Chapter 9

Identifying Changes in Trends of Summer Air Temperatures of the USA High Plains

Denis Mutiibwa, Ayse Kilic and Suat Irmak

Additional information is available at the end of the chapter

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Abstract

Change in climate variables, especially air temperature, can substantially impact water availability, use, management, allocation, and projections for rural and urban applications. This study presents analyses for detecting summer air temperature change by investigating trends of two separate climate-periods in the USA High Plains. Two trend periods, the *reference period* (1895–1930) and the *warming period* (1971–2006), were investigated using parametric and nonparametric methods. During the reference period, minimum air temperature (T_{min}) was statistically stationary at a nonsignificant increasing rate of 0.02°C/year. However, from early 1970s, T_{min} increased at a significant rate of 0.02°C/year. The maximum air temperature (T_{max}) had a weaker warming signal than T_{min} during the reference period. During the warming period, T_{max} had a cooling trend at a nonsignificant rate of −0.004°C/year. About 22% of the High Plains had significant warming trends before 1930. Compared to the summers before 1930, the summer temperatures of the High Palins since the 1970s increased, on average, by 0.86°C. Overall, parametric methods lead to the conclusion that 50% of the study area experienced a significant warming trend in T_{min}. In comparison, nonparametric methods indicated that 94% of the study area experienced a warming trend. Overall, in recent decades, summer average temperatures in the High Plains have been warming as compared to the early twentieth-century decades, and the warming is most likely driven primarily by increasing nighttime T_{min}.

Keywords: climate change, water resources, air temperature, USA High Plains, parametric and nonparametric tests, Kendall tau, generalized linear models

1. Introduction

The United Kingdom Meteorological Office Hadley Centre/Climate Research Unit (HadCRUT3) [1], the United States National Climatic Data Center (NCDC) [2], and the

Goddard Institute for Space Studies (GISS) [3] regularly monitor and update global and hemispheric surface temperature changes. The three institutions use similar data; however, they employ different interpolation techniques and 30-year climatological (base) periods (HadCRUT: 1961–1990, NCDC: 1901–2000, and GISS: 1951–1980) to construct global surface temperature anomalies. Despite the differences in methods, all three groups produced similar global temperature anomalies for the period of 1880–2009 [4]. These anomalies show evidence of a warming trend in temperatures over the period of 1880–2009. The global temperature anomalies presented by NCDC [4] and GISS [3] reveal three trend periods of distinct means and trends in global temperatures: the period of 1880–1930 with the mean value of −0.21°C; the period of 1935–1975 with the mean of about 0.0°C; and the period of 1976–2006 that has a warming trend of about 0.02°C/year. The HadCRUT global temperature anomalies have a similar profile; however, due to a variant base period of 1961–1990, the reference level (zero line) is shifted higher and the three mean values are offset from GISS and NCDC.

While aforementioned analyses provide global averages, changes in trends and magnitudes of climatic variables can vary between the regions. Thus, it is important to identify these changes locally, which can provide important and useful information on a variety of topics, including agricultural science and practices, hydrologic analyses, climate change studies, etc. The rationale of this study was to investigate the potential changes in regional temperatures starting from the early 1970s, by referencing that period to an earlier period with the least observed changes (warming) since the advent of temperature monitoring and archiving in the late nineteenth century. The two periods investigated are (i) 1895–1930 as the *reference period* and (ii) 1971–2006 as the *warming period.* The assumption of the reference period is that, as indicated in the NCDC, GISS, and HadCRUT data, this period has the least warming signal in measured temperature records, which started in the late nineteenth century. The years between the reference period and the warming period (1936–1965) were used as the 30-year climatological (base) period. This base period was selected as the independent period for estimating the anomalies of the reference period and warming period. The study was conducted on summer temperatures that were computed as the average of June, July, and August monthly temperatures.

Other studies [5–9] estimated trends in air temperatures and other variables, and their uncertainties, using various statistical methods to derive and test the trends and presented extrapolation methods used. Each statistical method can have advantages or disadvantages, depending on application characteristics and objectives of the study. Folland et al. [7] presented one of the earliest global and hemispheric surface warming trends that attempted to quantify the major sources of uncertainty. They calculated the global and hemispheric annual temperature anomalies by combining land surface air temperature and sea surface temperatures. They observed that the best linear fit to annual global surface temperature showed an increase of 0.61 ± 0.16°C between 1861 and 2000.

Time-dependent variables such as temperature have a probable confounding effect of serial autocorrelation that may violate statistical assumptions in some of the trend studies that fit simple ordinary least squares. This is because the standard errors of serially correlated variables are typically underestimated. Santer et al. [10] corrected the effects of serial correlation by adjusting the sample size to an equivalent sample size, which is regarded as the number of effectively independent observations in a sample. However, the student's *t*-test adjusted by the equivalent sample size performed poorly, because the equivalent sample size was poorly estimated and it was incorrectly assumed that the adjusted statistic has a student's *t* distribution under the null hypothesis [11].

In this study, parametric and nonparametric statistical methods are used to investigate trends in the air temperature series. The parametric method used the autoregressive process in the time series to fit generalized least squares that are superior to simple ordinary least squares. Autoregressive processes are used in climate research since they provide approximations of discretized ordinary linear differential equations subject to stochastic forcing [12]. For the nonparametric method, the Kendall tau trend analysis was applied in this study. The advantage of nonparametric methods is that the statistical assumption of normality in the data is not strictly necessary. The two statistical methods were combined to assess trends in the minimum air temperature (T_{min}), maximum air temperature (T_{max}), and mean air temperature (T_{mean}). This study has three specific objectives: (i) to characterize potential trend differences between the reference period and warming period in the summer temperatures of the High Plains, (ii) to identify the temperature variable with the warmest trend, and (iii) to analyze the performance of parametric and nonparametric statistical methods in characterizing trends in temperature series in terms of mean anomalies.

2. Materials and methods

2.1. Input data

Monthly data for T_{max}, T_{min}, and T_{mean} for 204 weather stations across the High Plains were obtained from the United States Historical Climatology Network (USHCN) (**Figure 1**). Data from all 204 stations were complete for the entire study period (1896–2006). Thus, the spatial sampling error was assumed homogenous for the entire study period. The USHCN data were downloaded from the NCDC [6] (http://www.ncdc.noaa.gov), which maintains, distributes, and conducts data quality checks. Inhomogeneity and missing data are typically caused by changes in instrumentation, measuring techniques, station location, observation frequency, and environment shifts due to relocations [13, 14]. The NCDC ensures good-quality data by subjecting the data to a comprehensive quality control, inhomogeneity correction, and removal of all monthly mean outliers that differed from their climatology by more than 2.5 standard deviations [15–17]. The NCDC homogenizes the dataset to remove impacts of urban warming and other artifacts on measured temperature [15, 18]. In the case of missing data, a network of surrounding stations is used to interpolate the missing values, thus producing a continuous data series.

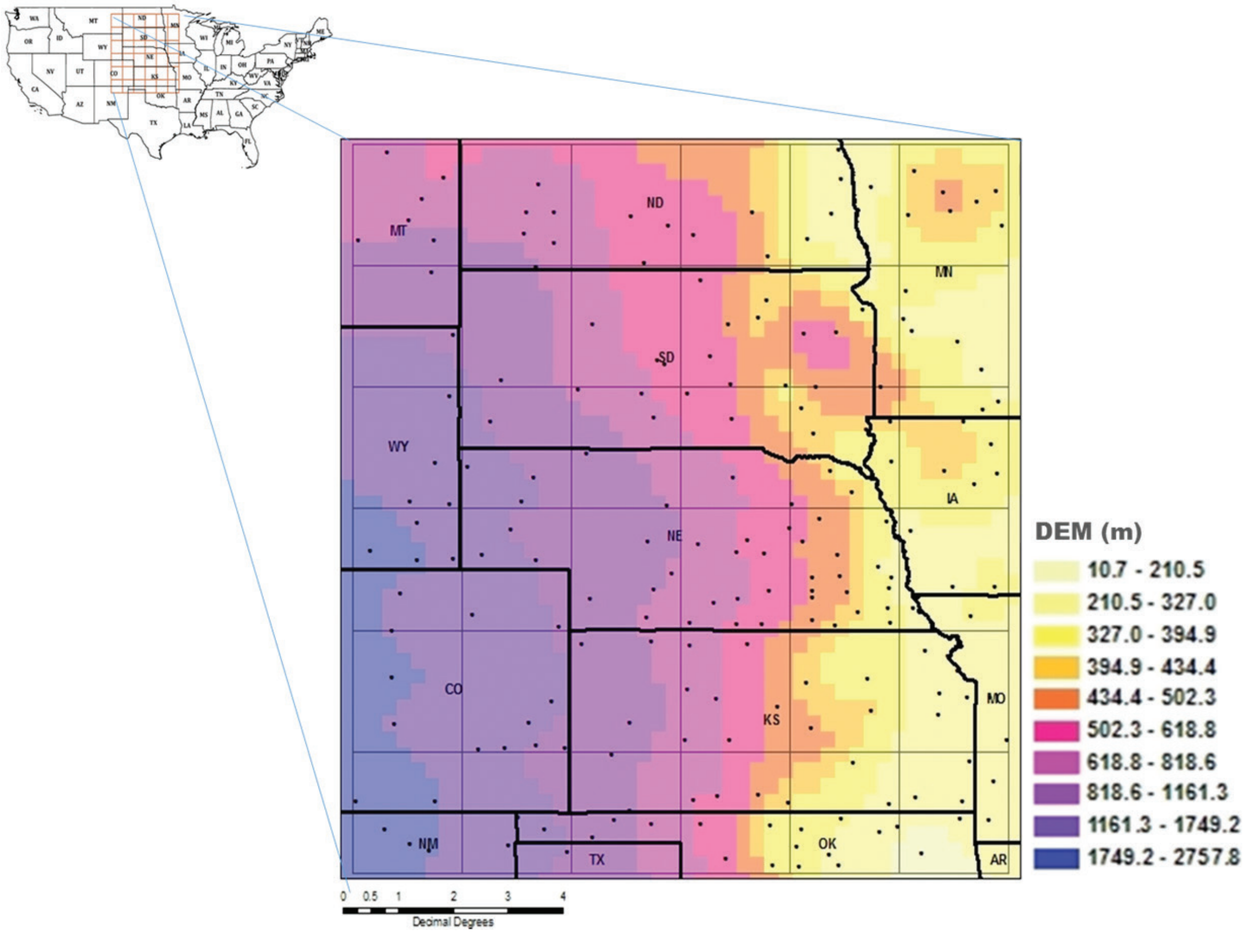

Figure 1. A map of the study region, the US High Plains, showing the locations of the weather stations (black dots) used in the study, and the elevation across the region in meters. DEM: Digital Elevation Model.

2.2. Spatial domain and gridding

The High Plains region of the central United States extends over 12 states: Nebraska, Kansas, and South Dakota as the main states of interest, surrounded by buffer areas of North Dakota, Minnesota, Wyoming, Montana, Colorado, Iowa, Missouri, Oklahoma, and Texas. The regional climate is described as middle-latitude dry continental climate with abundant sunshine, moderate precipitation, frequent winds, low humidity, and high evaporation rates [19]. This study divides the region into 36 grids of 2 degrees in size. On average, there were six weather stations in every grid. Studies have shown that monthly temperature anomalies are mainly a function of large-scale circulation patterns [20]. Therefore, the number of stations required to describe the monthly anomalies over an area is comparatively less extensive [20]. For instance, for a global terrestrial coverage at a 5-degree grid, estimates indicated that the effective number of independent stations at a monthly timescale was about 100 well-spaced sampling sites [21].

2.2.1. Creating anomalies and gridding

The monthly anomalies of T_{mean}, T_{min}, and T_{max} were computed based on the climate anomaly method (CAM) [22]. The period from 1936 to 1965 was considered the base period for determining the norm monthly temperatures for June, July, and August. The monthly anomalies at each station were derived as the difference between the actual monthly temperature and the respective mean monthly norm temperature. The summer anomalies were then computed as the average of the three monthly anomalies (June, July, and August) for each year. By averaging the summer anomalies of stations in each grid, a 2-degree grid of summer temperature anomalies was created over the entire High Plains region. For long-term average spatial variability across the region (**Figure 2**), the summer temperatures in each grid were averaged for the entire study period (1895–2006).

2.3. Parametric trend analysis

The generalized linear model (GLM) was used to estimate linear trends in the temperature series. The serial autocorrelation in the residual term was accounted for using the autoregressive error model, as described below. Considering a time series of summer temperature anomalies, y_t, from one of the grids in **Figure 1**, GLM estimates the trend (β) in the series as follows:

$$y_t = \alpha + t\beta + \omega_t, \quad t = l, \cdots n_t \tag{1}$$

The term ω_t represents the residuals that contain a deterministic process and a random process (errors) as:

$$\varepsilon_t = \omega_t\left(1 - \varphi_1 B - \varphi_2 B^2 - \cdots \varphi_p B^p\right) \;;\quad \varepsilon_t \sim IN(0, \sigma^2) \tag{2}$$

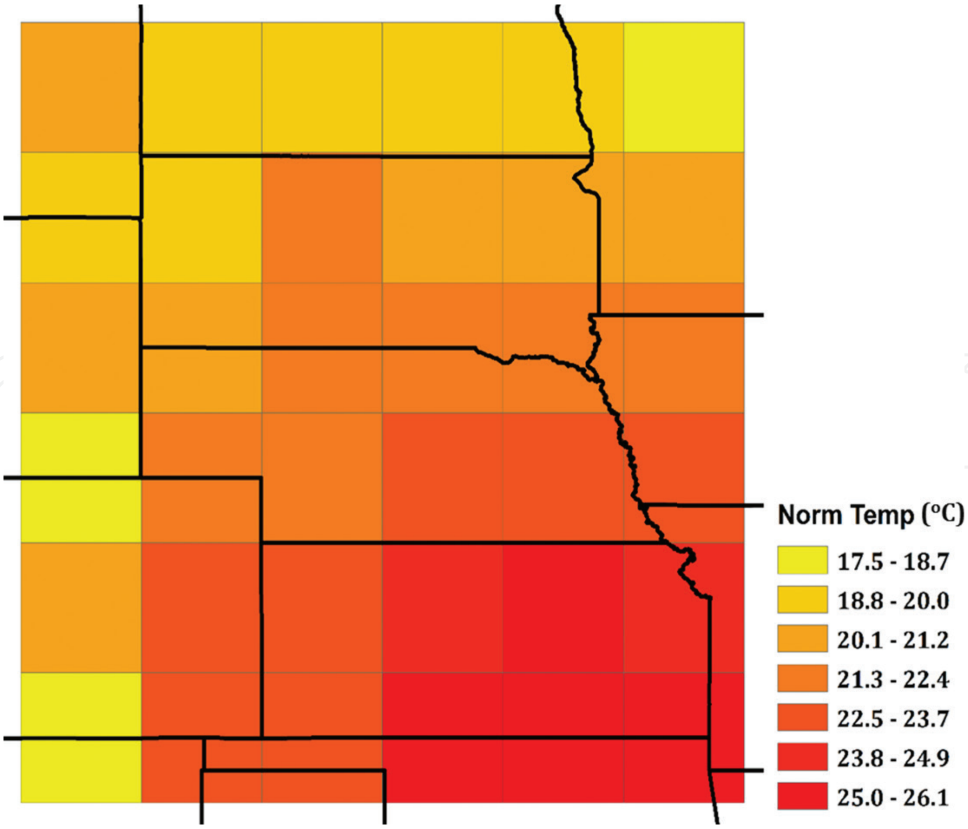

Figure 2. Spatial patterns of normal temperature across the US High Plains for the period from 1895 to 2006 in the summer months (June, July, and August).

where α is the intercept; n_t is the number of study years in a trend period (35 years); ϵ_t is the error term, which is assumed independent (I) and normally (N) distributed with a mean of 0 and a variance of $\varphi_p\sigma^2$; φ_p is the autoregressive error model parameter; p is the autoregressive order; and B is the backshift operator. The right-hand side of Eq. (2) represents the deterministic process imbedded in the residuals of Eq. (1). By removing the deterministic process from the residual term, the autoregressive error model generates independent and normally distributed errors that are critical for the maximum likelihood estimation of trend (β). The β estimates from the GLM are thus the unbiased and minimum variance estimators of trend in the temperature series. A parametric *t*-test was used to test the null hypothesis that the trend in the temperature series was zero at 0.05 level of significance. The *t*-statistic was computed as a quotient of estimated trend (β) and its standard error (S_β).

2.4. Nonparametric trend analysis

The Kendall tau [23], a nonparametric method, was used to determine trends in absolute values of average summer temperatures. The advantage of Kendall tau method over GLM is that the statistical assumption of normality is not strictly necessary and the test statistics are less impacted by outliers in the temperature series. This method has been used to compute trends in climatic and hydrological series [24, 25]. The method is actually applied on ranks of the absolute values; therefore, Kendall tau estimates are relative measures of strength and direction of actual trends. The trend estimates (Kendall tau) were tested at the 0.05 significance level.

3. Results and discussion

3.1. Spatial variation of summer temperatures in the High Plains

The summer norm temperatures of the High Plains in **Figure 2** are averages of 111 years (1895–2006). There is an expected north to south increasing trend in summer temperatures across the region. This spatial variability is driven by the cool air masses from the arctic in the northern part of the Plains and the warm air masses from the Gulf of Mexico in the southern part of the Plains. In the south of the region, there is another west to east increasing trend, which is associated with the elevation gradient across the Plains. Elevation across the Plains increases from less than 200 m in the east to more than 2700 m in the west (**Figure 1**). In the southwest of the Plains, another phenomenon caused by the Chinook winds is associated with the cooler summer temperatures in that region. These high westerly winds subject the Rocky Mountain range to periodic severe turbulence in summer. The winds have a strong cold frontal passage downslope; however, the winds eventually undergo an adiabatic warming process as they move eastward [26]. The effect of Chinook winds can be felt over 100 miles from the Rock Mountains before dissipating as the winds mix and saturate with the atmosphere.

3.2. Temporal variation of summer temperatures in the High Plains

The High Plains region T_{mean} anomalies (base period, 1935–1965) from 1895 to 2006, along with a 6-year moving average of the anomalies, and the Northern Hemisphere Land (NHL) summer temperature anomalies (base period, 1901–2000) are presented in **Figure 3**. There is higher variability in High Plains summer anomalies compared to the NHL because of increase in internal climate variability with decrease in regional size [27]. High Plains anomalies exhibit most of the region's extreme events, including droughts (e.g., 1930s Dust Bowl era), extreme warm and cool summers of the study period. The NHL anomalies are smoother, because the extreme events in one part of the region are likely smoothed by moderate conditions in other paths of the region.

Prior to 1930, **Figure 3** shows that the summer temperature anomalies were mostly below zero. The coolest summer of the study period was in 1915 at 3.44°C below the base period (1935–1965) norm. In the mid-1930s, the Plains experienced the worst drought of the study period. The drought was characterized by high temperatures, high winds, and low rainfall [28]. Temperatures in the drought years of 1934 and 1936 still hold the record of the top two hottest summers in the High Plains. The NHL anomalies do not explicitly feature the drought, an indication that the entire northern hemisphere was not in the drought during the 1930s. The drought peaked in 1936 and declined in the 1940s; however, summer temperatures never reached to pre-1930 conditions. Even though we did not calculate the trend and its significance, from the early 1940s to the 1960s, there appears to be an overall cooling, although there are years with positive anomalies (i.e., several consecutive years in the 1950s). According to Ref. [29], this cooling was observed across entire North America, lasting from 1945 to 1976.

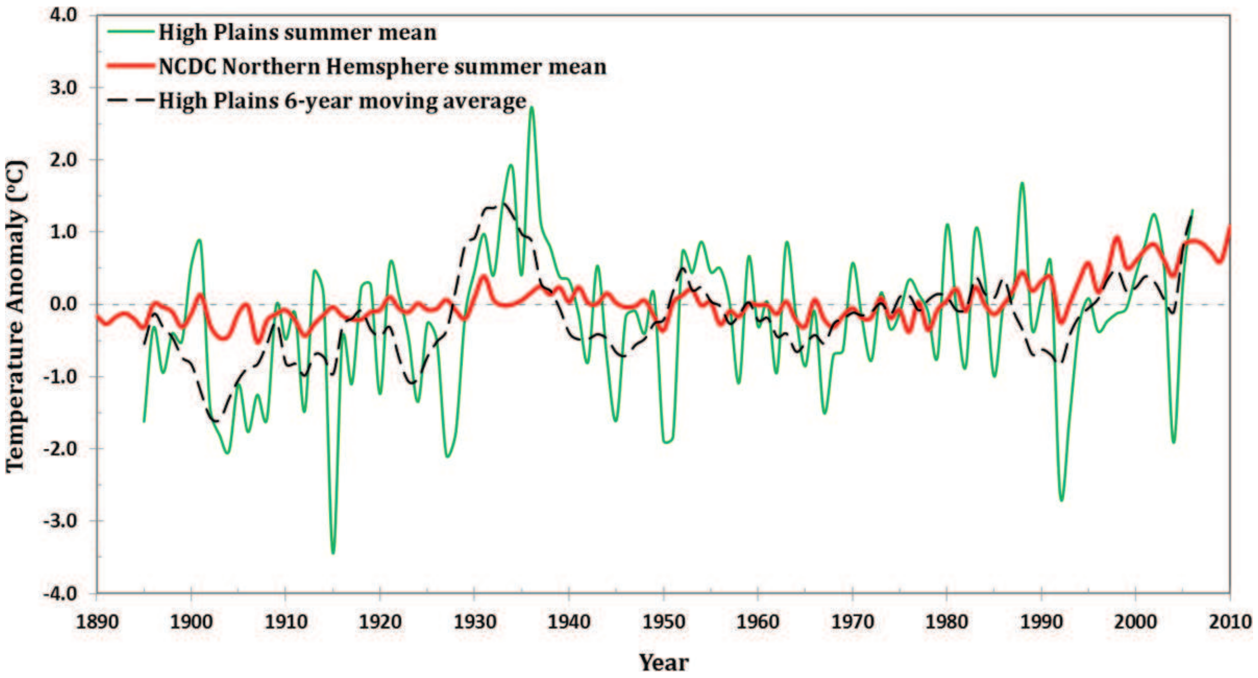

Figure 3. Comparison of variability and trends in the summer mean air temperature (T_{mean}) anomalies relative to 1935–1965 base period for the High Plains (solid green line) and the Northern Hemispheric summer land temperature anomalies relative to 1901–2000 base period (source: NCDC/NESDIS/NOAA, solid red line), and the 6-year moving average (dashed black line) summer T_{mean} anomalies relative to 1935–1965 base period for the High Plains region of the USA.

Since 1970s, the NHL anomalies indicate a warming trend that could be attributed to global warming, primarily due to increases in greenhouse gas emissions. In the High Plains anomalies, the warming trend is obscured by high variability in the series; however, the moving average elucidates the warming trend. Compared to the summers before 1930, the summer temperatures of the High Palins since the 1970s increased, on average, by 0.86°C. In a global study, Ref. [4] similarly observed that temperatures in the first decade of the twenty-first century were about 0.80°C warmer than the beginning of the twentieth century (1880–1920).

3.3. Trends in T_{min}

3.3.1. Parametric analysis

The maximum likelihood estimates of T_{min} trends for the two trend periods are presented in **Figure 4(a** and **b)**. During the reference period (**Figure 4a**), nine grids (25% of the High Plains) had significant warming trends. This warming trend occurred mainly in the northern part of the Plains. The trends were insignificant in the south part of the region. Across the High Plains, there is no statistically significant evidence of a trend in T_{min}.

Figure 4b shows the spatial trend patterns in T_{min} during the warming period. More area (50%) across the region, still mostly in the north, experienced significant warming in T_{min} during the warming period. Unlike the reference period, the overall T_{min} trend of the region in the warming period was significant at 0.02°C/year.

3.3.2. Nonparametric analysis

The nonparametric Kendall tau estimates of trend patterns in T_{min} are shown in **Figure 5(a** and **b)** (the trend estimates in **Figures 5**, **7**, and **9** are tau values, which are relative estimates

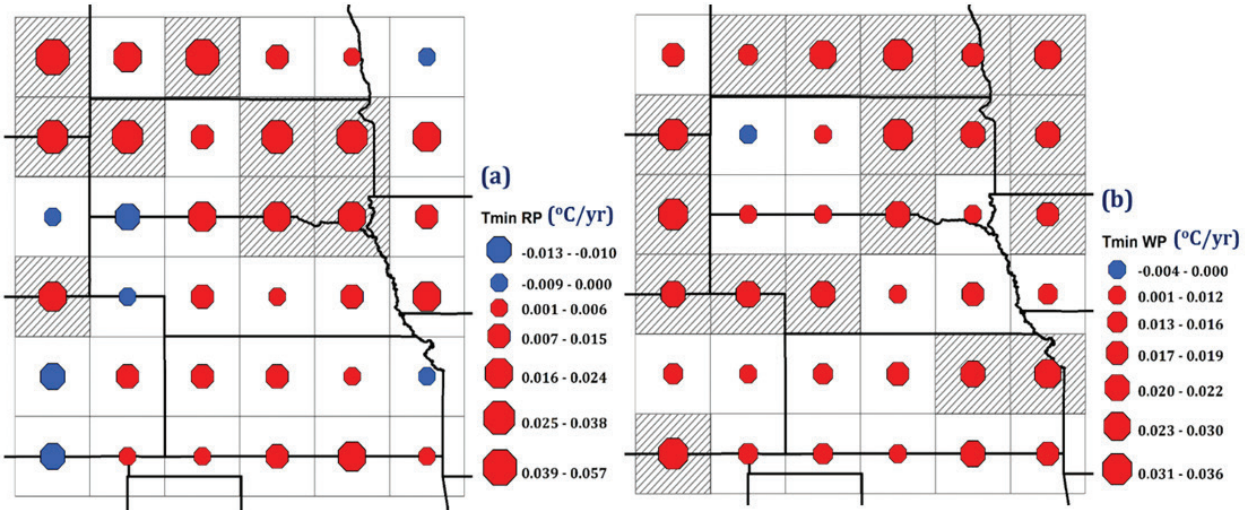

Figure 4. Spatial trend patterns of summer T_{min} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed from generalized linear models. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

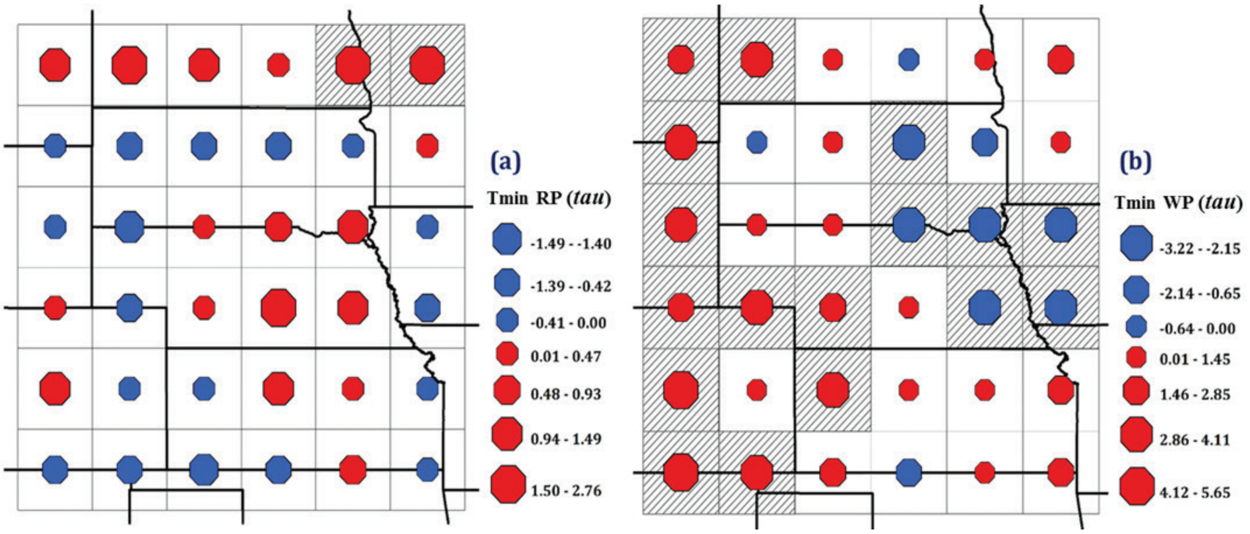

Figure 5. Spatial trend patterns of summer T_{min} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed by Kendall tau method. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

of strength and direction of the actual trends. These values describe the spatial variability of the trends across the region during the specified trend period). The Kendall tau analysis detected similar significant trend patterns as GLM in the northern part of the Plains during the reference period. About 22% of the High Plains had significant warming trends before 1930. The results from nonparametric and parametric analyses are comparable in identifying trend patterns during the reference period. During the warming period, however, Kendall tau test was more effective in detecting significant trends across the region (**Figure 5b**). According to Kendall tau, most of the region experienced significant warming during the warming period. The nonparametric test is effective in terms of identifying significant trends, because of its relative insensitivity to extreme values in the series. Both parametric and nonparametric analyses on T_{min} agreed that during the reference period the overall trend in T_{min} was stationary. And, since 1971, T_{min} has significantly increased at the rate of 0.02°C/year. Overall, parametric methods lead to the conclusion that 50% of the study area experienced a significant warming trend in T_{min}. In comparison, nonparametric methods indicated that 94% of the study area experienced a warming trend.

3.4. Trends in T_{max}

3.4.1. Parametric analysis

Figure 6(a and **b)** shows the maximum likelihood estimates of T_{max} trends for the two trend periods. The trends in T_{max} were mostly weaker than trends in the T_{min}. In **Figure 6a**, the trend patterns in reference period were only significant in four grids of the northern High Plains (11% of the High Plains). The magnitudes of the overall trend of the entire High Plains region during the reference period were insignificant at a rate of 0.01°C/year.

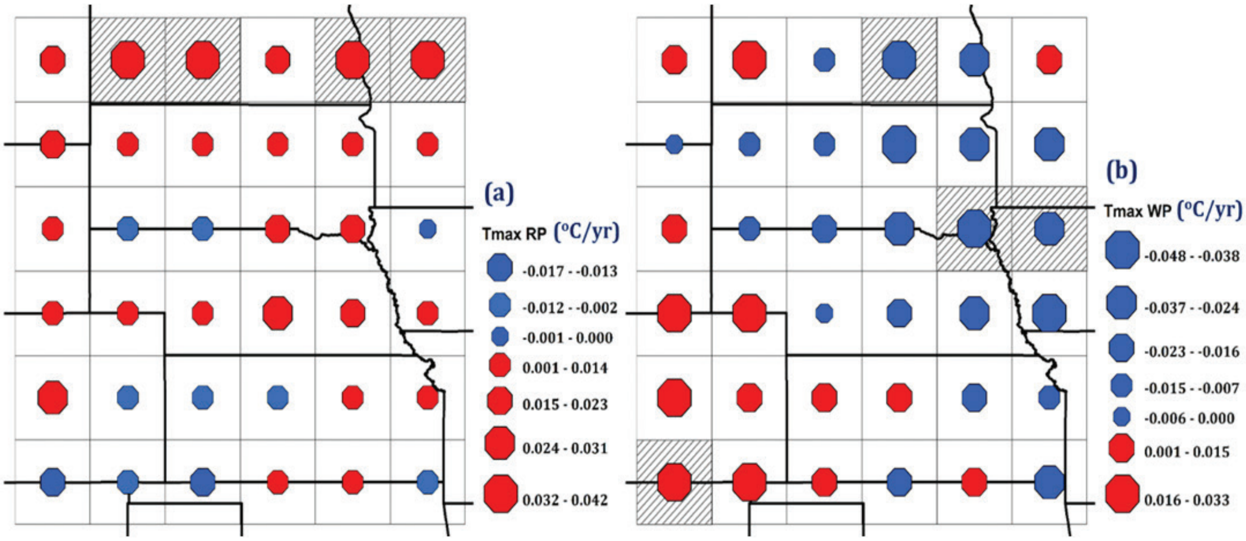

Figure 6. Spatial trend patterns of summer T_{max} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed from generalized linear models. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

During the warming period (**Figure 6b**), only one grid in the southwest of the High Plains had a significant warming trend in T_{max}. The other areas with significant trends had cooling effects. For the rest of the region, the trends were insignificant and many had a cooling effect. In fact, the overall trend in T_{max} during the warming period was insignificant with a cooling effect of −0.004°C/year. Folland et al. [7] also observed that in the last quarter of the twentieth century the Central United States cooled by 0.2–0.8°C in summer. While the significance is identified

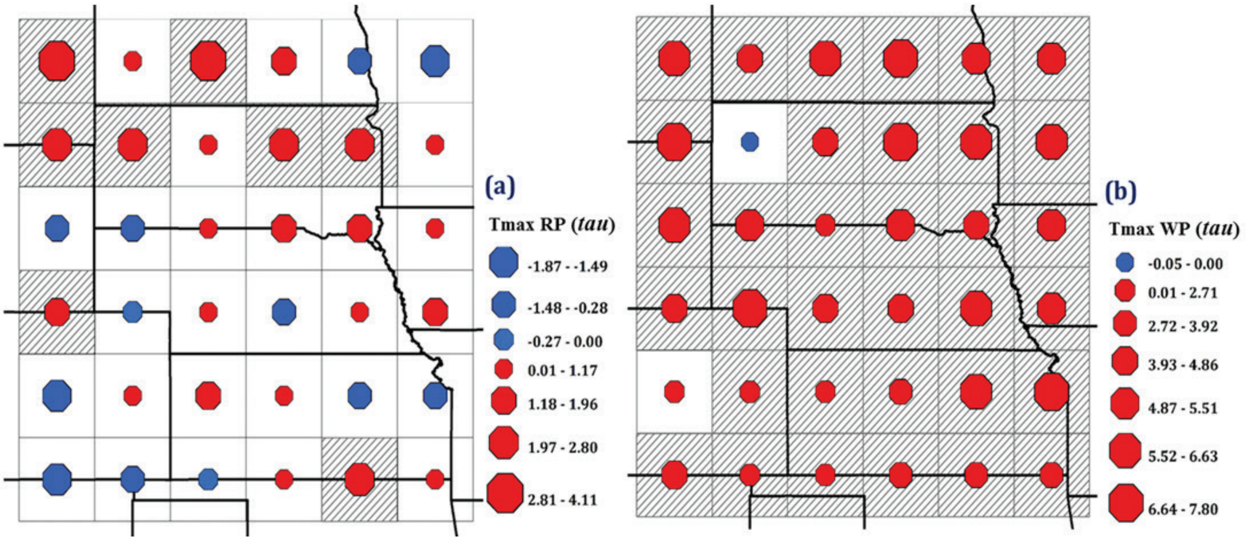

Figure 7. Spatial trend patterns of summer T_{max} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed by Kendall tau method. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

statistically in this and other studies, in practice, the error of measurement of Tair with various thermometers, including mercury thermometers used in historical datasets, is probably in the ±0.5°C range and, thus, a trend of −0.004°C/year might have a "statistical" significance but may not be truly a "physical significance," depending on the measurement resolution of the thermometers used.

3.4.2. Nonparametric analysis

The trend patterns in T_{max} determined by Kendall tau method are shown in **Figure 7(a** and **b)**. During the reference period, the Kendall tau trend patterns (**Figure 7a**) were similar to the GLM trend patterns (**Figure 6a**), with significant warming only observed in the northeast of the region. For the warming period (**Figure 7b**), more significant warming trends were detected by Kendall tau method, especially in the western part of the Plains. In the central-eastern part, the Plains experienced a significant cooling during the warming period (**Figure 7b**). As with the parametric method, the nonparametric overall trends in T_{max} during the reference and warming periods were also insignificant. A possible influence on T_{max} during the warming period is evaporative cooling from extensive irrigation practice in the High Plains during the summer months of June, July, and August. However, we have not conducted analyses to explicitly study whether irrigation practice is the cause of the trends. In addition to irrigation practices, other practices such as elevations; changes in land use, population, management practices, changes in the locations and surroundings, as well as instrumentation used in the weather stations from which climate were obtained, etc. can also influence trends and magnitudes in air temperatures, which were not considered in this study.

The potential impact(s) of land use (e.g., irrigation) impact on surface air temperature has been studied primarily using large-scale climate models with varying results. For example, Ref. [30] used a regional climate model, which showed the regional irrigation cooling effect (ICE) exists, opposite in sign to urban heat island effects. The magnitude of the ICE has strong seasonal variability, causing large dry-season decreases in monthly mean and maximum temperatures, but little change in rainy season temperatures. Their model produced a negligible effect on monthly minimum temperature. In California, the modeled regional ICE is of similar magnitude, but opposite sign, to predictions for future regional warming from greenhouse gases. Given their modeling results for California and the global importance of irrigated agriculture, they concluded that past expansion of irrigated land has likely affected observations of surface temperature, potentially masking the full warming signal caused by greenhouse gas increases.

Lara et al. [31] reported the seasonally varying temperature responses of four regional climate models (RCMs)—RSM, RegCM3, MM5-CLM3, and DRCM—to conversion of potential natural vegetation to modern land cover and land use over a 1-year period. Three of the RCMs supplemented soil moisture, producing large decreases in the August mean (−1.4 to −3.1°C) and maximum (−2.9 to −6.1°C) 2-m air temperatures where natural vegetation was converted to irrigated agriculture. Conversion to irrigated agriculture also resulted in large increases in relative humidity (9–36% absolute change). Modeled changes in the August minimum 2-m air temperature were not as pronounced or consistent across the models. Converting natural vegetation to urban land cover produced less pronounced temperature effects in all models, with the magnitude of the effect dependent upon the preexisting vegetation type and urban parameterizations. Their modeling results indicated that, overall, the RCM results indicate that the temperature impacts of land-use change are most pronounced during the summer months, when surface heating is strongest and differences in surface soil moisture between irrigated land and natural vegetation are largest.

Using ensemble simulations, Ref. [32] evaluated the impacts of irrigation changes on air temperatures in the twentieth century. Simulation results indicated that early in the century, irrigation was primarily localized over southern and eastern Asia, leading to significant cooling in boreal summer (June-August) over these regions. This cooling spread and intensified by the century's end, following the rapid expansion of irrigation over North America, Europe, and Asia. Irrigation also led to boreal winter (December-February) warming over parts of North America and Asia in the latter part of the century, due to enhanced downward longwave fluxes from increased near-surface humidity. They suggested, based on their modeling results, these trends reveal the varying importance of irrigation-climate interactions and suggest that future climate studies should account for irrigation, especially in regions with unsustainable irrigation resources. Lobell et al. [33] observed trends in Tmax were negative in irrigated areas of California and Nebraska, which they attributed to increase in latent heat flux and associated reduction in sensible heat flux. Irrigation development in the High Plains increased substantially over the last five decades. The irrigated area in the High Plains states increased from 8 million ha in 1980 to more than 13.4 million ha in 2000. In Nebraska, the total irrigated area has more than doubled in the last four decades, increasing from 1.6 million ha in 1970 to over 3.6 million ha in 2008 [34]. Other neighboring states also experienced considerable increases in irrigated acreage.

3.5. Trends in T_{mean}

3.5.1. Parametric analysis

In terms of trends in T_{mean} (**Figure 8a** and **b**), during the reference period, much of the High Plains did not experience significant trends, except the northern region (**Figure 8a**). For the rest of the Plains, the trend patterns are insignificant and many have a cooling effect. The overall trend during the reference period was stationary at a rate of 0.01°C/year. During the warming period (**Figure 8b**), with the exception of the western part of the plains, the rest of the region experienced insignificant trends. The overall warming period trend in T_{mean} was stationary at a rate of 0.01°C/year.

3.5.2. Nonparametric analysis

Trend patterns in T_{mean} obtained from the nonparametric procedure are shown in **Figure 9(a and b)**. During the reference period (**Figure 9a**), the results were similar to GLM findings, and the northwestern part of the Plains was the only area experiencing significant warming before the 1930s. The trend patterns during warming period that are presented in **Figure 9b** show that Kendall tau detected more significant trends in T_{mean} than GLM. Areas in east-central,

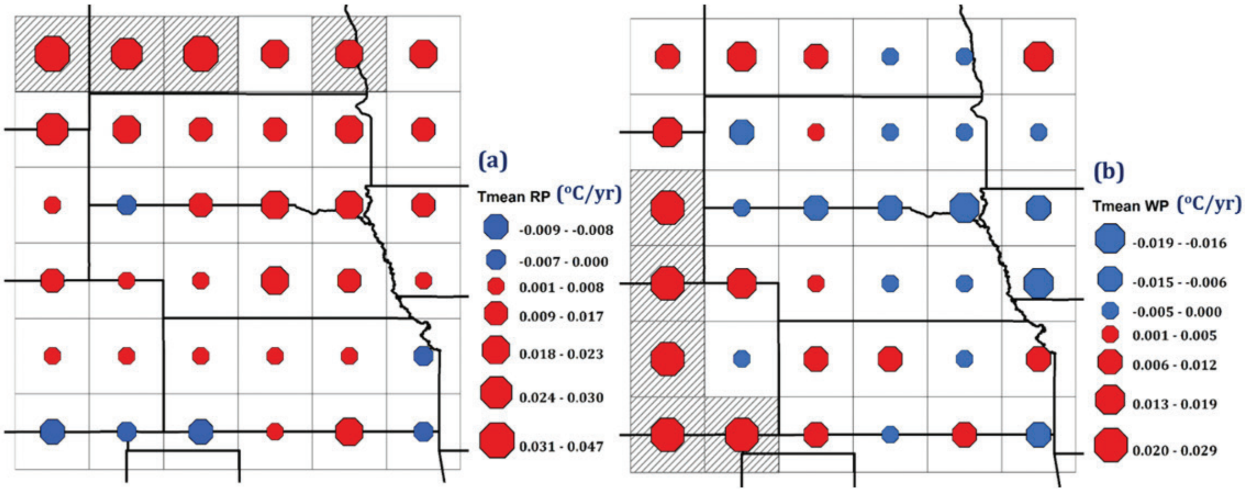

Figure 8. Spatial trend patterns of summer T_{mean} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed from generalized linear models. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

which had significant cooling trends in T_{max} (**Figure 7b**), had insignificant trends in T_{mean}, regardless of significant warming trends in T_{min} (**Figure 5b**). This suggests that the trends in T_{mean} are interactively influenced by the direction and magnitude of trends in T_{min} and T_{max}. For instance, some grids in the east of the region had a significant warming trend in T_{min} (**Figure 5b**) and significant cooling trend in T_{max} (**Figure 7b**), which resulted in an insignificant trend in T_{mean} (**Figure 9b**). Likewise, in the northern part of the High Plains, significant warming trends in T_{min} (**Figure 4b**), coupled with insignificant and significant cooling trends in T_{max} (**Figure 6b**), resulted in insignificant trends in T_{mean} (**Figure 8b**). Given that a significant trend

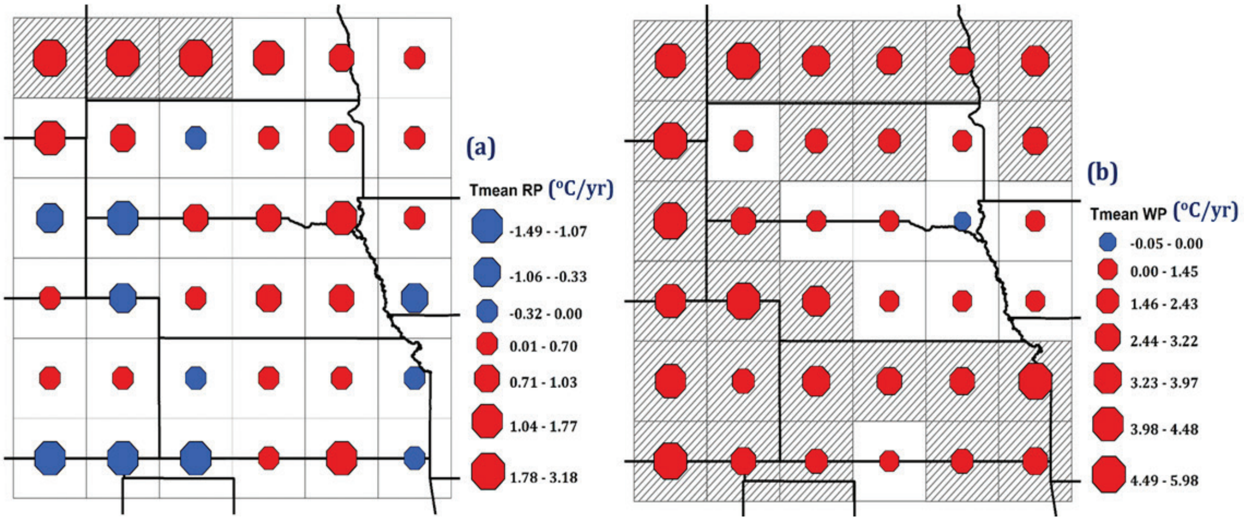

Figure 9. Spatial trend patterns of summer T_{mean} for (a) *reference period* (1895–1930) and (b) *warming period* (1971–2006) computed by Kendall tau method. The hatching shows areas where the trend was significant. The red and blue indicate warming and cooling trend effects, respectively. The trend estimates are in degrees Celsius per year. RP: reference period; WP: warming period.

in either T_{min} or T_{max} can be muted by the direction or strengthen of trend in the other, T_{mean} may be confounding to interpret and may not be an effective or ideal variable to investigate in climate change studies. In fact, Ref. [33] suggest that studies that assess impacts of climate change using only projections of T_{mean} risk over- or underestimation of uncertainties when considering process that respond differently to day and nighttime temperature.

4. Summary and conclusions

Change in climate variables, especially air temperature, can have significant impact(s) on water availability, use, management, allocation, and projections for rural and urban applications as temperature is one of the primary drivers of evaporative losses in urban and rural areas. Thus, understanding the climate change impact(s) on air temperature can aid in water use projections and other water availability assessments in urban and rural areas on large scales. We investigated trends in air temperatures of the US High Plains region in two trend periods: reference period (1895–1930) and warming period (1971–2006). Separating the data records into reference and nonreference, we think, is a unique aspect of this study that investigated long-term trends. The trend patterns were examined in T_{min}, T_{max}, and T_{mean} using parametric and nonparametric methods. The parametric method was beneficial in determining the absolute measure and direction of the trends and the nonparametric method was more effective in testing the significance of the trends. Studies that use two or more methods (parametric and nonparametric) to investigate climate parameters, especially on large scales, such as US High Plains, are useful as they may provide insight in terms of identifying the strengths and/or weakness of each method and, eventually, to rank the appropriate one. In this study, the parametric method was beneficial in determining the absolute measure and direction of the trends, but the nonparametric method was more statistically powerful in testing the significance of the trends.

The warming trends in T_{min} were stronger than in T_{max} and T_{mean}. From both trend methods, T_{min} had the biggest contrast between the reference period and the warming period. The overall trend in T_{max} over the High Plains during the warming period had an insignificant cooling effect. The trends from T_{mean} were confounded to be able to interpret since they interactively depended on the directions of trends in T_{min} and T_{max}. Both parametric and nonparametric methods showed that T_{min} was stationary during the reference period and significant warming during the warming period. In the warming period, the overall trend in T_{min} was significantly increasing by 0.02°C/year. One of the uncertainties or shortcomings of this study could be that the potential reasons of warming or cooling trends in air temperatures (e.g., changes in land use and land management, urbanization, irrigation development, and other factors) were not investigated. Further research is needed to investigate the potential interrelationships between temperature trends and change(s) in land surface characteristics on large scales. Another shortcoming of the study could be that the study focuses only on summer air temperature trends and magnitudes. However, the changes in spring, fall, and winter temperatures can also impact urban and rural water balances, especially in terms of dormant season evaporative losses, and investigating spring, fall, and winter temperature trends can be beneficial in several aspects of change in temperature impacts on urban and agricultural practices.

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Author details

Denis Mutiibwa[1], Ayse Kilic[2] and Suat Irmak[3]*

*Address all correspondence to: sirmak2@unl.edu

1 United States Department of Agriculture, Agricultural Research Service, Beltsville, MD, USA

2 School of Natural Resources and Civil Engineering Department, University of Nebraska-Lincoln, Lincoln, NE, USA

3 Department of Biological Systems Engineering, University of Nebraska-Lincoln, Lincoln, NE, USA

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