Comparison of three drought indices and their evolutionary characteristics in the arid region of northwestern China

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Abstract

Drought evolutions in the arid region of northwestern China from 1960 to 2010 were analyzed based on the standardized precipitation index (SPI), the standardized precipitation-evapotranspiration index (SPEI), and the self-calibrated Palmer drought severity index (SC-PDSI). All three forms of drought indices were significantly correlated with each other. No statistically significant differences were found for the severity of drought, as assessed by both the SPI and SPEI. The SC-PDSI was generally an index representing water deficits at a medium period. For the entire geographical area of study, wet conditions dominated during 1987–2010, whereas persistent drought conditions occurred from 1960 to 1986.

Keywords: drought indices comparisons; drought evolution; arid region of northwestern China

1. Introduction

Drought is a prolonged period of abnormally dry weather due to lack of precipitation, resulting in serious hydrological imbalance and moisture deficiency with respect to water use requirements (Mpelasoka et al., 2008). This deficiency has an impact on both surface water and groundwater resources and leads to reduction in water supply and quality, reduced agricultural productivity, diminished hydro-electric power generation, disturbed riparian and wetland habitats, as well as reduced opportunities for certain recreational activities (Vicente-Serrano et al., 2012). Drought is one of the most damaging natural hazards affecting many regions of northwestern China.

Drought indices have a wide range of applications, including drought monitoring, quantitative assessment, drought prediction, and development of management strategies under current climate (Karl, 1983), as well as under future climate changes associated with global warming. Among drought indices, the standardized precipitation index (SPI), the standardized precipitation-evapotranspiration index (SPEI), and the Palmer drought severity index (PDSI) are most commonly used (Mishra and Singh, 2011). The PDSI was one of the first procedures to demonstrate success at quantifying the severity of droughts across different climates (Palmer, 1965), although it had little applicability outside the United States (Kogan, 1995). In particular, the PDSI does not perform well in regions where there are extremes in the variability of rainfall or run-off, such as in Australia and South Africa (Burke et al., 2006). The self-calibrated Palmer drought severity index (SC-PDSI) automatically calibrates the behavior of the index at any location by replacing empirical constants in the index computation with dynamically calculated values (Wells et al., 2004). SC-PDSI is more spatially comparable than the PDSI. The use of different time scales by the SPI allows the effects of rainfall deficit on different water-resource components to be accounted for, making it robust. However, since it does not consider water balance, it is commonly recommended in data-limited areas for pragmatic reasons. Recently, a new drought index, the SPEI, proposed by Vicente-Serrano et al. (2010), was used for identifying drought periods. The SPEI combines the PDSI’s sensitivity to changes in evaporation demand caused by temperature fluctuations and trends, with the multitemporal nature and simple calculations of the SPI. Among the significant advantages of the SPEI is that, similar to the SPI, it can be calculated over different time scales to monitor droughts with respect to severity, duration, onset, extent, and completion. Given that none of the ‘major’ drought indices are inherently superior to the rest in all circumstances, some indices are better than others in terms of providing useful information from a management perspective. Comparing three indices (SC-PDSI, SPEI, and SPI) can therefore help in revealing which one has the greatest capacity to monitor the evolution and characteristics of drought in the arid region of northwestern China. So the objectives are (1) to compare the suitable of the SPI, SPEI, and SC-PDSI in the arid region of northwestern China, (2) to discuss the long-term variability of dry/wet conditions by the best index using rotated empirical orthogonal function (REOF) during 1960–2010.
2. Study area, data, and methods

2.1. Study area

The arid region of northwestern China is located in the innermost center of the Eurasian continent (Figure 1) and comprises an area between 34°–50°N, and 73°–108°E. The study area includes the Gansu Province, the northern Hui Autonomous Region of Ningxia, the western Inner Mongolia, the northern Qinghai Province, and the Uygur Autonomous Region of Xinjiang. Climate in this region is typical continental arid conditions, with little effects from the East Asian monsoon (Liu et al., 2010). The mean annual rainfall value in the whole study area is 172 mm. The annual rainfall in the area generally increased at the rate of 8.01 mm decade$^{-1}$ during the period from 1960 to 2010. The temperature in this region has risen by 0.35°C per decade, and significantly increasing trends have dominated throughout the whole year and in all seasons (Wang et al., 2013).

2.2. Data

Monthly variables were derived from daily mean temperature, daily maximum temperatures, daily minimum temperatures, wind speeds at 2 m height, relative humidity, sunshine duration and precipitation form 84 meteorological stations covered the study area were provided by the National Climate Center (NCC) of the China Meteorological Administration (CMA). The time series is from January 1960 to February 2011. After using the standard normal homogeneity test (Alexandersson, 1986) to check the internal homogeneity of the variables, and excluding stations that installed after 1960 and those with data gaps, 75 stations were finally selected for our study.

2.3. Calculation of SPI, SPEI and SC-PDSI

SPI is calculated based on accumulated precipitation data; and fitting the data to a parametric statistical distribution, then transforming the distribution to standard random variable with mean zero and variance of one (Mckee et al., 1993; Vicente-Serrano, 2006; Stagge et al., 2015). As the study area is an arid region, we tackled the estimation of SPI for months with zero accumulated precipitation according to the method used by Wu et al., 2007. The SPI enables the calculation of estimates of the duration, magnitude, and intensity of drought (Vicente-Serrano et al., 2004). SPEI is based on the probability distribution of the difference between precipitation and potential evapotranspiration (P-PET), cumulated over different time scales, and normalized the P-PET into a log-logistic probability distribution to obtain the SPEI index series (Vicente-Serrano et al., 2010). The P-PET is referred to climatic water balance, where monthly PET was computed using the Penman–Monteith equation (Vanderlinden et al., 2008). PDSI is based on calculation of the moisture departure between actual precipitation and the precipitation expected to occur for the average conditions of the climate, which implies performing a monthly water balance and the calibration of local monthly coefficients for the various terms of the soil water balance (Palmer, 1965). A common critique of the PDSI is the behavior of the index at various locations is inconsistent, making spatial comparisons of PDSI values difficult. The SC-PDSI automatically calibrates the behavior of the index at any location by replacing empirical constants in the index computation with dynamically calculated values (Wells et al., 2004).

2.4. Rotated empirical orthogonal function

Empirical orthogonal function (EOF) allows a time display and a space display of the space–time field that may be useful to represent the spatial and temporal variability of climate variables. A set of orthogonal functions to represent a time series is used as follows:

$$Z(x, y, t) = \sum PC(t) \times EOF(x, y)$$

where $Z(x, y, t)$ is the original time series as a function of time($t$) and space($x, y$) and probably correlated to each other. PC is the principal component time series, and EOF is the principal component loading patterns. Sometimes, the interpretation of the EOF patterns may be difficult because the adjacent modes are degenerate and the order of degenerate modes is arbitrary. REOF is introduced to resolve this. Rotation of the EOF patterns can systematically alter the structures of EOFs. The VARIMAX rotation method is chosen as this rotation algorithm of the REOF, which can maximizes the variance of squared correlations between each rotated principal component (RPC) and each variable. Through VARIMAX rotation method, we can get the rotated component loading patterns (REOFs), which reflected the spatial pattern of a variable, and also the RPCs, which reflected the time evolution of variables. Additional information on REOF analysis can be found in the review papers of Hannachi et al. (2007).

3. Results

3.1. Comparisons of drought indices

Figure 2 shows the correlation coefficients between SPI (SPEI) covers 1–48 months time scales. The relationships between drought indices at different time scales have high correlation coefficients. The patterns for the SPI and SPEI were quite similar; whereas, the correlations were slightly stronger for the SPEI than the SPI. For North Xinjiang, the relationships between each SPI covers different time scales exhibit a higher correlation coefficient than those of South Xinjiang and Hexi Corridor. This may be due to more homogeneity in the distribution of precipitation in North Xinjiang. For SPEI, North Xinjiang was observed to have the most significant correlations between each time scale, due to higher temperatures contributing significantly to the
The lowest correlations for both the SPI and SPEI were observed in the Hexi Corridor, due to the complex atmospheric circulation in this region. The correlation coefficient slope decreased when the time scale increased (Figure S1, Supporting information), indicating that there were higher coefficients between longer time scales and its nearby time scales. For example, in South Xinjiang, the SPEI at 22-month time scale (SPEI-22) has significant correlations with time scales that are larger than 22 months.

Figures 3(a) and (b) shows the average correlation coefficients between the indices (SPI and SPEI) at a certain time series and all of the time scales. The highest correlations in both SPEI and SPI were found at 16- to 36-month scales. For SPI, correlations are slightly higher in North Xinjiang, which suggests a consistent change in precipitation in North Xinjiang. The highest correlation was observed in South Xinjiang for SPEI, which indicates that the PET explains some of the variability for SPEI. The correlation coefficient between both series at a certain time lag is decreased when the time interval is increased (Figures 3(c) and (d)). For SPI, Hexi Corridor showed the largest decreased slope. For example, when the interval is 27 months, the correlation coefficient is 0.6 in South Xinjiang and North Xinjiang, while the Hexi Corridor decreased to 0.4. The SPEI in South Xinjiang showed the smallest decreased slope when the interval is increased. When the interval (lag) is 9 months, the correlation coefficient is more than 0.9 in South Xinjiang. When the interval increased to 27 months, the average correlation coefficients only decreased to 0.8. So due to the self-similarity between the neighbor time scale drought series, there is no need to analyze all time scales from 1 to 48 months. When the time scale is small, we should analyze the drought using additional time scales, due to fewer correlations between small scales and nearby scales. When the time scale is large, the sampling step size should be larger in order to avoid analysis surplus.

The correlation coefficients between SPI and SPEI in a given time scale are very high, especially for South Xinjiang and North Xinjiang (Figure 3(g)). For the Hexi Corridor, the correlation between SPI and SPEI decreased significantly when the time scale increased (Figure 3(g)). When considering the relationship between SC-PDSI and SPI or SPEI, there is a better correlation at the 9–20 months time scale for South Xinjiang and North Xinjiang (Figures 3(e) and (f)). So although the SC-PDSI is an index that frequently used worldwide, it can only represent medium droughts.

At 12-month time scale, scatter plots of SPI versus SPEI, SC-PDSI versus SPEI-12, and SC-PDSI versus SPI-12 are presented in Figure S2. When comparing SPI and SPEI, the similarity between them is higher in North Xinjiang. The relationships between SC-PDSI and SPEI-12 (SPI-12) showed linear scattering, while SC-PDSI and SPI-12 showed more scatter outliers in South Xinjiang. The Hexi Corridor showed less linear correlation coefficients for SC-PDSI and SPEI-12 (SPI-12), especially between SC-PDSI and SPEI-12.

### 3.2. Drought evolution determined by SPEI and SPI at various time scales

Figures 4(a)–(d) shows the evolution of SPI and SPEI over 3, 12, 24, and 36 months time scales from 1960 to 2010 in the whole study area. The evolution of each series was similar, suggesting a high degree of similarity between two series using different indices.
High temporal frequency of dry and moist periods were displayed in 3-month scale, which indicated wet alternates drought frequently in the arid region of northwestern China in seasonal scales (Figure 4(a)). When time scales increased, drought and moist periods showed a lower temporal frequency and a longer duration (Figures 4(b)–(d)). Two contrasting periods were evident during 1961–2010 for both SPI and SPEI: wet conditions dominated during the period 1987–2009; whereas, persistent drought conditions occurred from 1960 to 1986. According to the time series of SC-PDSI, the period 1987–2004 showed wet conditions, while the year before 1987 exhibited more drought conditions (Figure 4(e)). So the relative wet and drought period overlapped to some extent by applying the three indices. The differences between SPEI and SPI over various time scales were shown in Figure S3. The period 1987–2005 clearly exhibited more positive values, while the periods 1960–1986 and 2005–2010 showed more negative values (Figures S3(b)–(d)). So we conclude that 1987–2005 periods were wetter by using SPEI than using SPI. In contrast, the periods 1960–1986 and 2005–2010 were drier by applying SPEI than that of SPI. The 1987–2005 showed high precipitation and temperature (higher SPEI, Figure S3); the 1960–1986 observed lower precipitation and negative temperature anomalies (lower SPEI, Figure S3), while 2005–2010 showed lower precipitation but high
temperature (lower SPEI, Figure S3) (Wang et al., 2013; Li et al., 2016); which indicated that the drought evolution is mainly controlled by precipitation.

3.3. Spatial and temporal pattern using REOF

Before applying REOF, the dimensionality of SPEI-3 datasets is reduced by EOF analysis. The first 10 EOF modes are used as inputs in the REOF, which capture approximately 75% of the total variance. Taking into account the REOF and the variance explained by each rotated component, four main REOFs were identified in this study area. These four REOFs explain about 51% of the total variance of 10 EOFs (Figure 5).

Figure 5 shows that between the first four components (REOF-1 to -4), the regions with significant correlation do not overlap, being clearly spatially disjunctive. For SPEI-3, the REOF-1 highlights an area located in South Xinjiang, and explains around 18.7% of the total variance (Figure 5). This is the component that explains the largest area within the total study area when compared with the other REOFs. The second component, REOF-2, explains around 15.5% of the total variance, and abundantly clear that it is mainly representative of North Xinjiang. The third component, REOF-3, highlights the Hexi Corridor. Thus, the first three REOFs represent South Xinjiang, North Xinjiang, and the Hexi Corridor, respectively, which is consistent with the previous analysis when the entire study area is divided into those three regions.

Combined with the negative value in REOF-1 in South Xinjiang, the decreased RPC-1 before 2000 indicated wetness during this period. The REOF-2 (North Xinjiang) has positive values, with gradually increasing RPC-2 indicating gradual wetness in this region. This is consistent with You et al. (2011), who found that the enhanced westerly bring humid climate in Xinjiang resulted in decreased drought in Xinjiang regions during 1987–2003. While after 2000, the RPC-1 showed an increasing trend, which indicated the climate become dry in South Xinjiang. However, in Hexi Corridor (REOF-3), the increased RPC-3 showed dryness during this period (before 2000). This dryness trend may due to the weaker East Asian monsoon since 1980s, which resulted in a minimal amount of water vapor transmitted to the Hexi corridor (Xu et al., 2010).

REOF-4 exhibited larger values in southwestern Xinjiang, while with less explained variance (5.1%). The REOF-4 (southwestern Xinjiang) and RPC-4 were similar to the REOF-1 and RPC-1, which indicated that these two regions have the same drought patterns. The
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Figure 4. Drought evolution for SPEI, SPI, and SC-PDSI of the arid region of northwestern China.

12- and 24-month time scales have the same spatial patterns as the 3-month time scale (Figure S4), which indicates consistent drought patterns in the study area at different time scales.

4. Conclusions

In this paper, in order to provide a quantitative comparison of the various drought indices, we computed monthly values from 1960 to 2010 for SPEI, SPI, and SC-PDSI. The spatial pattern for droughts in the arid region of northwestern China is also presented by REOF. The main results and conclusions are summarized below:

(1) The relationships between each drought index at different time scales showed high correlation coefficients. The SPEI and SPI correlate well at a certain time series. The highest correlations were found at 16–36 months for both the SPEI and the SPI. For SPI, correlations are slightly higher in North Xinjiang, which suggests a consistent change of precipitation in North Xinjiang. The highest correlations for SPEI were observed in South Xinjiang, which indicates that the PET explains some of the variability for SPEI. The SC-PDSI data generally correlated well with the SPEI at time scales of 9–20 months. Thus, the SC-PDSI can be considered to be an index representing water deficits on a medium scale. This suggests that the SC-PDSI has a limited capacity to describe the effect of droughts on a range of natural systems.

(2) For the whole study area, SPI and SPEI in short timescales showed a high temporal frequency of dry and moist periods, while showed a lower temporal frequency and a longer duration with increasing timescales. Two contrasting periods were evident between 1961 and 2010 for both SPI and SPEI. Wet conditions dominated during the 1987–2010; whereas, persistent drought conditions occurred from 1960 to 1986. The REOF revealed four respective patterns: South Xinjiang, North Xinjiang, Hexi Corridor and southwestern Xinjiang. For the period before 2000, South Xinjiang and North Xinjiang were observed to exhibit a wetting trend, while the Hexi Corridor showed drying trend. The 12- and 24-month time scales have the same patterns as the 3-month time scale, which indicates consistent drought patterns in the study area at different time scales.
Figure 5. Spatial and temporal patterns of SPEI-3 using the REOF (a1–a4: spatial distribution of REOF-1 to -4, b1–b4: drought evolution of RPC-1 to -4).

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Supporting information

The following supporting information is available:

Appendix S1. Explanation about the Figure 2 and Figure 3.

Figure S1. Correlation coefficients between SPEI at a time scale and its nearby time scale.

Figure S2. Scatter plot between different drought indices at certain time scale.

Figure S3. The differences between SPEI and SPI at different time scales.

Figure S4. Correlations for SPEI-3, SPEI-12, and SPEI-24 at different REOFs.
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