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Hydro-Climatological Drought Analyses and Projections Using Meteorological and Hydrological Drought Indices: A Case Study in Blue River Basin, Oklahoma

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Abstract Understanding the characteristics of historical droughts will benefit water resource managers because it will reveal the possible impacts that future changes in climate may have on drought, and subsequently, the availability of water resources. The goal of this study was to reconstruct historical drought occurrences and assess future drought risk for the drought-prone Blue River Basin in Oklahoma, under a likely changing climate using three types of drought indices, i.e., Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI) and Standardized Runoff Index (SRI). No similar research has been conducted in this region previously. Monthly precipitation and temperature data from the observational period 1950–1999 and over the projection period 2010–2099 from 16 statistically downscaled Global Climate Models (GCM) were used to compute the duration, severity, and extent of

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meteorological droughts. Additionally, soil moisture, evapotranspiration (ET), and runoff data from the well-calibrated Thornthwaite Monthly Water Balance Model were used to examine drought from a hydrological perspective. The results show that the three indices captured the historical droughts for the past 50 years and suggest that more severe droughts of wider extent are very likely to occur over the next 90 years in the Blue River Basin, especially in the later part of the 21st century. In fact, all three indices display lower minimum values than those ever recorded in the past 50 years. This study also found that SRI and SPI (PDSI) had a correlation coefficient of 0.81 (0.78) with a 2-month (no appreciable) lag time over the 1950–2099 time period across the basin. There was relatively lower correlation between SPI and PDSI over the same period. Although this study recommends that PDSI and SRI are the most suitable indices for assessing future drought risks under an increasingly warmer climate, more drought indices from ecological and socioeconomic perspectives should be investigated and compared to provide a complete picture of drought and its potential impacts on the dynamically coupled nature-human system.

Keywords Blue River Basin · Drought index · Climate change · GCMs

1 Introduction

The Earth's average temperature is gradually increasing according to studies in the last 30 years (Piñol et al. 1998; Karl et al. 2009). Global Climate Models (GCMs) continue to show a significant increasing trend of Earth's average temperature over the next 90 years (Karl et al. 2009). Studies on climate change impacts have consequently become not only scientifically valuable, but also economically and socially necessary (Nordhaus 1994).

Drought is a common, widespread, and recurring climate-related hazard (Namias 1966). It occurs virtually in all climate zones and impacts the local ecological and social environment (Riebsame et al. 1991; Wang et al. 2003). Many drought events have been observed and recorded in human history (Stine 1994; Woodhouse and Overpeck 1998; Kim et al. 2002; Cook et al. 2004; Raziei et al. 2009; Yong et al. 2010). Among them, some events were so severe that local water resources were depleted and civilizations were forced out of their original settlements (Qin 2011). Predicting when and where a drought might happen and how severe it will become is very crucial for the sustained development of a society.

Drought is usually defined on the basis of the degree of dryness and the duration of the dry period (Palmer 1965). Landsberg (1982) considered drought to be a deficiency of precipitation over an extended period of time, which might result in a water shortage for some activity, group, or environmental sector. Scientists have developed four classifications to describe drought because it is such a complex phenomenon: meteorological drought, agricultural drought, hydrological drought, and socio-economic drought (Wilhite and Glantz 1985).

Meteorological drought is simply the departure from normal of meteorological variables that induces drying of the surface. It is region-specific since the atmospheric conditions of different areas have high local variability in space and time (National Drought Mitigation Center 2006). Agricultural drought indicates whether the water quantity in soil can meet the demand of plants at various growing stages. It occurs when the soil moisture fails to provide enough nourishment to the plants. Hydrological drought, which is initially caused by rainfall deficits, is normally associated with reservoirs or lake levels within a basin (Rathore 2004). It is important to note that the hydrological responses normally are latent to precipitation deficiencies in a basin.

Therefore, not all meteorological droughts will immediately trigger a hydrological drought because reservoir levels remain fairly constant over a short period of time. Socio-economic drought is different from the aforementioned types of droughts because it is a measure of the gap between supply and demand. If the water supply cannot meet the demand of water consumption such as hydroelectric power, food production, and fishery activities etc., a socio-economic drought will occur due to the demand–supply unbalance (National Drought Mitigation Center 2006).

Understanding the characteristics of historical droughts will benefit water resource managers because it will provide insight into the possible impacts of future climate changes (Edwards and McKee 1997). However, drought is difficult to quantify due to its dependence on different geographic regions, needs, and disciplinary perspectives (McKee et al. 1993). Various drought indices have been developed over the past few decades to assimilate thousands of bits of data on rainfall, snowpack, streamflow, and other water supply indicators into a comprehensible big picture (Heim 2002; Well et al. 2004; Jain et al. 2010). These drought indices were developed for different purposes. For example, the Standardized Precipitation Index (SPI) (McKee et al. 1993) was developed to indicate drought by analyzing precipitation variability. The Palmer Drought Severity Index (PDSI) (Palmer 1965) intended to provide more comprehensive information by taking into account more meteorological and hydrological components. Some newly developed indices such as the Reconnaissance Drought Index (RDI) (Tsakiris et al. 2007; Tsakiris 2008), was proposed to eliminate the shortcoming of SPI which does not account for evapotranspiration. The Standardized Precipitation Index (SPI), the most widely used drought index, and the Palmer Drought Severity Index (PDSI) are used in this study. A newly developed index called Standardized Runoff Index (SRI) (Vasiliades et al. 2011) was also used because it provides a hydrological drought assessment, a perspective that is inadequately assessed by SPI and PDSI.

The Blue River is particularly important to the state of Oklahoma and local surrounding communities. Historically, several Native American tribal communities have used the river as their important water source. Recently however, there have been increasingly competing demands from surrounding industrial and metropolitan areas located in Oklahoma and Texas (OWRB 2003). Although research on droughts in the southern U.S. using different drought indices has been conducted over the past few years (Wan et al. 2004; Narasimhan and Srinivasan 2005), studies that focus on the Blue River Basin have not been conducted.. This work is the first study that uses multiple indices to assess historical and future drought in the basin.

The goal of this study was to reconstruct historical drought occurrences and assess future drought risk (intensity, duration, and extent) for the drought-prone Blue River Basin in Oklahoma, under a changing climate. The first objective of this study was to construct the past drought conditions and predict future drought scenarios for the Blue River Basin using three types of drought indices, i.e., Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI) and Standardized Runoff Index (SRI), ranging from a meteorological drought index, a hydro-meteorological index to a hydrological index. The second objective was to examine the relationships among the three indices. The third objective was to find the most suitable drought index for the Blue River Basin under a changing climate. Detailed discussions of the three indices and the hydrological model are included in Section 2. Section 3 presents the results and discussion. The summary and the conclusions are presented in Section 4.

2 Study Region, Data, Model and Drought Indices

2.1 Study Region

The Blue River Basin is located in Southeastern Oklahoma with a drainage area of 1751 km^2 (Fig. 1), a relatively small basin that has experienced several severe droughts (1909–18, 1930–40 (the Dust Bowl), 1952–56, and 1962–72) over the past century.

2.2 Climate Data

Climate data of the study region were extracted and modeled for SPI, PDSI and SRI calculations. For this study, the observational data used were the gridded National Climatic Data Center (NCDC) Cooperative Observer station data, described by Maurer et al. (2002). The observational surface temperature (°C) and monthly precipitation (mm/day) data cover the time period from 1950 to 1999 in a monthly time step. . The data domain covers the continental U.S. and portions of southern Canada and northern Mexico at a 1/8 ° (~12 km) resolution. Projection data are archived from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase3 (CMIP3) multi-model dataset (Table 1). CMIP3 contains temperature and precipitation projections under three CO_2 emission scenarios (namely A2, A1B and B1) for the period of 2010–2099 and these data share the same resolution and coverage with the NCDC observation data.

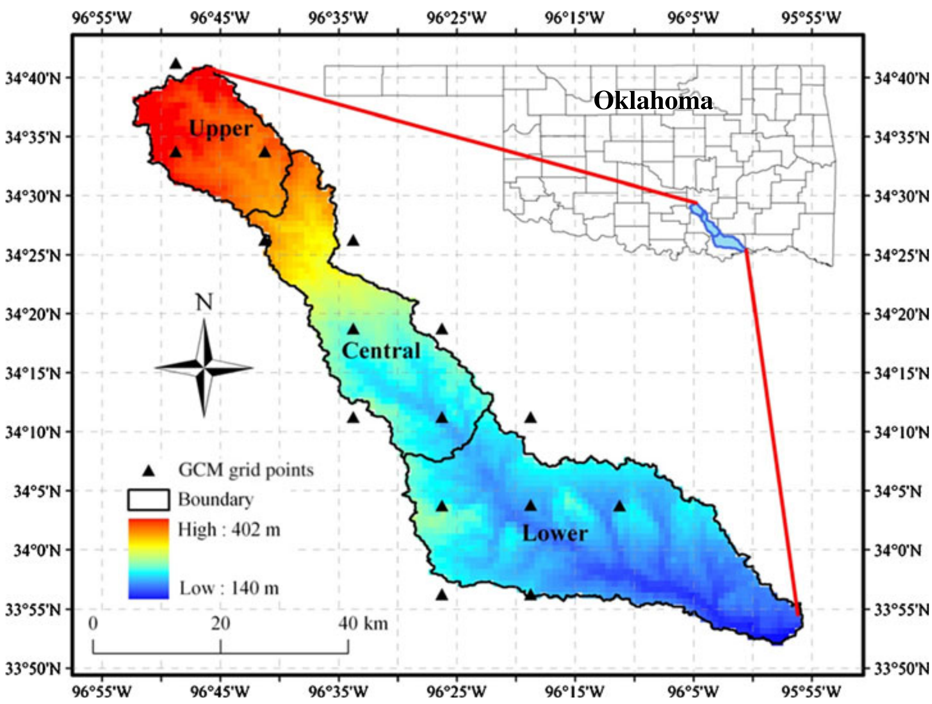

Fig. 1 The study area: Blue River Basin in Oklahoma. The triangle dots are GCM grid points

Table 1 Global Climate Models used in WCRP CMIP3 data

GCM Ensemble		
Modeling Group, Country	WCRP CMIP3 I.D.	Primary Reference
Bjerknes Centre for Climate Research	BCCR-BCM2.0	Furevik et al., 2003
Canadian Centre for Climate Modeling & Analysis	CGCM3.1 (T47)	Flato and Boer, 2001
Meteo-France/Centre National de Recherches Meteorologiques, France	CNRM-CM3	Salas-Melia et al., 2005
CSIRO Atmospheric Research, Australia	CSIRO-Mk3.0	Gordon et al., 2002
US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory, USA	GFDL-CM2.0	Delworth et al., 2006
US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory, USA	GFDL-CM2.1	Delworth et al., 2006
NASA/Goddard Institute for Space Studies, USA	GISS-ER	Russell et al., 2000
Institute for Numerical Mathematics, Russia	INM-CM3.0	Diansky and Volodin, 2002
Institut Pierre Simon Laplace, France	IPSL-CM4	IPSL, 2005
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan	MIROC3.2 (medres)	K-1 model developers, 2004
Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	ECHO-G	Legutke and Voss, 1999
Max Planck Institute for Meteorology, Germany	ECHAM5/ MPI-OM	Jungclaus et al., 2006
Meteorological Research Institute, Japan	MRICGCM2.3.2	Yukimoto et al., 2001
National Center for Atmospheric Research, USA	CCSM3	Collins et al., 2006
National Center for Atmospheric Research, USA	PCM	Washington et al., 2000
Hadley Centre for Climate Prediction and Research/ Met Office, UK	UKMO-HadCM3	Gordon et al., 2000

The two scenarios of the 21st century for future greenhouse gas emissions used in this study were A2 and A1B as defined in the IPCC Special Report on Emissions Scenarios (IPCC 2007). According to IPCC (2007), scenario A2 is a higher emission path and describes a higher population world where technological change and economic growth are more fragmented and slower. Scenario A1B is a middle emission path known as business-as-usual and describes a balanced world where people do not rely too heavily on any one particular energy source.

2.3 Thornthwaite Monthly Water Balance Model

The hydrological model used to simulate the hydrologic process and generate runoff output for SRI calculation is the Thornthwaite Monthly Water Balance Model (Fig. 2) driven by a graphical user interface. It is named after C.W. Thornthwaite who used water budget in climate classification (Thornthwaite 1948). An updated description is given by McCabe and Markstrom (2007). Input for this model is monthly temperature and precipitation. Outputs from the model include potential evapotranspiration (PET), soil moisture, actual evapotranspiration (AET), snow storage, surplus, and runoff total.

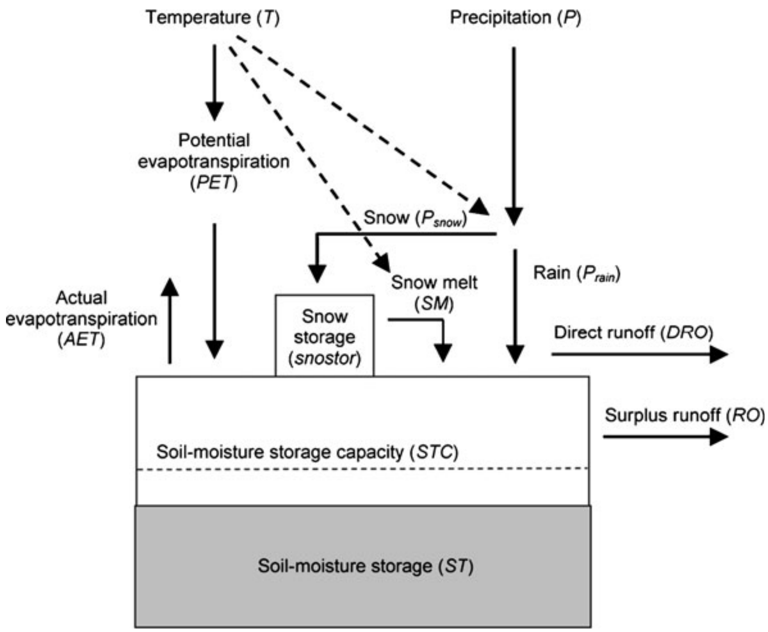

Fig. 2 The framework of Thornthwaite Monthly Water Balance Model (Credit: U. S. Geological Survey/ figure by McCabe and Markstrom 2007)

2.4 Drought Indices

2.4.1 SPI

Standardized Precipitation Index (SPI) is an indicator of meteorological drought, which is mainly caused by a deficiency of precipitation. McKee et al. (1993) tested this index on Fort Collins, CO observed precipitation data and calculated SPI for 3, 6, 12, 24, and 48-month time scales. SPI has a very straight-forward classification of different drought severities. When SPI is below −1.5, the drought condition is considered severe; when it reaches below −2 it is considered extreme. SPI is a probability based index, so the heaviness or lowness of a precipitation event in the SPI is relative to the rainfall characteristics of that area. A long-term precipitation record is needed in order to calculate SPI. Data from the long-term record are first fitted by a Gamma probability distribution, $G(x)$, (McKee et al. 1993).

$$G(x) = \frac{1}{\Gamma(\widehat{\alpha})} \int_0^x t^{\widehat{\alpha}-1} e^{-t} dt \tag{1}$$

Since the gamma function in undefined for x=0 and a precipitation distribution may contain zero values, the cumulative probability $H(x)$ becomes:

$$H(x) = q + (1-q)G(x) \tag{2}$$

where q is the probability of a zero. This distribution is then transformed into a standard normal distribution so that the mean SPI for the specific location becomes zero.

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad for\ 0 < H(x) \leq 0.5 \tag{3}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad for\ 0.5 < H(x) \leq 1.0 \tag{4}$$

Where

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad for\ 0 < H(x) \leq 0.5$$

$$t = \sqrt{\ln\left(\frac{1}{(1.0 - H(x))^2}\right)} \quad for\ 0.5 < H(x) < 1.0$$

$$\begin{aligned} c_0 &= 2.515517 \\ c_1 &= 0.802853 \\ c_2 &= 0.010328 \\ d_1 &= 1.432788 \\ d_2 &= 0.189269 \\ d_3 &= 0.001308 \end{aligned}$$

After the statistical fitting and transformation, region specific deviations are largely minimized.

Although SPI is fairly easy to calculate compared to the other indices (Alley 1984), it is very effective in providing early drought warning and drought damage control. However, the disadvantage of SPI is that it only considers one climate variable, precipitation, and not evapotranspiration or soil moisture, which are essential parameters in hydrological process. Therefore, comprehensive indices that involve more complex natural hydrological process should also be examined.

2.4.2 PDSI

Palmer Drought Severity Index is an indicator of hydro-meteorological drought that has been used for the last 45 years. Instead of taking only precipitation into account, PDSI also accounts for temperature which has a huge impact on evapotranspiration and soil moisture. This index provides a more comprehensive method to assess the impacts of climate change on drought since it requires more climate variables as input (Palmer 1965; Alley 1984; Guttman 1998).

PDSI is an indicator of prolonged soil moisture deficiency (Palmer 1965). While it estimates soil moisture using a simple two layer soil description, it has been shown to be strongly correlated (r=0.5–0.7) with measured soil moisture (Dai et al. 2004). The PDSI soil parameter used for a bucket water balance is the Available Water Content (AWC). AWC is the difference between the soil moisture at field capacity and the wilting point. For this study, AWC was determined from the State Soil Geographic Database (STATSGO) for the top 100 cm of the soil profile. The STATSGO soil database has a spatial resolution of 1 km. The deficit in soil moisture, d_i, measures the difference between observed precipitation and the required precipitation to maintain the long term monthly soil moisture (Well et al. 2004). The software package provided by the University of Nebraska (http://greenleaf.unl.edu/downloads/) calculated the PDSI on a monthly time step.

$$d_i = P - \widehat{P} = P - (\alpha PE + \beta PR + \gamma PRO + \delta PL) \tag{5}$$

where $a = \overline{E}\,\overline{T}/\overline{P}\,\overline{E}, \beta = \overline{R}/\overline{P}\,\overline{R}, \gamma = \overline{R}\,\overline{O}/\overline{P}\,\overline{R}\,\overline{O}$, and $\delta = L/\overline{P}\,\overline{L}$ for 12 months

PE Potential evapotranspiration
PR Potential recharge - the amount of moisture required to bring the soil to field capacity
PL Potential loss - the amount of moisture that could be lost from the soil to evapotranspiration provided precipitation during the period was zero
PRO Potential runoff PRO - the difference between the potential precipitation and the PR

The next step in the procedure is the climate characteristic value K. K helps standardize the index across varying climates.

$$K_i = \left(\frac{17.6}{\sum_{i=1}^{12} \overline{D}_i K_i'} \right) \left(1.5 \log_{10} \left[\frac{\frac{E[PE]+E[R]+E[RO]}{E[P]+E[L]} + 2.8}{E[D]} \right] + 0.5 \right) \tag{6}$$

The climate characteristic, K, and deficit, d, are then combined to form the moisture anomaly index, Z. This indicator is

$$Z = Kd \tag{7}$$

Finally, PDSI is computed using Eq. (8)

$$PDSI_i = 0.897 PDSI_{i-1} + 1/3 Z_i \tag{8}$$

PDSI has different classification from that of SPI. When PDSI is below −3, the drought condition is considered severe; when it is below −4, the drought condition is considered extreme.

2.4.3 SRI

Standardized Runoff Index (SRI) appeared in Vasiliades et al. (2011) as Water Balance Derived Drought Index. Input for this index is monthly streamflow data. Vasiliades et al. (2011) fitted monthly streamflow data into to Pearson type III distribution and transformed it using Box-Cox transformation (Box and Cox 1964) to remove skewness.

$$Y = \frac{X^\lambda - 1}{\lambda}, \lambda \neq 0 \tag{9}$$

$$Y = \ln(X), \lambda = 0 \tag{10}$$

Where X are the values of the original time series of surface runoff, Y are the values of the transformed time series, λ is a parameter for which the values of the transformed time series (Y) are normally distributed.

The transformed streamflow values are then standardized to translate into a standardized runoff index known as Z_{WBI}. SRI has the same classification with that of SPI; therefore the region-specific deviation is minimized since it is transformed to be standardized. SRI is fairly new compared to SPI and PDSI, so the fundamental idea of using SRI is to examine drought from a hydrological perspective and compare it with the traditional drought indices, namely SPI and PDSI.

3 Results and Discussion

3.1 The Past and Projected Future Climate of the Blue River Basin

The simulated outputs of temperature and precipitation from the 16 GCMs have been validated against the observations for the six-state SCIPP region of Southern US (Liu et al. 2012). Statistics show that the differences between the simulated and the observed are not discernable. Therefore, the projections can be used more confidently to support statements on projected changes in mean-annual temperature over a given region (Maurer et al. 2007).

The past 50 years of climate of the Blue River Basin was relatively warm and wet. Average temperatures ranged from 5 °C (41 °F) in the winter to about 28 °C (82 °F) in the summer. There was strong seasonality in precipitation. January, on average, received the least precipitation at around 50 mm (~2 in). May was the wettest month averaging over 140 mm (~5.5 in). July and August were fairly dry, and there was a secondary peak in precipitation during September. Annually, the basin averages about 1040 mm (41 in). In terms of temperature projection, air temperature over the basin is expected to warm by 2.0–4.8 °C by the end of the 21st century according to three different CO_2 emission scenarios (Fig. 3). The temperature increase will increase evapotranspiration in the basin, thus less water will be available if the basin does not receive enough recharge from the atmosphere or

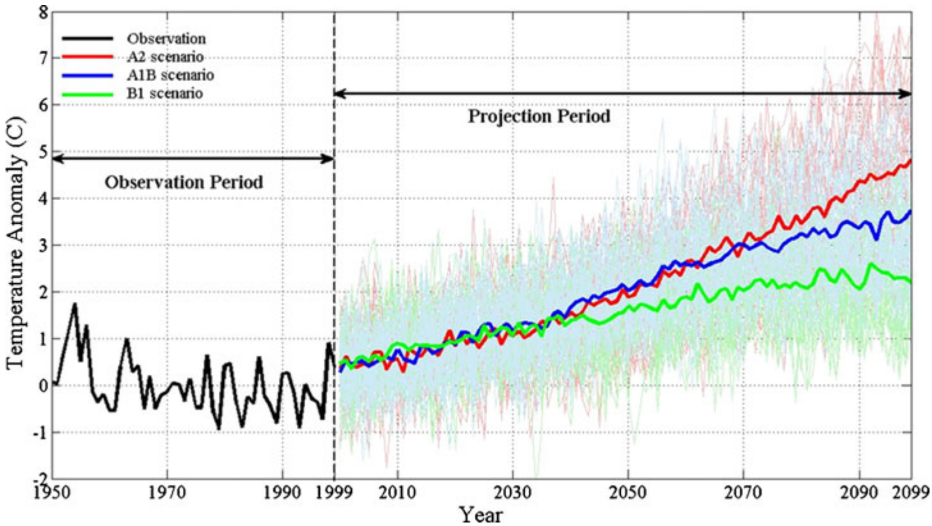

Fig. 3 Temperature change projection over the basin based on 1950–1999 mean under A2, A1B and B1 scenarios. The light lines are each individual members in the 16 GCMs. The bold lines are the ensemble means from 16 GCMs

underground. The precipitation anomaly time series is different however. There were no statistically significant trends in precipitation for any scenario when looking at each ensemble mean. This is due to trends averaging out when considering larger areas (Fig. 4). The Blue River Basin annual precipitation anomaly trends were +43 mm/century for B1, -14 mm/century for A1B, and −33 mm/century for A2. However, these are still not large relative changes. A 43 mm of increase is approximately a 4 % change compared to the average rainfall. The average annual precipitation amount might not change much but if the distribution changes it could have big implications for water resources and agriculture.

3.2 Rainfall-Runoff Model Calibration

Thornthwaite Monthly Water Balance Model is calibrated in order to generate confident future runoff under the A1B scenario. To calibrate the mode, input data of monthly temperature and precipitation for the Blue River Basin were retrieved from NCDC. The parameters were manually adjusted to generate the best agreement between observed and modeled runoff for the period June 1936 through August 2006 (Fig. 5). Statistical analysis was done to determine the performance of the model. The best agreement was obtained with the Nash-Sutcliffe coefficient of efficiency being 0.78 and a root mean square error of 12.9 mm/month. Assuming the parameters remain unchanged in the future scenarios, the well calibrated model was used to project future runoff given the projected temperature and precipitation.

3.3 Past and Future Drought

The Blue River Basin is located within the state of Oklahoma. Historical records show that Oklahoma experienced four major droughts in the 20th century: 1909–18, 1930–40 (the Dust Bowl), 1952–56, and 1962–72. According to Oklahoma Climatological Survey (OCS), while the drought of the 1930s is historically associated with the Dust Bowl of the Great

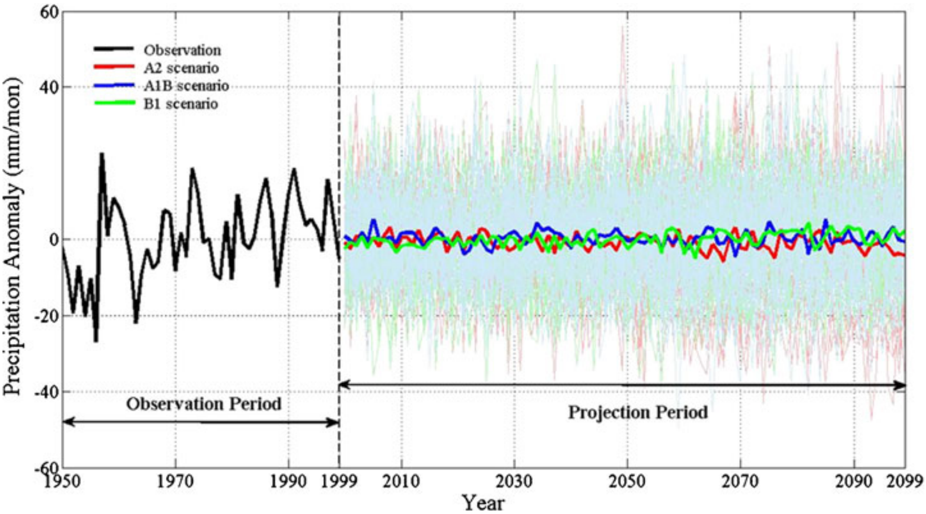

Fig. 4 Precipitation change projection over the basin based on 1950–1999 mean under A2, A1B and B1 scenarios. The light lines are each individual members in the 16 GCMs. The bold lines are the ensembles means from 16 GCMs

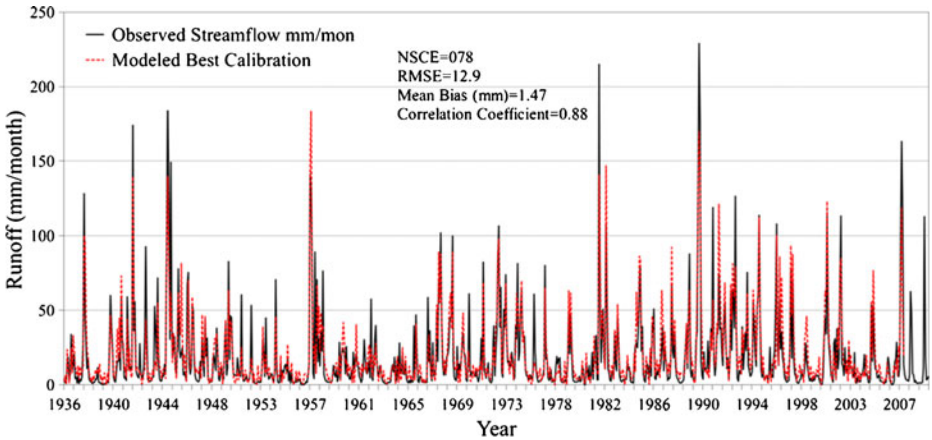

Fig. 5 Runoff calibration based on Thornthwaite Monthly Water Balance Model at Blue River Basin outlet

Plains, statistics show that the drought of the 1950s was more severe for Oklahoma as indicated by record low SPI and PDSI values (Arndt 2002). However, socio-economic impacts were less severe as Oklahoma's population learned to cope with the Dust Bowl and developed agricultural and water management practices that mitigated many of the worst impacts of the Dust Bowl. As can be seen from Fig. 6a panel 1, 12-month SPI shows extreme droughts from the beginning of 1950s to the end of the 1960s. The 1950s droughts were characterized by short periods of intense precipitation deficits and high temperatures interspersed with near-normal or above-normal precipitation. As shown in the figure, there was a long duration extreme drought between 1960 and 1965. This drought lasted almost 5 years without being interrupted by occasional wet spells. The drought intensity decreased due to above average rainfall in 1965 but another period extreme drought took hold near the end of 1960s. Other than the other mega drought near 1980, the Blue River Basin also experienced some dry spells and some wet spells after 1980.

PDSI provides a somewhat different account of Blue River Basin drought history (Fig. 6a). The 1950s and 1960s drought were roughly captured, but the onset and severity were slightly different than SPI. PDSI does not show the late-1970s drought that was accounted for by SPI. Additionally, PDSI shows that the Blue River Basin was mostly under wet conditions after 1980 except for one severe drought around 1981. This may be an artifact of the relatively cooler temperatures in the 1960s and 1970s relative to the 1950s, which lowered ET and consequently PDSI.

SRI, in this case, was very similar to SPI in terms of severity and timing of droughts. Figure 6b shows SRI has a 2 month lag time from SPI (CC reaches highest value of 0.81), indicating that the hydrological droughts for this period were not recognized until 2 months after the meteorological drought set in (Table 2). Although the wet spells appear more significant on the SRI panel, SRI successfully captures all the major droughts except the one in mid 1980s. In general, droughts shown on SRI mostly have a shorter duration than the same ones shown on SPI, and wet periods are longer than those on the SPI panel. RDI was also calculated and showed similar trends and patterns to SRI for the past and future.

For drought projections using SPI, ensemble mean monthly precipitation should not be used because the averaging process diminishes the monthly variation of precipitation which could generate misleading outputs. Therefore, one of the 16 GCMs –- GISS-ER is selected, because the GISS-ER simulation matched the 1950–1999 observational periods with the

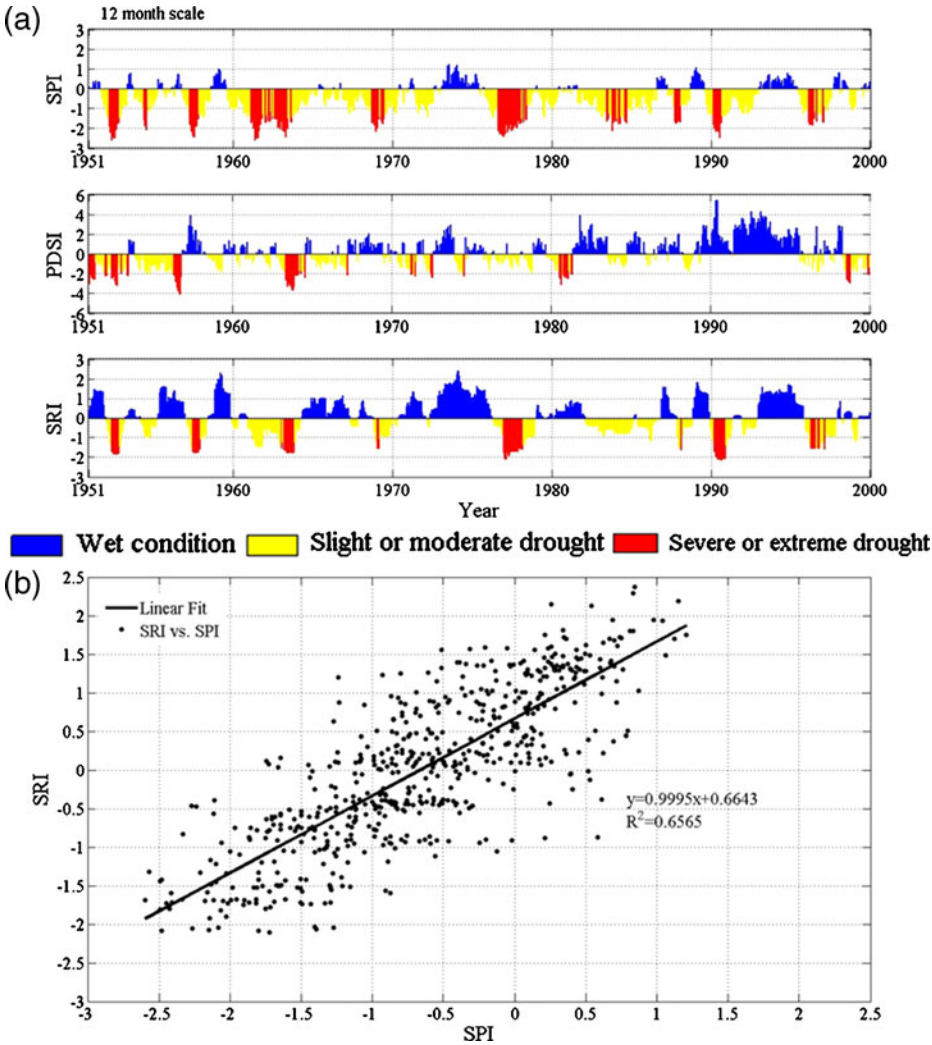

Fig. 6 (**a**) Historical time series variation of SPI, PDSI and SRI (**b**) Scatter plot of SPI vs. SRI and the linear regression line

most similarities from a statistical point of view (Liu et al. 2012). Hence, SPI-based drought projections are more accurate using the GISS-ER model.

Table 2 Correlation coefficient between drought indices for different lag times

		Time scale	Lag time					
			0 month	1 month	2 month	3 month	4 month	5 month
1950–1999	SPI vs. SRI	12 month	0.81	0.88	0.89	0.87	0.83	0.77
2010–2099	SRI vs. PDSI	12 month	0.78	0.23	0.23	0.23	0.24	0.23

Differences exist among the three indices for projections of drought conditions in Blue River Basin (Fig. 7a). SPI indicates one minor drought in the early 2020s, and the frequency and intensity of drought appear to increase substantially after 2050. PDSI and SRI show similar results and project many more droughts after 2050 The PDSI and SRI time series has a correlation coefficient of 0.78 (Fig. 7b) and they do not exhibit any time lag from one another (Table 2) (CC reaches its highest value at 0 month lag time). More drought events are displayed on the PDSI panel than on the SRI panel, and severe droughts on PDSI are projected to be more severe (PDSI<−5) than those on SRI, except for the early 2080s.

The Blue River Basin is projected to be nearly constantly under wet conditions before 2050 for both PDSI and SRI, with a slight decreasing trend of wetness from 2011 to 2050. It is not surprising to see that both PDSI and SRI demonstrate more severe and frequent drought after 2050, although the magnitude and timing of droughts are not exactly the same.

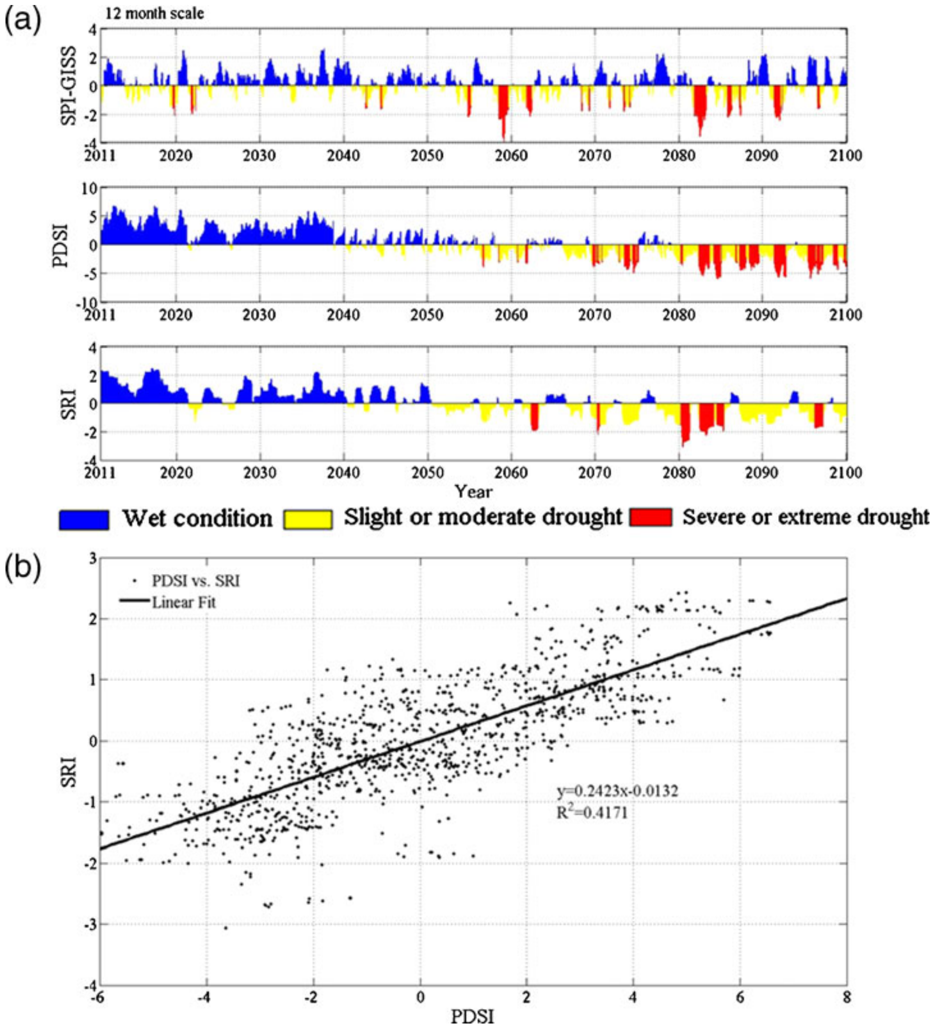

Fig. 7 (**a**) Projected time series variation of SPI, PDSI and SRI (**b**) Scatter plot of PDSI vs. SRI and the linear regression line

Based on the Thorthwaite Monthly Water Balance Model projection, the Blue River Basin is expected to have an increasing trend of ET and decreasing trend in total runoff under A1B scenario. Actual ET is expected to increase by up to 8 % on average and runoff is projected to decrease by more than 10 % by the end of the 21st century (Fig. 8). Accordingly, more water is going out as ET and less water will be available for surface runoff.

SPI, PDSI and SRI perspectives show that future droughts are likely to become more severe and frequent beginning in the late 2050s. Table 3 summarizes the minimum values of drought indices found in both historical and projection periods. In the past 50 years, the lowest value ever shown on SPI was −2.6, which indicates an extreme drought event; however, in the next 90 years SPI is projected to have values as low as −3.9, which indicates a much more extreme drought condition. PDSI and SRI also project more severe droughts in the future compared to the past 50 years (minimum value of −6 for PDSI and −3 for SRI).

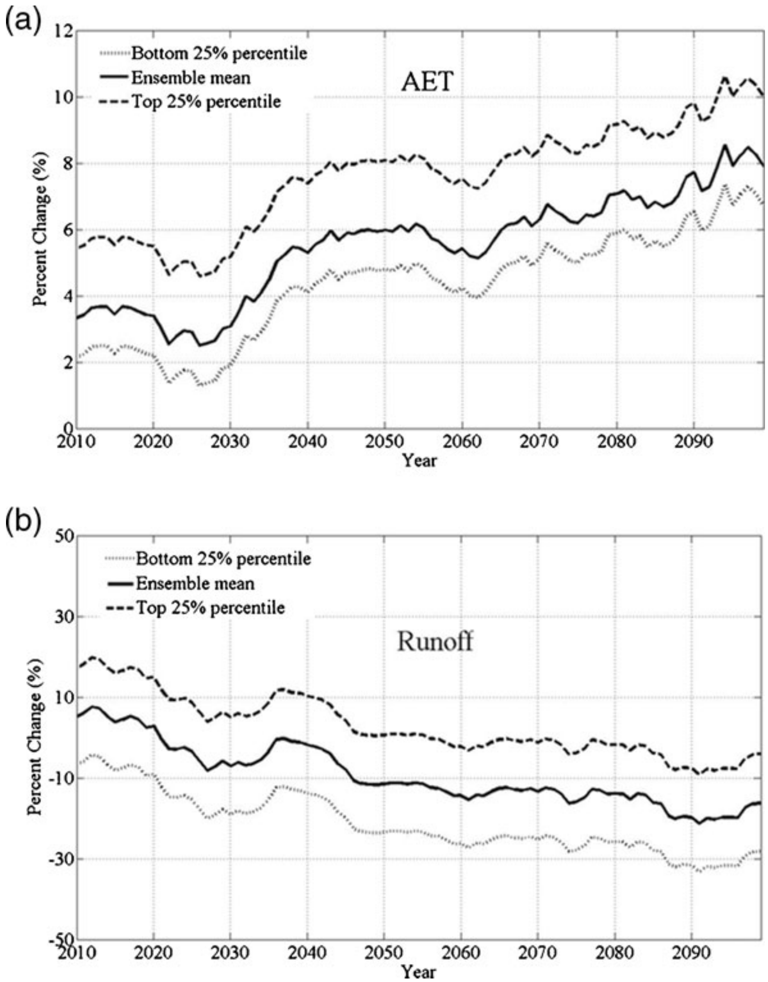

Fig. 8 (**a**) 10 years moving average of projected AET change as percentage of 1950-1999 mean (**b**) 10 years moving average of projected runoff change as percentage of 1950-1999 mean

Table 3 Minimum values in SPI, PDSI and SRI time series

Drought Index	Minimum Value	
	1950–1999	2010–2099
SPI	−2.6	−3.9
PDSI	−4.1	−6
SRI	−2.1	−3

Table 4 summarizes the number of drought events with different return periods indicated by the three indices. SPI and SRI follow standard normal distribution, so the thresholds for different return periods should remain the same in the future. Note that PDSI follows a Generalized Extreme Value (GEV) distribution, and the thresholds for different return periods in the future are found to be greatly decreased compared to the period of 1950 through 1999. In this table, the number of events indicated by PDSI is divided into two categories: one with the same thresholds as 1950–1999 (previous threshold, PTH), and one with the thresholds calculated based on PDSI from 2010–2099 (updated threshold, UTH). As can been seen from the table, PDSI indicates many more drought events per year for all the return periods if using the previous thresholds. With the updated threshold, the number of drought events per year for each return period from 2010–2099 display no significant different from that of 1950–1999. This indicate that the distribution of projected PDSI shift towards lower end of the values. SRI also projects drought frequency to increase in the future reaching the 30 and 40 year return period criteria, while the frequency decreases at the 10 and 20 year thresholds. SPI shows fewer droughts for 10, 20, and 30 return periods, but the 40 year return period droughts increase to 0.44 event per year compared to 0.34 event per year in the past. Therefore, drought in the Blue River Basin is projected to trend toward fewer but more intense droughts in the future as indicated by the three indices.

Table 5 shows the historical and projected area affected by severe or extreme droughts based on the basin division. Historically, the affected areas are almost equally distributed among the upper, central and lower Blue River Basin. Both SPI and PDSI show that an average of around 3 % of the area was affected by severe/extreme drought from 1950 to 1999; note that the lower region was slightly less affected than the upper and central regions. In terms of projections, SPI shows that an average of 25.6 %, 22.9 % and 20.6 % of the upper, central and lower Blue River Basin areas will be impacted by drought throughout the 21st century. Results from PDSI are displayed in two periods: almost no droughts are projected for the first 40 years while the second half of the 21st century sees an average of 23.5 %, 23.5 %, 22.2 % of the areas affected by severe or extreme drought. Overall, both

Table 4 Number of drought events exceeding different return period thresholds for SPI, PDSI and SRI

	1950–1999 # of events (# of events/year)			2010–2099 (A1B) # of events (# of events/year)			
RP*	SPI	PDSI	SRI	SPI_GISS	$PDSI_{PTH}$*	$PDSI_{UTH}$*	SRI
10 years	140 (2.8)	57 (1.14)	73 (1.46)	114 (1.27)	323 (3.59)	107 (1.19)	122 (1.36)
20 years	83 (1.66)	26 (0.52)	38 (0.76)	66 (0.73)	265 (2.94)	47 (0.52)	49 (0.54)
30 years	47 (0.94)	21 (0.42)	11 (0.22)	48 (0.53)	228 (2.53)	27 (0.3)	33 (0.37)
40 years	17 (0.34)	18 (0.36)	9 (0.18)	40 (0.44)	205 (2.27)	21 (0.23)	19 (0.21)

* RP stands for Return Period; PTH stands for Previous THreshold; UTH stands for Updated THreshold

Table 5 Percent of area under severe/extreme droughts for upper, central and lower Blue River Basin

Blue River Basin	1950–1999		2010–2099			
	SPI	PDSI	SPI-GISS	PDSI(2010–2049)	PDSI(2050–2099)	PDSI (total)
Upper	3.5 %	3.5 %	25.6 %	0.5 %	23.5 %	13.3 %
Central	3.5 %	2.8 %	22.9 %	0.5 %	23.5 %	13.6 %
Lower	3.2 %	2.7 %	20.6 %	0.83 %	22.2 %	12.8 %

SPI and PDSI project larger areas to be under severe or extreme droughts in the second half of the 21st century.

3.4 Discussions

Several sources of uncertainty exist when projecting future drought. One major component of uncertainty is the ability of GCMs to project future monthly precipitation. Even though we selected the statistically best-matched GCM with the most accurate observational baseline period to project droughts, future precipitation data is likely to vary somewhat from the GCM projections. Another issue is that under increasing temperature, SPI is less likely to correctly reflect future drought conditions under the ground since it, a meteorological drought indicator, does not take ET and soil moisture into consideration. As the major components in the hydrological cycle, ET and soil moisture can no longer be ignored in drought projections when the climate is expected to continue to warm. . Although PDSI is one of the most comprehensive drought indices used in the United States, it still has many limitations when trying to project drought in a changing climate. Available Water Content data from the current soil database, i.e. the STASTGO, are fixed values parallel to a changing Earth surface. The third uncertainty comes from the runoff predictions obtained via the Thornthwaite Monthly Water Balance Model, which might introduce some distortions in SRI due to model errors. The problem is examined and discussed by Loukas et al. (2008). Even though the model is well calibrated to minimize the errors, future predictions still consist of uncertainties from various sources. Therefore, the magnitude of uncertainties might be further aggregated after several levels of propagation. SRI seems to be the best index that could depict both the past and future drought, and potentially has the most agreements with SPI and PDSI as a whole. However, to understand and assess drought conditions from the atmosphere and on the ground, the three indices are collectively indispensable in order to come up with a comprehensive drought management plan.

4 Conclusions

This study analyzed the historical droughts of the Blue River Basin over the past 50 years and projected possible future droughts over the next 90 years under the A1B scenario, a very likely future climate in Southern US based on previous studies. Three types of drought indices (SPI, PDSI and SRI) capture the major droughts documented in history. In terms of timing and severity, SPI and SRI performed better and exhibited higher correlation with each other. The results projected by SPI, PDSI and SRI under the business as usual A1B scenario suggest that more drought events might occur in the second half of the 21st century. This could be caused by the fact that the precipitation predicted by GISS-ER shows a descending trend, while the temperature is slowly but constantly increasing after 2010. Moreover, the ET projected by the Thornthwaite Monthly Water Balance Model also has a significant increasing trend under such a warming climate. In the projection period, PDSI and SRI perform similarly because they both take into account the factors of soil moisture and ET. Collectively, the minimum values of the three indices for the future Blue River Basin are lower than those ever recorded in the past 50 years. Therefore, it is very likely that future drought in the Blue River Basin will be more severe and intense compared to the 1950–1999 period, especially for the second half of the 21st century.

In this study, SRI appears to be a better indicator for the study basin because: (1) SRI considers the changing climate which could play a rather significant role in future drought management; (2) Compared to PDSI which also considers temperature change, SRI provides drought information from a hydrological point of view, which is more applicable to water resources managers and local farming business; and (3) SRI functioned well in this research both for the past drought record reconstruction and for the future drought risk assessment under a changing climate.

In summary, this study found that the three indices (i.e. SPI, PDSI and SRI) captured the recorded droughts for the past 50 years and also suggested that more severe droughts are very likely to occur in the next 90 years over the Blue River Basin. This study also found that SRI has better agreements with the other two indices, with a high correlation coefficient (CC) of 0.81 (0.78) and 2-month (no appreciable) lag time from SPI (PDSI) over the 1950–2099 time period across the basin. The former correlation between SRI and SPI indicates that hydrological components (as indicated by SRI) respond slower to droughts than meteorological components (as indicated by SPI), and the latent time for the Blue River Basin is approximately 2 months. The latter correlation between SRI and PDSI indicate that the two drought indices respond to droughts with equal reaction time, that is to say there is no appreciable time lag between the two indicators. Although this study recommends that SRI is the more suitable indices to assess future drought risks under an increasingly warmer climate because they take into account of ET and soil moisture, more drought indices from ecological and socioeconomic perspectives should be investigated and inter-compared to provide a more complete picture of drought risks and its potential impacts on the nature-human coupled system.

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References

Alley WM (1984) The palmer drought severity index: limitations and assumptions. J Clim Appl Meteorol 23:1100–1109

Arndt DS (2002) The Oklahoma drought of 2001–2002. Oklahoma Event Summary. Oklahoma Climatological Survey

Box GEP, Cox DR (1964) An analysis of transformations. J Roy Stat Soc B 26:211–234

Cook ER, Woodhouse CA, Eakin CM, Meko DM, Stahle DW (2004) Long-term aridity changes in the western United States. Science 306:1015–1018
Dai A, Trenberth KE, Qian T (2004) A global data set of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming. J Hydrol 5:1117–1130
Edwards DC, McKee TB (1997) Characteristics of 20th century drought in the United States at multiple time scales. Climatology Report Number 97–2. Colorado State University, Fort Collins, Colorado
Guttman NB (1998) Comparing the Palmer drought index and the Standardized Precipitation Index. J Am Water Resour Assoc 34:113–121
Heim RR Jr (2002) A review of twentieth-century drought indices used in the United States. Bull Amer Meteor Soc 83:1149–1165
IPCC (2007) Climate change 2007: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M.Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
Jain S, Keshri R, Goswami A, Sarkar A (2010) Application of meteorological and vegetation indices for evaluation of drought impact: a case study for Rajasthan, India. Nat Hazard 54:643–656
Karl TR, Melillo JM, Peterson TC (eds) (2009) Global climate change impacts in the United States: a state of knowledge report from the U.S. Global Change Research Program. Cambridge University Press, New York
Kim TW, Valdes JB, Aparicio J (2002) Frequency and spatial characteristics of droughts in the Conchos River Basin, Mexico. Water Int 27(3):420–430
Landsberg HE (1982) Climatic aspects of drought. Bull Am Meteorol Soc 63:593–596
Liu L, Hong Y, Hocker EJ, Shafer AM, Carter ML, Gourley JJ, Bednarczyk NC, Adhikari P (2012) Analyzing projected changes and trends of temperature and precipitation in the southern U.S. from 16 downscaled global climate models under different emission scenarios. Theor Appl Climatol. doi:10.1007/s00704-011-0567-9
Loukas A, Vasiliades L, Tzabiras J (2008) Climate change effects on drought severity. D Adv Geosci 17:23–29
Maurer EP, Wood AW, Adam JC, Lettenmaier DP, Nijssen B (2002) A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States. J Climate 15:3237–3251
Maurer EP, Brekke L, Pruitt T, Duffy PB (2007) Fine-resolution climate projections enhance regional climate change impact studies. Eos Trans AGU 88(47). doi: 10.1029/2007EO470006
McCabe GJ, Markstrom SL (2007) A monthly water-balance model driven by a graphical user interface. U.S. Geological Survey Open-File Report 2007–1088, 12pp
McKee TB, Doesken NJ, and Kleist J (1993) The relationship of drought frequency and duration to time scales. Preprints. 8th Conference on Applied Climatology, pp. 179–184. January 17–22, Anaheim, California
Namias J (1966) Nature and possible causes of the northeastern United States Drought during 1962–1965. Mon Weather Rev 94(9):543–557
Narasimhan B and Srinivasan R (2005) Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. Agricultural and Forest Meteorology, Volume 133, Issues 1–4, 10 November 2005, Pages 69–88, ISSN 0168–1923, 10.1016/j.agrformet.2005.07.012
National Drought Mitigation Center (2006) Accessed 07/30/11: http://drought.unl.edu/whatis/indices.htm
Nordhaus W (1994) Managing the global commons: the economics of climate change. MIT Press, Cambridge, MA
OWRB (2003) The Arbuckle-Simpson hydrology study: management and protection of an Oklahoma water resource. November 2003
Palmer WC (1965) Meteorological drought. Research Paper No. 45. U.S. Weather Bureau
Piñol J, Terradas J, Lloret F (1998) Climate warming, wildfire hazard, and wildfire occurrence in coastal eastern Spain. Clim Chang 38:345–357
Qin SG (2011) Farmlands of ancient Loulan Kingdom before 1500 years and its environment. Quaternary sciences: the view from the mountains. 21–27 July 2011, Bern, Switzerland
Rathore MS (2004) State level analysis of drought policies and impacts in Rajasthan, India. Working paper 93, Drought Series, Paper 6, International Water Management Institute
Raziei T, Saghafian B, Paulo A, Pereira L, Bordi I (2009) Spatial patterns and temporal variability of drought in western Iran. Water Resour Manag 23(3):439–455. doi:10.1007/s11269-008-9282-4
Riebsame WE, Changnon SA, and Karl TR (1991) Drought and natural resources management in the United States: Impacts and implications of the 1987–89 Drought. Westview Press, 174pp
Stine S (1994) Extreme and persistent drought in California and Patagonia during mediaeval time. Nature 369:546–549
Thornthwaite CW (1948) An approach toward rational classification of climate. Geogr Rev 38:55–94
Tsakiris G (2008) Uni-dimensional analysis of droughts for management decisions. European Water 23(24):3–11

Tsakiris G, Pangalou D, Vangelis H (2007) Regional drought assessment based on the Reconnaissance Drought Index (RDI). Water Resour Manag 21:821–833

Vasiliades L, Loukas A, Liberis N (2011) A water balance derived drought index for Pinios River Basin, Greece. Water Resour Manag 25(4):1087–1101

Wan Z, Wang P and Li X (2004) Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the Southern Great Plains, USA. International Journal of Remote Sensing, Volume 25, Issue 1, doi: 10.1080/0143116031000115328

Wang J, Rich PM, Price KP (2003) Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int J Remote Sens 24:2345–2364

Well N, Goddard S, Hayes M (2004) A self-calibrating palmer drought severity index. J Clim 17(12):2335–2351

Wilhite D, Glantz M (1985) Understanding the drought phenomenon: the role of definition. Water Int 10:111–120

Woodhouse C, Overpeck J (1998) 2000 Years of drought variability in the central United States. Bull Am Meteorol Soc 79(12):2693–2714, American Meteorological Society

Yong B, Ren L-L, Hong Y, Wang J, Gourley JJ, Jiang S, Chen X, Wang W (2010) Hydrologic evaluation of multi-satellite precipitation analysis standard precipitation products in basins beyond its inclined latitude band: a case study in Laohahe River basin, China. Water Resour Res 46:W07542. doi:10.1029/2009WR008965