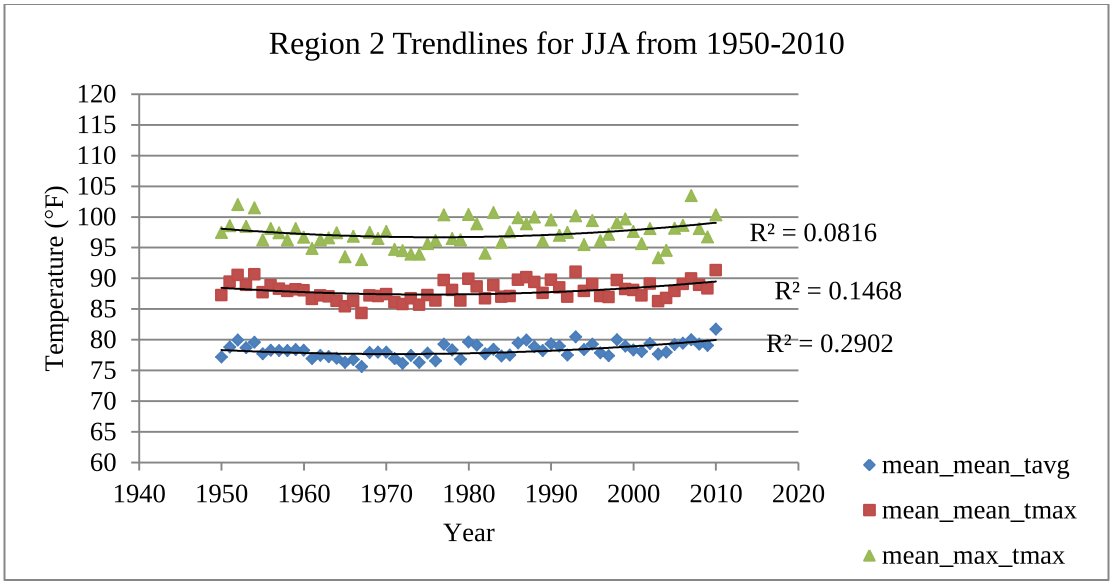

Figure 7: Region 2 historical data trend lines for all three indicators for JJA from 1950-2010.

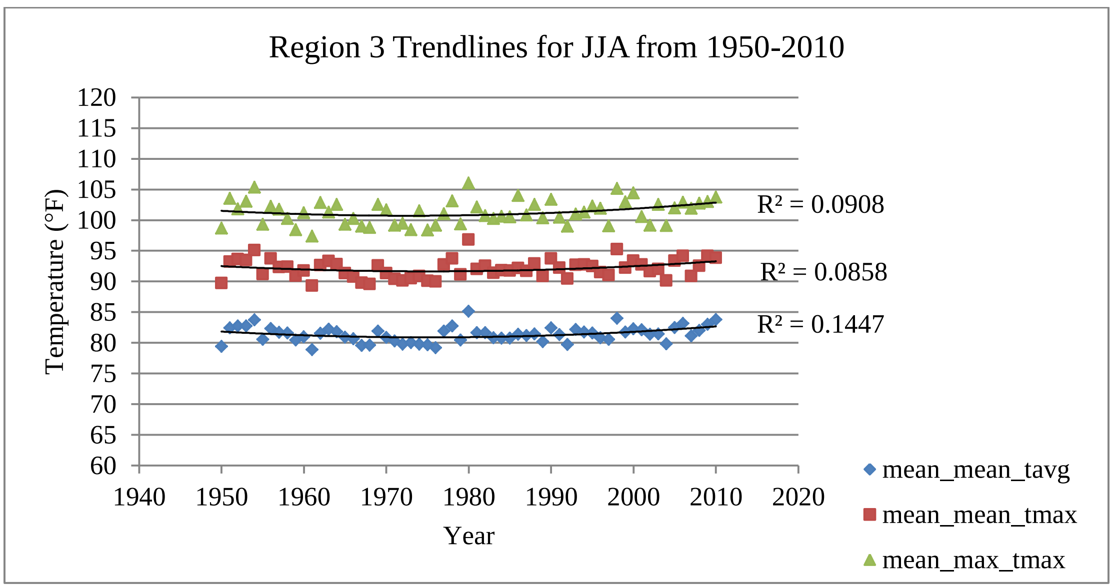

Figure 8: Region 3 historical data trend lines for all three indicators for JJA from 1950-2010.

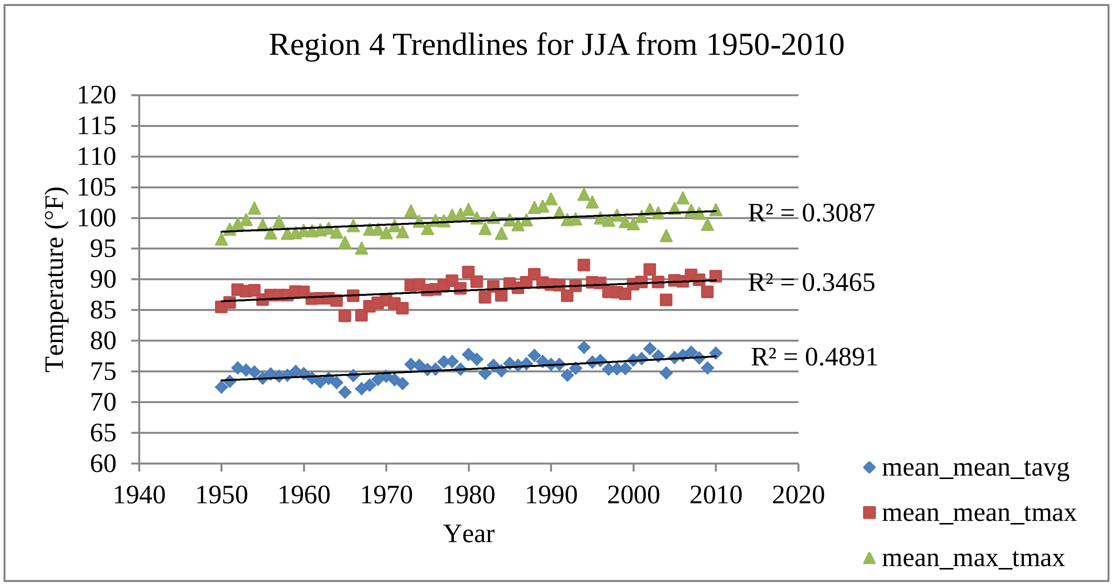

Figure 9: Region 4 historical data trend lines for all three indicators for JJA from 1950-2010.

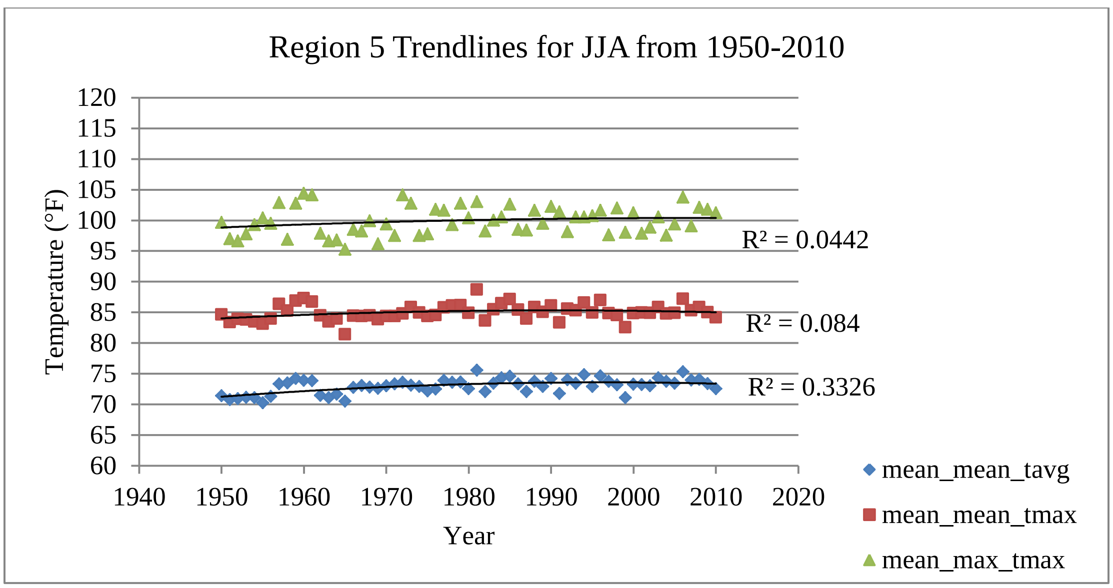

Figure 10: Region 5 historical data trend lines for all three indicators for JJA from 1950-2010.

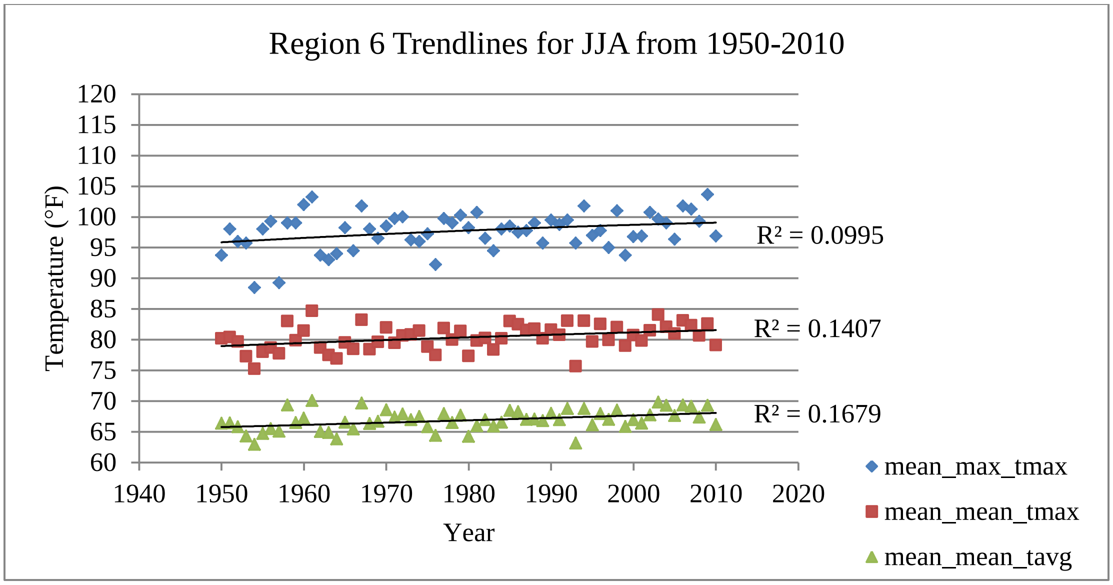

Figure 11: Region 6 historical data trend lines for all three indicators for JJA from 1950-2010.

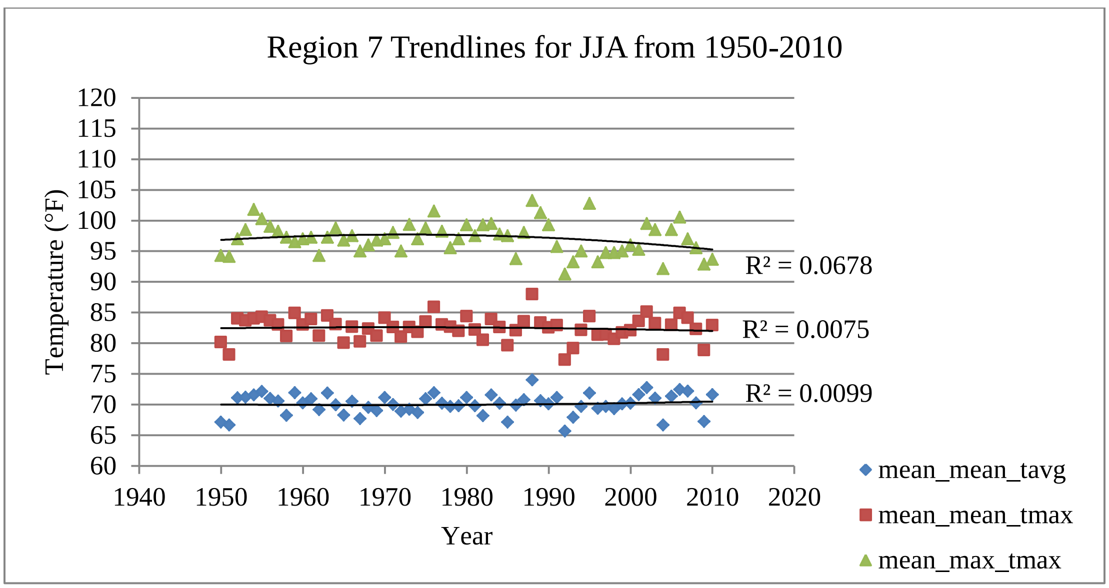

Figure 12: Region 7 historical data trend lines for all three indicators for JJA from 1950-2010.

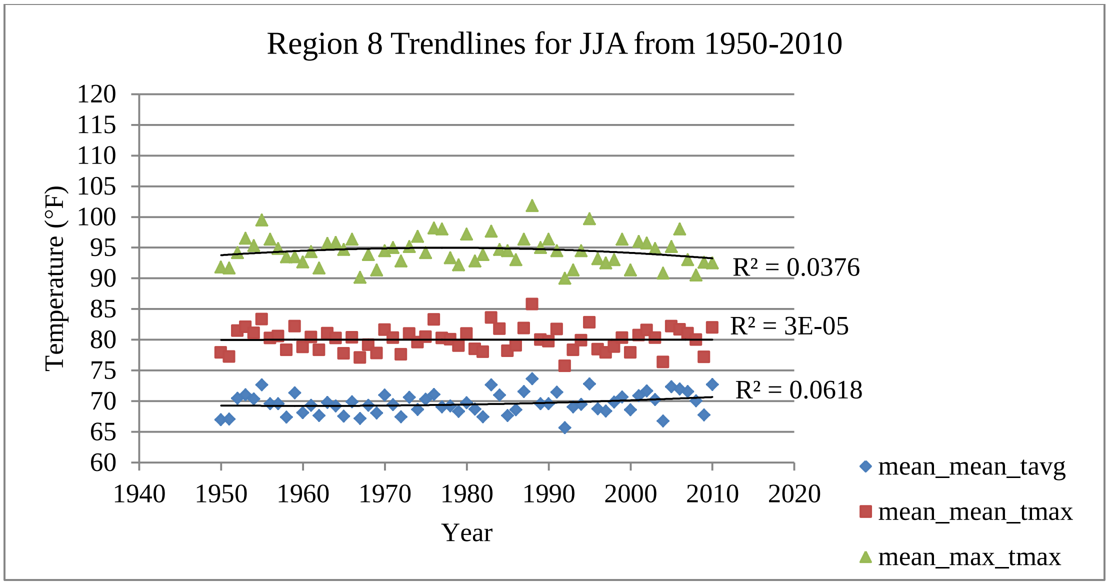

Figure 13: Region 8 historical data trend lines for all three indicators for JJA from 1950-2010.

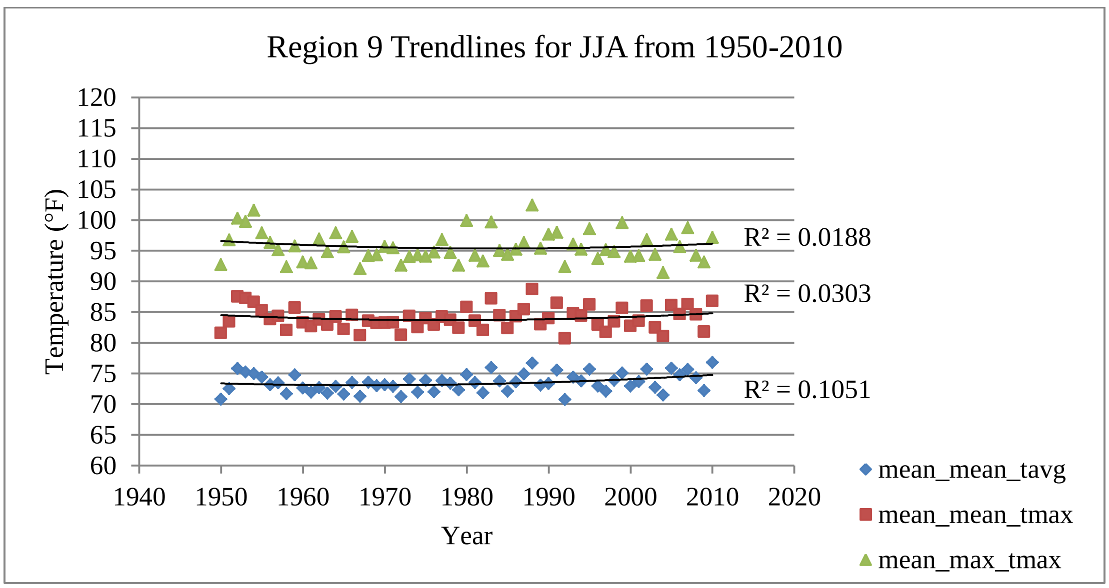

Figure 14: Region 9 historical data trend lines for all three indicators for JJA from 1950-2010.

Region	Avg_T _avg 2035	Avg_T _avg 2055	Avg_T_ max 2035	Avg_T_ max 2055	Max_ T_max 2035	Max_ T_max 2055	Trends (Avg_Tavg, Avg_Tmax, Max_Tmax)
1 (Northeast)	74.2	75.6	81.0	82.7	84.1	94.7	+, +, +
2 (Southeast)	83.8	88.3	88.0	93.6	98.5	97.4	+, +, +
3 (South)	86.2	90.3	92.1	93.2	97.6	101.3	+, +, +
4 (Southwest)	79.4	81.0	88.2	91.1	92.0	99.5	+, +, +
5 (West)	72.0	69.8	85.0	83.7	82.0	99.9	-,-,-
6 (Northwest)	69.2	70.1	80.4	82.3	82.8	97.7	+, +, +
7 (West North Central)	71.4	72.4	82.5	81.0	79.8	97.1	+,-,-
8 (East North Central)	72.7	74.5	80.0	79.9	79.8	94.5	+,-,-
9 (Central)	77.3	80.2	84.0	87.2	90.1	95.7	+, +, +

Table 5: Trends for each region with point estimates at 2035 and 2055 for all three indicators.

Region	Avg_T _avg 2035	Avg_T _avg 2055	Avg_T _max 2035	Avg_T _max 2055	Max_T _max 2035	Max_T _max 2055
1 (Northeast)	2.6	4.0	1.7	3.1	2.1	3.8
2 (Southeast)	5.6	10.0	5.7	10.5	6.4	12.1
3 (South)	4.8	8.9	1.1	5.5	5.4	9.9
4 (Southwest)	3.9	5.6	2.9	3.8	3.0	4.0
5 (West)	-1.0	-3.2	-1.3	-3.0	0.1	-0.6
6 (Northwest)	2.2	3.1	2.0	2.4	2.0	2.1
7 (West North Central)	1.3	2.4	-1.5	-2.6	-6.2	-11.2
8 (East North Central)	3.0	4.9	-0.1	-0.2	-4.8	-9.2
9 (Central)	3.8	6.7	3.2	6.1	2.6	5.3

Table 6: Deviation of point estimates at 2035 and 2055 from the temperature normal (average of each of the three indicators from 1950-2010).

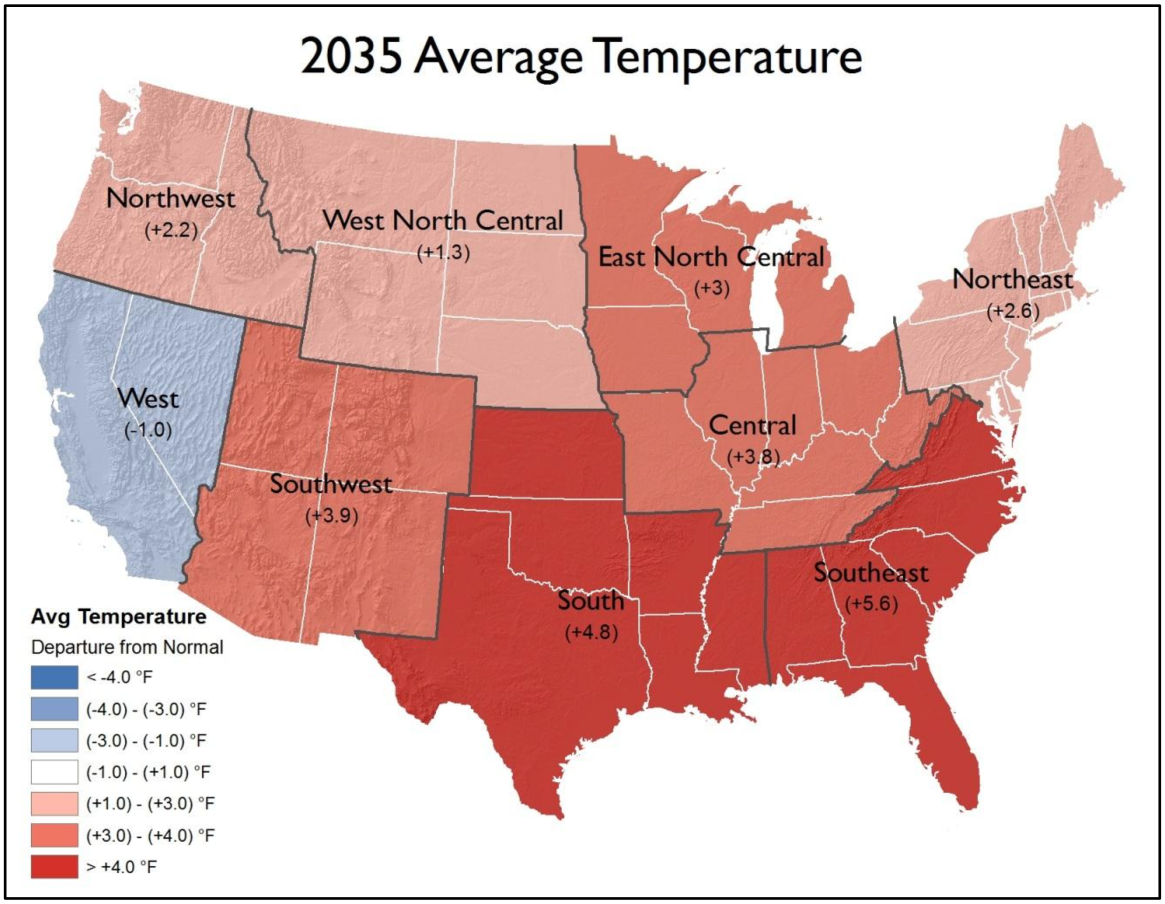

Figure 15: Regional deviations of average temperatures at 2035 from their temperature normal (regional average temperature from 1950-2010).

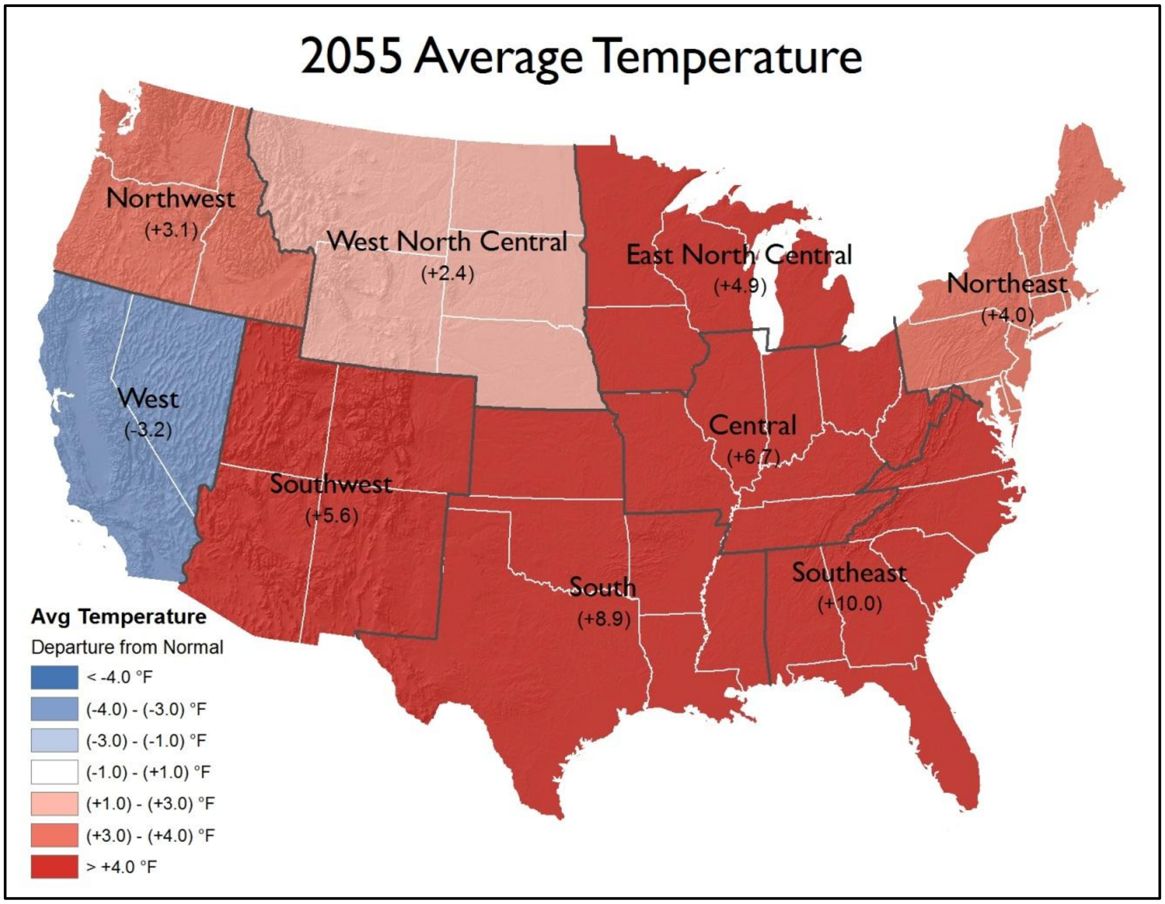

Figure 16: Regional deviations of average temperatures at 2055 from their temperature normal (regional average temperature from 1950-2010).

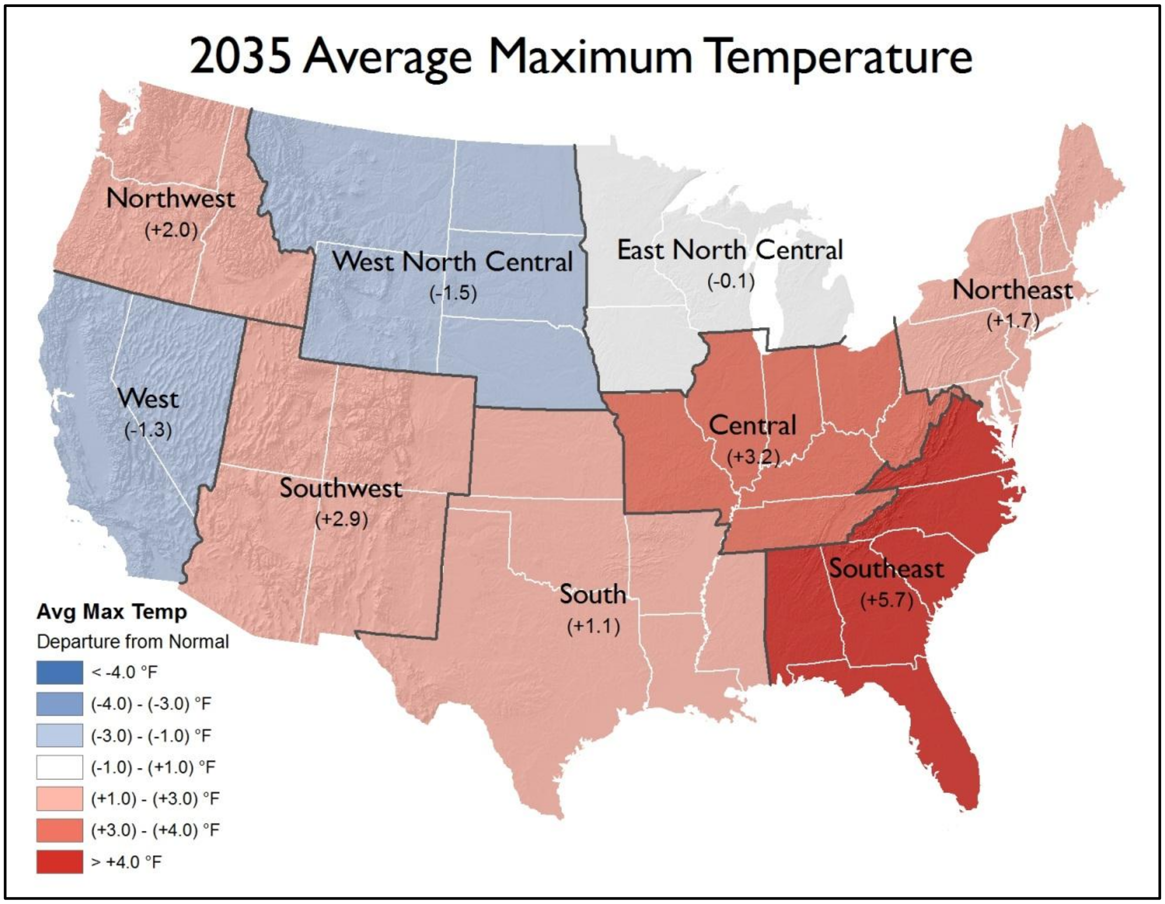

Figure 17: Regional deviations of average maximum temperatures at 2035 from their temperature normal (regional average maximum temperature from 1950-2010).

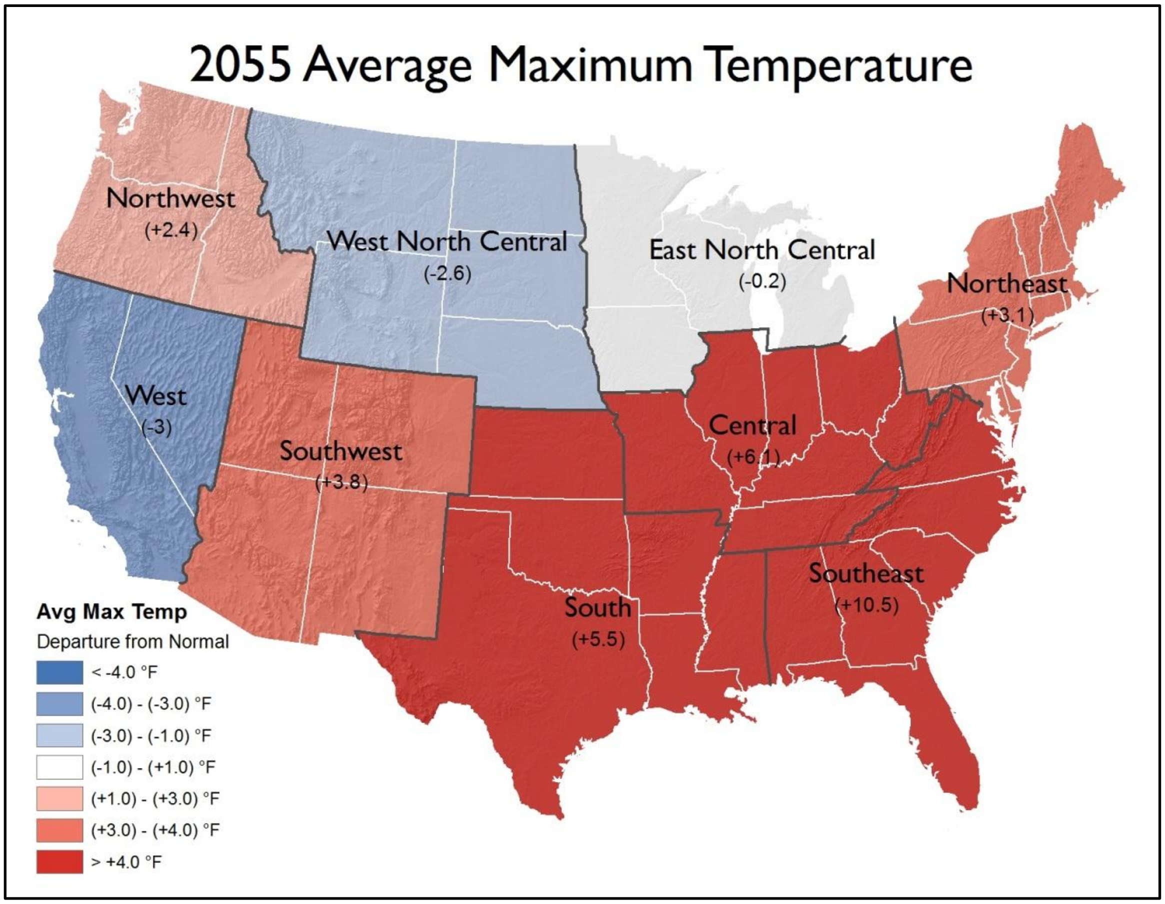

Figure 18: Regional deviations of average maximum temperatures at 2055 from their temperature normal (regional average maximum temperature from 1950-2010).

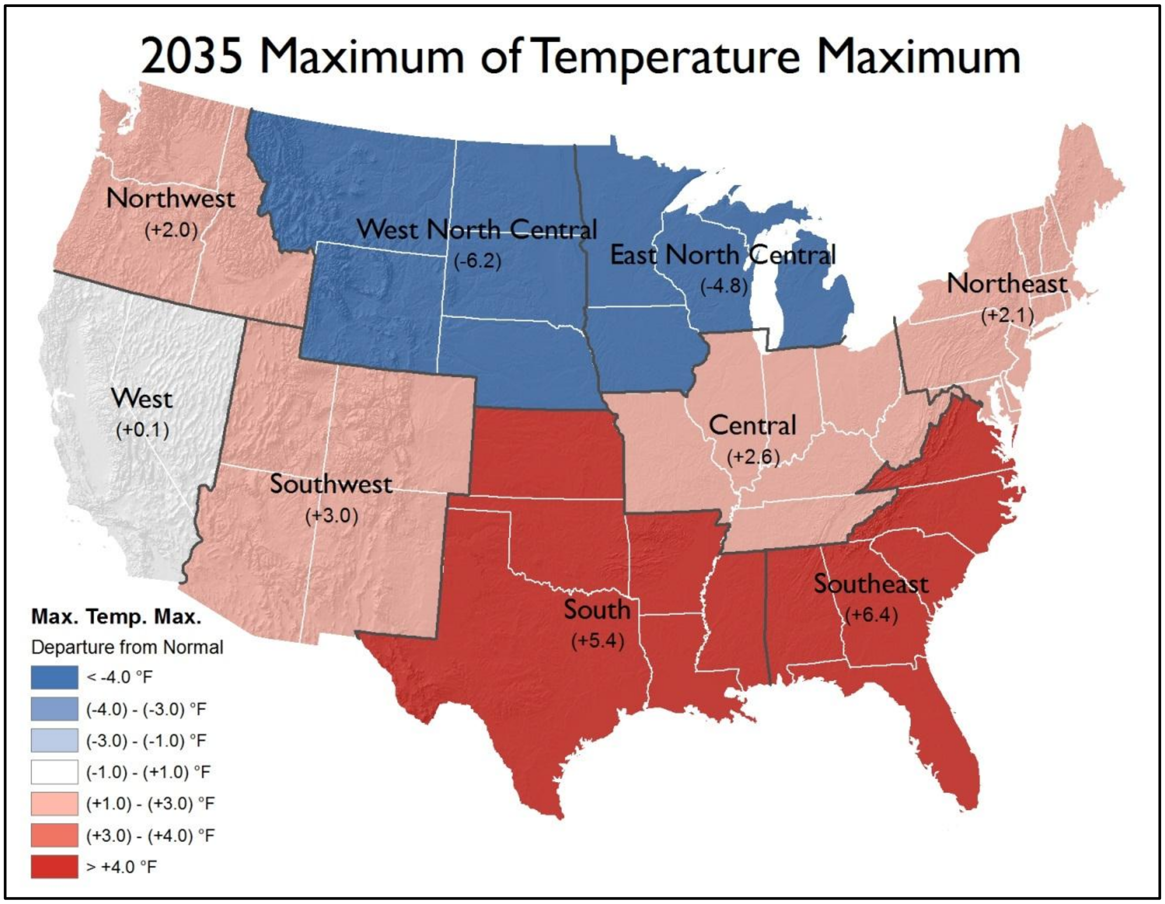

Figure 19: Regional deviations of maximum of maximum temperatures at 2035 from their temperature normal (regional maximum of maximum temperature from 1950-2010).

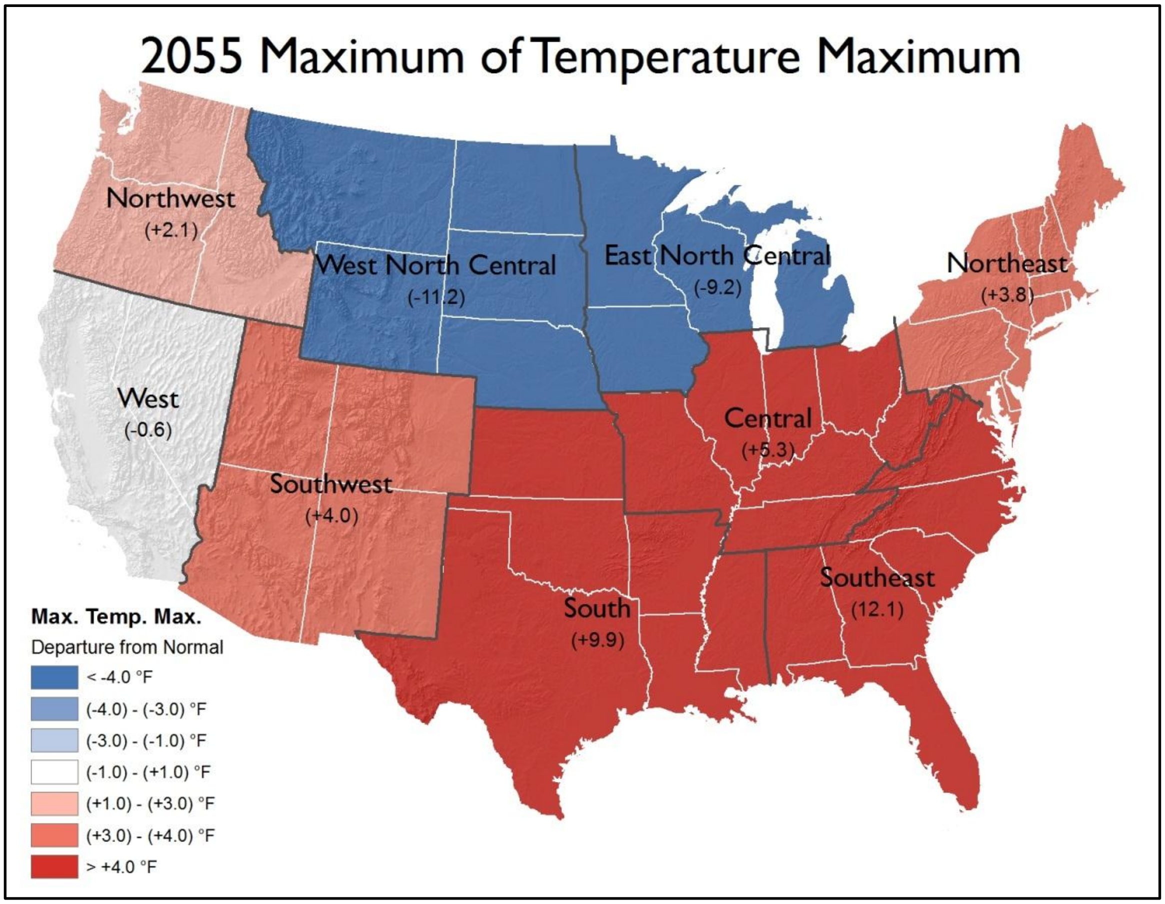

Figure 20: Regional deviations of maximum of maximum temperatures at 2055 from their temperature normal (regional maximum of maximum temperature from 1950-2010).

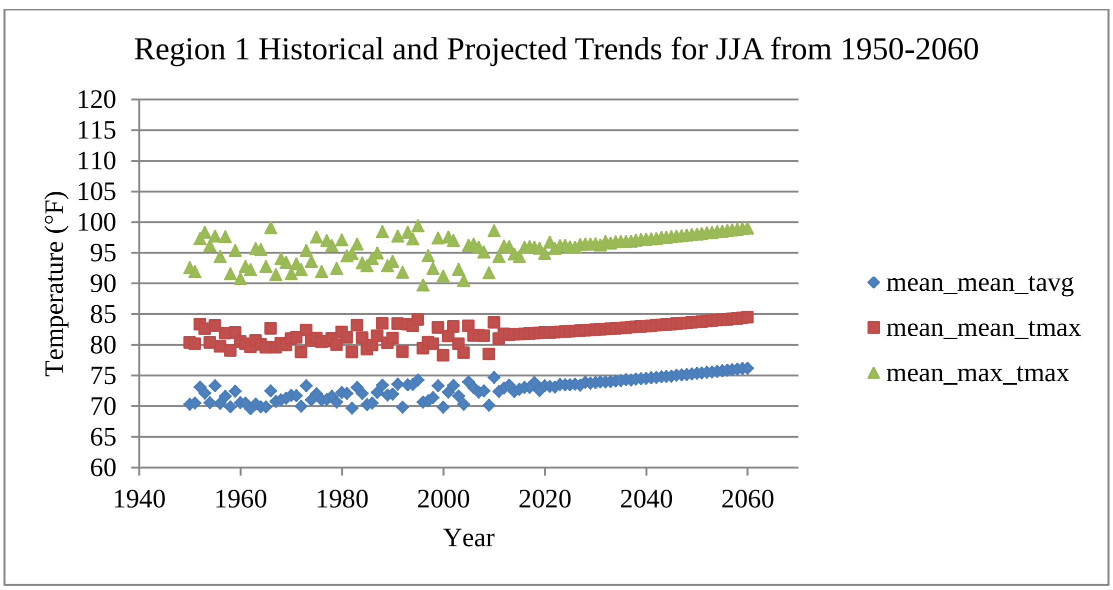

Figure 21: Region 1 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

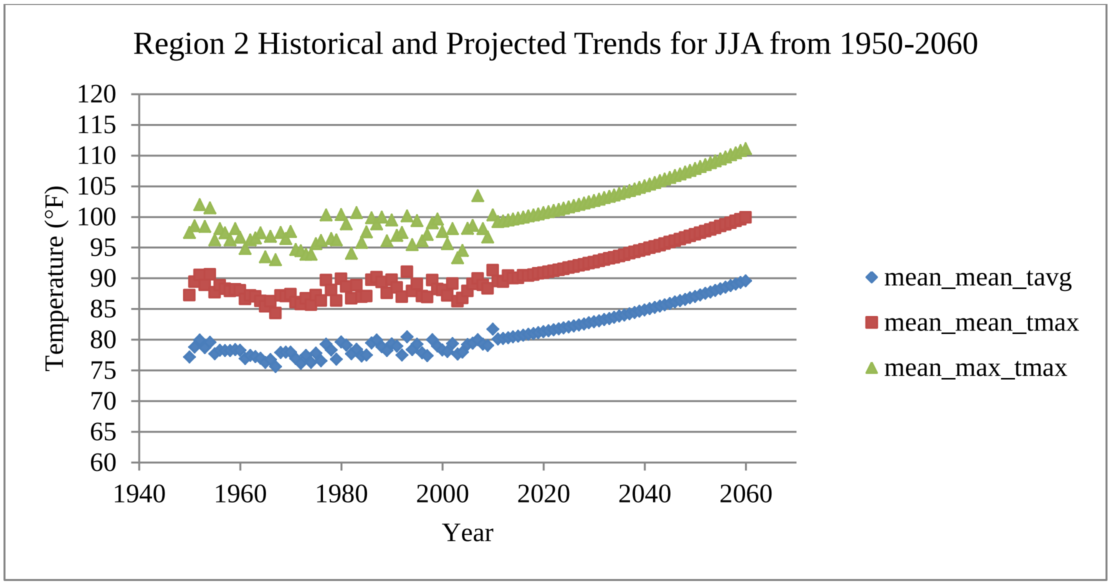

Figure 22: Region 2 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

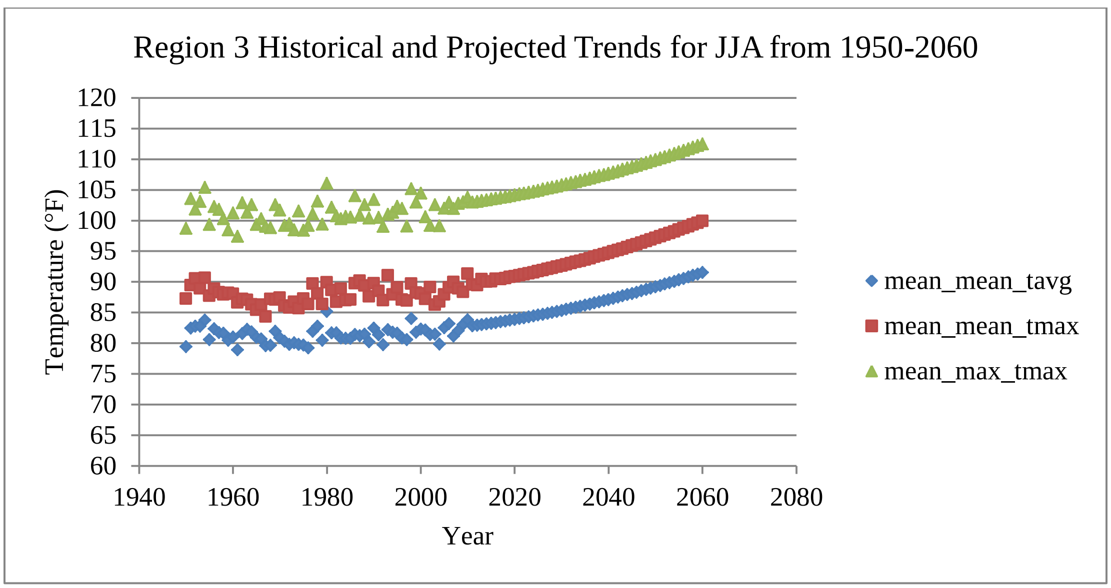

Figure 23: Region 3 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

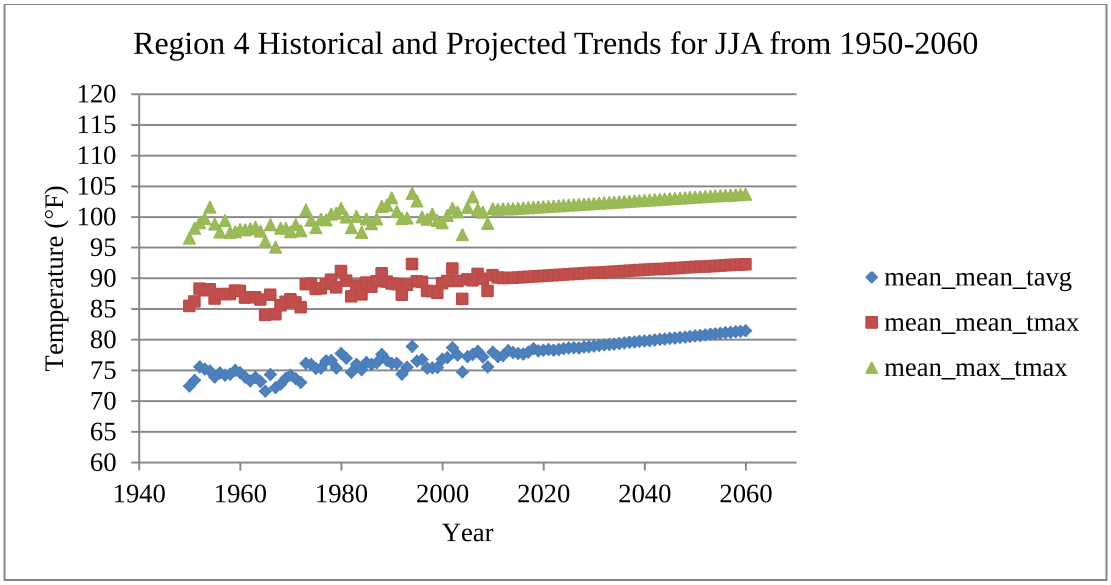

Figure 24: Region 4 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

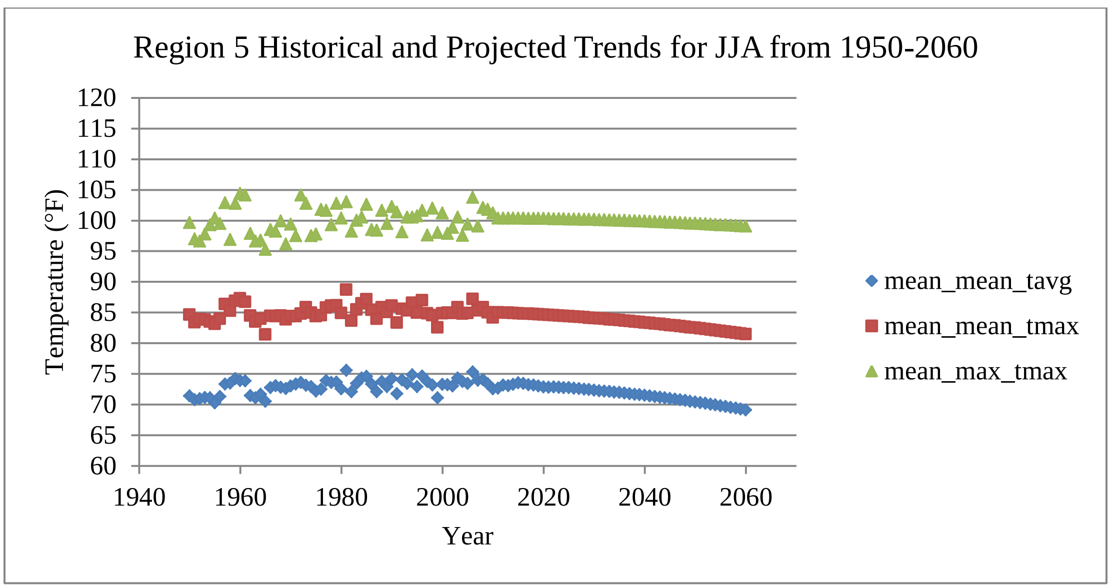

Figure 25: Region 5 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

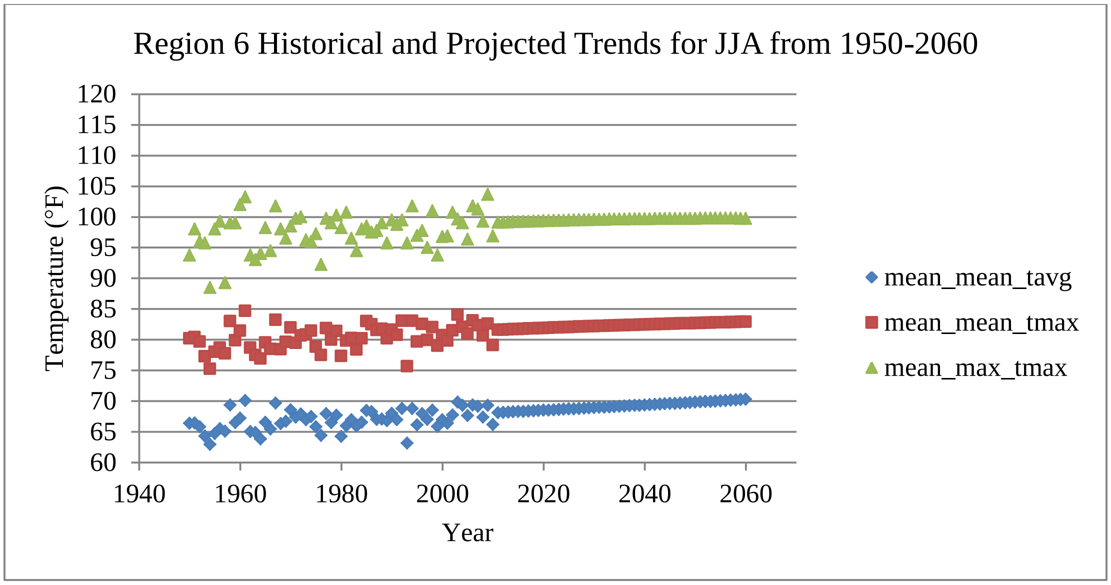

Figure 26: Region 6 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

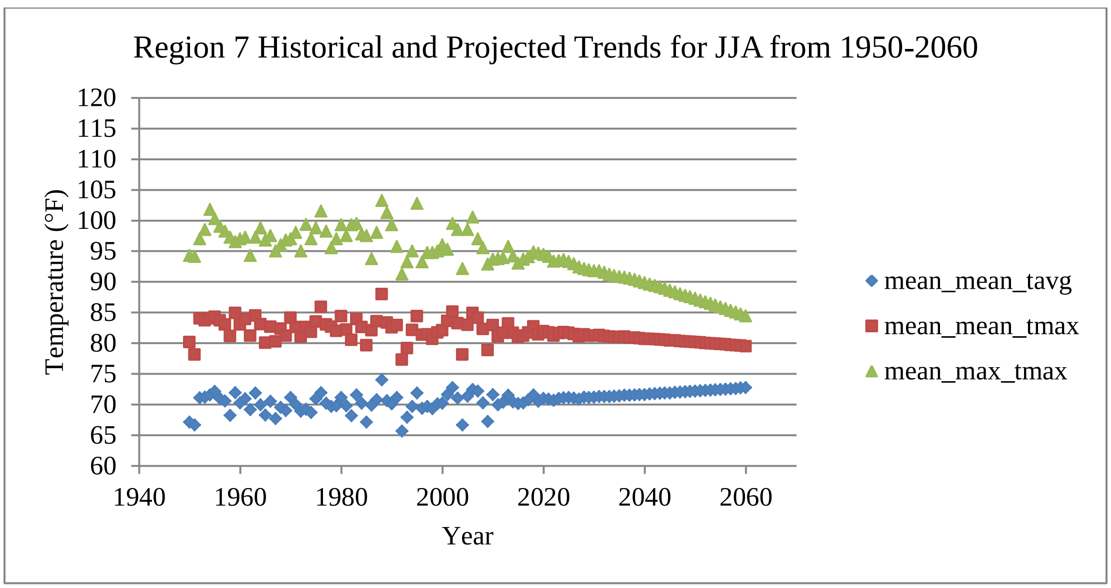

Figure 27: Region 7 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

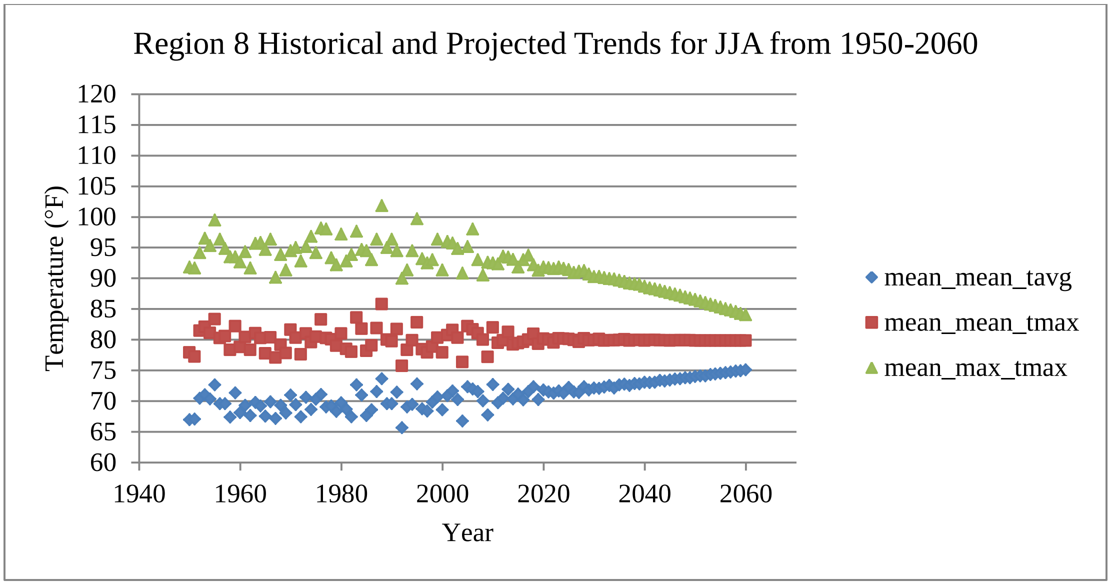

Figure 28: Region 8 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

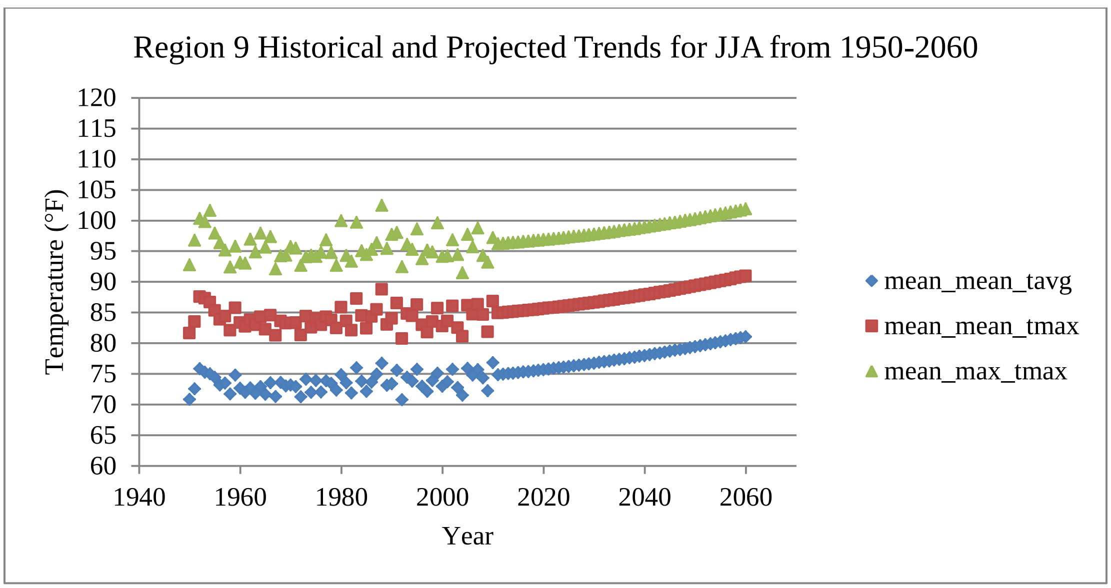

Figure 29: Region 9 historical and projected trends for Mean_Tavg, Mean_Tmax, and Max_Tmax for JJA from 1950-2060.

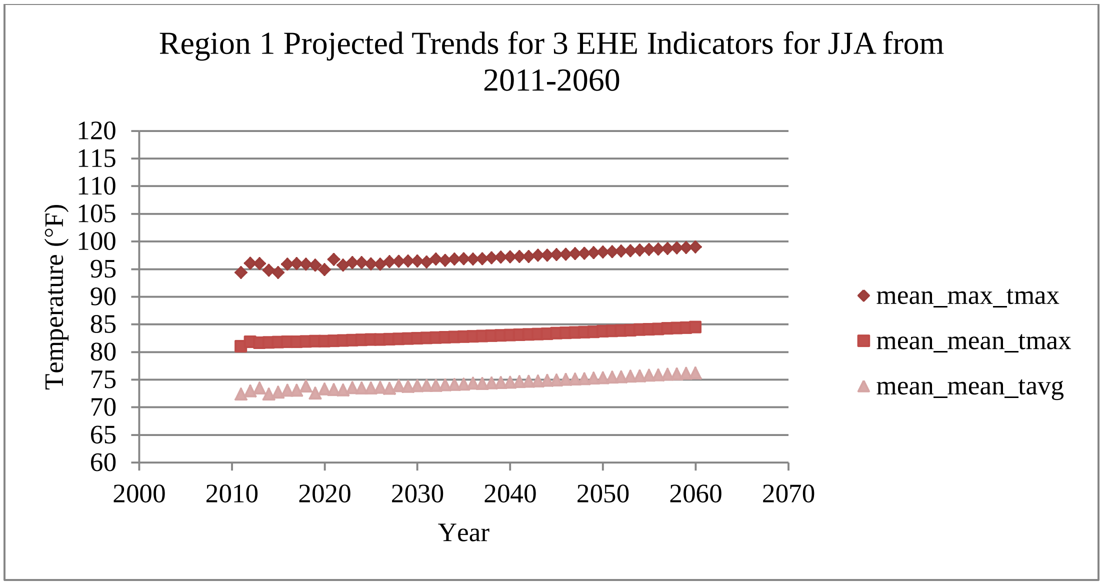

Figure 30: Region 1 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = 0.0004x^2 - 1.5571x + 1603$
Mean_Tmax: $y = 0.0003x^2 - 1.3207x + 1366.3$
Mean_Tavg: $y = 0.0004x^2 - 1.6355x + 1666.1$

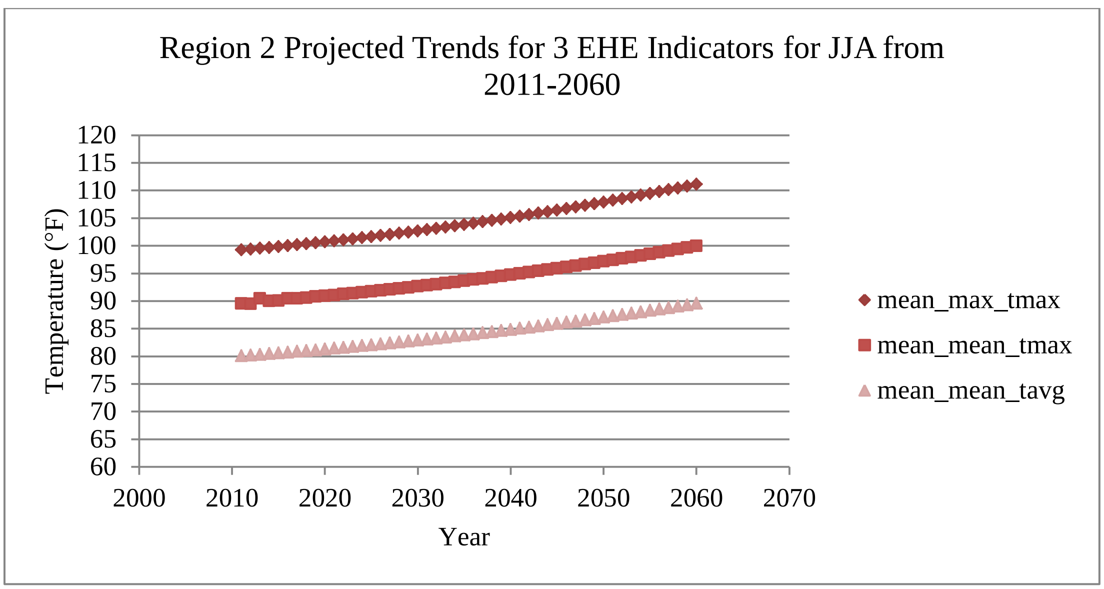

Figure 31: Region 2 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = 0.002x^2 - 8.0711x + 8071.1$
Mean_Tmax: $y = 0.0017x^2 - 6.8788x + 6881.4$
Mean_Tavg: $y = 0.0015x^2 - 5.9051x + 5897$

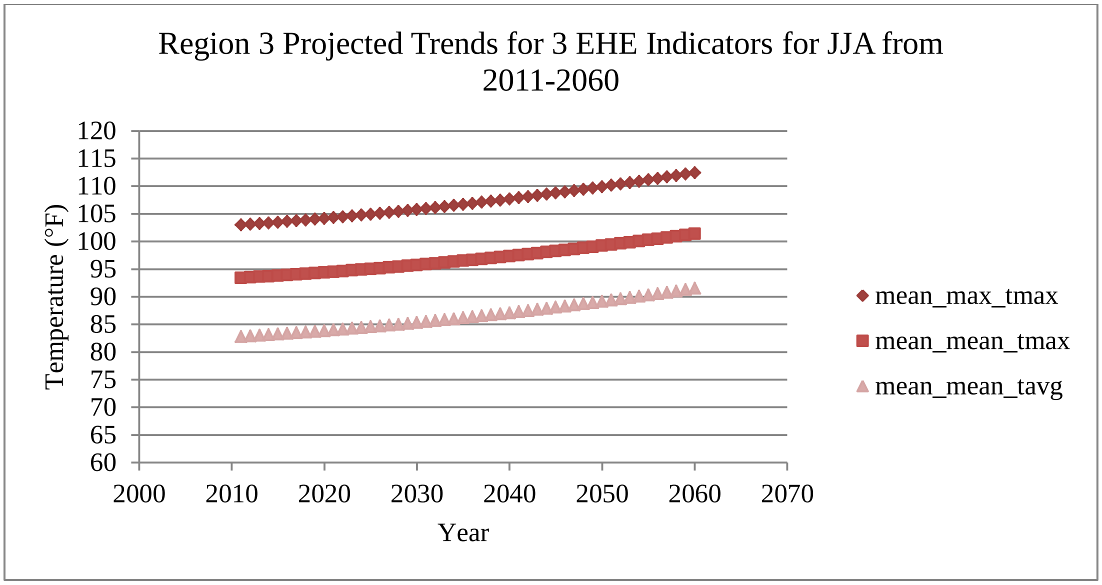

Figure 32: Region 3 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = 0.0015x^2 - 6.0719x + 6089.8$
Mean_Tmax: $y = 0.0013x^2 - 5.3105x + 5335.9$
Mean_Tavg: $y = 0.0015x^2 - 5.8453x + 5853.9$

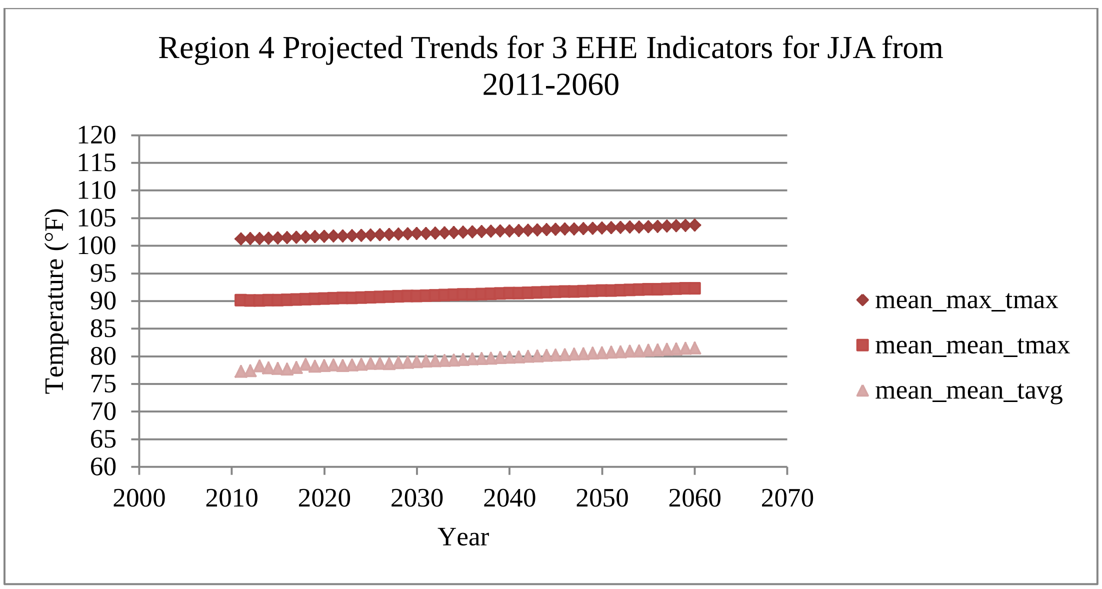

Figure 33: Region 4 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = -3E\text{-}05x^2 + 0.1793x - 131.63$
Mean_Tmax: $y = -2E\text{-}05x^2 + 0.118x - 77.081$
Mean_Tavg: $y = 0.0001x^2 - 0.4322x + 438.08$

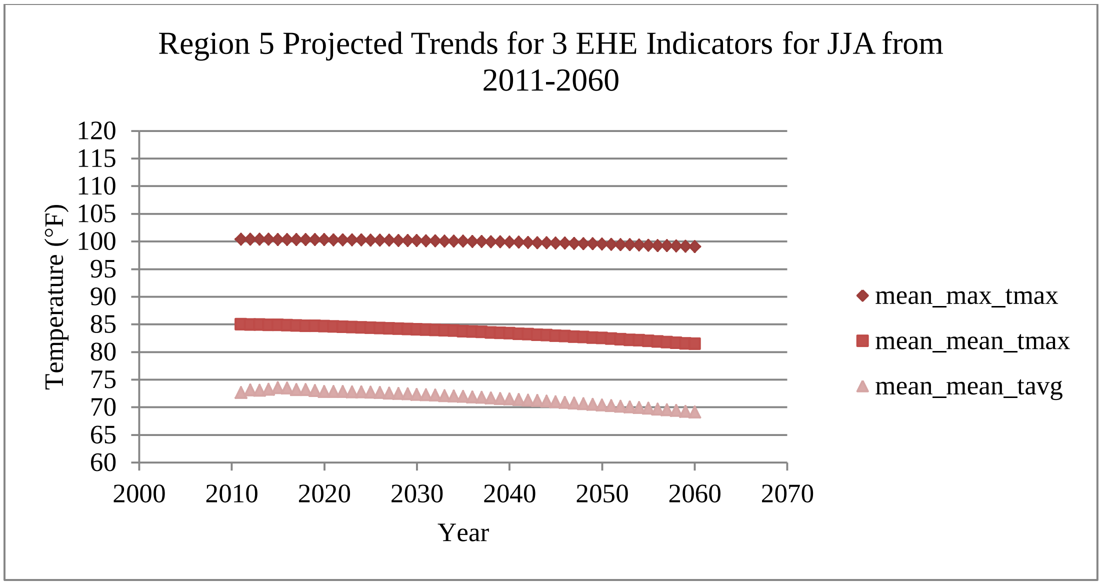

Figure 34: Region 5 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = -0.0005x^2 + 1.9043x - 1810.6$
Mean_Tmax: $y = -0.0008x^2 + 3.2021x - 3101.3$
Mean_Tavg: $y = -0.0013x^2 + 5.048x - 4979$

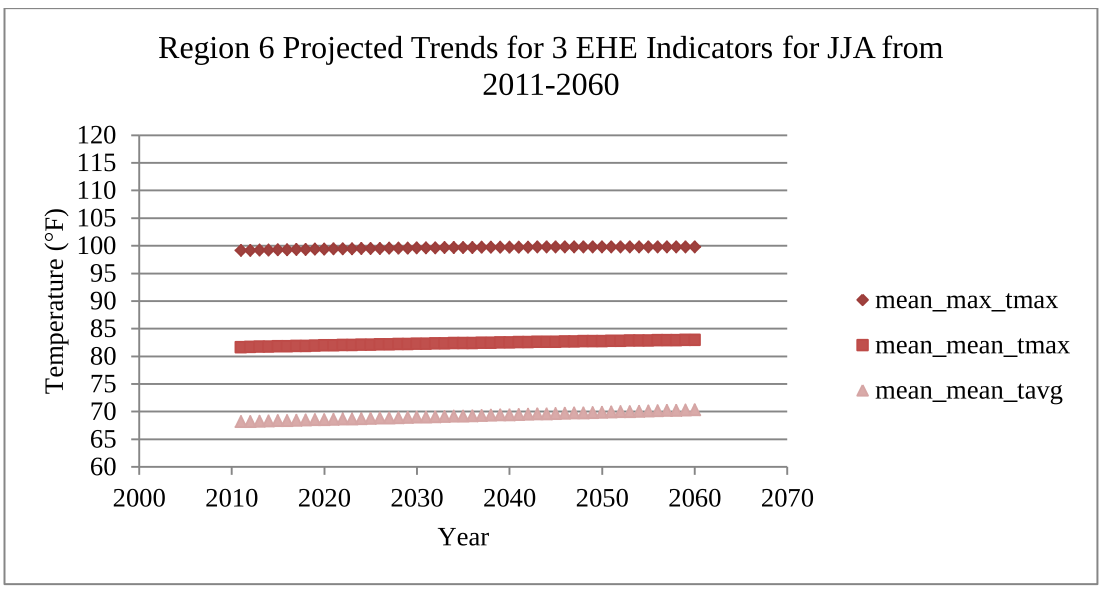

Figure 35: Region 6 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = -0.0005x^2 + 1.9043x - 1810.6$
Mean_Tmax: $y = -0.0008x^2 + 3.2021x - 3101.3$
Mean_Tavg: $y = -0.0013x^2 + 5.048x - 4979$

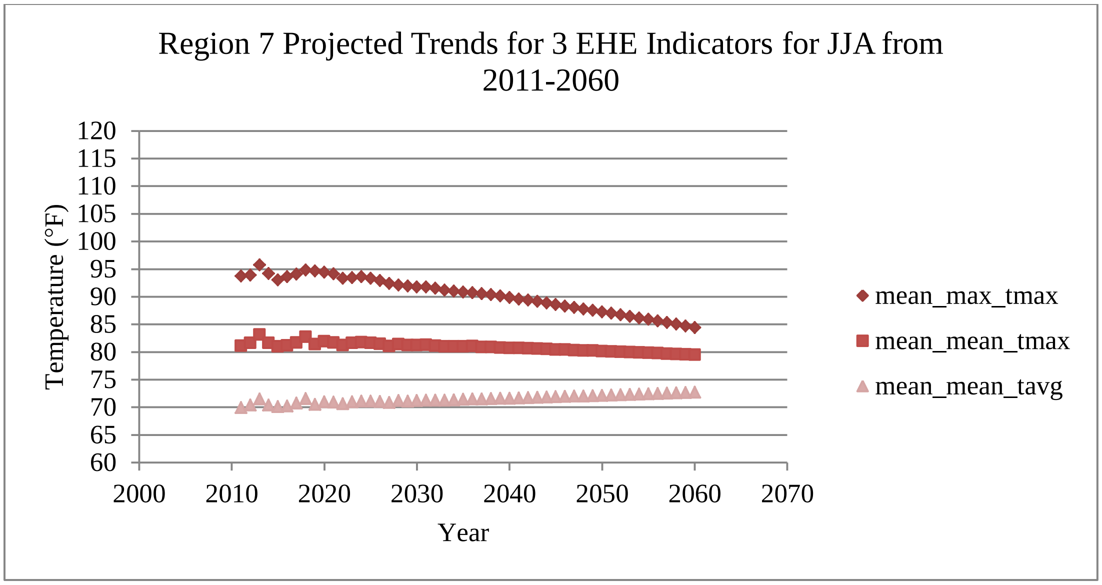

Figure 36: Region 7 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = -0.0024x^2 + 9.4837x - 9344.1$
Mean_Tmax: $y = -0.0006x^2 + 2.364x - 2275.1$
Mean_Tavg: $y = 0.0002x^2 - 0.8668x + 906.68$

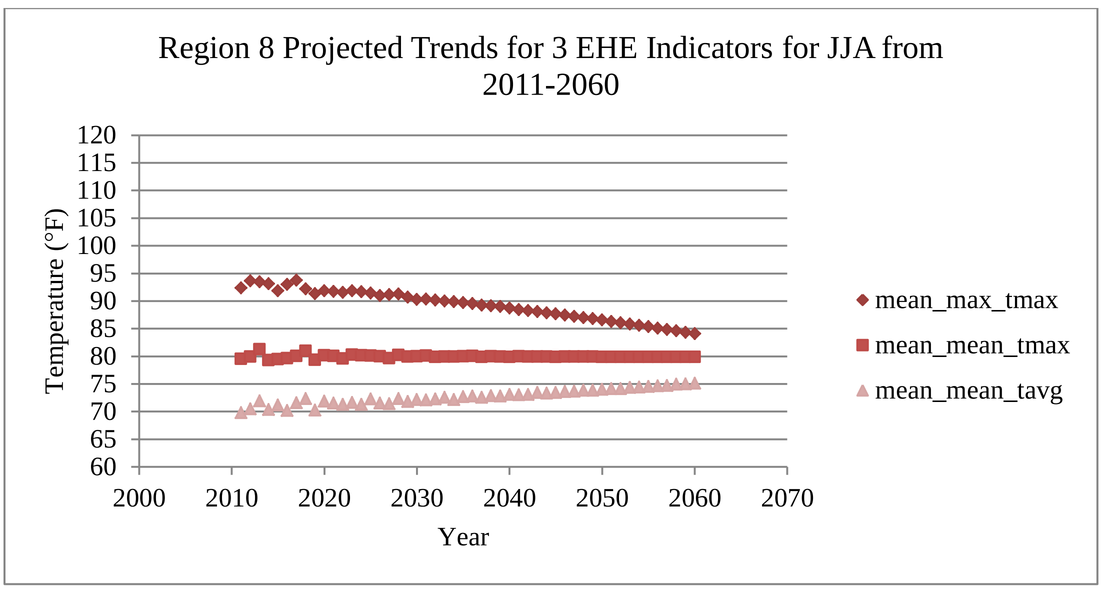

Figure 37: Region 8 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = -0.0024x^2 + 9.4837x - 9344.1$
Mean_Tmax: $y = -0.0006x^2 + 2.364x - 2275.1$
Mean_Tavg: $y = 0.0002x^2 - 0.8668x + 906.68$

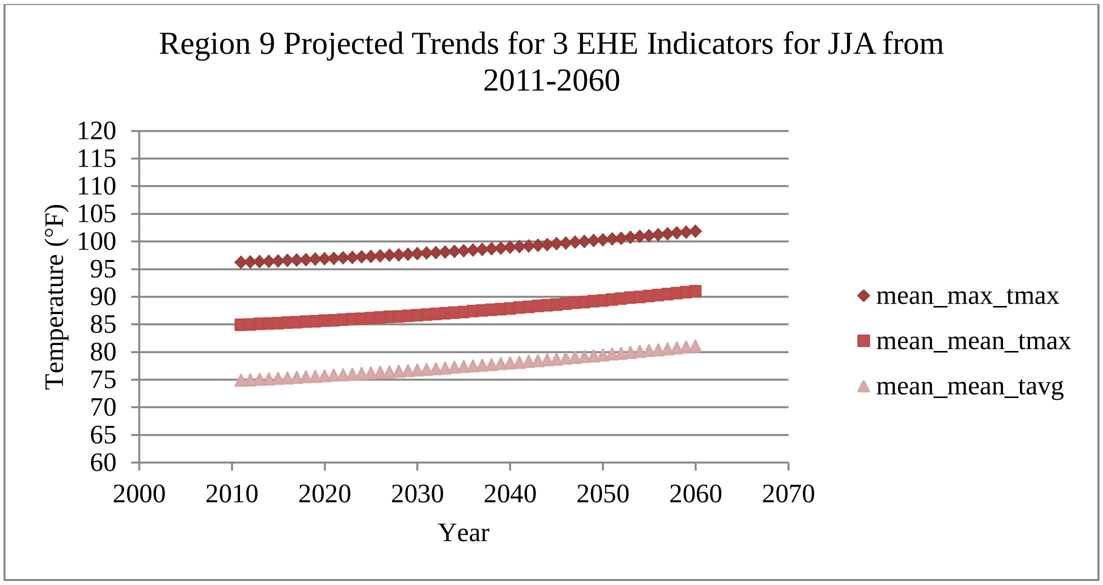

Figure 38: Region 9 projected trends for three EHE indicators for JJA from 2011-2060.
Max_Tmax: $y = 0.0011x^2 - 4.3793x + 4438.2$
Mean_Tmax: $y = 0.0011x^2 - 4.2378x + 4274.3$
Mean_Tavg: $y = 0.0009x^2 - 3.6637x + 3677.4$

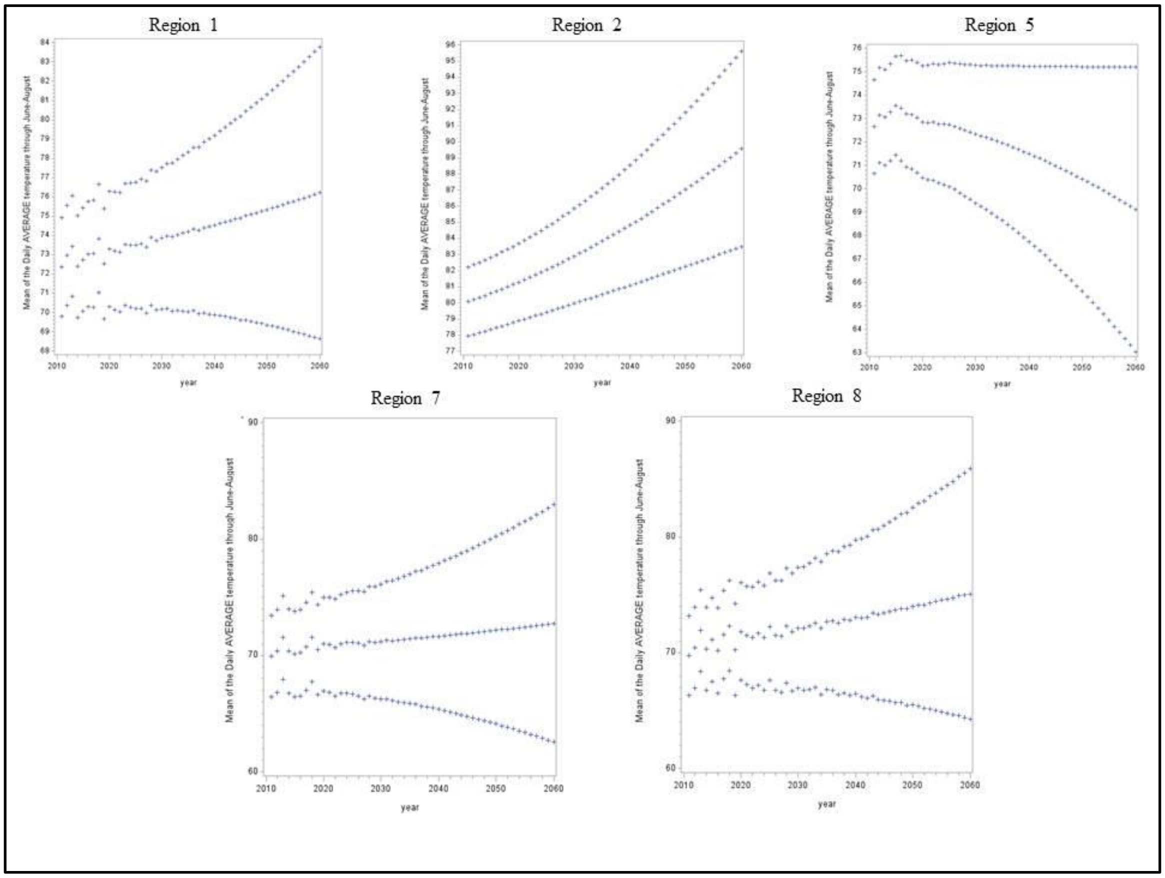

Figure 39: Regions 1, 2, 5, 7, and 8 Mean_Tavg projections with confidence intervals. The upper plotted line represents the upper bound for the 95% confidence intervals. The lower plotted line represents the lower bound for the 95% confidence intervals. The middle plotted line contains the projected point estimates.

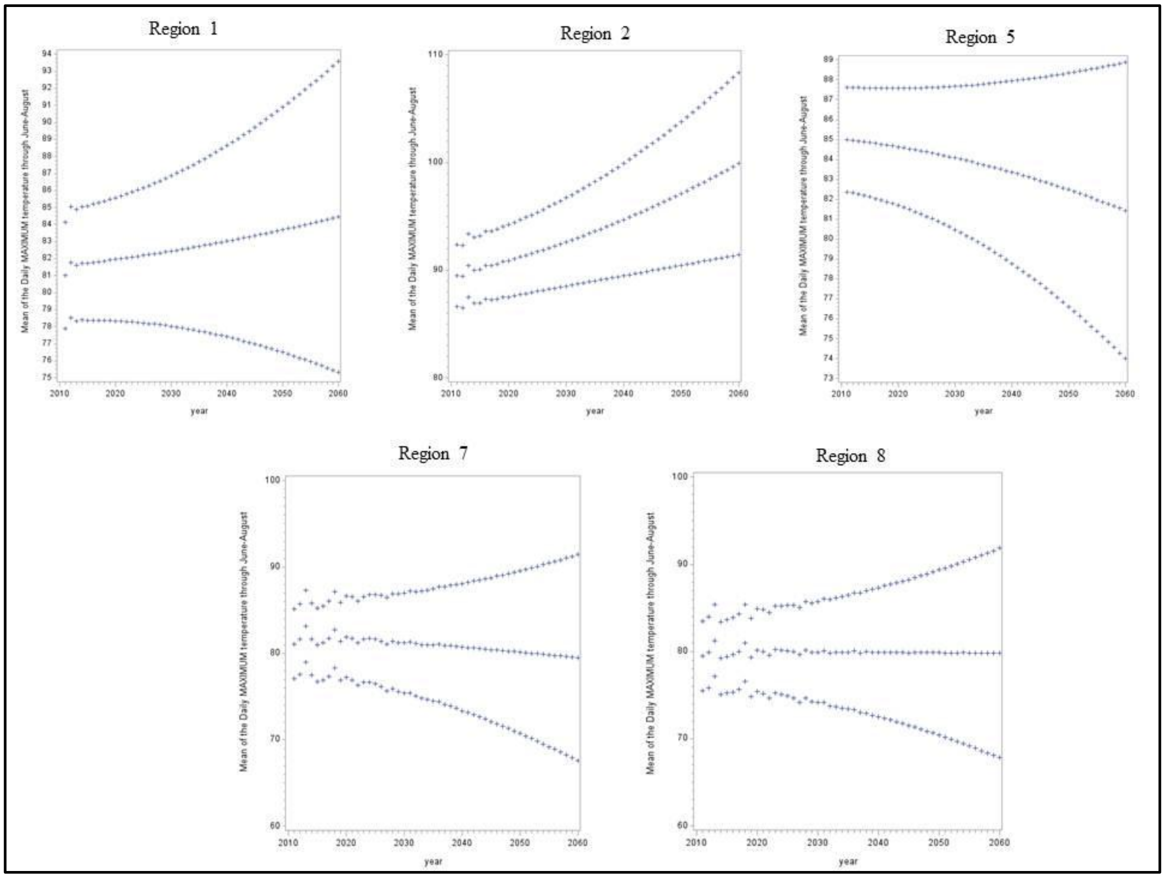

Figure 40: Regions 1, 2, 5, 7, and 8 Mean_Tmax projections with confidence intervals. The upper plotted line represents the upper bound for the 95% confidence intervals. The lower plotted line represents the lower bound for the 95% confidence intervals. The middle plotted line contains the projected point estimates.

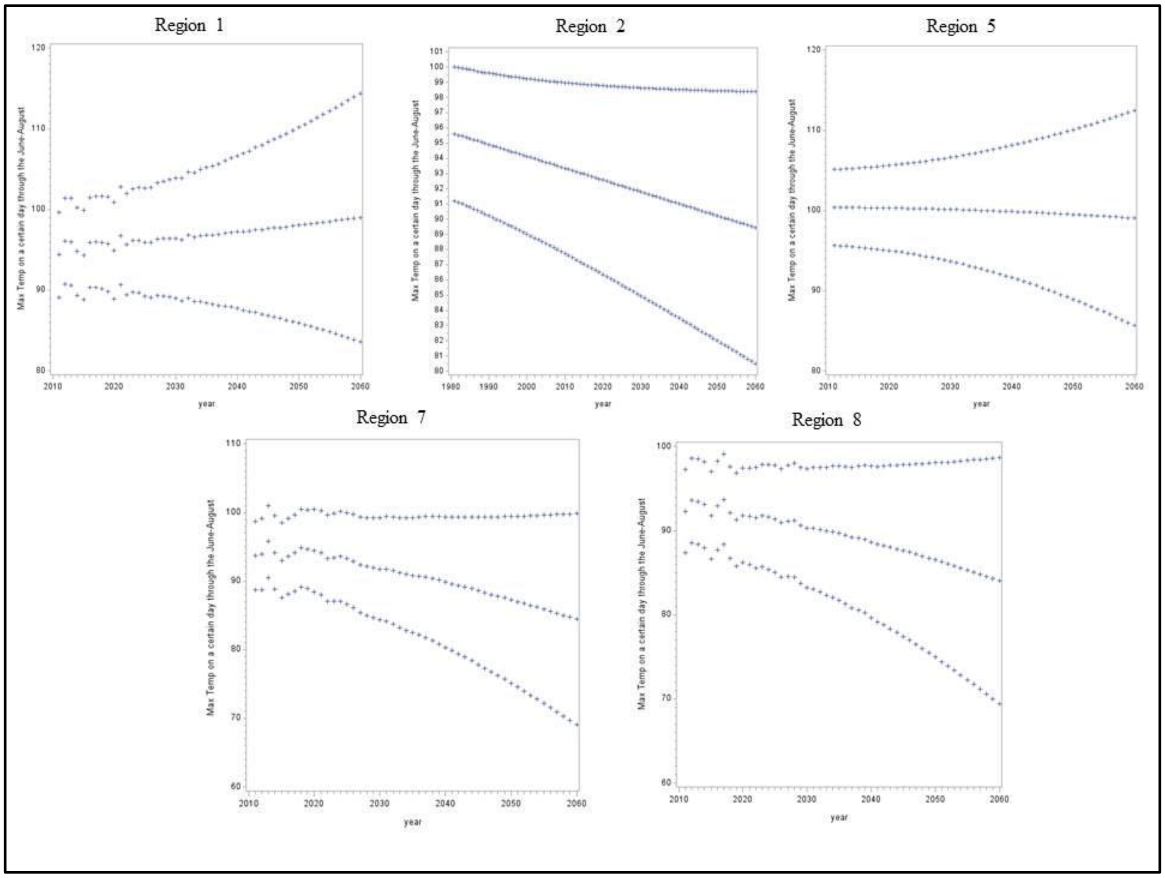

Figure 41: Regions 1, 2, 5, 7, and 8 Max_Tmax projections with confidence intervals. The upper plotted line represents the upper bound for the 95% confidence intervals. The lower plotted line represents the lower bound for the 95% confidence intervals. The middle plotted line contains the projected point estimates.

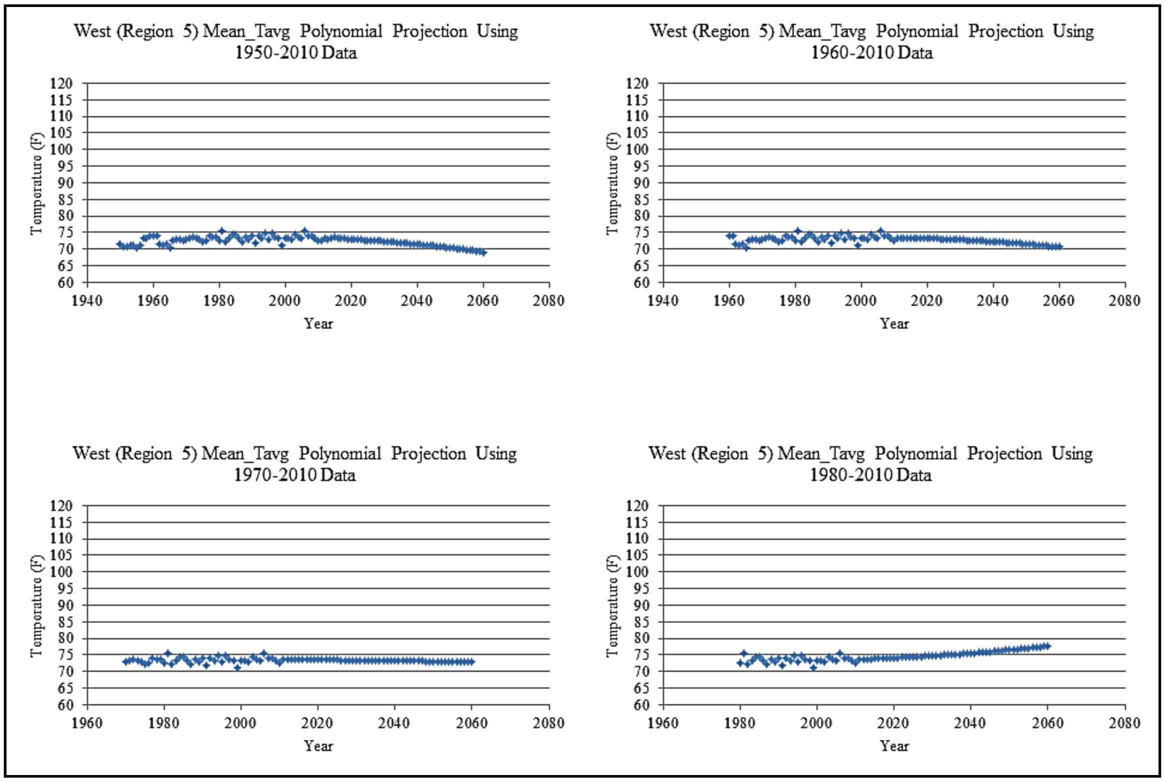

Figure 42: Region 5 projected trends for Mean_Tavg using different subsets of historical data.

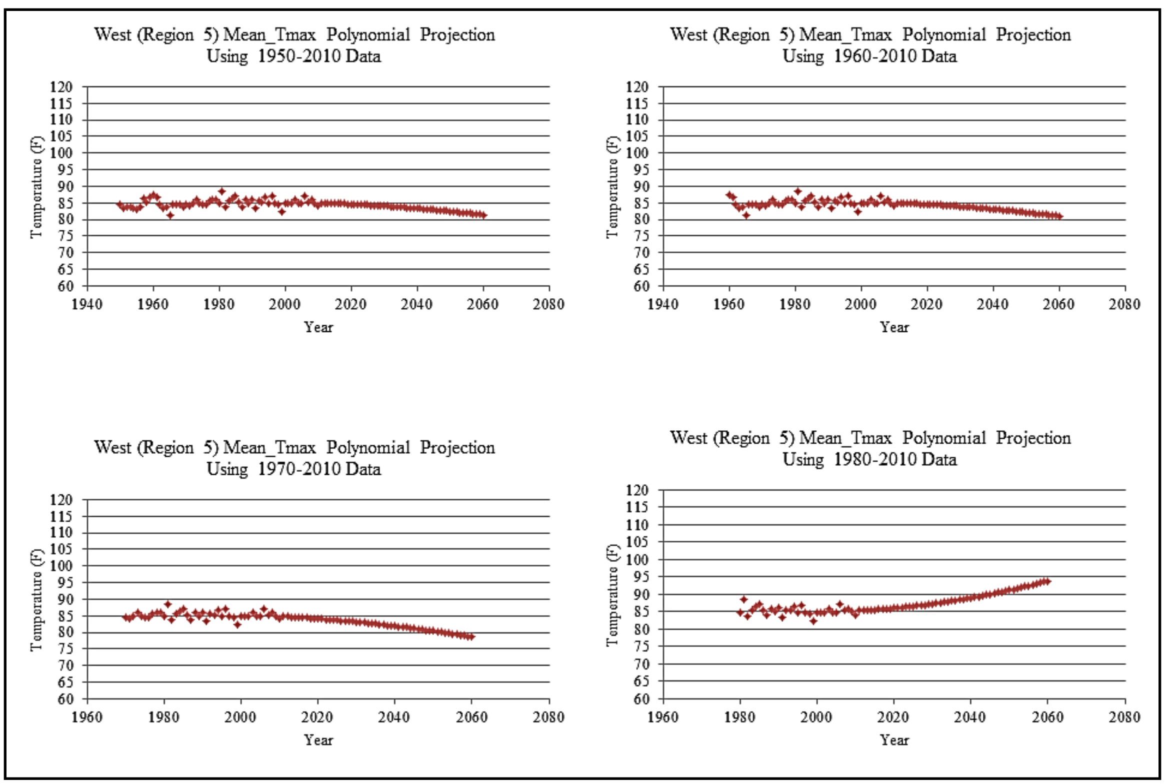

Figure 43: Region 5 projected trends for Mean_Tmax using different subsets of historical data.

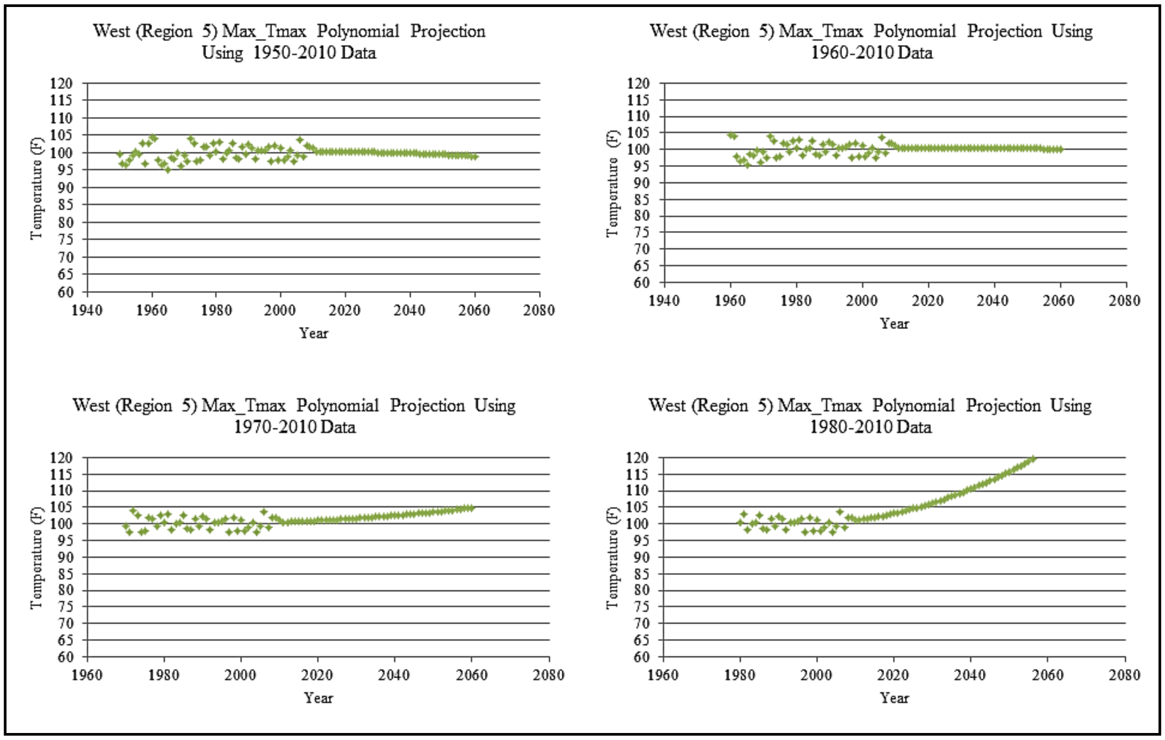

Figure 44: Region 5 projected trends for Max_Tmax using different subsets of historical data.

Region 1	**Avg_ T_avg 2035**	**Avg_ T_avg 2055**	**Avg_T _max 2035**	**Avg_T _max 2055**	**Max_ T_max 2035**	**Max_ T_max 2055**	**Trends (avg_avg, avg_max, max_max)**
Baltimore	78.2	80.5	87.0	88.5	101.0	103.7	+, +, +
Boston	71.3	71.5	78.6	78.2	93.8	91.8	+,+,-
Bridgeport	73.3	73.8	82.6	85.5	98.2	102.1	+, +, +
Buffalo	71.6	73.4	79.1	80.4	92.5	95.0	+, +, +
Burlington	71.3	73.8	80.5	81.9	92.3	91.5	+,+,-
Concord	70.0	71.4	80.3	80.6	95.7	96.3	+, +, +
Newark	75.5	74.9	84.7	85.1	103.7	108.7	-,+,+
New York*	**80.3**	**84.7**	**88.1**	**92.9**	**104.3**	**110.8**	**+, +, +**
Philadelphia	80.2	83.7	87.4	89.4	101.3	105.3	+, +, +
Pittsburgh	80.2	83.7	83.1	85.2	91.0	90.7	+,+,-
Providence	72.4	73.1	80.6	80.6	94.8	93.3	-,-,-
Rochester	72.4	73.1	78.2	77.9	91.2	90.7	+,-,-
Wilmington	75.9	76.8	85.3	86.7	98.5	100.7	+, +, +

Table 7: Temperature (°F) projection estimates and trends for all three indicators at 2035 and 2055 for cities in region 1 (Northeast). All temperatures are in degrees Fahrenheit.
*New York is bolded for comparison of this study's projected temperatures to that of existing GCM output for this city.

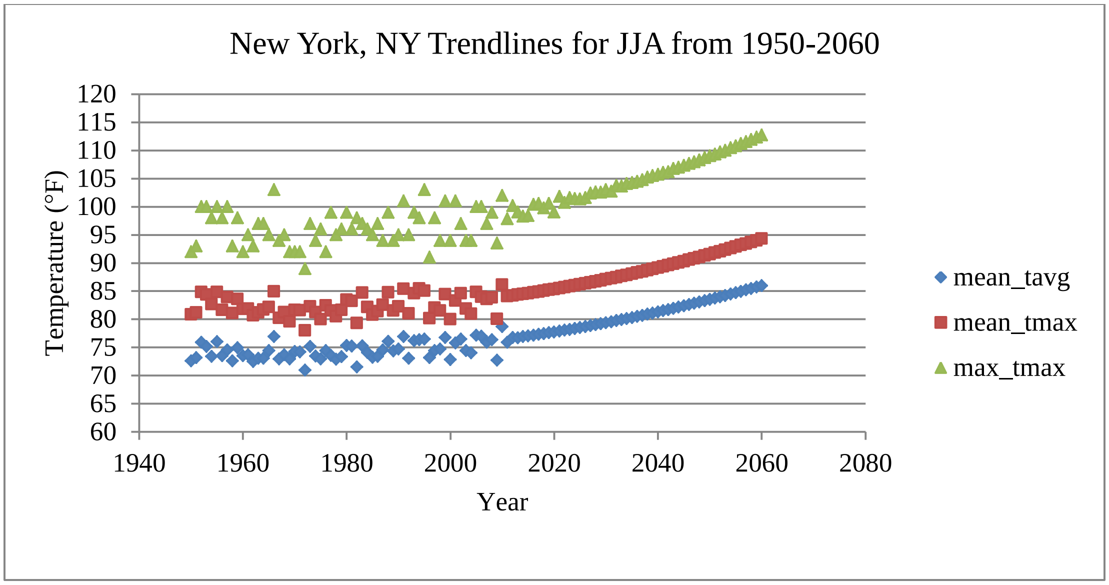

Figure 45: New York City historical and projected trends for all three indicators for JJA from 1950-2060.

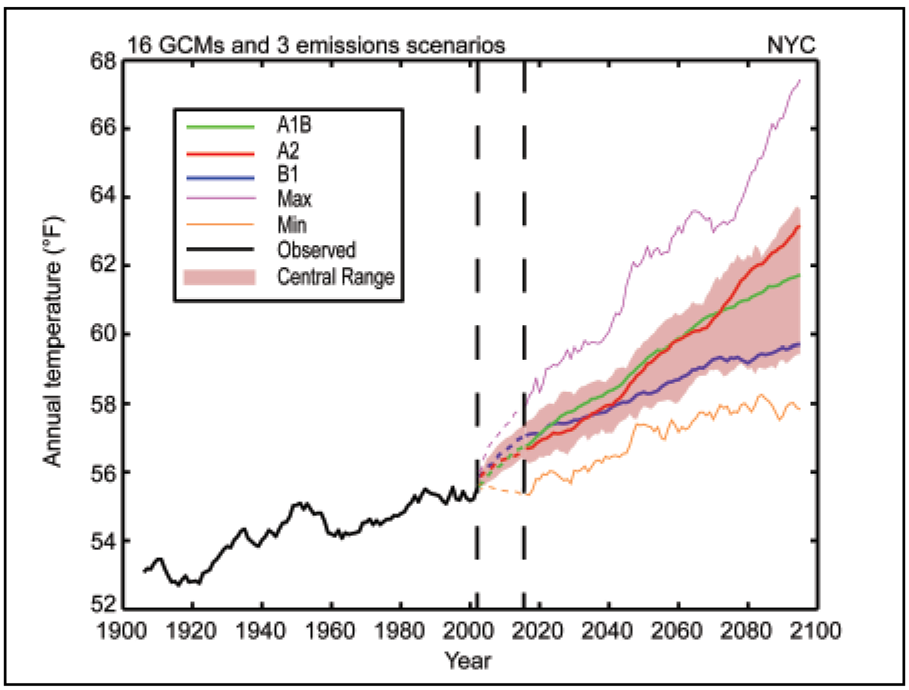

Figure 46: New York City historical and projected trends for annual temperature from 1910-2100 from the New York City Panel on Climate Change study [41].

	Temperature Normal*	Avg_Tmax in the 2020s (Deviation from Normal)	Avg_Tmax in the 2050s (Deviation from Normal)
Our Study	83.5	86.1 (+2.6)	92.8 (+9.3)
Panel on Climate Change Study	N/A	N/A (+1.5 to 3)	N/A (+3 to 5)

Table 8: Comparison of our study with New York City Panel on Climate Change study [41] for projected increases of temperature maxima in the 2020s and 2050s compared to baseline data. All temperatures are in degrees Fahrenheit.
*Temperature normal for our study is calculated using the mean of daily temperature maxima in JJA from 1950-2010.

Region 5	**Avg_T _avg 2035**	**Avg_T _avg 2055**	**Avg_T _max 2035**	**Avg_T _max 2055**	**Max_T _max 2035**	**Max_T _max 2055**	**Trends (avg_avg, avg_max, max_max)**
Bakersfield	79.1	76.2	92.9	90.0	106.8	105.3	-,-,-
Fresno	80.3	78.7	96.5	95.8	111.2	113.0	-,-,+
Las Vegas	96.5	101.4	105.4	108.2	114.5	116.4	+, +, +
Long Beach	63.5	55.8	74.2	67.7	83.4	69.4	-,-,-
Oakland	61.2	59.9	75.2	79.3	112.0	131.2	-,+,+
Sacramento*	**71.7**	**70.7**	**89.4**	**87.6**	**108.1**	**109.3**	**-,-,+**
San Diego	62.4	56.1	67.4	61.3	76.7	67.0	-,-,-
San Francisco	60.9	59.7	68.8	66.0	87.6	82.8	-,-,-

Table 9: Temperature (°F) projection estimates and trends for all three indicators at 2035 and 2055 for cities in region 5 (West). All temperatures are in degrees Fahrenheit.
*Sacramento is bolded for comparison of this study's projected temperatures to that of existing data for this city.

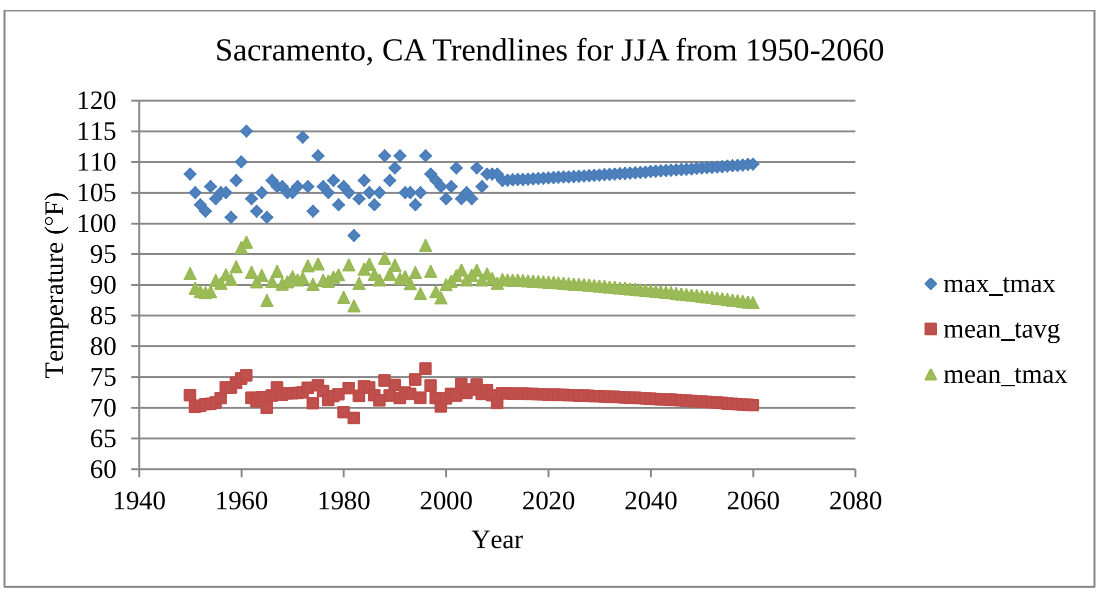

Figure 47: Sacramento, CA historical and projected trends for all three indicators for JJA from 1950-2060.

	Temperature Normal*	Average Summer Temperatures by 2050 (Deviation from Normal)
Our Study's findings for Sacramento	72.2	71.0 (-1.2)
Higher A2 Scenario for Sacramento	N/A	N/A (+5.4 to 10.8)
Lower B1 Scenario for Sacramento	N/A	N/A (+2.7 to 7.2)

Table 10: Comparison of our study with Mastrandrea and Luers (2012) study for projected increases of average summer temperatures in Sacramento, CA by mid-century (2050) compared to baseline data. All temperatures are in degrees Fahrenheit.
*Temperature normal for our study is calculated using the mean of daily average temperatures in JJA from 1950-2010.

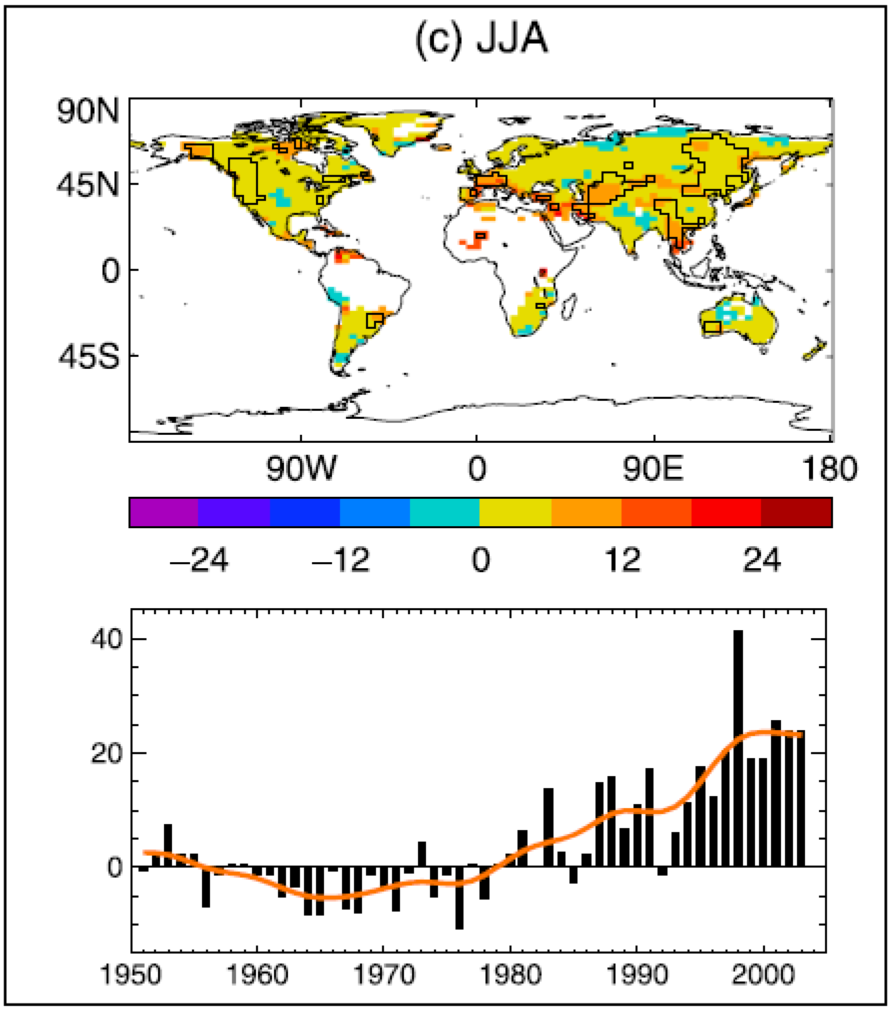

Figure 48: Alexander et al. (2006) study on seasonal occurrence of warm nights in days for June-August. Seasonal results for warming are significant, and insignificant for cooling.