THE SPATIAL AND DYNAMIC PATTERNS OF CLIMATE VARIABILITY AND CHANGE IN THE UNITED STATES

by

Haley Noel Bell

A Thesis Submitted to the Faculty of the

DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF SCIENCE

In the Graduate College

THE UNIVERSITY OF ARIZONA

2024

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

As members of the Master's Committee, we certify that we have read the thesis prepared by: Haley Noel Bell
titled:

and recommend that it be accepted as fulfilling the thesis requirement for the Master's Degree.

Tauhidur Rahman — Date: Aug 13, 2024

Russell Tronstad
Russell Tronstad (Aug 13, 2024 13:45 PDT)
Russell Tronstad — Date: Aug 13, 2024

Serkan Aglasan — Date: Aug 14, 2024

Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

We hereby certify that we have read this thesis prepared under our direction and recommend that it be accepted as fulfilling the Master's requirement.

Tauhidur Rahman — Date: Aug 13, 2024
Thesis Committee Co-Chair
Agricultural and Resource Economiics

Russell Tronstad
Russell Tronstad (Aug 13, 2024 13:45 PDT)
Russell Tronstad — Date: Aug 13, 2024
Thesis Committee Co-Chair
Agricultural and Resource Economics

Signature:
H. Noelle Noel Bell (Jul 18, 2024 14:43 CDT)

Email: noelbell@arizona.edu

ACKNOWLEDGEMENTS

I would like to extend my sincere gratitude to the University of Arizona's Department of Agricultural and Resource Economics, its faculty, and its graduate students for making my pursuit of both academic and personal development outstandingly enjoyable and meaningful. I would also like to express my appreciation for the support and feedback I received from Dr. Russell Tronstad and Dr. Serkan Aglasan throughout the production of my thesis. Finally, I am profoundly grateful to Dr. Tauhidur Rahman, for mentoring me throughout most of my academic career and instilling in me the vim and courage to grow as a scholar, professional, and human. Thank you to my sister, Mariah, whom I am profoundly lucky to have as my best friend forever and for all time. To all my loved ones, friends, and family alike, thank you for believing in me and supporting me as I have grown.

LAND ACKNOWLEDGEMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

Table of Contents

Abstract

Many adaptation and mitigation measures related to climate change require a temporally relevant understanding and for action to be taken at all levels of political jurisdiction. We analyze the developments of county experiences from the years 1895 to 2023 within the CONUS, Western U.S., Arizona, and Minnesota by employing numerous methods. The first descriptive statistical methods examine overall trends and discern how average, maximum, and minimum temperatures and precipitation patterns have changed in variability, spatial variation, as well as how the distributions have developed over time. Polarization indices are then used to analyze how the climatic experiences of counties have grown, be it more similar or less similar. We find that, for most counties, temperature variables have decreased in variability and precipitation has negligibly changed, implying a convergence of temperature ranges and minute shifts in the variability of precipitation. For most counties, the polarization of temperature variables has also decreased, while the polarization of precipitation has changed very little, suggesting that county experiences of temperature across the United States have generally become more alike and that precipitation experiences have changed little. Meanwhile, elements of spatial variation are exhibited through varying levels of significance across our selected regions, and the primarily opposing directions of results in Arizonan summers, which frequently exhibit increases in both variability and polarization.

1 Introduction

In the academic world, the perturbation of the Earth's climate by human activity is generally a well-recognized actuality, and increasingly unusual weather trends stand as testimony to the fact that the Earth's climate is changing. A study by the National Aeronautics and Space Administration (NASA) asserts that the last 10 years have been the warmest in recorded history (Bardan, 2024). Furthermore, a temperature analysis led by the Goddard Institute for Space Studies (GISS) at NASA states that since the 1880s, Earth's average global temperature has been increasing at a non-constant rate, as there has been a nearly 2°F increase since the late 1800s, with the majority of these increases having occurred since the year 1975 (GISTEMPT Team, 2024; Lenssen et al., 2019). Meanwhile, the Wisconsin Department of Natural Resources predicts that with the accelerating pace by which the earth is warming, global temperatures will rise by an even higher 3.6-7.2°F by the year 2100 (Wisconsin Department of Natural Resources, 2024). Although researchers have long since been investigating the nature of climate change, the growing severity of the matter illuminates the importance of understanding the intricacies of how the natural environment is developing. These trends not only impose insidious threats to Earth's habitability but also have had immediate consequences for people's well-being. Tol (2018) studies the economic effects of climate change across the globe and combines the estimates of other studies to provide a condensed approximation stating that, globally, a temperature increase of 2.5°C would make the average person feel as though she or he had lost approximately 1.3% of her or his income. Although some scholars disagree on whether economic impacts will be positive or negative, it is widely recognized that while initial impacts are subject to debate, further warming will lead to net economic damages (d'Arge et al., 1982). Hsiang et al. (2017) estimates the economic damage specifically within the U.S. that may be caused by climate change in the future. They predict significant economic damages of 1.2% costs to GDP per +1°C rise in temperature on average. Additionally, they predict greater impacts in the southern U.S. and systematically higher costs to low-income counties. Meanwhile, they expect positive impacts in parts of New England and the Pacific Northwest. With the exacerbation of the climate, spatial variation becomes more apparent as different regions face unique challenges that worsen at incongruent rates. While almost all climates are experiencing rising temperatures, some regions are changing so drastically that the local climate is growing less recognizable.

Alongside the progression of climate change, the behaviors of passing seasons have increasingly been met with surprise and confusion. Many buildings in the Northeast and Mid-Atlantic had never experienced high enough temperatures in any part of the year to warrant the use of air conditioning units. Consequently, many buildings in these regions were never equipped with AC units. In recent years, however, many are dealing with such drastically higher summer temperatures that AC units are needed, and all too many people are finding themselves in houses lacking the equipment to be properly cooled. Anomalies like uncharacteristic snow or rain in unexpected seasons, or remarkably hot days in what are classified as winter months, are occurrences that seem to be growing in incidence. While most other regions experience rising temperatures at varying rates, however, the southeastern United States is one of the few places in the world that is experiencing wetting and cooling trends (Portmann et al., 2009). The ways in which the direct and indirect impacts of climate change manifest are experienced differently across the United States. Studies (see, e.g., Portmann et al., 2009; Wang et al., 2009; Fan and Carroll, 2012) have explored regionality (spatial variation) in the U.S. and found sizable differences between regions. In terms of climate change, spatial variation is the idea that the impacts of climate change manifest dissimilarly across different regions. Understanding how different regions experience climate change informs us on how to better address it. As such, many researchers have taken to examining how spatial variation manifests in historical climatic patterns (e.g., Wang et al., 2009; Fan and Carroll, 2012; Portmann et al., 2009) but do so using a variety of different methods and resources. Wang et al. (2009) and Fan and Carroll (2012) both use data that only extends from the year 1950 to 2000, while data used by Portmann et al. (2009), which spans the years from 1950 to 2006, is slightly more recent, but still lacks analysis of recent years. While we expect most of our findings to corroborate the patterns and conclusions reached in the existing literature, the pace at which climate change is accelerating suggests that the years since 2006 may be subject to considerably different results in terms of trend significance. Given growingly unusual weather patterns, an updated understanding of climatic developments may better protect against unexpected shifts in climatic trajectories. Further, we use different analytical methods than the aforementioned studies in an attempt provide new insights into the intricacies of climatic developments.

The goal of this study is also to investigate the development of spatial variation, but at a more precise level than is taken on by other studies. With different regions facing the impacts of climate change differently, a thorough understanding of how climate change is manifesting for local areas is paramount. The importance is particularly stressed by the fact that many policy decisions regarding climate change, such as adaptive measures, are made at the county level. Optimizing responses, adaptation, and mitigation of negative impacts requires the enactment of national, state, and local policies (Howe et al., 2015). First, we will conduct a descriptively elementary analysis of how the climatic variables belonging to United States counties are changing to understand how different regions, variables, and seasons have developed since the year 1895. We will then follow Park and Shin (2023) and employ rigorous tests of polarization to further analyze the variables with the goal of better understanding how climatic experiences between counties have evolved. Section 2 presents literature that is relevant to our study and describes how our work is related to and differs from that of other researchers. Section 3 describes the source, composition, and structure of our data. Section 4 will describe our methods. Section 5 presents our results and observations. Section 6 will discuss limitations to our study and potential future avenues of study. Section 7 will conclude.

2 Related Studies

A recent study that correlates closely with the focuses of our own is Gao et al. (2023); a UK-based study that uses data from 37 stations for the period 1950 to February 2023 and a panel data model to investigate the seasonal and spatial variation in climatic variables. Although secular increases in temperature are present across nearly all locations, they find almost unanimous temperature trends but variations in the trends of rainfall. This study, however, was based in the United Kingdom. Our goals are nearly identical to this recently published study, but instead cover the scope of the contiguous United States. Portmann et al. (2009) is another study whose interests are aimed at examining similar climatic trends and exploring the dynamics of regional and seasonal variations as they relate to climate change. Portmann and co-authors explore temperature extremes and their relationship to precipitation in the United States, with a targeted approach to analyzing the peculiarly negative temperature trends of the southern region. They use station-level data from the National Centers for Environmental Information's (NCEI) Global Historical Climatology Network Daily (GHCND) for daily mean, maximum, and minimum temperatures and precipitation amounts as recorded by thousands of weather stations across the United States with a focus on the years 1950-2006. The data is aggregated into 5°

longitude bins for regions between 30-40°N and 40-50°N latitude to analyze the spatial dynamics of temporal and seasonal climatic trends. Variables are observed on daily, monthly, bimonthly, and seasonal scales. They use significance testing and percentile exceedance trends to measure how different parts of distribution are affected differently. Exceedance rate percentiles are calculated using 5-day windows about that day for all years within the data. They measure the days that surpass the 90^{th} percentile (90PET) and those that fall below the 10^{th} percentile (10PET) for each year and determine the trends in exceedance rates over time. They found distinct differences in trends between the daily minimum and maximum temperatures, strong anticorrelation between daily temperatures and hydrologic cycles, and a strong presence of spatial variation. The relationship between temperature and hydrologic cycles was also found to be most pronounced in the May-June period for the southeastern U.S. and to a lesser extent during July-August in the northern region.

The correlation displays significant seasonal and spatial variation as it is absent in the southern U.S. for the November-December period and in the northern U.S. for the November-April period. Further, in terms of spatial variation, while trends in maximum temperature vary greatly across the U.S. from east to west, and to a lesser extent from north to south, minimum temperatures remain relatively homogenously increasing across the United States. Variation between variables is also found to be present, as trends for maximum temperature's 90PET show a stronger correlation with precipitation than compared to mean or minimum temperatures, suggesting that maximum temperature extremes are more sensitive to precipitation. This relationship between temperatures and precipitation values implies that wetter conditions are associated with fewer extremely hot days, underscoring the impact of the hydrological processes on temperature extremes. Overall, their findings highlight the importance of analyzing the temperature distributions and their extremes to gain a better understanding of spatial climate trends and the broader implications associated. We aim to contribute to the understanding of climatic variables' distribution dynamics by using polarization indices and empirically testing the changes in distributions over time. Further, the dataset we use, NClimDiv (as discussed in section 3), improves upon many of the limitations and issues associated with the GHCND dataset as well as provides an updated analysis and results that are more relevant in terms of recency.

A study done by Wang et al. (2009) investigates observed trends in surface air temperature and precipitation across the U.S., with a focus on seasonality and spatial variability. With a time frame somewhat similar to Portmann et al. (2009), Wang et al. (2009) uses grid-based data from the CRU TS 2.1 dataset that covers the global land surface of the United States through the period 1950 to 2000. Using the NASA NSIPP-1 Atmospheric General Circulation Model (AGCM) and empirical orthogonal functions (EOF), they analyze the effects of changing sea surface temperatures (SST) and find that long-term patterns of climate variability in the Pacific Ocean (Pacific Decadal Variability, also known as PDV) play a significant role in seasonal and regional variations observed across United States climatic trends. They find that the PDV EOF, particularly SST anomalies in the Pacific, are the primary drivers of observed cooling and wetting trends in the central U.S. during late summer and fall, while the Atlantic Multidecadal Variability (AMV) also contributes to these trends. Global warming, on the other hand, mainly induces a general warming and drying effect on the U.S. as a whole. The AGCM simulations show that observed climatic trends are the result of a combination of decadal variability and global warming influences, where the former has had a greater impact on trends found within the central United States. Wang et al. (2009) underscores the importance of decadal variability in understanding regional climate variations.

Fan and Caroll (2012) use regional, state-organized data gathered from the website of the National Climate Data Center (NCDC) of NOAA and regression analysis to explore trends in annual temperature and precipitation from the year 1931 to 2000 across four regions of the U.S.: the Pacific West, South Atlantic, North Central, and Northeast. They consider values with a $p<0.0001$ to be statistically significant and find their preliminary analysis of mean annual temperature to reveal no significant trends in any of the aforementioned regions. When calculating the five-year moving average for mean annual temperature and annual total precipitation, however, they find a significant increase of 0.62°C in the Pacific West and an increase of 10.4 centimeters in the precipitation of the North Central Region. Both Fan and Carroll (2012) and Wang et al. (2009) speculate that much of the spatial variation and seasonality found to be present from 1950 to 2000 may be explained by changes in SST. Furthermore, all three studies provide strong evidence for the presence of spatial and seasonal variation in climate change trends.

Trenberth (2011) examines the shifts in precipitation with climate change and, like Portmann (2009), maintains that global warming has directly influenced precipitation. The study uses meteorological observations and model outputs covering global, oceanic, and land domains, but with a focus on the United States. Sourced from IPCC reports, scientific articles, and climate model simulations, Trenberth uses a mixture of both historical climate data and model projections to analyze trends and make future predictions regarding changes in temperature and precipitation. Trenberth uses the Clausius-Clapeyron equation to better understand the relationship between temperature and water vapor. Due to surface drying caused by heating trends, the intensity and duration of drought spells has increased. Alongside other authors (e.g., Groisman et al., 2005), Trenberth reports that even while instances of precipitation are sparser, storms (thunderstorms, snowstorms, extratropical rain, tropical cyclones, etc.) are producing greater precipitation events in each instance, reporting notable increase in heavy precipitation events and a subsequent increase in the frequency and severity of flooding. Interestingly, this pattern also occurs in regions with overall decreasing amounts of rainfall. Trenberth also finds several common issues associated with climate models, stating their tendency to simulate rainfall events that occur too frequently, early, and with underestimated intensity. Further results reveal increasing trends in humidity and total column water vapor (TPWV) consistent with global warming, as well as notable shifts in the regional patterns of precipitation.

In a study by Hay (2014) that investigates climatological mechanisms driving climate change, he states that the overall increasing frequency of extreme weather events like unprecedentedly high and low temperatures, unusual amounts of rainfall and snowfall, and the increased frequency of powerful storms, etc., are the harbingers of climate change. Hay uses data from various studies and observations, including temperature records, ice sheet measurements, and wildfire statistics. Hay finds that global warming has led to an increase in droughts and wildfires in the United States, which have subsequently become significant contributors to CO_2 emissions. The melting of the Greenland Ice Sheet is also a matter of direct concern as the resulting potential sea level rise can impact U.S. coastal regions. Further, increased soot accumulation on ice caused by industrial activities reduces the reflectivity of ice and subsequently exacerbates the melting process. Additionally, Hay discusses how regional effects of global dimming masked the warming trend but did not halt the long-term rise in temperatures driven by CO_2 emissions. Hay's results indicate that the U.S. is experiencing more frequent and severe instances of extreme weather events, such as record high or low temperatures, changes in precipitation, and droughts. The findings suggest that the climate is becoming increasingly unstable, and that the instability manifests in the form of increasingly unusual weather patterns.

An aspect of spatial variation is observable as the inverse relationship discussed by Portmann and colleagues is most pronounced in the southern United States, and to a lesser extent in the northern United States. Portmann and co-authors later postulate that biogenic and anthropogenic factors may play a role in the linkages between temperature and precipitation. The data used by Portmann et al. (2009), however, has a few issues associated. While our dataset (to be discussed in section 3.) is derived from a divisional database (NClimDiv), the database from which our database originates has been adjusted to account for many of the issues associated with divisional databases. Further explanation regarding these improvements will be discussed in section 3. Furthermore, by choosing to partition boundaries based on county bounds as opposed to divisional boundaries, our two studies hold different contributions and implications for policy development and future research. We take on a county-level approach to analysis in an effort to follow the understood importance of well-informed county-level adaptation measures as discussed by other researchers (see, e.g.; Hsiang et al. 2017; Howe et al., 2015). By using counties as our method of organizing, we target our focus on developing a better understanding of how climate change relates to local climates and local levels of governmental authority.

Other studies have found shifts in climatic spatial variation and variability, but our study offers an improvement in terms of recency, a unique focus on counties, and unexplored methodologies. The goal of our study is to, in terms of observational coverage and temporal length, provide an expansive view of climate change's developmental patterns and spatial variations. With the accelerating nature of climate change, many of the climate's developments have picked up speed in recent years, and our analysis offers both an overview of recent progressions and reaches back further to the year 1895 in order to provide an extensive view of temporal movements (Barden, 2024). Alongside our support in the illumination of present trends, we aim to contribute new information and insights using methods which have not yet been applied to the topics of regionality and spatial variation. We aim to accomplish this by examining the polarization present in climatic variables to gather more insight into the intricacies of these trends. To do so, we replicate the methods used by Park and Shin (2023) by using the same 3 indices their study uses the Wolfson index, the Lee and Shin index, and the Esteban and Ray index. Through our application of different statistical methodologies and use of more recent data at belonging to an infrequently studied scope, we hope to contribute new and refreshed perspectives on how climatic variables have developed in the past 128 years. Our data provides a refreshed understanding of how regionality and spatial variation may have developed in recent years, while our methods used will allow for a different perspective of the intertemporal distributional developments.

3 Data

The data used in our study comes from NOAA's Monthly U.S. Climate Divisional Database (NClimDiv). Our dataset uses a 5km gridded approach and comprises monthly county observations for four different variables from the years 1895-2023, ranging from the contiguous United States (CONUS). Vose et al (2014) discusses the methods used, stating NClimDiv was transitioned to a 5km gridded structure through use of a spatial downscaling method that uses observations from weather stations across the U.S. to interpolate and average air temperatures. Challenges regarding topographic and network variability are often associated with divisional

analysis, where the consistency of data is often compromised through inhomogeneous conditions across collection spaces. To address many of the challenges with time series data ranging as far back as the late 1800s, several modifications were made to NClimDiv, which now serves as an improved version of its predecessor: the GHCNd. NClimDiv improves upon the GHCNd by addressing several challenges. To help minimize biases associated with topographic and network variability, they use climatologically aided interpolation to divide the Earth's surface into a grid of cells, each measuring 5km by 5km. For the GHCNd, the primary networks included in the data were the Cooperative Observer (COOP) program and the Automated Surface Observing System (ASOS). NClimDiv provides improved coverage by including use of values from the National Interagency Fire Center Remote Automatic Weather Station Network (excluding precipitation data), the USDA Snow Telemetry network, the Environment Canada network, and a portion of Mexico's Servicio Meterologico Nacional network. The NCEI also uses a pairwise homogenization algorithm to account for undocumented inhomogeneities and historical shifts such as those in measurement instrumentation. These modifications alongside the unchanging structure of county boundaries (with county boundaries conforming to their current-day bounds) provides more historically reliable and consistent values for counties throughout time.
Urbanization is another common concern associated with climate data that has been addressed by NClimDiv. The updated adjustment methods considers both documented and undocumented changepoints in temperature records caused by factors such as station relocations, gradual environmental changes around the station, and changes in measurement instrumentation as discussed above. Among other purposes, the homogenization algorithm discussed in Menne et al. 2009 is used to adjust urbanization and the impacts of urban heat islands on temperature measurements (Menne et al. 2009). The homogenization, in general, is not used to enforce an

absolute standard, but aims to remove the effects of relative bias changes that have occurred through the history of stations' observations by using a pairwise comparison algorithm that identifies and adjusts for inconsistencies between the data of a station and its surrounding neighbors. The data is resultingly homogenized to remove unrepresentative trends caused by factors such as urban heat islands and changes in instrumentation.

Selection speed was a significant barrier to the data collection process. While region-wide and state-wide data are available for download on the NOAA website, neither includes county level precision. Thus, county-level data needs to be downloaded individually. Furthermore, the NOAA interface only allows for county-level data to be downloaded for a single county and selected variable at a time. To collect the data for every county within the CONUS, we wrote a web scraper using python to collect all variables for all counties automatically. Our code uses a URL encoded with specifications for the parameters of state, county, and variable. The code makes a GET request to the URL, and the NOAA server then responds with a CSV file matching the parameters specified in the GET request. Although all the parameters could be set in a requested URL, the counties were denoted by a numeric value (e.g., 001). This value increased with the county for each state alphabetically. That is, the numeric ordering of counties for each state matched the alphabetical ordering. Unfortunately, this number representation of the county did not increase linearly, nor did it increase with any pattern. The first county for a state could be 001, while the second could be 002, 003, 009, or any other number greater than the first county's number value. This is true for the third county in relation to the second county and so on.

Rather than attempt to discern each county's number representation, we calculated the first and last county's numeric representation and made requests for all numeric representations in between. This allowed us to acquire all county data. This did, however, often involve making numerous invalid requests to the NOAA server. To be conscientious of NOAA's resources and to avoid getting deny-listed by the server, we ran the script state by state to avoid sending too many requests, both valid and invalid, at one time. After collecting all files, we then aggregated the files into one and grouped all variables and counties for a state together. The aspects of interest (state, county, date, value) were isolated and extracted from the downloaded files, then rearranged into an alphabetically organized panel data format. Robustness checks were then run to ensure that the data collection process was run successfully and accurately and that no errors in the code or process had compromised the integrity of the data retrieved. Files generated using the script were compared to files downloaded manually from the NOAA website and no differences were found. Descriptive statistics were also generated for county values across states and were checked for accuracy and consistency across time, and no extreme or discernibly erroneous values were observed.

3.1 Coverage

In its entirety, our dataset contains 128 years of monthly data (containing all months of the year) for 48 states and 3,080 counties, totaling approximately 4.8 million observations. For our purposes, we subset 4 different regions into their own respective data frames. The CONUS, containing all 48 contiguous states; the Western U.S., containing the 11 states west of the 100th meridian, Arizona, and Minnesota. A unique number of counties, and thus unique sample size, is associated with each region. The CONUS contains 3,080 counties (≈ 4.8 million observations), the Western U.S. contains 480 counties (≈631,000 observations), Arizona contains 15 counties (≈23,000 observations), and Minnesota contains 85 counties (≈131,000 observations). County lines in the NClimDiv retain their current form throughout history. Given our methodologies and that our focus aimed at the analysis of county experiences, inhomogeneous county sizes are inconsequential for our analysis. Although datum for Alaska are available, its availability is limited. Historical data for Alaska does not start until the year 1925. Datum for Hawaii are not currently available through NOAA. Data for all other states and counties is complete throughout the entire period and for all variables. The 4 variables we utilize in our analysis are average temperature, maximum temperature, minimum temperature, and precipitation. A readme file accessible through the NOAA website describes the calculation process of all temperature variables and precipitation (National Centers for Environmental Information, 2017). All temperature variables, average, maximum, and minimum temperatures, are calculated as the average of all daily values within a given month within a county. Valid monthly values are stipulated such that fewer than 4 consecutive daily values are missing, and no more than 5 values in total are missing. Precipitation is defined as the number of inches of rain experienced within a given scope, and at the county level, is calculated as the total number of inches rained in a county over a given month.

4 Methodology

4.1 Descriptive Pattern

Although our dataset contains observations for all months of the year, we conduct our analysis through winter (December, January, February) and summer (May, June, July) for all variables. To track the trends and movements of climatic variables over time, we use a few different methods. Given the vastness of our data and analytical goals, calculations for most of the methodologies (Standard deviation, coefficient of variation, kernel density estimations, and polarization indices) are automated using RStudio. The process is done by isolating and computing results for unique combinations of region, variable, and month. For standard deviation, coefficient of variation, and the polarization indices, these unique combinations then run through each year from 1895 to 2023. From each year, a value is then contributed to a resulting subset of aggregated yearly values and graphically represented.

The first of the methods which we will discuss is standard deviation (σ). The standard deviation for a given variable is calculated across counties for a given variable for every year, resulting in an individual standard deviation for every variable in each year. The standard deviation for each month is calculated separately, where an annual data point is collected and contributed towards a collection of 128 separate values.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{1}$$

In this regard, μ represents the mean of all counties within a scope, x_i represents the value of the given individual county, and N represents the total number of counties within the given scope (e.g. N=3,080 for the CONUS). Because we have data for the entire scope of our study, we calculate the population standard deviation. By doing this, our goal is to observe the trends of deviation for each unique combination of region, variable, and month, and subsequently gain insight into if and how the variability for each given combination is changing.

Next, to provide a normalized perspective of trends over time by accounting for a diverse range of temperature averages across counties, we generated the coefficient of variation (CV) alongside standard deviation. Calculations for the coefficient of variation follow the same iterative pattern as σ. CV, is defined as:

$$CV = \frac{\sigma}{\mu}$$

(2)

where mean value μ and standard deviation σ are calculated across counties for the selected variable in the given month for each year. Using the same method throughout, values for σ and CV are calculated for each of our selected variables in each of our selected regions. By calculating the CV, we once again aim to observe if and how variability is changing, but with the added adjustment of normalized changes. The structure of the graphs of standard deviation and coefficient of variation are essentially identical. The y-axis represents the value for either CV or σ, and the x-axis denotes years. Each data point represents the value of either CV or σ for a given year, while red data points labeled with a year denote outliers whose values lie within the 98^{th} percentile. The straight blue trendline follows the pattern of data for a given unique combination of region, variable, and month.

For our generation of the 25 hottest and coolest counties, we separated our observations for our variable of interest into 6 different subsets for our different years: 1895, 1925, 1955, 1985, 2005, and 2023. We order observations in descending order of either hottest (highest value for maximum temperature) or coldest (lowest values for minimum temperature) and gather the top 25 observations for each. We then analyze how the allocation of "hotspots" and "cold spots" changes over time by comparing which of the original locations from the 1895 list have been replaced. For hotspots and cold spots, we use July and January as our points of reference, respectively. We undergo this analysis of shifts in rankings in order to gain further insight into spatial changes and whether there have been lasting changes in which areas have been exhibiting the most extreme weather. If the climate is not meaningfully changing, then we expect the hotspots and cold spots to remain largely the same throughout time. Conversely, if the climate is meaningfully changing, then we expect to see inconsistent or sporadic ranking patterns.

Next, we compute the kernel density estimations (KDE) for the same combinations (region, county, variable, and month) using the *density()* function in RStudio. For the descriptive statistics piece of our analysis, this provides us with a provisional "snapshot" of the distributions' shapes over time. We calculate KDEs using two different methods. The first follows the intuition of a moving average and is calculated using 30-year increments, except for the 8-year period between the years 2015 and 2023. For the second method, we calculate the KDE once every 30 years. Here, instead of holding the KDE as the summation of 30 years for each, the second method only considers one year's observations for each KDE. The first method provides a smoother, more visually appealing, and digestible way of examining changing distributions over time. However, being the summation of 30-year intervals, a degree of change is lost using this method, as the KDEs are smoothed by gradually shifting values. Although relatively sporadic in appearance and interpretability, the second method demonstrates a fuller extent of change, without any bias from gradual shifts in value. These methods, however, provide a broad and less rigorous understanding of the selected climatic variables. While our descriptive statistics provide an overview of the circumstances, we use polarization indices to contribute empirical evidence to the discussion of how climatic variables have developed to impact the experiences of U.S. counties.

A key aspect of our analysis is how results from one region relate to another. If spatial variation is present and regions experience climate change dissimilarly, then we should expect to see differing results between regions. For example, if the CV for the CONUS is negatively sloping over time, we question whether a similar negative sloping CV can be observed in regions like the Western U.S., Arizona, or Minnesota. Another aspect to consider is the level of significance being exhibited by different regions throughout the months. To investigate the presence of spatial variation, we compute the same descriptive statistics for all of our regions of study and compare them against each other. We will first analyze the differences across the CONUS, then we will compare those trends against those observed in the Western U.S., Arizona, and Minnesota.

4.4 Polarization Indices

The final medium of observation employs polarization indices. While determining the stochastic dominance of one period's distribution over the other's rigorously asserts whether the distribution has changed to a significant degree, polarization indices provide insight into the intricacies of how the distributions of our variables have changed over time. Our polarization indices use similar computational patterns to the aforementioned methods when calculating the descriptive statistics but offer more rigorous inferences regarding the trends in our variables of interest over time. As polarization increases or decreases over time, county experiences may become more or less distinct from one another. In the case of increasing polarization, we expect to see a growing tendency of counties to cluster, insinuating more dissimilar weather experiences between counties. In the case of decreasing polarization, we expect to see less clustering of counties, insinuating that the weather experiences between counties are becoming more similar.

The formulas for the Wolfson Bipolarization index, Lee & Shin index, and the Esteban & Ray index are provided and discussed in the section ahead.

$$WI = \frac{(\mu_2 - \mu_1)}{y_{med}} - \frac{y_{mean}}{y_{med}} \cdot G \tag{3}$$

The Wolfson bipolarization index (WI) provides insight into the degree of separation between two distinct poles. A declining WI signals that a variable is growing less polarized and that the division between two bipolarized clusters for a variable is diminishing. An increasing WI indicates that there is a clearer, greater division between the high-value and low-value county clusters. The WI is useful for identifying the formation or disappearance of distinct modes.

$$LSI = \frac{\mu_2 - \mu_1}{\mu} \cdot \pi_1 \pi_2 \cdot \left\{ (1-\theta)\left(\frac{\pi_1}{\delta_{11}/\delta}\right)^{\alpha} + \theta\left(\frac{\pi_2}{\delta_{22}/\delta}\right)^{\alpha} \right\} \tag{4}$$

The Lee & Shin bipolarization index (LSI) nests multiple different indexes into one to provide a broad overview of the polarization present and assesses differences in values across time, and the ways in which the LSI develops over time lend inference into how clustering tendencies have progressed, providing insight into the modality of a distribution. For example, a decreasing value for the LSI over time signals that the experiences of counties within high-value and low-value clusters are becoming more alike. Conversely, a rising value for LSI implies that the experiences within county clusters are becoming more different.

$$ERI = \frac{\frac{(\mu_2 - \mu_1)}{2}}{y_{mean}} \cdot \pi_1 \pi_2 \cdot ({\pi_1}^{\alpha} + {\pi_2}^{\alpha}) \tag{5}$$

The Esteban & Ray bipolarization index (ERI) indicates the intensity by which a distribution is divided into distinct, well-separated groups, and considers both the size and distance between clusters. An increasing value of the ERI suggests the polarization between county clusters is increasing and becoming more pronounced and impactful. For the aforementioned equations, μ_1, μ_2, and μ, represent, respectively, the means for our selected variables' low and high value groups. The values μ_1 and μ_2 are then divided by the population mean: μ. Characters π_1 and π_2 represent the aforementioned groups' shares of the overall population such that $\pi_1+\pi_2=1$. θ is the level of weight placed on the group with a higher value. δ_{kk} is the measure of a group's internal dispersion for a given group k, while δ represents a measure of overall dispersion. Our sensitivity parameter α differentiates a group's similarity $\{(1- \theta)\ldots\}$and from the between group's difference (Park and Shin, 2020).

One of the largest benefits of employing polarization indices is the ease of usage and interpretability. To observe the development of polarization over time, it can be visualized through the observed movements of the index over time. To achieve our goals of analyzing the development of polarization indices throughout the years, we determine and visualize our given index for every year. Like the methods of our code before, we once again calculate the indices for all regions, variables, months, and years by iterating through all combinations. To do this, we take our selected index (Wolfson, Lee & Shin, or Esteban & Ray), variable and month, then iterate each over each year from 1895 to 2023. The result is a graph for every combination of county, variable, and month, which contains within it a point for every year of observation. Similar to the graphs for standard deviation and coefficient of variation, the y-axis yields the value for the index value while the x-axis denotes the year. Lines are connected between each data point, resultingly, each peak represents the value of the index in a given year. Red points labeled with years are once again outliers which belong to the 98th percentile. Here, the straight red trendline follows the overall pattern of the data, while the curving blue line follows the movements of data points throughout the years.

5 Results

5.1 Descriptive Patterns

Results for the standard deviation of average temperature in winter show relatively weak amounts of change during the beginning and end of winter but show slightly more intense change during January. In December, only Minnesota shows any level of significant change, being a decrease in variability. For January, all regions aside from Arizona have decreased in variability. For February, only Minnesota and the Western U.S. show significant levels of change in the variability, both again having decreased. During summer, we observe generally more significant changes in terms of both intensity and frequency. For the CONUS and Arizona, we see significant changes all through summer. Meanwhile, Minnesota has only significantly changed in July and June. Meanwhile, the Western U.S. shows no significant change during any summer month. All significant changes in Arizona are increases in the variability and all significant changes in the remaining regions are decreases. With the standard deviation of maximum temperature for winter, we observe significant decreases in the variability of Arizona and Minnesota for all months, while the CONUS and Western U.S. show no significant changes during any winter month. For the summer months, the CONUS has significantly decreased in variability during June and August, while Arizona and Minnesota show significant increases and decreases in variability, respectively, during the months of July and August. The West exhibits no significant change in variability for any of the summer months. For the standard deviation of minimum temperature for winter, significant changes in the variability can be observed for all regions and months except for the CONUS, Western U.S., and Minnesota during December. All significant instances of change for the CONUS, Western U.S., and Minnesota have decreased in variability, while Arizona has only increased. During summer months, we observe significant decreases in the variability across the CONUS for all months, while the Western U.S. shows no significant changes during any. Meanwhile, Arizona shows very strong significant increases in variability during all summer months. In Minnesota, we observe a significant increase during June and a significant decrease during August. For the standard deviation of precipitation, we only observe two significant instances of change. The first is a weakly significant increase in Minnesota's variability during December, while the second is a significant increase in the CONUS during June.

For coefficient of variation across our scopes, we see spatial variation in differences between scopes and seasonality in differences between seasons. Average temperature across all scopes shows generally low levels of significant change fewer instances of change during winter months, with approximately half of the results showing insignificant change. Furthermore, for average temperature in winter months, variability in Arizona follows the direction of trends in the CONUS, the Western U.S., and MN by increasing in variability. Average temperature in Arizona during summer months, however, trends in the opposite direction to the other three scopes and exhibits significant increases in variability for all summer months. The other three scopes display more significant changes in variability during summer months. For which, all combinations of month and scope show significant decreases in variability, with the exception of Minnesota and the Western U.S. during the month of June. The coefficient of variation of maximum temperature holds many of the same trends as with average temperature, except with higher levels of significance and more frequent cases of significant change. Arizona, especially, shows the most change, then Minnesota. Arizona once again follows the direction of trends in the other three scopes during winter months. For summer months, Arizona shows no significant change during June and July, but shows increasing variability in August. The CONUS and

Western U.S. show relatively moderate decreases in variability during summer months, while Minnesota shows no change in June, and strong decreases in variability during July and August. Similarly to the aforementioned temperature variables, the coefficient of variation for minimum temperature in winter months shows relatively moderate changes, with all significant changes in the CONUS and Western U.S. being decreases in variability. Interestingly, the CONUS and Western U.S. exhibit the most significant changes during winter. Arizona shows no significant changes until February, which increases in variability, while Minnesota does not change significantly for any winter month. During summer months, more significant changes are once again observed in terms of both frequency and intensity. In this case, Arizona shows the most significant change, followed by the CONUS, then the Western United States. Minnesota has only changed significantly in August. The CONUS, Western U.S., and Minnesota again have only decreased in variability for significant instances of change, while Arizona has only increased. Precipitation only shows weakly significant change in Minnesota during December, which has decreased in variability, and August, which has increased in variability. No other regions or months exhibit significant change in variability.

In our calculation of cold spots and hotspots, we find noteworthy variation and fluctuations across years, indicating meaningful changes in climate hotspots and cold spots over the years, subsequently supporting the argument of spatially evolving climate hotspots as time progresses. Hotspot fluctuations range from 40% to 64% loss of original locales, and cold spot fluctuations range from 36% to 80% loss of original locales. Figures 3 and 4 show a steady ascent in both maximum and minimum temperatures. From July 1895 to July 2023, the average maximum temperature among the 25 hottest counties across the U.S. rose from 97.06 °F to 104.62 °F: a 7.78% increase. On the other hand, from 1895 to 2023, the average minimum temperature among the 25 coolest counties across the U.S. went from -16.32 °F to 1.51 °F: approximately a 109% increase. From this, we infer that temperatures across the board are rising and that cooler temperatures are rising faster than warmer temperatures. From our kernel density estimations, we gain different forms of insight regarding the development of our climatic variables over time. We observe dramatic shifts and variation in the distributions of all variables and regions, with some converging to multimodality, bimodality, or unimodality, and others exhibiting no particular pattern but still demonstrating notable intemporal variation. A consistent theme between all temperature variables, however, is a gradual increase in temperature.

5.4 Polarization Indices

The WI for average temperature in winter months shows decreasing polarization values for all statistically significant changes. The CONUS, Western U.S., and Arizona show similar levels of significance throughout the winter months, while Minnesota only shows a significant decrease in February. Summer months generally exhibit more instances and greater intensities of change, although with different patterns. For all months, Arizona holds strongly significant increases in polarization, while Minnesota shows similarly increasing polarization during June, but decreasing polarization during July and August. The CONUS and Western U.S. decrease for all significant instances, while the CONUS has significantly changed in all summer months, and the Western U.S. only in August. For maximum temperature in winter months, greater statistical significance can be found in Arizona and Minnesota than in the CONUS and Western United States. All of which have decreased in polarization for significant instances. For summer months, all regions show relatively weak levels of change, with Arizona only showing a significant change by increasing in August. The CONUS is the only region to have significantly changed in June, while Minnesota is the only region to have significantly changed by decreasing in July. In

August, all regions show significant change, with Minnesota showing a strong decrease in polarization. The CONUS and Western U.S. have also decreased in polarization during August. The WI for minimum temperature in winter across all regions again exhibits less significance than in summer, with the CONUS being the only region to statistically change during December and January by decreasing. During February, the CONUS and Western U.S. decrease significantly, while Arizona increases, and Minnesota shows no significant change. For summer months, we observe moderate to strong changes in the polarization for all regions and months except for the Western U.S. in June and Minnesota in July. Polarization has strongly increased for both Arizona and Minnesota in June and continues to increase strongly for Arizona for July and August. Minnesota has decreased in polarization during August. The CONUS and Western U.S. show also show declines in polarization for all summer months, aside from the Western U.S. in June which shows no significant change. No significant changes are exhibited in the WI of precipitation for any regions or months.

The LSI of average temperature in December only exhibits statistically significant change in Arizona, which has decreased. For January the CONUS, Western U.S., and Arizona show significant decreases in the polarization, while only the CONUS and Western U.S. exhibit significant change in February. All statistically significant changes in the LSI during winter are decreases in the polarization. Summer also shows relatively low levels of change, although higher than that found during winter. For June, the CONUS has significantly decreased in polarization, while Minnesota has increased, and the Western U.S. and Arizona show no significant changes. During July, no region shows any significant change in polarization. August, however, holds significant change for all regions, with all but Arizona decreasing in polarization. Maximum temperature in December shows no significant change in any of the regions, while only Minnesota and the CONUS show significant change (decreases) in January. For February, all regions except Arizona show significant change, where all have decreased in polarization. For the LSI of maximum temperature in summer, we see few statistically significant instances of change. In June, the CONUS is the only region to have statistically significantly changed in polarization, while in July, only Minnesota has changed significantly. In August, only the CONUS and Minnesota show significant changes. All significant changes in the LSI of maximum temperature decreases. The LSI of minimum temperature shows generally less statistical significance than the WI of minimum temperature but shows more significant change than the LSI of average and maximum temperature. The LSI of minimum temperature for the CONUS and Western U.S. has statistically significantly decreased in polarization for all winter months, while Arizona and Minnesota show no significant change for any winter month except for Arizona in December which has decreased in polarization. For summer months, however, Arizona and Minnesota have significantly changed in polarization for all months except July, where Minnesota shows no significant change. Arizona has increased in polarization for all summer months, while Minnesota has strongly increased in June, and decreased in August. Meanwhile, the CONUS has significantly decreased in June and August, and the Western U.S. has significantly decreased in July and August. Similar to the WI, precipitation has not significantly changed for any regions or months.

For the ERI of average temperature, we once again observe generally more statistically significant changes in summer than in winter. Arizona is the only region to have significantly changed in polarization during December, where it has weakly declined. For January, only Minnesota shows no significant change in polarization, while all other regions have declined. Meanwhile, in February, Arizona is the only region to not statistically change, while all other regions have significantly decreased in polarization. Arizona has significantly increased in polarization for all summer months, with changes in August being the strongest. Regarding the other three regions, only the CONUS has significantly changed in June, while only Minnesota has in July. All three regions significantly change in August, with Minnesota showing the strongest. All significant changes in the CONUS, Western U.S., and Minnesota exhibit decreases in the ERI of average temperature. Maximum temperature in December shows significant decreases in the polarization of both Arizona and Minnesota, while January and February show significant decreases in the polarization of all regions. Interestingly, summer shows less change than winter. In June, the CONUS is the only region to significantly change, while in July, Minnesota is the only one. In August, all regions have significantly decreased in polarization, except for Arizona which has significantly increased. Notably, Minnesota shows a strong decline in polarization in July and a very strong decline in August. The ERI of minimum temperature shows relatively low levels of significance in winter in terms of both intensity and frequency. In December, only the CONUS shows a weak decrease in polarization and in January, only the CONUS and Western U.S. show significant decreases. Results for February are largely the same, but with Arizona weakly increasing. The CONUS and Arizona have significantly changed for all summer months, with the CONUS only decreasing in polarization, and Arizona only having increased. The Western U.S. and Minnesota only decrease in instances of significance, but changes are insignificant for Minnesota in July, and for the Western U.S. in June. Unlike those for the WI and LSI, results for the ERI of precipitation exhibit two significant instances of change. Both belonging to Minnesota, we observe a decrease in the polarization during December, and an increase during August.

6 Limitations

A valuable future component of this study is the addition of stochastic dominance theory as a methodology. While the methodologies explored in this study provide a comprehensive understanding of how climatic variables in the United States have developed over time, the addition of stochastic dominance testing would provide a way in which to empirically state whether the distributions of climatic variables have significantly changed over time. We propose for this to be done by comparing the distributions of climatic variables across 30-year periods. Stochastic dominance testing is a methodology which could add to the analytical efficacy of our research, while further extensions into the analysis of precipitation may help to ameliorate potential gaps in understanding. In our study, precipitation was widely found to hold no statistical significance. Perhaps the addition of other climatic variables related to the hydrologic cycle may provide greater insight. Possible limitations with our analysis of the variable precipitation are associated with the time frame. Although daily data is more precise, it still may not be precise enough to gain a proper understanding of changes in precipitation. Hourly observations or inches per hour may be necessary in order to effectively evaluate patterns. Due to time constraints, we were unable to conduct our analysis on several additional variables such as cooling degree days, heating degree days, and the drought indices PDSI, PHDI, PMDI, and Palmer-Z. Further exploration of spatial variation and variability extended to the aforementioned variables may provide valuable insights into gaps of understanding. Additionally, exploration of other variables such as cloud cover or SST may provide further understanding into the patterns observed in this study.

7 Conclusions

7.1 Descriptive Pattern

Aside from suspected regionally and seasonally varying results, U.S. counties are decreasing in variability, depolarizing, and experiencing the most severe changes during summer and in minimum temperature. Sharp declines in the variability of our temperature variables in both summer and winter show a trend toward decreasing diurnal temperature ranges, particularly within the summer months. Within the CONUS, all significant instances of change show declining variability. This suggests that the United States and the counties within are overall experiencing homogenizing temperature ranges.

For standard deviation across the CONUS, our selected temperature variables show significant declines in variability for both winter and summer, although to a greater degree during the summer months. Precipitation shows almost no significant changes in variability. For the CV calculations, we generally see more statistically significant changes compared to those observed with standard deviation. For the CVs of maximum temperature and minimum temperature, changes are approximately the same as they were for standard deviation. The CVs of average temperature, however, show more significant changes than standard deviation in general. The CVs of precipitation show almost no statistically significant changes. In summary, our analysis of the standard deviation and CV for climatic variables across the CONUS indicates significant declines in temperature variability for both winter and summer, with changes in summer being overall more pronounced, particularly for Arizona and Minnesota. Precipitation reveals the least significant change, and out of all variables, minimum temperature for both the standard deviation and CV shows the strongest overall changes, suggesting either a stabilization or convergence at the lower end of temperatures ranges. These shifts indicate meaningful changes and a general trend towards tighter temperature ranges on average and that the underlying temperature distribution has become more uniform with the range of temperatures experienced becoming smaller for regions like the CONUS, Western U.S., and mostly in significant instances of change in Minnesota. We also find a trend of sporadically positioned hotspots and cold spots throughout United States counties. The rankings of hotspots and cold spots across the U.S. are both unstable throughout the years, with cold spots showing a higher degree of fluctuation. Similarly inconstant patterns are found in the KDE of U.S. counties. Weighty shifts in the modality and positions of KDE distributions can be observed, with KDEs of temperature variables all incrementally moving to higher temperature values as a whole. Both the increases in temperature and the dramatically shifting structures of KDEs suggest that the distributions of our climatic variables have meaningfully changed since the year 1895.

Except for the Western U.S., which generally shows the least significant changes over time, we observe generally stronger trends in our analysis of AZ and MN. This is likely due to their smaller scale and subsequently lower degree of regional diversity which may dilute results found in the CONUS and the Western United States. The Western U.S. generally mirrors those exhibited in the CONUS, with a few differences. AZ, however, shows frequently dissimilar trends in terms of both intensity and direction, while Minnesota shows occasionally dissimilar trends in terms of intensity and direction. The same pattern of increasing temperatures for the generated KDEs can be observed for regions other than that of the CONUS. The Western U.S., AZ, and MN all also share the same pattern of gradually shifting outwards to higher average temperatures. AZ typically exhibits trends opposite to those observed in the CONUS and the Western U.S., while MN occasionally does the same. While the CONUS and the Western U.S. generally exhibit decreasing diurnal temperature ranges, results for AZ show meaningful increases in temperature variability. The resulting conclusion of our preliminary analysis is that variability and its trends are strongly subject to spatial variation. For the Western and Arizonan counties, precipitation results hold no significant changes in the variability of rainfall for σ or CV, while the CONUS and MN show very few and relatively weak significant changes in variability. The tendency for values observed by the coefficient of variation to be more intense and statistically significant than those observed with standard deviation indicates that relative changes in variability are more pronounced. As a whole, it’s important to consider that, while temperatures in general are homogenizing, they’re doing so with an overall upward trajectory.

7.2 Polarization Indices

Across the CONUS, our results of the WI show generally decreasing trends in polarization across most variables and months, indicating a mix of diverging and converging climatic disparities between counties. For instance, August and December underwent increases in polarization for all temperature variables except minimum temperature, which holds a significant and substantial decrease in polarization. Meanwhile, all other significant changes in polarization have been downward in trajectory. Precipitation for the CONUS was not found to hold any significant changes. Due to its vast geographical diversity, the Western region presents a unique climatic profile yet holds a consistent direction of decreasing polarization. All variables and months with significant changes have experienced a decrease in polarization, with minimum temperature in summer (July and August) and average temperature in winter (January and February) showing the strongest declines in polarization. Although with lower levels of significance, WI results show that maximum temperature has also decreased in polarization, meaning all temperature variables in the Western U.S. have depolarized. Consistently half of the months hold significant changes, with changes in July significant in average and maximum temperature, July significant in minimum temperature, and August and February always significant. On the other hand, precipitation shows no significant changes during any months.

Calculations for the WI in Arizona also present a more varied image. Aside from minimum temperatures in June, all significant changes in summer reveal increasing degrees of polarization among the temperature variables. While presenting decreasing polarization, aside from minimum temperature in February, winter months for average temperatures and minimum temperatures reveal less significant and more uncommon instances of change, except for maximum temperature, which shows substantial levels of significance in all three months.

Results for the WI in summers are inverse to those in winter, with strong changes in summer average and minimum temperatures but mostly unchanging polarization in maximum temperatures. Similarly to the CONUS, results for WI in Minnesota show mostly decreasing but occasionally increasing polarization among significant variables and months. The only instances of significant and increasing polarization are during July for average temperatures, December for maximum temperatures, and August in minimum temperatures. All other significant results show a decline in polarization. Maximum temperature holds more frequency and intensity of significant instances for both winter and summer than minimum and average temperature, which both have undergone relatively low levels of change in polarization.

The LSI for the CONUS indicates varied trends across variables and months. For the CONUS, there's a mix of increasing and decreasing levels of polarization for average and maximum temperatures, but only instances of decreasing polarization in minimum temperatures, which also has experienced the strongest changes in polarization across winter and summer. Average temperature holds the second most drastic shift in polarization, while minimum temperatures hold the least, and precipitation once again holds no significant changes. LSI results for the Western U.S. show almost exclusively decreasing changes in polarization among significant month and variable combinations, the exception being an increase in polarization during July for minimum temperatures. The remainder of significant instances have depolarized, with the most substantial changes seen in minimum temperatures, and precipitation once again holding no significant changes. Average temperature holds near identical changes in polarization as were revealed with calculations of the WI. Contrary to the tendency of Arizona to experience the most extreme changes, calculations of the LSI in AZ result in modest levels of polarization in average temperatures, and no significant changes in maximum temperature. Meanwhile, minimum temperature experiences strong increases during summer, aside from a depolarizing June, and only one instance of faintly significant change in winter. While average and maximum temperatures in Minnesota have only experienced depolarization, minimum temperatures have only polarized. Furthermore, average and minimum temperatures have only experienced significant changes during summer, while maximum temperature has seen high levels of significant change in the latter two months of both winter and summer.

Results for the ERI across the CONUS once again show significant changes in bipolarization across different variables. Minimum temperatures have undergone significant changes in all months, with all except December having decreased in polarization. Average temperatures have also firmly decreased in polarization in winter and June, but August shows a significant increase in polarization. Maximum temperatures have undergone a moderate degree of change and show a mix of depolarization and polarization in winter and summer, respectively. Lastly, precipitation has undergone no significant changes in polarization. The Western U.S. holds similar patterns of change in average temperatures for the ERI as were revealed in our calculations of the WI and LSI, and once again has significantly depolarized in January, February, and August. Meanwhile, maximum temperature holds the same patterns of change as the WI, where all the same months have depolarized, but to a lesser degree. Minimum temperature has depolarized for the latter two thirds of winter and summer. Like the CONUS and all results beforehand, ERI results for precipitation reveal no changes in polarization. Results for the ERI of average temperature in Arizona hold the same magnitudes and directions of change as are observed with the WI, with significant changes in the polarization of all summer months, December, and January, where all but July and August have depolarized. Minimum temperatures have polarized dramatically in all summer months, and faintly significantly in February.

Conversely, maximum temperatures have inverse patterns of depolarization, where all winter months have experienced considerable degrees of depolarization, and August shows weak depolarization. Precipitation has once again experienced no changes in polarization. Lastly, patterns of change for the ERI of Minnesota follow the same significance patterns as that of the WI, in that all the same months hold the same direction of change, aside from July which has depolarized. Degrees of significance are also near identical between the ERI and WI of Minnesota, aside from July where significance is fainter.

Ultimately, minimum temperature has undergone the most dramatic changes and has mostly depolarized, intensity of changes is then followed by average temperature, then closely followed by maximum temperature. Results for the ERI in Minnesota reveal the first instance of statistically significant changes in the polarization of precipitation. In this case, precipitation shows faint significance of polarization in August and depolarization in December. With most months, variables, and regions experiencing a depolarization of values, we find empirical support for the growing disparity between county experiences across most United States regions. Furthermore, in the diversity of findings, while most regions, variables, and months are experiencing depolarization, not all are. Our main findings from polarization conclude that United States counties are largely depolarizing, although significant spatial variation and seasonality assign this as a general statement and not accurate for all observations. The overall decrease in polarization of WI temperature variables, aside from Arizona, across United States counties indicates a reduction in the gap of climatic experiences between counties, and that climatic conditions are becoming more similar across counties. The varying degrees of significant change between all regions support speculations regarding the presence of spatial variation. The varied nature of polarization in Arizona also indicates the presence of spatial variation. While the Arizonan winter temperatures across counties are generally exhibiting less clustering tendencies, experiences of summer temperatures across counties in Arizona are mostly on the course to grow more intensely different and polarized. Similarly, depolarizing results present for the LSI of temperature variables indicate that there is an overall reduced polarization between county experiences and a more homogenized distribution of weather conditions, except for with minimum temperature during Arizonan summers. Lastly, with ERI also largely following trends of depolarization, it suggests that counties are overall experiencing fewer extremely different weather patterns in terms of intensity and frequency, with Arizonan counties once again being the exception and increasing in polarization for average and minimum temperatures in summer. Although most months and regions exhibit declines in polarization, it's important to recognize the distinct presence of spatial variation within our results.

As a whole, the weather experiences of United States counties are growing more similar, although with significant regional exceptions. The mechanisms as to why these changes are occurring are not tested rigorously in this study, and further analysis of reasons will be left to the expertise of climate scientists. We do, however, mention a few aspects which may have some bearing on the presence of regionally unique climatic developments. While colder and flatter regions like Minnesota or larger regions like the CONUS and Western U.S. may be overall depolarizing, counties belonging to other regions like Arizona may be subject to polarizing summer temperature ranges and growing disparities between county experiences in summer months. We suspect this may be due to either the hotter and dryer climate present in Arizona, or the topographic diversity of the region. The theory of hotter and dryer climate of Arizona contributing to the spatial variation lends support for the findings by Portmann et al (2009) which found that dryer conditioners are associated with greater temperature extremes. We would expect results for counties or regions with similar climatic compositions and/or topographic makeups also to exhibit similar results and overall increases in temperature polarization during summer. Lastly, across most of our results, summer months, specifically August, as well as minimum temperatures, are the factors that exhibit the greatest changes in terms of both intensity and frequency. Minimum temperatures exhibiting the steepest trends and most significant levels of change hold two notable conclusions: either nocturnal temperatures are rising at a rate faster than diurnal temperatures, or colder regions are in general are warming faster than hotter regions. Both possibilities conclude that colder temperatures are rising faster than warmer temperatures. The CONUS, Arizona, and Minnesota all frequently show strong levels of significant change among our methodologies, but the steepest trends are observed in Arizona and Minnesota. In the case of polarization, results observed within the Western U.S. are once again hypothesized to be diluted by the distribution of reasonably climatically and topographically balanced counties. Lastly, while other studies have provided evidence for meaningful changes in the precipitation across the United States (e.g. Fan & Carroll, 2012; Portmann et al., 2009; Trenberth, 2011; Wang et al., 2009), we find no evidence for the U.S. as a whole exhibiting significant changes in the variability of rainfall. Our findings do not challenge the findings of other researchers which assert changes in precipitation. Instead, our results simply insinuate that the variability and polarization of rainfall has only very slightly significantly change.

8. Graphs and Figures

Figure 1. Distribution of Hottest U.S. Counties (Maximum Temperature in July)

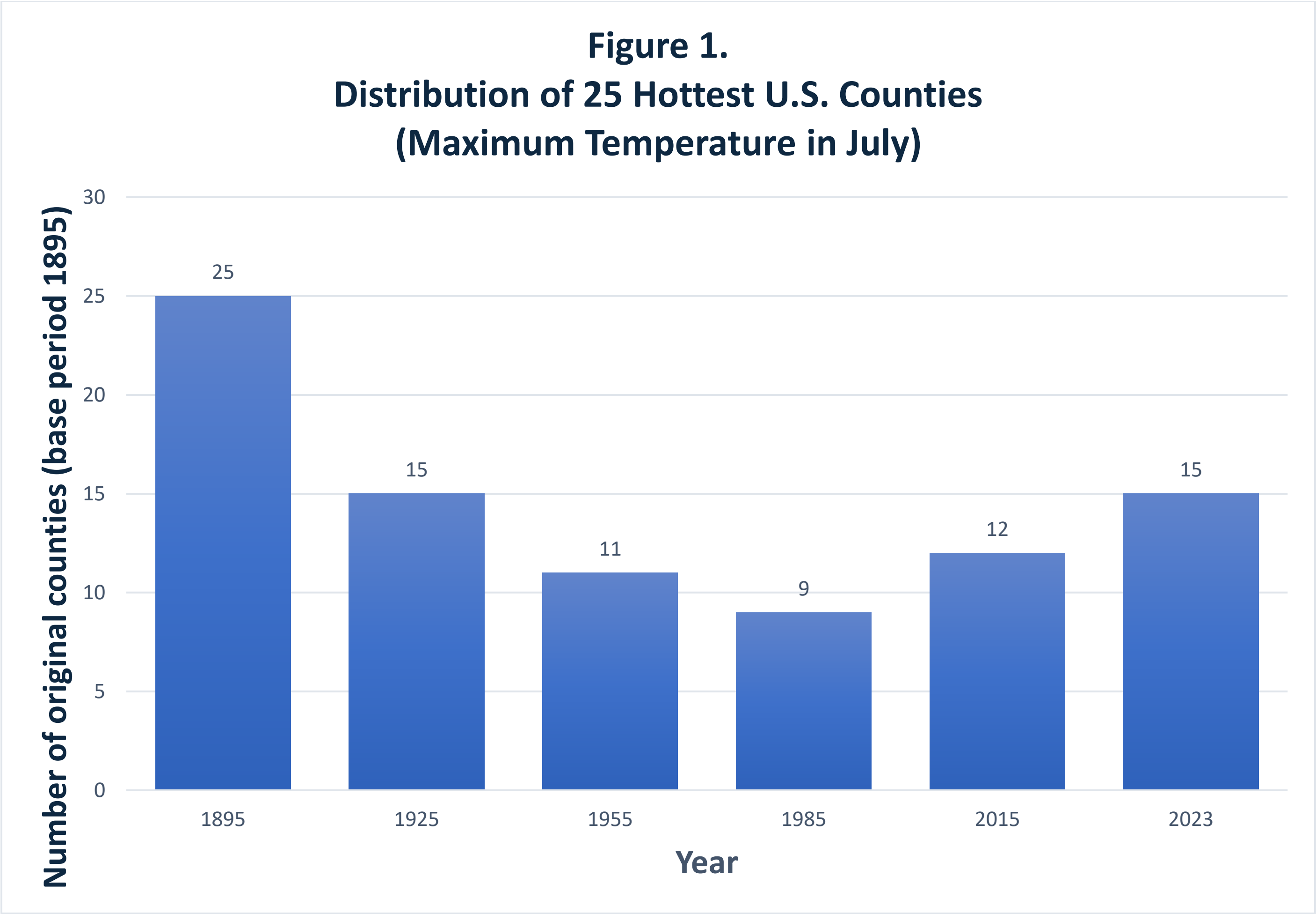


Figure 2. Distribution of 25 Coolest U.S. Counties (Minimum Temperature in January)

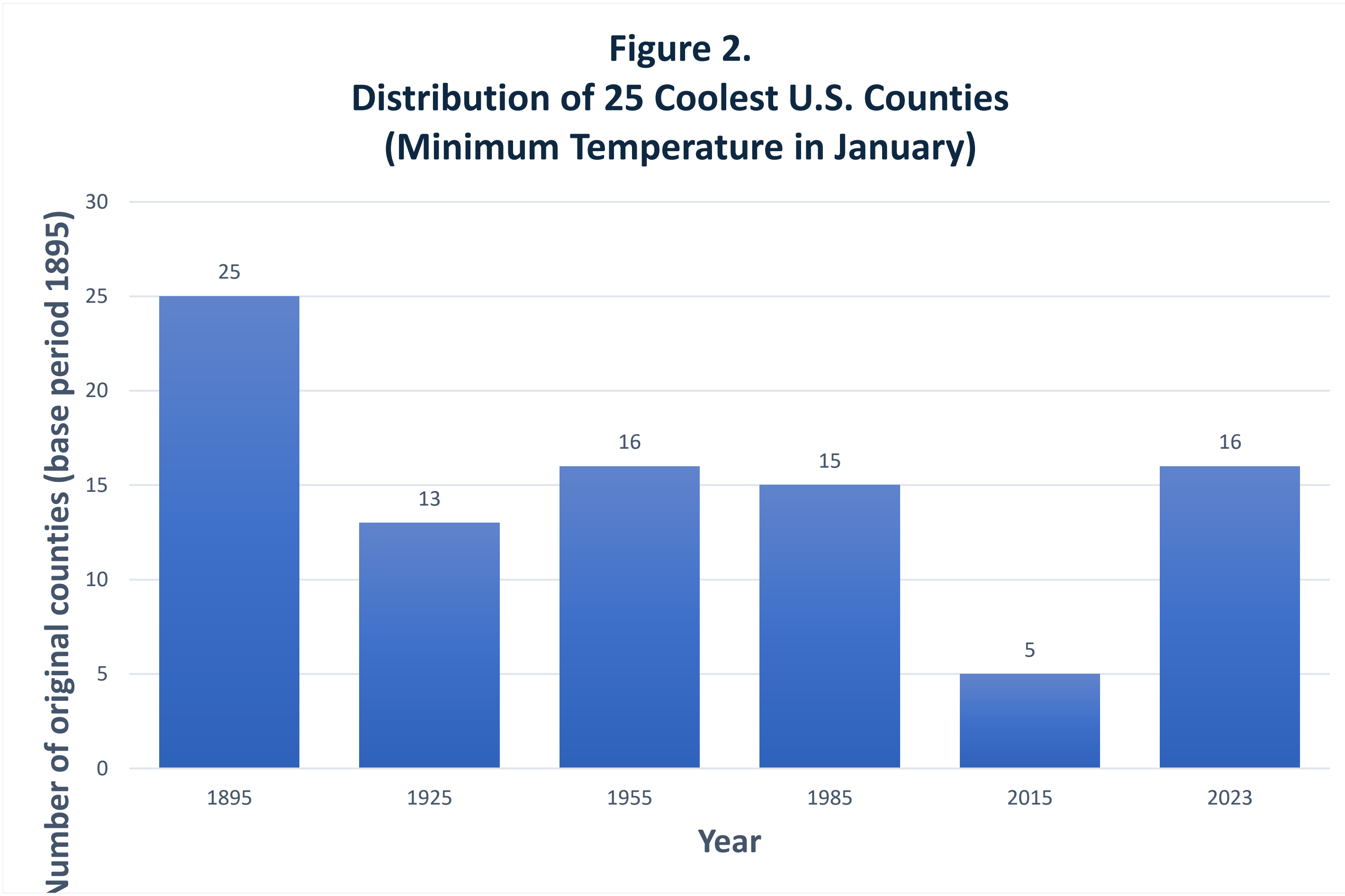
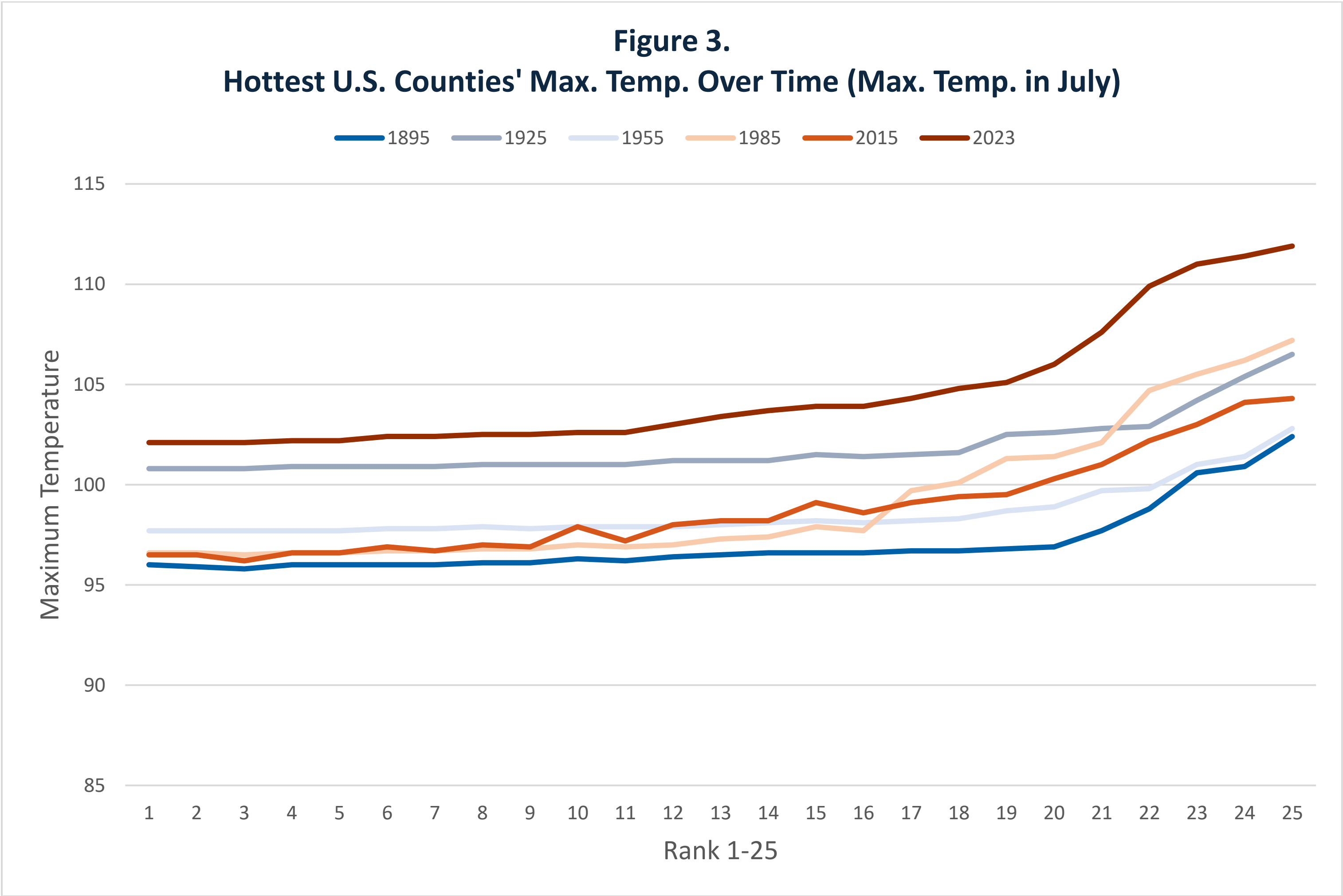


Figure 3. Hottest U.S. Counties' Max. Temp. Over Time (Max. Temp. in July)



Figures 4. Coolest U.S. Counties' Min. Temp. Over Time (Min. Temp. in July)

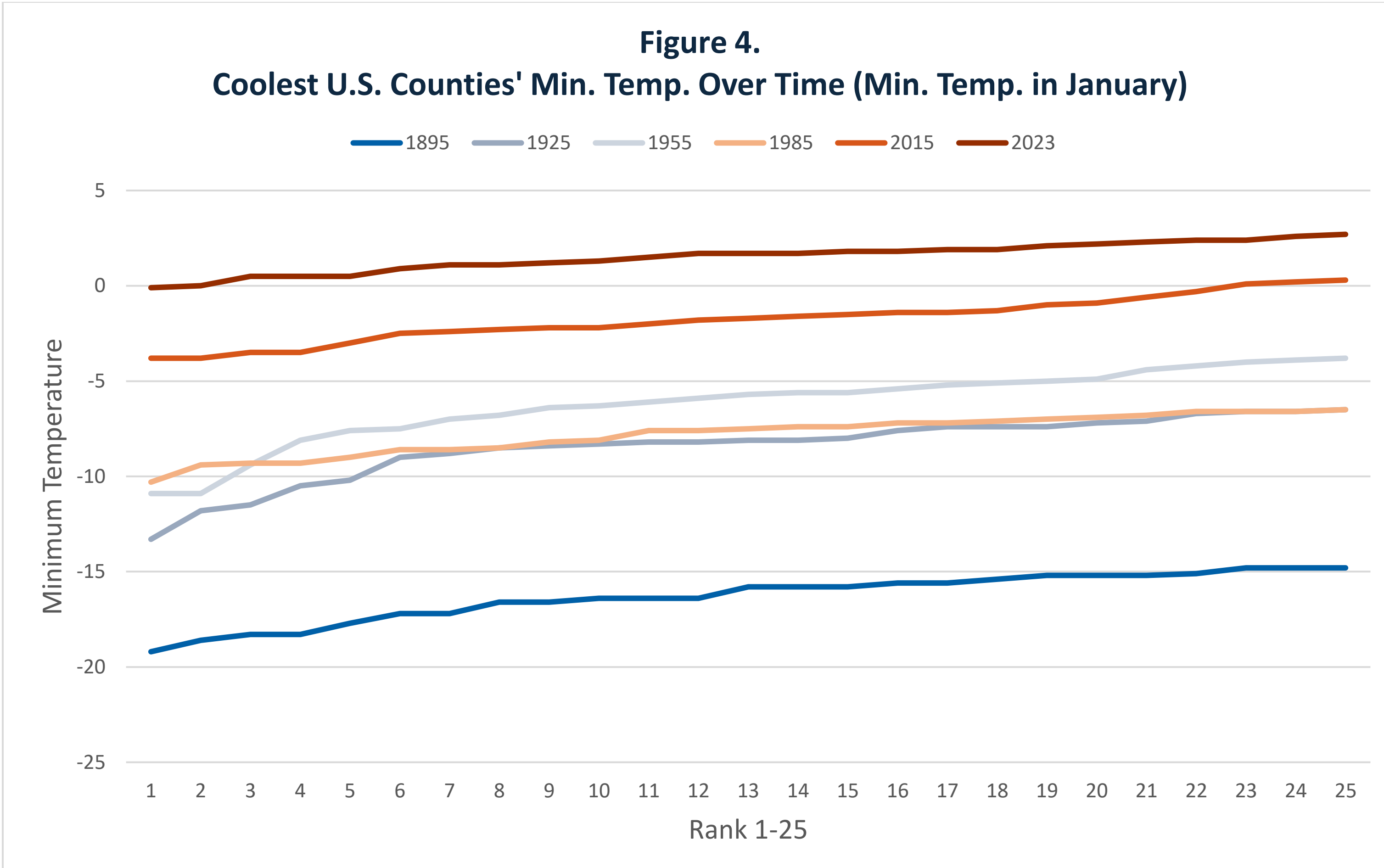
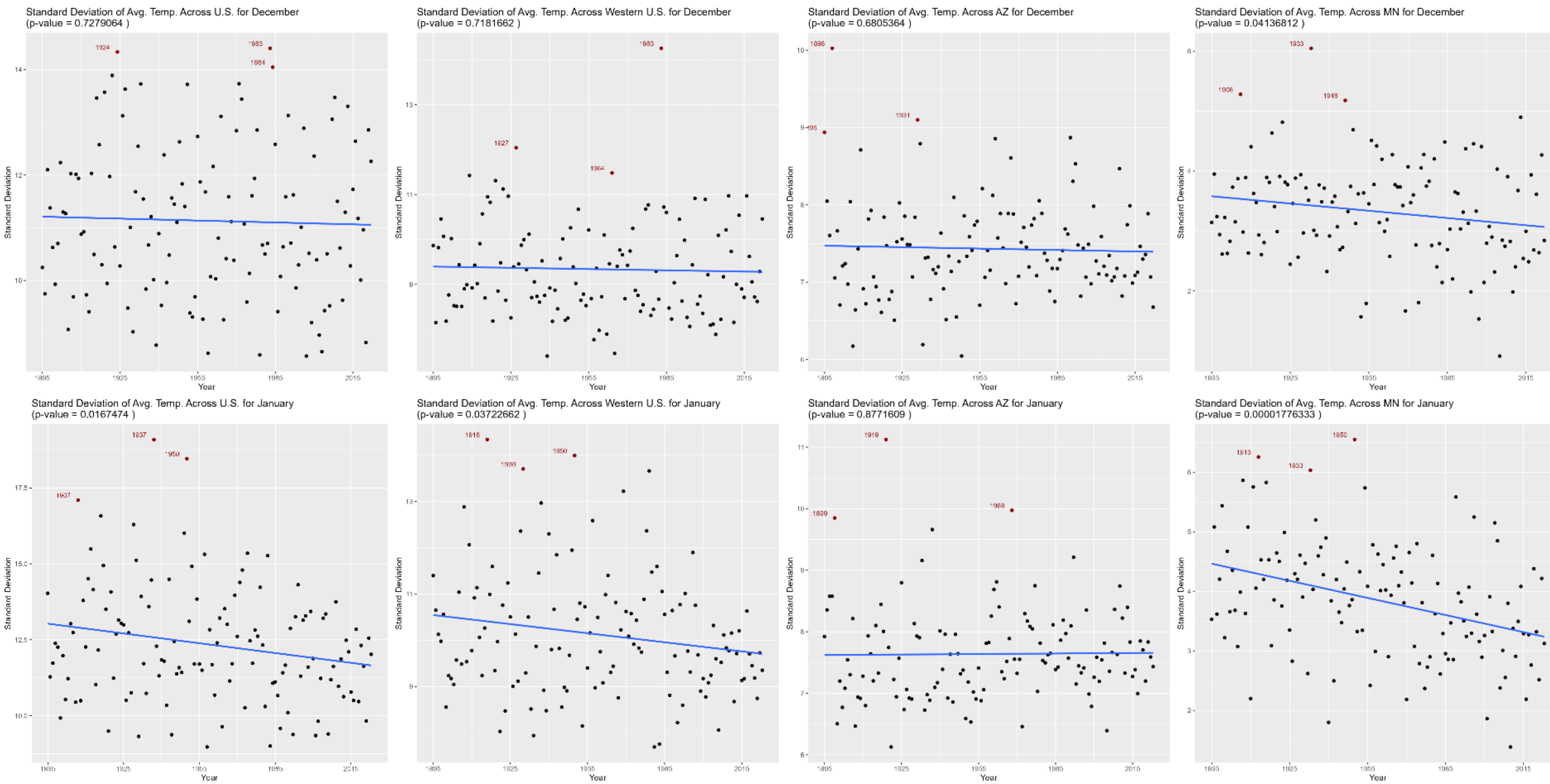
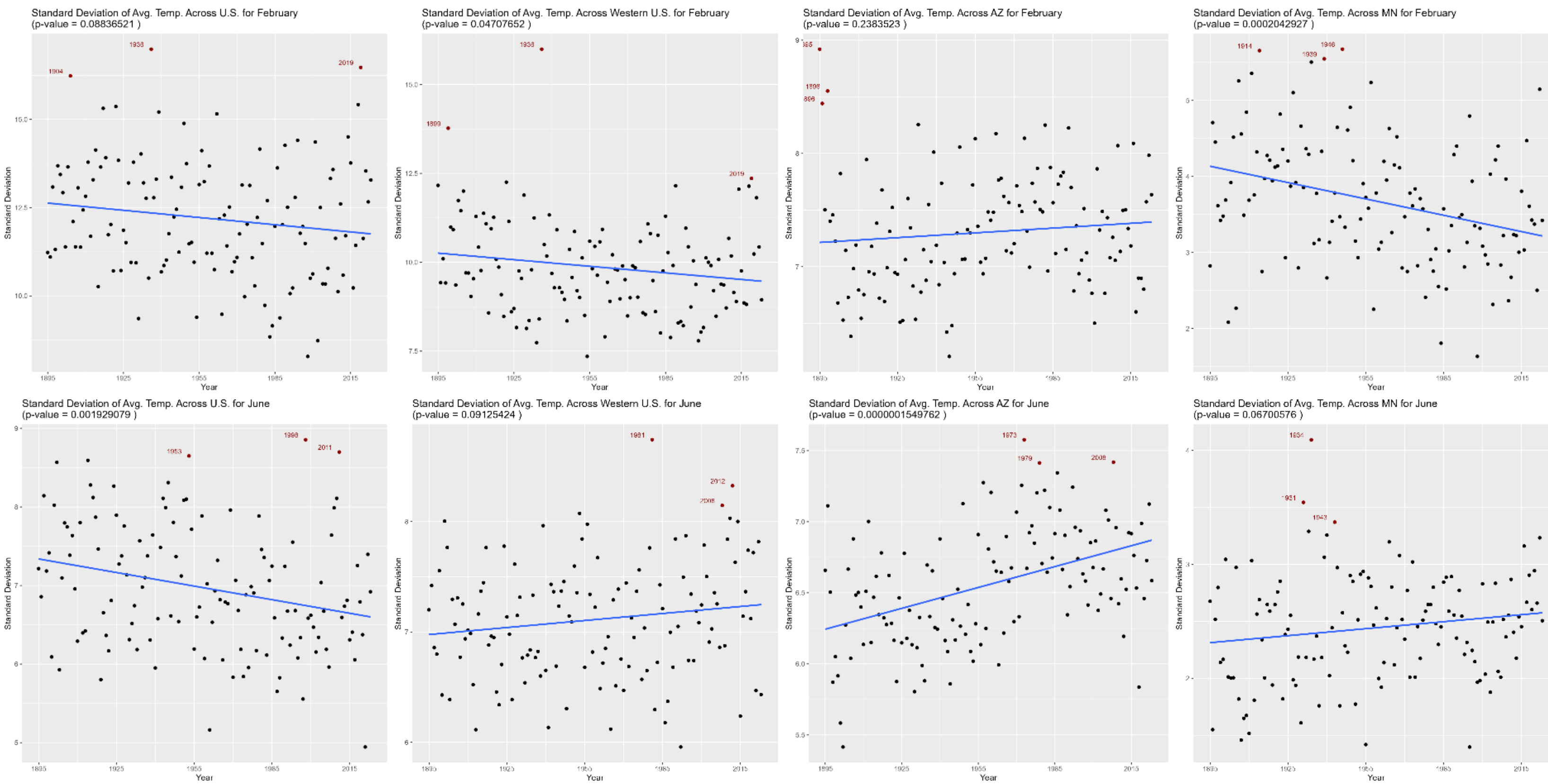


Figure 4.
Coolest U.S. Counties' Min. Temp. Over Time (Min. Temp. in January)
1895
1925
1955
1985
2015
2023
Minimum Temperature
5
0
-5
-10
-15
-20
-25
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Rank 1-25

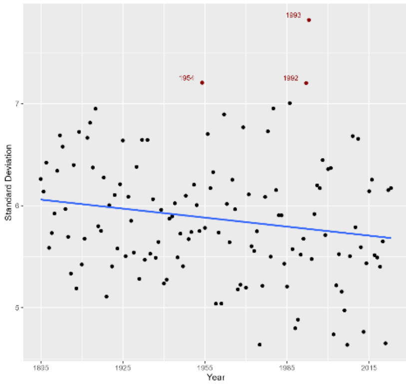
Appendix

Table 1. Standard Deviation of Average Temperature across US counties over time

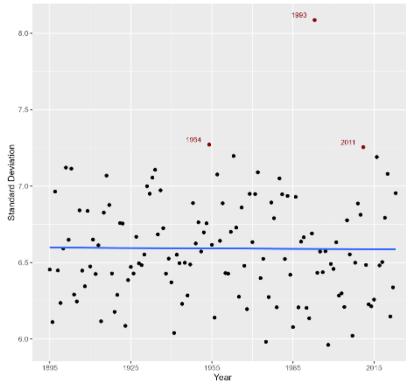



Standard Deviation of Avg. Temp. Across U.S. for February
(p-value = 0.08836521)
Standard Deviation of Avg. Temp. Across Western U.S. for February
(p-value = 0.04707652)
Standard Deviation of Avg. Temp. Across AZ for February
(p-value = 0.2383523)
Standard Deviation of Avg. Temp. Across MN for February
(p-value = 0.0002042927)
Standard Deviation of Avg. Temp. Across U.S. for June
(p-value = 0.001929079)
Standard Deviation of Avg. Temp. Across Western U.S. for June
(p-value = 0.09125424)
Standard Deviation of Avg. Temp. Across AZ for June
(p-value = 0.0000001549762)
Standard Deviation of Avg. Temp. Across MN for June
(p-value = 0.06700576)
Standard Deviation
Year

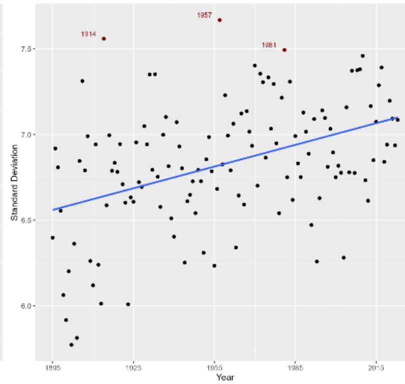
Standard Deviation of Avg. Temp. Across U.S. for July
(p-value = 0.03730572)



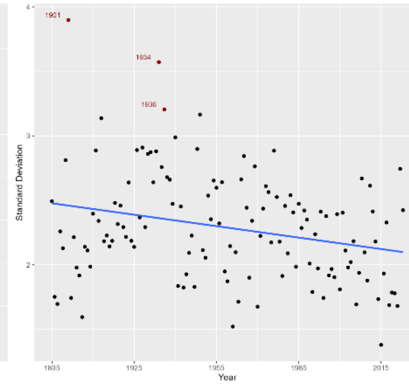
Standard Deviation of Avg. Temp. Across Western U.S. for July
(p-value = 0.9143086)



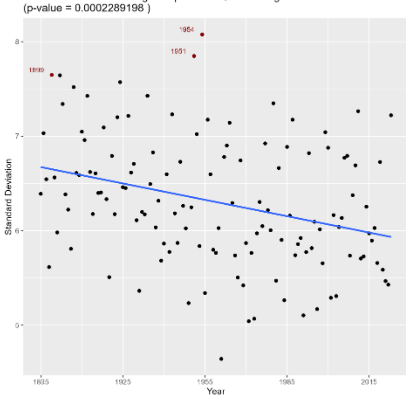
Standard Deviation of Avg. Temp. Across AZ for July
(p-value = 0.0000006553789)



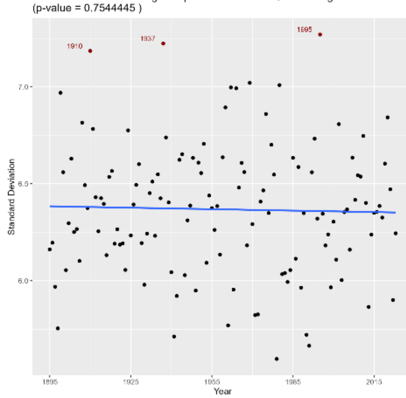
Standard Deviation of Avg. Temp. Across MN for July
(p-value = 0.002757074)



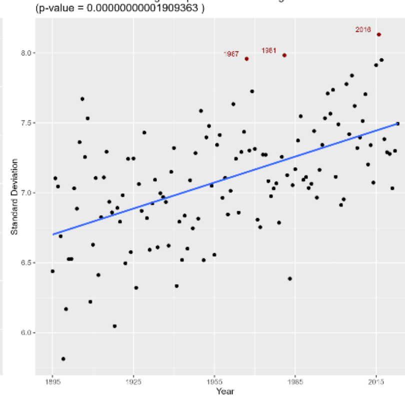
Standard Deviation of Avg. Temp. Across U.S. for August
(p-value = 0.0002289198)



Standard Deviation of Avg. Temp. Across Western U.S. for August
(p-value = 0.7544445)



Standard Deviation of Avg. Temp. Across AZ for August
(p-value = 0.00000000001909363)



Standard Deviation of Avg. Temp. Across MN for August
(p-value = 0.000000000005097977)

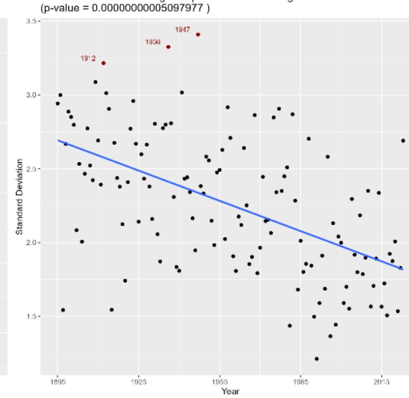
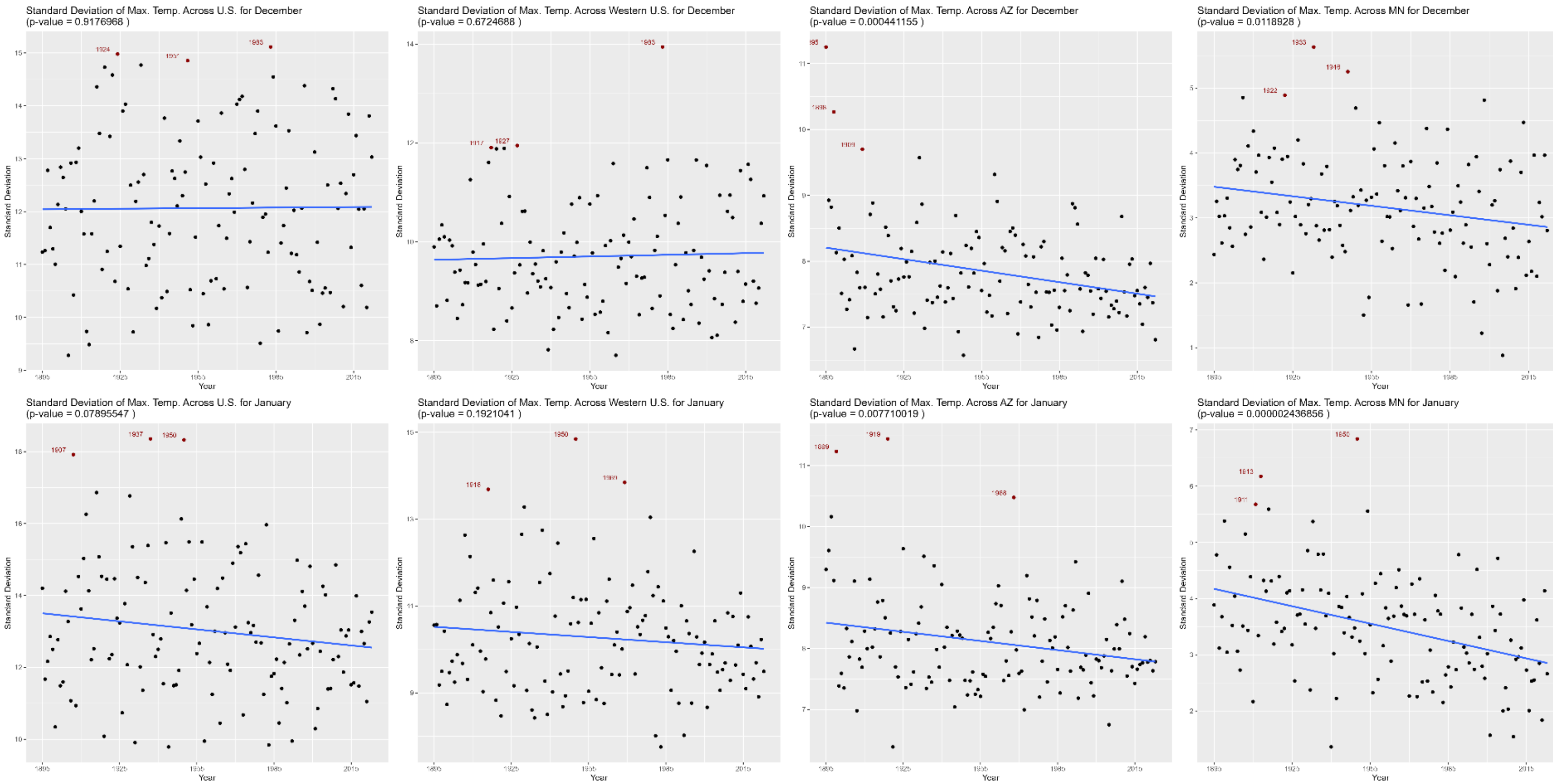
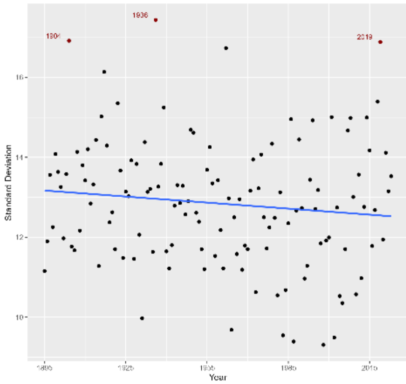


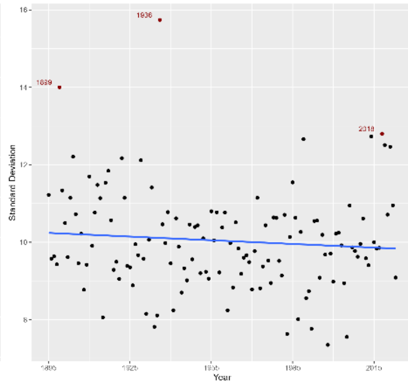
Table 2. Standard Deviation of Maximum Temperature across US counties over time



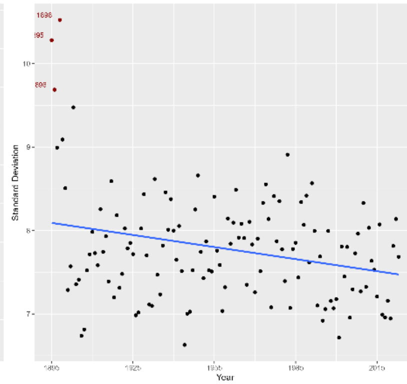
Standard Deviation of Max. Temp. Across U.S. for February
(p-value = 0.1824329)



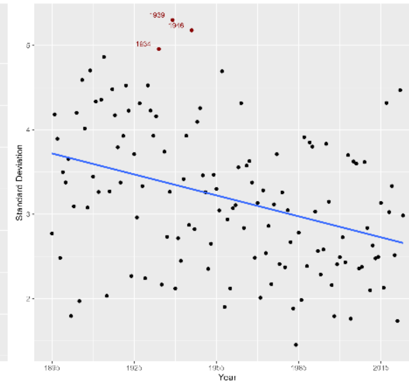
Standard Deviation of Max. Temp. Across Western U.S. for February
(p-value = 0.2997662)



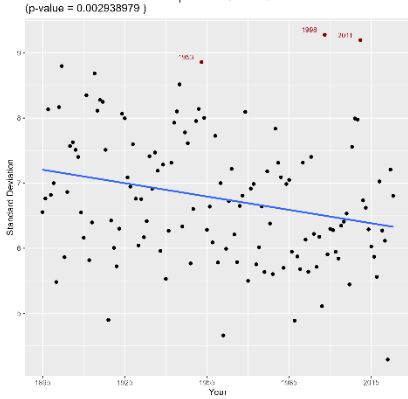
Standard Deviation of Max. Temp. Across AZ for February
(p-value = 0.001602433)



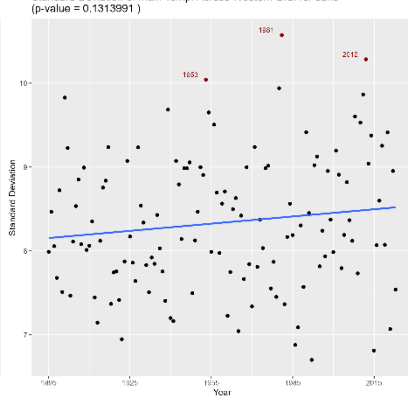
Standard Deviation of Max. Temp. Across MN for February
(p-value = 0.00002350483)



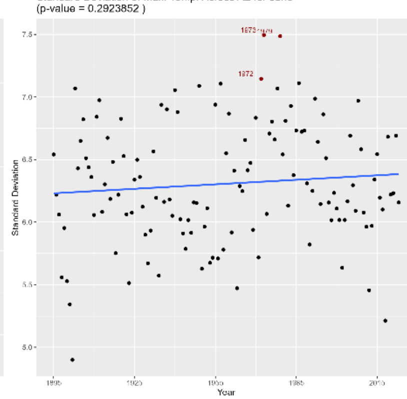
Standard Deviation of Max. Temp. Across U.S. for June
(p-value = 0.002938979)



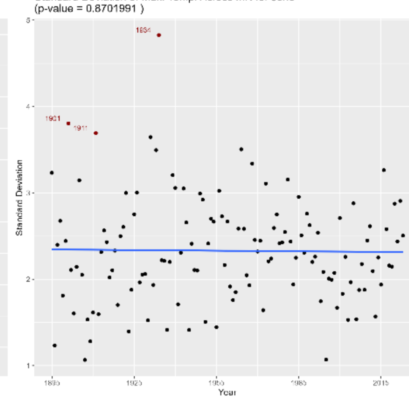
Standard Deviation of Max. Temp. Across Western U.S. for June
(p-value = 0.1313991)



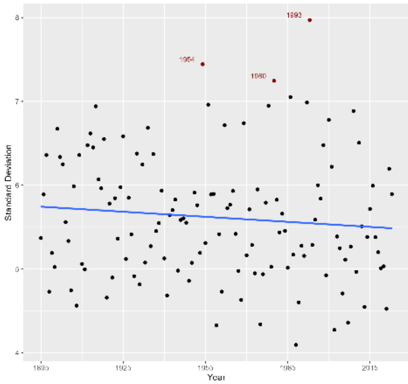
Standard Deviation of Max. Temp. Across AZ for June
(p-value = 0.2923852)



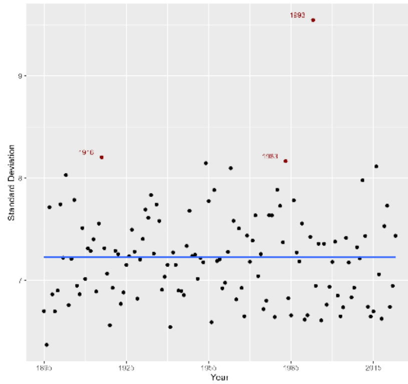
Standard Deviation of Max. Temp. Across MN for June
(p-value = 0.8701991)



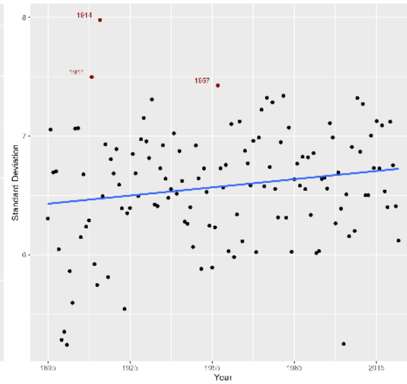
Standard Deviation of Max. Temp. Across U.S. for July
(p-value = 0.2556503)



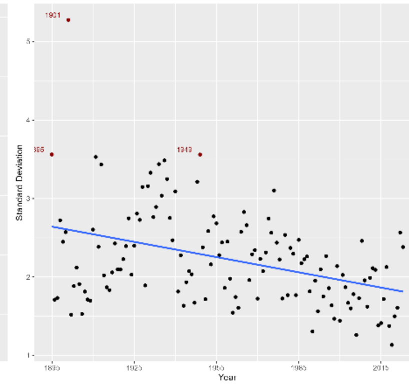
Standard Deviation of Max. Temp. Across Western U.S. for July
(p-value = 0.9988979)



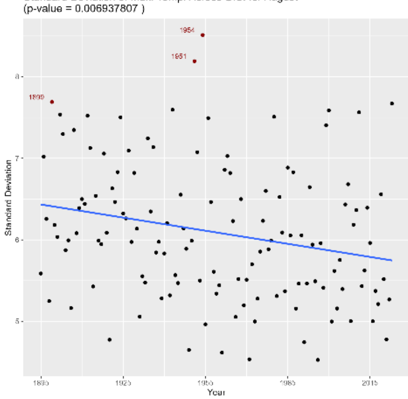
Standard Deviation of Max. Temp. Across AZ for July
(p-value = 0.04307976)



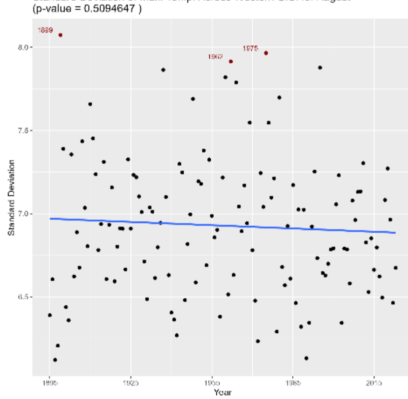
Standard Deviation of Max. Temp. Across MN for July
(p-value = 0.000003904416)



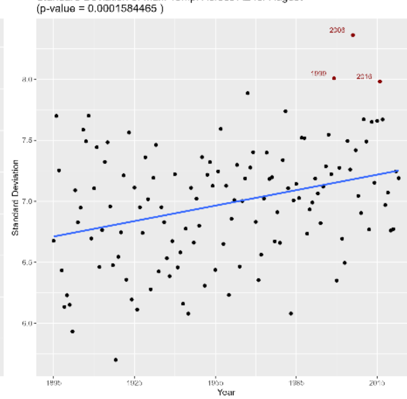
Standard Deviation of Max. Temp. Across U.S. for August
(p-value = 0.006937807)



Standard Deviation of Max. Temp. Across Western U.S. for August
(p-value = 0.5094647)



Standard Deviation of Max. Temp. Across AZ for August
(p-value = 0.0001584465)



Standard Deviation of Max. Temp. Across MN for August
(p-value = 0.000000000000396512)

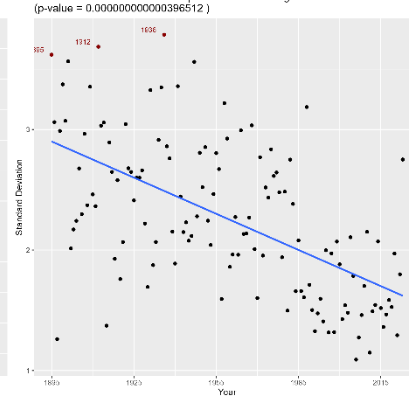
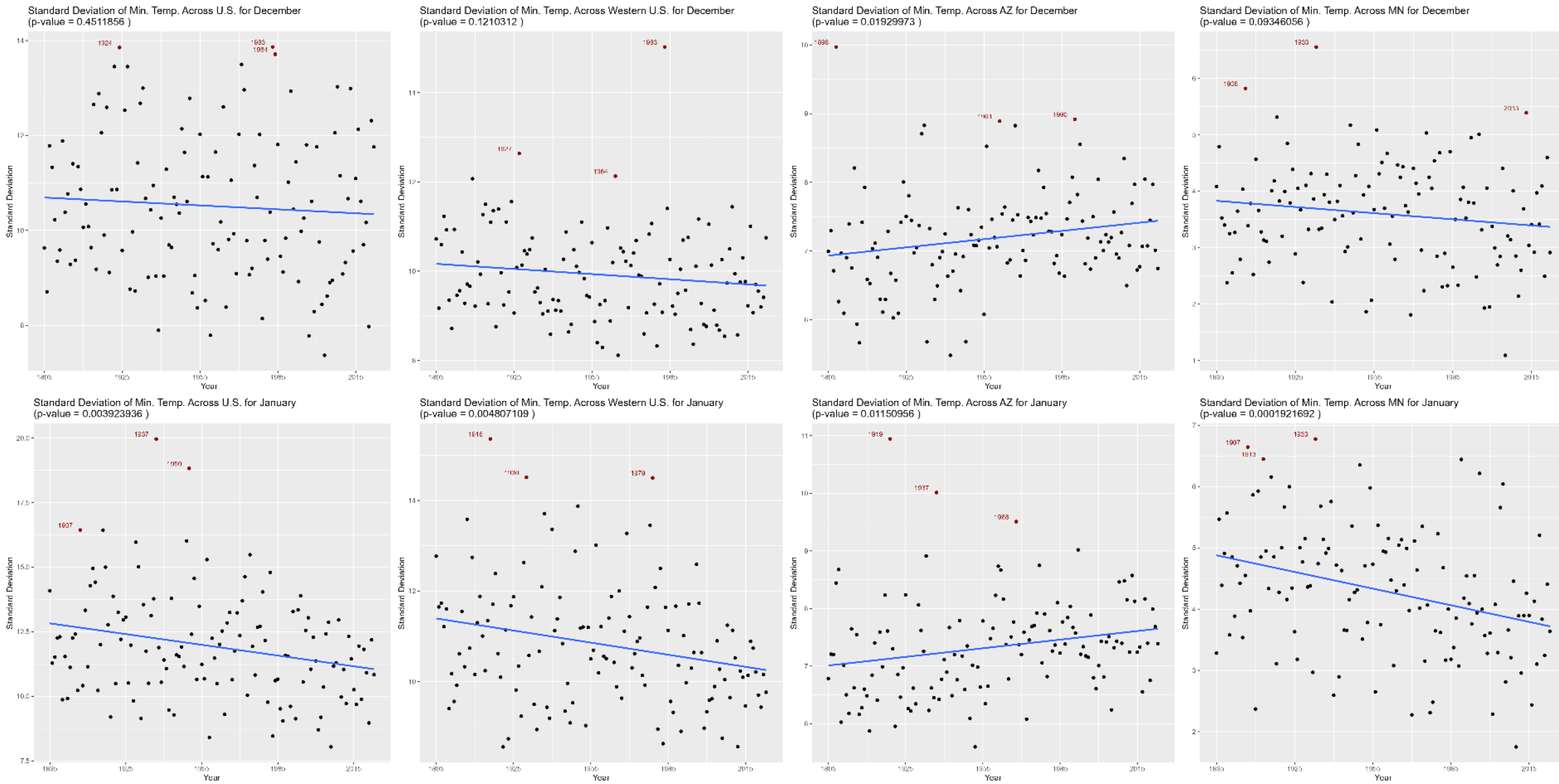
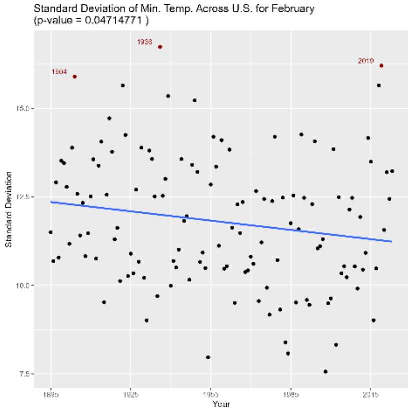
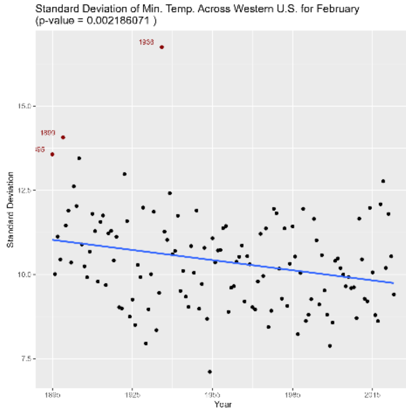
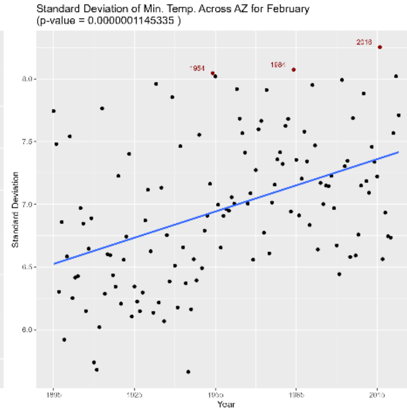


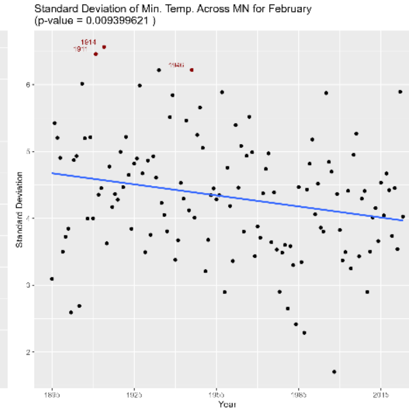
Table 3. Standard Deviation of Minimum Temperature across US counties over time

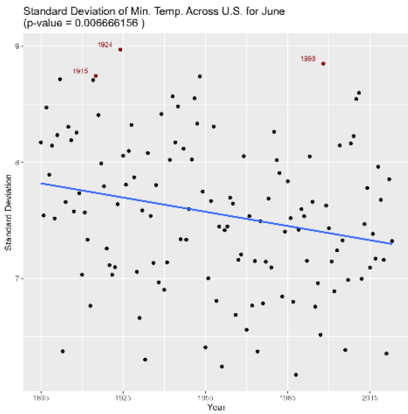


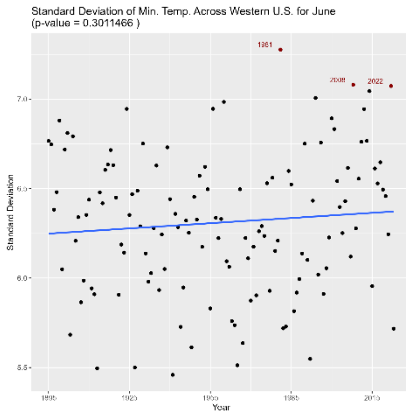

Standard Deviation of Min. Temp. Across U.S. for February
(p-value = 0.04714771)
Standard Deviation
Year

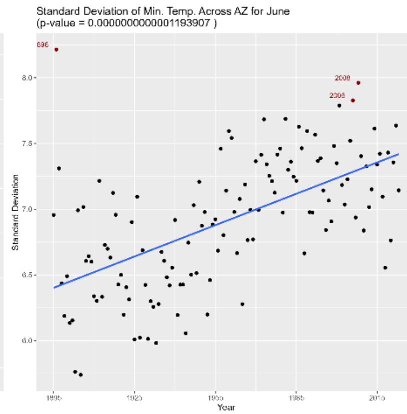

Standard Deviation of Min. Temp. Across Western U.S. for February
(p-value = 0.002186071)
Standard Deviation
Year

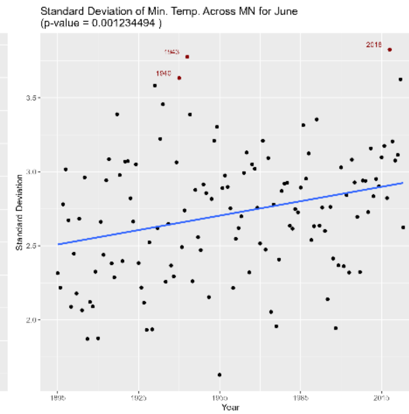

Standard Deviation of Min. Temp. Across AZ for February
(p-value = 0.0000001145335)
Standard Deviation
Year


Standard Deviation of Min. Temp. Across MN for February
(p-value = 0.009399621)
Standard Deviation
Year

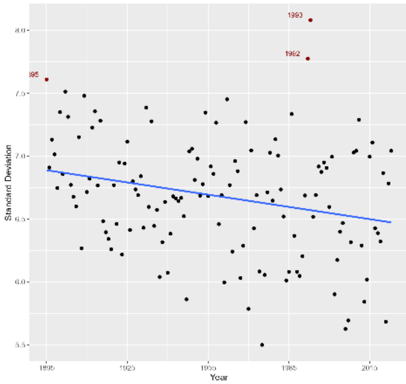

Standard Deviation of Min. Temp. Across U.S. for June
(p-value = 0.006666156)
Standard Deviation
Year


Standard Deviation of Min. Temp. Across Western U.S. for June
(p-value = 0.3011466)
Standard Deviation
Year

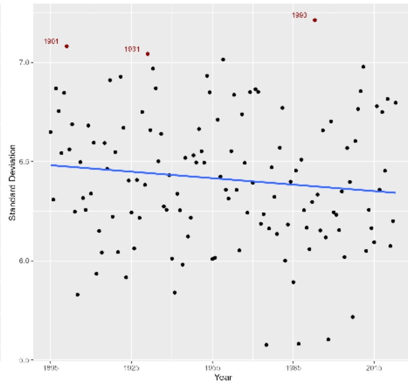

Standard Deviation of Min. Temp. Across AZ for June
(p-value = 0.0000000000001193907)
Standard Deviation
Year


Standard Deviation of Min. Temp. Across MN for June
(p-value = 0.001234494)
Standard Deviation
Year

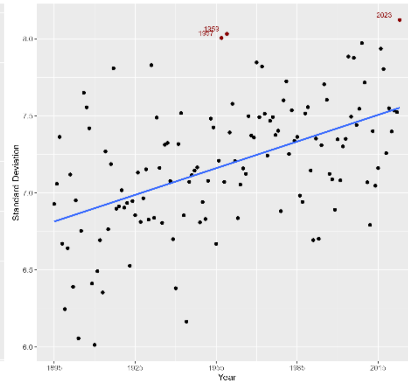
Standard Deviation of Min. Temp. Across U.S. for July
(p-value = 0.003413679)



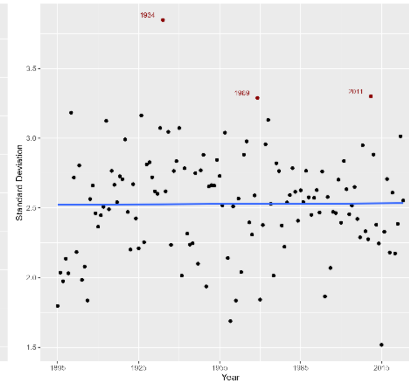
Standard Deviation of Min. Temp. Across Western U.S. for July
(p-value = 0.1715266)



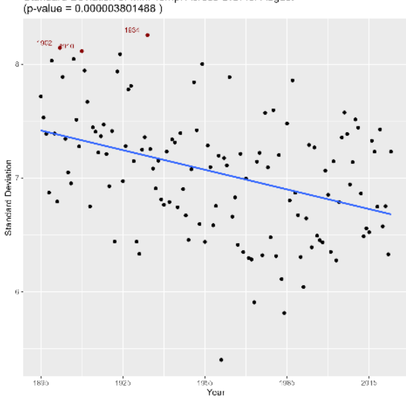
Standard Deviation of Min. Temp. Across AZ for July
(p-value = 0.0000000008640642)



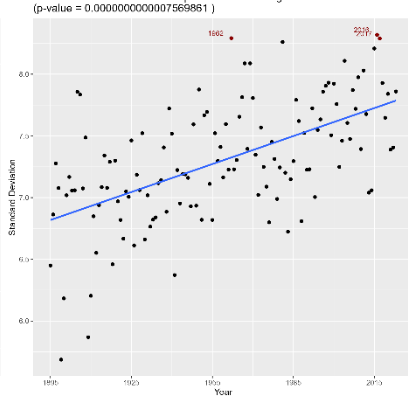
Standard Deviation of Min. Temp. Across MN for July
(p-value = 0.9253418)



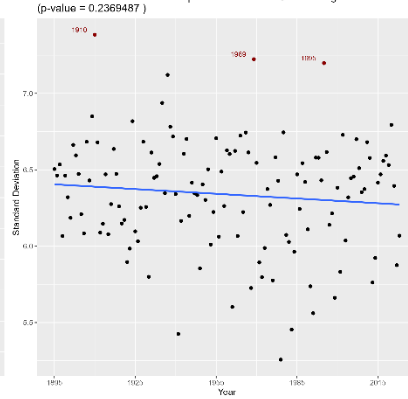
Standard Deviation of Min. Temp. Across U.S. for August
(p-value = 0.000003801488)



Standard Deviation of Min. Temp. Across AZ for August
(p-value = 0.0000000000007569861)



Standard Deviation of Min. Temp. Across Western U.S. for August
(p-value = 0.2369487)



Standard Deviation of Min. Temp. Across MN for August
(p-value = 0.001744605)

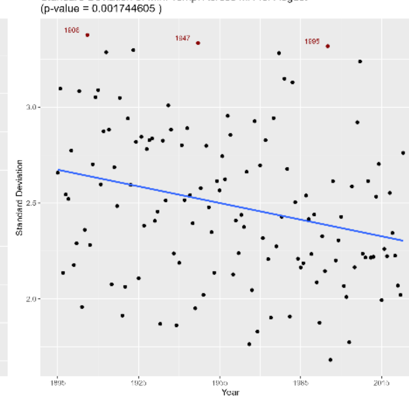
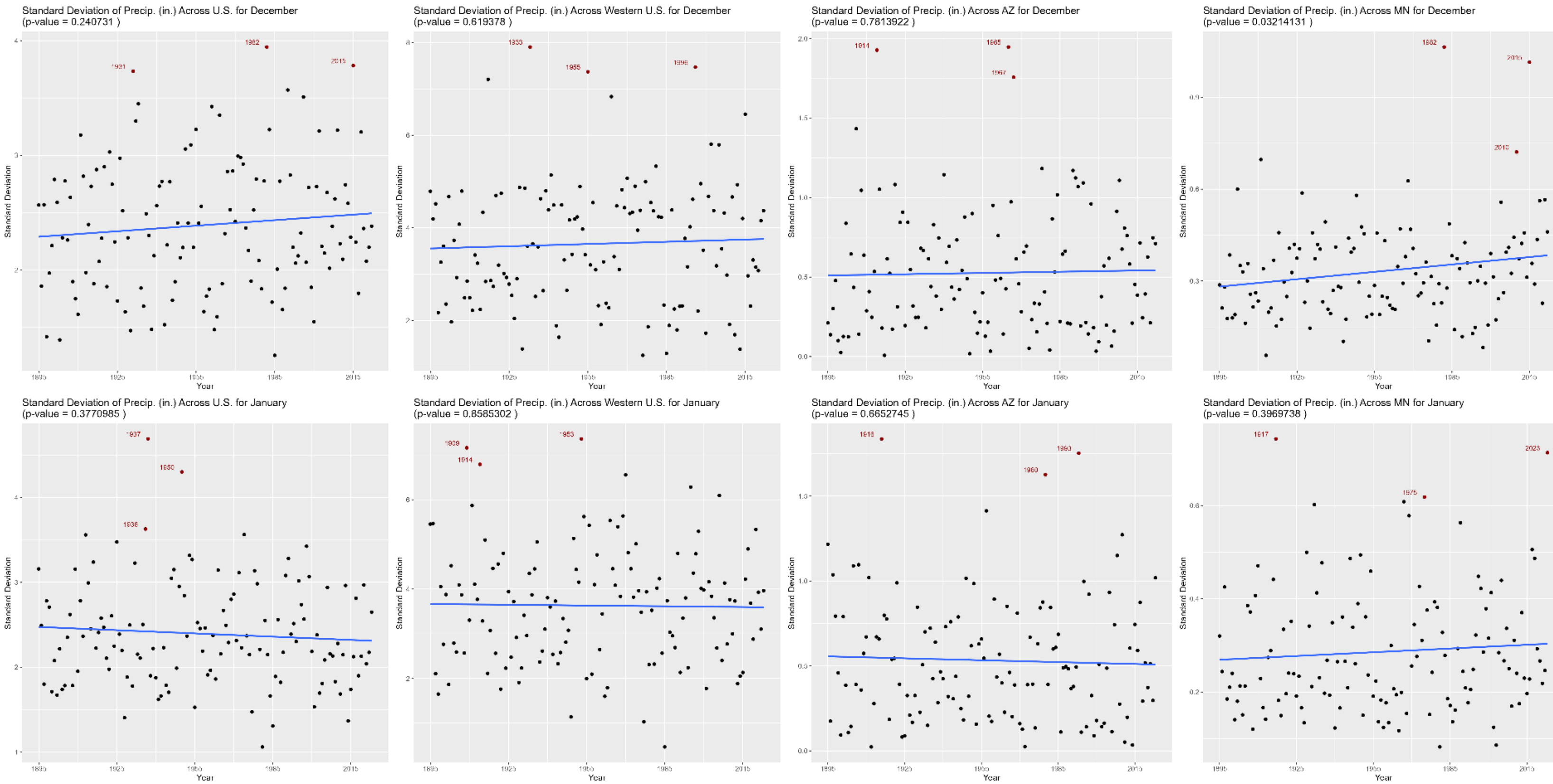
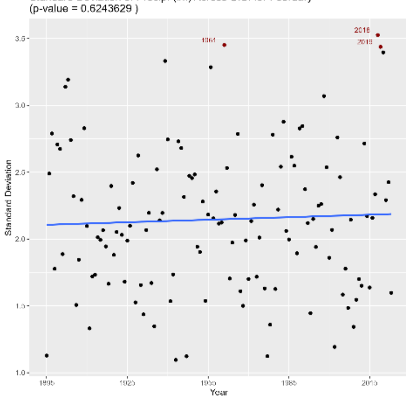


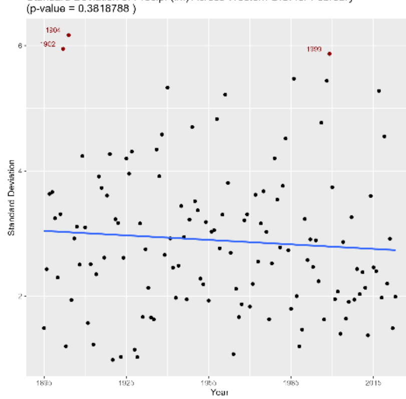
Table 4. Standard Deviation of Precipitation across US counties over time



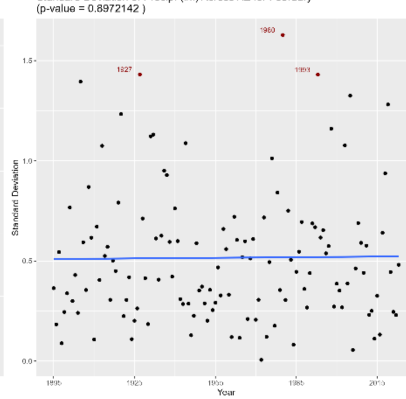
Standard Deviation of Precip. (in.) Across U.S. for February
(p-value = 0.6243629)



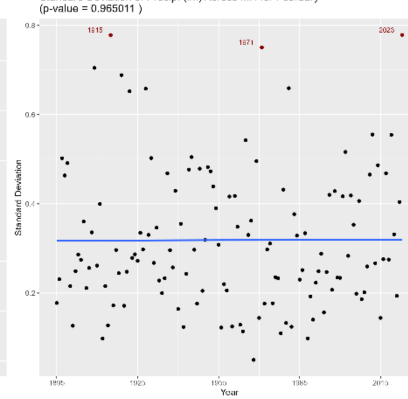
Standard Deviation of Precip. (in.) Across Western U.S. for February
(p-value = 0.3818788)



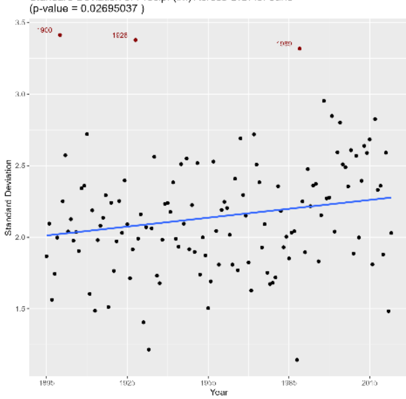
Standard Deviation of Precip. (in.) Across AZ for February
(p-value = 0.8972142)



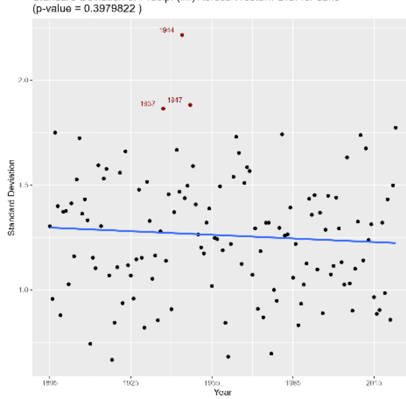
Standard Deviation of Precip. (in.) Across MN for February
(p-value = 0.965011)



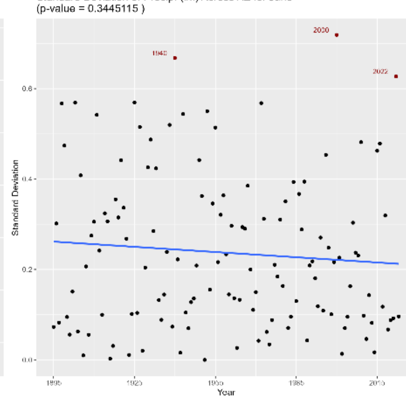
Standard Deviation of Precip. (in.) Across U.S. for June
(p-value = 0.02695037)



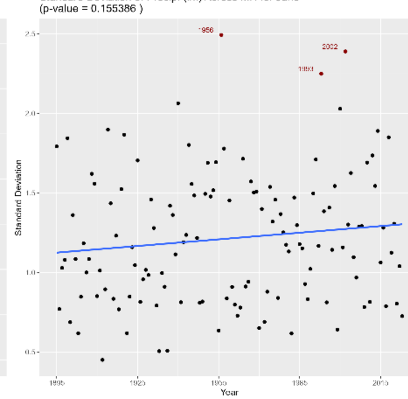
Standard Deviation of Precip. (in.) Across Western U.S. for June
(p-value = 0.3979822)



Standard Deviation of Precip. (in.) Across AZ for June
(p-value = 0.3445115)



Standard Deviation of Precip. (in.) Across MN for June
(p-value = 0.155386)



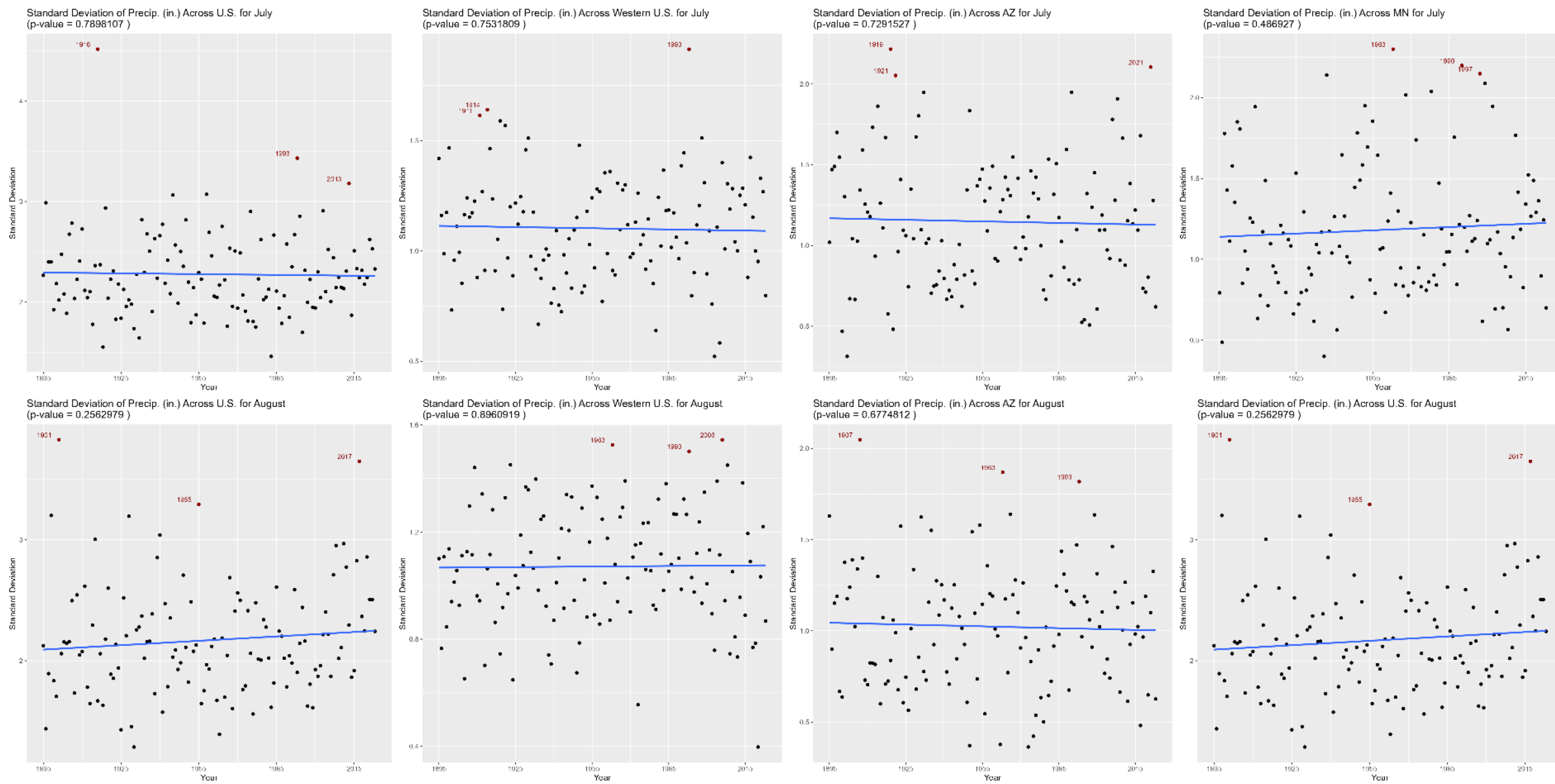
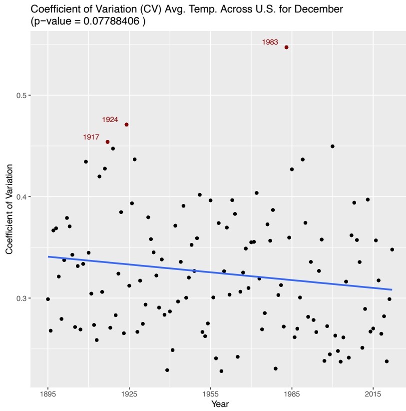
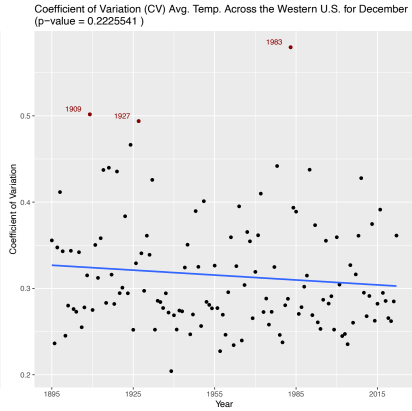
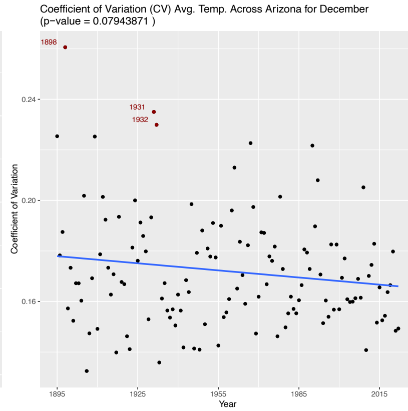
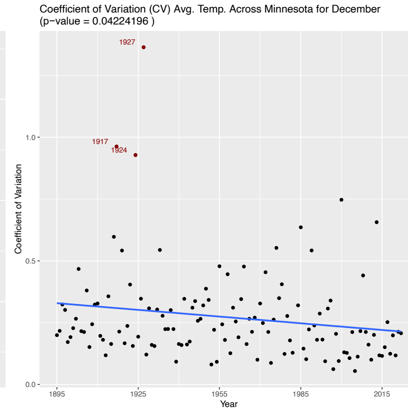


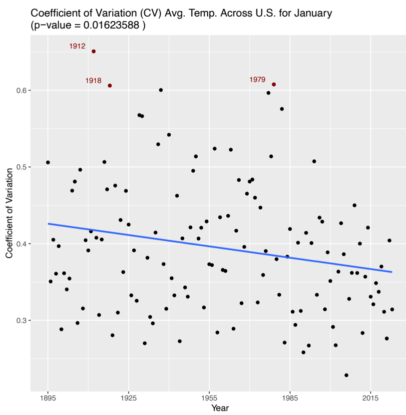
Table 5. Coefficient of Variation in Average Temperature across US counties over time

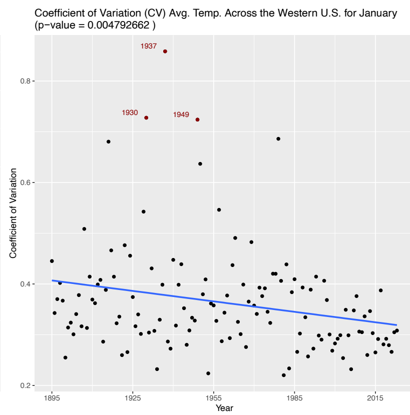

Coefficient of Variation (CV) Avg. Temp. Across U.S. for December
(p−value = 0.07788406)
1983
1924
1917
Coefficient of Variation
Year

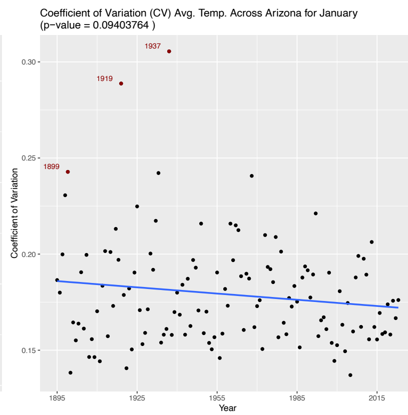

Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for December
(p−value = 0.2225541)
1983
1909
1927
Coefficient of Variation
Year

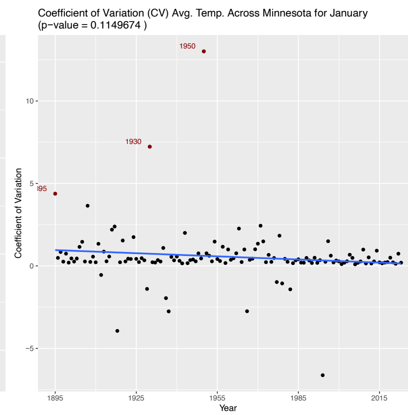

Coefficient of Variation (CV) Avg. Temp. Across Arizona for December
(p−value = 0.07943871)
1898
1931
1932
Coefficient of Variation
Year

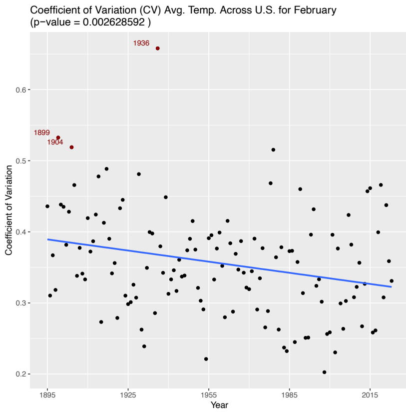

Coefficient of Variation (CV) Avg. Temp. Across Minnesota for December
(p−value = 0.04224196)
1927
1917
1924
Coefficient of Variation
Year

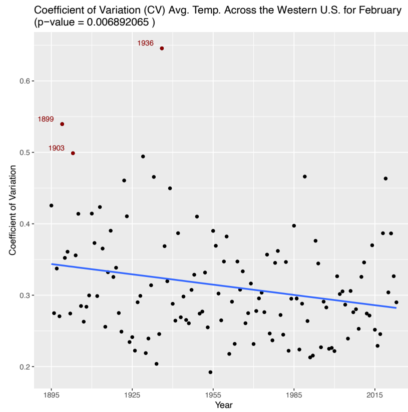

Coefficient of Variation (CV) Avg. Temp. Across U.S. for January
(p−value = 0.01623588)
1912
1918
1979
Coefficient of Variation
Year

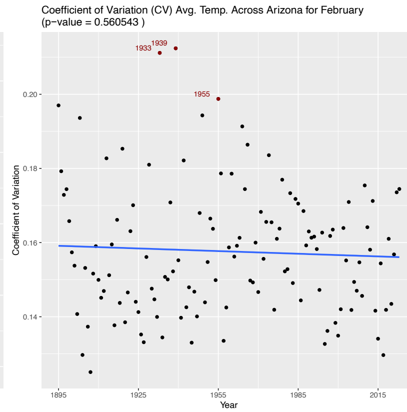

Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for January
(p−value = 0.004792662)
1937
1930
1949
Coefficient of Variation
Year

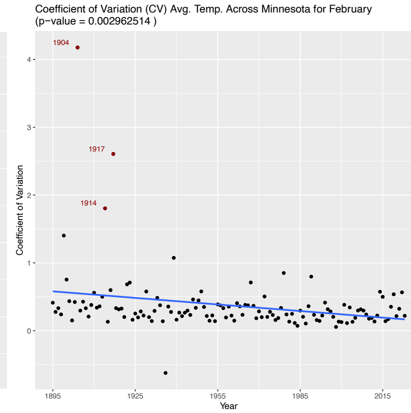

Coefficient of Variation (CV) Avg. Temp. Across Arizona for January
(p−value = 0.09403764)
1937
1919
1899
Coefficient of Variation
Year

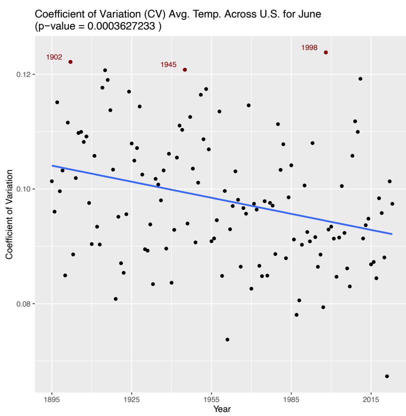

Coefficient of Variation (CV) Avg. Temp. Across Minnesota for January
(p−value = 0.1149674)
1950
1930
Coefficient of Variation
Year

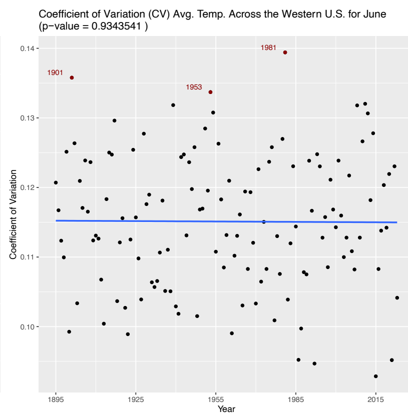

Coefficient of Variation (CV) Avg. Temp. Across U.S. for February
(p−value = 0.002628592)
1936
1899
1904
Coefficient of Variation
Year

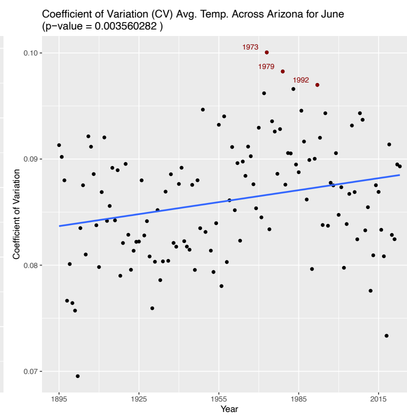

Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for February
(p−value = 0.006892065)
1936
1899
1903
Coefficient of Variation
Year

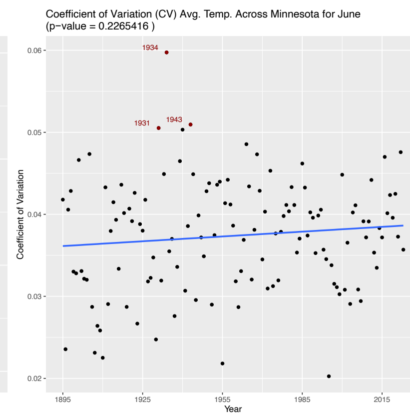

Coefficient of Variation (CV) Avg. Temp. Across Arizona for February
(p−value = 0.560543)
1933
1939
1955
Coefficient of Variation
Year

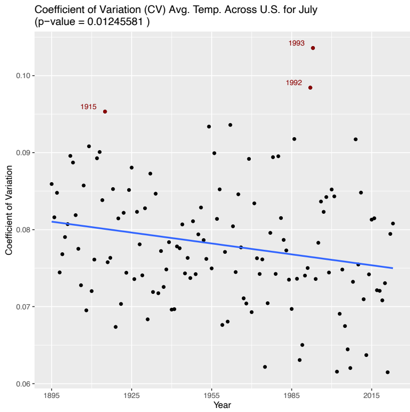

Coefficient of Variation (CV) Avg. Temp. Across Minnesota for February
(p−value = 0.002962514)
1904
1917
1914
Coefficient of Variation
Year

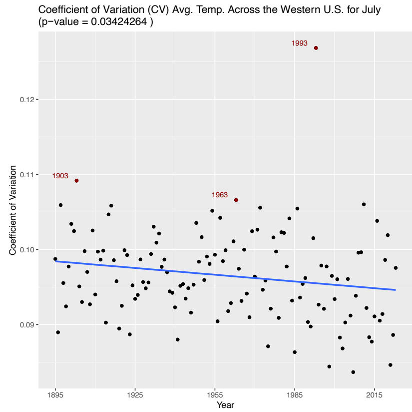

Coefficient of Variation (CV) Avg. Temp. Across U.S. for June
(p−value = 0.0003627233)
1902
1945
1998
Coefficient of Variation
Year

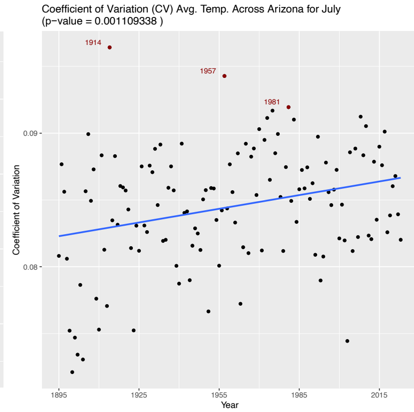

Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for June
(p−value = 0.9343541)
1901
1953
1981
Coefficient of Variation
Year

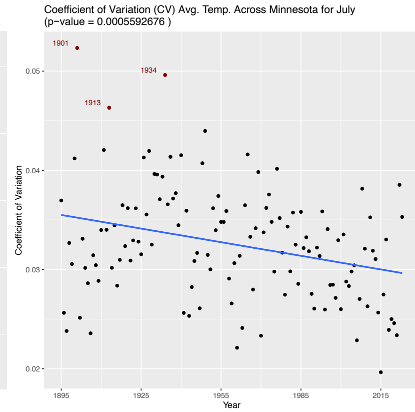

Coefficient of Variation (CV) Avg. Temp. Across Arizona for June
(p−value = 0.003560282)
1973
1979
1992
Coefficient of Variation
Year

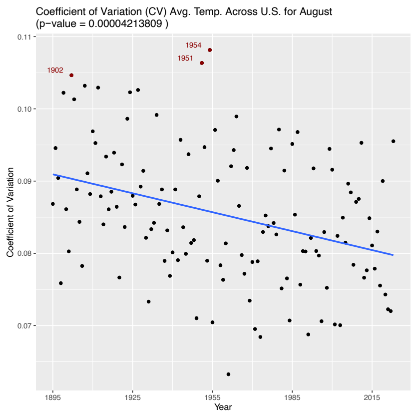

Coefficient of Variation (CV) Avg. Temp. Across Minnesota for June
(p−value = 0.2265416)
1934
1931
1943
Coefficient of Variation
Year

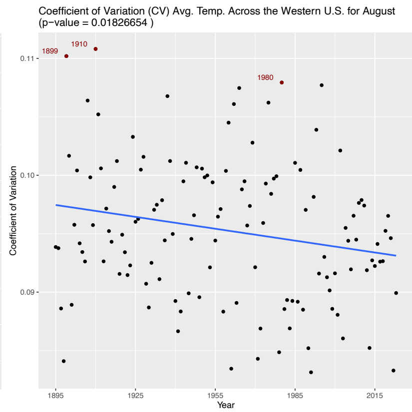

Coefficient of Variation (CV) Avg. Temp. Across U.S. for July
(p−value = 0.01245581)
1993
1992
1915
Coefficient of Variation
Year

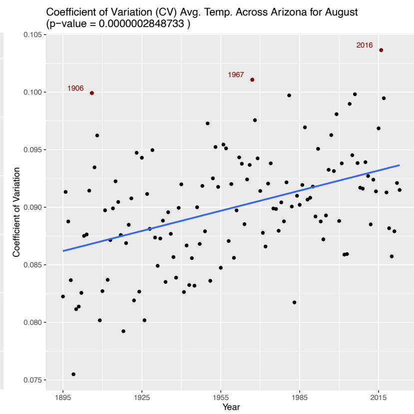

Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for July
(p−value = 0.03424264)
1993
1903
1963
Coefficient of Variation
Year


Coefficient of Variation (CV) Avg. Temp. Across Arizona for July
(p−value = 0.001109338)
1914
1957
1981
Coefficient of Variation
Year


Coefficient of Variation (CV) Avg. Temp. Across Minnesota for July
(p−value = 0.0005592676)
1901
1934
1913
Coefficient of Variation
Year


Coefficient of Variation (CV) Avg. Temp. Across U.S. for August
(p−value = 0.00004213809)
1954
1951
1902
Coefficient of Variation
Year


Coefficient of Variation (CV) Avg. Temp. Across the Western U.S. for August
(p−value = 0.01826654)
1910
1899
1980
Coefficient of Variation
Year


Coefficient of Variation (CV) Avg. Temp. Across Arizona for August
(p−value = 0.0000002848733)
2016
1967
1906
Coefficient of Variation
Year

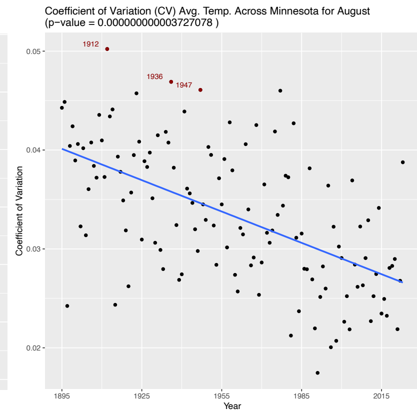
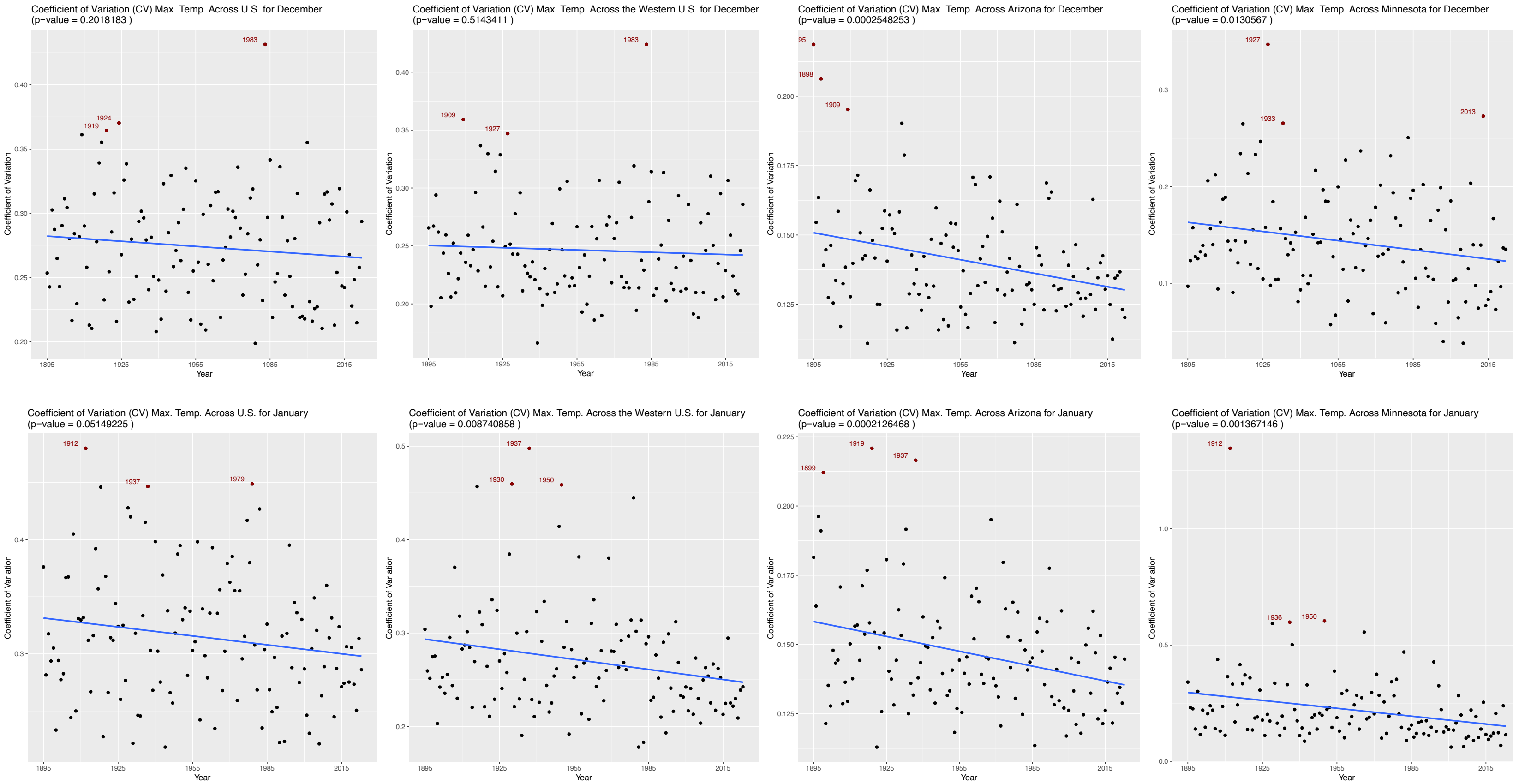
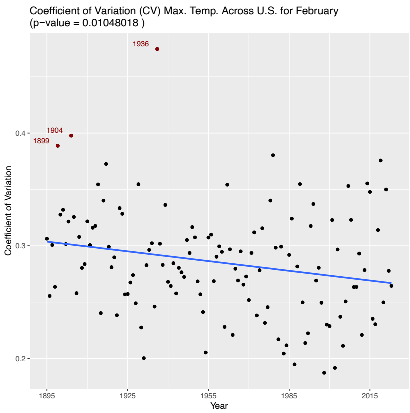
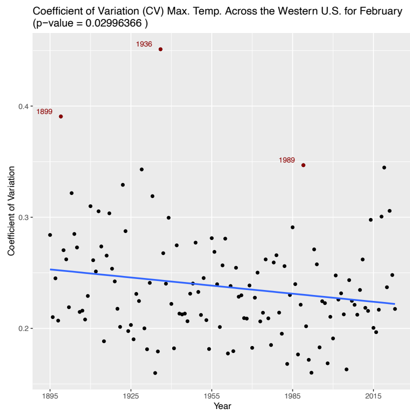
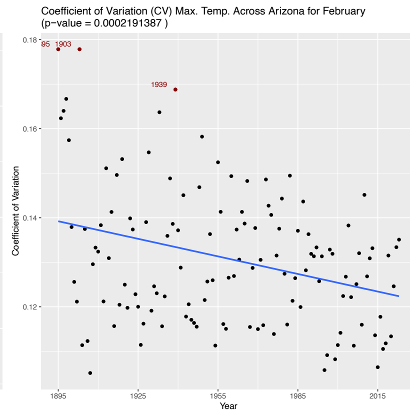

Coefficient of Variation (CV) Avg. Temp. Across Minnesota for August
(p−value = 0.000000000003727078)
1912
1936
1947
Coefficient of Variation
Year

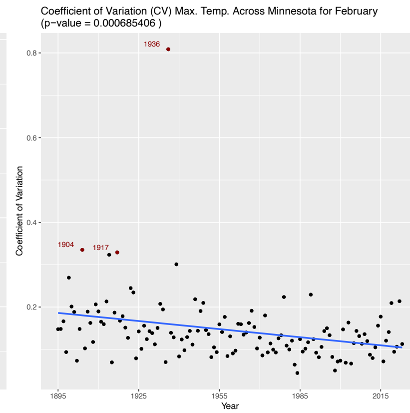
Table 6. Coefficient of Variation in Maximum Temperature across US counties over time

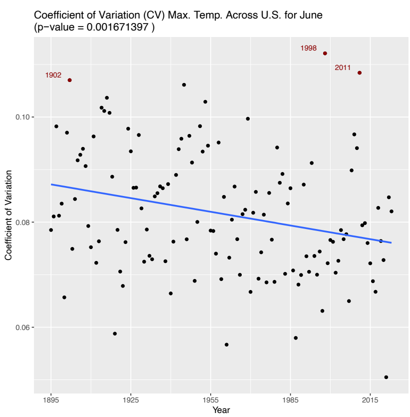


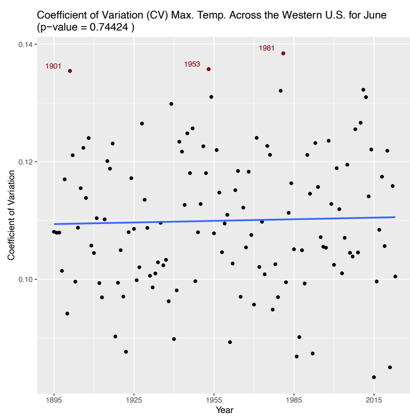

Coefficient of Variation (CV) Max. Temp. Across U.S. for February
(p−value = 0.01048018)
Coefficient of Variation
Year
1936
1904
1899

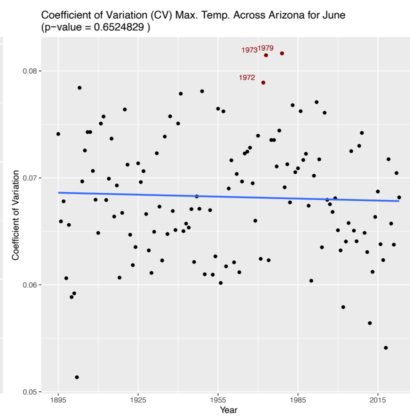

Coefficient of Variation (CV) Max. Temp. Across the Western U.S. for February
(p−value = 0.02996366)
Coefficient of Variation
Year
1936
1899
1989

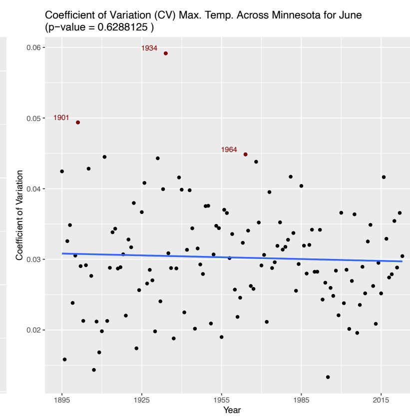

Coefficient of Variation (CV) Max. Temp. Across Arizona for February
(p−value = 0.0002191387)
Coefficient of Variation
Year
95
1903
1939

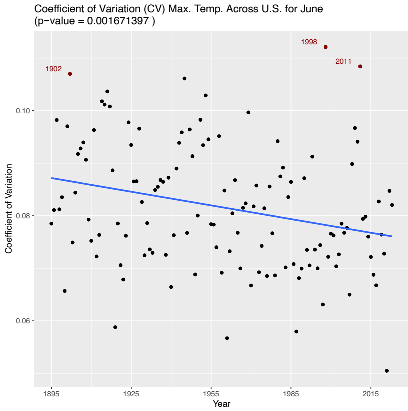

Coefficient of Variation (CV) Max. Temp. Across Minnesota for February
(p−value = 0.000685406)
Coefficient of Variation
Year
1936
1904
1917

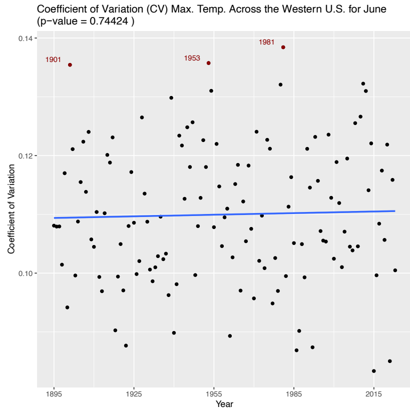

Coefficient of Variation (CV) Max. Temp. Across U.S. for June
(p−value = 0.001671397)
Coefficient of Variation
Year
1998
1902
2011

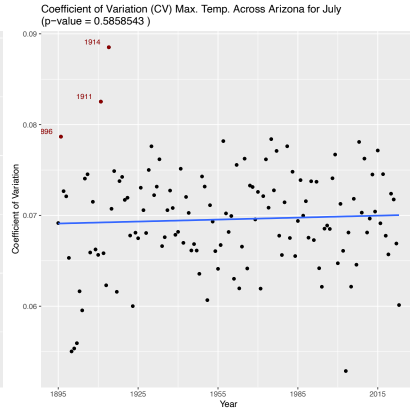

Coefficient of Variation (CV) Max. Temp. Across the Western U.S. for June
(p−value = 0.74424)
Coefficient of Variation
Year
1981
1901
1953

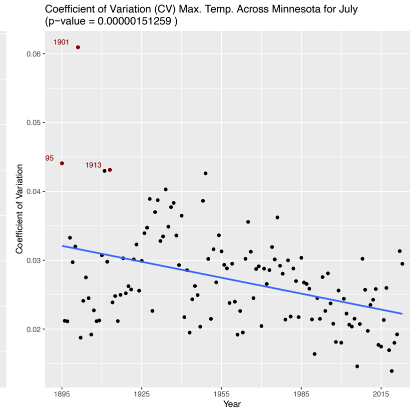

Coefficient of Variation (CV) Max. Temp. Across Arizona for June
(p−value = 0.6524829)
Coefficient of Variation
Year
1973
1979
1972

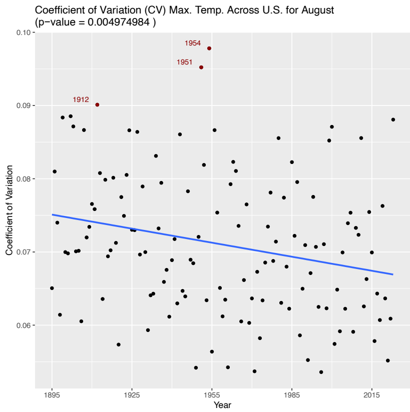

Coefficient of Variation (CV) Max. Temp. Across Minnesota for June
(p−value = 0.6288125)
Coefficient of Variation
Year
1934
1901
1964

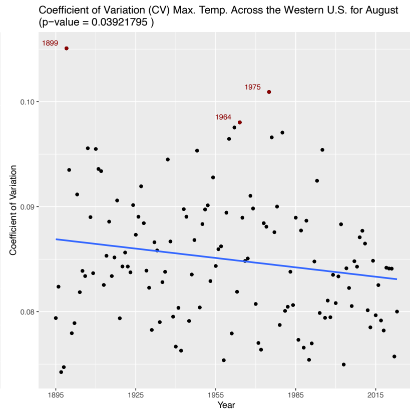

Coefficient of Variation (CV) Max. Temp. Across U.S. for June
(p-value = 0.001671397)
1902
1998
2011
Coefficient of Variation
Year

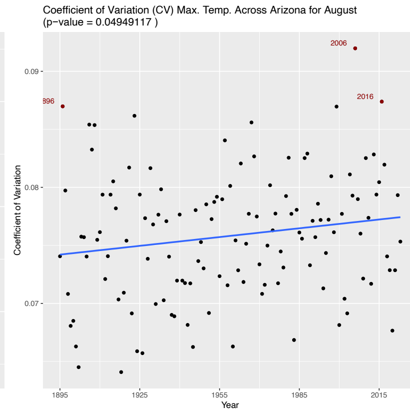

Coefficient of Variation (CV) Max. Temp. Across the Western U.S. for June
(p-value = 0.74424)
1901
1953
1981
Coefficient of Variation
Year


Coefficient of Variation (CV) Max. Temp. Across Arizona for July
(p-value = 0.5858543)
1914
1911
Coefficient of Variation
Year


Coefficient of Variation (CV) Max. Temp. Across Minnesota for July
(p-value = 0.00000151259)
1901
1913
Coefficient of Variation
Year


Coefficient of Variation (CV) Max. Temp. Across U.S. for August
(p-value = 0.004974984)
1954
1951
1912
Coefficient of Variation
Year


Coefficient of Variation (CV) Max. Temp. Across the Western U.S. for August
(p-value = 0.03921795)
1899
1975
1964
Coefficient of Variation
Year


Coefficient of Variation (CV) Max. Temp. Across Arizona for August
(p-value = 0.04949117)
2006
2016
Coefficient of Variation
Year

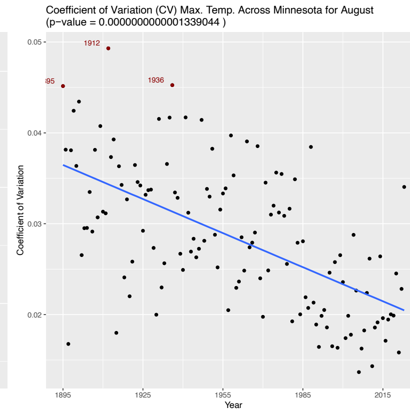
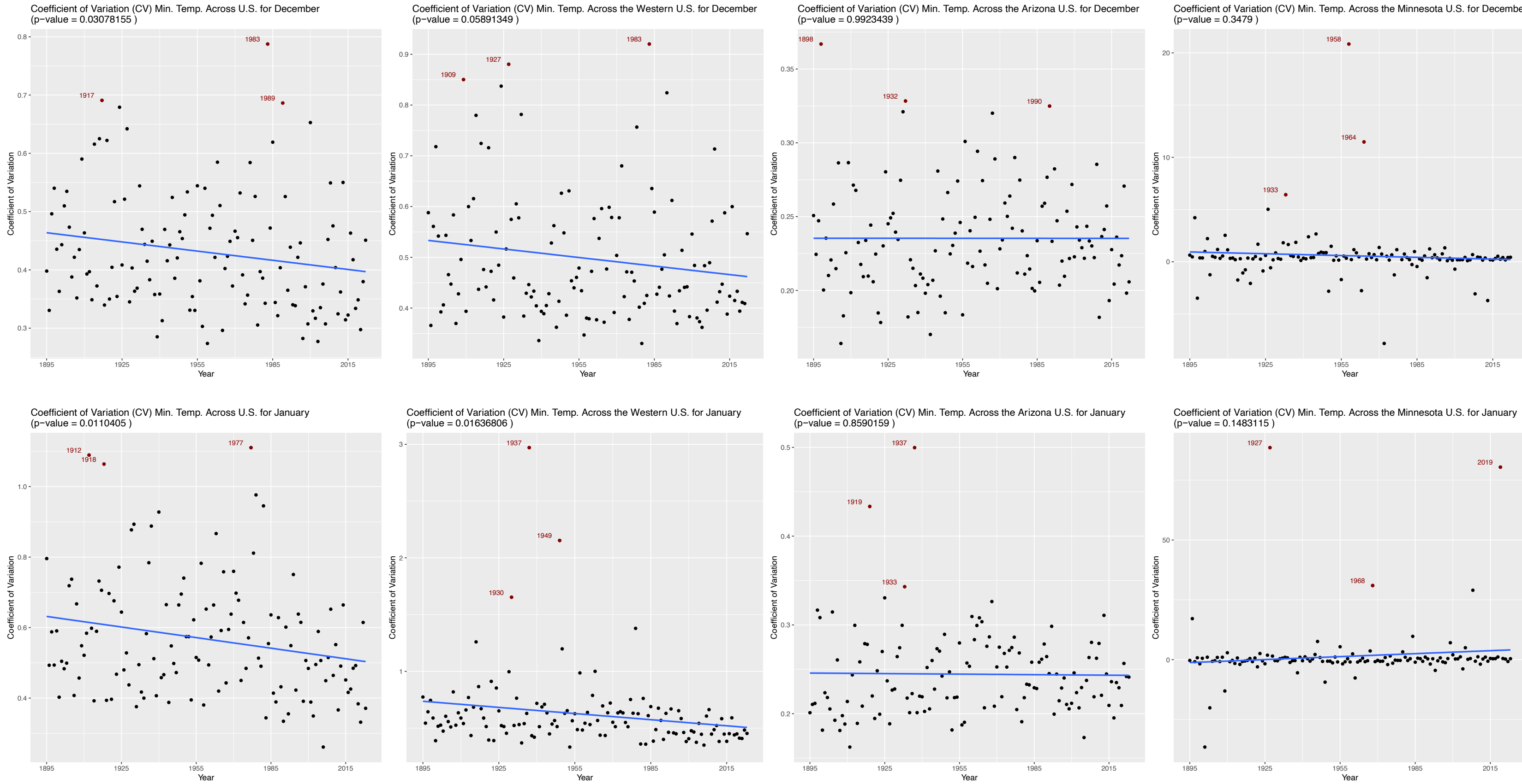
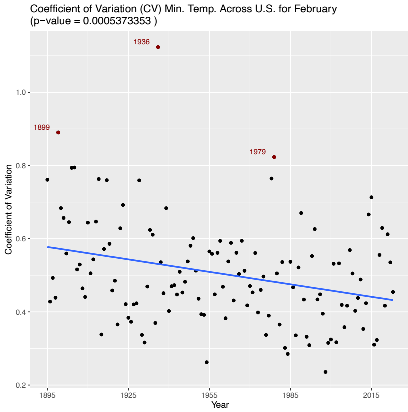
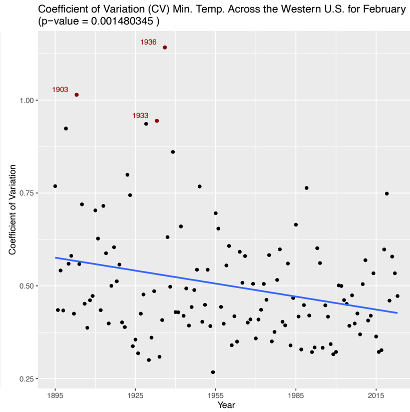
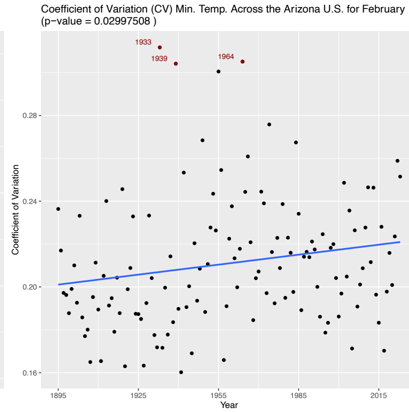

Coefficient of Variation (CV) Max. Temp. Across Minnesota for August
(p-value = 0.0000000000001339044)
1912
1936
Coefficient of Variation
Year

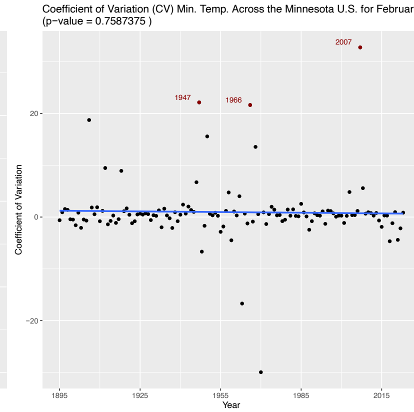
Table 7. Coefficient of Variation in Minimum Temperature across US counties over time

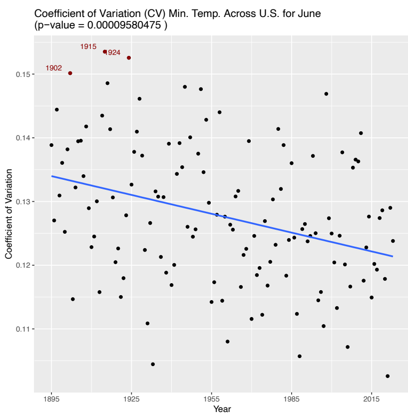


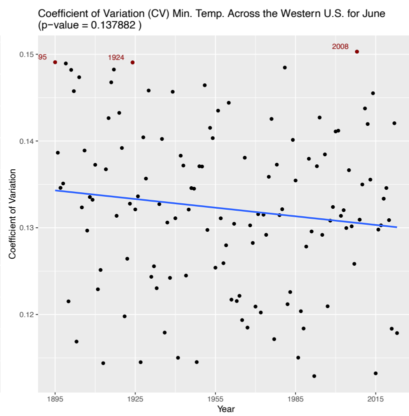

Coefficient of Variation (CV) Min. Temp. Across U.S. for February
(p−value = 0.0005373353)
1936
1899
1979
Coefficient of Variation
Year

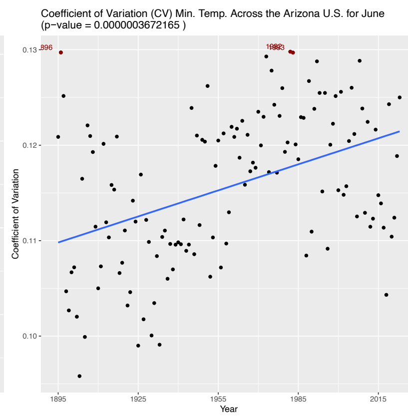

Coefficient of Variation (CV) Min. Temp. Across the Western U.S. for February
(p−value = 0.001480345)
1936
1903
1933
Coefficient of Variation
Year

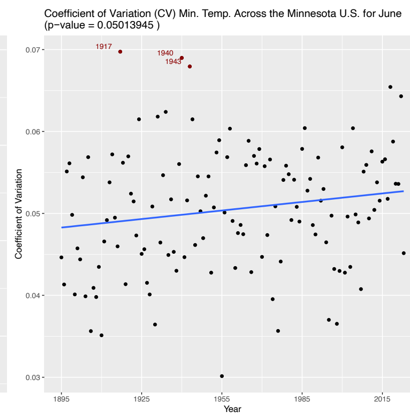

Coefficient of Variation (CV) Min. Temp. Across the Arizona U.S. for February
(p−value = 0.02997508)
1933
1939
1964
Coefficient of Variation
Year

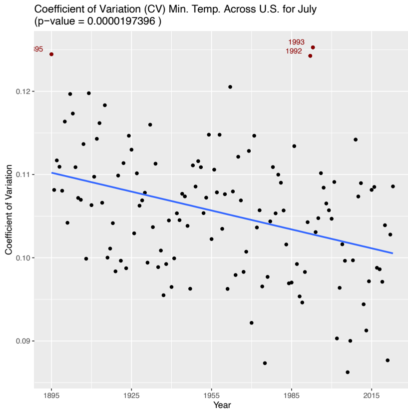

Coefficient of Variation (CV) Min. Temp. Across the Minnesota U.S. for February
(p−value = 0.7587375)
2007
1947
1966
Coefficient of Variation
Year

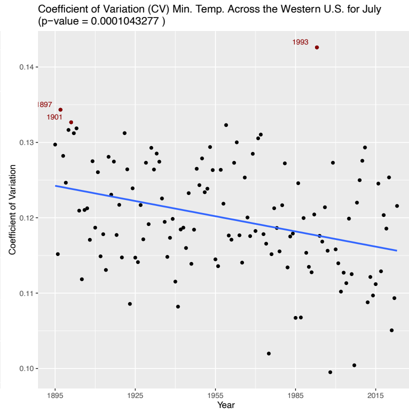

Coefficient of Variation (CV) Min. Temp. Across U.S. for June
(p−value = 0.00009580475)
1915
1924
1902
Coefficient of Variation
Year

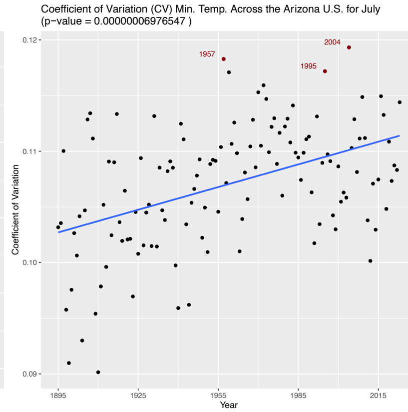

Coefficient of Variation (CV) Min. Temp. Across the Western U.S. for June
(p−value = 0.137882)
1924
2008
Coefficient of Variation
Year

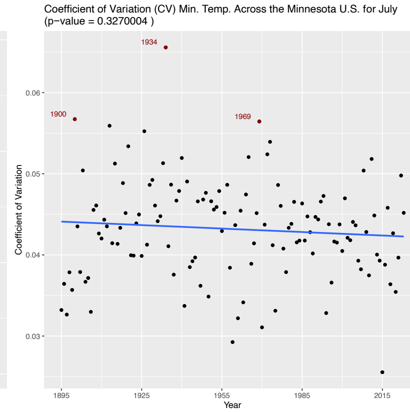

Coefficient of Variation (CV) Min. Temp. Across the Arizona U.S. for June
(p−value = 0.0000003672165)
Coefficient of Variation
Year

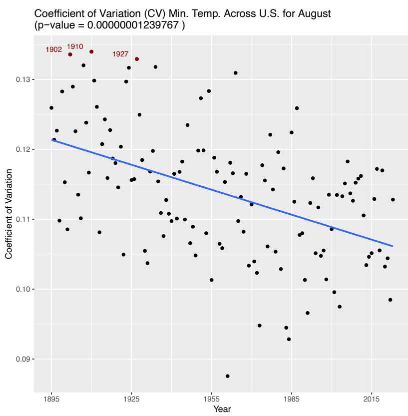

Coefficient of Variation (CV) Min. Temp. Across the Minnesota U.S. for June
(p−value = 0.05013945)
1917
1940
1943
Coefficient of Variation
Year

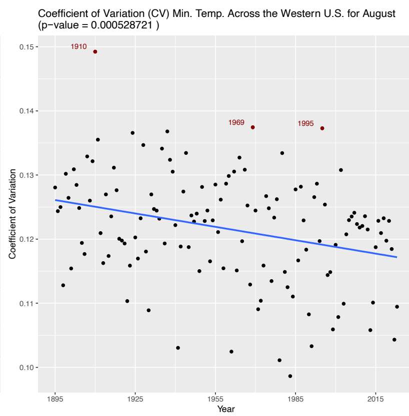

Coefficient of Variation (CV) Min. Temp. Across U.S. for July
(p−value = 0.0000197396)
Coefficient of Variation
Year
1993
1992

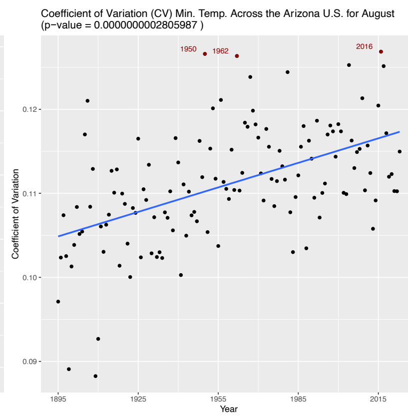

Coefficient of Variation (CV) Min. Temp. Across the Western U.S. for July
(p−value = 0.0001043277)
Coefficient of Variation
Year
1901
1993


Coefficient of Variation (CV) Min. Temp. Across the Arizona U.S. for July
(p−value = 0.00000006976547)
Coefficient of Variation
Year
1957
1995
2004


Coefficient of Variation (CV) Min. Temp. Across the Minnesota U.S. for July
(p−value = 0.3270004)
Coefficient of Variation
Year
1900
1934
1969


Coefficient of Variation (CV) Min. Temp. Across U.S. for August
(p−value = 0.00000001239767)
Coefficient of Variation
Year
1902
1910
1927


Coefficient of Variation (CV) Min. Temp. Across the Western U.S. for August
(p−value = 0.000528721)
Coefficient of Variation
Year
1910
1969
1995


Coefficient of Variation (CV) Min. Temp. Across the Arizona U.S. for August
(p−value = 0.0000000002805987)
Coefficient of Variation
Year
1950
1962
2016

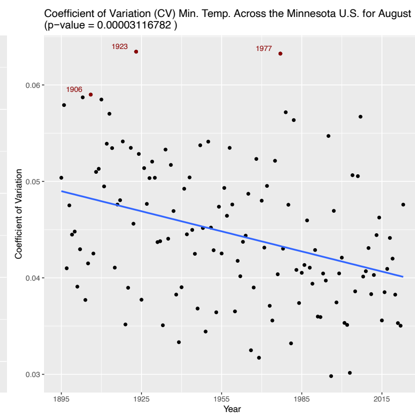
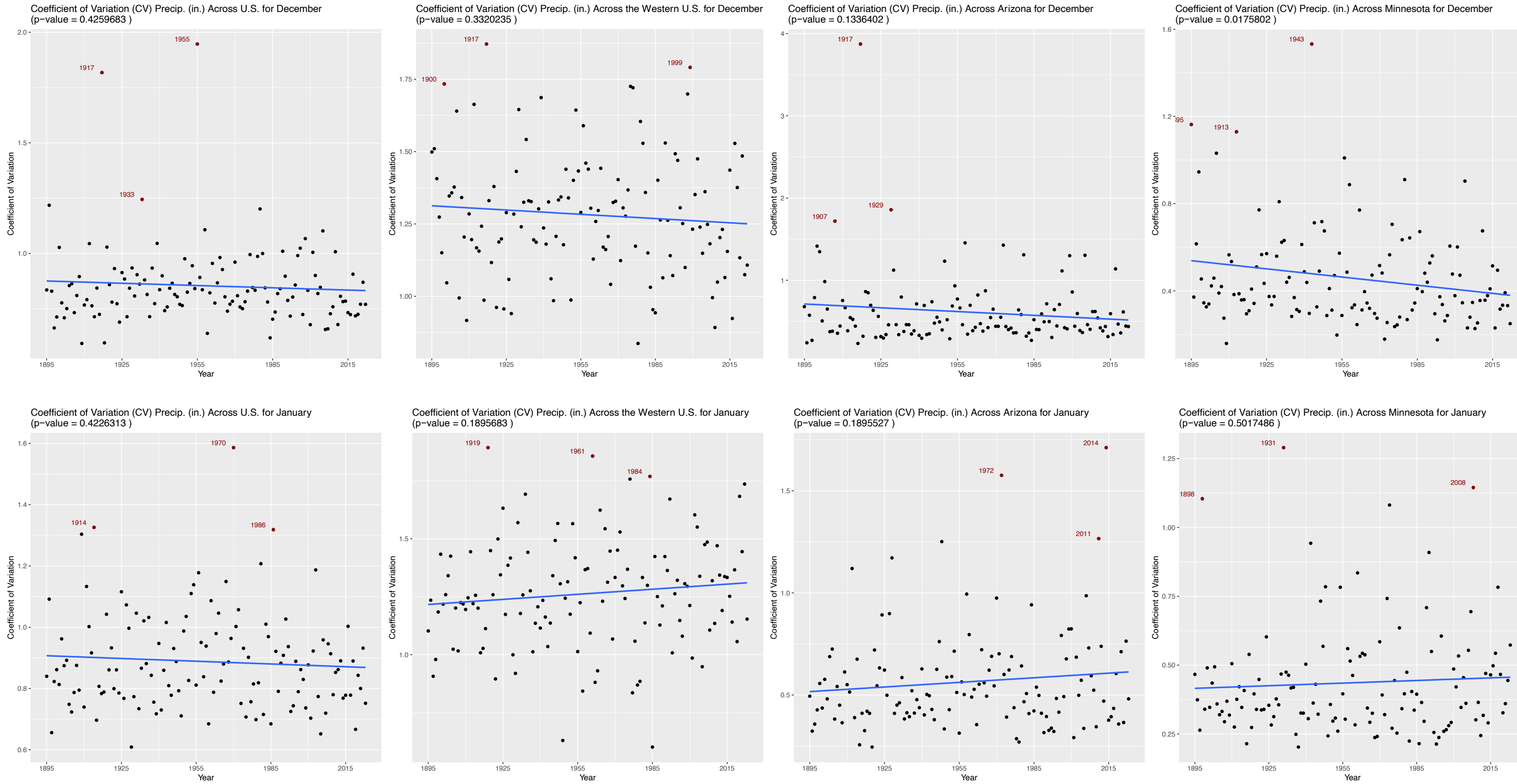
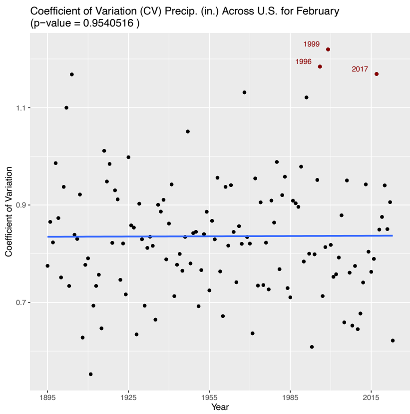
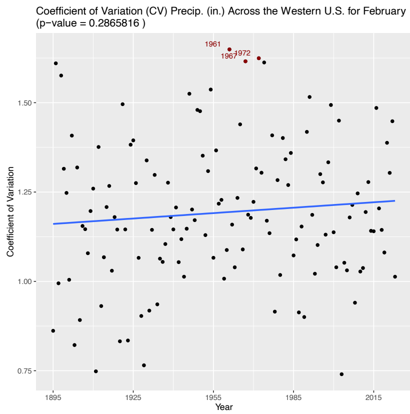
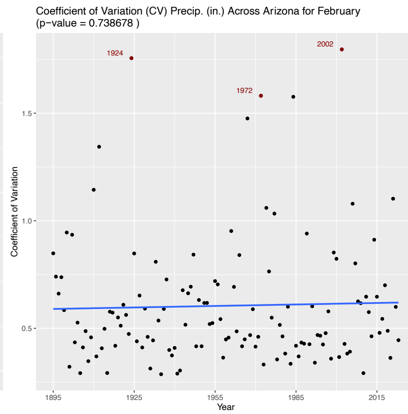

Coefficient of Variation (CV) Min. Temp. Across the Minnesota U.S. for August
(p−value = 0.00003116782)
Coefficient of Variation
Year
1906
1923
1977

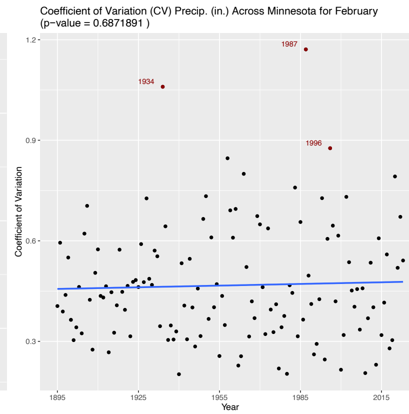
Table 8. Coefficient of Variation in precipitation across US counties over time

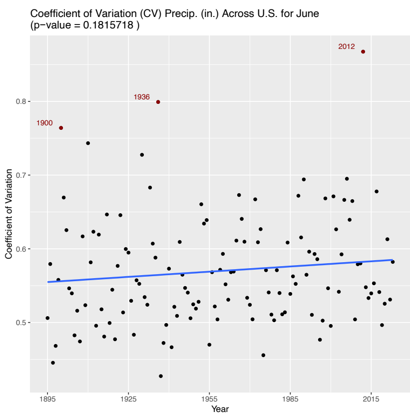


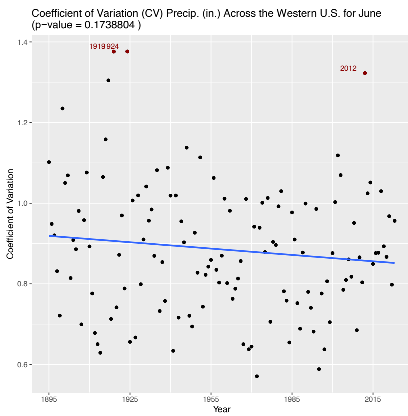

Coefficient of Variation (CV) Precip. (in.) Across U.S. for February
(p−value = 0.9540516)
Coefficient of Variation
Year
1999
1996
2017

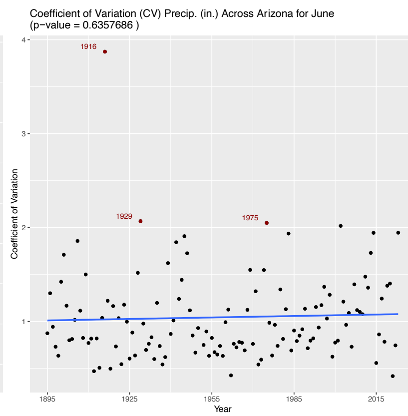

Coefficient of Variation (CV) Precip. (in.) Across the Western U.S. for February
(p−value = 0.2865816)
Coefficient of Variation
Year
1961
1967
1972

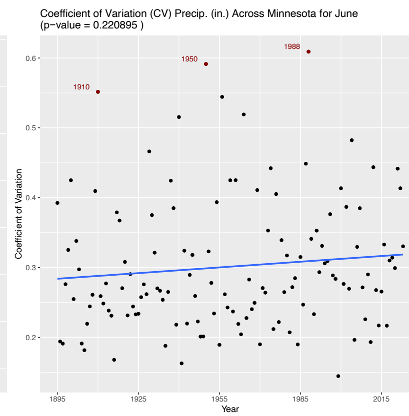

Coefficient of Variation (CV) Precip. (in.) Across Arizona for February
(p−value = 0.738678)
Coefficient of Variation
Year
1924
2002
1972


Coefficient of Variation (CV) Precip. (in.) Across Minnesota for February
(p−value = 0.6871891)
Coefficient of Variation
Year
1987
1934
1996


Coefficient of Variation (CV) Precip. (in.) Across U.S. for June
(p−value = 0.1815718)
Coefficient of Variation
Year
2012
1936
1900


Coefficient of Variation (CV) Precip. (in.) Across the Western U.S. for June
(p−value = 0.1738804)
Coefficient of Variation
Year
1919
1924
2012


Coefficient of Variation (CV) Precip. (in.) Across Arizona for June
(p−value = 0.6357686)
Coefficient of Variation
Year
1916
1929
1975


Coefficient of Variation (CV) Precip. (in.) Across Minnesota for June
(p−value = 0.220895)
Coefficient of Variation
Year
1988
1950
1910

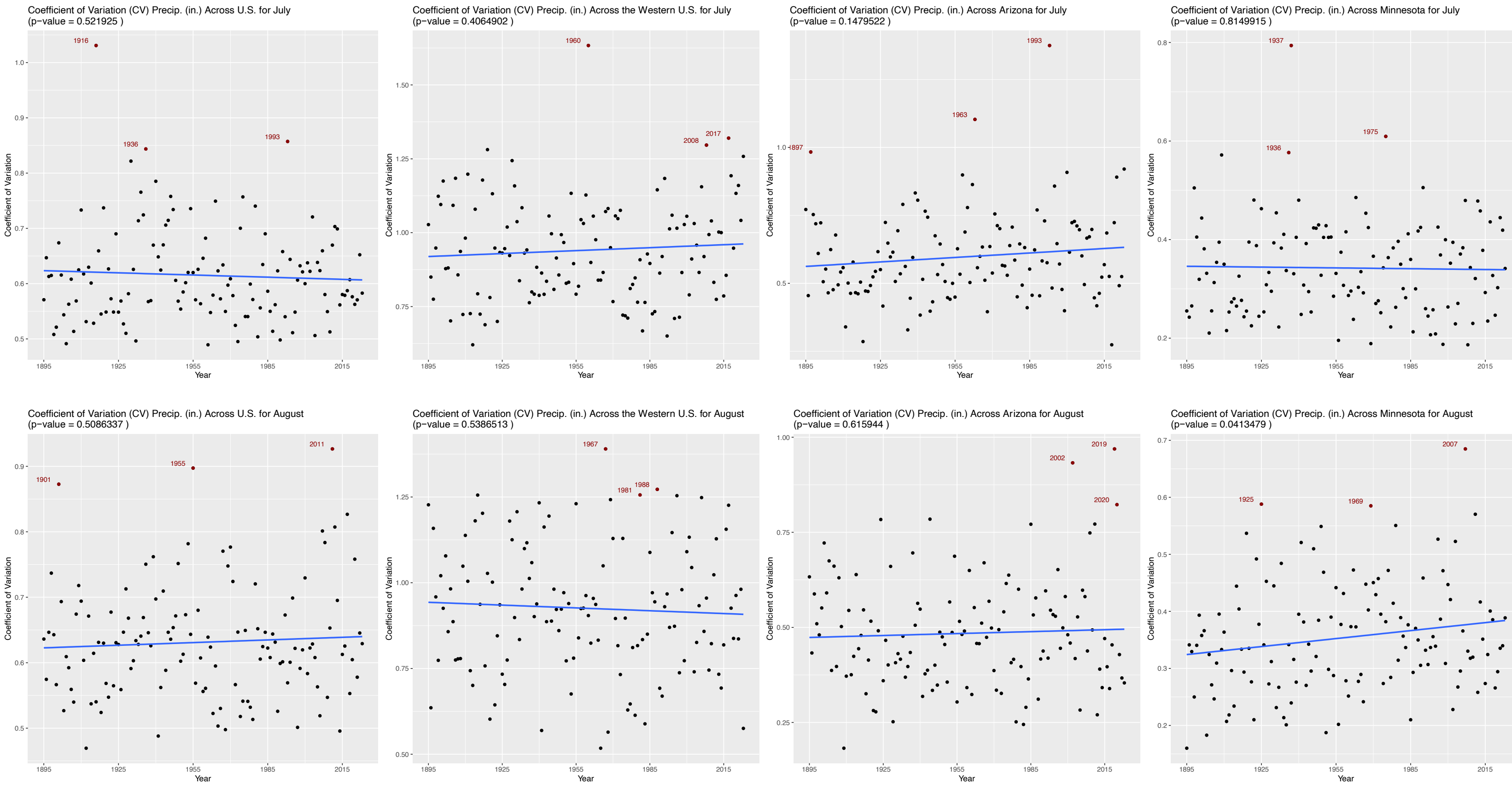
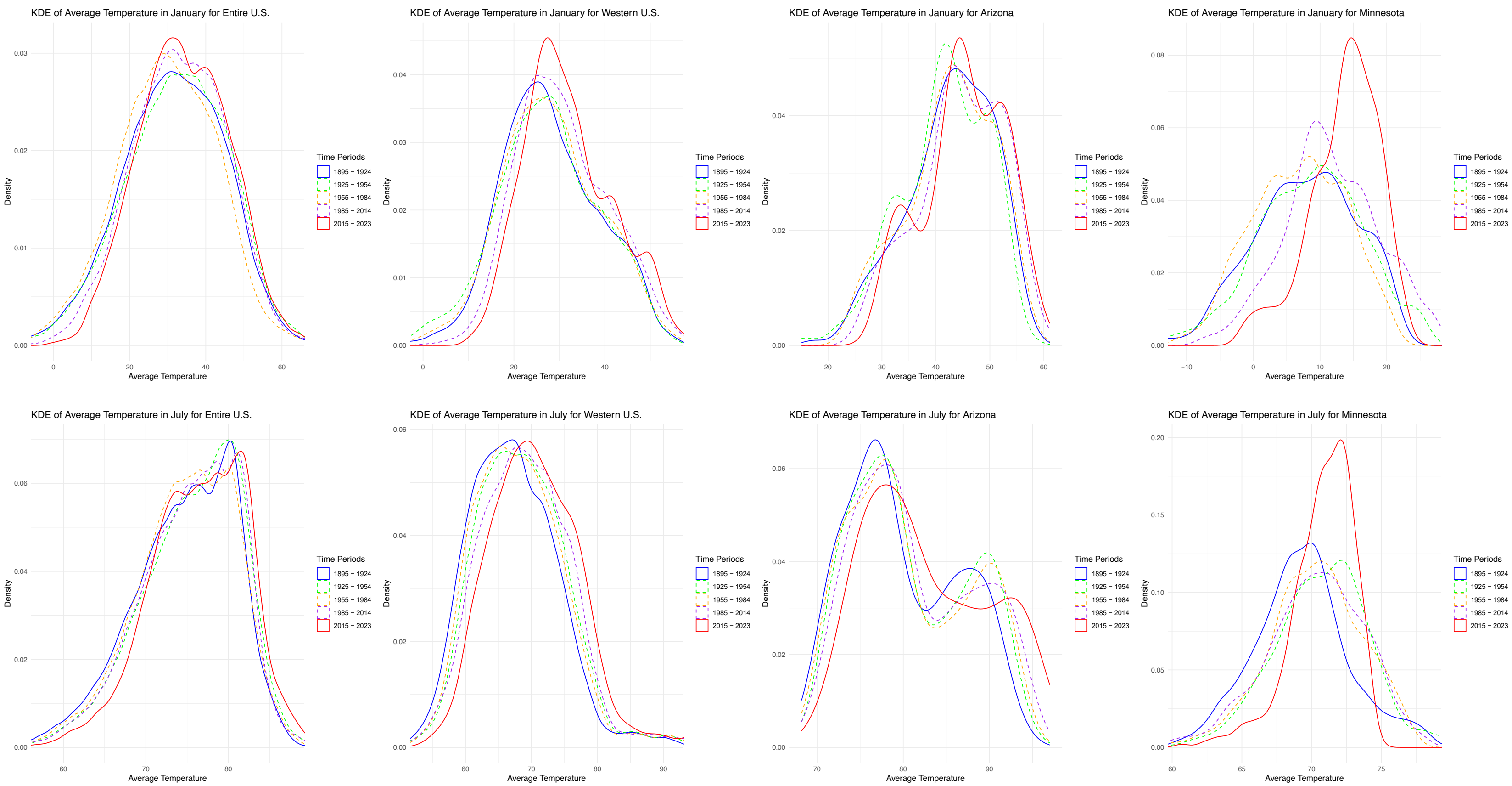
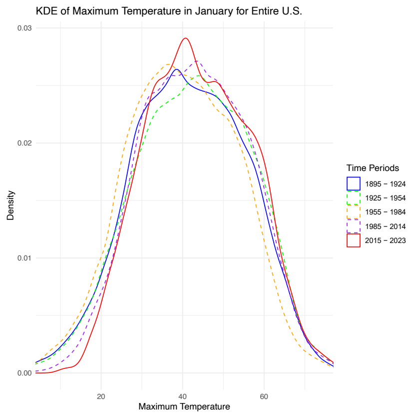
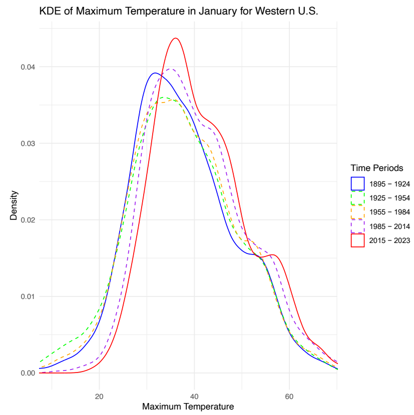
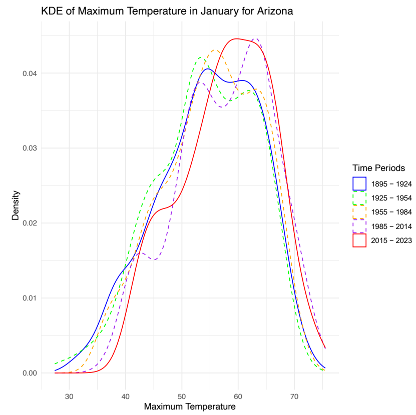


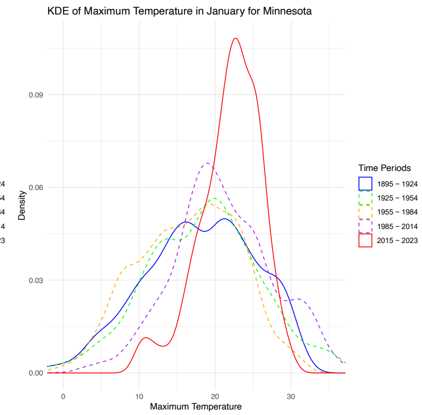
Table 9. Kernel Density Estimations (Moving Average) for Average Temperature, Maximum Temperature, Minimum Temperature, Precipitation

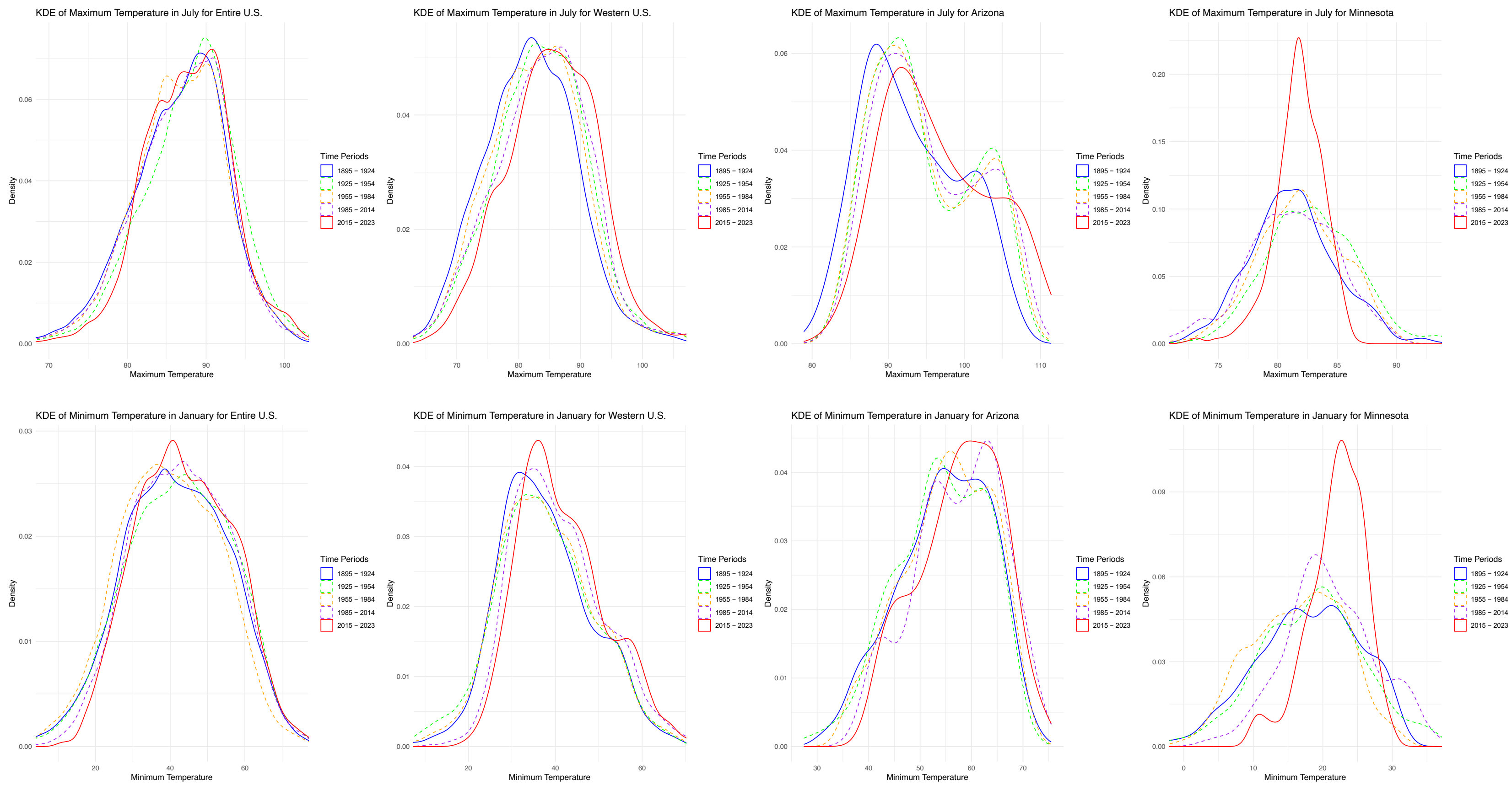

KDE of Average Temperature in January for Entire U.S.
KDE of Average Temperature in January for Western U.S.
KDE of Average Temperature in January for Arizona
KDE of Average Temperature in January for Minnesota
KDE of Average Temperature in July for Entire U.S.
KDE of Average Temperature in July for Western U.S.
KDE of Average Temperature in July for Arizona
KDE of Average Temperature in July for Minnesota
Density
Average Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023


KDE of Maximum Temperature in January for Entire U.S.
Density
Maximum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

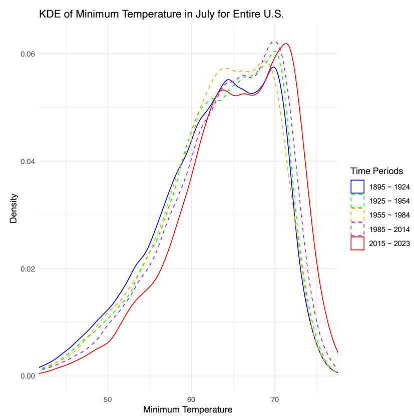

KDE of Maximum Temperature in January for Western U.S.
Density
Maximum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

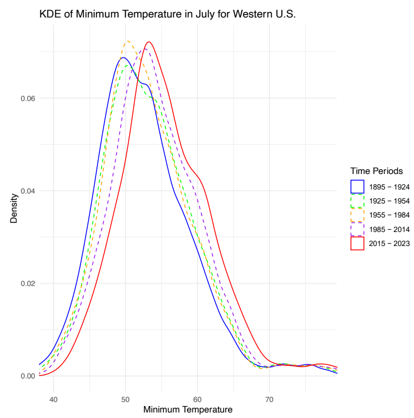

KDE of Maximum Temperature in January for Arizona
Density
Maximum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

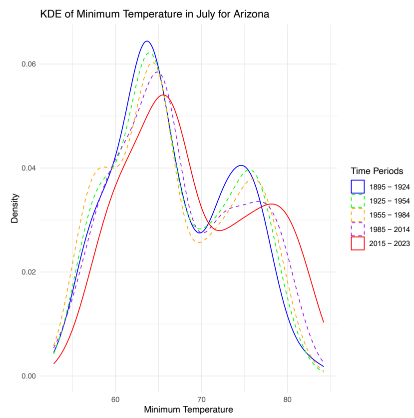

KDE of Maximum Temperature in January for Minnesota
Density
Maximum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

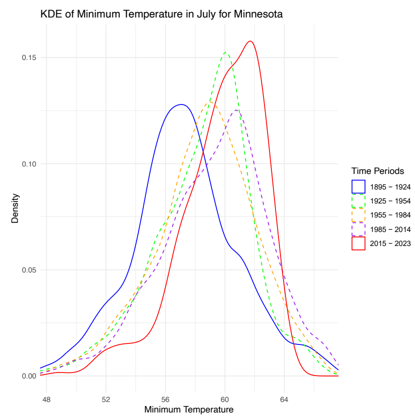


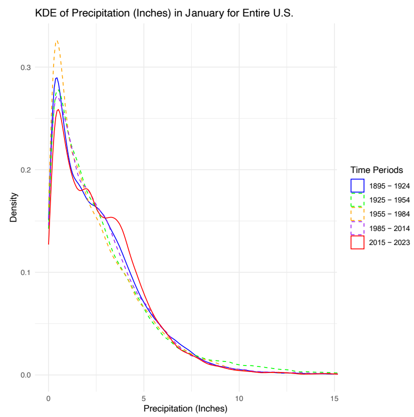
KDE of Maximum Temperature in July for Entire U.S.
KDE of Maximum Temperature in July for Western U.S.
KDE of Maximum Temperature in July for Arizona
KDE of Maximum Temperature in July for Minnesota
KDE of Minimum Temperature in January for Entire U.S.
KDE of Minimum Temperature in January for Western U.S.
KDE of Minimum Temperature in January for Arizona
KDE of Minimum Temperature in January for Minnesota
Density
Maximum Temperature
Minimum Temperature
Time Periods
1895 - 1924
1925 - 1954
1955 - 1984
1985 - 2014
2015 - 2023

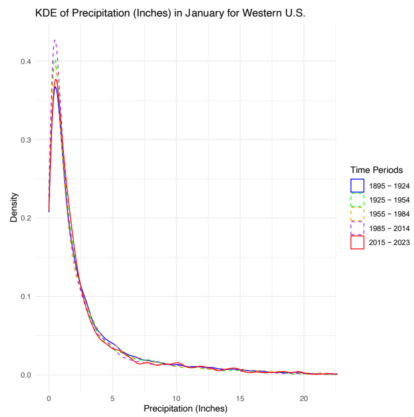

KDE of Minimum Temperature in July for Entire U.S.
Density
Minimum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

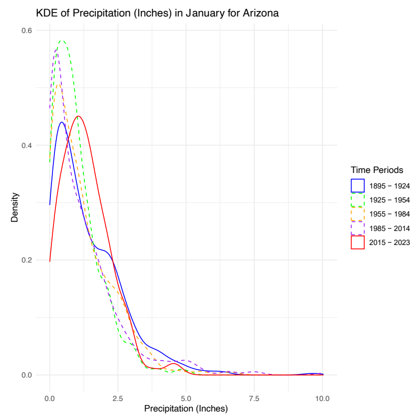

KDE of Minimum Temperature in July for Western U.S.
Density
Minimum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

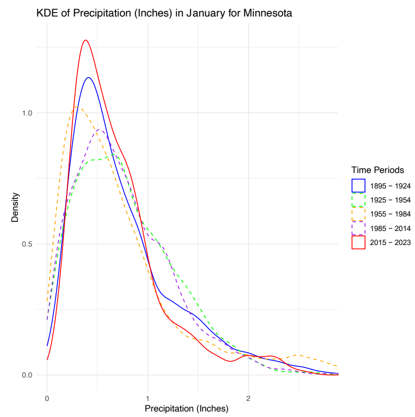

KDE of Minimum Temperature in July for Arizona
Density
Minimum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

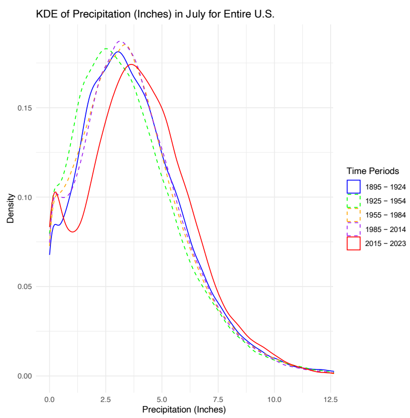

KDE of Minimum Temperature in July for Minnesota
Density
Minimum Temperature
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023


KDE of Precipitation (Inches) in January for Entire U.S.
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

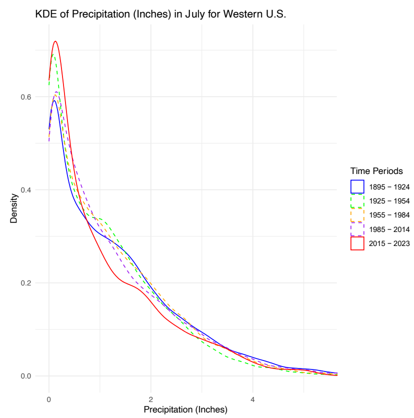

KDE of Precipitation (Inches) in January for Western U.S.
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023


KDE of Precipitation (Inches) in January for Arizona
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

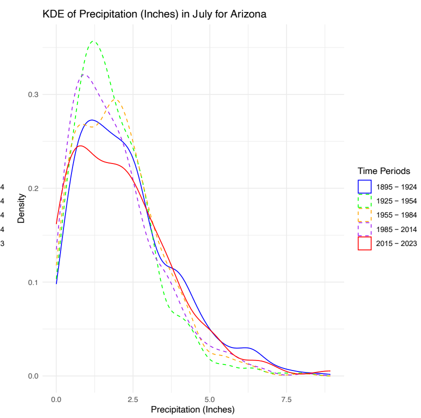

KDE of Precipitation (Inches) in January for Minnesota
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



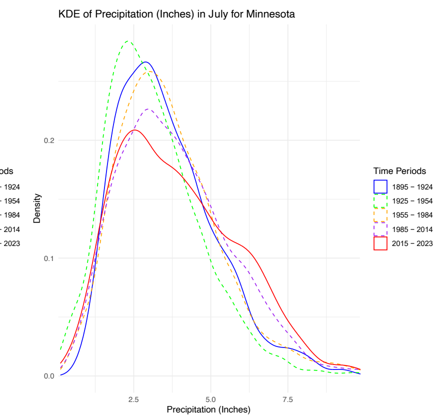
KDE of Precipitation (Inches) in July for Entire U.S.
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



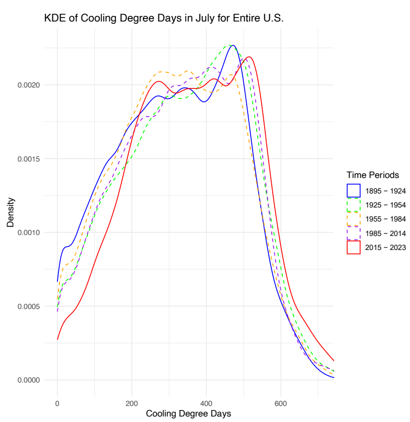
KDE of Precipitation (Inches) in July for Western U.S.
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



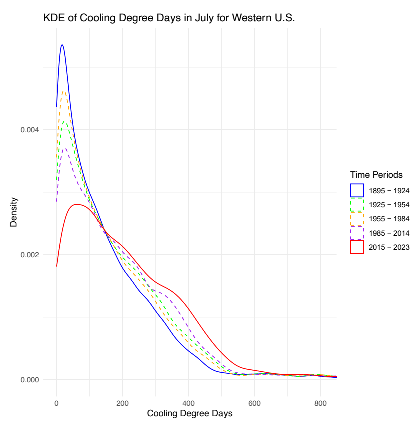
KDE of Precipitation (Inches) in July for Arizona
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



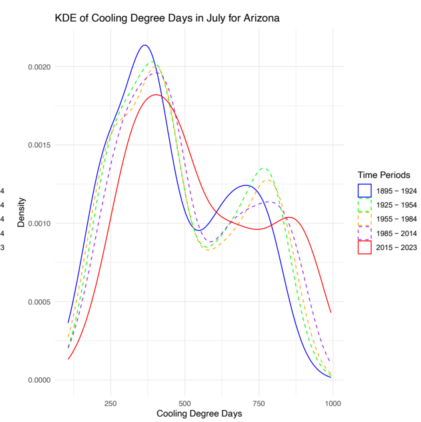
KDE of Precipitation (Inches) in July for Minnesota
Density
Precipitation (Inches)
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



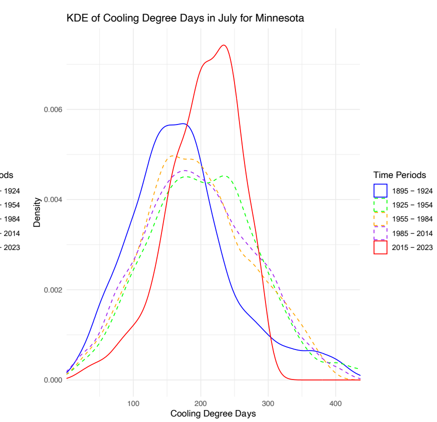
KDE of Cooling Degree Days in July for Entire U.S.
Density
Cooling Degree Days
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



KDE of Cooling Degree Days in July for Western U.S.
Density
Cooling Degree Days
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023

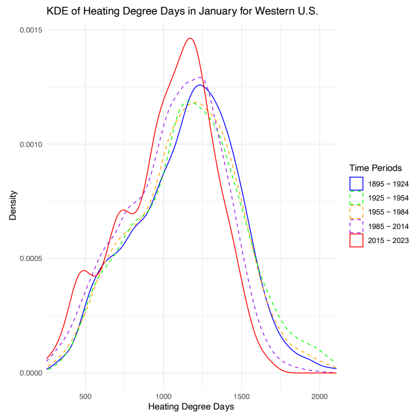


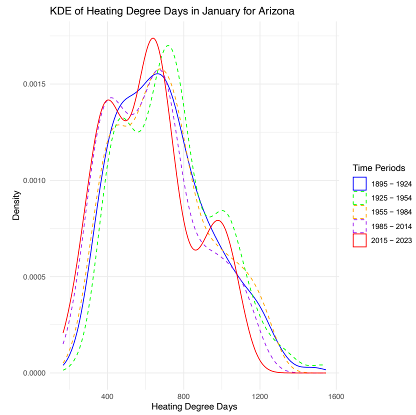
KDE of Cooling Degree Days in July for Arizona
Density
Cooling Degree Days
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023



KDE of Cooling Degree Days in July for Minnesota
Density
Cooling Degree Days
Time Periods
1895 – 1924
1925 – 1954
1955 – 1984
1985 – 2014
2015 – 2023


KDE of Heating Degree Days in January for Entire U.S.
Density
0.00100
0.00075
0.00050
0.00025
0.00000
500
1000
1500
2000
Heating Degree Days
Time Periods
1895 - 1924
1925 - 1954
1955 - 1984
1985 - 2014
2015 - 2023


KDE of Heating Degree Days in January for Western U.S.
Density
0.0015
0.0010
0.0005
0.0000
500
1000
1500
2000
Heating Degree Days
Time Periods
1895 - 1924
1925 - 1954
1955 - 1984
1985 - 2014
2015 - 2023


KDE of Heating Degree Days in January for Arizona
Density
0.0015
0.0010
0.0005
0.0000
400
800
1200
1600
Heating Degree Days
Time Periods
1895 - 1924
1925 - 1954
1955 - 1984
1985 - 2014
2015 - 2023

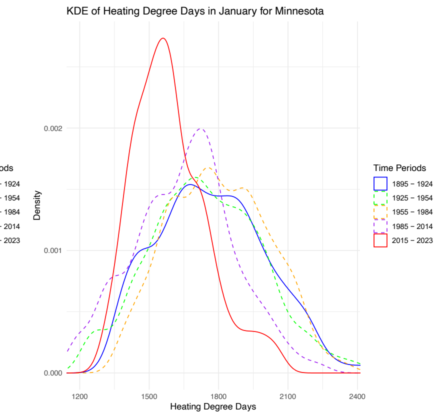
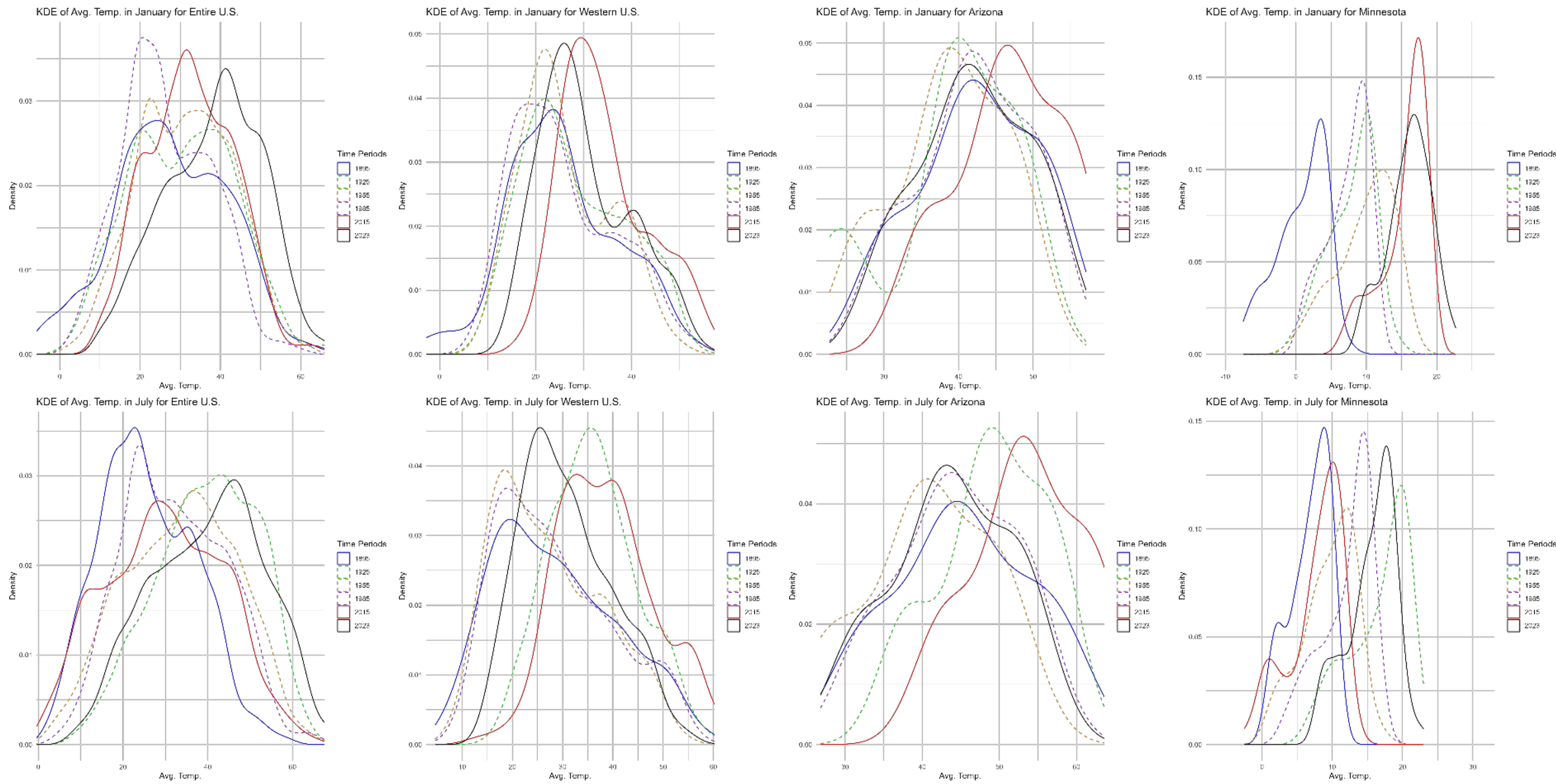
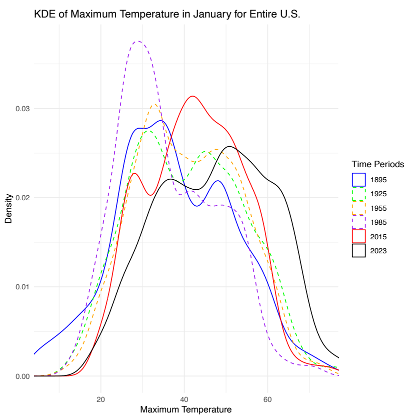
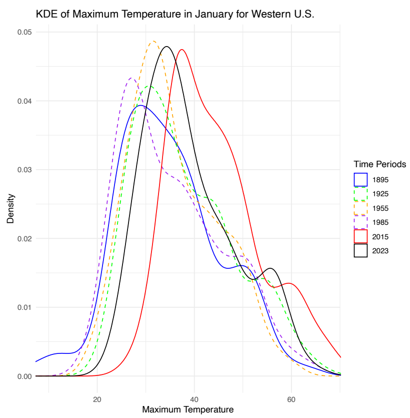
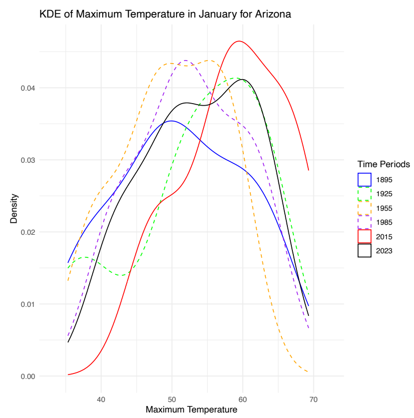

KDE of Heating Degree Days in January for Minnesota
Density
0.002
0.001
0.000
1200
1500
1800
2100
2400
Heating Degree Days
Time Periods
1895 - 1924
1925 - 1954
1955 - 1984
1985 - 2014
2015 - 2023

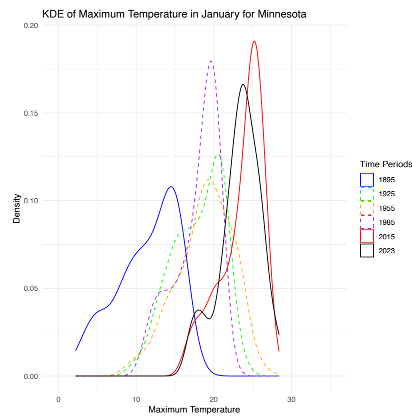
Table 10. Kernel Density Estimations (Single Year) for Average Temperature, Maximum Temperature, Minimum Temperature, Precipitation

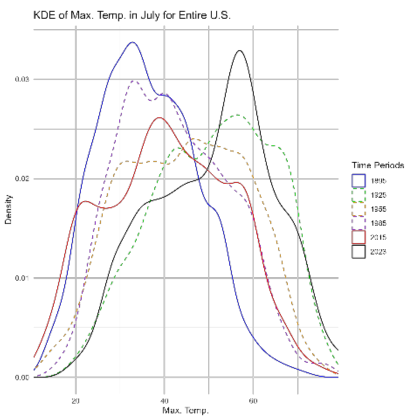


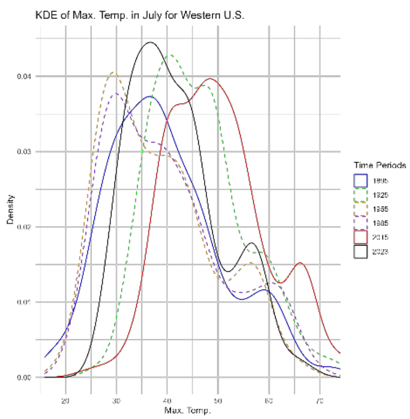

KDE of Maximum Temperature in January for Entire U.S.
Density
Maximum Temperature
Time Periods
1895
1925
1955
1985
2015
2023

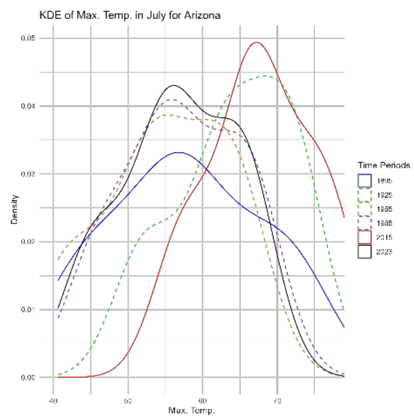

KDE of Maximum Temperature in January for Western U.S.
Density
Maximum Temperature
Time Periods
1895
1925
1955
1985
2015
2023

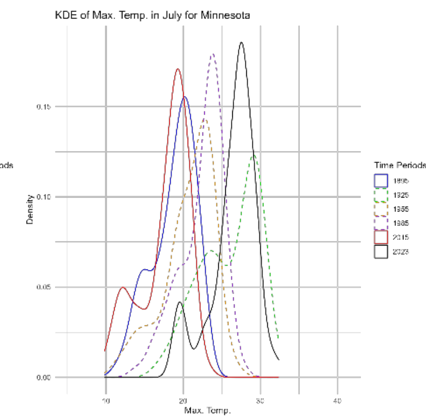

KDE of Maximum Temperature in January for Arizona
Density
Maximum Temperature
Time Periods
1895
1925
1955
1985
2015
2023

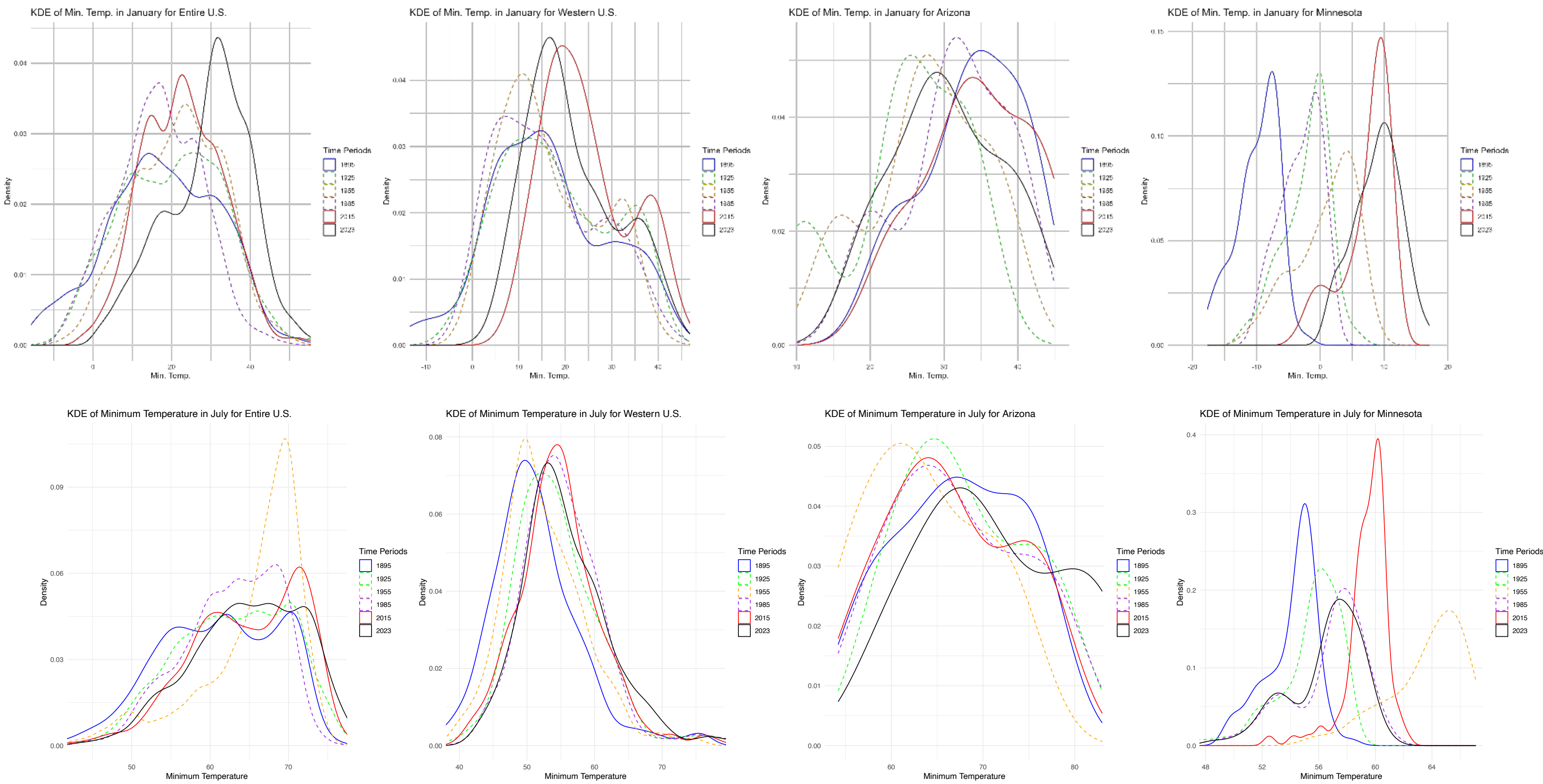

KDE of Maximum Temperature in January for Minnesota
Density
Maximum Temperature
Time Periods
1895
1925
1955
1985
2015
2023

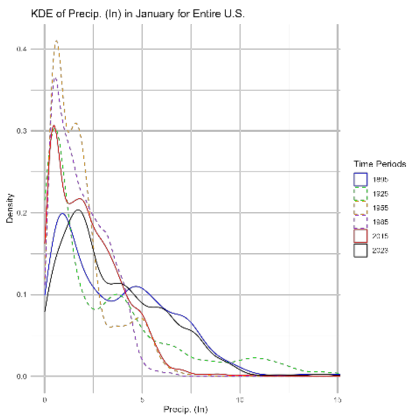

KDE of Max. Temp. in July for Entire U.S.
Density
Max. Temp.
Time Periods

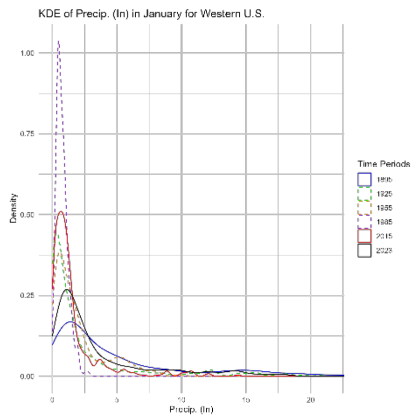

KDE of Max. Temp. in July for Western U.S.
Density
Max. Temp.
Time Periods

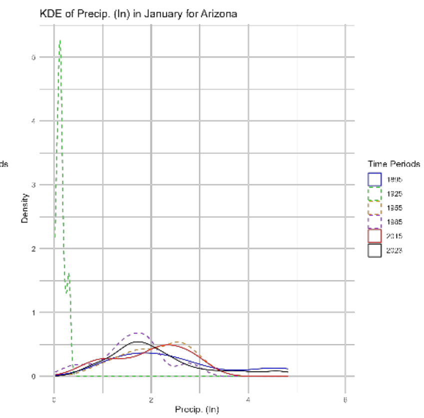

KDE of Max. Temp. in July for Arizona
Density
Max. Temp.
Time Periods

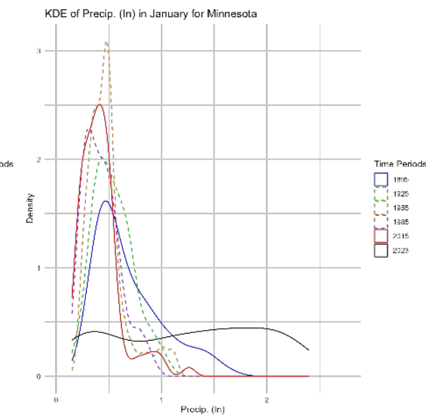

KDE of Max. Temp. in July for Minnesota
Density
Max. Temp.
Time Periods

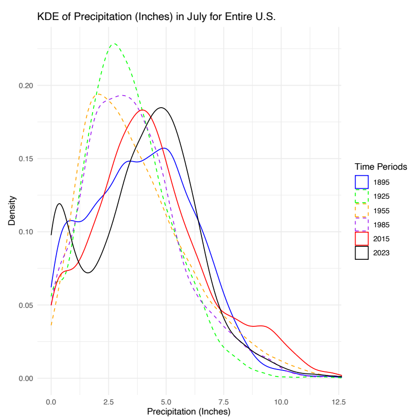

KDE of Min. Temp. in January for Entire U.S.
KDE of Min. Temp. in January for Western U.S.
KDE of Min. Temp. in January for Arizona
KDE of Min. Temp. in January for Minnesota
Min. Temp.
Density
Time Periods
1895
1925
1955
1985
2015
2023
KDE of Minimum Temperature in July for Entire U.S.
KDE of Minimum Temperature in July for Western U.S.
KDE of Minimum Temperature in July for Arizona
KDE of Minimum Temperature in July for Minnesota
Minimum Temperature

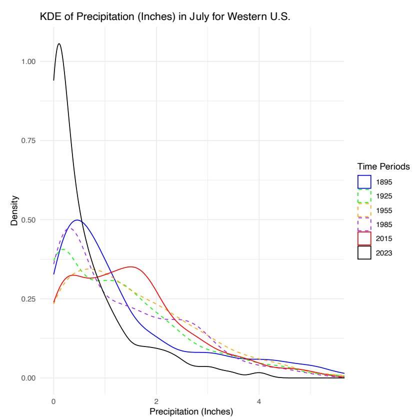

KDE of Precip. (In) in January for Entire U.S.
Density
Precip. (In)
Time Periods
1895
1925
1955
1985
2015
2023

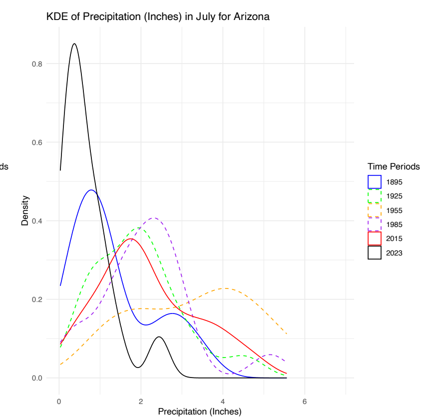

KDE of Precip. (In) in January for Western U.S.
Density
Precip. (In)
Time Periods
1895
1925
1955
1985
2015
2023


KDE of Precip. (In) in January for Arizona
Density
Precip. (In)
Time Periods
1895
1925
1955
1985
2015
2023


KDE of Precip. (In) in January for Minnesota
Density
Precip. (In)
Time Periods
1895
1925
1955
1985
2015
2023


KDE of Precipitation (Inches) in July for Entire U.S.
Density
Precipitation (Inches)
Time Periods
1895
1925
1955
1985
2015
2023


KDE of Precipitation (Inches) in July for Western U.S.
Density
Precipitation (Inches)
Time Periods
1895
1925
1955
1985
2015
2023


KDE of Precipitation (Inches) in July for Arizona
Density
Precipitation (Inches)
Time Periods
1895
1925
1955
1985
2015
2023

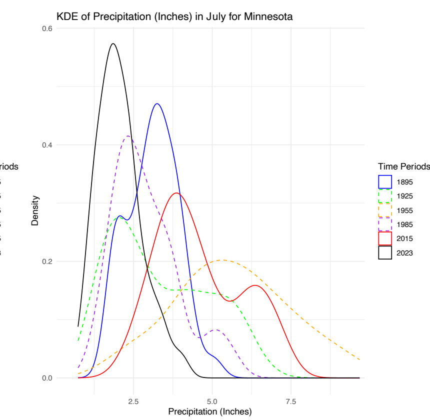
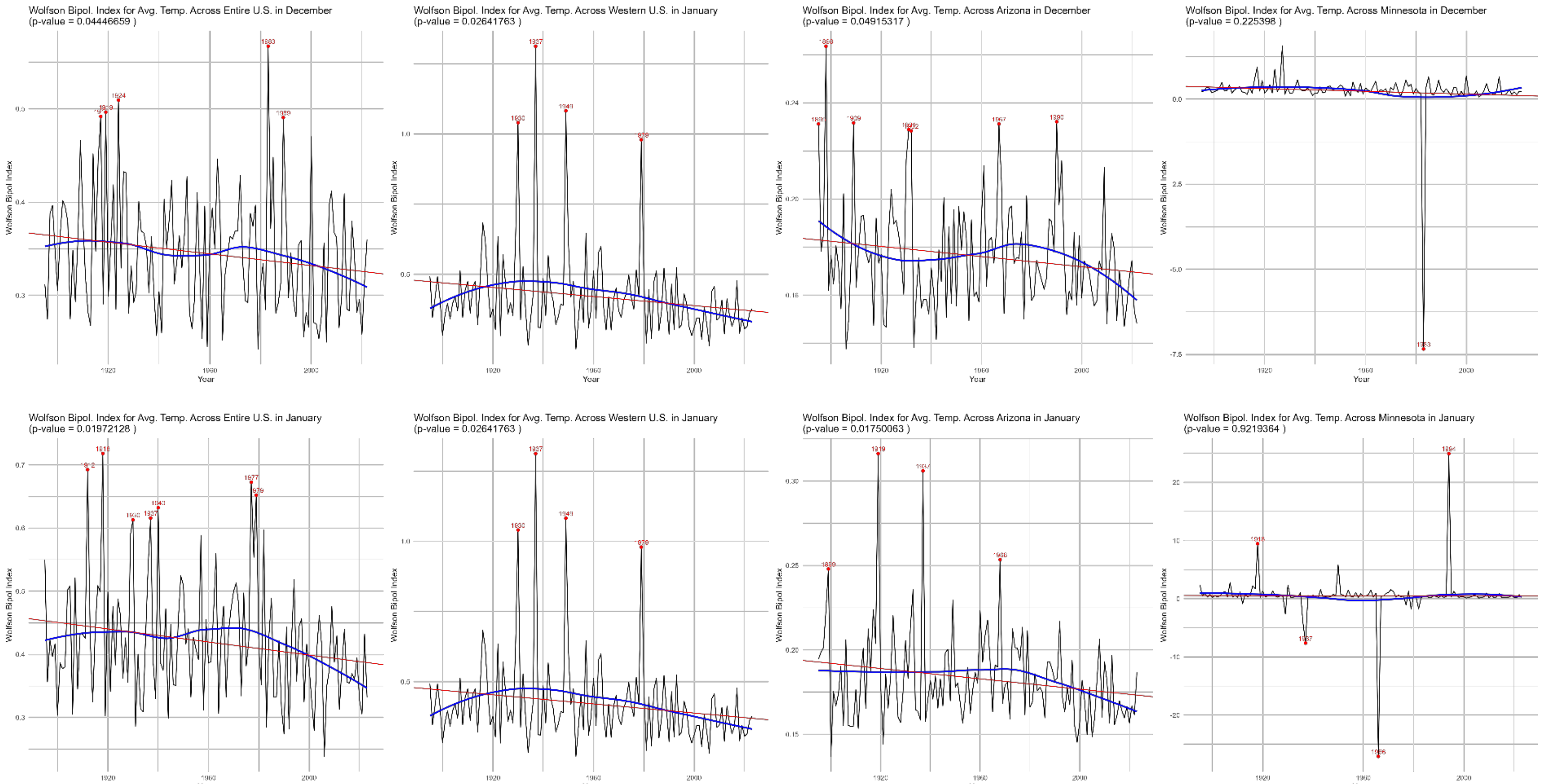
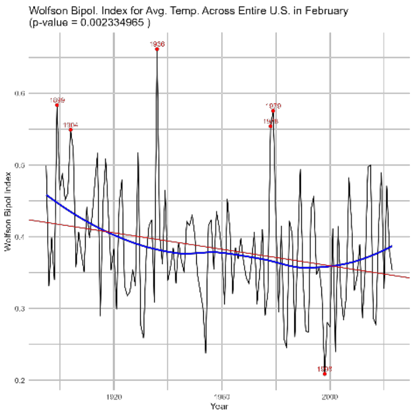
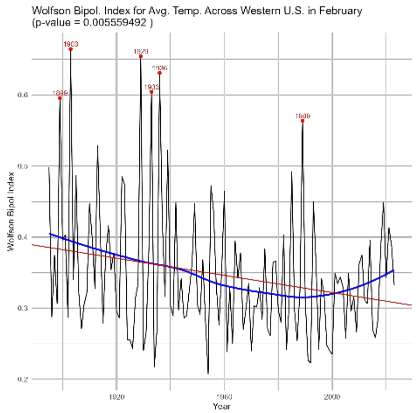
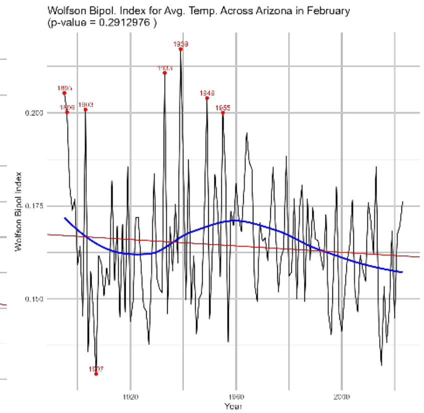

KDE of Precipitation (Inches) in July for Minnesota
Density
Precipitation (Inches)
Time Periods
1895
1925
1955
1985
2015
2023

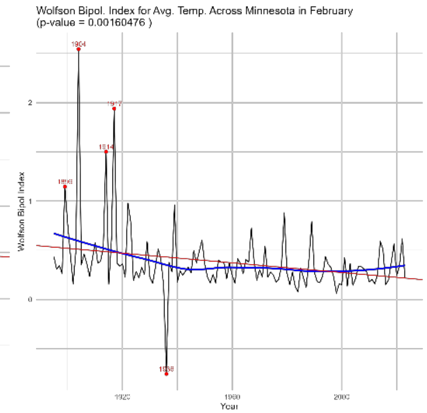
Table 11. Wolfson Polarization Index: Average Temperature

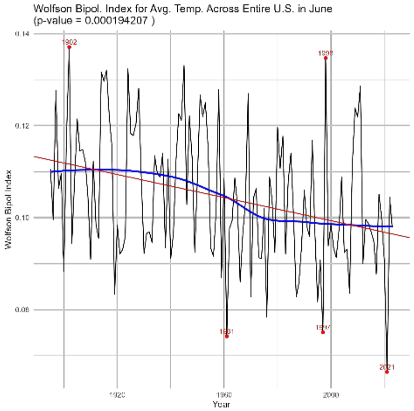


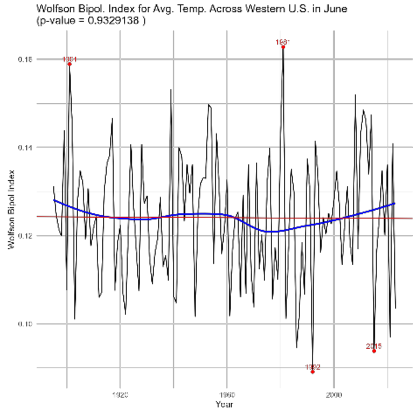

Wolfson Bipol. Index for Avg. Temp. Across Entire U.S. in February
(p-value = 0.002334965)
Wolfson Bipol Index
Year

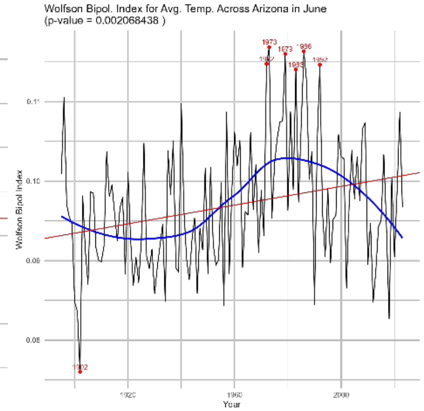

Wolfson Bipol. Index for Avg. Temp. Across Western U.S. in February
(p-value = 0.005559492)
Wolfson Bipol Index
Year

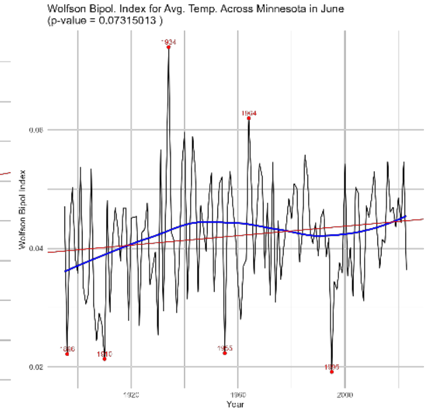

Wolfson Bipol. Index for Avg. Temp. Across Arizona in February
(p-value = 0.2912976)
Wolfson Bipol Index
Year

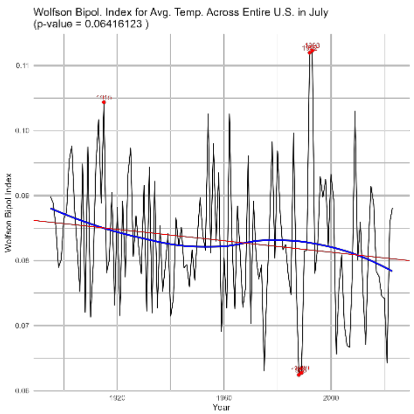

Wolfson Bipol. Index for Avg. Temp. Across Minnesota in February
(p-value = 0.00160476)
Wolfson Bipol Index
Year

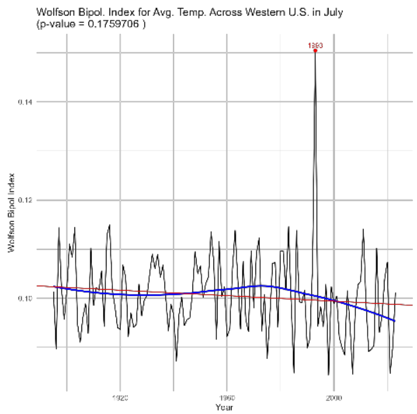

Wolfson Bipol. Index for Avg. Temp. Across Entire U.S. in June
(p-value = 0.000194207)
Wolfson Bipol. Index
Year

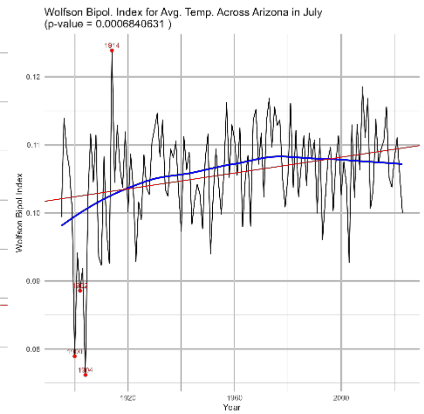

Wolfson Bipol. Index for Avg. Temp. Across Western U.S. in June
(p-value = 0.9329138)
Wolfson Bipol. Index
Year

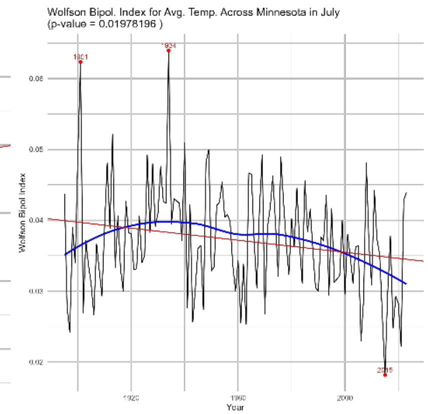

Wolfson Bipol. Index for Avg. Temp. Across Arizona in June
(p-value = 0.002068438)
Wolfson Bipol. Index
Year

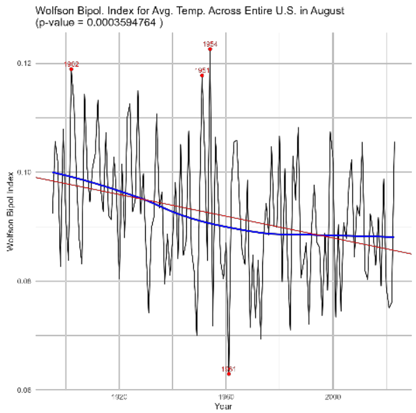

Wolfson Bipol. Index for Avg. Temp. Across Minnesota in June
(p-value = 0.07315013)
Wolfson Bipol. Index
Year

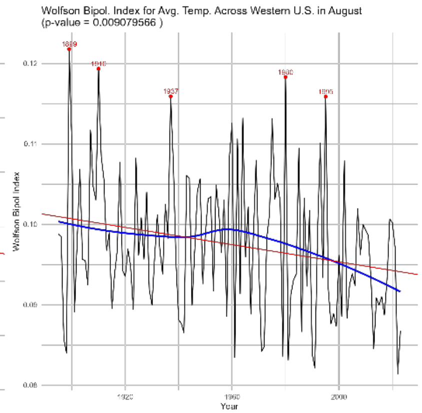

Wolfson Bipol. Index for Avg. Temp. Across Entire U.S. in July
(p-value = 0.06416123)
Wolfson Bipol. Index
Year

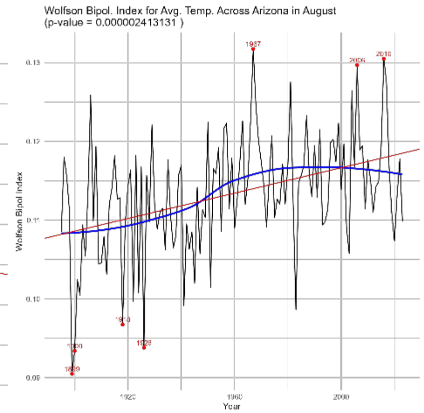

Wolfson Bipol. Index for Avg. Temp. Across Western U.S. in July
(p-value = 0.1759706)
Wolfson Bipol. Index
Year


Wolfson Bipol. Index for Avg. Temp. Across Arizona in July
(p-value = 0.0006840631)
Wolfson Bipol. Index
Year


Wolfson Bipol. Index for Avg. Temp. Across Minnesota in July
(p-value = 0.01978196)
Wolfson Bipol. Index
Year


Wolfson Bipol. Index for Avg. Temp. Across Entire U.S. in August
(p-value = 0.0003594764)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Avg. Temp. Across Western U.S. in August
(p-value = 0.009079566)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Avg. Temp. Across Arizona in August
(p-value = 0.000002413131)
Wolfson Bipol Index
Year

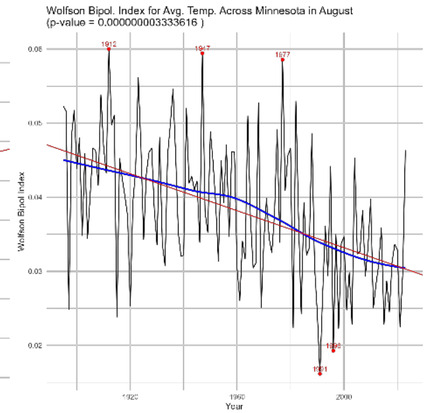
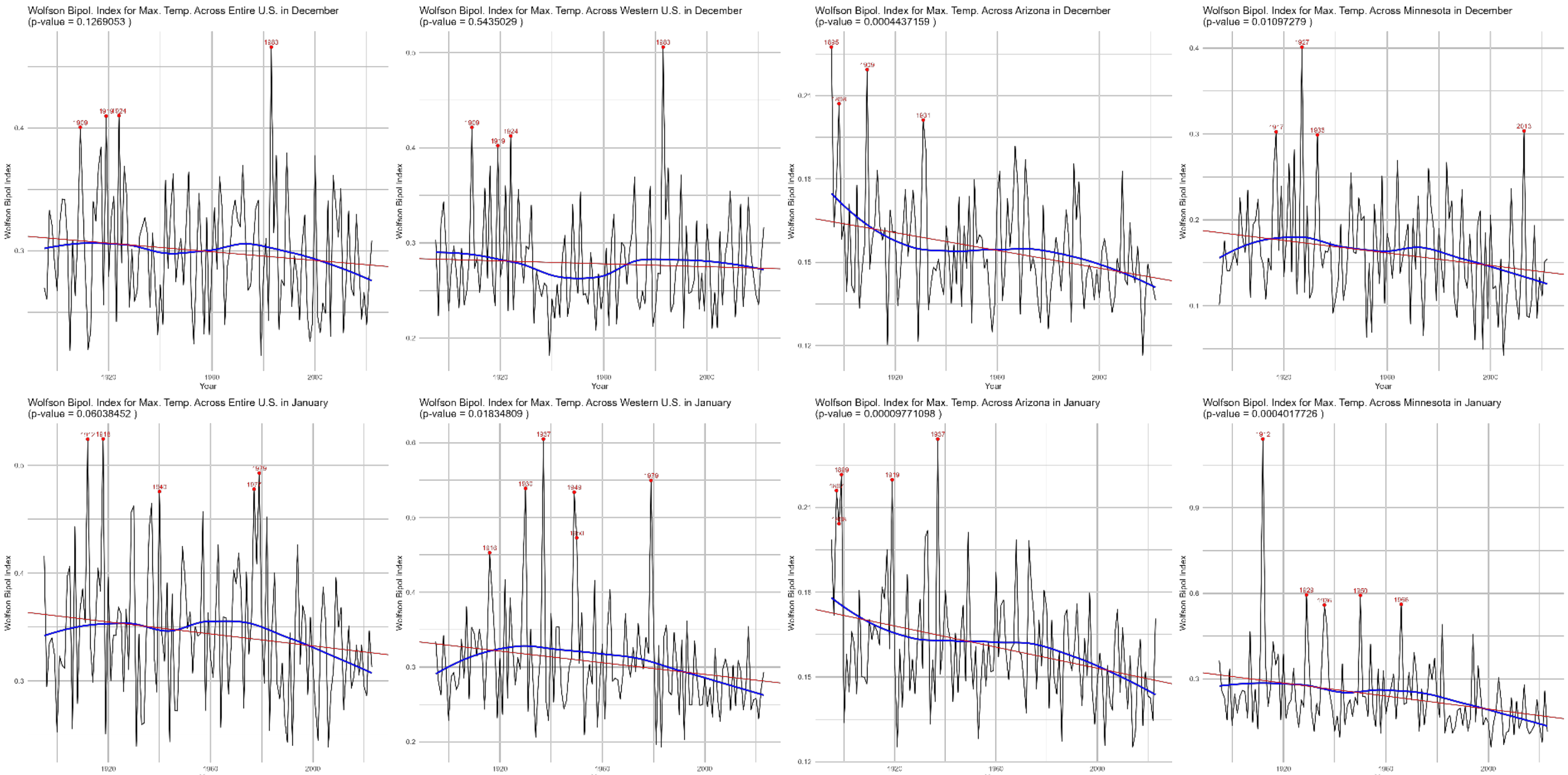
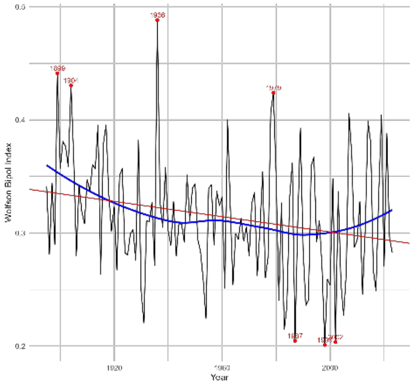

Wolfson Bipol. Index for Avg. Temp. Across Minnesota in August
(p-value = 0.000000003333616)
Wolfson Bipol Index
Year

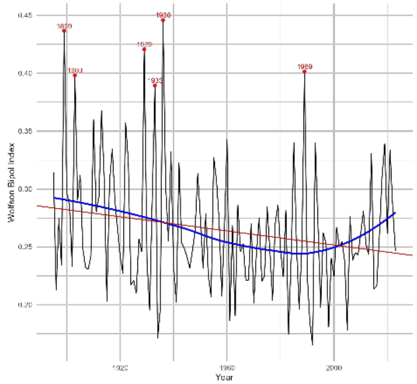
Table 12. Wolfson Polarization Index: Maximum Temperature



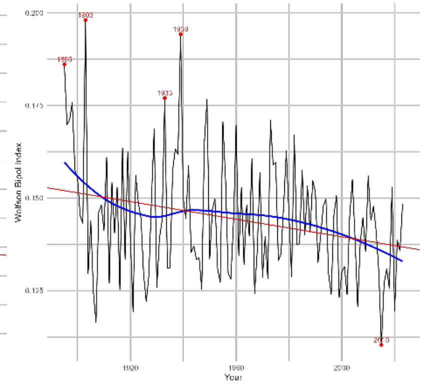
Wolfson Bipol. Index for Max. Temp. Across Entire U.S. in February
(p-value = 0.007206958)



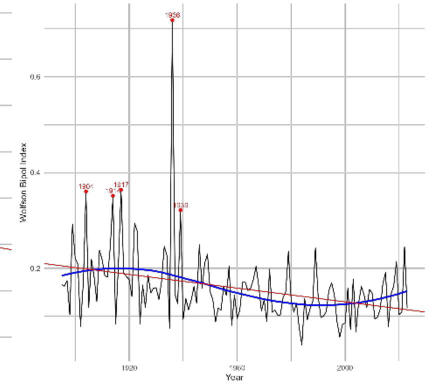
Wolfson Bipol. Index for Max. Temp. Across Western U.S. in February
(p-value = 0.01916722)



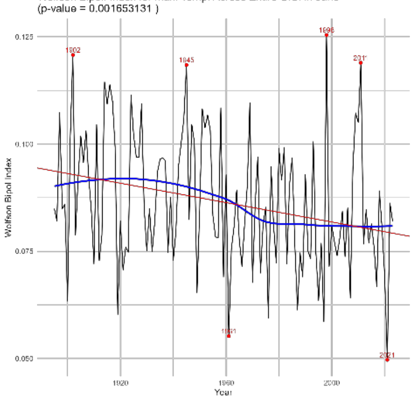
Wolfson Bipol. Index for Max. Temp. Across Arizona in February
(p-value = 0.001802804)



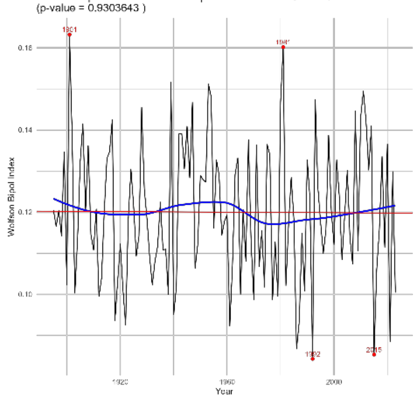
Wolfson Bipol. Index for Max. Temp. Across Minnesota in February
(p-value = 0.00008608273)



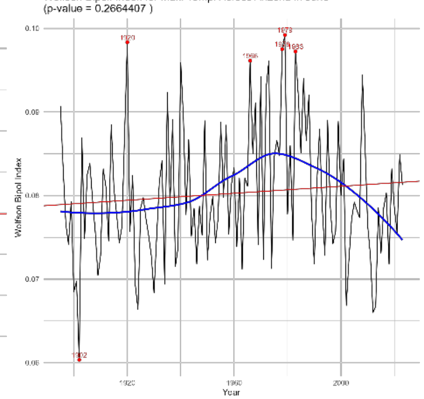
Wolfson Bipol. Index for Max. Temp. Across Entire U.S. in June
(p-value = 0.001653131)



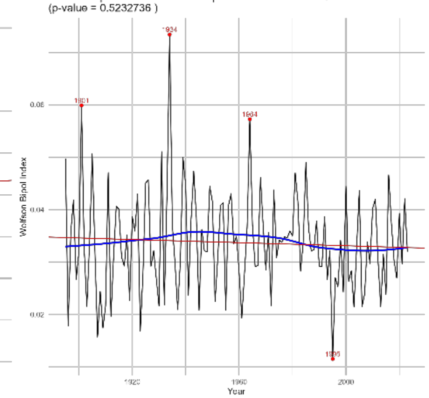
Wolfson Bipol. Index for Max. Temp. Across Western U.S. in June
(p-value = 0.9303643)



Wolfson Bipol. Index for Max. Temp. Across Arizona in June
(p-value = 0.2664407)



Wolfson Bipol. Index for Max. Temp. Across Minnesota in June
(p-value = 0.5232736)



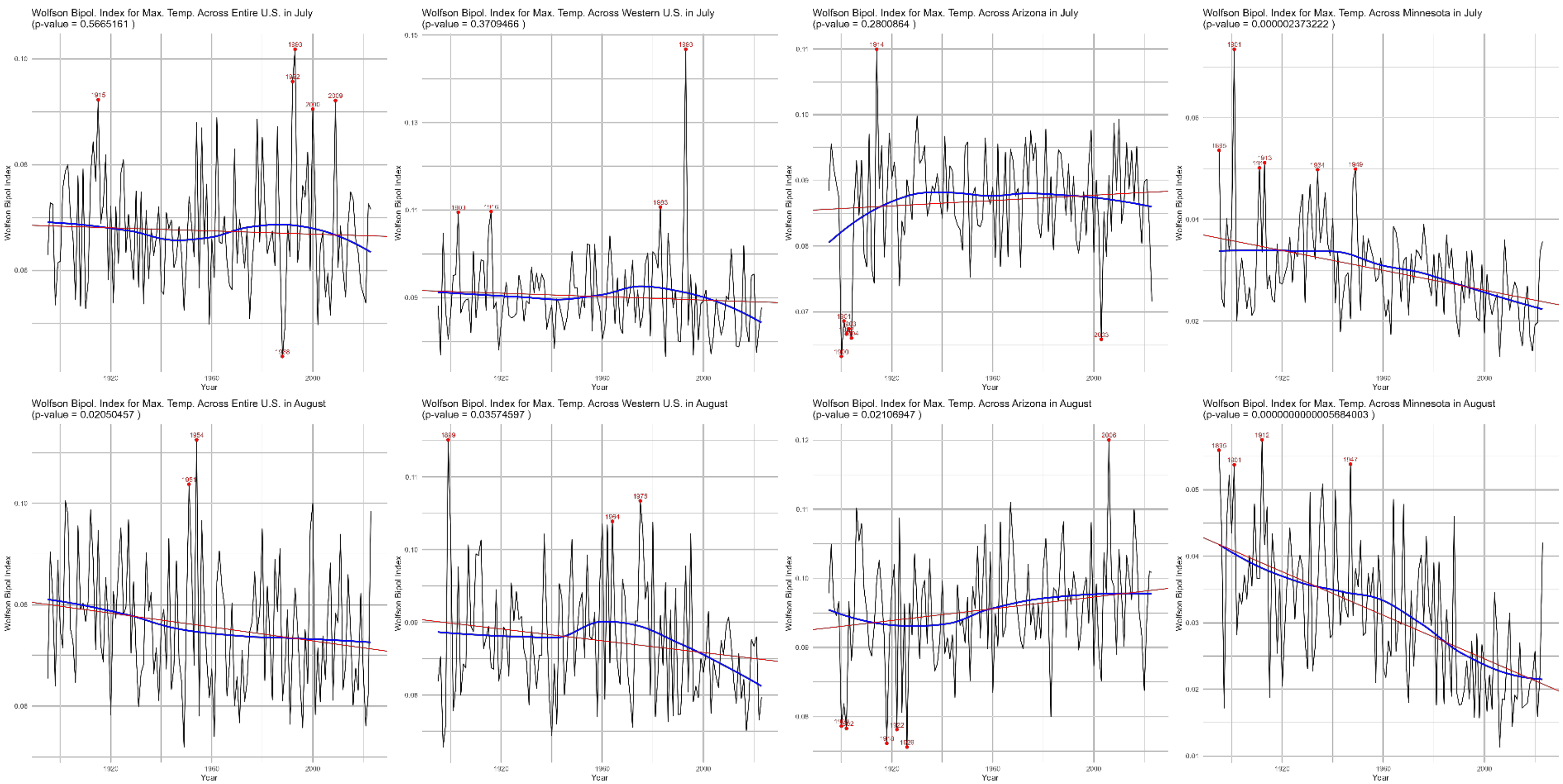
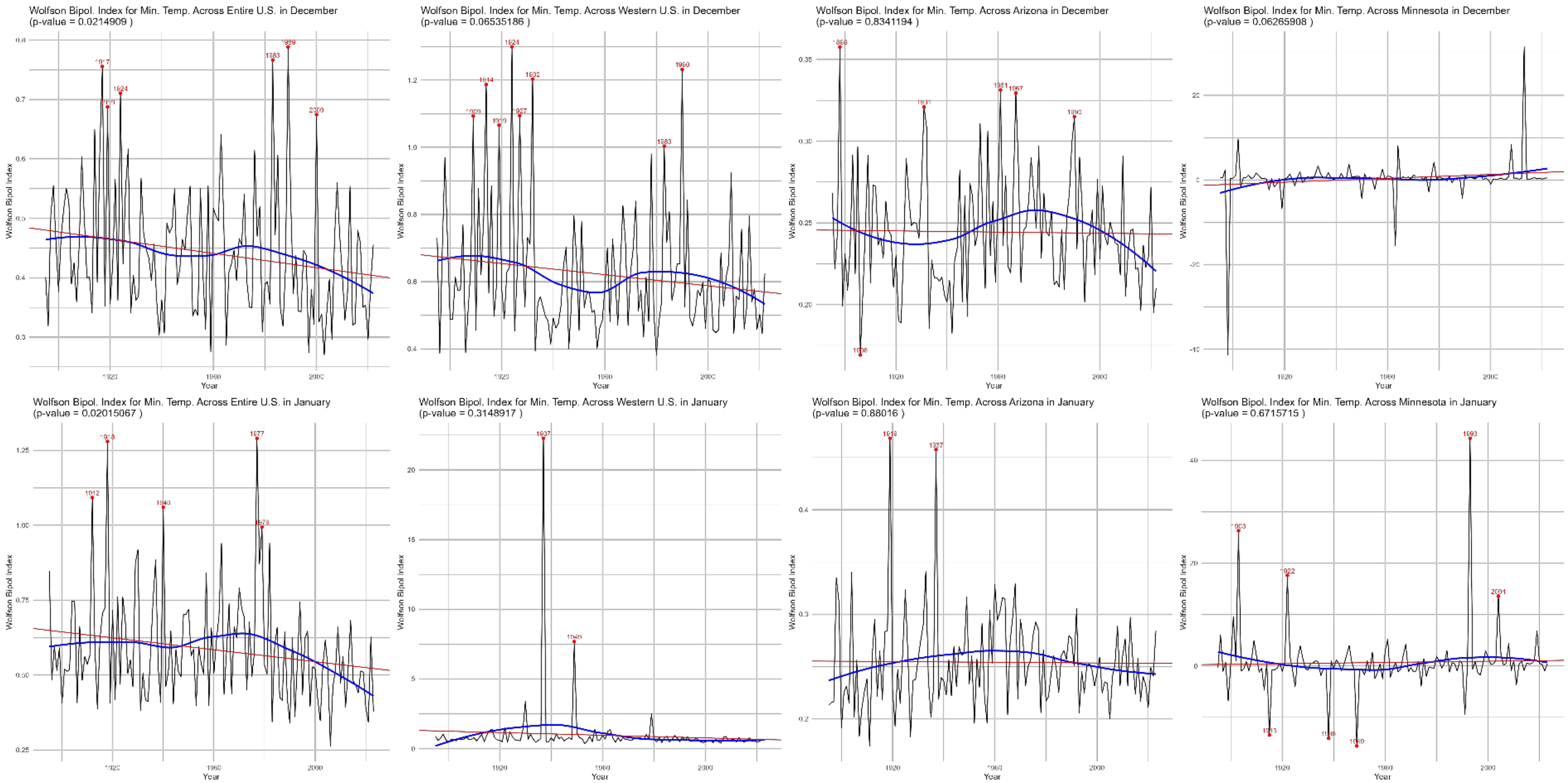
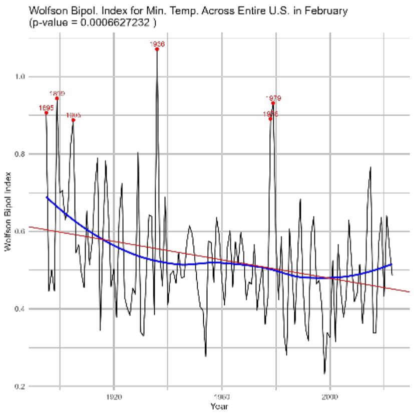
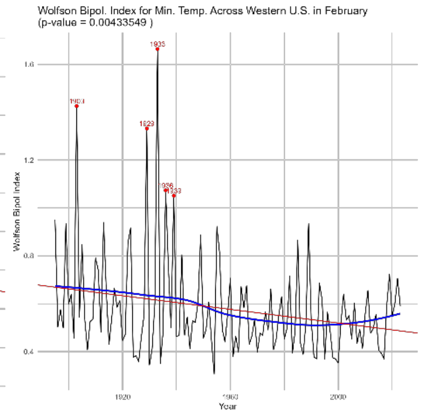
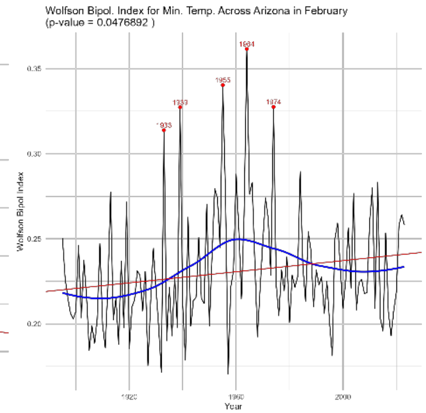

Wolfson Bipol. Index for Max. Temp. Across Entire U.S. in July
(p-value = 0.5665161)
Wolfson Bipol. Index for Max. Temp. Across Western U.S. in July
(p-value = 0.3709466)
Wolfson Bipol. Index for Max. Temp. Across Arizona in July
(p-value = 0.2800864)
Wolfson Bipol. Index for Max. Temp. Across Minnesota in July
(p-value = 0.000002373222)
Wolfson Bipol. Index for Max. Temp. Across Entire U.S. in August
(p-value = 0.02050457)
Wolfson Bipol. Index for Max. Temp. Across Western U.S. in August
(p-value = 0.03574597)
Wolfson Bipol. Index for Max. Temp. Across Arizona in August
(p-value = 0.02106947)
Wolfson Bipol. Index for Max. Temp. Across Minnesota in August
(p-value = 0.0000000000005684003)
Wolfson Bipol Index
Year

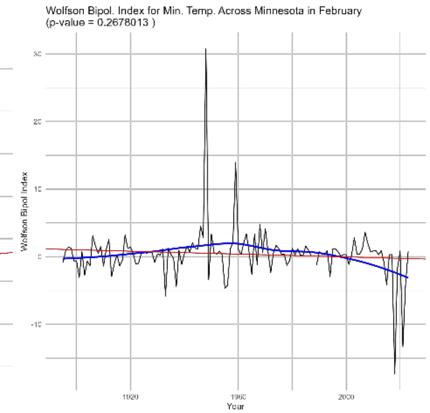
Table 13. Wolfson Polarization Index: Minimum Temperature

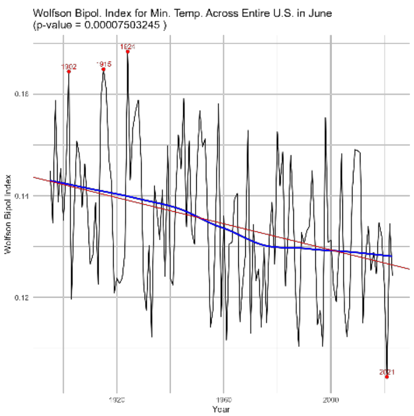


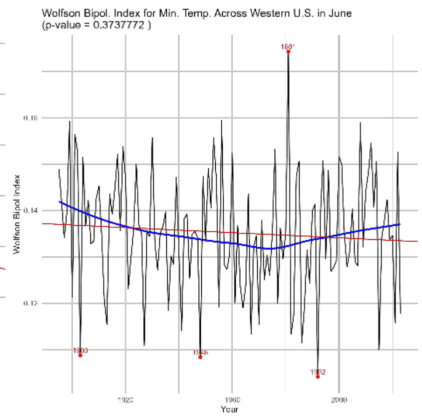

Wolfson Bipol. Index for Min. Temp. Across Entire U.S. in February
(p-value = 0.0006627232)
Wolfson Bipol. Index
Year

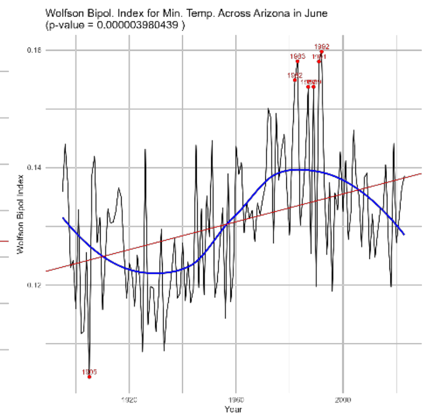

Wolfson Bipol. Index for Min. Temp. Across Western U.S. in February
(p-value = 0.00433549)
Wolfson Bipol. Index
Year

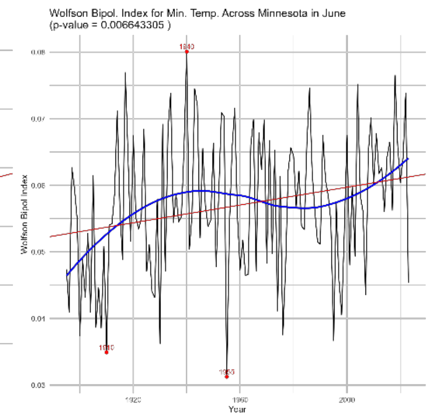

Wolfson Bipol. Index for Min. Temp. Across Arizona in February
(p-value = 0.0476892)
Wolfson Bipol. Index
Year

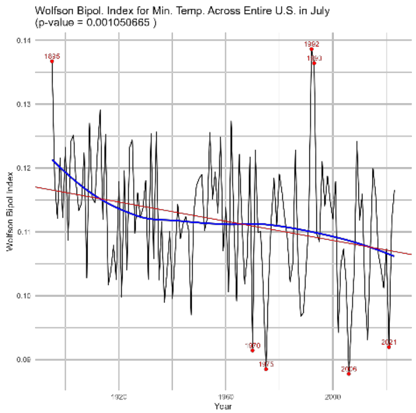

Wolfson Bipol. Index for Min. Temp. Across Minnesota in February
(p-value = 0.2678013)
Wolfson Bipol. Index
Year

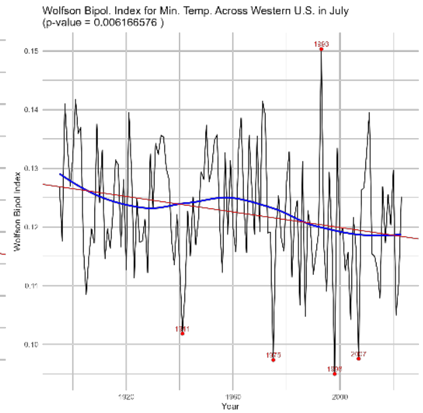

Wolfson Bipol. Index for Min. Temp. Across Entire U.S. in June
(p-value = 0.00007503245)
Wolfson Bipol. Index
Year

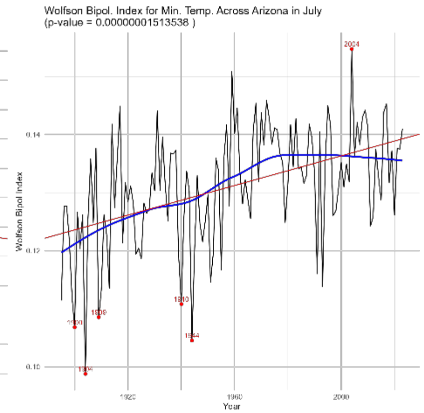

Wolfson Bipol. Index for Min. Temp. Across Western U.S. in June
(p-value = 0.3737772)
Wolfson Bipol. Index
Year

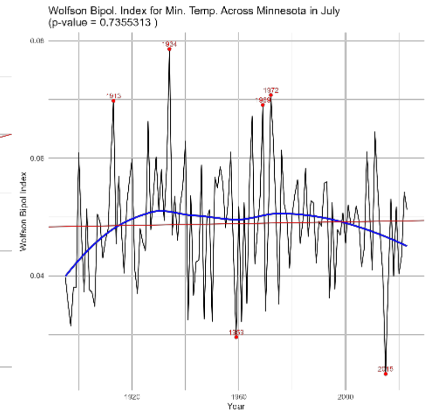

Wolfson Bipol. Index for Min. Temp. Across Arizona in June
(p-value = 0.000003980439)
Wolfson Bipol. Index
Year

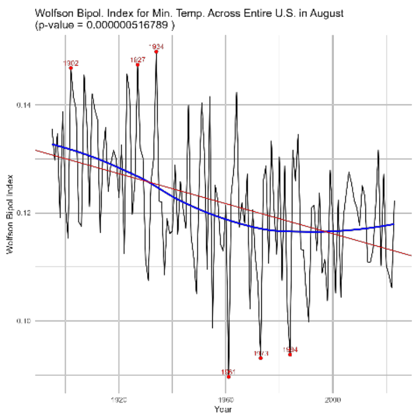

Wolfson Bipol. Index for Min. Temp. Across Minnesota in June
(p-value = 0.006643305)
Wolfson Bipol. Index
Year

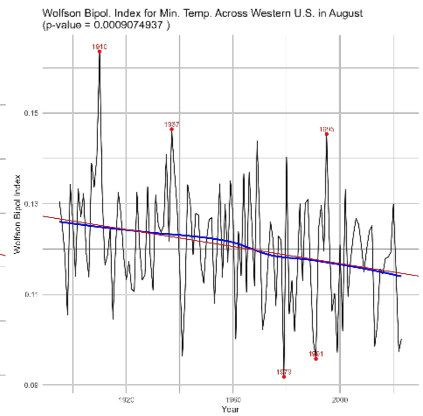

Wolfson Bipol. Index for Min. Temp. Across Entire U.S. in July
(p-value = 0.001050665)
Wolfson Bipol Index
Year

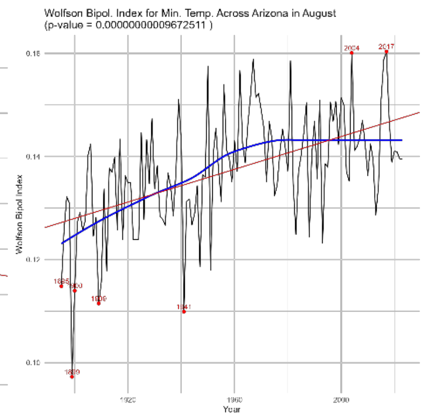

Wolfson Bipol. Index for Min. Temp. Across Western U.S. in July
(p-value = 0.006166576)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Min. Temp. Across Arizona in July
(p-value = 0.00000001513538)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Min. Temp. Across Minnesota in July
(p-value = 0.7355313)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Min. Temp. Across Entire U.S. in August
(p-value = 0.000000516789)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Min. Temp. Across Western U.S. in August
(p-value = 0.0009074937)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Min. Temp. Across Arizona in August
(p-value = 0.0000000009672511)
Wolfson Bipol Index
Year

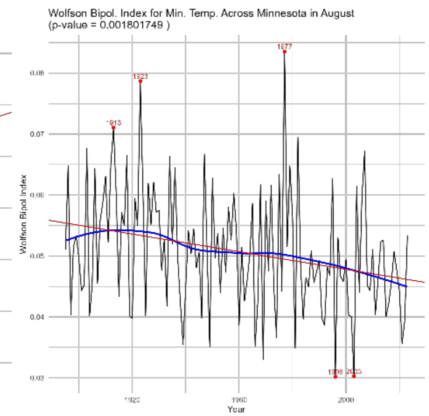
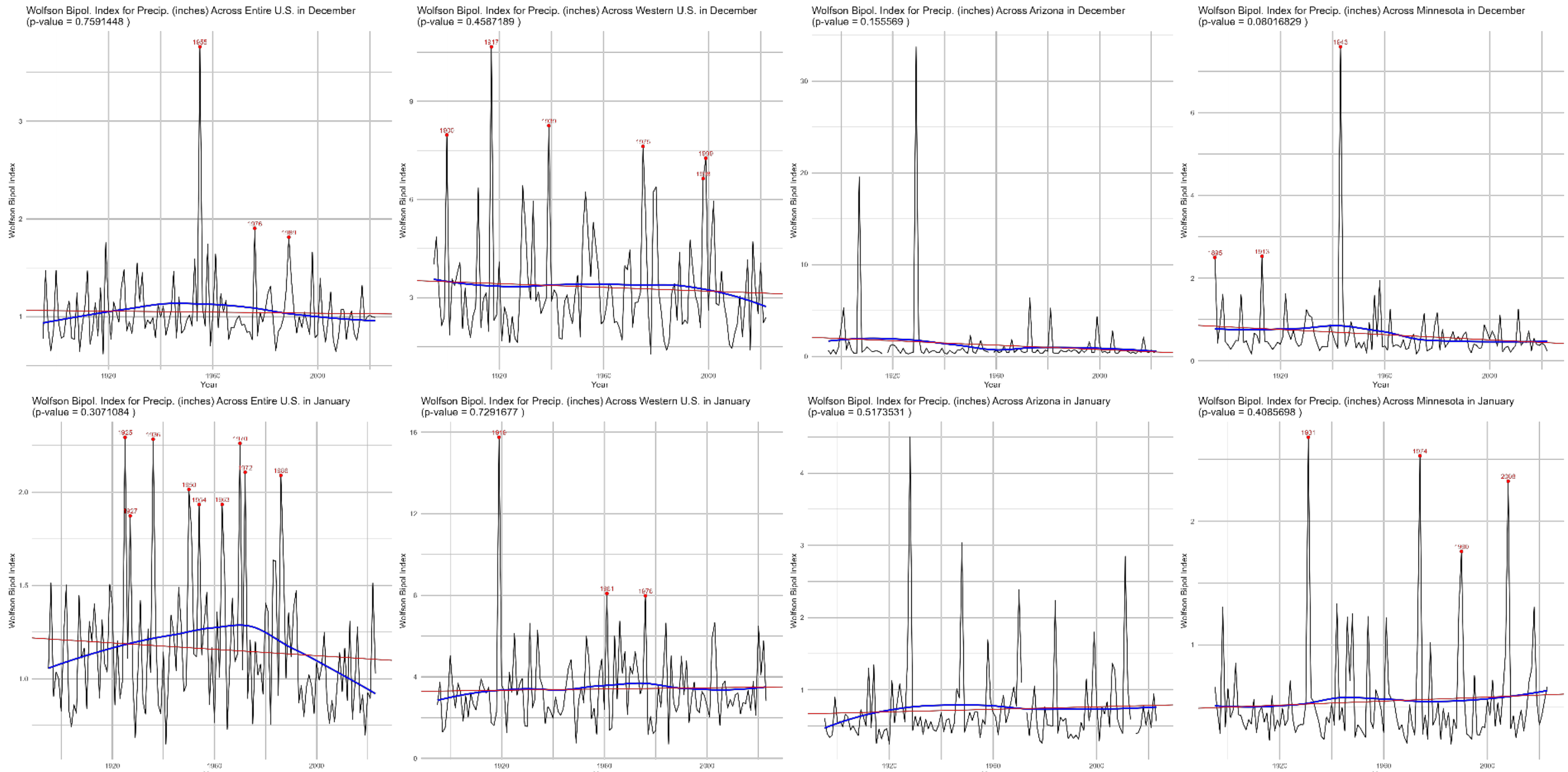
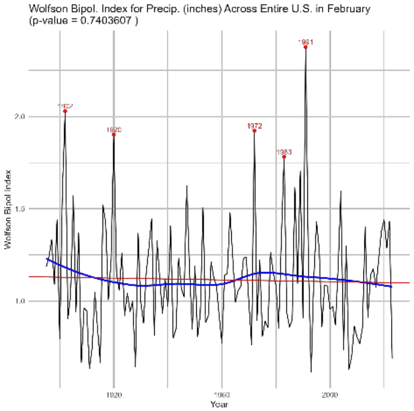
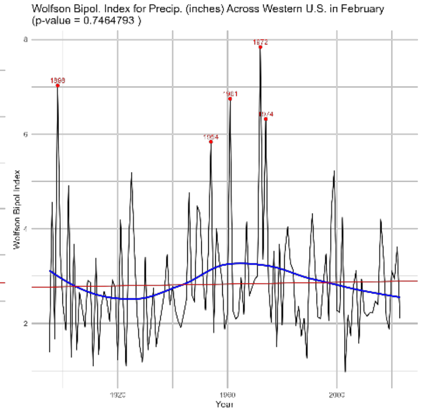
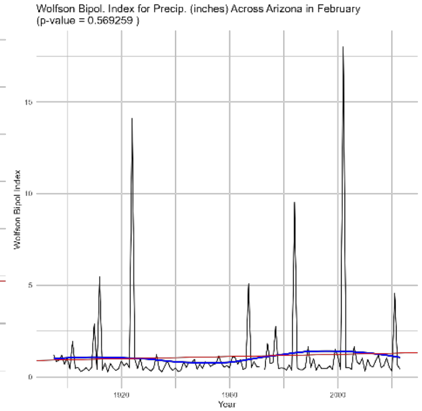

Wolfson Bipol. Index for Min. Temp. Across Minnesota in August
(p-value = 0.001801749)
Wolfson Bipol Index
Year

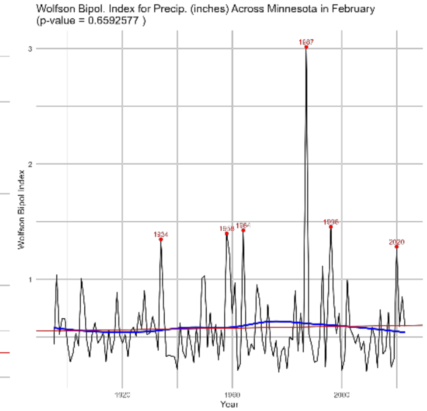
Table 14. Wolfson Polarization Index: Precipitation

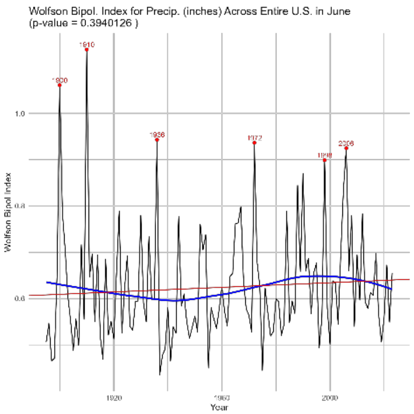


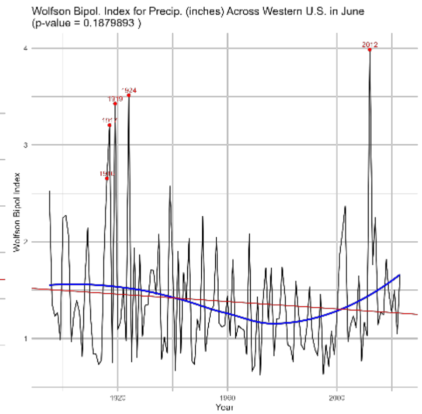

Wolfson Bipol. Index for Precip. (inches) Across Entire U.S. in February
(p-value = 0.7403607)
Wolfson Bipol Index
Year

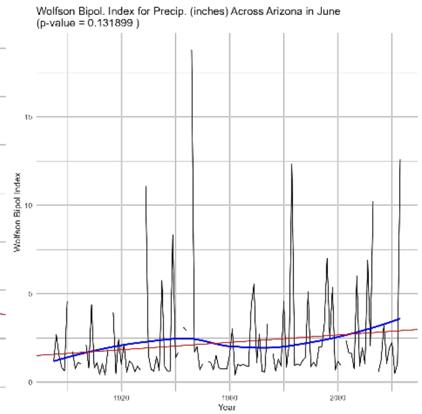

Wolfson Bipol. Index for Precip. (inches) Across Western U.S. in February
(p-value = 0.7464793)
Wolfson Bipol Index
Year

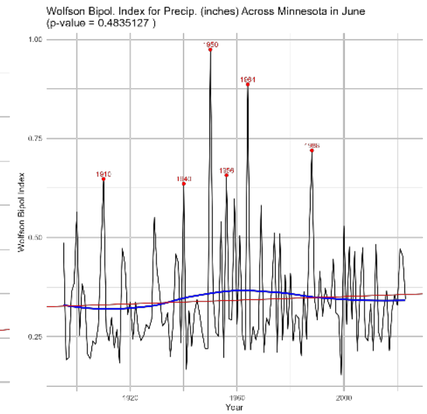

Wolfson Bipol. Index for Precip. (inches) Across Arizona in February
(p-value = 0.569259)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Precip. (inches) Across Minnesota in February
(p-value = 0.6592577)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Precip. (inches) Across Entire U.S. in June
(p-value = 0.3940126)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Precip. (inches) Across Western U.S. in June
(p-value = 0.1879893)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Precip. (inches) Across Arizona in June
(p-value = 0.131899)
Wolfson Bipol Index
Year


Wolfson Bipol. Index for Precip. (inches) Across Minnesota in June
(p-value = 0.4835127)
Wolfson Bipol Index
Year

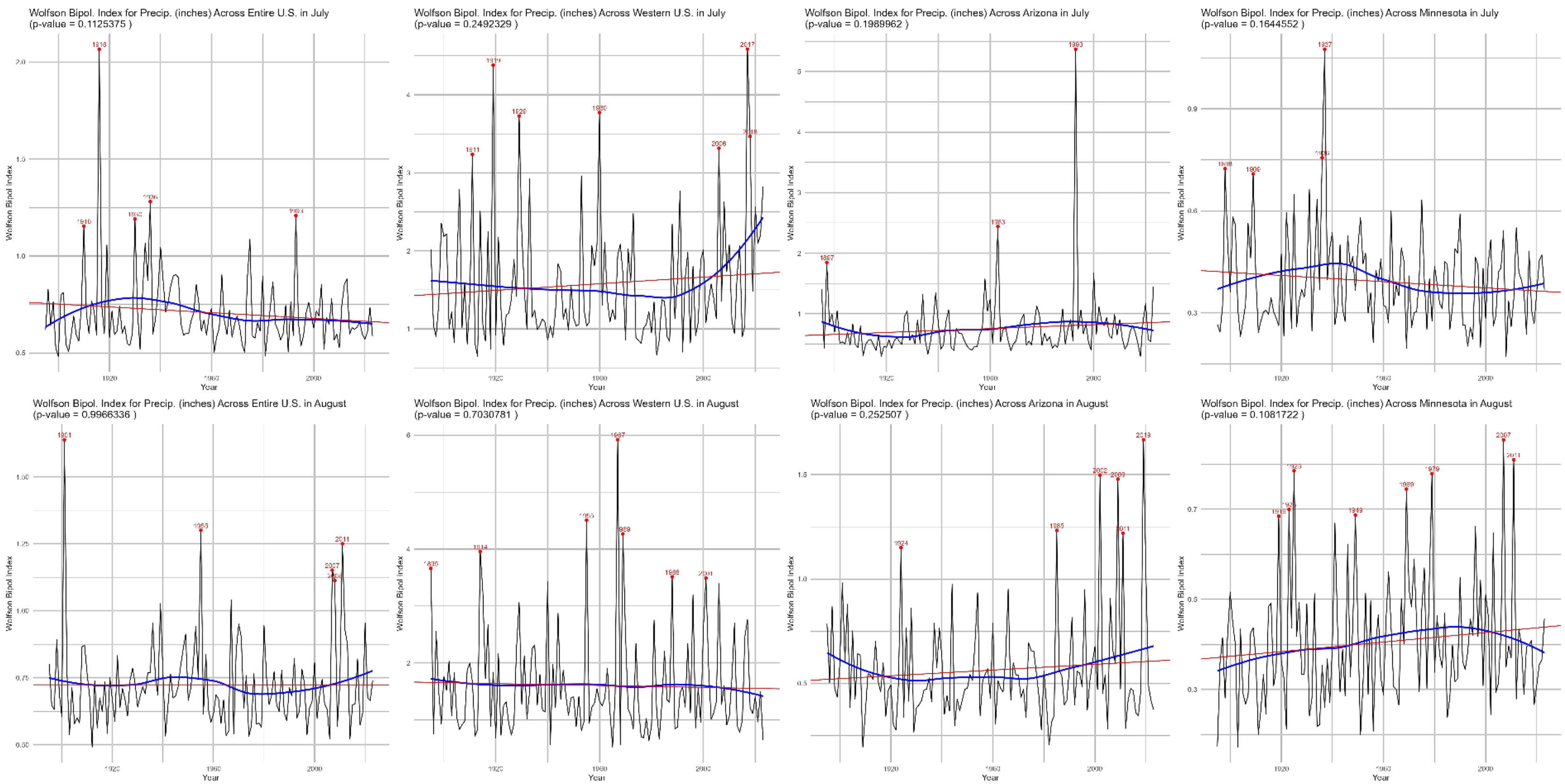
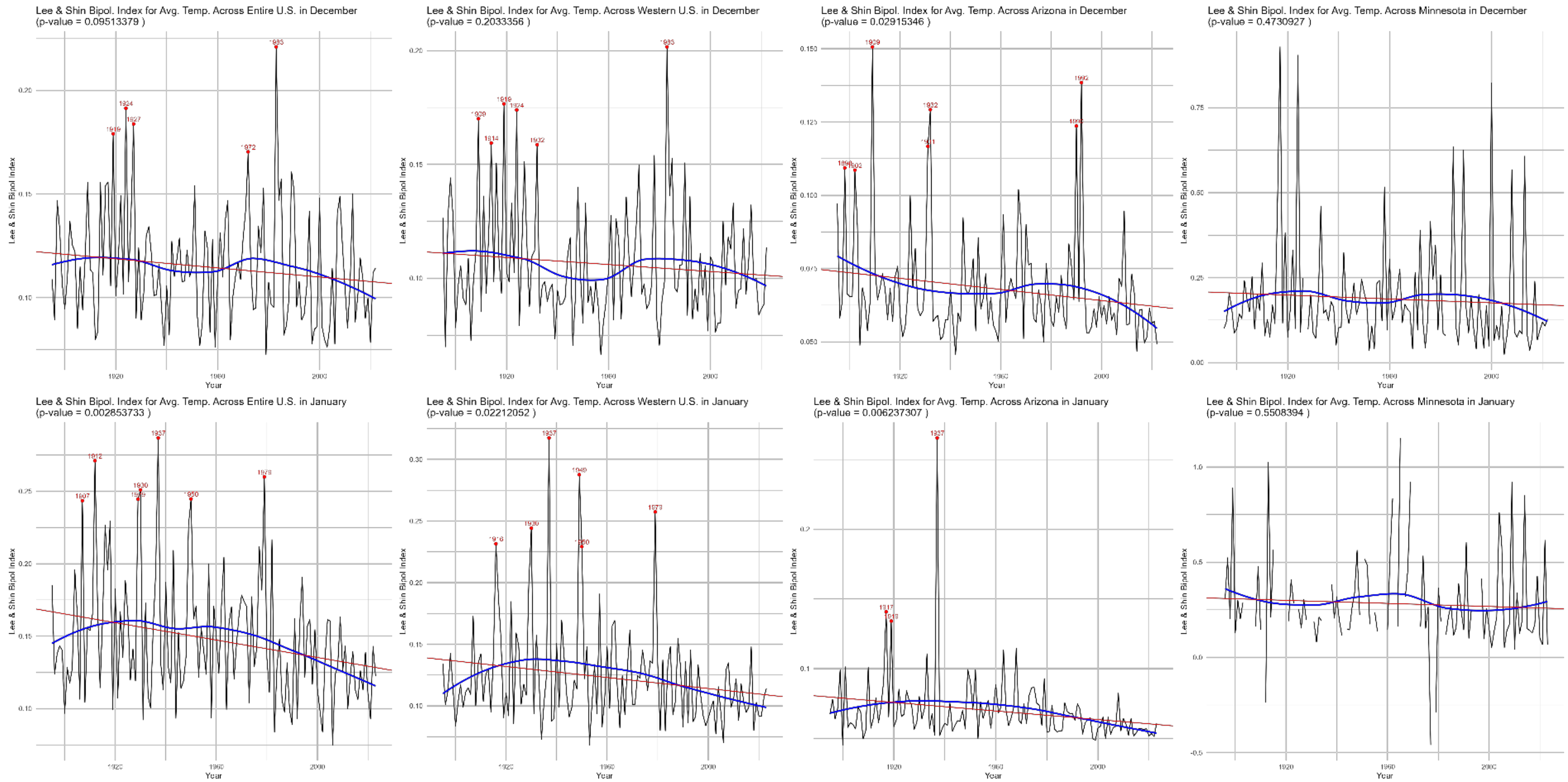
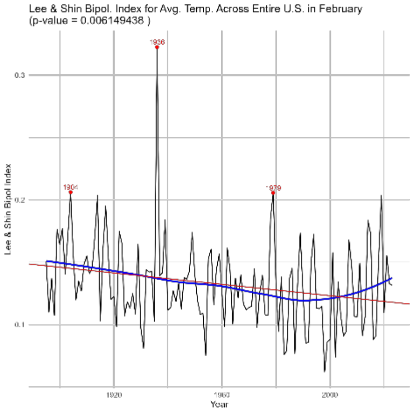
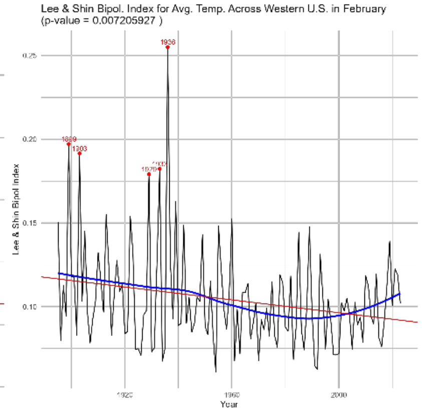
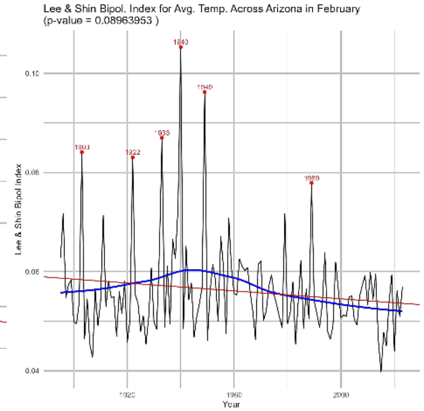

Wolfson Bipol. Index for Precip. (inches) Across Entire U.S. in July
(p-value = 0.1125375)
Wolfson Bipol. Index for Precip. (inches) Across Western U.S. in July
(p-value = 0.2492329)
Wolfson Bipol. Index for Precip. (inches) Across Arizona in July
(p-value = 0.1989962)
Wolfson Bipol. Index for Precip. (inches) Across Minnesota in July
(p-value = 0.1644552)
Wolfson Bipol. Index for Precip. (inches) Across Entire U.S. in August
(p-value = 0.9966336)
Wolfson Bipol. Index for Precip. (inches) Across Western U.S. in August
(p-value = 0.7030781)
Wolfson Bipol. Index for Precip. (inches) Across Arizona in August
(p-value = 0.252507)
Wolfson Bipol. Index for Precip. (inches) Across Minnesota in August
(p-value = 0.1081722)
Wolfson Bipol Index
Year

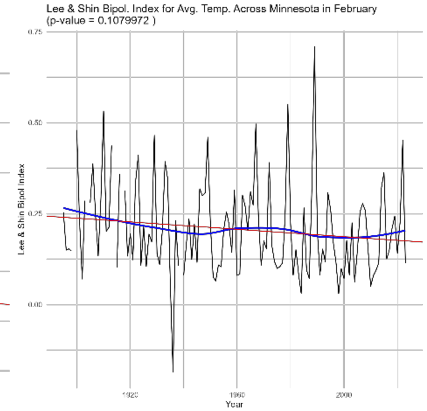
Table 15. Lee & Shin Index: Average Temperature

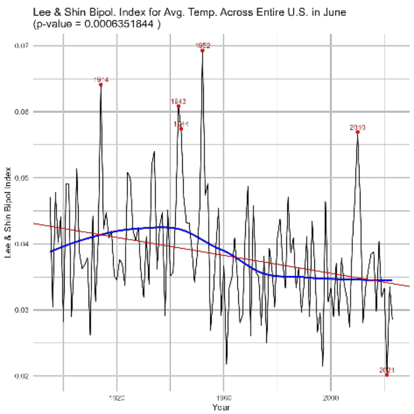


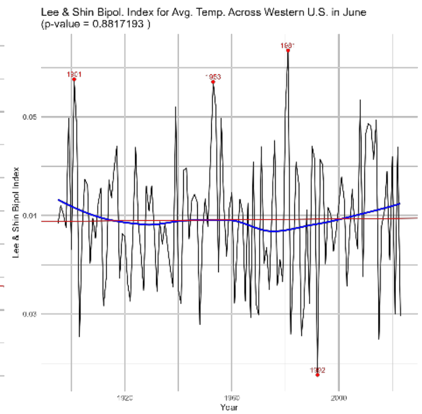

Lee & Shin Bipol. Index for Avg. Temp. Across Entire U.S. in February
(p-value = 0.006149438)
Lee & Shin Bipol Index
Year

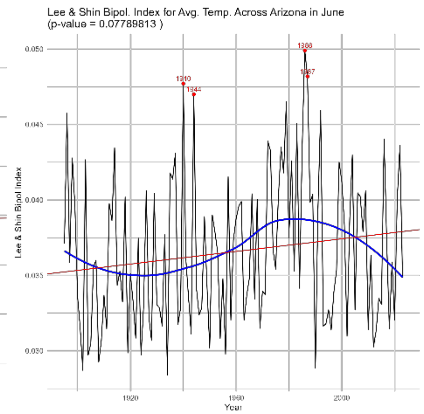

Lee & Shin Bipol. Index for Avg. Temp. Across Western U.S. in February
(p-value = 0.007205927)
Lee & Shin Bipol Index
Year

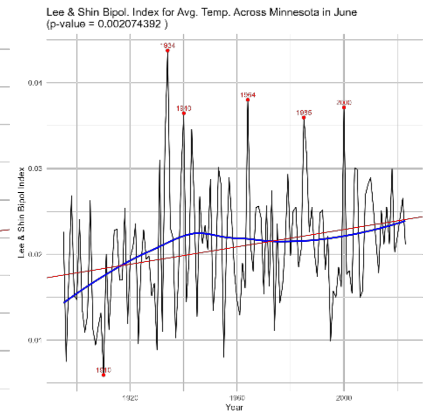

Lee & Shin Bipol. Index for Avg. Temp. Across Arizona in February
(p-value = 0.08963953)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Avg. Temp. Across Minnesota in February
(p-value = 0.1079972)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Avg. Temp. Across Entire U.S. in June
(p-value = 0.0006351844)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Avg. Temp. Across Western U.S. in June
(p-value = 0.8817193)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Avg. Temp. Across Arizona in June
(p-value = 0.07789813)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Avg. Temp. Across Minnesota in June
(p-value = 0.002074392)
Lee & Shin Bipol Index
Year

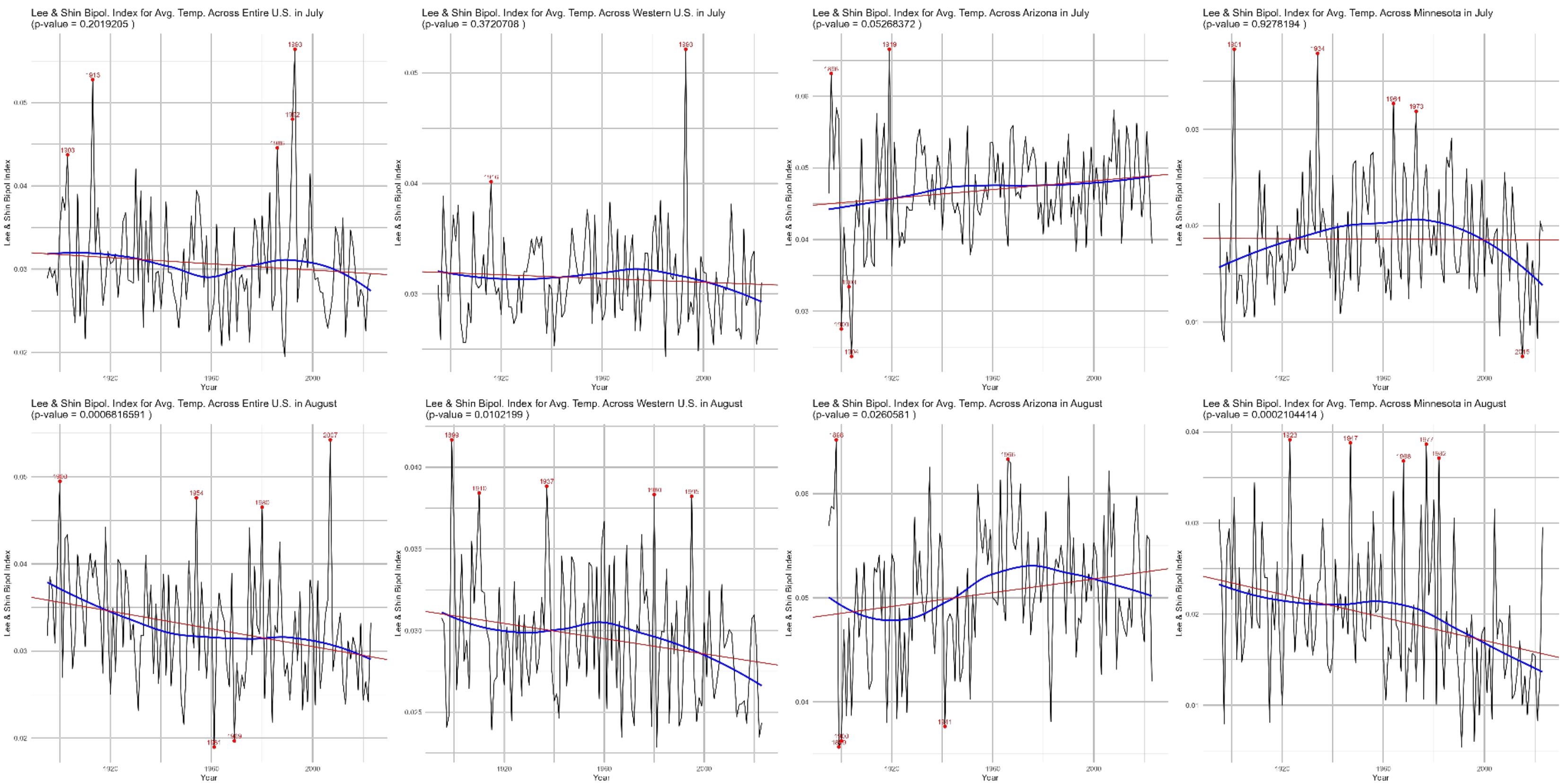
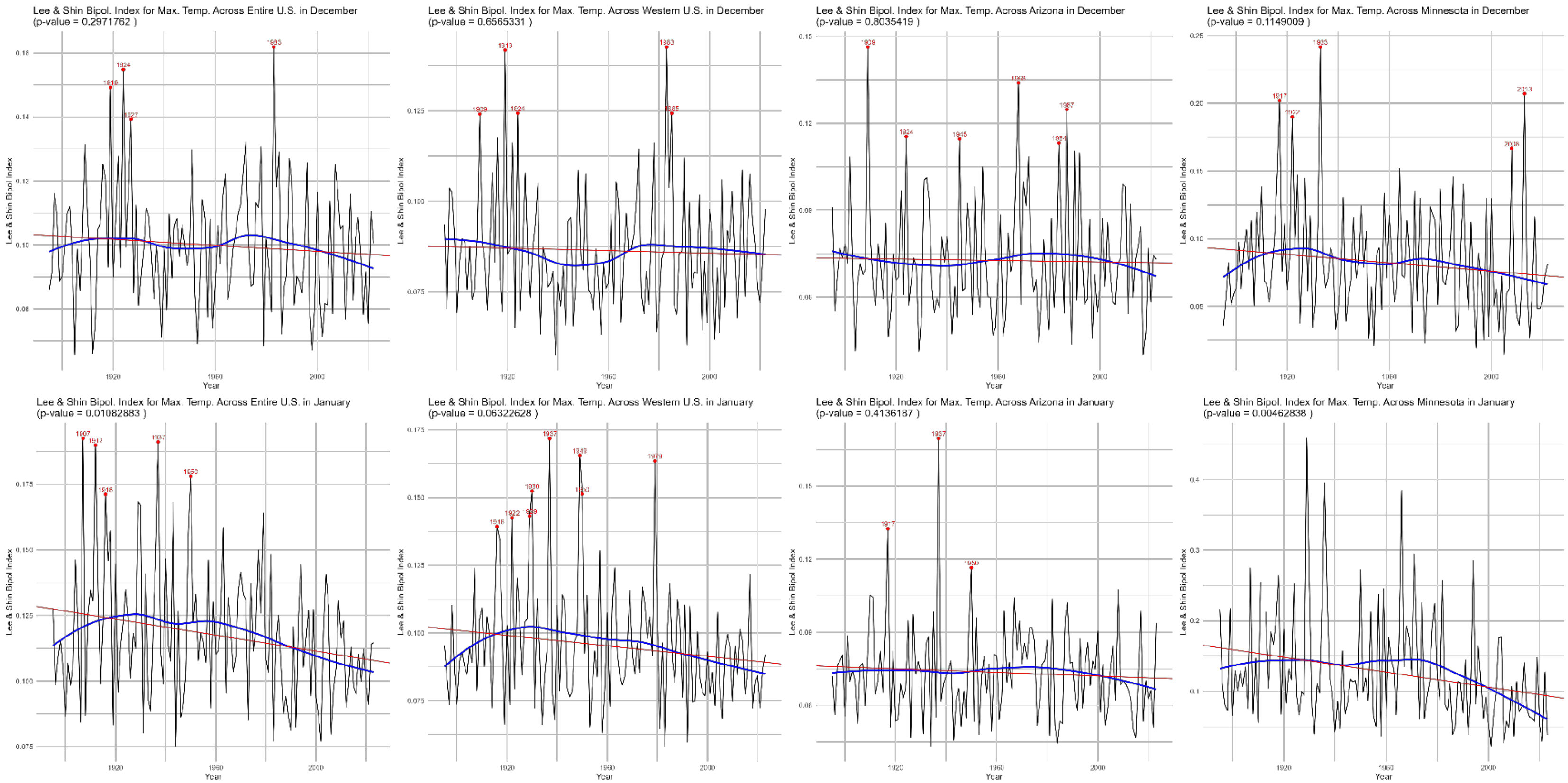
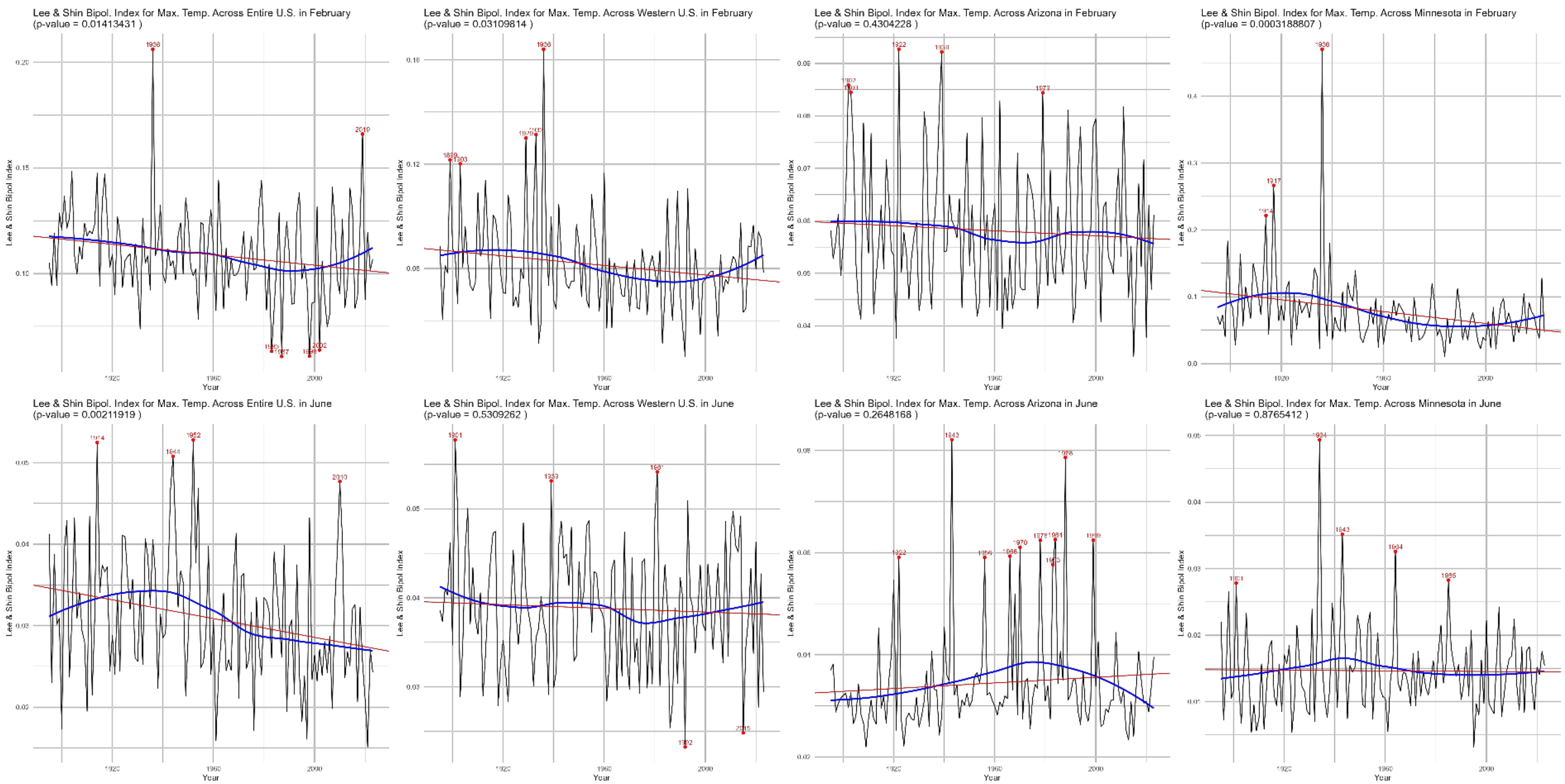
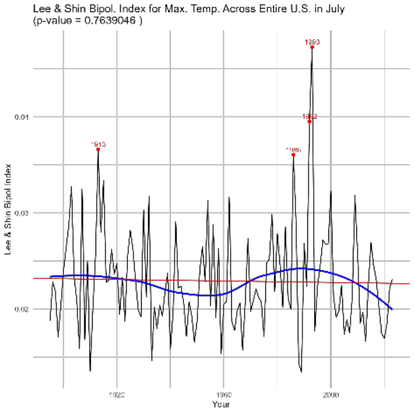
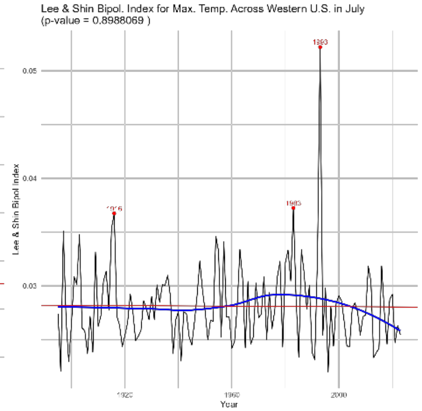

Lee & Shin Bipol. Index for Avg. Temp. Across Entire U.S. in July
(p-value = 0.2019205)
Lee & Shin Bipol. Index for Avg. Temp. Across Western U.S. in July
(p-value = 0.3720708)
Lee & Shin Bipol. Index for Avg. Temp. Across Arizona in July
(p-value = 0.05268372)
Lee & Shin Bipol. Index for Avg. Temp. Across Minnesota in July
(p-value = 0.9278194)
Lee & Shin Bipol. Index for Avg. Temp. Across Entire U.S. in August
(p-value = 0.0006816591)
Lee & Shin Bipol. Index for Avg. Temp. Across Western U.S. in August
(p-value = 0.0102199)
Lee & Shin Bipol. Index for Avg. Temp. Across Arizona in August
(p-value = 0.0260581)
Lee & Shin Bipol. Index for Avg. Temp. Across Minnesota in August
(p-value = 0.0002104414)
Lee & Shin Bipol Index
Year

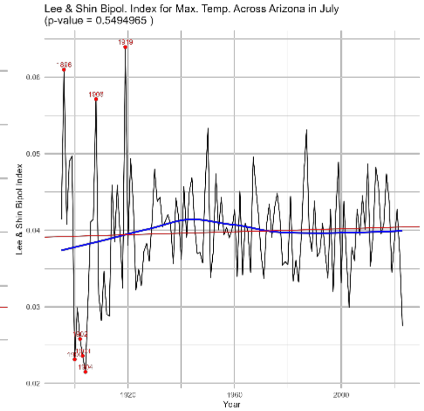
Table 16. Lee & Shin Index: Maximum Temperature

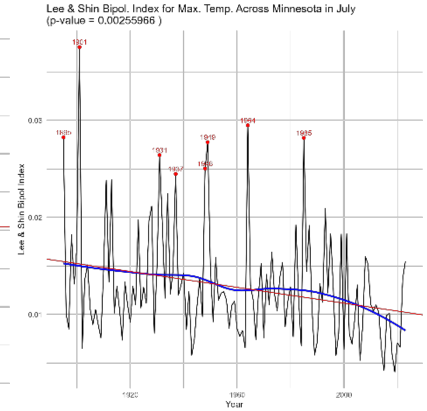


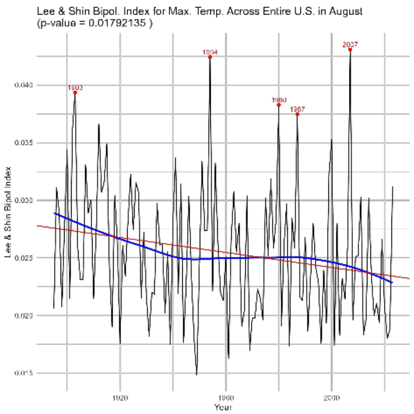

Lee & Shin Bipol. Index for Max. Temp. Across Entire U.S. in February
(p-value = 0.01413431)
Lee & Shin Bipol. Index for Max. Temp. Across Western U.S. in February
(p-value = 0.03109814)
Lee & Shin Bipol. Index for Max. Temp. Across Arizona in February
(p-value = 0.4304228)
Lee & Shin Bipol. Index for Max. Temp. Across Minnesota in February
(p-value = 0.0003188807)
Lee & Shin Bipol. Index for Max. Temp. Across Entire U.S. in June
(p-value = 0.00211919)
Lee & Shin Bipol. Index for Max. Temp. Across Western U.S. in June
(p-value = 0.5309262)
Lee & Shin Bipol. Index for Max. Temp. Across Arizona in June
(p-value = 0.2648168)
Lee & Shin Bipol. Index for Max. Temp. Across Minnesota in June
(p-value = 0.8765412)
Lee & Shin Bipol Index
Year

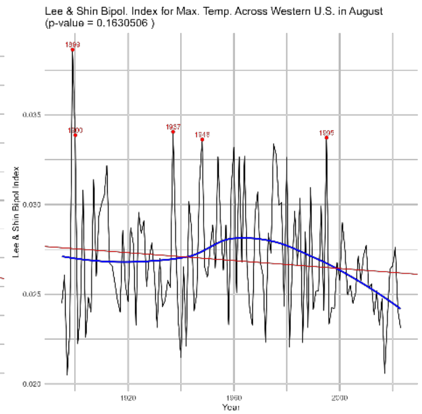

Lee & Shin Bipol. Index for Max. Temp. Across Entire U.S. in July
(p-value = 0.7639046)
Lee & Shin Bipol Index
Year

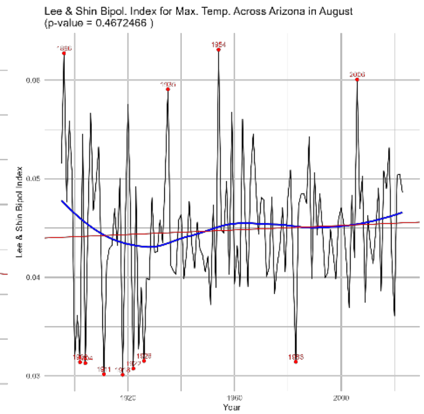

Lee & Shin Bipol. Index for Max. Temp. Across Western U.S. in July
(p-value = 0.8988069)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Max. Temp. Across Arizona in July
(p-value = 0.5494965)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Max. Temp. Across Minnesota in July
(p-value = 0.00255966)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Max. Temp. Across Entire U.S. in August
(p-value = 0.01792135)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Max. Temp. Across Western U.S. in August
(p-value = 0.1630506)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Max. Temp. Across Arizona in August
(p-value = 0.4672466)
Lee & Shin Bipol Index
Year

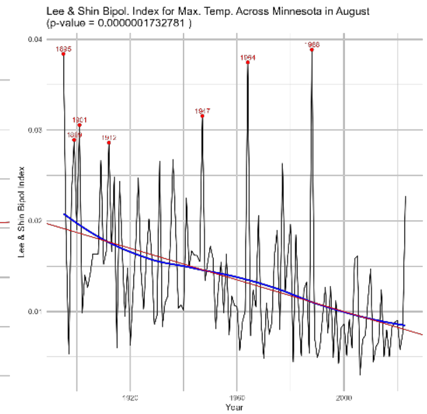
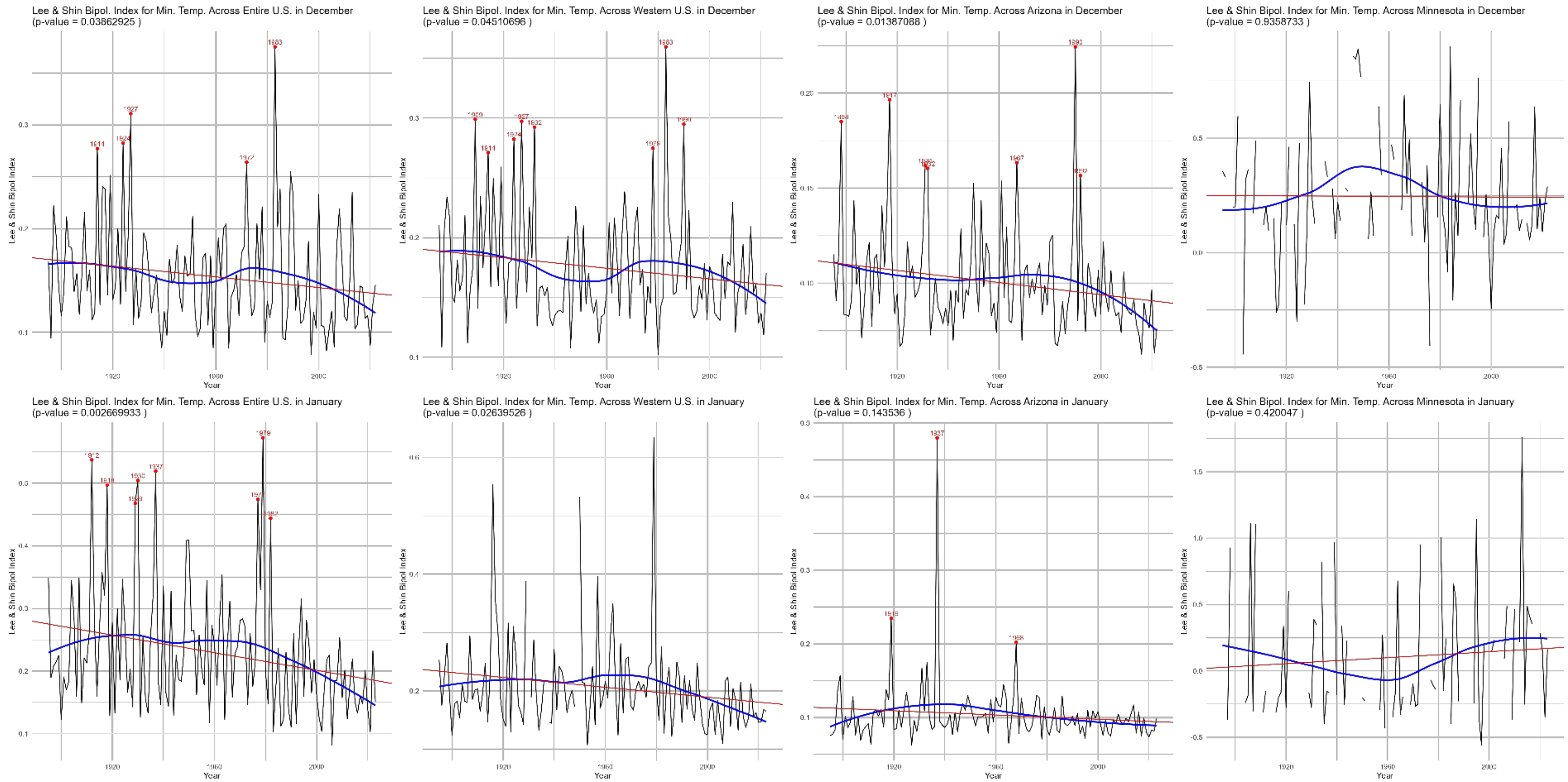
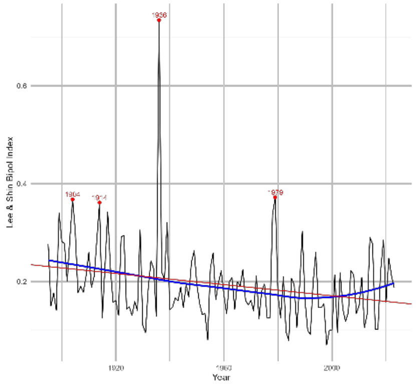

Lee & Shin Bipol. Index for Max. Temp. Across Minnesota in August
(p-value = 0.0000001732781)
Lee & Shin Bipol Index
Year

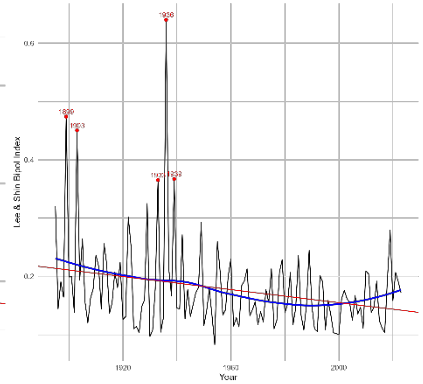
Table 17. Lee & Shin Index: Minimum Temperature



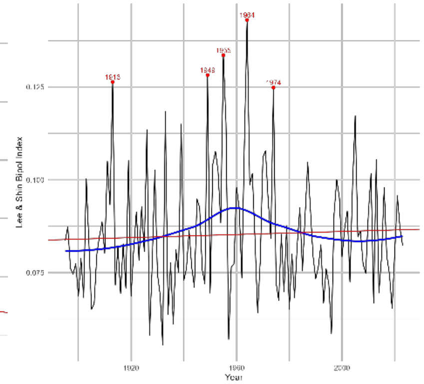
Lee & Shin Bipol. Index for Min. Temp. Across Entire U.S. in February
(p-value = 0.003243562)



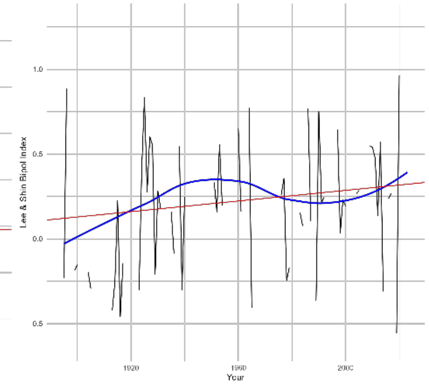
Lee & Shin Bipol. Index for Min. Temp. Across Western U.S. in February
(p-value = 0.002125561)



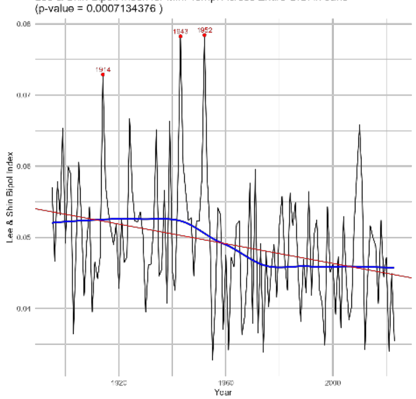
Lee & Shin Bipol. Index for Min. Temp. Across Arizona in February
(p-value = 0.6050226)



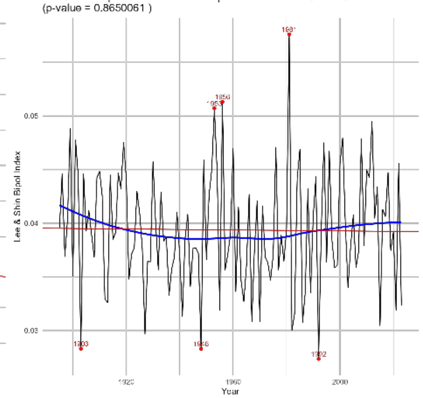
Lee & Shin Bipol. Index for Min. Temp. Across Minnesota in February
(p-value = 0.2075552)



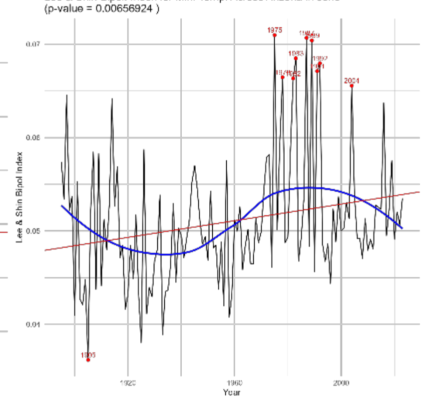
Lee & Shin Bipol. Index for Min. Temp. Across Entire U.S. in June
(p-value = 0.0007134376)



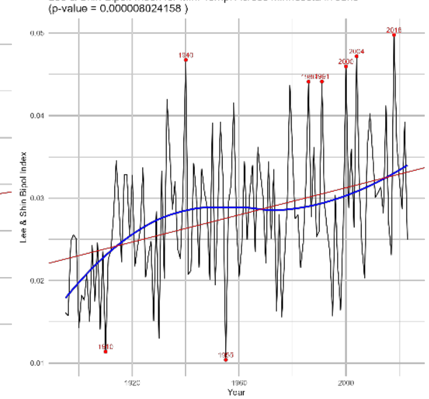
Lee & Shin Bipol. Index for Min. Temp. Across Western U.S. in June
(p-value = 0.8650061)



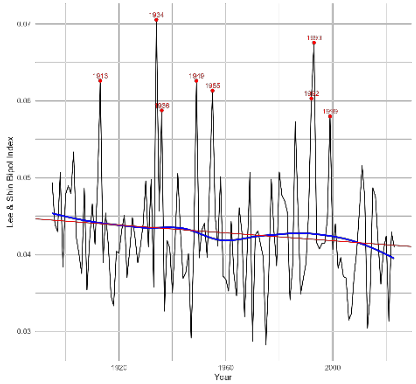
Lee & Shin Bipol. Index for Min. Temp. Across Arizona in June
(p-value = 0.00656924)



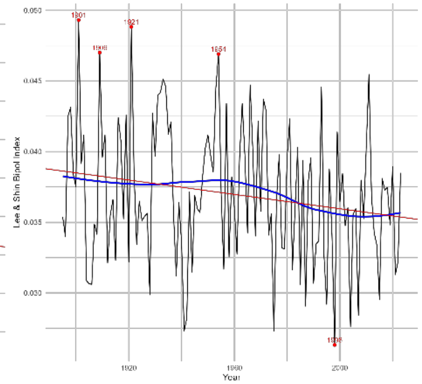
Lee & Shin Bipol. Index for Min. Temp. Across Minnesota in June
(p-value = 0.000008024158)



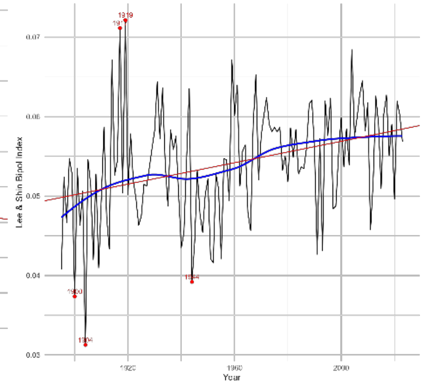
Lee & Shin Bipol. Index for Min. Temp. Across Entire U.S. in July
(p-value = 0.1532113)



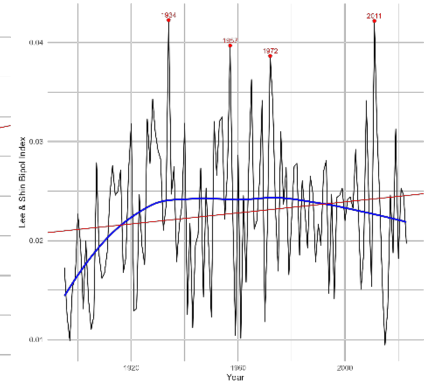
Lee & Shin Bipol. Index for Min. Temp. Across Western U.S. in July
(p-value = 0.02782149)



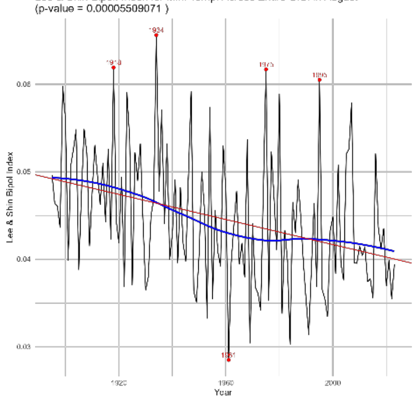
Lee & Shin Bipol. Index for Min. Temp. Across Arizona in July
(p-value = 0.00004635058)



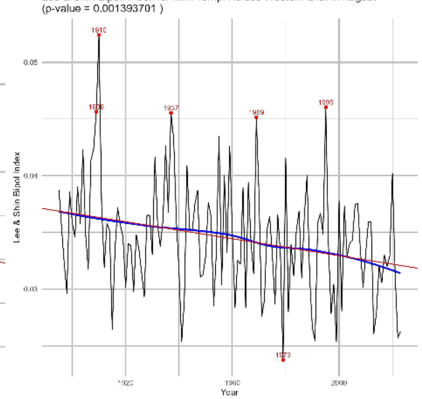
Lee & Shin Bipol. Index for Min. Temp. Across Minnesota in July
(p-value = 0.09464392)



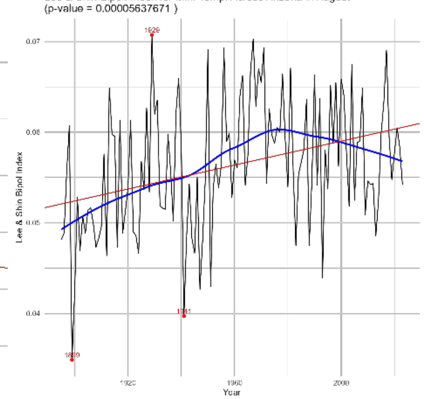
Lee & Shin Bipol. Index for Min. Temp. Across Entire U.S. in August
(p-value = 0.00005509071)



Lee & Shin Bipol. Index for Min. Temp. Across Western U.S. in August
(p-value = 0.001393701)



Lee & Shin Bipol. Index for Min. Temp. Across Arizona in August
(p-value = 0.00005637671)



Lee & Shin Bipol. Index for Min. Temp. Across Minnesota in August
(p-value = 0.04453515)

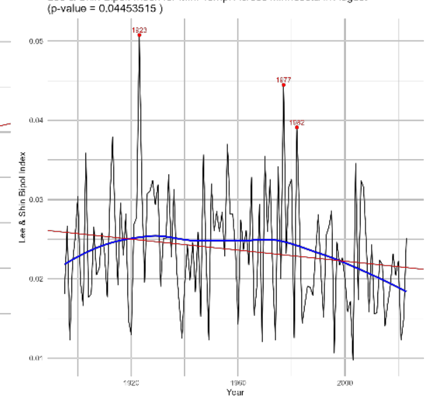
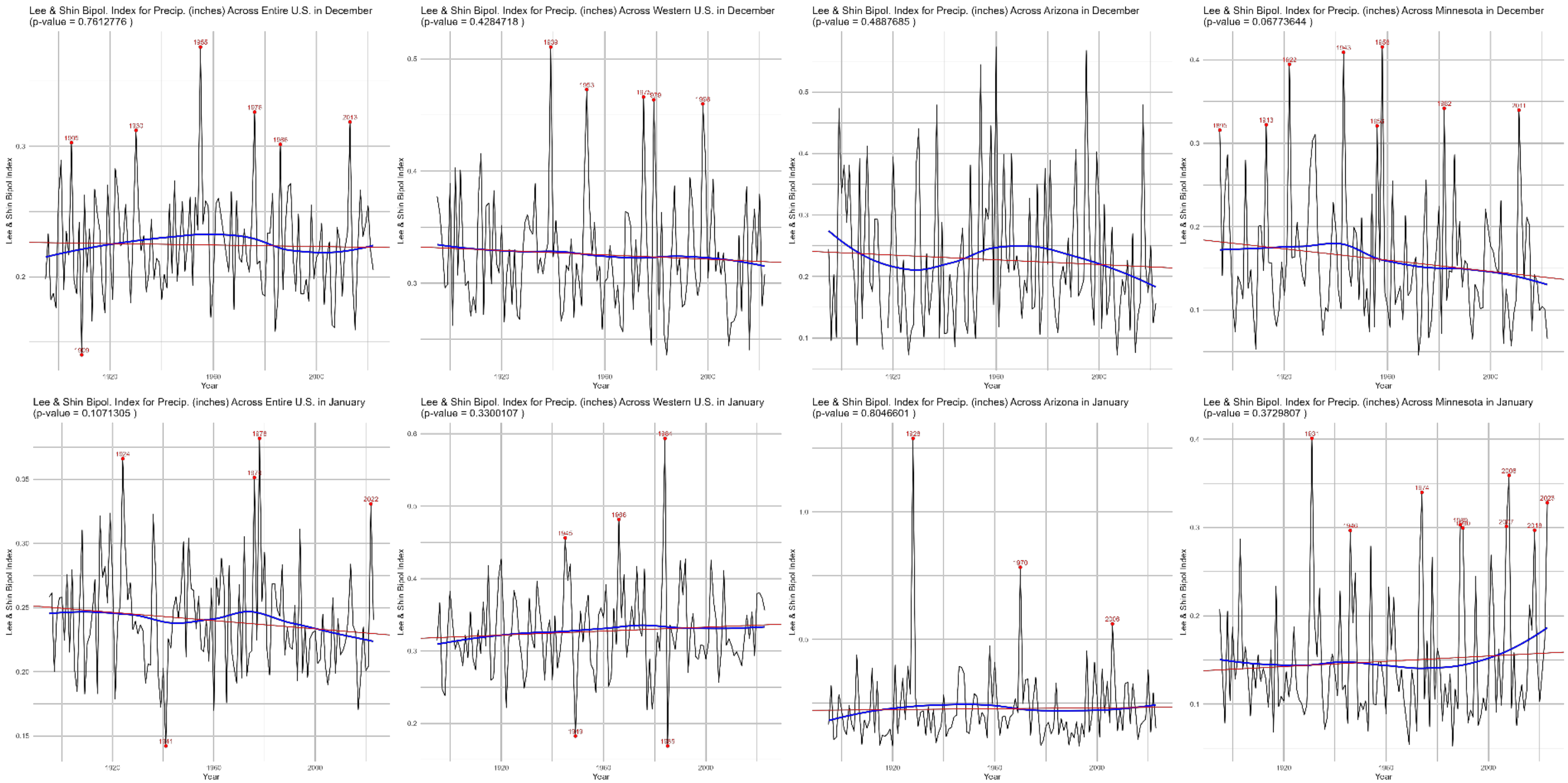
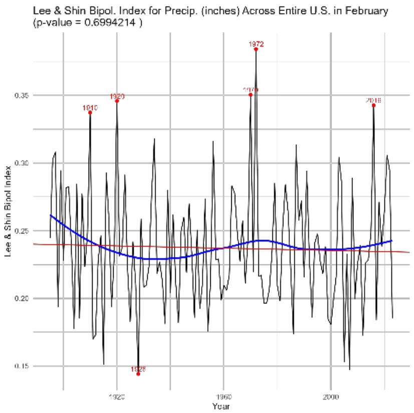
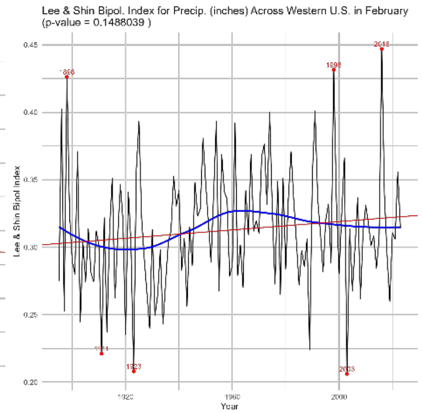
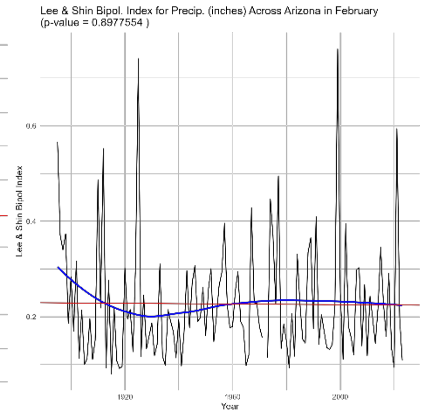


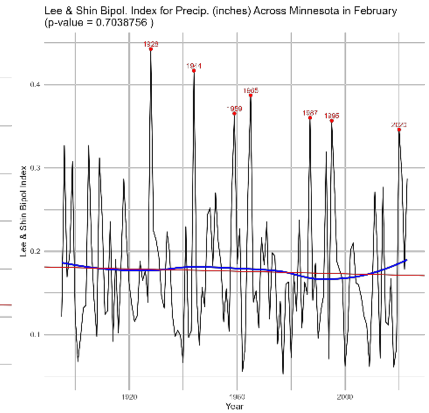
Table 18. Lee & Shin Index: Precipitation

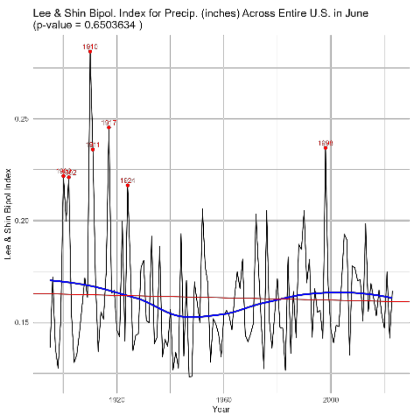


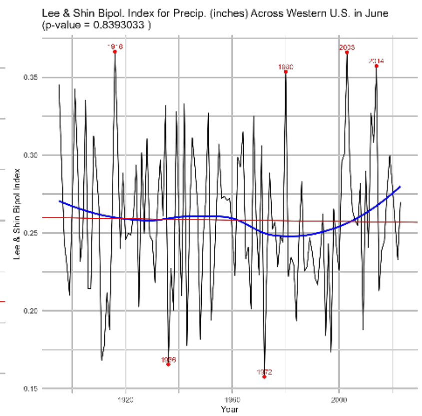

Lee & Shin Bipol. Index for Precip. (inches) Across Entire U.S. in February
(p-value = 0.6994214)
Lee & Shin Bipol Index
Year

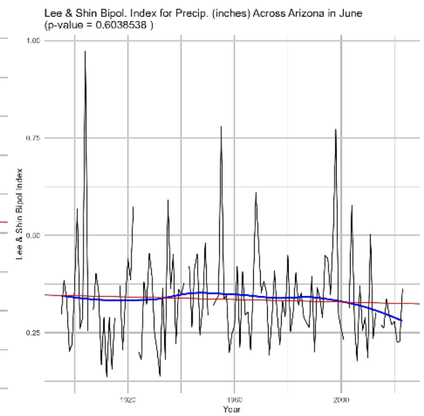

Lee & Shin Bipol. Index for Precip. (inches) Across Western U.S. in February
(p-value = 0.1488039)
Lee & Shin Bipol Index
Year

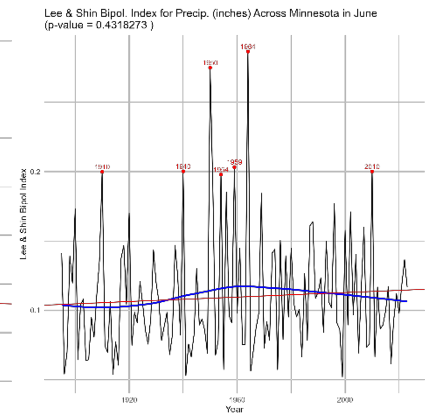

Lee & Shin Bipol. Index for Precip. (inches) Across Arizona in February
(p-value = 0.8977554)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Precip. (inches) Across Minnesota in February
(p-value = 0.7038756)
Lee & Shin Bipol Index
Year

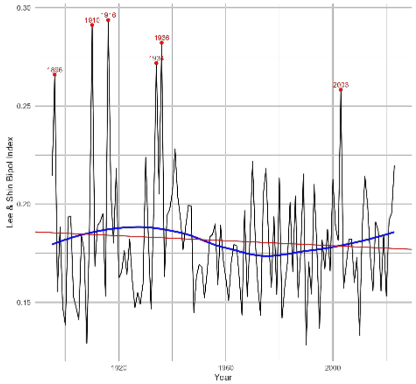

Lee & Shin Bipol. Index for Precip. (inches) Across Entire U.S. in June
(p-value = 0.6503634)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Precip. (inches) Across Western U.S. in June
(p-value = 0.8393033)
Lee & Shin Bipol Index
Year

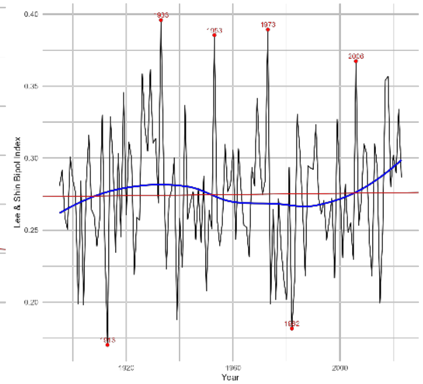

Lee & Shin Bipol. Index for Precip. (inches) Across Arizona in June
(p-value = 0.6038538)
Lee & Shin Bipol Index
Year


Lee & Shin Bipol. Index for Precip. (inches) Across Minnesota in June
(p-value = 0.4318273)
Lee & Shin Bipol Index
Year

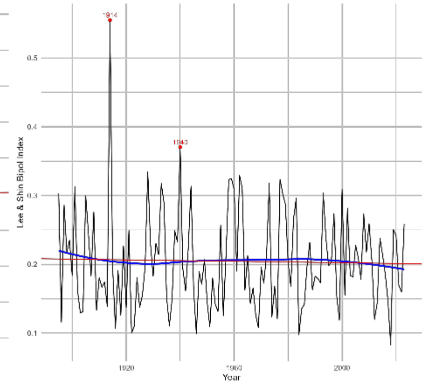
Lee & Shin Bipol. Index for Precip. (inches) Across Entire U.S. in July
(p-value = 0.3895094)



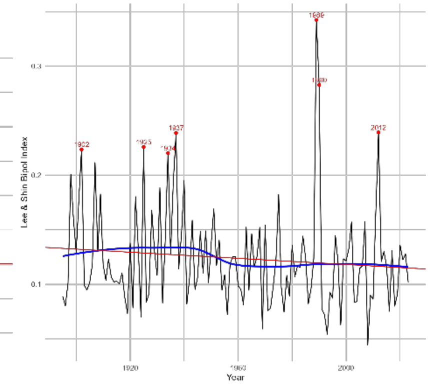
Lee & Shin Bipol. Index for Precip. (inches) Across Western U.S. in July
(p-value = 0.84384)



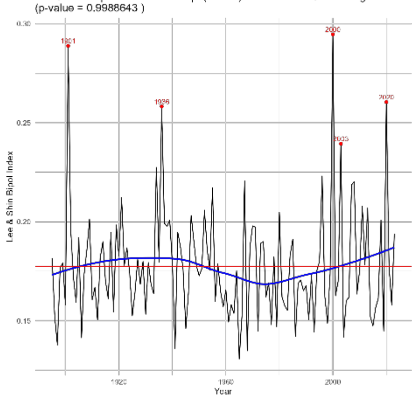
Lee & Shin Bipol. Index for Precip. (inches) Across Arizona in July
(p-value = 0.7617815)



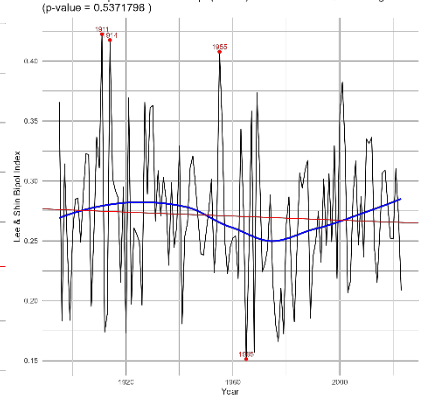
Lee & Shin Bipol. Index for Precip. (inches) Across Minnesota in July
(p-value = 0.1990154)



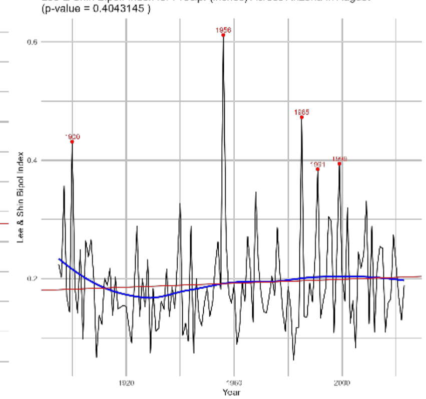
Lee & Shin Bipol. Index for Precip. (inches) Across Entire U.S. in August
(p-value = 0.9988643)



Lee & Shin Bipol. Index for Precip. (inches) Across Western U.S. in August
(p-value = 0.5371798)



Lee & Shin Bipol. Index for Precip. (inches) Across Arizona in August
(p-value = 0.4043145)



Lee & Shin Bipol. Index for Precip. (inches) Across Minnesota in August
(p-value = 0.1252171)

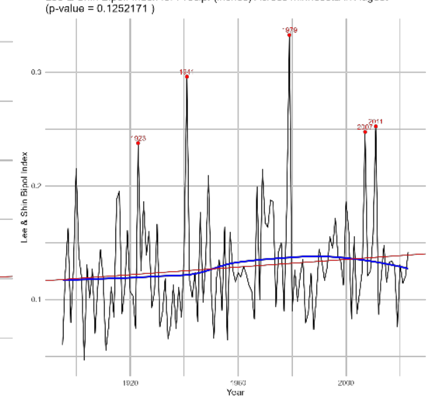
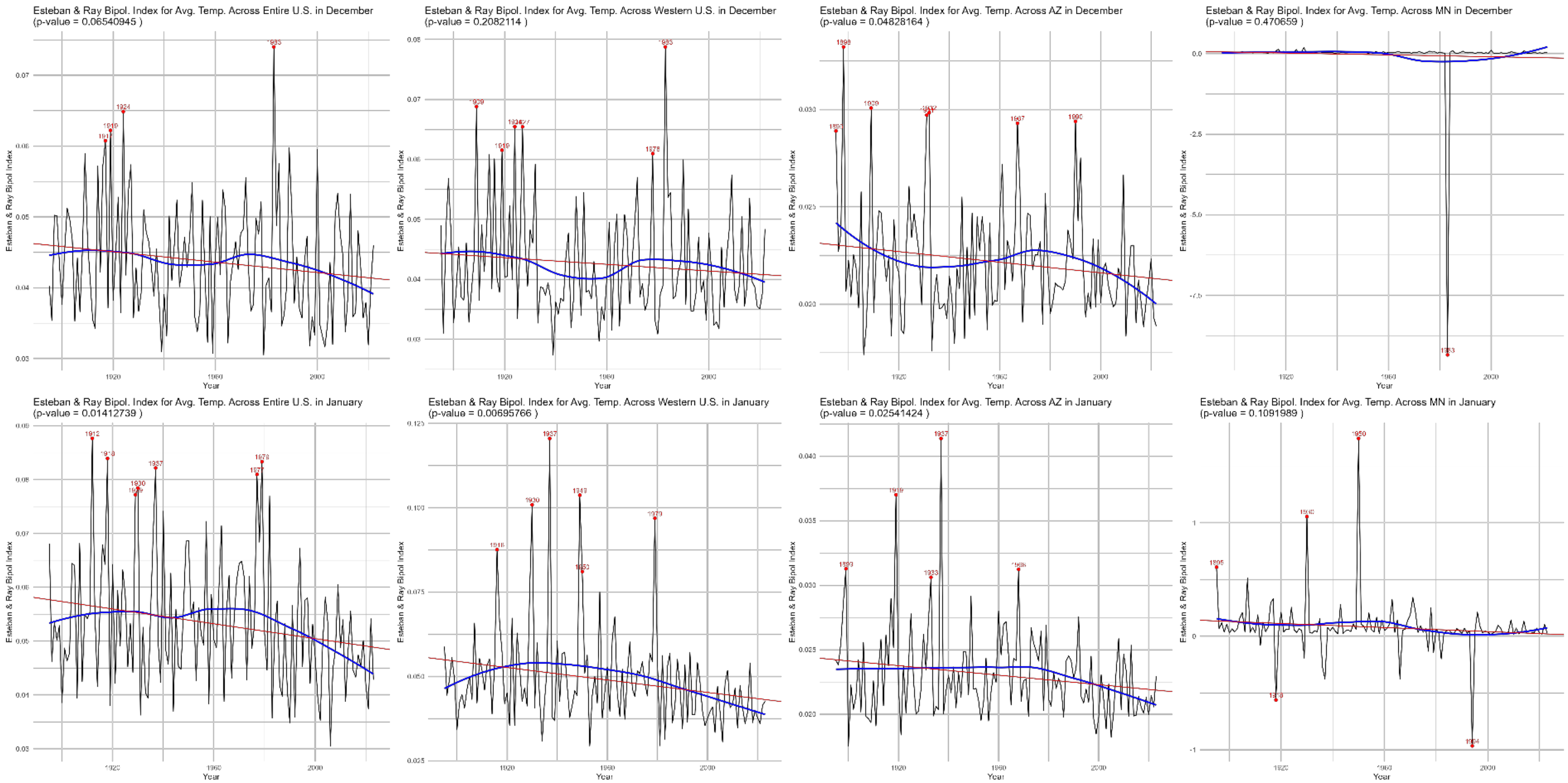
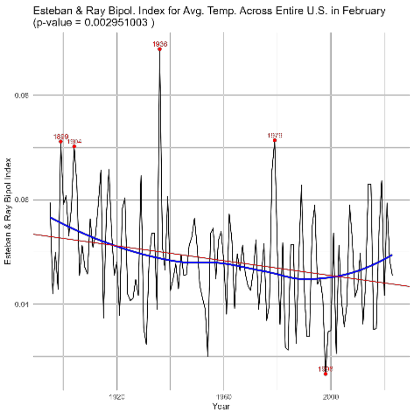
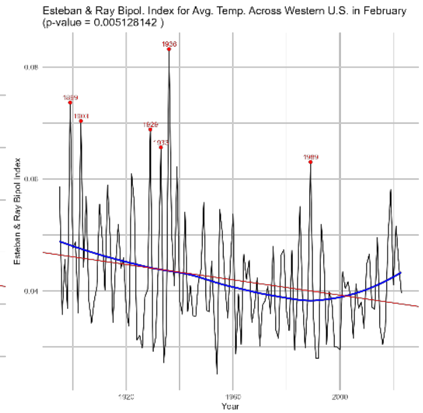
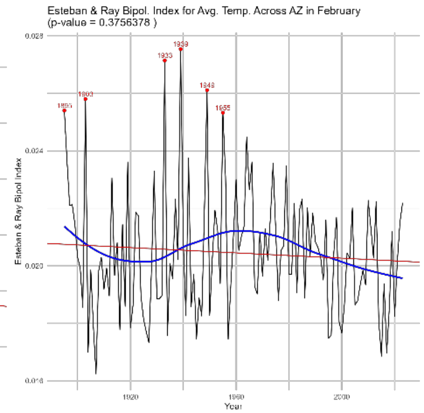


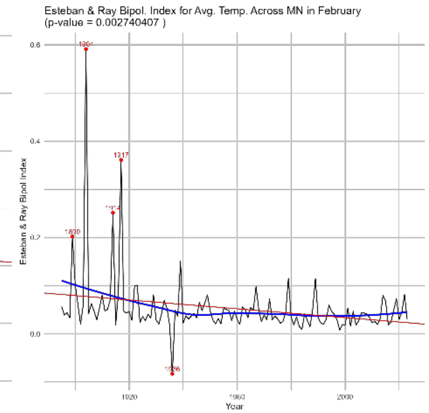
Table 19. Esteban & Ray Index: Average Temperature

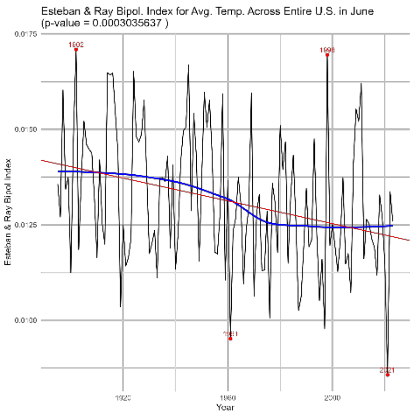


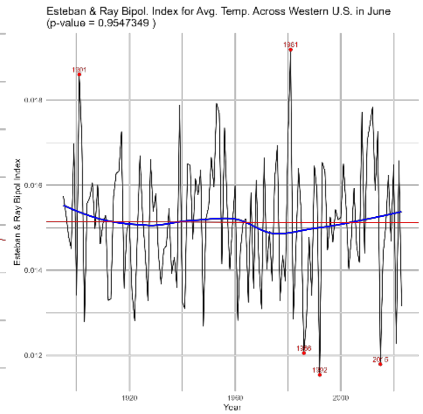

Esteban & Ray Bipol. Index for Avg. Temp. Across Entire U.S. in February
(p-value = 0.002951003)
Esteban & Ray Bipol Index
Year

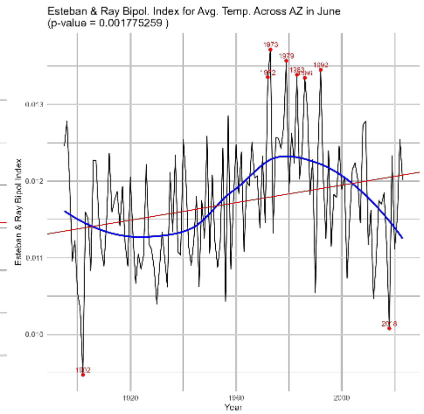

Esteban & Ray Bipol. Index for Avg. Temp. Across Western U.S. in February
(p-value = 0.005128142)
Esteban & Ray Bipol Index
Year

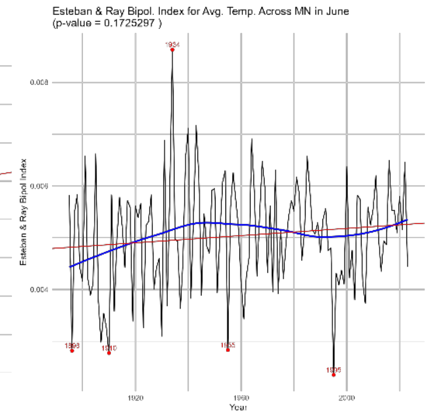

Esteban & Ray Bipol. Index for Avg. Temp. Across AZ in February
(p-value = 0.3756378)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Avg. Temp. Across MN in February
(p-value = 0.002740407)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Avg. Temp. Across Entire U.S. in June
(p-value = 0.0003035637)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Avg. Temp. Across Western U.S. in June
(p-value = 0.9547349)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Avg. Temp. Across AZ in June
(p-value = 0.001775259)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Avg. Temp. Across MN in June
(p-value = 0.1725297)
Esteban & Ray Bipol Index
Year

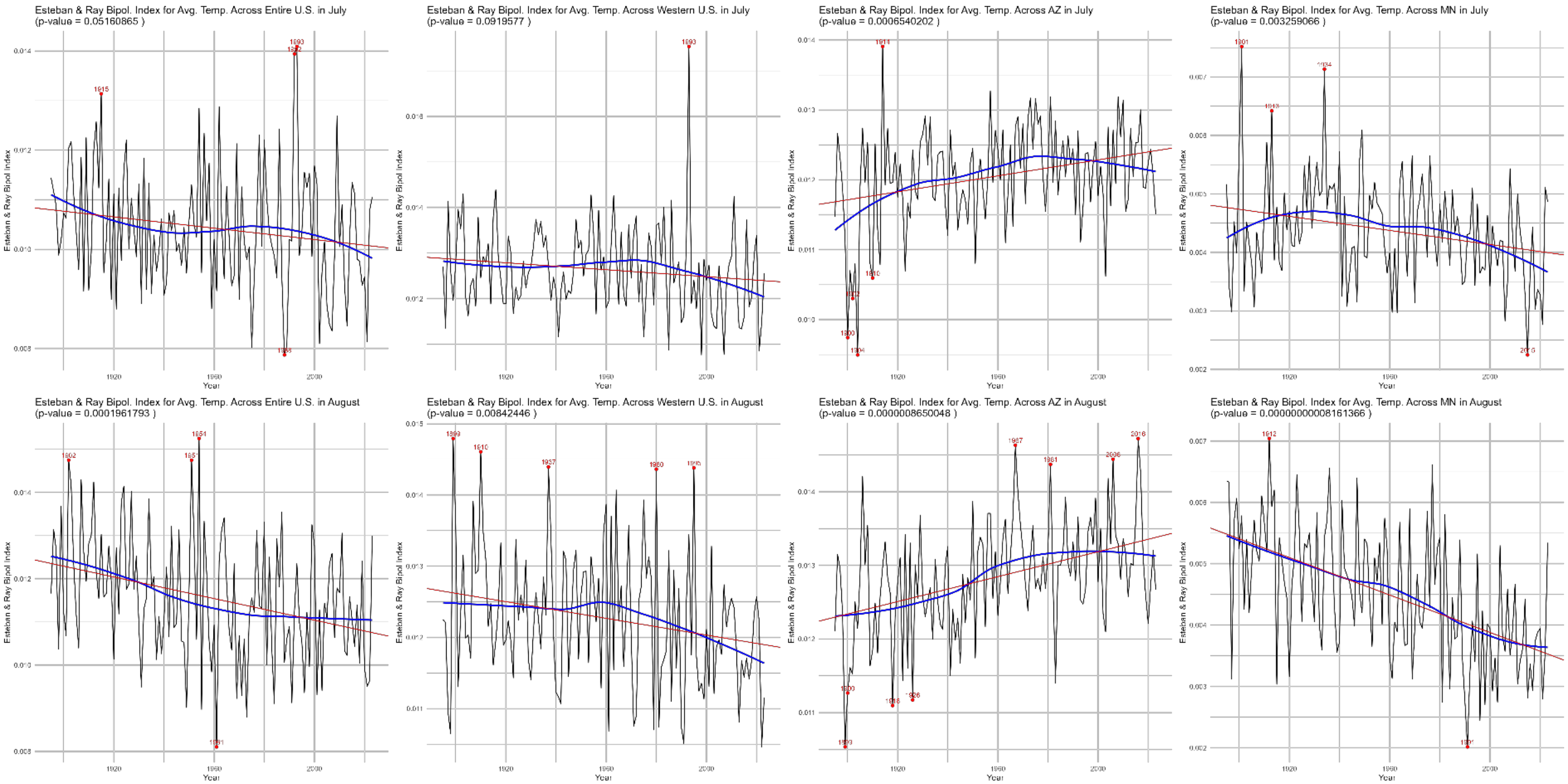
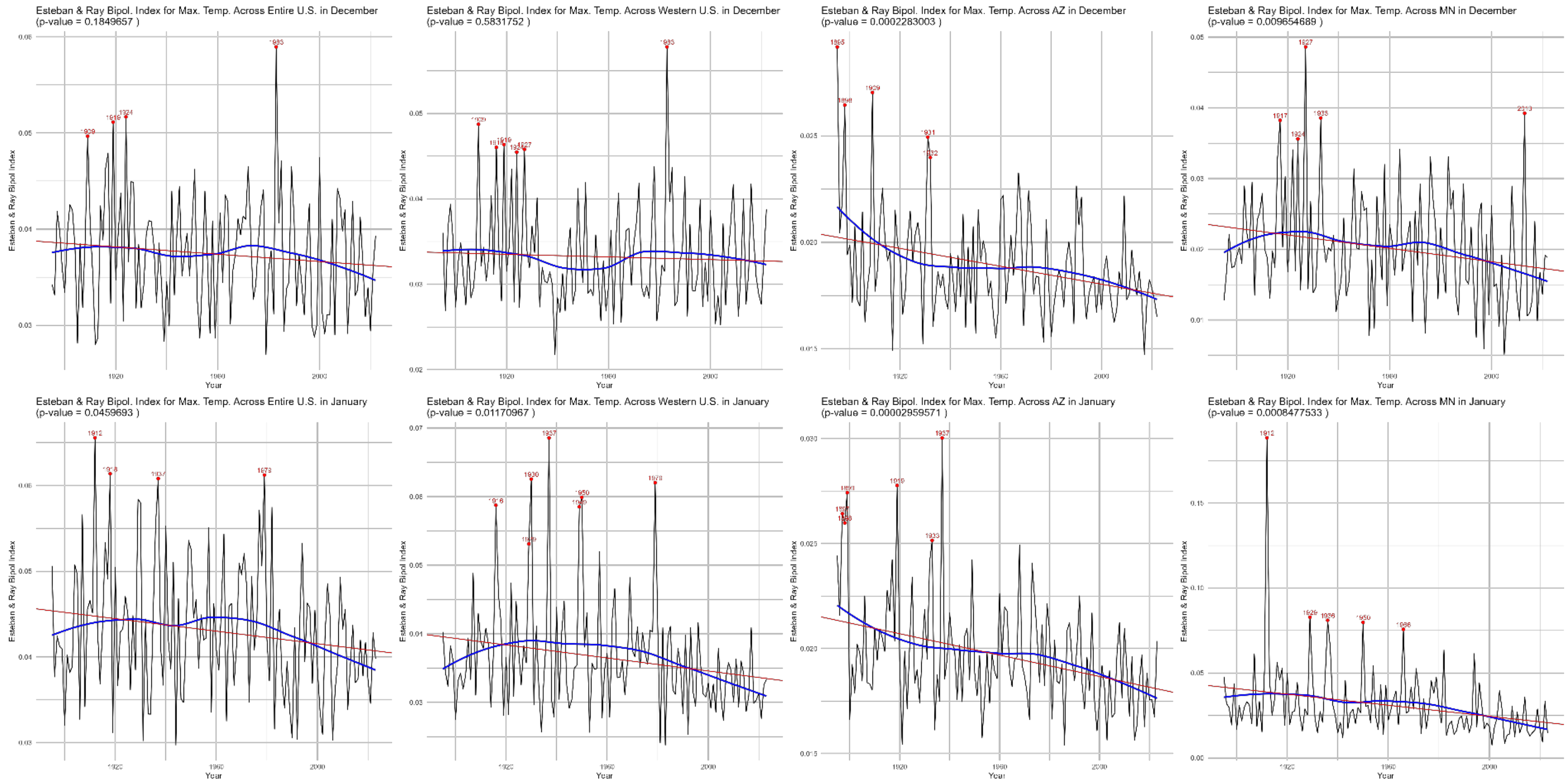
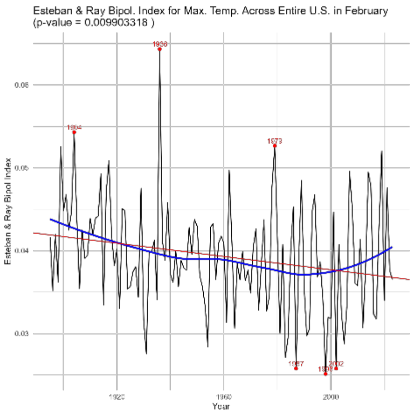
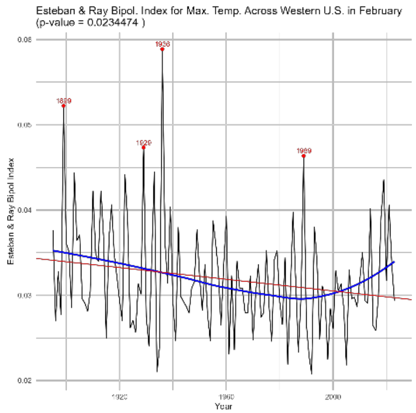
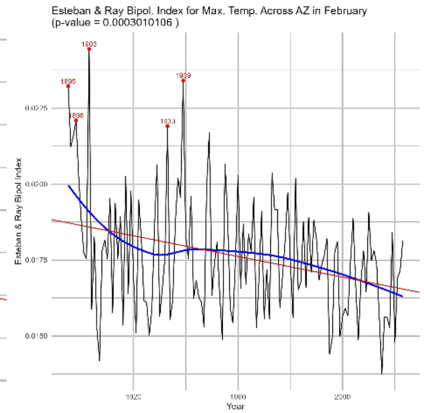

Esteban & Ray Bipol. Index for Avg. Temp. Across Entire U.S. in July
(p-value = 0.05160865)
Esteban & Ray Bipol. Index for Avg. Temp. Across Western U.S. in July
(p-value = 0.0919577)
Esteban & Ray Bipol. Index for Avg. Temp. Across AZ in July
(p-value = 0.0006540202)
Esteban & Ray Bipol. Index for Avg. Temp. Across MN in July
(p-value = 0.003259066)
Esteban & Ray Bipol. Index for Avg. Temp. Across Entire U.S. in August
(p-value = 0.0001961793)
Esteban & Ray Bipol. Index for Avg. Temp. Across Western U.S. in August
(p-value = 0.00842446)
Esteban & Ray Bipol. Index for Avg. Temp. Across AZ in August
(p-value = 0.0000008650048)
Esteban & Ray Bipol. Index for Avg. Temp. Across MN in August
(p-value = 0.00000000008161366)
Esteban & Ray Bipol Index
Year

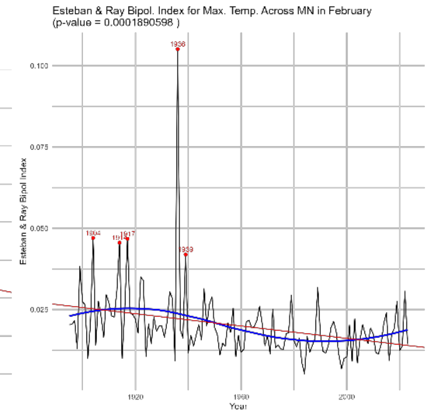
Table 20. Esteban & Ray Index: Maximum Temperature

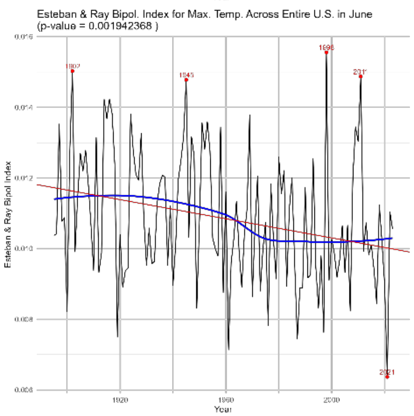


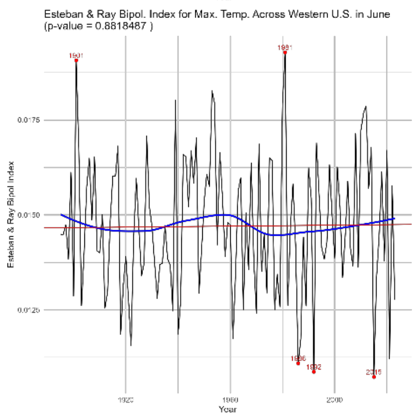

Esteban & Ray Bipol. Index for Max. Temp. Across Entire U.S. in February
(p-value = 0.009903318)
Esteban & Ray Bipol Index
Year

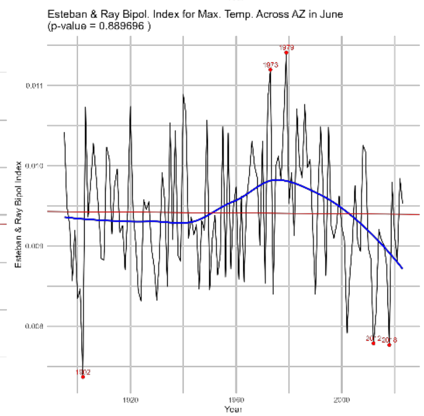

Esteban & Ray Bipol. Index for Max. Temp. Across Western U.S. in February
(p-value = 0.0234474)
Esteban & Ray Bipol Index
Year

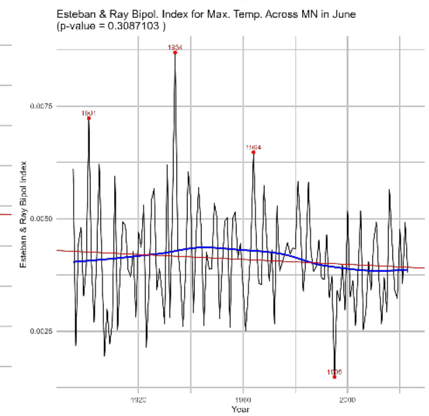

Esteban & Ray Bipol. Index for Max. Temp. Across AZ in February
(p-value = 0.0003010106)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Max. Temp. Across MN in February
(p-value = 0.0001890598)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Max. Temp. Across Entire U.S. in June
(p-value = 0.001942368)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Max. Temp. Across Western U.S. in June
(p-value = 0.8818487)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Max. Temp. Across AZ in June
(p-value = 0.889696)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Max. Temp. Across MN in June
(p-value = 0.3087103)
Esteban & Ray Bipol Index
Year

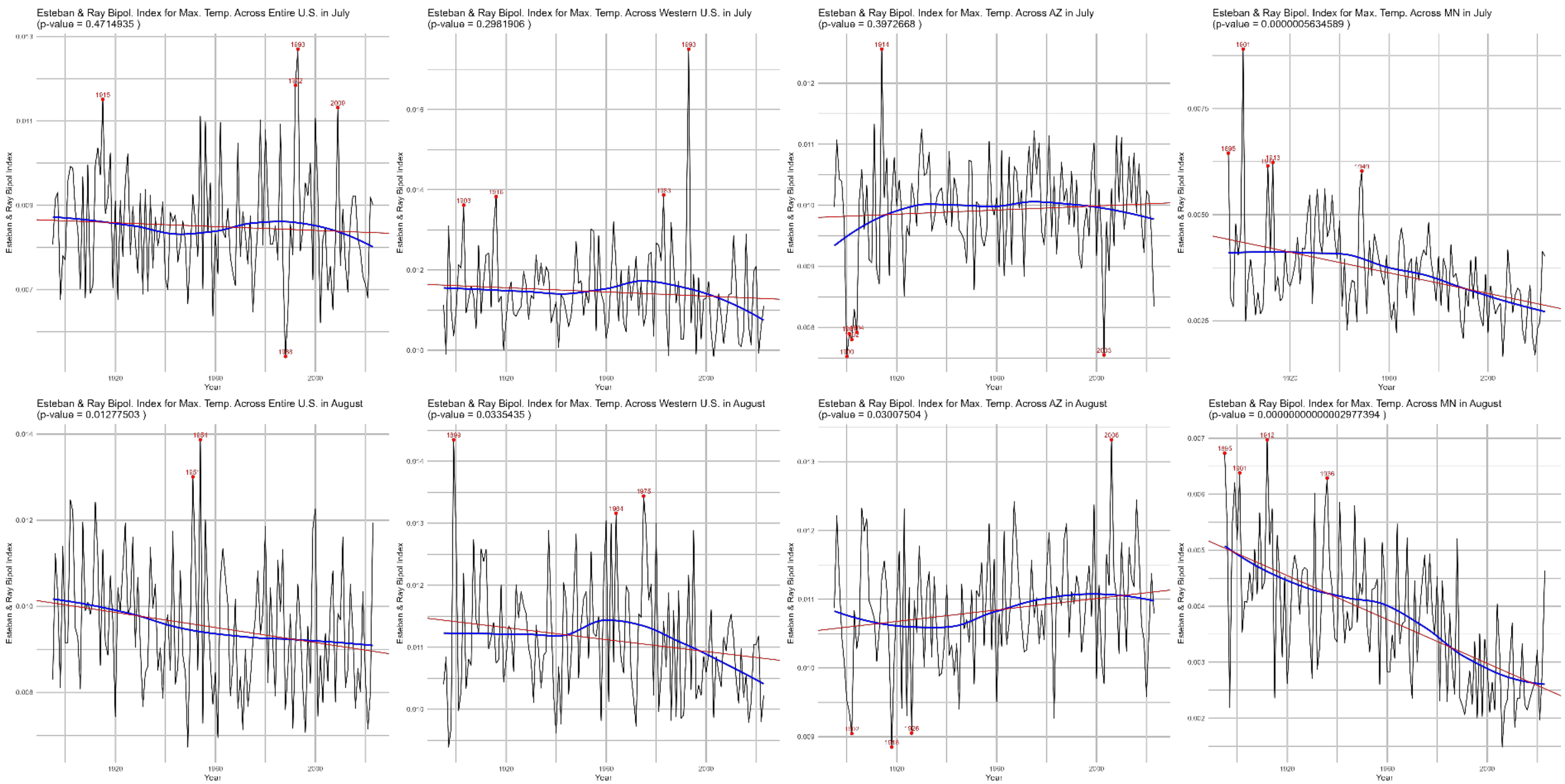
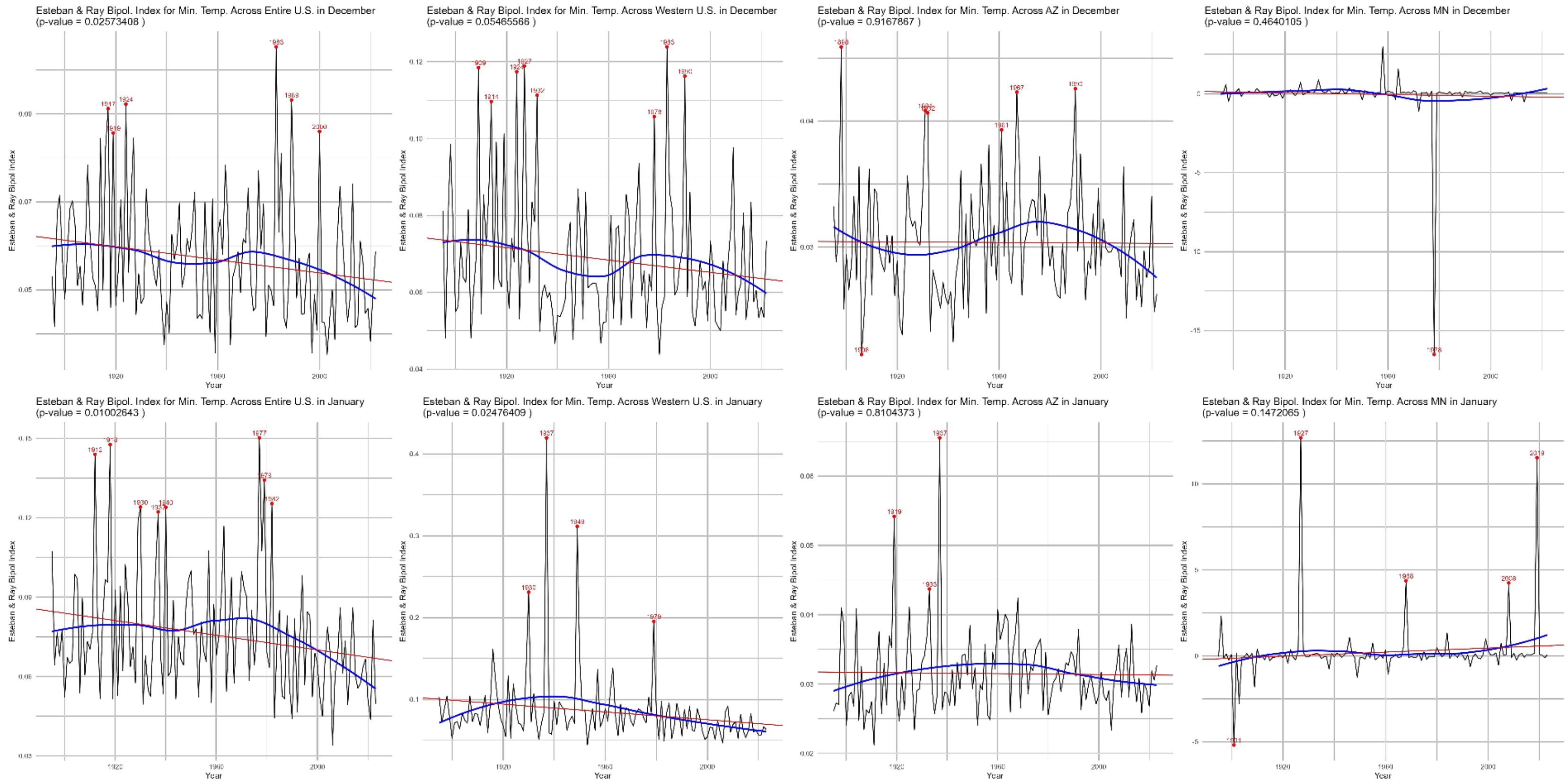
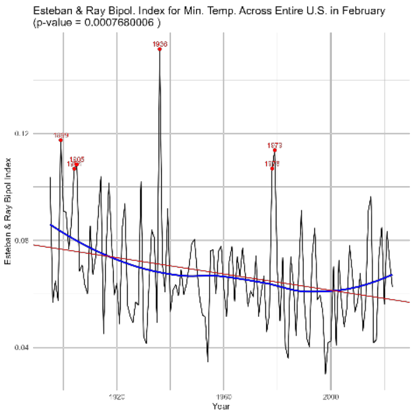
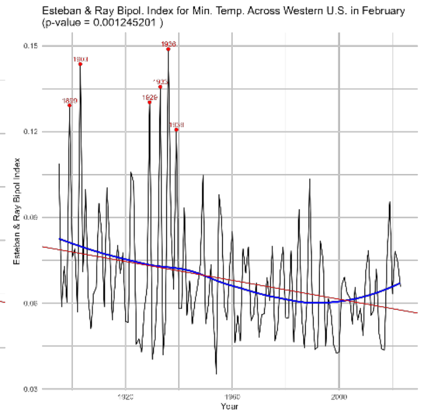
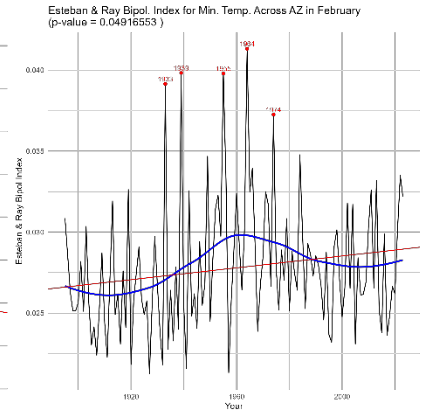

Esteban & Ray Bipol. Index for Max. Temp. Across Entire U.S. in July
(p-value = 0.4714935)
Esteban & Ray Bipol. Index for Max. Temp. Across Western U.S. in July
(p-value = 0.2981906)
Esteban & Ray Bipol. Index for Max. Temp. Across AZ in July
(p-value = 0.3972668)
Esteban & Ray Bipol. Index for Max. Temp. Across MN in July
(p-value = 0.0000005634589)
Esteban & Ray Bipol. Index for Max. Temp. Across Entire U.S. in August
(p-value = 0.01277503)
Esteban & Ray Bipol. Index for Max. Temp. Across Western U.S. in August
(p-value = 0.0335435)
Esteban & Ray Bipol. Index for Max. Temp. Across AZ in August
(p-value = 0.03007504)
Esteban & Ray Bipol. Index for Max. Temp. Across MN in August
(p-value = 0.00000000000002977394)
Esteban & Ray Bipol Index
Year

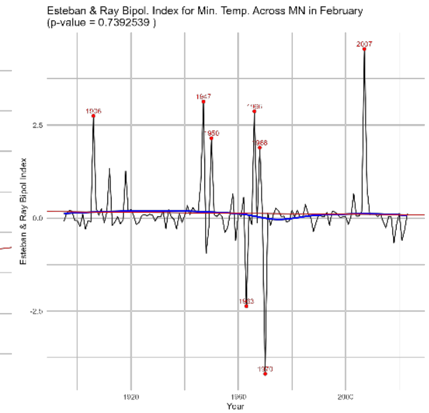
Table 21. Esteban & Ray Index: Minimum Temperature

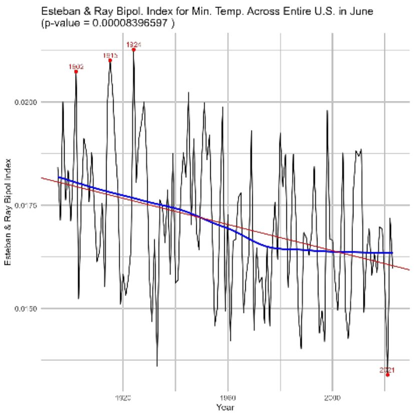


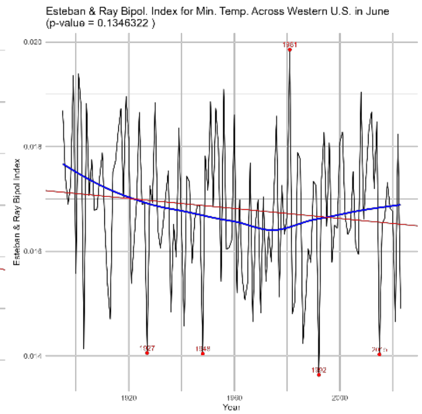

Esteban & Ray Bipol. Index for Min. Temp. Across Entire U.S. in February
(p-value = 0.0007680006)
Esteban & Ray Bipol Index
Year

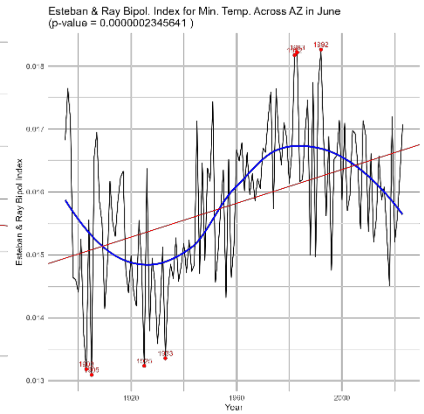

Esteban & Ray Bipol. Index for Min. Temp. Across Western U.S. in February
(p-value = 0.001245201)
Esteban & Ray Bipol Index
Year

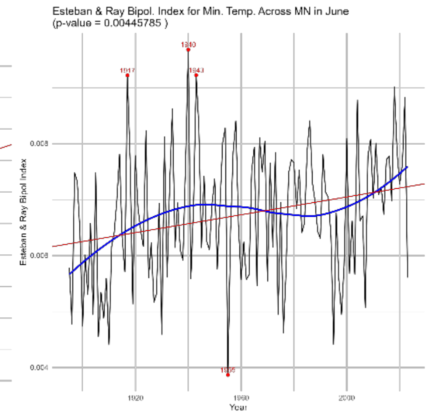

Esteban & Ray Bipol. Index for Min. Temp. Across AZ in February
(p-value = 0.04916553)
Esteban & Ray Bipol Index
Year

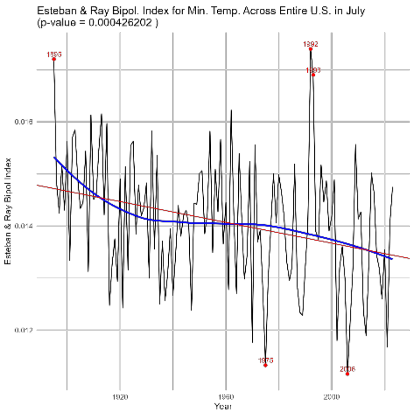

Esteban & Ray Bipol. Index for Min. Temp. Across MN in February
(p-value = 0.7392539)
Esteban & Ray Bipol Index
Year

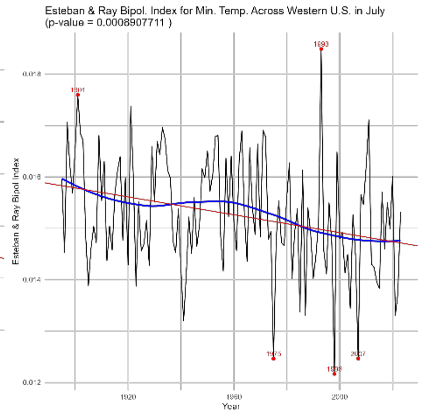

Esteban & Ray Bipol. Index for Min. Temp. Across Entire U.S. in June
(p-value = 0.00008396597)
Esteban & Ray Bipol Index
Year

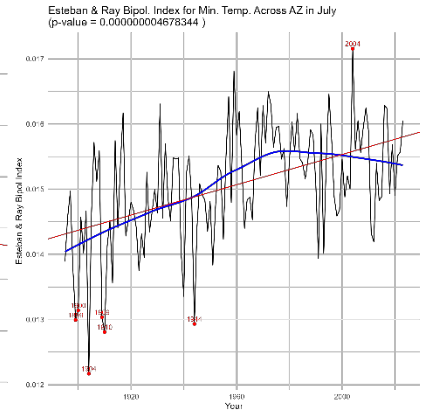

Esteban & Ray Bipol. Index for Min. Temp. Across Western U.S. in June
(p-value = 0.1346322)
Esteban & Ray Bipol Index
Year

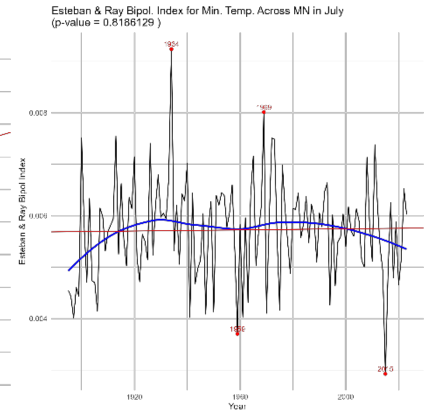

Esteban & Ray Bipol. Index for Min. Temp. Across AZ in June
(p-value = 0.0000002345641)
Esteban & Ray Bipol Index
Year

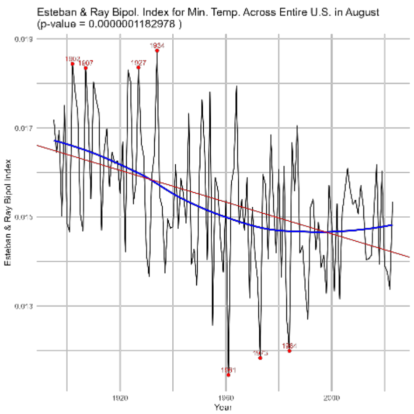

Esteban & Ray Bipol. Index for Min. Temp. Across MN in June
(p-value = 0.00445785)
Esteban & Ray Bipol Index
Year

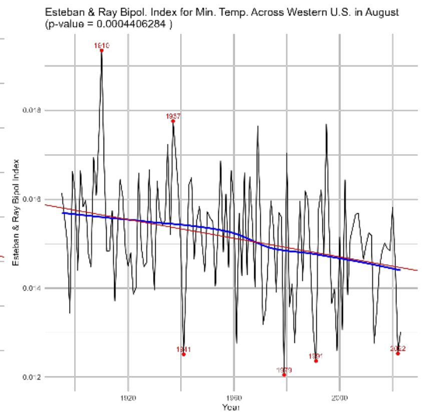

Esteban & Ray Bipol. Index for Min. Temp. Across Entire U.S. in July
(p-value = 0.000426202)
Esteban & Ray Bipol Index
Year

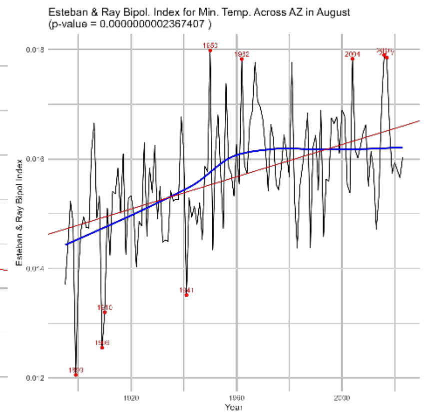

Esteban & Ray Bipol. Index for Min. Temp. Across Western U.S. in July
(p-value = 0.0008907711)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Min. Temp. Across AZ in July
(p-value = 0.000000004678344)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Min. Temp. Across MN in July
(p-value = 0.8186129)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Min. Temp. Across Entire U.S. in August
(p-value = 0.0000001182978)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Min. Temp. Across Western U.S. in August
(p-value = 0.0004406284)
Esteban & Ray Bipol Index
Year


Esteban & Ray Bipol. Index for Min. Temp. Across AZ in August
(p-value = 0.0000000002367407)
Esteban & Ray Bipol Index
Year

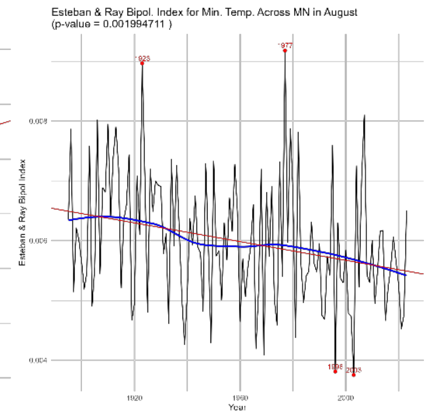
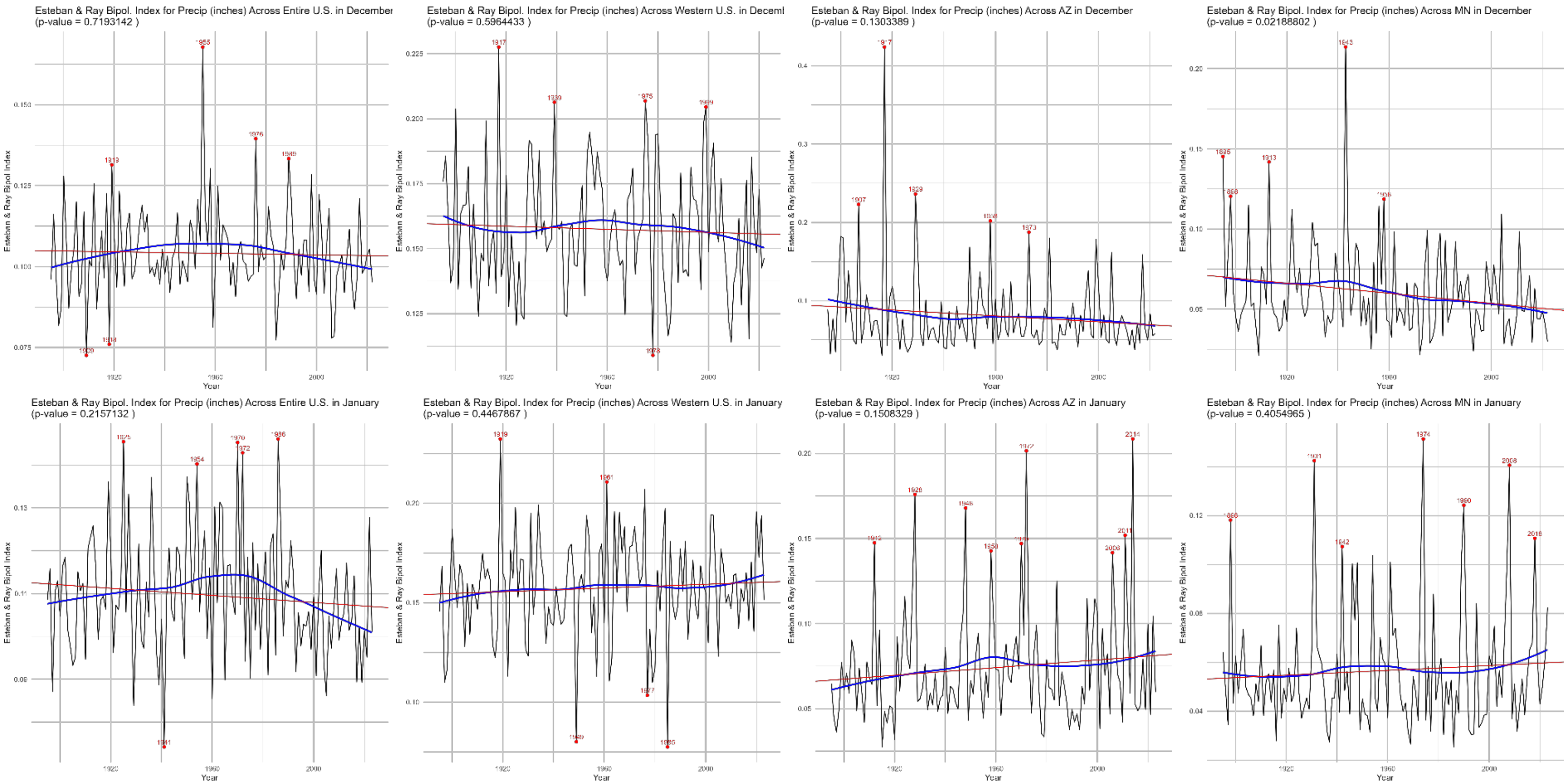
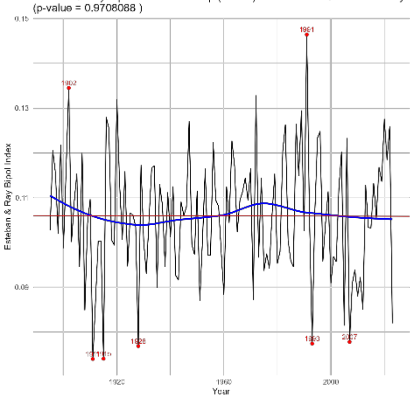

Esteban & Ray Bipol. Index for Min. Temp. Across MN in August
(p-value = 0.001994711)
Esteban & Ray Bipol Index
Year

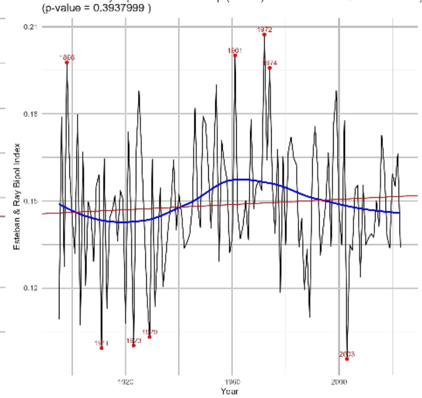
Table 22. Esteban & Ray Index: Precipitation



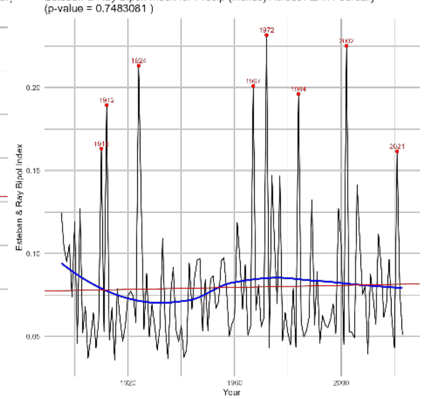
Esteban & Ray Bipol. Index for Precip (inches) Across Entire U.S. in February
(p-value = 0.9708088)



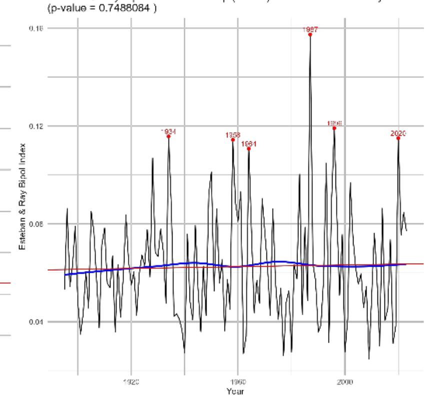
Esteban & Ray Bipol. Index for Precip (inches) Across Western U.S. in February
(p-value = 0.3937999)



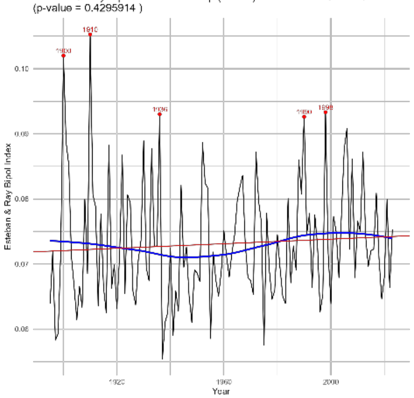
Esteban & Ray Bipol. Index for Precip (inches) Across AZ in February
(p-value = 0.7483081)



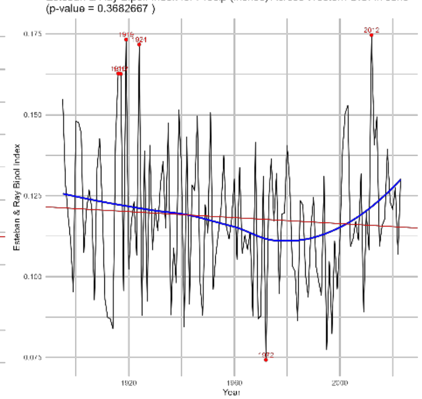
Esteban & Ray Bipol. Index for Precip (inches) Across MN in February
(p-value = 0.7488084)



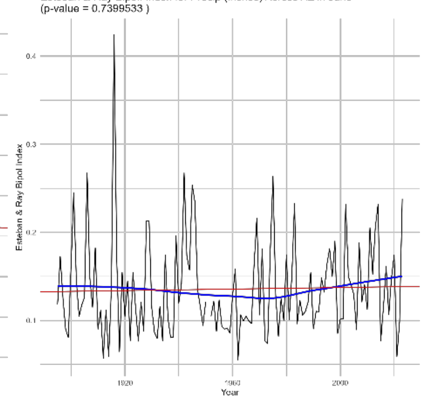
Esteban & Ray Bipol. Index for Precip (inches) Across Entire U.S. in June
(p-value = 0.4295914)



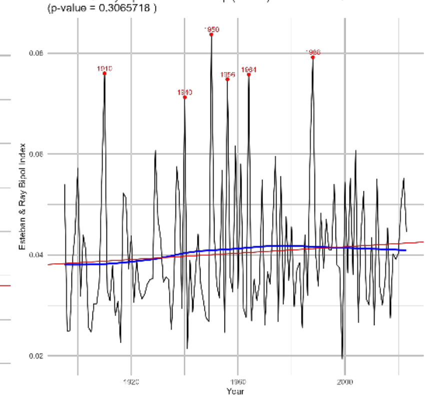
Esteban & Ray Bipol. Index for Precip (inches) Across Western U.S. in June
(p-value = 0.3682667)



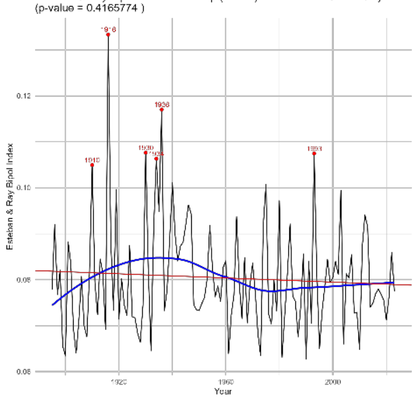
Esteban & Ray Bipol. Index for Precip (inches) Across AZ in June
(p-value = 0.7399533)



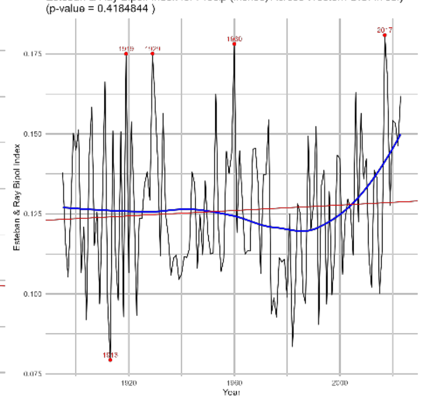
Esteban & Ray Bipol. Index for Precip (inches) Across MN in June
(p-value = 0.3065718)



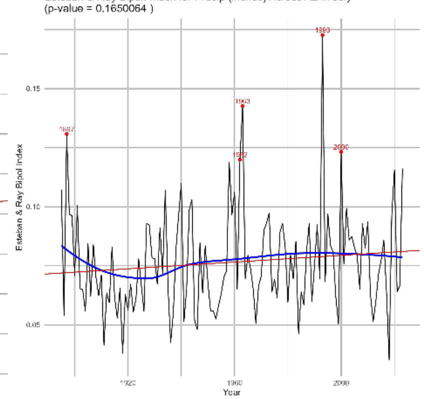
Esteban & Ray Bipol. Index for Precip (inches) Across Entire U.S. in July
(p-value = 0.4165774)



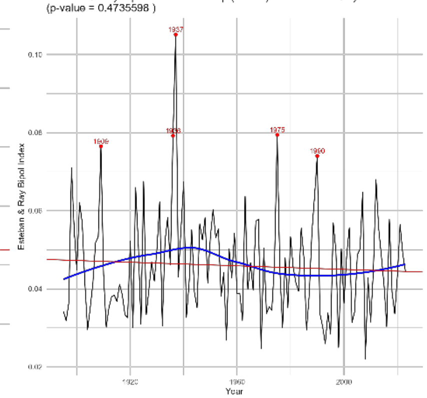
Esteban & Ray Bipol. Index for Precip (inches) Across Western U.S. in July
(p-value = 0.4184844)



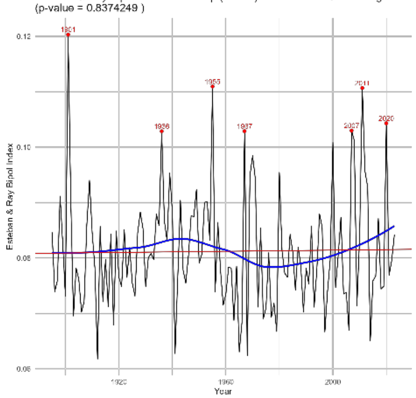
Esteban & Ray Bipol. Index for Precip (inches) Across AZ in July
(p-value = 0.1650064)



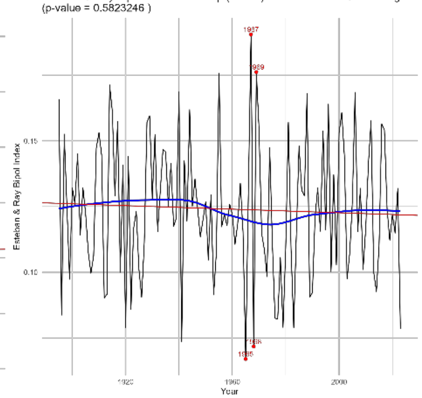
Esteban & Ray Bipol. Index for Precip (inches) Across MN in July
(p-value = 0.4735598)



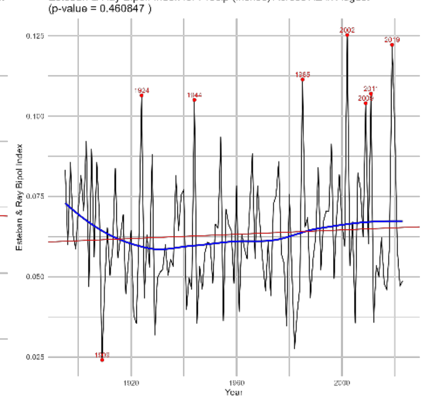
Esteban & Ray Bipol. Index for Precip (inches) Across Entire U.S. in August
(p-value = 0.8374249)



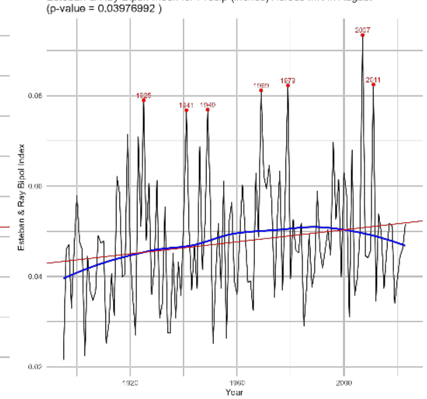
Esteban & Ray Bipol. Index for Precip (inches) Across Western U.S. in August
(p-value = 0.5823246)



Esteban & Ray Bipol. Index for Precip (inches) Across AZ in August
(p-value = 0.460847)



Esteban & Ray Bipol. Index for Precip (inches) Across MN in August
(p-value = 0.03976992)



9. References

Bardan, Roxana. “NASA Analysis Confirms 2023 as Warmest Year on Record”. NASA. January 12, 2024.

Barrett, G. F., & Donald, S. G. (2003). Consistent Tests for Stochastic Dominance. *Econometrica*, *71*(1), 71–104. http://www.jstor.org/stable/3082041

D’Arge, R., Schulze, W.D., Brookshire, D. (1982). Carbon Dioxide and Intergenerational Choice. American Economic Review, vol. 72, issue 3, 251-56.

Fan, W. and M. Carroll, C. (2012), "Regional trend of climatic change in the USA", *World Journal of Science, Technology and Sustainable Development*, Vol. 9 No. 1, pp. 38-44. https://doi.org/10.1108/20425941211223615

GISTEMP Team. (2024). *GISS Surface Temperature Analysis (GISTEMP), version 4*. NASA Goddard Institute for Space Studies. Dataset accessed 2024-04-16 at https://data.giss.nasa.gov/gistemp/.

Groisman, P. Y., Knight, R. W., Easterling, D. R., Karl, T. R., Hegerl, G. C., & Razuvaev, V. N. (2005). Trends in Intense Precipitation in the Climate Record. *Journal of Climate*, *18*(9), 1326-1350. https://doi.org/10.1175/JCLI3339.1

Hay, William & Emeritus, Professor. (2014). The accelerating rate of global change. Rendiconti Lincei. Scienze fisiche e naturali. Rendiconti Lincei online. 10.1007/s12210-014-0287-z.

Howe, P., Mildenberger, M., Marlon, J. *et al.* Geographic variation in opinions on climate change at state and local scales in the USA. *Nature Clim Change* **5**, 596–603 (2015). https://doi.org/10.1038/nclimate2583

Lenssen, N., G. Schmidt, J. Hansen, M. Menne, A. Persin, R. Ruedy, and D. Zyss, 2019: Improvements in the GISTEMP uncertainty model. *J. Geophys. Res. Atmos.*, **124**, no. 12, 6307-6326, doi:10.1029/2018JD029522.

Menne, M.J., C.N. Williams Jr., and R.S. Vose, 2009: The United States Historical Climatology Network monthly temperature data—Version 2. *Bulletin of the American Meteorological Society*, 90, 993-1007.

National Weather Service. *What Are Heating and Cooling Degree Days*. Source URL: https://www.weather.gov/key/climate_heat_cool

NOAA National Centers for Environmental information. USCRN/USRCRN Monthly Files. July, 2017. Retrieved from: https://www.ncei.noaa.gov/pub/data/uscrn/products/monthly01/readme.txt

NOAA National Centers for Environmental information, Climate at a Glance: County Time Series, published June 2024, retrieved December 2023, from https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/time-series

Park, S., & Shin, D. (2020). Recent changes in the nature of distribution dynamics of US county incomes. *Journal of Applied Econometrics, 35*(5), 618-640. https://doi.org/10.1002/jae.3006

Portmann, R. W., Solomon, S., & Hegerl, G. C. (2009). Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proceedings of the National Academy of Sciences*, *106*(18), 7324-7329. https://www.researchgate.net/publication/24311584_Spatial_and_Seasonal_Patterns_in_Climate_Change_Temperatures_and_Precipitation_Across_the_United_States

Richard S. J. Tol. (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy*, 4-25. https://doi.org/10.1093/reep/rex027

Hsiang, S., Kopp, R. E., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K., & Houser, T. (2017). Estimating economic damage from climate change in the United States. *Science, 356*(6345), 1362-1369. https://doi.org/10.1126/science.aal4369

Sergei Schaub. (2022). Stodom: Estimating Consistent Tests for Stochastic Dominance. Agroscope. URL https://rdrr.io/cran/stodom/

Trenberth, Kevin E. (2011). Changes in precipitation with climate change. National Center for Atmospheric Research.

Wang, H., Chen, J., Hoerling, M., Kumar, A. and Pegion, P. (2009), "Attribution of the seasonality and regionality in climate trends over the United States during 1950-2000", Journal of Climate, Vol. 22 No. 10, pp. 2571-90.

Wisconsin Department of Natural Resources. (2024). The Science of Climate Change. https://dnr.wisconsin.gov/climatechange/science

Vose, R.S., Applequist, S., Durre, I., Menne, M.J., Williams, C.N., Fenimore, C., Gleason, K., Arndt, D. 2014: Improved Historical Temperature and Precipitation Time Series For U.S. Climate Divisions *Journal of Applied Meteorology and Climatology*. DOI: 10.1175/JAMC-D-13-0248.1