Vol. 77: 181–192, 2019
https://doi.org/10.3354/cr01550

CLIMATE RESEARCH
Clim Res

Published online February 28

Spatiotemporal variations in temperature persistence in the south-central United States

Zachary T. Leasor[1,*], Steven M. Quiring[1], Trent W. Ford[2], D. Brent McRoberts[3]

[1]Department of Geography, Ohio State University, Columbus, OH 43210, USA
[2]Department of Geography and Environmental Resources, Southern Illinois University, Carbondale, IL 62901, USA
[3]Department of Geography, Texas A&M University, College Station, TX 77843, USA

ABSTRACT: Improved seasonal forecasting can help to mitigate the impacts of prolonged extreme heat, a prominent climate hazard in the south-central United States. Temperatures in this region exhibit significant temporal autocorrelation on monthly to seasonal timescales, and the magnitude of temperature persistence can provide useful information for seasonal climate forecasts. This study examines spatiotemporal variations in temperature persistence in the south-central US using high-resolution temperature data from 1900–2015. Consistent with previous studies, temperature persistence varies substantially across the region and is strongest during the summer months. Statistically significant temporal autocorrelations are primarily observed on a monthly timescale; however, at some locations, temperature persistence is also statistically significant at 3 mo timescales. This research builds upon previous findings by using the skill of monthly persistence forecasts to examine how temperature persistence varies with the magnitude of temperature anomalies. Results show that forecast skill regularly increases as the magnitude of the temperature anomalies increase. For example, anomalously warm temperatures during the spring can serve as an early warning for a warmer than normal summer. Our results suggest that persistence forecasts can aid in the subseasonal-to-seasonal prediction of temperatures, particularly when anomalous conditions occur.

KEY WORDS: Seasonal forecasting · Air temperature · Climate · High temperature events · Variability

1. INTRODUCTION

Surface air temperatures can persist on timescales of weeks, months, and even years. Consequently, atmospheric persistence is an essential component of climate forecasting. One of the simplest methods for forecasting on subseasonal-to-seasonal timescales involves persisting an initial set of conditions into the future (Doblas-Reyes et al. 2013). Persistence is commonly used at subseasonal-to-seasonal timescales as a baseline metric for forecast skill. Persistence is also used as a predictor variable in operational statistical forecast tools developed by the Climate Prediction Center (CPC) such as canonical correlation analysis, screening multiple linear regression, and the optimal climate normal method (O'Lenic et al. 2008). Previous research has shown that persistence-based monthly temperature forecasts provide statistically significant improvements over climatology-based forecasts at 1 mo (Dickson 1967) and 3 mo timescales (Namias 1978).

Subseasonal-to-seasonal forecast skill and the sources of forecast skill vary by season. The highest forecast skill occurs during the cool season and is primarily attributed to teleconnections and resultant circulation patterns (Peng et al. 2012). Persistence-based temperature forecasts tend to have higher forecast skill during the warm season, especially

*Corresponding author: leasor.4@osu.edu

in continental locations (Dickson 1967, Namias 1978, Barnett 1981, Barnett & Preisendorfer 1987, Lyon 1991, Peng et al. 2012). Evidence suggests that temperature persistence is closely related to quasi-stationary geopotential height patterns at the 500 mb (Lyon 1991) and 700 mb (Namias 1978, van den Dool et al. 1986) levels. These upper-level patterns over the Pacific Ocean have an inverse relationship with temperature persistence in the United States due to downstream modifications of the Rossby wave train. Negative geopotential height anomalies over the Pacific Ocean lead to the persistence of anomalously warm conditions over the United States, whereas positive height anomalies lead to the persistence of cooler than normal conditions (Lyon 1991). During the cool season, persistent geopotential height patterns may be attributed to the well-known relationship between Northern Hemisphere climatic variability and teleconnections such as ENSO (Yu et al. 2015). During the warm season, boundary conditions (i.e. land–atmosphere interactions) can also be an important contributor to temperature persistence. When temperatures are higher, latent heat fluxes near the surface decrease because evapotranspiration is limited by lower soil moisture (Fischer et al. 2007). Thus, a positive land–atmosphere feedback cycle can occur as sensible heat fluxes increase and warm the boundary layer atmosphere. These 2 mechanisms explain some of the intra-regional variations in temperature persistence within the south-central US.

The spatiotemporal characteristics of temperature persistence have been well documented in previous studies (Dickson 1967, Namias 1978, van den Dool et al. 1986, Lyon 1991). Temperature persistence tends to be higher in coastal locations than in continental locations. The strongest areas of persistence in the US are located along the Pacific and Atlantic coastlines due to the influence of sea surface temperatures (Monetti et al. 2003) and a prevailing sea breeze, which dampens seasonal variations in temperature (Namias 1978, van den Dool et al. 1986). This study reexamines spatiotemporal variations in temperature persistence using a high-resolution gridded data set. It focuses on the south-central US (Texas, Oklahoma, Arkansas, Louisiana, Mississippi, and Tennessee) because this study was supported by the Southern Climate Impacts Planning Program (SCIPP; www.southernclimate.org).

Research examining temperature persistence has been largely absent in recent years. Previous studies have provided adequate descriptions of spatiotemporal trends in monthly temperature persistence. Based on these findings, persistence has been assimilated as a predictor in complex statistical and dynamical forecasts which have replaced simple persistence forecasts. As a result, persistence may be overlooked as a source of forecast skill despite situations in which the use of persistence could yield skillful forecasts. For example, do anomalously warm conditions tend to be more or less persistent than near-normal temperatures? Few studies have examined whether temperature persistence is a function of the magnitude of antecedent temperature anomalies. In this study, we examine spatiotemporal variations in temperature persistence using a high-resolution data set as well as performing a comprehensive examination of persistence forecast skill and examining how skill varies with antecedent conditions. This is important because it may lead to improved forecast accuracy during anomalous conditions, such as heat events. Prolonged extreme heat is a frequent climate hazard within the south-central US, where portions of the SCIPP region have been identified as hotspots of increased land–atmosphere coupling (Koster et al. 2004). Current seasonal forecasts struggle to accurately predict temperatures within the SCIPP region (Livezey & Timofeyeva 2008). Two of the most notable heat events in the south-central US occurred in the summer of 1980 (Lyon & Dole 1995) and the summer of 2011, when the state of Texas observed its highest monthly temperature on record (Hoerling et al. 2013). Both extreme heat events persisted for many months and are evident when examining mean monthly maximum temperatures. Extreme and prolonged heat can result in stress on the body and cause a wide variety of health problems including dehydration, heat stroke, and a variety of pulmonary and cardiovascular maladies (Kalkstein & Greene 1997). Better planning is essential for preventing heat-related deaths, and improved seasonal climate forecasting is an important component of mitigation efforts (Changnon et al. 1996, Lowe et al. 2016).

2. DATA

We used monthly temperature data from Parameter-Elevation Regression on Independent Slopes Model (PRISM; Daly et al. 1994). PRISM was developed by the Spatial Climate Analysis Service at Oregon State University and provides temperature data on a 4 km grid. These data are interpolated using a climate–elevation regression on temperature measurements made by 11 different observation networks, including the Cooperative Observer Program (COOP)

and Automated Surface Observing Systems (ASOS) networks (Daly et al. 2000). This study specifically used the PRISM 'AN81m' data set, which is enhanced by climatological-aided interpolation (CAI). The climatological normals of nearby stations are weighted by elevation, distance, clustering, and topography and estimated using a 2-layer atmosphere, terrain weights, and coastal proximity (Daly et al. 1994, Daly 2000). The PRISM model develops a unique calculation for each grid cell, providing a versatile approach for different climatic types (Daly et al. 2000).

Daly et al. (2008) used a jackknife cross-validation to assess the accuracy of PRISM temperature data. The mean absolute error (MAE) for July maximum temperatures was less than 1°C across the south-central US, except for western Texas and 3 isolated stations located elsewhere, with no evidence of any systematic biases (Daly et al. 2008). When PRISM was compared to 2 widely used gridded products, WorldClim and Daymet, PRISM temperature data were found to be more accurate (Daly et al. 2008). The high quality and stringent vetting of PRISM temperature data makes it an ideal data set for studying temperature persistence.

Monthly maximum temperature from 1900–2015 were extracted for 75 312 PRISM grid cells in the south-central US. Temperature data (T) were deseasonalized by converting the values to anomalies (T') using Eq. (1), where m is a given month and y is a given year:

$$T'(y,m) = T'(y,m) - \overline{T}(m) \tag{1}$$

These data were acquired from the PRISM data set, and the 30 yr normal ($\overline{T}$) was calculated using data from 1981–2010.

3. METHODS

3.1. Temporal autocorrelation

Temperature persistence is defined as the magnitude of correlation between temporally adjacent values (i.e. autocorrelation; Chandrasekhar & Dimri 2014). Our goal was to find instances of red noise, defined in this study as a positive autocorrelation between 2 monthly vectors of temperature anomalies. Our analysis rarely identified any statistically significant monthly persistence beyond timescales of 3 mo. Therefore, this study focused on 1 and 3 mo temperature persistence. Positive temperature persistence indicates the continuation of a monthly temperature regime. An example of positive temperature persistence is when a month with above-normal temperatures is followed by another month with above-normal temperatures. Pearson's correlation coefficient (r) was used to calculate the autocorrelation between 2 vectors of temperature anomalies (Weida 1927, McGrew & Monroe 2009), given as:

$$r(t_0,t_k) = \frac{\sum_{i=1}^{n}(x_0(i)-\overline{x}_0)(x_k(i)-\overline{x}_k)}{\sum_{i=1}^{n}(x_0(i)-\overline{x}_0)\sum_{i=1}^{n}(x_k(i)-\overline{x}_k)} \tag{2}$$

where x_0 is a temperature anomaly for the initial month (t_0) of year i, x_k is a temperature anomaly for the month (t_k) with k-lag (in months) after the initial month, and n is the number of years in the time series.

Since we are analyzing temperatures in anomaly space (i.e. $\overline{x}_0 = \overline{x}_k = 0$), the correlation in Eq. (2) can be simplified to:

$$r(t_0,t_k) = \frac{\sum_{i=1}^{n}x_0(i)x_k(i)}{\sum_{i=1}^{n}x_0(i)\sum_{i=1}^{n}x_k(i)} \tag{3}$$

The temporal autocorrelation calculated in Eq. (3) gives a normalized indicator $r(t_0, t_k)$, with positive values indicating persistence of temperatures and negative values indicating a reversal in the temperature regime (i.e. above-normal temperatures to below-normal temperatures, or vice versa). We conducted a 2-tailed Student's t-test for autocorrelation against the null hypothesis of no correlation using $\alpha = 0.05$ (95% significance). The t-statistic for Pearson's correlation (from McGrew & Monroe 2009), using τ to differentiate from t, is:

$$\tau(t_0,t_k) = \frac{r(t_0,t_k)\sqrt{n-2}}{\sqrt{1-r^2(t_0,t_k)}} \tag{4}$$

3.2. Heidke skill scores

We also examined the Heidke skill scores (HSS) of persistence-based temperature forecasts. While correlations were used to identify spatiotemporal patterns of persistence, HSS values can identify conditions when persistence plays an important role in seasonal prediction. The HSS framework for evaluating forecast skill begins by grouping monthly temperature anomalies into terciles, such that forecasts can be identified as 'above normal', 'normal', or 'below normal', each having an equal probability of occurrence. Temperature data are classified as terciles based on the percentiles of the monthly temperature distribution. The HSS metric is computed as:

$$HSS = \frac{C - E}{N - E} \quad (5)$$

where C is the number of correct forecasts, N is the total number of forecasts, and E is the number of random (climatology) forecasts expected to verify. 1HSS values greater than zero indicate the ability of a forecast using persistence to improve upon one only utilizing climatology (i.e. skill). Utilizing HSS values allows us to quantify the value of using persistence for seasonal temperature forecasting over using only a climatological forecast. To create each forecast, observations for a given month, n, are used as predictions for time lags of one (n + 1) and three (n + 3) months. If the predicted tercile matches the tercile of the temperature observations, a correct forecast is produced.

3.3. Conrad continentality index

The Conrad continentality index was used to examine the relationship between continentality and temperature persistence (Conrad 1946). The difference in continental and marine climates is best described by variations in the annual temperature range. The Conrad continentality index (k_c) is frequently expressed as a percentage and calculated as:

$$k_c = \frac{1.7A}{\sin\ (\varphi + 10°)} - 14 \quad (6)$$

where A is the difference in mean monthly temperatures between the warmest and coldest months and φ is the latitude. The Conrad index can be used to compare the continentality between locations, where higher values indicate more continental climates.

4. RESULTS

4.1. Seasonality of temperature persistence

Fig. 1 illustrates how persistence varies on both monthly (Fig. 1A) and seasonal (Fig. 1B) timescales. The medians in Fig. 1 are based on all 75 312 vector pairs in our study region. The strongest 1 mo temperature persistence occurs during the summer, with a median value of r(Jul, Aug) = 0.44. The strength of temperature persistence steadily decreases throughout the fall with a minimum median value of r(Nov, Dec) = 0.11. The cool season maximum r occurs in January–February, with a median value of r(Jan, Feb) = 0.27. The greatest variability in temperature persistence across the study region occurs in March–April.

While the magnitude of the 3 mo autocorrelations are generally weaker (Fig. 1B) than those at 1 mo (Fig. 1A), there is still evidence of seasonality. The maximum 3 mo autocorrelation is r(Jun, Sep) = 0.27 and the minimum is r(Jan, Apr) = 0.01. The seasonal variations in 3 mo temperature persistence are similar to the 1 mo persistence, but they occur 2–3 mo earlier. For example, the strength of the 3 mo temperature persistence increases from January through June, while the strength of the 1 mo persistence increases from March to August. There is a relative maximum that occurs in October, coinciding with the secondary maximum that occurs in January for the 1 mo persistence. Temperature persistence was also examined at longer timescales (6, 9, and 12 mo), but there were no statistically significant patterns in our study region.

4.2. Spatial variability of temperature persistence

4.2.1. One-month autocorrelations

The variations in temperature persistence across the study region are shown for both 1 mo (Fig. 2) and 3 mo timescales (Fig. 3). Most locations that are close to the Gulf of Mexico tend to have statistically significant temperature persistence at the 1 mo timescale throughout the year (Fig. 2). This is in agreement with previous studies that found the strongest temperature persistence in coastal locations (Namias 1978, van den Dool 1984, van den Dool et al. 1986, Eichner et al. 2003, Monetti et al. 2003, Triacca et al. 2014). However, there is substantial spatial variability in the strength of temperature persistence across the south-central US. During the winter (DJF), the strongest autocorrelations are found in locations close to the Gulf of Mexico, although autocorrelations are statistically significant across most of the study area in January. Beginning in February, the locations with the strongest 1 mo temperature persistence shifts into southwestern Texas (the region near the Rio Grande bordering Mexico), and this lasts through spring. Beginning in June, the core region with the strongest temperature persistence shifts northeastward into Oklahoma and southwestern Arkansas. These findings also agree with previous research which found that temperature persistence is strongly related to continentality during the summer (Dickson 1967, Namias 1978, Barnett & Preisendorfer 1987, Lyon 1991). In July, west Texas

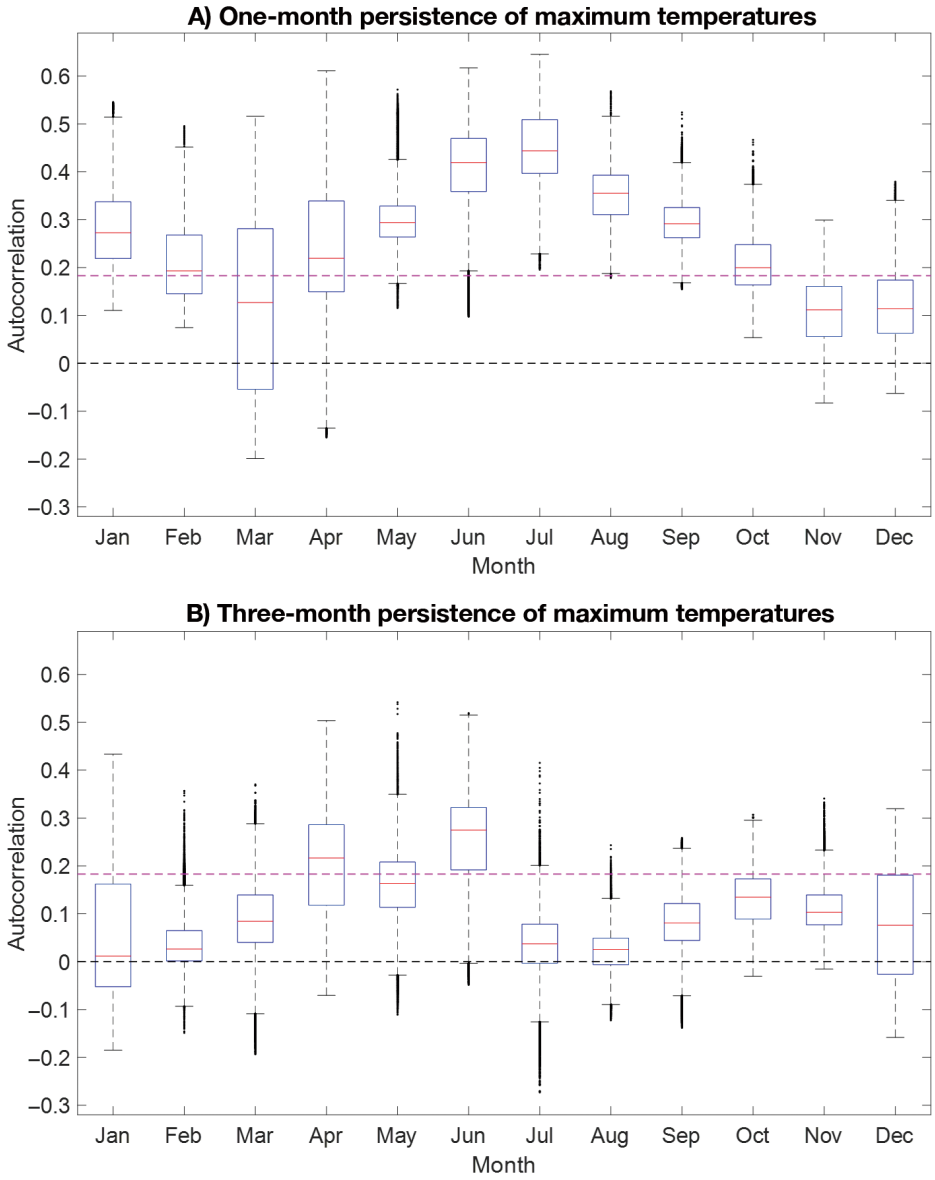

Fig. 1. Distributions of temporal autocorrelations of temperatures at (A) 1 mo and (B) 3 mo time lags. The month along the *x*-axis represents the initial month, and the autocorrelation reflects the strength with which the initial temperature anomaly persists. Horizontal black dashed line: an autocorrelation of zero; magenta dashed line: the critical autocorrelation value (0.183) for a 95% significance level. The top of each box represents the 75th percentile of the distribution; the bottom represents the 25th percentile. Solid red line: median of the distribution; whiskers extend to ±2.7 SD from the mean and all other values are considered outliers and plotted as black dots

is the region with the weakest temperature persistence, but by October, the strongest temperature persistence is again found in southwestern Texas.

It is also instructive to compare months with fundamentally different spatial patterns of temperature persistence. In March, there is a strong gradient in temperature persistence across the study region from southwest to northeast. The autocorrelations vary from −0.2 near the Ozark Mountains to 0.5 in southwest Texas. However, in July, relatively strong autocorrelations are found throughout most of the study region and the range of autocorrelations is much less (~0.45). The relatively weak temperature persistence during July in western Texas may be due to the onset of the North American Monsoon (NAM). The NAM influences much of the southwestern US during the summer and is responsible for the majority of the annual precipitation. This may contribute to the relative low temperature persistence in the western part of the study region during this time.

Outside of the NAM, there are statistically significant autocorrelations which occur during most months in southwestern Texas. However, they are somewhat at odds with the expected relationship between persistence and continentality. Outside of the summer months, most previous research found that temperature persistence is weaker in continental locations (e.g. van den Dool et al. 1986). Perhaps the limited precipitation and higher temperatures in this region allows land–atmosphere interactions to con-

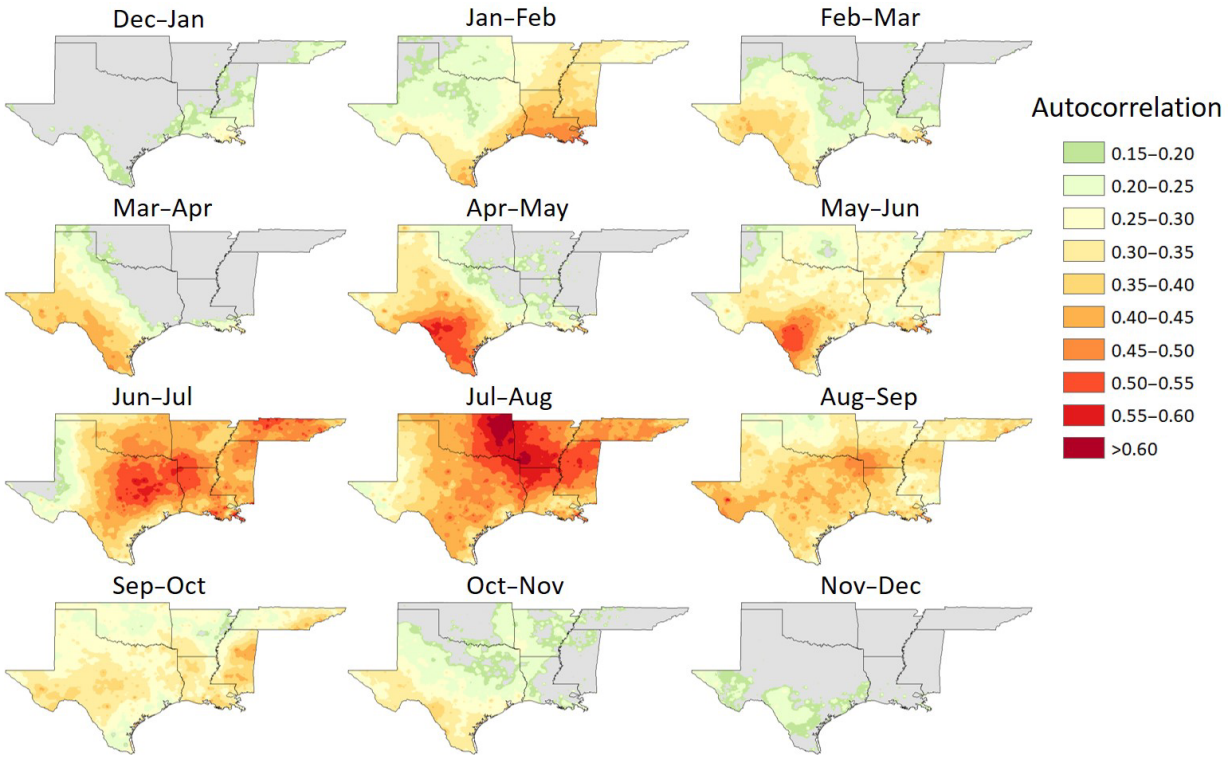

Fig. 2. Temporal autocorrelations of maximum monthly temperatures at a 1 mo time lag. Only positive autocorrelations which are statistically significant at a 95 % confidence level are displayed

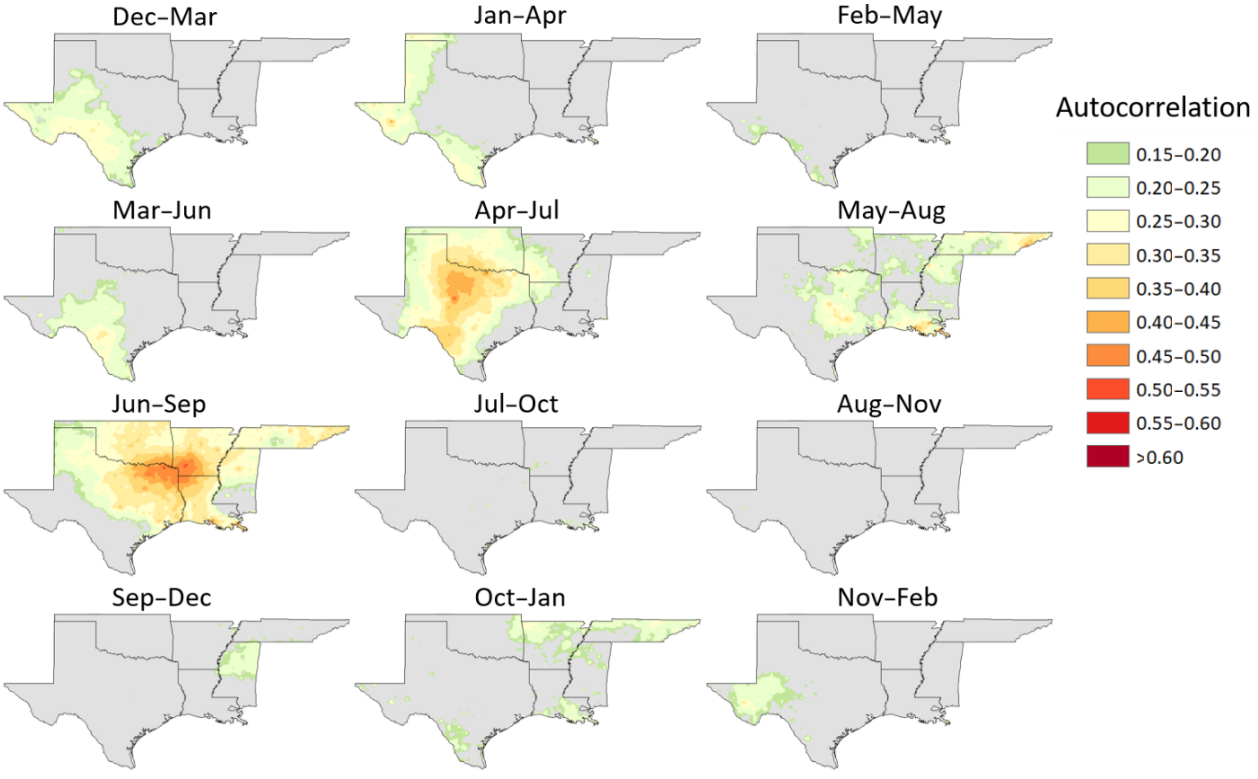

Fig. 3. Temporal autocorrelations of maximum monthly temperatures at a 3 mo time lag. Only positive autocorrelations which are statistically significant at a 95 % confidence level are displayed

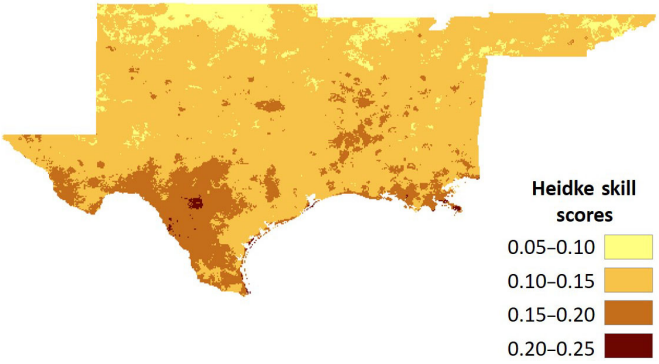

Fig. 4. Heidke skill scores for all 1 mo temperature persistence forecasts made from January 1900 to November 2015

trol temperature persistence in a lengthier warm season relative to the study area, as Lyon (1991) suggested. Namias (1978) and Lyon (1991) both suggested that temperature persistence is correlated to persistent flows at the 500 mb level. In the cool season, southwest Texas is typically too far south of the polar branch of the jet stream to be affected, leading to persistent zonal flow.

Temperature persistence is weak during the winter months at most locations in the study region. The northern portions of the study region have the weakest temperature persistence in the winter, although there is a widespread increase in temperature persistence during January. According to Lyon (1991), persistent circulation patterns are often responsible for increases in temperature persistence during winter. During spring, weak 1 mo autocorrelations are widespread throughout the eastern portion of the study region. The negative autocorrelations in the northeast cover more than one-third of the study region. This is likely due to this area's proximity to a climatological storm track (Namias 1978) and high month-to-month variability as the jet stream retreats northward during the spring (Hoskins & Hodges 2002). Small changes in the mean storm track from March to April can diminish any temperature persistence signals.

4.2.2. Three-month autocorrelations

There are fewer statistically significant autocorrelations at the 3 mo than at the 1 mo timescale. However, there are still coherent spatial patterns in 3 mo temperature persistence (Fig. 3). During the cool season, the only statistically significant autocorrelations are in southwestern Texas. Starting in April, there is a large area of statistically significant temperature persistence covering about 59% of the study region. During the warm season, the strongest temperature persistence is in continental locations, similar to the spatial patterns of 1 mo temperature persistence. The 3 mo temperature persistence maxima occur in April and June, suggesting that there is an established spatial pattern of persistence during spring and early summer. Namias (1978) also found significant autocorrelations at a seasonal (3 mo) timescales to be widespread across the south-central US during spring and summer. Both of these results suggest that both springtime and early summertime maximum monthly temperatures have an impact on temperatures during the subsequent season. The relative decrease in persistence during May could be attributed to a transition between the patterns of persistence during spring and early summer. It is also evident that persistence is strongest in early summer and there is a sharp decrease in persistence beginning in July. The 3 mo temperature persistence during late summer and fall is not statistically significant. This suggests that there are both spatial and temporal variations in temperature persistence in the south central US. Therefore, temperature persistence can be an important source of monthly-to-seasonal forecast skill, but only in certain locations and months.

5. HEIDKE SKILL SCORES

5.1. Overall performance of one-month persistence forecasts

The mean forecast skill for all 1 mo persistence forecasts across the study region (Fig. 4) confirms that persistence-based forecasts have more skill than a climatology-based forecast. HSS values are consistently positive for all 1 mo forecasts, indicating that a persistence-based forecast accurately predicts the correct monthly temperature tercile more than one-third of the time. Even the minimum skill score of 0.054 indicates an improvement (~4%) from the climatology-based forecast. The mean forecast skill in each month shows a coherent spatial pattern (Fig. 4). Forecast skill tends to be lower in continental locations and higher in maritime locations. However, these spatial variations may be driven by latitude rather than continentality. The highest skill scores (>0.15) are found in coastal locations and most of southwestern Texas. In these areas, more than 43% of persistence tercile forecasts are correct. High temperature persistence in southwestern Texas was also noted using temporal autocorrelations in Section 4.2.1.

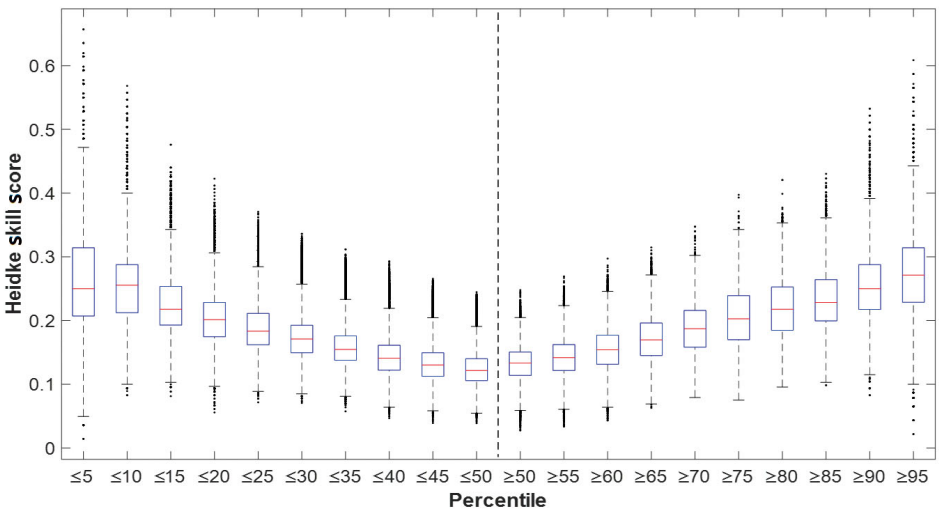

Fig. 5. Heidke skill scores for all 1 mo temperature persistence forecasts made from January 1900 to December 2015 according to the percentile of the antecedent monthly temperature. The top of each box represents the 75th percentile of the distribution; the bottom represents the 25th percentile. Solid red line: median of the distribution; whiskers extend to ±2.7 SD from the mean and all other values are considered outliers and plotted as black dots

The largest HSS value of 0.24 is associated with a continental location in southern Texas. The lowest skill scores are largely concentrated in northern Oklahoma, northern Arkansas, and Tennessee. The evaluation of all forecasts confirms that persistence forecasting is consistently higher than climatology-based forecasts.

5.2. Application to extreme heat events

Fig. 5 shows that there is a relationship between the magnitude of the antecedent monthly temperature percentile and the HSS. That is, the skill of persistence-based temperature forecasts increases as a function of the magnitude of the antecedent temperature anomalies. The median skill score for 1 mo forecasts approximately doubles when comparing all forecasts (0.13) to forecasts when the antecedent temperature is greater than or equal to the 90th percentile (0.25). This relationship is also apparent when examining the persistence of below-normal temperatures. The median skill score is 0.26 when the antecedent temperature is less than or equal to the 10th percentile. It should be noted that the variability in HSS values also increases when binning antecedent temperature because of the decreasing sample size. For example, 696 forecasts are evaluated when antecedent temperatures greater than or equal to the 50th percentile while only 70 forecasts are evaluated for the 95th percentile. When the sample size is reduced, each individual forecast holds more weight in the skill score calculation, increasing the variability. The skill of all 1 mo persistence forecasts is largely due to the increase in persistence with increasing or decreasing antecedent temperature percentiles. The median skill scores for forecasts when antecedent temperatures are below normal (0.16) and above normal (0.18) are higher than when antecedent temperatures are near normal (0.04). However, even when temperatures are near normal, persistence-based forecasts perform better than climatology-based forecasts in 92% of grid cells.

Fig. 6 shows that anomalous temperatures lead to increases in 1 mo persistence forecast skill for at least 35% of the study area. This is consistent for all months of the year. When antecedent monthly temperatures are greater than or equal to the 90th percentile, there is an increase in 1 mo forecast skill for at least 70% of the region from May to January. Accordingly, the smallest increases in forecast skill occur during the spring for both anomalously cool and warm conditions. The spatial patterns of 1 mo forecast skill given antecedent temperatures greater than the 90th percentile are amplified when compared to general 1 mo temperature persistence in Section 4.2.1. For example, a strong dipole of skill scores was present in April as opposed to a widespread increase in forecast skill during the summer months.

Skillful forecasts of extreme heat in the south-central US are of particular interest. Therefore, we identified antecedent conditions that have a tendency to lead to extreme heat. This is defined as skill scores that indicate a greater than 50% chance of persistence when antecedent temperatures are greater than or equal to the 90th percentile. At a 1 mo timescale, most of the study area displays the tendency for warm temperatures to persist from May to September (Fig. 7). This tendency is widespread during June (88%) and July (89%). This is not surprising given that this

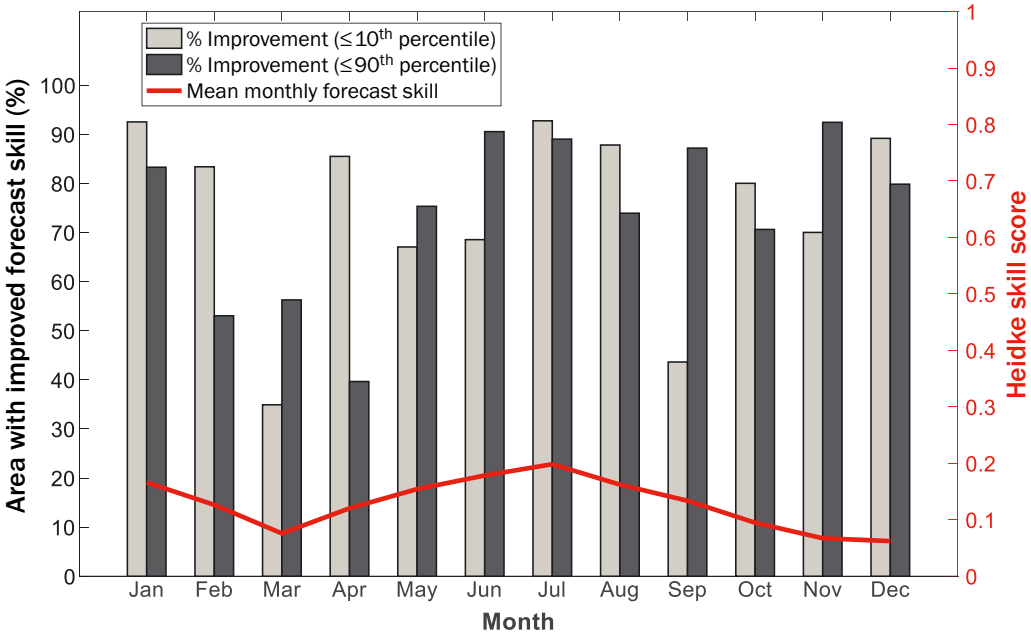

Fig. 6. Seasonal distribution of improvements in 1 mo temperature persistence forecast skill (Heidke skill score [HSS] values) when antecedent anomalies are greater than or equal to the 90th percentile and less than the 10th percentile. Forecast improvement is expressed as a percent area, or the percentage of grid cells with a higher skill score for forecasts using extreme antecedent anomalies compared to forecasts using all anomalies. The mean monthly skill score represents the average monthly HSS value for all 1 mo temperature persistence forecasts made from January 1900 to November 2015

region is a hotspot for land–atmosphere interactions (Koster et al. 2004, Merrifield et al. 2017). These positive land–atmosphere feedbacks may lead to increased temperature persistence during the warmest months. In addition, there is also a tendency for warmer than normal temperatures to persist across the majority of the study area in January.

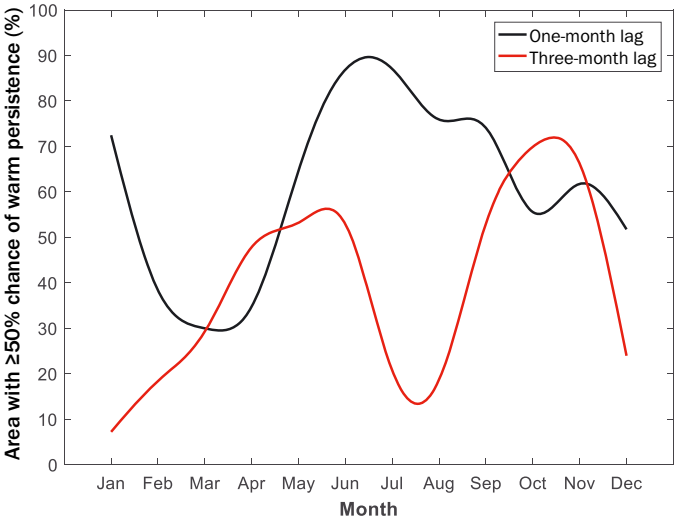

Fig. 7. Percentage of grid cells with a greater than 50% chance of correct forecasts given antecedent temperatures greater than or equal to the 90th percentile. The skill scores represents the average monthly Heidke skill score value for all 1 mo temperature persistence forecasts made from January 1900 to November 2015. Data were smoothed using a piecewise polynomial computed for p = 0.95

There are also months where large portions of the study area exhibit the tendency for anomalously warm temperatures to persist when considering the 3 mo timescale (Fig. 7). Similar to Fig. 1, seasonal trends in 3 mo persistence are offset from those observed at a 1 mo timescale. There are 2 peaks in 3 mo persistence, once from April to June and another from September to November. Both of these show that persistence-based temperature forecasts are skillful in approximately half of the study region. This finding is significant, because it indicates that anomalously warm springtime temperatures (e.g. April) can be used as a skillful predictor of extreme summer temperatures. This is particularly pronounced in the northern part of the study region. In addition, when temperatures are anomalously warm in early summer (e.g. June), this is also associated with increased forecast skill. However, anomalously warm temperatures during July and August do not provide skillful forecasts of fall temperatures. The tendency for 3 mo persistence also exists during September to November for the majority (>55%) of the study area. While this is interesting, extreme heat is less likely to result in adverse health or environmental impacts in fall.

6. SUMMARY AND DISCUSSION

This study utilized a high-resolution data set to establish a temperature persistence climatology for the south-central US. Our results affirm many of the findings of past studies. Similar to Barnett & Preisendorfer (1987), Dickson (1967), Lyon (1991), Namias (1978), van den Dool (1984), and van den Dool et al. (1986), our work demonstrates that the strongest temperature persistence occurs in summer. Temperature persistence at a 1 mo timescale was also statistically significant in January for much of the study region (Dickson 1967, Lyon 1991). Namias (1978) found statistically significant autocorrelations at 3 to 6 mo timescales during spring and summer. This agrees with the lag in the seasonal cycle of temperature persistence that we found in our study (Figs. 1b & 7). For example, we found that most locations had significant 3 mo autocorrelations from April to June.

Our results also illustrate that monthly temperature persistence varies spatially within the south-central US, as van den Dool et al. (1986) suggested. Fig. 8 utilizes the Conrad index (Conrad 1946) to explore the relationship between persistence and continentality. There are moderate to strong correlations between temperature persistence and continentality during the fall and winter (Fig. 8A,D). This suggests that, on average, temperature persistence increases as one moves closer to the coast. Interestingly, during the summer, the strongest temperature persistence occurs at locations that are ~400 km inland from the Gulf of Mexico (Fig. 2). As Fig. 8C shows, most of the highest autocorrelations during summer months occur with moderate values of the Conrad index. These locations are still close enough to the Gulf of Mexico to experience the moderating influence of the ocean, but there are obviously other factors that are also important for explaining the spatial patterns in temperature persistence (Namias 1978, van den Dool 1984, Van den Dool et al. 1986). As a result, the correlation coefficient, which should measure a linear relationship between continentality and persistence, fails to capture the quadratic trend during summer months (Fig. 8C). Lyon (1991) suggested that the inland maxima in summertime temperature persistence (seen in Fig. 8C) can be partly attributed to land–atmosphere interactions. Strong land–atmosphere coupling influences much of our study region. While it was not an objective of this study to conduct an attribution analysis to identify all of the factors that explain the patterns of temperature persistence in the south-central US, the locations and times when temperature persistence is strongest are consistent with when and where land–atmosphere interactions are thought to be most influential (Koster et al. 2004, Merrifield et al. 2017).

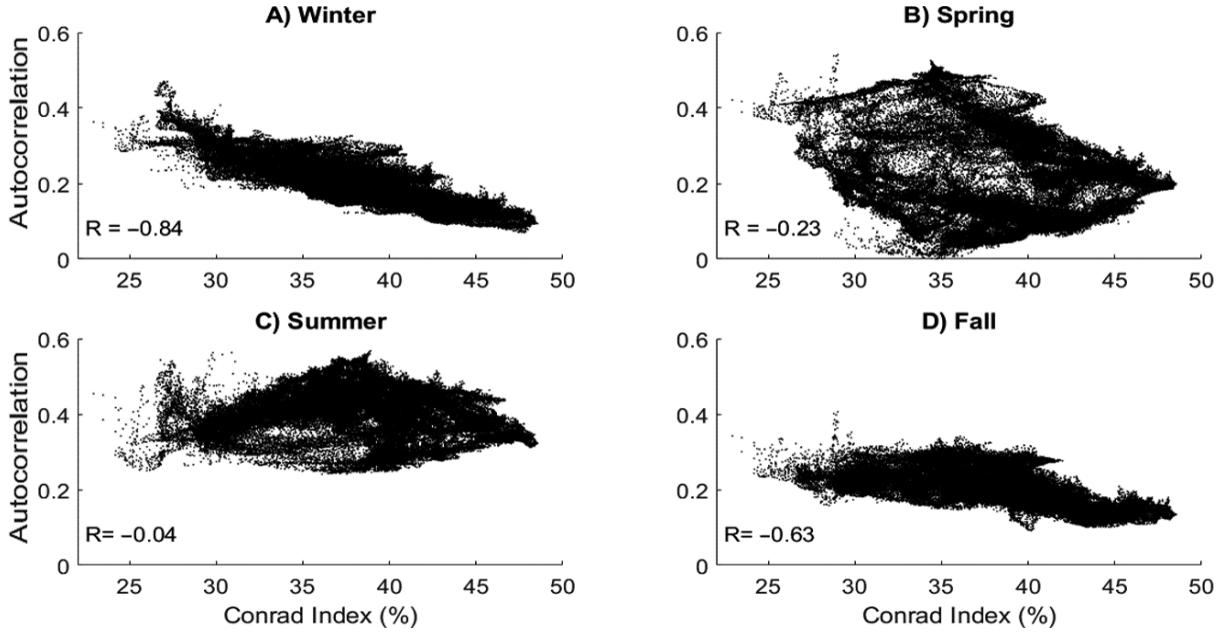

Fig. 8. Relationship between the temporal autocorrelation of monthly temperatures in the south central US and the Conrad index of continentality. For each season, the monthly temporal autocorrelations were averaged at each grid cell. The coefficient of correlations displayed quantify the relationship between the temporal autocorrelation and the Conrad index. The climatological seasons are constructed as follows: (A) Winter (DJF), (B) Spring (MAM), (C) Summer (JJA), and (D) Fall (SON)

The most significant finding of this study is that there is a systematic increase in temperature persistence with more anomalous antecedent temperatures. The use of the HSS allows us to quantify this effect. Both anomalously warm and cool temperatures promote temperature persistence. While anomalous conditions promote higher persistence forecast skill, there are seasonal variations in the strength of this effect. Persistence of anomalously warm temperatures is most important during the summer. Lyon & Dole (1995) found that extreme heat during the summer tends to persist until a strong, dynamically forced atmospheric event disrupts the feedback cycle. Additionally, anomalously warm temperatures during spring were also shown to be a skillful predictor of above-normal summer temperatures. Perhaps this is due to the higher potential evapotranspiration associated with high temperatures during the warm season. Previous research has shown that low soil moisture can provide early warning of extreme heat events (Ford & Quiring 2014).

The results of this study provide information to inform the development of more skillful seasonal temperature forecasts. Persistence is a basic, yet important, source of subseasonal-to-seasonal forecast skill. Knowledge of where and when persistence is strong can help to identify conditions when persistence can be used as a successful forecasting technique. Many previous studies have examined the characteristics of temperature persistence, but failed to demonstrate seasonal predictability using persistence. Therefore, we have demonstrated the utility of this information using monthly tercile temperature forecasts. Our results show that the importance of persistence grows with the magnitude of the antecedent temperature anomalies. When there are large temperature anomalies, the skill for 1 mo temperature persistence forecasts increases. This study recommends the use of both 1 and 3 mo persistence forecasts when forecasting anomalously warm temperatures during the summer. This information can enhance seasonal forecast skill in a region that frequently experiences the adverse effects of extreme heat events.

Acknowledgements. We acknowledge the PRISM climate group from Oregon State University for allowing this the use of high-resolution gridded climatic data sets. Additionally, we thank SCIPP, as part of NOAA RISA, for providing the funding for this project.

LITERATURE CITED

Barnett TP (1981) Statistical prediction of North American air temperatures from Pacific predictors. Mon Weather Rev 109:1021–1041

Barnett TP, Preisendorfer R (1987) Origins and levels of monthly and seasonal forecast skill for United States surface air temperatures determined by canonical correlation analysis. Mon Weather Rev 115:1825–1850

Chandrasekhar E, Dimri V (2014) Introduction to wavelets and fractals. In: Chandrasekhar E, Dimiri VP, Gadre VM (eds) Wavelets and fractals in earth system sciences. Taylor & Francis, Boca Raton, FL, p 1–28

Changnon SA, Kunkel KE, Reinke BC (1996) Impacts and responses to the 1995 heat wave: a call to action. Bull Am Meteorol Soc 77:1497–1506

Conrad V (1946) Methods in climatology. Harvard University Press, Cambridge, MA

Daly C, Neilson RP, Phillips DL (1994) A statistical-topographic model for mapping climatological precipitation over mountainous terrain. J Appl Meteorol 33:140–158

Daly C, Taylor GH, Gibson WP, Parzybok TW, Johnson GL, Pasteris PA (2000) High-quality spatial climate data sets for the United States and beyond. Trans ASABE 43:1957–1962

Daly C, Halbleib M, Smith JI, Gibson WP and others (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int J Climatol 28:2031–2064

Dickson RR (1967) The climatological relationship between temperatures of successive months in the United States. J Appl Meteorol 6:31–38

Doblas-Reyes FJ, García Serrano J, Lienert F, Biescas AP, Rodrigues LRL (2013) Seasonal climate predictability and forecasting: status and prospects. Wiley Interdiscip Rev Clim Change 4:245–268

Eichner JF, Koscielny-Bunde E, Bunde A, Havlin S, Schellnhuber HJ (2003) Power-law persistence and trends in the atmosphere: a detailed study of long temperature records. Phys Rev E Stat Nonlin Soft Matter Phys 68:046133

Fischer EM, Seneviratne SI, Vidale PL, Lüthi D, Schär C (2007) Soil moisture–atmosphere interactions during the 2003 European summer heat wave. J Clim 20:5081–5099

Ford TW, Quiring SM (2014) In situ soil moisture coupled with extreme temperatures: a study based on the Oklahoma Mesonet. Geophys Res Lett 41:4727–4734

Hoerling M, Kumar A, Dole R, Nielsen-Gammon JW and others (2013) Anatomy of an extreme event. J Clim 26: 2811–2832

Hoskins BJ, Hodges KI (2002) New perspectives on the Northern Hemisphere winter storm tracks. J Atmos Sci 59:1041–1061

Kalkstein LS, Greene JS (1997) An evaluation of climate/mortality relationships in large US cities and the possible impacts of a climate change. Environ Health Perspect 105:84–93

Koster RD, Dirmeyer PA, Guo Z, Bonan G and others (2004) Regions of strong coupling between soil moisture and precipitation. Science 305:1138–1140

Livezey RE, Timofeyeva MM (2008) The first decade of long-lead US seasonal forecasts: insights from a skill analysis. Bull Am Meteorol Soc 89:843–854

Lowe R, García-Díez M, Ballester J, Creswick J, Robine JM, Herrmann FR, Rodó X (2016) Evaluation of an early-warning system for heat wave-related mortality in Europe: implications for sub-seasonal to seasonal forecasting and climate services. Int J Environ Res Public Health 13:206

Lyon B (1991) An observational study of persistent tempera-

ture anomalies over the North American region. PhD dissertation, Massachusetts Institute of Technology, Cambridge, MA

Lyon B, Dole RM (1995) A diagnostic comparison of the 1980 and 1988 US summer heat wave-droughts. J Clim 8: 1658–1675

McGrew JC Jr, Monroe CB (2009) Statistical relationships between variables: correlation. In: An introduction to statistical problem solving in geography. Waveland Press, Long Grove, IL, p 239–251

Merrifield A, Lehner F, Xie SP, Deser C (2017) Removing circulation effects to assess central US land-atmosphere interactions in the CESM large ensemble. Geophys Res Lett 44:9938–9946

Monetti RA, Havlin S, Bunde A (2003) Long-term persistence in the sea surface temperature fluctuations. Physica A 320:581–589

Namias J (1978) Persistence of US seasonal temperatures up to one year. Mon Weather Rev 106:1557–1567

O'Lenic EA, Unger DA, Halpert MS, Pelman KS (2008) Developments in operational long-range climate prediction at CPC. Weather Forecast 23:496–515

Peng P, Kumar A, Halpert MS, Barnston AG (2012) An analysis of CPC's operational 0.5-month lead seasonal outlooks. Weather Forecast 27:898–917

Triacca U, Pasini A, Attanasio A (2014) Measuring persistence in time series of temperature anomalies. Theor Appl Climatol 118:491–495

van den Dool HM (1984) Long-lived air temperature anomalies in the midlatitudes forced by the surface. Mon Weather Rev 112:555–562

van den Dool HM, Klein WH, Walsh JE (1986) The geographical distribution and seasonality of persistence in monthly mean air temperatures over the United States. Mon Weather Rev 114:546–560

Weida FM (1927) On various conceptions of correlation. Ann Math 29:276–312

Yu B, Zhang X, Lin H, Yu JY (2015) Comparison of wintertime North American climate impacts associated with multiple ENSO indices. Atmos-Ocean 53:426–445

Editorial responsibility: Filippo Giorgi, Trieste, Italy

Submitted: June 13, 2018; Accepted: November 29, 2018
Proofs received from author(s): January 11, 2019