Use of Historical Data to Assess Regional Climate Change

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ABSTRACT

Time series of historical annual average temperature, total precipitation, and extreme weather indices were constructed and analyzed for 103 (for temperature indices) and 115 (for precipitation indices) U.S. cities with climate records starting earlier than 1900. Mean rate of change and related 95% confidence bounds were calculated for each city using linear regression for the full periods of record. Box–Cox transformations of some time series of climate records were performed to address issues of non-normal distribution. Thirteen cities among the nine U.S. climate regions were selected and further evaluated with adequacy diagnoses and analyses for each month. The results show that many U.S. cities exhibit long-term historical increases in annual average temperature and precipitation, although there are spatial and temporal variations in the observed trends among the cities. Some cities in the Ohio Valley and Southeast regions exhibit decreasing or statistically nonsignificant increasing trends in temperatures. Many of the cities exhibiting statistically significant increases in precipitation are in the Northeast and Upper Midwest regions. The records for the cities are individually unique in both annual and monthly change, and cities within the same climate region sometimes exhibit substantially different changes. Within the full periods of record, discernible decade-long subrends were observed for some cities; consequently, analysis of selected shorter periods can lead to inconclusive and biased results. These statistical analyses of constructed time series of city-specific long-term historical climate records provide detailed historical climate change information for cities across the United States.

1. Introduction

Climate is unique in each region and climate change in different locations can be significantly different (Martel et al. 2018; Deser et al. 2014). Despite numerous existing studies on the changing climate on global (Hartmann et al. 2013), national (Melillo et al. 2014; Wuebbles et al. 2017), and state scales (Shortle et al. 2015), assessments of regional climate change, especially for city scales, are crucial for many purposes, including infrastructure engineering. Evaluation of the location-specific regional climate record can provide detailed information about climate variability in a region, how the climate in a region has changed, and what the climate in a region may

be like in the near future. A considerable number of cities and stations in the United States have archived daily temperature and precipitation records from as early as the 1870s and such records can provide valuable information of relatively long-term regional climate change.

Previous studies have performed extensive analyses of historical station-level climate data and such analyses often involve the spatial aggregation of local stations. The aggregation techniques include averaging of gridded cells (Smith et al. 2013), area-weighted averaging (Kunkel et al. 1999), and weighting algorithms (Alexander et al. 2006). Depending on different interests and analysis purposes, the lengths of records for aggregation have varied; examples include 1979–2011 (Smith et al. 2013), 1951–2003 (Alexander et al. 2006), 1950–2007 (Peterson et al. 2013), 1895–2000 (Kunkel et al. 2003), and 1895–2010 (Kunkel et al. 2013). The sizes of regional areas for which data have been aggregated have also varied, from grids of $2.5^{\circ} \times 3.75^{\circ}$ (Caesar et al. 2006) and $4^{\circ} \times 5^{\circ}$ (Kunkel et al. 2003) to the U.S. climate divisions (Kunkel 2003; Vose et al. 2014) and the U.S. climate regions (Smith et al. 2013). Moreover,

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different climate variables have been analyzed in different studies, such as frequency of threshold exceedance (Kunkel et al. 2013) and parameters for general extreme distribution (DeGaetano 2009).

While it is useful to assess climate trends at regional levels such as gridded cells and climate divisions, robust assessment of long-term historical climate records at an individual location/city is often of significant interest for practical applications such as design, management, and operation of infrastructure, including the need for changing building codes to account for climate change factors, the need for modifying stormwater management design with consideration of increasing extreme precipitation, and the need for modifying building operations (Younger et al. 2008; ASCE 2015).

The objective of this study was to assess regional climate change in the United States by compiling long-term historical climate records for cities in the contiguous United States, working with the original daily temperature and precipitation records, and evaluating with statistical methods the variability and underlying trends in the time series of temperature, precipitation, and their extremes. A better understanding of historical climate variability and climate trends for cities in different regions can facilitate comparison of climate change between cities and between regions, enhance the understanding of city-scale historical climate change across the country, and lay the groundwork for using the historical climate record to provide regional near-term climate forecasts.

2. Background—Evaluation of regional climate trends

Among a range of statistical approaches to assess the time series of past climate records and differentiate the anthropogenic changes from the climate variability, often referred as “exploratory data analysis” (Schneider and Held 2001), conventional linear regression remains as the mostly used approach. It is worth noting that the various statistical approaches may have different definitions of climate variability and the results for underlying trend are dependent on the selected statistical methods (Franzke 2012). The linear regression method, by taking the rate of change estimated from a linear trendline as the underlying trend and the fluctuations from the trendline as the climate variability, can be found in numerous studies of nonstationary historical climate trends, including Groisman et al. (2004) for annual temperature and precipitation records in the United States, Menne et al. (2009) for monthly temperature record in the United States, and Bindoff et al. (2013) and Eastoe and Tawn (2009) for global temperature and precipitation records. Using linear estimation assumes

the underlying trend is linear during the full period of record, while the actual climate records can be nonlinear (Franzke 2010).

Several methods have been employed to address nonlinearity in climate records; however, no single method significantly outperforms the others and linear regression can still provide reasonable results. Sophisticated statistical methods have been utilized to assess the nonlinearity include wavelet transform (Lau and Weng 1995) and empirical mode decomposition (Huang et al. 1998; Carmona and Poveda 2014; Islam Molla et al. 2006). Franzke (2012) has analyzed surface temperature variability and underlying trend with various statistical approaches and suggests that simpler methods like ordinary linear regression can provide reasonable results in trend detection, although methods like empirical mode decomposition and wavelet transform perform better with data showing nonlinearity.

Of common interest in evaluation of the long-term climate record is identification of the “climate normal” and its possible evolution with time. The World Meteorological Organization (WMO) recommends a period of 30 years as the most appropriate length to represent “normal,” and average values of measurements from 30-yr climatological records are typically used to represent “climate normal” (WMO 2011). The climate normal is updated each decade, and the recent climate normal in 2018 is from the period 1981–2010 (WMO 2011). With the consideration of nonstationary climate, previous investigators have discussed the need for updating of the method of determining climate normal with the “optimal climate normal” (OCN) (Huang et al. 1996). The OCN method identifies the optimal number of years for calculation of seasonal climate normals instead of using 30 years (Huang et al. 1996). The OCN method currently adopted by the National Weather Service (NWS) Climate Prediction Center utilizes the past 10 (or 15) years for temperature and precipitation records (Wilks 2013).

Besides the OCN method, climate normals can be updated with estimations of underlying trends using linear trend or hinge trend methods (Guttman 1989; Livezey et al. 2007; Wilks and Livezey 2013). While a linear trend is assumed in the linear trend method, the hinge trend method assumes the climate was stationary until 1975 and evaluates climate normal with linear regression for the period after 1975 (Livezey et al. 2007). The “Local Climate Analysis Tool”, developed by the National Oceanic and Atmospheric Administration (NOAA), is available online (<https://nws.weather.gov/lcat/home>) and offers the OCN, exponential weighted moving average, and hinge trend methods to assess regional climate records (Timofeyeva-Livezey et al. 2015).

Other tools like “Climate at A Glance” (NOAA/NCEI 2018a) and “The Climate Explorer” (NOAA 2018) also offer access to historical temperature and precipitation data and downscaling climate projections for different regions and cities. However, only climate records at currently active weather stations are provided for the U.S. cities in these tools while many cities archive climate records starting from as early as 1870s.

A “reference period” or “baseline period” is often used in evaluating historical climate data and there are no standard criteria for selection of this period. Reference periods used in various studies can be significantly different. The Intergovernmental Panel on Climate Change (IPCC) has utilized the period of 1961–90 as the reference period in their last four assessment reports (ARs) (Houghton et al. 1996, 2001; Hartmann et al. 2013; Trenberth et al. 2007). The use of a 30-yr interval for reference period is based on the WMO’s 30-yr climate normal (WMO 2011) and 1961–90 is kept as the reference period by the IPCC to enable comparisons with previous ARs (Hartmann et al. 2013). The U.S. National Climate Assessment (NCA) reports, on the other hand, use the period from 1901 to 1960 as the reference period for their analyses. According to the third NCA report (Melillo et al. 2014), the reference period starts at 1901 because climate records in the United States before 1901 are limited and unreliable, and the period ends at 1960 because human-induced forcing has accelerated starting from 1960.

The selection of reference period can be significant in determining the historical climate normal and calculating the changes between a recent period and the reference period. For example, selection of a relatively cold period for the reference period can lead to a larger number of extreme warm events calculated from a climate record. The use of a reference period inherently induces bias into an analysis, and different reference periods used in different studies can make the comparison of the analyses difficult. Therefore, the use of a reference period must be considered carefully in analyses of historical climate data. In this study, when a baseline period was required for the calculation of an extreme weather index, the period from the start of record to the end of 1987 was employed as the reference period (with the lengths varying among cities).

The 2017 U.S. National Climate Assessment showed a 1.2°F increase of annual average temperature in comparing the 1986–2015 average temperature to that from 1901 to 1960 as the reference period, and a U.S. average of 4% annual precipitation increases during 1901–2015 (Wuebbles et al. 2017). Temperature extreme indices were observed in the NCA to exhibit spatial trends. For example, “almost all locations east of the Rocky Mountains” have exhibited decreases in annual warmest

temperatures, comparing the 1986–2016 average to the 1901–60 average (Wuebbles et al. 2017). Great regional variations have also been identified for temperature changes (Easterling 2000), such as the “warming hole” in the Southeast United States (Easterling 2000; Meehl et al. 2012). Precipitation records, including extremes, also exhibit temporal and spatial variations across the United States; for example, high precipitation amounts were observed from the 1890s to 1900s, decreases in the 1920s, and increases in the 1990s (Kunkel et al. 2003); the western United States has exhibited no significant changes in precipitation while the Midwest, Southeast, and Northeast regions exhibited significant increases (Kunkel et al. 2013; Mass et al. 2011).

3. Methodology

a. Data compilation, quality assurance, and homogenization

For evaluation of a long-term climate record, the continuity and quality of climate data need to be ensured (Menne et al. 2012; Trenberth et al. 2007). The daily maximum and minimum temperature and daily precipitation record were obtained from the Applied Climate Information System (ACIS), developed by the NOAA Northeast Regional Climate Center (NRCC) (DeGaetano et al. 2015). The historical climate data provided by ACIS are from the Global Historical Climatology Network–Daily (GHCN-Daily) dataset (DeGaetano et al. 2015). The GHCN-Daily dataset combines climate datasets from various sources (Menne et al. 2012) and the most relevant one for this study was the dataset of the Cooperative Observer Program (COOP). Currently managed by NWS, COOP is a climate observing network and was established under an act of the U.S. Congress in 1890 whereas some stations began operation long before 1890 (Leeper et al. 2015). The GHCN-Daily climate data have undergone multi-tiered quality assurance checks for research applications like climate analysis (Menne et al. 2012).

Data in the current version of the GHCN-Daily climate database have not been homogenized for systematic biases, however, including instrument changes, station location changes, site characteristics changes, and the urbanization effect (Menne et al. 2012). Such inhomogeneities were identified and adjusted in the current versions of GHCN-Monthly and United States Historical Climatology Network (USHCN)-Monthly datasets for the temperature records (Lawrimore et al. 2011; Menne et al. 2009). As shown in Menne et al. (2009), homogenization of such biases can lead to annual differences of 0.2°C (0.36°F) for time of observation adjustment and annual differences of 0.3°C (0.54°F) for pairwise

TABLE 1. The 13 selected cities and their threaded stations (AP = Airport, WSO = Weather Service Office; WB = Weather Bureau; WSFO = Weather Service Forecast Office; USC = University of Southern California).

Climate region	City	City ID	Period of daily temp record	Period of daily precip record	Station name	Distance to the first station (mi)
Northeast	Philadelphia	PHL	1874–2017	1873–2017	Philadelphia	—
					Philadelphia Intl AP	7.1
	Pittsburgh	PIT	1875–2017	1871–2017	Pittsburgh WSO City	—
					Allegheny County AP	7.77
Southeast	Atlanta	ATL	1879–2017	1879–2017	Pittsburgh Intl AP	11.53
					Atlanta WB City	—
					Atlanta Hartsfield Intl AP	8.95
Ohio Valley (Central)	Chicago	CHI	1873–2017	1871–2017	Chicago WB City 2	—
					Chicago University	7.12
					Chicago Midway AP	12.54
					Chicago O'Hare Intl AP	17.26
	Columbus, OH	CMH	1879–2017	1879–2017	Columbus	—
Upper Midwest (East North Central)	Detroit	DET	1874–2017	1871–2017	Columbus Intl AP	6.54
					Detroit	—
					Detroit City AP	5.63
					Detroit Metro AP	16
Northern Rockies and Plains (West North Central)	Omaha	OMA	1871–2017	1871–2017	Omaha	—
					Omaha WSFO	8.158
					Omaha Eppley Airfield	3.5
South	Houston	HOU	1892–2017	1889–2017	Houston WB City	—
					Houston Intercontinental AP	14.75
	San Antonio	SAT	1886–2017	1886–2017	San Antonio	—
					San Antonio Stinson AP	7.688
Southwest	Denver	DEN	1872–2017	1872–2017	San Antonio Intl AP	6.601
					Denver WSO City	—
					Denver Stapleton	6.12
					Denver Intl AP	18.23
	Phoenix	PHX	1896–2017	1896–2017	Phoenix City	—
Northwest	Seattle	SEA	1894–2017	1894–2017	Phoenix AP	4.76
					Seattle WB City	—
					Seattle Tacoma Intl AP	14.228
West	Los Angeles	LAX	1878–2017	1878–2017	Los Angeles Downtown/USC	—

algorithm adjustment. Data homogenization has increased the historical trends from 0.018°C (0.032°F) decade^{-1} to 0.075°C (0.135°F) decade^{-1} for the annual daily maximum/minimum temperature in the United States (Menne et al. 2009). Different stations may be modified with different annual adjustments and exhibit different changes in historical trends. Section A in the online supplemental material provides an analysis of such homogenization efforts for the San Antonio, Texas, station [San Antonio International Airport (Intl AP)] as an example.

Because the homogenized GHCN-Daily or USHCN-Daily datasets are still under development (Menne et al. 2015), the calculations of extremes require the input of daily temperature and precipitation records; to allow the comparisons between average temperature/precipitation and their extremes, analyses using the current non-homogenized GHCN-daily datasets in this study were performed. Note that the recent study of Hausfather et al. (2016) shows, the records from the U.S. Climate

Reference Network validate the homogenization efforts in USHCN-monthly datasets; however, such adjustments of systematic bias will not affect the key findings in this study. Currently nonhomogenized GHCN-daily data are widely used in the previous studies such as NCA reports and IPCC ARs (Wuebbles et al. 2017; Hartmann et al. 2013), especially for extreme events. It is recognized, though, that the use of homogenized GHCN-Daily datasets, once available, can potentially improve the results of this study, especially the understanding of the significance of the historical temperature trends.

Annual average temperature, total precipitation, and extreme weather indices were then constructed and analyzed for U.S. cities with climate records starting earlier than 1900. Based on location and data longevity and continuity, a group of 13 cities was selected for further analysis, including analyses on monthly indices and different periods of record. Table 1 shows the 13 cities selected as examples, their distribution among the

TABLE 2. Extreme weather indices utilized in this study. Note that for the threshold-related indices, the period before 1988 (to the end of 1987) was selected as the reference period; the actual lengths of the reference period are dependent on each city's period of record. For the monthly extreme weather indices, the thresholds were calculated based on the record from each month.

ID	Index name	Index definition	Units
TXx	Warmest daily $T_{\max}$	Maximum value of daily maximum temperature	°F
TNx	Warmest daily $T_{\min}$	Maximum value of daily minimum temperature	°F
TXn	Coldest daily $T_{\max}$	Minimum value of daily maximum temperature	°F
TNn	Coldest daily $T_{\min}$	Minimum value of daily minimum temperature	°F
TX90p	Warm days	Percentage of time when daily max temperature > 90th percentile	%
TN90p	Warm nights	Percentage of time when daily min temperature > 90th percentile	%
TX10p	Cold days	Percentage of time when daily max temperature < 10th percentile	%
TN10p	Cold nights	Percentage of time when daily min temperature < 10th percentile	%
RX1day	Wettest day	Maximum 1-day precipitation	in.
RX5day	Wettest consecutive 5 days	Maximum consecutive 5-day precipitation	in.
R95p	Precipitation from very wet days	Total precipitation amount from days > 95th percentile	in.

nine climate regions in United States, and their periods of temperature and precipitation records.

The climate record for each city does not come from one single station; the complete temperature and precipitation records are constructed based on records from multiple local stations, as shown in Table 1 for the 13 cities as examples. The station selection was based on NRCC's "ThreadEx" project, which combined daily temperature and precipitation extremes at 255 NOAA Local Climatological Locations, representing all large and medium cities in the United States (Owen et al. 2006). The criteria and process used for the selection of the local stations were as described by Owen et al. (2006). The currently active weather forecasting station for each city, typically the main local airport, is the preferred starting station to compile the record backward. When this station runs out of record, other stations, preferably local Weather Service/Bureau stations, are then utilized to extend the record as far back in time as possible. Any gap of more than six months of record was filled with another station's record. Only one station's record is used for any overlapping period. For example, the complete climate record of Pittsburgh was constructed using the record from the Pittsburgh Intl AP station (from 2017 to 1948), the Allegheny County AP station (from 1947 to 1935), and the Pittsburgh Weather Service Office (WSO) City station (from 1935 to 1875 or 1871 for precipitation). The threaded station information in the ThreadEx project can be accessed in ACIS (NOAA/NCEI 2018b). Although the compilation of a climate record for a city based on multiple stations can cause an overall increasing or decreasing shift in temperature data in the time series (magnitude of 1°–3°F for a typical temperature record; see section B of the supplemental material), the distances between selected stations for each city are within 40 km (about 25 miles), which are often considered within "close proximity" (Menne et al. 2012), and thus assessment of such compiled temperature

and precipitation records was performed. Studies have also shown that the selection of neighboring stations for "gap filling" in temperature record should consider a maximum radius of about 40 km or perhaps somewhat farther (Tardivo and Berti 2014), and the number of stations should not exceed four (Eischeid et al. 1995).

Daily time series of climate data were then constructed for 210 U.S. cities that have climate records starting earlier than 1900. However, missing data were identified for some cities as the result of GHCN-D data quality assurance or missing data from the original station records. To ensure the assessment quality, any year that had more than 10 days of daily data missing for a particular city was removed from the time series for that city; and cities with more than 5% of missing years in the time series were removed from the analyses (except Houston and Los Angeles, which had only slightly higher than 5% missing years). Consequently, 103 cities in the United States were analyzed for the selected temperature indices and 115 cities were analyzed for the precipitation indices.

b. Extreme weather indices and reference period

To assess changes in extreme weather for each city, 11 extreme weather indices were identified and calculated for each city. Table 2 shows the definitions, ID codes, and explanations of the 11 indices used in this study. These indices were selected based on the indices defined and used in the IPCC ARs [i.e., the WMO's Expert Team on Climate Change Detection and Indices (ETCCDI)] and include eight indices for temperature extremes and three indices for precipitation extremes (Zhang et al. 2011; Bindoff et al. 2013; Hartmann et al. 2013; AghaKouchak et al. 2013).

Prior to the calculation of percentile-based indices, certain thresholds need to be determined from a reference period. As mentioned previously, the selection of a reference period inherently causes bias and must be done

carefully and with transparent justification. With the consideration of the WMO's 30-yr climate normal and consideration of including a longer record for the historical period, the last 30 years (i.e., 1988–2017 for analysis in 2018) was selected as the recent period in this study and the period prior to 1988 (to the end of 1987) was selected as the historical period, with the length of record dependent on each city's particular historical record. Consequently, the reference period employed was different from the ones used in the IPCC ARs or the one used in the NCAs.

c. Time series analyses

Statistical trend analysis using linear regression can be applied to constructed time series of long-term climate records to differentiate the underlying trend from natural variability. The natural variations can be frequent and have only a few years in a cycle such as El Niño–Southern Oscillation (ENSO) (Hartmann et al. 2013). A simple moving-average filter (Karl et al. 1995; von Storch and Zwiers 1999) can be and was also utilized in this study to separate short-term periodical climate variability or high-frequency climate signals from the climate records and to illustrate the climate trend over time. In this study, analyses of climate data with 10-yr moving-average filtering were performed and provided for annual time series in all 103/115 cities. Note that the selection of a 10-yr moving average was for consistency with the OCN method used by the NWS Climate Prediction Center for temperature (Wilks 2013), and the 10-yr filter was applied to both temperature and precipitation indices for consistency. Section C of the supplemental material provides further discussion of the moving-average filter method employed.

In addition to the high-frequency variations, climate records can still be influenced by decade-long climate variability or subrends. Such decade-long subrends can be the result of global or regional variability and some examples in the United States include the “Dust Bowl” period in the 1930s, the “Global Cooling” period in the early 1970s, the “Pacific Climate Shift” in 1976 and 1977, and the climate change “Hiatus” period in the early 2000s (Rosenzweig and Hillel 1993; Miller et al. 1994; Peterson et al. 2008; Rajaratnam et al. 2015). These longer-period variations can “shift” the climate records from normal for more than 10 years, cause the outcome of linear regression to be extremely sensitive to the selection of the assessed period, and thus lead to inconclusive results. This is a primary reason why different selections of reference period can lead to different conclusions as mentioned earlier.

The decade-long subrends in climate records are often described as the “stochastic” trend (Kaufmann et al. 2013; McKittrick and Vogelsang 2014; von Storch 1993). To evaluate periodical variability of this type, linear

regression analysis can be performed for different lengths of periods to assess how the results differ. While a best-fitting line may not accurately capture the historical climate change for a particular climate record, linear regression can be a powerful tool to understand the magnitude of climate variability and underlying climate trend when coupled with statistical inference.

d. Linear regression analysis

In linear regression analysis, the best-fitting line is estimated as that with the least squares errors between the observed y_i values and predicted $\hat{y}_i$ values. Observed y_i values are the time series of actual climate variables and predicted $\hat{y}_i$ values are the climate variables estimated from the best-fitting line with

$$\hat{y}_i = \hat{\beta}_1 x_i + \hat{\beta}_0, \quad (1)$$

where x_i is the predictor x at time t , $\hat{\beta}_1$ is the slope of the best-fitting line, and $\hat{\beta}_0$ is the intercept of the best-fitting line.

The confidence bounds at the 100 $(1 - \alpha)$ percent level for the slope of the best-fitting line (the rate of change) are given as (von Storch and Zwiers 1999; Montgomery et al. 2016)

$$\left(\hat{\beta}_1 - \frac{t_{\alpha/2, n-2} \hat{\sigma}_E}{\sqrt{S_{XX}}}, \hat{\beta}_1 + \frac{t_{\alpha/2, n-2} \hat{\sigma}_E}{\sqrt{S_{XX}}} \right), \quad (2)$$

where $t_{\alpha/2, n-2}$ is the quantile of the t distribution with $n - 2$ degrees of freedom at the 100 $(1 - \alpha)$ percent level, $\hat{\sigma}_E$ is the standard deviation of square errors and equal to $\text{SSE}/n - 2$, S_{XX} is the sum of square errors for predictor x , and SSE is the sum of square errors.

In this study, confidence bounds at the 95% level for the rate of change were calculated for annual temperature, precipitation, and extreme weather indices for all analyzed cities. Historical trends that remained positive (or negative) within these bounds were considered statistically significant.

The root-mean-square error (RMSE) is

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}. \quad (3)$$

RMSE is a metric showing how the observed y_i values are distributed along the linear trend line, and the value of RMSE can be seen as a metric indicating the magnitude of climate variability from the underlying trend (Timofeyeva-Livezey et al. 2015).

As the number of predictor variables and the numerator degree of freedom are both one for the time series analyses, the significance of the regression F is given as

FIG. 1. Historical annual average temperature and total precipitation record of (top) Chicago and (bottom) Phoenix. Each dot represents one temperature or precipitation record, and the blue line shows the smoothed 10-yr moving-average time series.

$$F = \frac{SSR}{SSE/(n-2)}, \quad (4)$$

where F values follow the f distribution $F_{\alpha,1,n-2}$ (von Storch and Zwiers 1999; Montgomery et al. 2016) and SSR is the sum of square errors associated with the linear regression. Note that while similar quantitative significance test methods such as the Mann-Kendall test can be utilized to evaluate the significance levels, calculation of F values was preferred because linear regression was the core method used in this study.

RMSE and F values were calculated in the analyses on the data for the 13 selected cities. As the 13 cities have 120–150 years of records, the f distribution yields F critical values between 3.92 and 3.84 with 95% confidence. Therefore, if the F values are larger than approximately 3.9, the null hypothesis of no significantly linear trend can be rejected. In other words, if the F

value is larger than 3.9, the linear trend in the time series is statistically significant (at the 95% level).

Based on the statistics calculated from the regression analysis, the confidence intervals for the mean response, indicating the range of mean response at each point of time, and the prediction intervals, indicating the range of individual prediction of y value at each point of time, can be estimated to demonstrate the regression uncertainty as well. Equations for these intervals' calculations are provided in section D of the supplemental material. In this study, the climate records from the 13 selected cities were analyzed with the confidence and prediction intervals.

e. Linear regression diagnoses

When implementing a model to conduct statistical analysis, it is important to evaluate its appropriateness for the particular dataset. In this case, linear regression

FIG. 2. Annual (left) average temperature and (right) total precipitation anomalies of the 103 U.S. cities (for temperature) or 115 U.S. cities (for precipitation) applied with a 10-yr moving-average filter for the periods of record. Numbers of cities for each year are shown below the temperature and precipitation graphs. The temperature and precipitation anomalies were calculated first based on the reference period, and then the anomalies were applied with the simple 10-yr moving-average filter. The period before 1988 (to the end of 1987) was selected as the reference period (the red dashed line shows the reference level, and the blue dashed line shows the year of 1988, which is the starting year for the recent 30-yr period). Note that the 10-yr moving-average filter assigned the average values to the last years, i.e., the value in the graph for each year represents the average of the observations from past 9 and current years. Variations in the numbers of cities are due to the missing values because of quality control.

analysis for time series of climate variables requires three assumptions, namely that the residuals from regression need to be 1) independent (no temporal correlation), 2) normally distributed, and 3) consistent in variance. Climate records for a subgroup of 13 selected cities were evaluated with the linear regression diagnoses.

As previously mentioned, the time series of annual climate record, especially the temperature record, is likely to contain stochastic trends (or autocorrelation of the residuals), which means that successive climate records can maintain serial dependence (Kaufmann et al. 2013; Montgomery et al. 2016). While more comprehensive methods to determine the magnitude of stochastic trends in climate records exist (Kaufmann et al. 2013; Mckittrick and Vogelsang 2014), this study utilizes the sample autocorrelation function (ACF) to test for autocorrelation in the residuals (NIST/SEMATECH 2013).

To evaluate whether the residuals were normally distributed, four types of residual plots were plotted and assessed, including the normal probability plot, the residuals versus fitted values plot, the histogram of residuals, and the plots of residuals in chronological order.

Various statistical theories and methods for assessment of climate records are available to address the

non-normal distribution issue (e.g., general extreme value, generalized Pareto, and Poisson distribution; Hennemuth et al. 2013), and such analyses were performed in a number of previous studies (DeGaetano and Zarrow 2011; Cheng et al. 2014; Cheng and Aghakouchak 2014). However, there are still several challenges in doing so and resistance to use these distributions in the climate change research community (Katz 2010).

For indices that do not show ideal normal distribution, the Box-Cox transformation (Box and Cox 1964) was performed in this study. The Box-Cox transform is within the exponential family and a common method to normalize variables for a linear regression analysis. It transforms the y values into a new series using the following equation (Box and Cox 1964):

$$y_i^{(\lambda)} = \begin{cases} \frac{y_i^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0, \\ \log(y_i), & \text{if } \lambda = 0, \end{cases} \quad (5)$$

where λ is the transformation coefficient and its values can be estimated by selecting the λ value that maximizes the log-likelihood function for each time series. After the transformation, the new time series is fitted with

FIG. 3. Mean rates of change for annual (top) average temperature and (bottom) total precipitation for 103 U.S. cities (or 115 cities for precipitation records) over their full periods of record. The slopes of the best-fitting line from the linear regression were calculated as the mean rates of change. Similar to other indices that are presented in later graphs, for temperature indices red colors indicate warming trends and blue colors indicate cooling trends, while for precipitation indices green colors indicate wetter trends and yellow colors indicate drying trends. Cities with darker colors exhibit greater rates of change.

linear regression and then reverse transformation is performed to convert data back to the original scale. Consequently, an average rate of change was calculated. Further discussions of these procedures are provided in section D of the supplemental material.

To evaluate if residuals stay within the same variance around the fitting line, RMSE values and F values were calculated based on different periods of record for the selected 13 cities to evaluate climate variability and underlying trend (Timofeyeva-Livezey et al. 2015; von Storch and Zwiers 1999; Montgomery et al. 2016), respectively. If the magnitude of variability stays the same and no clear stochastic trend exists, a clearer linear trend can be observed from a longer record, with RMSE values staying at the same level and F values increasing (and F critical values decreasing).

4. Results and discussion

a. Annual average temperature and total precipitation

The time series of annual average temperature and total precipitation for Phoenix and Chicago are shown in Fig. 1, as examples. The time series of the other 11 selected cities

are provided in section C of the supplemental material as additional examples. As shown in Fig. 1, Phoenix and Chicago exhibit notable difference in historical temperature and precipitation changes. A substantial increase of annual average temperature in Phoenix over the period 1896–2017 can be observed in Fig. 1, whereas the temperature increase in Chicago over the period 1873–2017 is observable but less in magnitude. In regard to precipitation, there clearly is an increasing trend in annual precipitation for Chicago, although high annual precipitation during the late 1880s causes the rate of increase to be lower over the entire period of record. Phoenix, on the other hand, has a more stationary annual precipitation record, showing no substantial increase or decrease.

Figure 2 shows the annual average temperature and total precipitation anomalies relative to the selected reference period (from the beginning of the record to the end of 1987) for all analyzed cities during their full periods of record and with a 10-yr moving-average filter applied (to remove high-frequency components in time series). Relative to the precipitation trends, temperature trends are more consistent and follow similar overall stochastic changes (i.e., similar discernible decade-long subrends).

FIG. 4. Annual average temperature record of Pittsburgh using linear regression analysis for different time periods (every 30, 60, and 100 years, and the full period of record). The linear regression analysis was applied (left) without and (right) with fixed intercepts between. Linear regression was conducted for the earliest parts of the record as well, despite that the lengths of these parts of the record were shorter than the required lengths, i.e., 30-, 60-, or 100-yr periods.

A warm period in the 1930s–1940s and a cold period in the 1960s–1970s can be readily observed for most cities from Fig. 2. The recent period (the past 30 years) is overall warmer than the pre-1988 period. Precipitation is more localized and has larger year-to-year fluctuations while temporal variations can also be observable (e.g., the wet period during the earliest periods of record). Precipitation changes for the past 30 years vary in different cities as well, with the recent 30-yr precipitation level higher than the historical level in some cities and lower than the historical level in some cities.

Figure 3 shows the results of the mean rate of change for annual average temperature and precipitation records in all analyzed U.S. cities. During the full periods of record, annual average temperatures increase in many of the cities (with rates of change at $0.01^{\circ}\text{--}0.02^{\circ}\text{F yr}^{-1}$) across the United States with some exceptions in the Ohio Valley, Northwest, and Southeast regions. Cities in the West, Northeast, and Southwest regions exhibit

the highest increases in annual temperature (many with rates more than $0.02^{\circ}\text{F yr}^{-1}$). A large number of U.S. cities exhibit increase in annual precipitation (with rates from 0.01 to 0.05 in. yr^{-1}). Cities in the Northeast, Ohio Valley, South, and Upper Midwest regions exhibit the highest increases in annual total precipitation (more than 0.03 in. yr^{-1}), while the precipitation changes in the west of the country have lower rates of change (between -0.01 and 0.01 in. yr^{-1}). These results in climate region level are consistent with the findings in previous studies such as the 2017 NCA report (Wuebbles et al. 2017). As Fig. 3 shows, cities in spatial proximity do not necessarily exhibit similar temperature and precipitation changes, suggesting that location-specific climate records should be examined for practical applications of historical climate study.

Figure 4 shows the result of using ordinary linear regression on the annual average temperature record for Pittsburgh with different time periods. Because of the

FIG. 5. Annual average temperature and total precipitation record of Phoenix using linear regression analysis with 95% confidence and prediction intervals. Confidence intervals are the prediction of the mean response, indicating the uncertainty of the rate of change due to climate variability, while prediction intervals are the individual prediction at each point, indicating the magnitude of climate variability.

cold period between the 1960s and late 1970s, the temperature trends at Pittsburgh are ambiguous, with the past 30–60 years showing increases and the past 100 years of the full record showing decreases. Therefore, with the same temperature dataset and the same linear regression analysis, the conclusions for the temperature trend can vary from increasing to decreasing based on the selection of the study period. Figure 4 demonstrates the importance of assessing climate trend with different lengths of record and the importance of understanding and differentiating climate variability. Similarly, high precipitation amounts during the earliest part of records as shown in Fig. 2, also observed in previous studies (Easterling 2000; Kunkel et al. 2003), can potentially lower historical precipitation trends.

Figure 5 provides the linear regression analyses for the annual temperature and precipitation records of Phoenix with statistical inference. The slopes of the temperature and precipitation fitting lines (the rates of change) can vary within the confidence intervals [the upper and lower bounds for the slope can be directly

calculated from Eq. (2)], indicating the uncertainty of climate trend due to climate variability (Timofeyeva-Livezey et al. 2015). Additionally, prediction intervals can be interpreted as the fluctuations of climatological variables relative to the underlying climate trend (von Storch and Zwiers 1999). Because of the substantial underlying increasing trend, the changes of the temperature record in Phoenix are mostly affected by this increasing trend instead of climate variability. On the other hand, the precipitation record in Phoenix is mostly affected by climate variability. Although the slope of the best-fitting line is negative, the rate of change within the 95% confidence bounds varies from positive to negative, indicating a strong influence from climate variability and a rather stationary precipitation record.

Figures 6 and 7 show the linear regression analysis results for the annual temperature and precipitation records in all analyzed U.S. cities and 13 selected cities with statistical inference. The 95% confidence bounds for the rate of change were estimated for all of the cities and additionally RMSE and F values were calculated for the 13 selected cities. While many cities in the United States exhibit a positive mean rate of change in annual average temperature, cities in the Ohio Valley and Southeast regions do not often exhibit a statistically significant increase. Further, many cities in the United States do not exhibit statistically significant changes in annual total precipitation; cities with statistically significant increases are often located in the Northeast and Upper Midwest regions. As observed in the 13 selected cities, more cities exhibit statistically significant changes in temperature while precipitation is more localized and larger variations are observed in precipitation records.

b. Linear regression analysis adequacy diagnoses

The adequacy and appropriateness of linear regression for the temperature, precipitation, and the 13 extreme indices was assessed. Detailed discussion of these diagnoses is provided in section D of the supplemental material.

The tests on autocorrelation revealed that some of the time series do exhibit autocorrelation (i.e., temporal correlation) in the residuals from linear regression, demonstrating the existence of stochastic subrends in the time series. In such time series, the first-order autoregressive model was integrated in the linear regression model to reduce the autocorrelation, but the improvement was nonsignificant. A previous study evaluated the accuracy of different models assuming nonlinearity and stochastic trend in the temperature record and found that no model performed significantly better than the others in trend detection, including the ordinary linear regression model (Franzke 2012). Therefore, this study

FIG. 6. Rates of annual average temperature change in (top) 103 U.S. cities and (bottom) 13 selected cities for their full periods of record. The maps with upper and lower bounds show the 95% confidence bounds for the rate of change. Cities that have opposite colors in the two bounds do not have statistically significant trends. The circles with black frames show the results of the 13 selected cities. In the bar graphs, the white line in the middle is mean rate of change (equal to the slope of the best-fitting line), the number on top is the RMSE value, and the number on the bottom is the significance of the regression F value. RMSE indicates the magnitude of climate variability while the F value has to be larger than 3.9 to indicate a significant trend.

did not integrate the linear regression model with autoregressive correction but instead used different lengths of record to assess the stochastic trends. To assess further the stochastic trend in the temperature or precipitation record, other more comprehensive techniques like empirical mode decomposition or the augmented Dickey Fuller

statistic can be utilized in the city-level climate records (Franzke 2012; Kaufmann et al. 2013).

Residual plots were developed and the results are summarized in Table 3 for normal distribution diagnosis. Analysis of the residuals indicates that the linear regression of annual average temperature and total

FIG. 7. Rates of annual total precipitation change in (top) 115 U.S. cities and (bottom) 13 selected cities for their full periods of record. The maps with upper and lower bounds show the 95% confidence bounds for the rate of change. Cities that have opposite colors in the two bounds do not have statistically significant trends. The circles with black frames show the results of the 13 selected cities. In the bar graphs, the white line in the middle is mean rate of change (equal to the slope of best-fitting line), the number on top is the RMSE value, and the number on the bottom is the significance of regression F value. RMSE indicates the magnitude of climate variability while the F value has to be larger than 3.9 to indicate a significant trend.

precipitation satisfies the normal distribution assumption, while linear regression fits of several extreme weather indices do not. Table 3 indicates which of the fits of the extreme weather indices follow normal distributions.

A Box-Cox transformation can be applied to address the non-normally-distributed issue for the

threshold-related indices for annual data but is not ideal for the monthly data. This is because these monthly threshold-related indices have small and discrete numbers (often less than 3 days per year) and are not appropriate to be fitted with linear regression, even with transformation. Therefore, while linear regression with a

Box–Cox transformation was still applied to the monthly threshold-related data time series for consistency in this study, the use and interpretation of these results should be done with caution.

The RMSE values for the linear regressions of the annual data stayed within the 10% range among the calculations from the different lengths of record for the 13 selected cities, indicating constant variance of residuals. Moreover, as RMSE is an indication of climate variability, this result demonstrated constant climate variability within the time series and the benefit of using a longer climate record to reduce the impact from climate variability in the linear regression analysis. However, RMSE values for time series with a strong underlying stochastic trend (e.g., the annual temperature record in Pittsburgh) did not show significant changes with respect to different lengths of record. Therefore, use of RMSE to indicate climate variability has limitations in identifying and differentiating underlying stochastic trend. The use of RMSE and F values for different lengths of record to understand and evaluate climate variability and stochastic trend will be discussed later.

The results of the linear regression diagnostic tests indicate that while linear regression is commonly used in historical climate data analyses, linear regression may be potentially inappropriate because of temporal correlation and non-normal distribution, especially for changes in extreme weather indices. Individual climatological time series can exhibit unexpected characteristics that can violate the linear regression assumptions.

c. Extreme weather indices

Linear regression was applied to the 11 extreme weather indices for the 103/115 U.S. cities. Based on Table 3, a Box–Cox transformation was applied to the marked indices. The 95% confidence bounds for the rate of change were estimated. Figures 8 and 9 show the linear regression results for the temperature indices while Figs. 10 and 11 show the results for the precipitation indices (the mean rates of change for all analyzed cities are presented in Figs. 8 and 10 while Figs. 9 and 11 show results of temperature extreme indices and three precipitation extreme indices in the 13 selected cities). Analyses of statistical inference on the extreme weather indices for all the U.S. cities evaluated and other indices for the 13 selected cities are provided in sections E and F of the supplemental material.

Consistent with the changes in annual average temperature, temperature extremes in most cities exhibit increases. Cities that exhibit larger increases in average temperature tend to have larger changes in these indices, showing larger increases in annual temperature extremes, more warm days and nights, and fewer cold

TABLE 3. Adequacy of linear regression analysis on the annual and monthly indices. Note: “LR” means the ordinary linear regression was applied, “Box–Cox” means the variables for this index can be improved with the Box–Cox transformation and the linear regression with the Box–Cox transformation was applied, and the χ symbol means the variables still do not exhibit ideally normal distribution, despite the Box–Cox transformation. While linear regression with the Box–Cox transformation was still applied to these indices marked with χ for consistency in this study, the use and interpretation of these results should be done with caution.

Indices	Annual	Monthly
Average temperature	LR	LR
Total precipitation	LR	Box–Cox
Warmest daily $T_{\max}$	LR	LR
Warmest daily $T_{\min}$	LR	LR
Coldest daily $T_{\max}$	LR	LR
Coldest daily $T_{\min}$	LR	LR
Warm days	Box–Cox	χ
Warm nights	Box–Cox	χ
Cold days	Box–Cox	χ
Cold nights	Box–Cox	χ
Wettest day	Box–Cox	Box–Cox
Wettest consecutive 5 days	Box–Cox	Box–Cox
Precipitation form very wet days	Box–Cox	χ

days and nights. Note that the cold days and nights utilize red colors for negative rates of change and blue colors for positive ones. The geographic patterns of historical rates of change in the United States vary somewhat for the different indices; for example, cities in the Ohio Valley and Upper Midwest regions often show decreases in the warmest temperature indices (with rates between 0° and $-0.03^\circ\text{Fyr}^{-1}$) while cities that exhibit decreases in the coldest daily minimum temperature are mostly located in the Southeast region (with rates between 0° and $-0.03^\circ\text{Fyr}^{-1}$). The four threshold-related indices (TX90p, TN90p, TN10p, and TX10p) have similar geographic patterns corresponding to the four extreme temperature indices (TXx, TNx, TXn, and TNn). The findings of decreases in some extreme temperature indices in the Southeast United States are consistent with previous studies such as those of Meehl et al. (2012) and Peterson et al. (2013). However, the results of maximum temperatures show that larger areas of the United States have exhibited historical increases compared to previous studies such as Peterson et al. (2013) and Wuebbles et al. (2017) (supplemental material sections C and E provide additional results). This difference is potentially due to the different indices analyzed, different methods employed, and longer periods of records assessed in this study (a relative cold period in the earliest part of records shown in Fig. 2 as an example).

The changes of extreme precipitation are consistent with the changes in total precipitation, and a similar

FIG. 8. Mean rates of annual temperature extreme indices change in 103 U.S. cities for the full periods of record. The top four graphs (indices) utilize the same legend with the unit of degree Fahrenheit per year and the bottom four graphs (indices) utilize the legend with the unit of percentage per year. Color coding for the cold days and nights is opposite to other indices. For cold days and nights, red colors indicate negative rates of change in the annual percentage of cold days and nights (showing warming trends) while blue colors indicate positive rates of change (i.e., showing cooling trends).

geographic pattern of changes in these indices is observed. Cities that exhibit larger increase of total precipitation tend to have larger increase in the annual maximum precipitation and precipitation amounts from very wet days. Similar to the total precipitation, the precipitation extreme indices show greater increases in the cities of the Northeast, Ohio Valley, South, and Upper Midwest regions. While previous studies have

shown statistically significant increasing trends for precipitation extremes in the Midwest, Southeast, and Northeast regions and overall in the United States (Kunkel et al. 2007, 2013), results in this study indicate that many cities with statistically significant increases (at the 95% level) are within the Northeast and Upper Midwest regions, as shown in Fig. 7 for total precipitation (graphs for extremes are provided in section E

FIG. 9. Rates of change for annual temperature related extreme weather indices in the 13 selected U.S. cities for their full periods of record. The included indices in this figure are TXx, TNn, TN90p, and TX10p. These blue bars show the 95% confidence intervals for the rate of change. The white line in the middle indicates the mean rate of change over the full record (does not equal to the slope of best-fitting line when the Box-Cox transformation is utilized), the number on top is the RMSE value, and the number on the bottom is the significance of the regression F value. RMSE indicates the magnitude of climate variability while the F value has to be larger than 3.9 to indicate a statistically significant trend.

of the supplemental material). This is potentially due to different precipitation indices analyzed and longer periods of record in this study with high precipitation amounts observed in the earliest part of records.

d. Monthly changes

Linear regression analyses with RMSE and F values for all the annual and monthly time series of the 13 selected cities are provided in section F of the supplemental material. According to these results, monthly temperature indices exhibit larger variability than the annual ones, while monthly precipitation indices display smaller variability than the annual ones. Changes

for the same months among different indices are consistent in most cases, yet a significant increase or decrease in an annual index of a city does not necessarily mean the city has significant increases or decreases in individual months.

The results indicate that annual changes in temperature, precipitation, and extreme weather indices can be substantially different among cities and these differences are even greater for the monthly changes. Cities in spatial proximity do not necessarily exhibit similar temperature and precipitation changes. For example, Columbus (Ohio) exhibits the highest increases of precipitation and precipitation extreme events in June and July, while

FIG. 10. Mean rates of annual precipitation extreme indices change in 115 U.S. cities over the full periods of record. Maximum 1-day and consecutive 5-day precipitation utilize the same legend with units of inch per year while the precipitation from very wet days utilizes a different legend with the same units of inch per year.

Detroit (Michigan) exhibits the highest increases in April and August and some decreases in June and July.

e. Analyses with different lengths of record

To evaluate further the decade-long subrends (or stochastic trends) in annual temperature and precipitation records, the F values were assessed for different lengths of time periods for the 13 selected cities. Figure 12 shows linear regression analyses on the annual average temperature and total precipitation data for different periods of record in Phoenix, Columbus, and Pittsburgh. Linear regression analyses with different periods of record for the other 10 selected cities are provided in section H of the supplemental material.

Because the F values indicate the significance of linear regression, Fig. 12 can be used to evaluate the adequacy of using linear regression and to identify discernible decade-long subrends by comparing the F values for different periods. For examples, as presented in Fig. 12, Columbus exhibits nonsignificant increasing temperature

trend for the past 100 years but significant increasing trend for the past 60 years; the temperature record for Pittsburgh yield significant decreasing trend for the full period of record but significant increasing trend for the past 60 years.

Given the existence of discernible subrends, linear regression can be inconclusive and inappropriate when only one period of record is assessed and historical comparisons between separate short periods of climate records can also potentially cause bias. Using the framework of applying linear regression with different periods of record can identify the existence of such subrends. This is a crucial aspect to consider for decision making when linear regression analysis is conducted to assess regional climate trends.

5. Summary and conclusions

Location-specific and long-term historical climate change assessment is valuable for practical applications,

FIG. 11. Rates of change for annual precipitation related extreme weather indices in the 13 selected U.S. cities for their full periods of record. The blue bars show the 95% confidence intervals for the rate of change. The white line in the middle indicates the mean rate of change over the full record (does not equal to the slope of best-fitting line), the number on top is the RMSE value, and the number on the bottom is the significance of regression F value. RMSE indicates the magnitude of climate variability while the F value has to be larger than 3.9 to indicate a statistically significant trend.

such as infrastructure engineering and adaptations. While various studies have evaluated historical climate change for individual stations across the United States, such analyses have involved the aggregation of various stations in larger regions or a relatively short-term historical period assessment, thus not providing location-specific or temporal details of regional climate change information. This study aimed to utilize long-term climate records from individual cities to provide climate change assessment in specific locations and for their full periods of record.

Historical annual and monthly average temperature and precipitation records were compiled for cities in the contiguous United States with climate records starting earlier than 1900. Available, quality-assured daily temperature and precipitation data were acquired from the ACIS database, developed by NOAA's Northeast Regional Climate Center. Eleven extreme weather indices were calculated from the daily temperature and precipitation data. The historical mean rates of change (and related 95% confidence bounds) in annual average

temperature, total precipitation, and extreme weather indices were calculated for more than 100 U.S. cities. Thirteen cities were selected to apply further linear regression analyses with adequacy diagnoses and analyses for each month. The output dataset from this study can be accessed via the Carnegie Mellon University KiltHub repository at https://kiltHub.cmu.edu/projects/Use_of_historical_data_to_assess_regional_climate_change/61538.

A large number of U.S. cities show increases in temperature and precipitation, although regional variations have been observed for both temperature and precipitation changes. Many cities in the Ohio Valley and Southeast regions show decreases or nonsignificant increases in temperatures. Cities in the Northeast, Ohio Valley, South, and Upper Midwest regions show the highest increases in precipitation while many of cities exhibiting statistically significant increases are in the Northeast and Upper Midwest regions. Moreover, cities in spatial proximity do not necessarily exhibit similar temperature and precipitation changes and cities within same climate regions may exhibit substantially different trends.

FIG. 12. Rates of annual average temperature and total precipitation change for past 30-, 60-, and 100-yr periods and the full period of record for Columbus, Phoenix, and Pittsburgh. The white line in the middle indicates the mean rate of change. The F values have to be larger than 3.9 (approximately) for full record, 3.936 for 100 years of record, 4.001 for 60 years of record, and 4.171 for 30 years of record to yield a 95% significance of regression.

Variations among cities in trends for extreme temperature indices have been observed. More cities show increases in coldest daily $T_{\max}$ and $T_{\min}$ than other indices, consistent with previous work (Peterson et al. 2013). However, this study shows more cities/locations exhibiting increases in warmest daily $T_{\max}$ than the results from previous studies (Peterson et al. 2013; Wuebbles et al. 2017), potentially due to different methods applied and analysis of longer periods of record in this study.

Temporal variations in trends for cities have also been observed for time series of temperature and precipitation indices, especially for temperature. Discernible decade-long subrends are evident and can potentially shift the trend analysis to be inconclusive when only a

short period of record is analyzed. Due to these subrends, historical comparisons between short periods of climate records can also potentially cause bias. From the analyses conducted here, many U.S. cities with statistically significant increases (at 95% level) in total precipitation and precipitation extremes are within the Northeast and Upper Midwest regions but not in the Southeast region, a somewhat different finding from previous studies (Kunkel et al. 2013; Wuebbles et al. 2017). This difference is potentially due to different precipitation indices analyzed and longer periods of assessing records in this study.

Along with temporal correlation, time series of temperature and precipitation variables may exhibit

nonnormally distributed errors and violate the assumptions for linear regression. Individual time series of climate records at specific locations can have unique characteristics in terms of historical change, normal distribution, and temporal correlation, comparing to the regional characteristics.

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