Ensemble Forecasts of Drought Indices Using a Conditional Residual Resampling Technique

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ABSTRACT

The historical climate record and seasonal temperature and precipitation records provide useful datasets for making short-term drought predictions. A variety of methods have exploited these resources, but few have quantitatively measured uncertainties associated with predictions of drought index values commonly used in management plans. In this paper, stochastic approaches for estimating uncertainty are applied to drought index predictions. National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) seasonal forecasts and resampling of nearest-neighbor residuals are incorporated to measure uncertainty in monthly forecasts of Palmer drought severity index (PDSI) and standardized precipitation index (SPI) in central South Carolina. Kuiper skill scores of PDSI indicate good forecast performance with up to 3-month lead time and improvements for 1-month-lead SPI forecasts. NOAA CPC climate outlook improved the forecast skill by as much as 40%, and the degree of improvement varies by season and forecast lead time.

1. Introduction

Drought is part of natural climate variability, but anticipating its occurrence remains challenging because some parts of the hydrologic cycle (e.g., precipitation, soil moisture, or groundwater level) are not easily forecast. Yet, the desire to mitigate impacts on agriculture and water resources (Steinemann 2006) has resulted in the development of drought prediction methods. As long as perfect drought forecasts with long lead times remain elusive, predictions should include reliable uncertainty measures. Water managers contend with multiple uncertainties; identifying their source and magnitude can improve decision making (Jacobs and Pulwarty 2003; Garrick et al. 2008).

Drought forecasts, or efforts to characterize drought intensity, frequency, and recurrence, rely on a variety of methods. Some have used run theory (Yevjevich 1967; Saldarriaga and Yevjevich 1970; Sen 1976, 1977; Moye et al. 1988). Others have used stochastic models such as Markov chain and renewal models. For example, Kendall and Dracup (1992), Loaiciga and Leipnik (1996), and Rao and Padmanabhan (1984) used autoregressive models to predict the Palmer drought severity index (PDSI). Lohani and Loganathan (1997) used a Markov chain model to forecast PDSI values and tried to incorporate the forecast in an early drought warning system. Mishra and Desai (2005) used a parametric autoregressive model to forecast the standardized precipitation index (SPI). They preserved observed probability density functions (PDF) and made good predictions with 1–2-month lead time. Other methods have addressed the nonlinear features of drought. Kim et al. (2003) used wavelet transforms and neural networks to capture nonlinear features of the PDSI for forecasting. In a similar way, Mishra and Desai (2006) used a feed-forward neural network model for drought prediction. Both the autoregressive and neural network models focus on prediction of mean drought stage, but they do not incorporate analysis of uncertainties associated with drought predictions.

Stochastic approaches provide a method of quantifying the uncertainties associated with a drought forecast. Overall mean forecasts preserve observed probability
density functions, but consideration of forecast uncertainty helps the model to predict variability associated with upcoming drought status. Although uncertainty analysis is relatively rare in drought forecasting, modeling and forecasting uncertainties have been discussed extensively in hydrology: input uncertainty, parameter uncertainty, and model uncertainty have been examined to provide ensemble streamflow simulations. For example, Carpenter and Georgakakos (2004) used a Monte Carlo technique to examine the impact of input uncertainty on ensemble streamflow simulations. Carbone and Dow (2005) applied an ensemble technique for drought index forecasts by resampling historical data. This work demonstrates the benefit of an ensemble approach for drought forecasting. Ensemble techniques provide valuable information to decision makers who need to know the uncertainty associated with drought forecasts.

This paper applies the methods for ensemble forecasts, widely used in hydrology, to drought forecasts. We develop an autoregressive model using the historical record to produce drought index forecasts and then resample the residuals to generate forecast ensembles. Whereas most previous methods constrain uncertainty measures within the bounds of the historical record, residual resampling allows consideration outside of these bounds. We follow the basic residual resampling steps of the modified $K$-NN method (where $K$ is the number of neighbors and NN stands for nearest neighbor) used in the ensemble streamflow prediction work of Prairie et al. (2006) that significantly enhance the forecast performance. However, the method is considerably modified to incorporate available seasonal temperature and precipitation forecasts provided by the National Oceanographic and Atmospheric Administration Climate Prediction Center (NOAA CPC). Section 2 of the paper describes the study basin and data used in this study. Forecast model and ensemble generation procedure are introduced in section 3, followed by the study results presented in section 4. Section 5 summarizes the findings and discusses related research issues.

2. Study region and data

Drought forecasts will be made for South Carolina climate division 6. This division covers 12 106 km$^2$ of central South Carolina (see http://www.cdc.noaa.gov/data/usclimdivs/data/map.html) and is located entirely within NOAA’s forecast division 13, which includes 88 642 km$^2$ of interior North and South Carolina. A prolonged drought affected this region from 1998 to 2002 and triggered active research on drought monitoring and forecasting (e.g., Carbone and Dow 2005).

Temperature and precipitation were compiled from the National Weather Service Cooperative Observer Program (COOP) database. To consider the recent climate regime, only the 1971–2000 period is used in this research. Eight individual weather stations falling inside South Carolina climate division 6 were used to test our forecast method (Fig. 1; Table 1). Less than 10% of monthly temperature and precipitation values were missing from the dataset. Missing values were filled using the 30-yr (1961–90) daily averages. This temporal substitution has proven to be more accurate than spatial interpolation from neighboring stations (Robeson and Janis 1998). The PDSI was calculated for each station using that station’s monthly temperature and precipitation values and soil input parameters appropriate to the climate division. The SPI was calculated for each station at multiple intervals. Below, we present the analysis using 3-month SPI values.

3. Forecast of drought indices

a. Drought indices

Various indices have been developed to declare and compare drought events (Heim 2002). Among many drought indices, PDSI and SPI are used in this study because the two indices are relatively important in decision making in South Carolina.
The PDSI is a simple water balance index based on the actual versus “climatically appropriate” monthly values of precipitation, evapotranspiration, recharge, runoff, and loss. Its calculation includes a moisture anomaly index, calculated from the difference between the actual and long-term-average monthly precipitation. Palmer (1965) classified drought in four severity classes using empirical relationships between accumulated Z-index values and dry-period duration from the 13 driest periods in central Iowa and western Kansas. His monthly drought severity equation is

$$X_i = 0.897X_{i-1} + Z_i/3,$$  \hspace{1cm} (1)

where $X_i$ and $Z_i$ are the PDSI and Z-index values for the $i$th month. The first term of the equation introduces an autoregressive process; this memory built into the PDSI varies by location and season but approximates 1 yr (Guttman 1998; Heim 2002). By contrast, the SPI is a moving-average process based on the cumulative probability of total precipitation for various duration periods (e.g., 1, 2, 3, 6, 9, 12, and 24 months). The PDSI and SPI are linearly related (Guttman 1998), and both indices have strong month-to-month correlation that can be exploited for forecast purposes. Figure 2 shows the autocorrelation of PDSI and SPI with various lags. PDSI has longer memory than the SPI and, therefore, changes more slowly. Autocorrelation of the 3-month SPI with 1-month lag approximates the autocorrelation of the PDSI with 3-month lag in this climate division (Fig. 2). This supports the broader findings of Guttman (1998).

b. Forecast

The suggested drought-indices forecast is based on the mean forecast capability of a nonparametric monthly autoregressive model. Given the monthly historical time series, ensemble forecasts of a drought index are generated by estimating 1) the mean forecast of the target month with a given lag, 2) weights of historical years based on available climate outlook, and 3) resampling of model residuals from the conditioned year pool.

The mean drought forecast for a target month is estimated by a locally weighted polynomial (LWP) function (Loader 1999). As a nonparametric autoregressive model, LWP is a flexible model to explain nonlinear data (Rajagopalan and Lall 1998). A general form of local regression with one predictor variable is

$$p_i = \mu(x_i) + e_i,$$  \hspace{1cm} (2)

where $\mu(x_i)$ is the appropriate polynomial function and $e_i$ is the estimation error.

Although we apply a linear function, appropriate for this research, the polynomial function of the model could be of higher order. Optimal model fit is determined with proper neighbor size (sliding window) around each target. Using general cross-validation statistics (GCV), best neighbor size is determined based on the number of predictor variables and the estimation error:

$$\text{GCV} = \frac{\sum_{i=1}^{m} e_i^2}{\frac{1}{n} \left( 1 - \frac{m}{n} \right)^2},$$  \hspace{1cm} (3)

where $e_i$ is the error, $n$ is the number of data points, and $m$ is the number of parameters. In this method, historical drought indices for the previous month serve as a predictor vector to estimate the mean drought index for a target month.

Residual resampling uses NOAA CPC’s categorical forecast by adjusting weights to the historical years according to the forecast PDF shift of temperature and precipitation. Currently, NOAA/CPC provides temperature and precipitation outlooks for the contiguous United States at various time scales ranging from 6 days to 13 months (http://www.cpc.ncep.noaa.gov/products/forecasts/). At the time of writing, the past forecast archive could be found online (http://www.
Fig. 2. Exploring lagged autocorrelations of monthly drought indices: (a) PDSI (1950–2004) and (b) SPI (1961–2004). Each small circle represents a single year at station ID 380736. Autoregressive models (solid line) are determined by locally weighted polynomial functions.
cpc.ncep.noaa.gov/products/archives/long_lead/llarc.ind.php). Carbone and Dow (2005) used these forecasts to condition resampling from the historical record.

Ensemble forecasts of monthly drought indices are generated by the detailed procedure given below:

1) Estimate an autoregressive model for a target month based on history,

\[ I_m = f(I_{m-1}) \]  

where \( I \) is a drought index, \( m \) is the target month, and \( I \) is the forecast lead time (1, 2, or 3 months).

2) Save the residuals (\( e_i \)) of the estimated model.

3) Calculate the mean forecast value of the target month (\( I_m \)) using the current month’s drought index (\( I_{m-1} \)).

4) Pick only the residuals that are nearest neighbors (up to 20 in this study) of the current drought condition (inside the window around the current month’s condition in Fig. 3). Because the sampling window is centered at the current drought condition, only the residuals calculated from conditions that are similar to the current climate conditions will be selected. This will ensure proper variability is regenerated in ensemble forecasts. For example, a poor (good) monthly autocorrelation at the current drought condition will produce larger (smaller) errors and eventually will result in more (less) variable ensemble forecasts.

5) Resample the stored residuals to generate an ensemble forecast of drought indices. Residuals are resampled by giving more weight to the years that have the climate conditions (precipitation and temperature) that are similar to the target month. This includes the following steps based on the work of Carbone and Dow (2005):

(I) Estimate the terciles of historical observations of temperature and precipitation.

(II) Make a \( 3 \times 3 \) contingency table (nine categories) that contains the years of three different climate conditions—above normal, below normal, and near normal—for both temperature and precipitation.

(III) Adjust the sampling frequency from nine categories based on the CPC probabilistic forecast of the target month. For example, an additional 10% forecast for below-normal precipitation forces the selection of 43.3% of the historical years (rather than 33.3%) from the below-normal precipitation bin.

(IV) Sample as many residuals as needed for the ensemble forecast based on the explained weighting scheme.

6) Add the resampled residuals to the mean forecast to produce the ensemble forecast.

4. Results

The ensemble forecast was tested using the jackknife technique (Quenouille 1956). For the entire time period, the years of the target month were removed one by one to build a model and estimate ensemble forecast members. Note that January forecasts were estimated by the previous year’s months (December for lag-1 estimation, November for lag-2 estimation, and October for lag-3 estimation).

Figures 4–7 summarize the results of forecast ensembles and their PDFs in comparison with observed drought indices. Overall, forecast ensemble members capture observed drought indices well. As expected, forecast performance drops in longer-time-lag forecasts because the autocorrelation between the target month and current month gets weaker along the time lag (Fig. 2).

We verified the skill of the suggested ensemble forecast technique on the basis of accuracy and variability. First, to check the accuracy of the mean forecast at stations, the Kuiper skill score (KSS) is calculated with a \( 3 \times 3 \) contingency table (Wilks 1995). KSS is a categorical forecast skill measure similar to Heidke skill score. Based on the U.S. Drought Monitor categories from the National Drought Mitigation Center, drought conditions are organized into three categories (Tables 2, 3). Conditions wetter than Drought Monitor index D0 fall in stage 1, D0 and D1 fall in stage 2, and D2–D4
fall in stage 3. Stage 1 marks the establishment of mild drought, stage 2 indicates moderate drought, and stage 3 denotes drought that has a severe impact on agricultural and domestic water usage. Only those time series that have negative PDSI or SPI are considered for skill-score calculations. KSS of stations are calculated as follows:

$$KSS = \frac{A + E + I - (A + B + C)(A + D + G) + (B + E + H)(D + E + F) + (C + F + I)(G + H + I)}{n - \frac{(A + D + G)^2 + (B + E + H)^2 + (C + F + I)^2}{n^2}}. \quad (5)$$

where $A, B, C, \ldots, I$ are the number of observed and forecast pairs in the contingency table (Table 2) and $n$ is the number of total forecast pairs. For example, $A$ is the number of forecast mild dry months that were actually observed as the same condition.

KSS shows that our nonlinear mean forecast model successfully reproduced observed drought conditions, with performance varying among the stations (Fig. 4). KSS of 1 means perfect forecast skill, and 0 means the same skill as the reference forecast (climatological value). Median KSS of PDSI ensemble forecasts are overall 0.49 and 0.27 for lag 1 and lag 2, respectively. This is a considerable improvement over the forecasts using the linear regression model (0.31 and 0.24, respectively) or even the autoregressive model (0.38 and 0.24, respectively). The skill of the SPI forecasts showed a similar result but was generally lower than that of PDSI. This reflects the fact that the SPI has less memory of the previous climate condition and weaker autocorrelation than the PDSI. Median KSS (Fig. 4b) is 0.105 for both lag-1 and lag-2 forecasts.
FIG. 5. Ensemble forecast of PDSI for station 380736 in 2000 with various lead times (1, 2, and 3 months). The top two rows are the boxplots and rank histograms for the forecasts without CPC climate outlook information. The bottom two rows are the forecasts using CPC climate outlook information. Box plots show the ensemble range, and solid circles show observed monthly values.
Ranked histograms and box plots of ensemble forecasts are shown in Figs. 5 and 6. The length of the boxes indicates the interquartile range of the 1000 generated ensemble indices for each month at Bishopville, South Carolina (station 380736), and the whiskers show the 5th and 95th percentile range; the horizontal line in the box is the median. A larger box length indicates increased variability in the index forecasts.
FIG. 7. PDFs of ensemble forecasts: (a) PDSI and (b) SPI. Box plots represent the ensemble forecast, and solid lines show observed PDFs.
Rank histograms are a useful tool for performing visual examinations of a forecast ensemble set. Although rank histograms can be misinterpreted because of conditional bias, improper selection of grid points, or errors in observations, they are effective and useful for testing our ensemble forecast, along with other performance measures presented in this work (Hamill 2001). In an ideal case, a rank histogram should have a flat shape (i.e., observations are uniformly located throughout the entire ensemble range). The rank histogram is computed as follows: assume that there are \( n \) ensemble forecast members and one point of observed drought index value for a given month. Based on the rank of the observation among the \( n + 1 \) points, the plotting position of the observed value is calculated for each month. The plotting position of this observation \( x_0 \) in the vector \( X = (x_1, x_2, \ldots, x_n, x_0) \) is calculated as

\[
pp = \frac{\text{rank}(x_0)}{n+2},
\]

where \( pp \) is the plotting position and \( n \) is the total number of ensemble members in each month. Then, the frequency of this calculated position \( pp \) for each predefined bin is added along the time series. If the variability of forecast ensemble members is kept too small, observations are more likely to be found outside the ensemble range, and a rank histogram should be in a U shape. If the ensemble range is too large, then the histogram will have an inverted U shape. Although the rank histogram is not a perfect measure of forecast ensembles, a flat histogram is generally accepted as a good indication that the forecast monthly indices explain observed variability properly with a good forecast of mean value.

Table 2: The 3 \( \times \) 3 contingency table for forecast skill analysis.

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Obs</th>
<th>Mild dry</th>
<th>Moderate dry</th>
<th>Severe dry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild dry</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td></td>
</tr>
<tr>
<td>Moderate dry</td>
<td>D</td>
<td>E</td>
<td>F</td>
<td></td>
</tr>
<tr>
<td>Severe dry</td>
<td>G</td>
<td>H</td>
<td>I</td>
<td></td>
</tr>
</tbody>
</table>

* The U.S. Drought Monitor.

Figures 5 and 6 show the improvement of ensemble spread with the adjusted resampling technique based on climate outlook. The top two rows are box plots of forecast ensembles and rank histograms without seasonal climate forecasts. The forecast ensembles of the top two rows suggest that the observed indices are often located outside the range of generated ensembles. However, the overall rank histogram does not show significant skew. The U-shaped rank histogram is mostly flat, with two spikes at the lowest and highest ends, indicating that the forecast ensemble does not capture drought uncertainty. The variability of generated forecast ensembles for both PDSI and SPI improved with seasonal climate forecasts, as shown in the bottom-row panels of Figs. 5 and 6. Rank histograms show slight skew for 2- and 3-month-lag forecasts, but it is minimal relative to the overall forecast improvement. Similar improvements are observed in other years and stations repeatedly.

Variability of the forecast ensemble members should show PDFs that are similar to those of the observations. In Fig. 7, PDFs of ensembles are plotted as box plots together with observed PDFs. It is clear that observed indices are captured well in our ensembles in different seasons. For PDSI, observed PDFs are in the interquartile ranges of ensemble PDFs except for November. Although capturing observed PDFs is more challenging in the SPI ensemble forecast, observed PDFs are rarely located in the outlier range of the ensemble PDFs.

To test how the accuracy of CPC seasonal forecast affects the drought forecasts, we examined temperature and precipitation archives in the CPC database. For consistency, observed mean values of the 1971–2000 period were used. Tercile forecasts (below normal, near normal, and above normal) of precipitation and temperature were compared with the observed values. The upper and lower breakpoints that divide observed temperature and precipitation into tercile categories were also obtained from the CPC archive compiled from the 1971–2000 observations. Figure 8 shows a very different annual quality of CPC 1-month outlook between temperature and precipitation. This suggests that the impact of CPC forecast skill of temperature and precipitation on our ensemble forecast needs to be examined separately. Because the CPC outlook skill varies through

Table 3: Drought state category.

<table>
<thead>
<tr>
<th></th>
<th>Mild dry</th>
<th>Moderate dry</th>
<th>Severe dry</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDSI</td>
<td>From 0 to −0.9</td>
<td>From −1.0 to −2.9</td>
<td>≤−3.0</td>
</tr>
<tr>
<td>SPI</td>
<td>From 0 to −0.4</td>
<td>From −0.5 to −1.2</td>
<td>≤−1.3</td>
</tr>
<tr>
<td>Drought Monitor</td>
<td>D0-D1</td>
<td>D2-D4</td>
<td></td>
</tr>
<tr>
<td>Explanation</td>
<td>Climate condition is going into mild drought stage</td>
<td>Going into drought stage; voluntary water use restriction starts</td>
<td>Water use restriction imposed; crop damage likely; high fire risk</td>
</tr>
</tbody>
</table>
the seasons in a single year, detailed forecast performances are shown in small bars at the bottom of the annual plots. Bars located over the horizontal line indicate right-category forecasts (above, near, and below normal), and the ones below the line indicate wrong-category forecasts.

In Fig. 9, forecast qualities of PDSI are shown based on CPC outlook skills and forecast lead times. The impact on drought forecast quality is shown in black and gray lines separating better-CPC-temperature-outlook years and poor-outlook years, respectively. The years with better-forecast seasons (2 or 3 months are correctly forecast in Fig. 8a) are picked as a set of better-forecast years, and the years with poorly forecast seasons (0 or only 1 month is correctly forecast) are picked as a set of poorly forecast years. An accurate temperature outlook led to better drought forecast skill (better-forecast years are shown with black lines; poorly forecast years are shown with gray lines), but the amount of improvement varies by season. Figure 9a suggests that the seasonal quality of drought forecast was greatly improved with a better climate outlook during winter and spring (January–March and April–June). In general, a good climate forecast led to better drought forecast performance for 1–2-month lead time.

However, improvement of PDSI forecast quality using CPC precipitation outlook is mixed (Fig. 9b). Although 1–2-month-lead KSS of PDSI forecast for better-CPC-precipitation-outlook years (picked years vary by month) are higher than those of poor-CPC-outlook years in winter and spring, the skills are also often lower in other seasons. For example, the skills of all three lead-time forecasts in better-CPC-precipitation-outlook years are lower than in poor-outlook years in July–September. Despite the mixed skills, Figs. 9a and 9b both show that the quality of lag-1 forecasts is higher.
than longer-lead-time forecasts, with both better precipitation and temperature outlook (black and gray solid lines), except for the July–September forecasts.

5. Discussion

The main purpose of this work is to provide a simple nonparametric autoregressive method to produce an ensemble forecast of drought indices based on the historical record and seasonal temperature and precipitation forecasts. Our technique employs two statistical methods: 1) an evaluation of the residuals of an established autoregressive model and 2) a resampling of the weighted residuals using available seasonal precipitation and temperature forecasts. Those resampled residuals are added to the monthly mean forecast of the autoregressive model. This conditional residual resampling makes the forecast ensemble members shift toward the expected climate condition predicted by CPC.

Monthly autocorrelations of two commonly used drought indices, PDSI and SPI, are exploited for mean forecasts in this study. Because drought indices have built-in memory, an autoregressive model is a good model for mean forecasts. PDSI has longer memory of drought condition than SPI does, and this property is verified from the mean forecast skill score (Fig. 4). The skill score of 1-month-lag SPI was only comparable to lower skills of 3-month-lag PDSI. The graphs of lagged monthly autocorrelation in Fig. 2 suggest additional research questions. Outliers and large changes of month-to-month mean model fit are often observed near extreme hydrologic conditions. Additional research is needed to better understand these findings.

Weighted resampling of model residuals is based on the CPC temperature and precipitation outlook. With this method, ensemble forecasts are implicitly conditioned to consider the predicted climate condition. Figures 5 and 6 demonstrate the success of the technique. The CPC climate outlook adjusted the weights of residuals to steer the generated ensembles toward the correct drought status (dry or wet). These adjusted ensembles also captured observations well with larger variability. Box plots show wider interquartile range but a small number of outliers beyond the whiskers. This implies that our forecast ensemble has a proper range with evenly distributed members.

The amount of forecast improvement seems to be limited by the accuracy of climate information (better or poor forecasts), which is given by the CPC outlook used in this study. Figure 9 suggests that a better CPC outlook (with higher forecast skills) does not always guarantee improved drought forecasts, but the authors observed improvement in many cases. It would be very useful to include other climate forecast products in various lead times to test the potential improvement of the suggested drought indices’ forecasts.

Figure 9 shows that improvement of drought forecasts depends heavily on the quality of the temperature outlook, but this is not always true with precipitation outlook. This might be because the improvement of a good precipitation outlook from a bad outlook is still marginal relative to that of temperature. It is also reasonable to think that the forecast skill of precipitation and temperature has a combined impact on this drought forecast.

To obtain good variability in our forecast ensemble, residuals were sampled from only a limited number of nearest neighbors (step 4 described in section 3). A heuristic sample size selection of $k = (n)^{1/2}$ is usually widely accepted (Gangopadhyay et al. 2005) while other considerations are also available for a forecast using shorter time series (Prairie et al. 2006).

The methods described above have several practical applications. Water resource managers and other decision makers in drought-sensitive sectors would benefit from
knowing the confidence associated with future drought conditions (Garrick et al. 2008). In many cases, state or other government agencies declare specific drought stages on the basis of indicator thresholds and probability of exceedance in future months. The strategy described above exploits the historical climate record and incorporates seasonal forecasts and residual resampling to provide quantitative measures of drought forecast confidence intervals. Because of this focus on resampling residuals, uncertainty measures are not constrained by the observations of the historical record. Such consideration has particular significance when a historical data record is short or in circumstances of changes in mean climate or climate variability. These advantages can be translated for decision makers by clearly and accurately stating the probability associated with future drought stages. The medium for such a presentation could be through the state climatology network or appropriate drought-response committee meetings.

Overall, improved ensemble drought indices’ forecast skill of a nonlinear model over a linear model is clearly shown. Also, CPC climate outlook is used to improve short-term ensemble forecasts. However, the improvement of longer-term forecasts using CPC outlook is complicated. Further potential research topics include several ideas from our findings: the interaction between seasonal CPC outlook skills and drought condition, forecast improvements using other available climate forecast products, forecast skill variance among climate stations, and changes of forecast skills due to annual/seasonal climate variability (i.e., wet/dry years or seasons), natural climate change, or anthropogenic forcing.

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