Meteorological Drought Analysis with Different Indices for the Betwa River Basin, India

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Abstract

Climate change is adversely affecting the development, management, and planning of surface and groundwater resources. The meteorological drought becomes a severe natural problem, and it can occur in any climatic region of the world. So, monitoring and minimizing drought is a crucial stage for analyzing and predicting drought impacts. A single drought index can't assess each aspect of the meteorological drought. In this study, we considered seven drought indices such as the Standardized Precipitation Index (SPI), China Z Index (CZI), Modified China Z Index (MCZI), Percent Normal drought index (PNI), Deciles Index (DI), Rainfall Anomaly Index (RAI), and Z-score index (ZSI). The drought was analyzed for 3, 6, 9, and 12 months' time-step, and drought classification and threshold values were estimated. SPI showed maximum correlation values (0.389, 0.412, 0.560, and 0.996) for 3, 6, 9, and 12-month time steps compared to the other drought indices. The value of correlation is increased with the increase in time step for all drought indices; therefore, the accuracy of drought assessment also increases with an increase in time step. The Mann-Kendall's trend test was analyzed at a 5% level of significance for drought assessments. The drought magnitude and severity of the Betwa river basin were estimated based on the meteorological data (Rainfall) for the year between 1970 to 2014.

Keywords: Betwa river basin; Meteorological drought; Precipitation; Drought indices; Drought classification; Climate change; Severity;

1. Introduction

Research must link different meteorological drought indices with the impact of drought on society. Previously, some researchers have established this link with narrow impact measures. A period of abnormally dry weather leads to drought in a specific climatic region, and it can be observed that the vegetation cover in that region is changed. It was observed that the frequency and intensity of the drought was increased in the last three decades. So, many parts of the world were suffered from severe water crises (Dai et al., 2004; Ghulam et al., 2008). Intergovernmental Panel on Climate Change (IPCC, 2008) was projected the severe droughts increase in the future. Especially during the summer months.

Mckee et al. (1993) and Guttman (1999) recommended standardized precipitation drought indices as a candidate drought index in their study. The SPI was selected because the European researchers were predominantly recommended for meteorological studies. It became a popular choice among the researchers because it is probabilistic, simple, depends on a single variable (precipitation), and consistent in the interpretation. This technique can be easily used in risk management and decision analysis at different periods. Knutson et al. (1998) showed the adverse effect drought on society's environment, social and economic aspect. Obasi et al. (1994) studied that the meteorological and hydrological extremes are directly or indirectly responsible for 85% of natural disasters. Drought is the least understood natural hazard phenomenon that affects more people than any other natural hazard. Although, it is a slow-developing phenomenon (Wilhite, 2000). Several researchers were developed computer-based programs to estimate drought indices (Wu et al., 2001). Smakhtin and Hughes (2007) used a software package to estimate the Deciles index, Effective drought index, and SPI. It provided several options such as month selection and type of drought study. Ji and Peters (2003) established a link between the meteorological drought indices and the vegetation response.

SPI is considered a new drought index and widely accepted in all continents of the Earth to monitor real-time drought events. Morid et al. (2006) used historical meteorological and hydrological data to estimate and compare drought indices. Most of the drought indices are calculated based on the Gamma distribution. The possibility of the precipitation of all stations and regions may not be appropriate for the Gamma distribution (Blain 2011). Tsakiris et al. (2013) suggested an operational management system for drought-prone areas. This system established a relationship between specific variables and drought. The consequences of each aspect of the system were discussed because the drought was considered a natural hazard phenomenon. Jain et al. (2015) compared the SPI, EDI, CZI, RD, and statistical Z-score drought indices in the drought-prone area of the Ken river basin, India. The severity of drought indices was estimated for 1, 3, 6, 9, and 12-month time step and indices values compared with each other.

China-Z index (CZI) was introduced for monitoring the drought and severity. Initially, it was used for a one-month time scale to monitor China Ju et al. (1997). Shahabfar and Eitzinger (2009) showed that the CZI was helpful in monitoring the field-based drought indices with significant statistical significance. Salehnia et al. (2017) assessed several drought indices to estimate the severity of the drought events for the Kashafrood basin of Iran. The drought indices were correlated with the AgMERRA precipitation data. Li et al. (2017) studied that drought risk mitigation can be effectively understood by using meteorological drought analysis on a global scale. Kao and Govindaraju (2008) suggested that the dependence structure of the hydroclimatic variables can be modeled by using Copula with any form of the marginal distribution. Tencer et al. (2014) recognized that precipitation significantly impacts agricultural, environmental, and industrial activities. These activities govern the droughts and the water shortage in the soil moisture and groundwater (Najafi et al., 2017). Haied et al. (2017) conducted a drought characterization study for the Wadi Djelfa-Hadjia sub-basin of Algeria.

SPI, DI, and RDI drought indices for intensity and magnitude of drought estimation. Daneshmand and Mahmoudi (2017) observe the rainfall increase caused the variation in the properties of spatial-temporal droughts in Irian. Mahmoudi et al. (2019) evaluated the sensitivity of the precipitation drought indices at annual, monthly, and seasonal scales. The correlation coefficient of each index was obtained above the time scale. Abbasian et al. (2021) studied the precipitation-temperature Deciles index bivariate by using Copula to assess the severity and intensity of future drought. The Copula model projected the numbers of the hot and dry months would appear between $2060 - 2080$.

The natural phenomenon could be considered as the primary cause behind the droughts. Still, some of the studies are showed that the water resources (groundwater, surface water) which are directly under the impact of humans are two times more vulnerable than the less interference water resources (precipitation, snow cover) (Shaban, 2009). Edossa et al. (2010) conducted a drought analysis for the Awash River basin, Ethiopia. Hydrological and meteorological data were considered for this study. SPI indices were estimated using spatial and temporal meteorological data sets and ArcGIS software for the severity maps generation. Dogan et al. (2012) estimated drought in multiple time steps played a significant role in regional level estimation.

Patel et al. (2007) analyzed the 160 rainfall station precipitation data in the Gujrat region and emphasized SPI 3 for spatial patterns of meteorological droughts and severity. Surendran et al. (2019) estimated drought indices for India's arid, semi-arid, and humid regions using DrinC software. SPI indices showed seven drought years in arid, four drought years in semi-arid and humid regions. Similarly, RDI indices showed eleven drought years in semi-arid and humid regions and ten years in arid regions. The frequency of drought is increased in northern China, the USA, and southern Australia. This is significant evidence that global warming plays a vital role in extreme climatic events (Sheffields and Woods, 2008). Anil and Indira (2007); GOI

(2016) analyzed that India faced the worst meteorological droughts in $1917-1918, 1965-1966, 1986-1987, 2009$, and 2012 in the last century.

Hangshing and Dabral (2018) used Achemedean and Metaelliptical copulas to model SPI drought indicators at multiple time scales. These copulas were used for trivariate and bivariate joint distribution. Schwarz information criterion (SCI) and Akaike information criterion were used for model selection. Standardized precipitation index and Reconnaissance drought index are considered to be recently developed indices. Most of the drought studies in Korea were conducted based on these indices (Jang 2018). Khan et al. (2018) considered four drought indices to detect drought variability. This study was conducted at five and two meteorological stations of the Songhua River basin and Indus river basin. The result showed a 6-month time-scale for the Indus River basin, and the 12-month time-scale for the Songhua River basin was most appropriate for drought indices. The occurrence of droughts is a very common phenomenon in the Betwa river basin. The past records of rainfall patterns of the region show decreasing trend of rainfall in the most of the districts. The decrease in rainfall falls in the range of 0.674 to 6.46 mm/year. Hamirpur, Mahoba, and Jhansi districts exhibited increasing rainfall trends in the range of 0.854 to 1.474 mm/year (Desai et al. 2019). However, the summer rainfall has no trend in seasonal and yearly rainfall. In the case of summer rainfall, a decreasing trend was observed in the basin (Suryavanshi et al. 2014). Bhunia et al. (2020) used SPI to quantify drought in the Purulia, Bankura, and Midnapur districts of West Bengal. Drought frequency and trend were analyzed by Gumbel type I distribution and Mann-Kendal's test. They were found that most of the rain gauges of the study area found negative SPI value. It means the study area comes under a drought-prone area. Khan et al. (2020) used Artificial Neural Network (ANN) and ARIAM model to predict drought in the Langat river basin, Malesia. SPI and Standard index for annual precipitation (SIAP) were used to analyze the historical drought events. The Hybrid ANN-ARIMA model showed an improved correlation coefficient over

ANN and ARIMA models. Singh and Sharma (2021) applied an auto-regressive moving average (ARMA) linear model for drought forecasting in the Betwa river basin. SPI was used as a drought severity index. They found ARMA (2,0) was the best suitable model for this study area, and observed precipitation was compared with the estimated precipitation. Wu et al. (2021) used multi-time-scale SPI and standardized streamflow (SSI) for the estimation of hydrological and meteorological drought. The correlation analysis of precipitation and non-linear response were compared, and possible differences in the propagation threshold were analyzed. They have also conducted a drought study at the sub-basin level in south China.

The aim of the present study is to compute the qualitative state of drought events in the river basin. Drought monitoring at various time scales plays a significant role in the identification of short-term drought periods within the long-term wet period or short-term wet period within long-term drought. Drought indices can simplify complex meteorological events and effective communication tool for diverse public audiences. Irrespective of the available potential of water resources in India, some catchments have been facing droughts. Betwa river basin is one of them, and the frequency of droughts in this basin has increased in the past few decades. The average area precipitation of the Betwa river basin is used in the study.

1.1 A brief description of the study area and rainfall data set

The study has been carried for the Betwa river basin, a tributary of the Yamuna River. Most of the region of this basin is considered to be drought-prone in central India. The basin lies between the latitude $23^{\circ}51'E$ to $25^{\circ}55'E$ and longitude $77^{\circ}15'N$ to $79^{\circ}45'N$ with the elevation between $300m$ to $700m$ from mean sea level (Fig. 1). The study area is located in the sub-humid and semi-arid region with the four seasons such as rainy, dry, winter, and very dry. Most of the rainfall occurred during the rainy season (June-September), and the average annual rainfall of the basin varies from $700mm$ to $1200mm$.

(Please insert Fig. 1 here)

The rainfall in the Betwa region is non-uniform in regards to space and time, as the upper half of the basin receives more rainfall than the lower half. Rainfall forms a significant source of groundwater recharge in the area. Hence, the development of the groundwater recharge in the basin is very poor due to the rugged topography and inconsistent rainfall pattern in the basin. Groundwater recharge is highly uneven and unpredictable throughout the year and has to be estimated separately for monsoon and non-monsoon. Recharge from rainfall in the entire basin for the monsoon only because 80–85% of the total rainfall occurs in this season. Groundwater recharge from rainfall in the monsoon season accounts for about 80 − 85% of the total annual rainfall, and just 15–20% of rainfall occurs in non-monsoon seasons. Recharge in non-monsoon can be assumed to be negligible (Jeet et al. 2019). The average area precipitation of the Betwa river basin is used in the study (Fig. 2), and the mean monthly rainfall of the basin can be downloaded from http://www.mpwrd.gov.in/betwa-basin website. Kaliasote, Bah, Halali, Budhna, and Bina are the major tributaries of this river basin.

(Please insert Fig. 2 here)

2. Methodology

In the study, monthly precipitation (Rainfall) data from 1970 to 2014 is used to estimate meteorological drought indices. Seven meteorological events are applied for the severity and duration analysis of droughts. These drought indices are Standardized Precipitation Index (SPI), Percent of Normal Precipitation (PN), Deciles Index (DI), China Z-Index (CZI), Modified China Z-Index, Rainfall Anomaly Index (RAI) and, Z-Score. These indices are the numerical representation and technical indicator of the drought severity. It is assessed using rainfall as a meteorological input. A brief description of all the above drought indices is given below:

2.1 Standardized Precipitation Index (SPI)

The SPI of any rain gauge station is calculated based on the historical long-term precipitation data. This precipitation data is fitted in the Gamma probability distribution and transformed into the normal distribution. So, the mean SPI of the desired rain gauge data becomes zero (Mckee et al. 1993). Multiple time scales such as $1, 3, 9, 12$, etc. month can identify various types of drought. SPI has been successfully used in the various regions of the world because of its reliability and ability to address drought for various time-scales (Guttman 1999; Vincente-Serrana et al. 2004; Pandey et al. 2008; Edossa et al. 2010; Zhai et al. 2010; Singh and Sharma 2021; etc.). The probability distribution of the Gamma function can be defined as follows:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}; \text{ for } x > 0 \quad (1)$$

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \quad (2)$$

$x > 0, \beta > 0$, shape parameter (α) and, scale parameter (β) are estimated from the likelihood function such as:

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \quad (3a)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \quad (3b)$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (3c)$$

The cumulative probability of the precipitation for desired rain gauge and time-scale can be defined as follows:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \quad (4a)$$

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x t^{\hat{\alpha}-1} e^{-t} dt \; ; t = x/\hat{\beta} \quad (4b)$$

The rainfall event may contain zero value, but the Gamma function can't be defined at $x = 0$. So, the cumulative probability distribution of the Gamma function described as given below:

$$H(x) = q + (1 - q)G(x) \quad (5)$$

Where q is the probability of zero precipitation. After that $H(x)$ is transformed into the normal distribution with zero mean and unit variance.

2.2 Percent of Normal (PN) precipitation

Percent normal is the straightforward drought measurement index. It is the ratio of the normal precipitation (p_i) to the actual precipitation (p) and they are expressed in the percentage. At least 30 years of data is required to estimate the percent normal index, and it can be calculated for various time scales such as weekly, monthly, seasonally, and yearly. Although, it is the simplest index to calculate but alone, it can't be used for decision masking statements (Willeke et al. 1994). PN drought index is calculated at a station using the following formula:

$$PN = \frac{p_i}{p} \times 100 \quad (6)$$

2.3 Deciles Index (DI)

Gibbs and Maher (1967) developed the Deciles index for drought estimation from the historical data in Australia. Long-term precipitation (monthly, seasonally, or annually) data can be used for the study. The data set is arranged into descending or ascending order to formulate the frequency distribution. If precipitation data does not follow the normal distribution, it should be normalized by normalization methods. The data is divided into several groups of the normal distribution, and each group is known as Decile. The first Decile is less than 10% precipitation of total precipitation. The second Decile is less than 20% precipitation of total precipitation. The fifth and last Decile is less than 50% precipitation of the total precipitation (Table 1).

2.4 Z-Score Index (ZSI)

Z-Score Index does not require the transformation of the precipitation data in the Pearson type-III distribution or Gamma distribution. Morid et al. (2006), Patel et al. (2007), etc., were analyzed drought by using ZSI. Z-Score index is computed by the following equation.

$$ZSI = \frac{(x_{ij} - \bar{x})}{\sigma_i} \quad (7)$$

Where $\bar{x}$ and σ_i are the mean and standard deviation of each time-scale. x_{ij} is the precipitation for j^{th} month i^{th} and length.

2.5 China Z-Index (CZI) and Modified China-Z Index (MCZI)

China-Z Index is related to the Wilson-Hilferty cube root transformation (Wilson and Hilferty 1931). Assuming that the precipitation follows the Person Type III distribution. The following equations compute the CZI.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (8)$$

$$C_s = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n \times \sigma^3} \quad (9)$$

$$CZI = \frac{6}{C_s}\left(\frac{C_s}{2}(Z - Score) - 1\right)^{1/3} - \frac{6}{C_s} + \frac{C_s}{6} \quad (10)$$

Where C_s is the coefficient of skewness, and σ is the standard deviation of n number of observations.

The Modified China Z-Index is calculated similarly as China Z-Index while the median of the precipitation is used instead of the mean of the precipitation data.

2.6 Rainfall Anomaly Index (RAI)

Rainfall Anomaly Index (RAI) was introduced by Van-Roony (1965). It is basically a ranking procedure to assign the degree of positive and negative precipitation between +3 to -3. It can be applied for both monthly and annual precipitation time-scale. RAI is computed by using the following equations.

$$RAI = 3\left[\frac{p-\bar{p}}{\bar{m}-\bar{p}}\right] \quad (11a)$$

And if $p < \bar{p}$, then

$$RAI = -3\left[\frac{p-\bar{p}}{\bar{X}-\bar{p}}\right] \quad (11b)$$

Where p and $\bar{p}$ are the precipitation and mean precipitation value. $\bar{m}$ and $\bar{X}$ are the mean of ten maximum and ten minimum precipitation values of the data set.

(Please insert Table 1 here)

3 The Mann-Kendall (MK) trend analysis test

Mann (1945) and Kendall (1975) specified the Mann-Kendall trend statistics. MK test is used for statistically increasing or decreasing trends in long-term temporal data set. It is based on the null hypothesis (H_0) and alternate hypothesis (H_1). The null hypothesis represents the nonexistence of trend, while the alternate hypothesis represents the existence of a significant falling or rising trend in the data set.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sign(x_j - x_i) \tag{12}$$

$$Sign(x_j - x_i) = \begin{cases} +1;\ if\ (x_j - x_i) > 0 \\ 0;\ if\ (x_j - x_i) = 0 \\ -1; if\ (x_j - x_i) < 0 \end{cases} \tag{13}$$

Where x_i and x_j values of the data series and $x_j > x_i$. For sample size $(n > 10)$, the variance is considered to be zero.

$$\mu(s) = 0 \tag{14}$$

$$\sigma^2(s) = n(n-1)(2n+5) - \frac{\sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \tag{15}$$

Where m and i are the numbers of tie (t_i) extent and tie group (z_s) is computed as:

$$z_s = \begin{cases} \frac{s-1}{\sqrt{\sigma^2(s)}};\ if\ s > 0 \\ 0;\ if\ s = 0 \\ \frac{s-1}{\sqrt{\sigma^2(s)}}; if\ s < 0 \end{cases} \tag{16}$$

On the basis of 5% significance level, if $\alpha \leq 0.05$ (s value), i.e., $z_s = 1.96$; then the alternate hypothesis is rejected, or the alternate hypothesis is accepted. While $\alpha \geq 0.05$, the null hypothesis is accepted.

3.1 Sen's slope estimator

Sen slope (Q) was developed to estimate the magnitude of trend in the long time-series data (Sen 1968). It precisely detects the linear relationship because it can't be affected by the outliners in the data. Positive Sen's slope indicated the increasing trend, while negative Sen's slope indicated the decreasing trend in the data.

$$Q = \frac{x_j - x_i}{j - i}; i < j \tag{17}$$

The number of observations (n) is only one datum in each time period then, $N = \frac{n(n-1}{2}$ and if more time period, then, $N < \frac{n(n-1}{2}$.

The N value of the Sen's slope arranged from smallest to largest, and the median of the Sen's slope is estimated as given below:

$$Q_{med} = \begin{Bmatrix} Q_{\left[\frac{(N+1)}{2}\right]}; if\ N\ is\ odd \\ \frac{Q_{[N/2]} + Q_{[(N+2)/2]}}{2}; if\ N\ is\ even \end{Bmatrix} \tag{18}$$

3.2 Pearson Correlation coefficient

The Pearson correlation coefficient measures the linear dependence of two series of random variables. It is the ratio of the covariance of series to the products of standard deviations, and it ranges between +1 to -1 (Rodgers and Nicewander 1988).

$$r = \frac{\sum(x_i - \bar{x})\sum(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2} \times \sqrt{\sum(y_i - \bar{y})^2}} \tag{19}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i,\ \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{20}$$

4 Results and Discussion

The standardized precipitation index (SPI) is the most widely used drought index across various parts of the world. It is found suitable for the Asian region as well (Smaktin and Hughes 2004). China Z index, Modified China Z index, and Z score index are primarily used in Asian regions. DI, PN, RAI are used in the study due to their simplicity in the calculation. Most of the rainfall occurred during the monsoon period in the study area and showed high rainfall variability from month to month. Therefore, we decided to compute the different drought indices in 3, 6, 9, and 12-month time steps for the average area rainfall of the basin. One-month time step can't describe drought situation appropriately (Jain et al. 2015). So, it is not included in the study. The drought indices have a different range of values to classify the drought severity. So, generally, moderate, severe, and extremely severe range indices are used to compare the droughts at various time steps. The range of drought indices and their severity are shown in Table 1.

The SPI, CZI, and MCZI can be classified on a similar drought severity scale, ranging between −3 to +3. From this study, it is observed that SPI, CZI, and MCZI have an almost similar number of months in each type of severity (moderate, severe, and extreme severe) for each time step. Most of the SPI, CZI, and MCZI values were falling under near normal and moderately drought zone. Few months of various time steps showed under severe drought zone, and three months of the year 1979 have extremely droughts in each time-step while one month of the year 2014 showed extremely drought for 6, 9, and 12-month time-step. The single-single month of the year 2002 and 2006 showed extreme drought for 3, and 6-month time steps, respectively (Fig. 3).

(Please insert Fig. 3 here)

The DI, PN, RAI, and ZSI have different drought classification scales. Most of the indices lie in the range of near normal and moderate droughts, and a significant number of values also lie in the range of severe and extreme droughts (Fig. 4). Therefore, drought indices showed high severity than the SPI, CZI, and MCZI. The DI showed almost similar severity for each time step, and one month in each year it is occurred in the extreme drought range. This trend can't be observed in the other indices so; it seems to be a hypothetical estimation. At the 12-month time step, PN was not shown any value in the extreme drought range. Apart from these other time steps, a significant number of indices values are ranging in the extreme and severe drought zone. RAI and ZSI drought indices are showed most of their values in the near normal and moderate drought range similar to the SPI, CZI, and MCZI, but these indices also have significant numbers in the extreme and severe drought zone.

(Please insert Fig. 4 here)

Mann-Kendall's trend test showed a negative value for each drought indices while p value of trend is positive. A similar hypothesis was found for each index, i.e., the null hypothesis is accepted with decreasing trend at a 5% level of significance. The Sen's slope represents the magnitude of the increasing or decreasing slope of the MK trend test. It was found to be the negative value (declining) for all indices except for PN 3, DI 3, DI 6, DI 9, and DI 12 (Table 2).

(Please insert Table 2 and Fig. 5 here)

All drought indices are positively correlated except MCZI at a 3-month step size, and they can be compared based on Pearson's correlation for the same time step. SPI was highly correlated in each time step precipitation data compared with the remaining indices. The values of correlation coefficient of SPI were 0.389, 0.412, 0.560, and 0.996 for 3, 6, 9, and 12-month time steps, respectively. Apart from SPI, several other indices such as CZI, RAI, ZSI, and MCZI were also showed good correlation except MCZI 3. So, MCZI can't be considered for the smaller time step. It was observed that the correlation of all indices is increasing with an increase in time (Fig. 5). It means drought estimation is more accurate for higher time steps compared to the smaller time step.

It was found to be very interesting that the number of extremely drought months of SPI, CZI, MCZI, ZSI, and RAI indices are increasing with an increase in 3, 6, and 9-month time steps. While severely and moderately number of drought months are increasing in 3, and 6-month time step and decrease in 12-month time step. For DI indices, Extremely, severely, and moderately drought months are almost the same in each time step, while the PN index showed the decreasing trend in the number of drought months as we described earlier that the type of droughts is characterized based on severity and duration. The drought months in 3, 6, 9, and 12-month time steps for various indices during 1970 to 2014 for the Betwa river basin are presented in Table 3.

(Please insert Table 3 and Fig. 6 here)

It can be noted from Fig. 6 that the occurrence of the extreme, severe, and moderate drought events showed a decreasing trend in 3, 6, 9, and 12-month time steps. Fig. 6 (a-c) showed that extremely and severely drought events range from 0.56% to 2.78%. While moderately drought events are comparatively more, i.e., ranging from approximately 1% to 11%. Also, in Fig. 6 (d-f), the extreme drought events range from 17.41% to 34%, while severe and moderately drought events range from approximately 5.51% to 32.59%. Fig. 6(g) showed extreme, severe, and moderate drought events are ranging from 2% to 5%, 9% to 11%, and 10% to 25%, respectively. It can be observed that the extreme drought events are very less than the severe and moderate drought events during 1970 to 2014 in the Betwa river basin.

It was observed that if drought is occurred during the monsoon period, then it can be continued till the next monsoon period unless excess rainfall was occurred during the non-monsoon period. This phenomenon has happened because most of the rainfall was occurred during the monsoon period in this basin. The indices used in the study are computed based on the area average monthly precipitation data. The drought management and trend analysis are necessary because it controls the climate change. All indices were showed good correlation and Mann-Kendall's trend test. It is appropriate to say that the SPI is the best-suited drought index for drought forecasting in the Betwa river basin, but RAI, CZI, ZSI, and MCZI can also be considered because their indices follow a similar trend as SPI. But MCZI can't consider smaller time steps. It is recommended that these groups of indices can be considered for other river basins with similar morphological and hydrographic features.

5 Conclusions

Precipitation always plays an important role in drought assessment. Researchers have different views on drought assessment because drought identification is quite a challenging task. Some of the researchers believe that drought occurred due to insufficient rainfall. At the same time, others believe that the precipitation-based drought indices are not sufficient for drought assessment. Therefore, more meteorological-based drought indices are required for accurate drought assessment. This study used a group of seven drought indices (SPI, CZI, MCZI, DI, PN, RAI, and CZI) for drought estimation in the Betwa river basin. Based on the study following conclusion remarks are given below:

1. Mostly SPI, CZI, and MCZI values range in the normal and moderately drought zone. Few months of various time step falls in the range of severely drought zone and three months of the year 1979 have extreme droughts in each time step while one month of the year 2014 showed extremely drought for $6, 9$, and 12-month time-step. The year 2002 and 2006 showed $1-1$ month under extreme drought for 3, and 6-month time step.
2. RAI and ZSI drought indices have most of their values in the near normal and moderate drought range similar to the SPI, CZI, and MCZI, while these indices have significant numbers in the extreme and severe drought zone.
3. It was found to be the negative value (decreasing) for all indices except for PN 3, DI 3, DI 6, DI 9, and DI 12, i.e., the null hypothesis (H_0) is accepted with decreasing trend in the data. The Pearson's correlation coefficient of SPI was $0.389, 0.412, 0.560$, and 0.996 for $3, 6, 9$, and 12 $-$month time steps. Apart from SPI, several other indices such as CZI, RAI, ZSI, and MCZI were also showed good correlation except MCZI 3.
4. The number of extremely drought months for SPI, CZI, MCZI, ZSI, and RAI is increasing with the increase in time step while severely and moderately number of

drought months are increasing in 3 and 6-month time steps and decrease in 12-month time step.

5. The occurrence of the extreme, severe, and moderate drought events showed a decreasing trend in 3, 6, 9, and 12-month time steps. The extreme drought events are very less than the severe and moderately drought events from 1970 to 2014 in the Betwa river basin.

Finally, it is concluded that the SPI is the best drought index compared to other indices for the management and modeling of drought. Apart from SPI, RAI and CZI can also be used for drought assessment. Furthermore, more studies are required on local climatic conditions with meteorological data to uncertainty in drought assessment to suggest a better tool for managing and planning water resources in the Betwa river basin.

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Data availability: All data used in the study are freely available on http://www.mpwrd.gov.in/betwa-basin website.

Code availability: No code was developed in the current study.

Declarations

Conflicts of interest: The authors declare no competing interests.

Ethics approval: The authors paid attention to the ethical rules in the study. There is no violation of ethics.

Consent to participate: The data of this research were not prepared through a questionnaire.

Consent for publication: If this manuscript is accepted, it can be published in the Theoretical and Applied Climatology journal.

References

Abbasian MS, Najafi MR, Abrishamchi A (2021) Increasing risk of meteorological drought in the Lake Urmia basin under climate change: introducing the precipitation–temperature deciles index. Journal of Hydrology 592:125586. https://doi.org/10.1016/j.jhydrol.2020.125586

Anil KR, Indira H (2007) Multiple impacts of droughts and assessment of drought policy in major drought Prone States in India. The Planning Commission, Government of India, New Delhi.

Bhunia P, Das P, Maiti R (2020) Meteorological drought study through SPI in three drought prone districts of West Bengal, India. Earth Systems and Environment 4(1):43-55. https://doi.org/10.1007/s41748-019-00137-6

Blain GC (2011) Standardized precipitation index based on Pearson type III distribution. Revista Brasileira de Meteorologia 26(2):167-180. http://dx.doi.org/10.1590/S0102-77862011000200001

Dai A, Trenberth KE, Qian T (2004) A global dataset of Palmer Drought Severity Index for 1870–2002: Relationship with soil moisture and effects of surface warming. Journal of Hydrometeorology 5(6):1117-1130. https://doi.org/10.1175/JHM-386.1

Daneshmand H, Mahmoudi P (2017) Estimation and assessment of temporal stability of periodicities of droughts in Iran. Water Resources Management 31(11):3413-3426. https://doi.org/10.1007/s11269-017-1676-8

Desai SUJEET, Singh DK, Islam A, Sarangi A, Khanna MANOJ (2019) Trend analysis of climatic variables in Betwa river basin. Indian J. Agric. Sci 89(6):1033-1038.

Dogan S, Berktay A, Singh VP (2012) Comparison of multi-monthly rainfall-based drought severity indices, with application to semi-arid Konya closed basin, Turkey. Journal of Hydrology 470:255-268. https://doi.org/10.1016/j.jhydrol.2012.09.003

Edossa DC, Babel MS, Gupta AD (2010) Drought analysis in the Awash river basin, Ethiopia. Water resources management 24(7):1441-1460. https://doi.org/10.1007/s11269-009-9508-0

Gibbs WJ, Maher JV (1967) Rainfall deciles as drought indicators, bureau of meteorology bulletin no. 48. Commonwealth of Australia, Melbourne, 29.

Ghulam A, Qin Q, Kusky T, Li ZL (2008. A re-examination of perpendicular drought indices. International Journal of Remote Sensing 29(20):6037-6044. https://doi.org/10.1080/01431160802235811

GOI (2016) Manual for drought management. Department of Agriculture, Cooperation & Farmers Welfare Ministry of Agriculture & Farmers Welfare, Government of India, New Delhi

Guttman NB (1999) Accepting the standardized precipitation index: a calculation algorithm 1. JAWRA Journal of the American Water Resources Association 35(2):311-322. https://doi.org/10.1111/j.1752-1688.1999.tb03592.x

Haied N, Foufou A, Chaab S, Azlaoui M, Khadri S, Benzahia K, Benzahia I (2017) Drought assessment and monitoring using meteorological indices in a semi-arid region. Energy Procedia 119:518-529. https://doi.org/10.1016/j.egypro.2017.07.064

Hangshing L, Dabral PP (2018) Multivariate frequency analysis of meteorological drought using Copula. Water resources management 32(5):1741-1758. https://doi.org/10.1007/s11269-018-1901-0

Jain VK, Pandey RP, Jain MK, Byun HR (2015). Comparison of drought indices for appraisal of drought characteristics in the Ken River Basin. Weather and Climate Extremes 8:1-11. https://doi.org/10.1016/j.wace.2015.05.002

Jang D (2018) Assessment of meteorological drought indices in Korea using RCP 8.5 scenario. Water 10(3):283. https://doi.org/10.3390/w10030283

Jeet P, Singh DK, Sarangi A (2019) Groundwater potential in a drought prone Betwa river basin, Bundelkhand. Indian Journal of Agricultural Sciences 89(10):1623-1627.

Ji L, Peters AJ (2003) Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. Remote Sensing of Environment 87(1):85-98. https://doi.org/10.1016/S0034-4257(03)00174-3

Xiaosheng J, Xianwei Y, Lijuan C, Youmin W (1997) Research on determination of station indexes and division of regional flood/drought grades in China. J Appl Meteor Sci, 8(1):26-33. http://qikan.camscma.cn/jamsweb/en/article/id/19970104

Kao SC, Govindaraju RS (2008) Trivariate statistical analysis of extreme rainfall events via the Plackett family of copulas. Water Resources Research 44(2). https://doi.org/10.1029/2007WR006261

Khan MI, Liu D, Fu Q, Faiz MA (2018) Detecting the persistence of drying trends under changing climate conditions using four meteorological drought indices. Meteorological Applications 25(2):184-194.
https://doi.org/10.1002/met.1680

Khan MMH, Muhammad NS, El-Shafie A (2020) Wavelet based hybrid ANN-ARIMA models for meteorological drought forecasting. Journal of Hydrology 590:125380. https://doi.org/10.1016/j.jhydrol.2020.125380

Knutson C, Hayes M, Phillips T (1998) How to reduce drought risk.

Lee Rodgers J, Nicewander WA (1988) Thirteen ways to look at the correlation coefficient. The American Statistician 42(1):59-66. https://doi.org/10.2307/2685263

Li Y, Yao N, Sahin S, Appels WM (2017) Spatiotemporal variability of four precipitation-based drought indices in Xinjiang, China. Theoretical and Applied Climatology 129(3):1017-1034. https://doi.org/10.1007/s00704-016-1827-5

Mahmoudi P, Rigi A, Kamak MM (2019) Evaluating the sensitivity of precipitation-based drought indices to different lengths of record. Journal of Hydrology 579:124181. https://doi.org/10.1016/j.jhydrol.2019.124181

McKee TB, Doesken NJ, Kleist J (1993, January). The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology (Vol. 17, No. 22, pp. 179-183).

Morid S, Smakhtin V, Moghaddasi M (2006) Comparison of seven meteorological indices for drought monitoring in Iran. International Journal of Climatology: A Journal of the Royal Meteorological Society 26(7):971-985. https://doi.org/10.1002/joc.1264

Najafi MR, Zwiers FW, Gillett NP (2017) Attribution of observed streamflow changes in key British Columbia drainage basins. Geophysical Research Letters 44(21):11-012. https://doi.org/10.1002/2017GL075016

Obasi GOP (1994) WMO's role in the international decade for natural disaster reduction. Bulletin of the American Meteorological Society 75(9):1655-1661. https://www.jstor.org/stable/26231968

Pandey RP, Dash BB, Mishra SK, Singh R (2008) Study of indices for drought characterization in KBK districts in Orissa (India). Hydrological Processes: An International Journal 22(12):1895-1907. https://doi.org/10.1002/hyp.6774

Patel NR, Chopra P, Dadhwal VK (2007) Analyzing spatial patterns of meteorological drought using standardized precipitation index. Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling 14(4):329-336. https://doi.org/10.1002/met.33

Salehnia N, Alizadeh A, Sanaeinejad H, Bannayan M, Zarrin A, Hoogenboom G (2017) Estimation of meteorological drought indices based on AgMERRA precipitation data and station-observed precipitation data. Journal of arid land 9(6):797-809. https://doi.org/10.1007/s40333-017-0070-y

Sen PK (1968) Estimates of the regression coefficient based on Kendall's tau. Journal of the American statistical association 63(324):1379-1389. https://doi.org/10.2307/2285891

Shahabfar A, Eitzinger J (2009, April). An evaluation of drought indices in different climatic regions. In EGU General Assembly Conference Abstracts (p. 456). https://ui.adsabs.harvard.edu/abs/2009EGUGA..11..456S/abstract

Shaban A (2009) Indicators and aspects of hydrological drought in Lebanon. Water resources management 23(10):1875-1891. https://doi.org/10.1007/s11269-008-9358-1

Sheffield J, Wood EF (2008) Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. Climate dynamics 31(1):79-105. https://doi.org/10.1007/s00382-007-0340-z

Singh U, Sharma PK (2021) Drought forecasting using the stochastic model in the Betwa river basin, India. Modeling Earth Systems and Environment 1-16. https://doi.org/10.1007/s40808-021-01187-4

Smakhtin VU, Hughes DA (2007) Automated estimation and analyses of meteorological drought characteristics from monthly rainfall data. Environmental Modelling & Software 22(6):880-890. https://doi.org/10.1016/j.envsoft.2006.05.013

Surendran U, Anagha B, Raja P, Kumar V, Rajan K, Jayakumar M (2019) Analysis of drought from humid, semi-arid and arid regions of India using DrinC model with different drought indices. Water Resources Management 33(4):1521-1540. https://doi.org/10.1007/s11269-019-2188-5

Suryavanshi S, Pandey A, Chaube UC, Joshi N (2014) Long-term historic changes in climatic variables of Betwa Basin, India. Theoretical and applied climatology 117(3):403-418. https://doi.org/10.1007/s00704-013-1013-y

Tencer B, Weaver A, Zwiers F (2014) Joint occurrence of daily temperature and precipitation extreme events over Canada. Journal of Applied Meteorology and Climatology 53(9):2148-2162. https://doi.org/10.1175/JAMC-D-13-0361.1

Tsakiris G, Nalbantis I, Vangelis H, Verbeiren B, Huysmans M, Tychon B, ... Batelaan O (2013) A system-based paradigm of drought analysis for operational management. Water resources management 27(15):5281-5297. https://doi.org/10.1007/s11269-013-0471-4

Vicente-Serrano SM, González-Hidalgo JC, de Luis M, Raventós J (2004) Drought patterns in the Mediterranean area: the Valencia region (eastern Spain). Climate Research 26(1):5-15. https//doi.org/10.3354/cr026005

Wilhite DA (2000) Drought as a natural hazard: concepts and definitions. https://digitalcommons.unl.edu/droughtfacpub/69/

Willeke G, Hosking JRM, Wallis JR, Guttman NB (1994) The national drought atlas. Institute for water resources report, 94. US Army of corps engineeres

Wilson EB, Hilferty MM (1931) The distribution of chi-square. proceedings of the National Academy of Sciences of the United States of America 17(12):684.

Wu J, Chen X, Yao H, Zhang D (2021) Multi-timescale assessment of propagation thresholds from meteorological to hydrological drought. Science of The Total Environment 765:144232. https://doi.org/10.1016/j.scitotenv.2020.144232

Wu H, Hayes MJ, Weiss A, Hu Q (2001) An evaluation of the Standardized Precipitation Index, the China-Z Index and the statistical Z-Score. International Journal of Climatology: A Journal of the Royal Meteorological Society 21(6):745-758. https://doi.org/10.1002/joc.658

Van Rooy MP (1965) A rainfall anomaly index independent of time and space, NOTOS.

Zhai J, Su B, Krysanova V, Vetter T, Gao C, Jiang T (2010) Spatial variation and trends in PDSI and SPI indices and their relation to streamflow in 10 large regions of China. Journal of Climate 23(3):649-663. https://doi.org/10.1175/2009JCLI2968.1

Figures

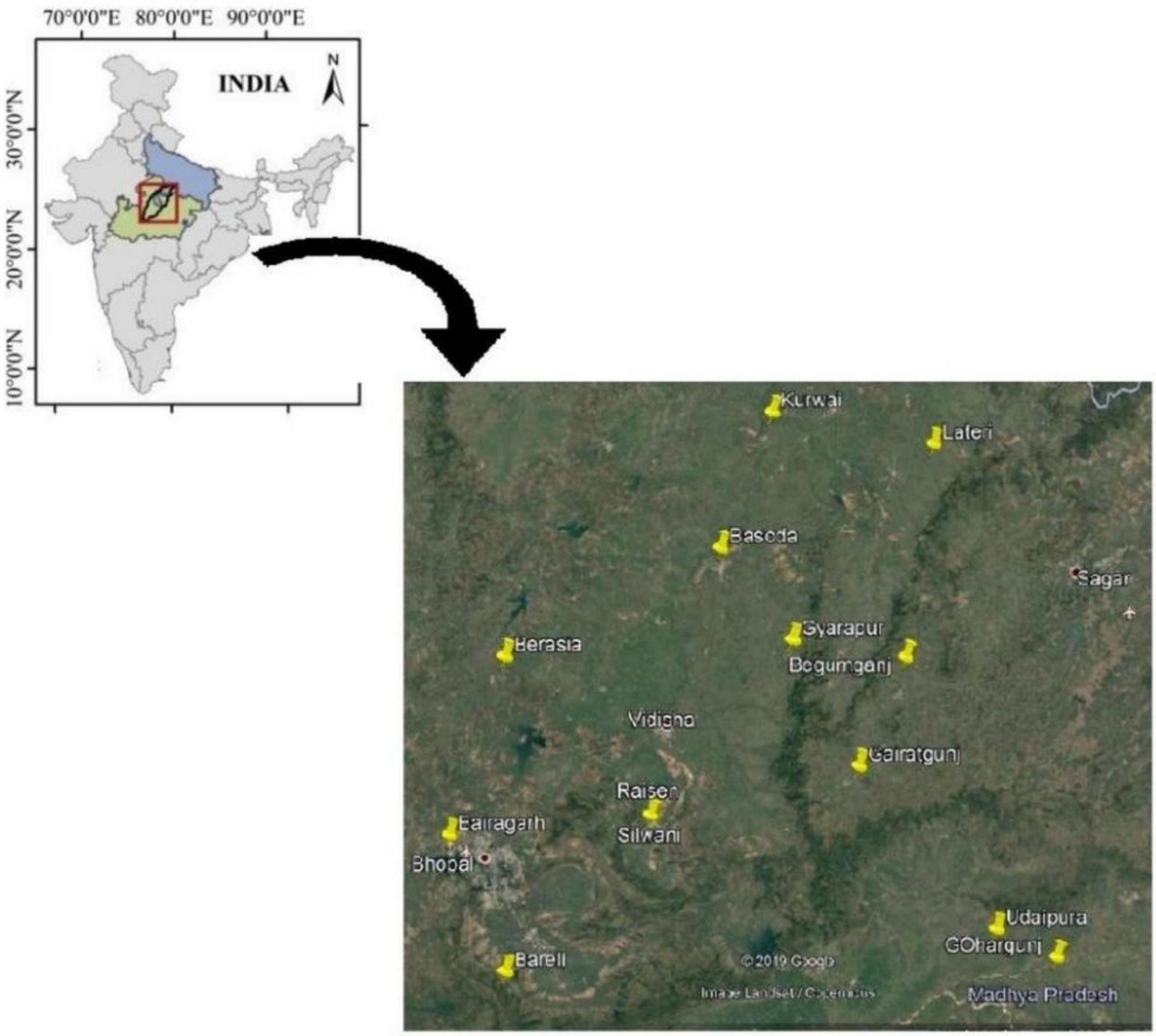

Figure 1

Location map and rain gauge stations of the study area.

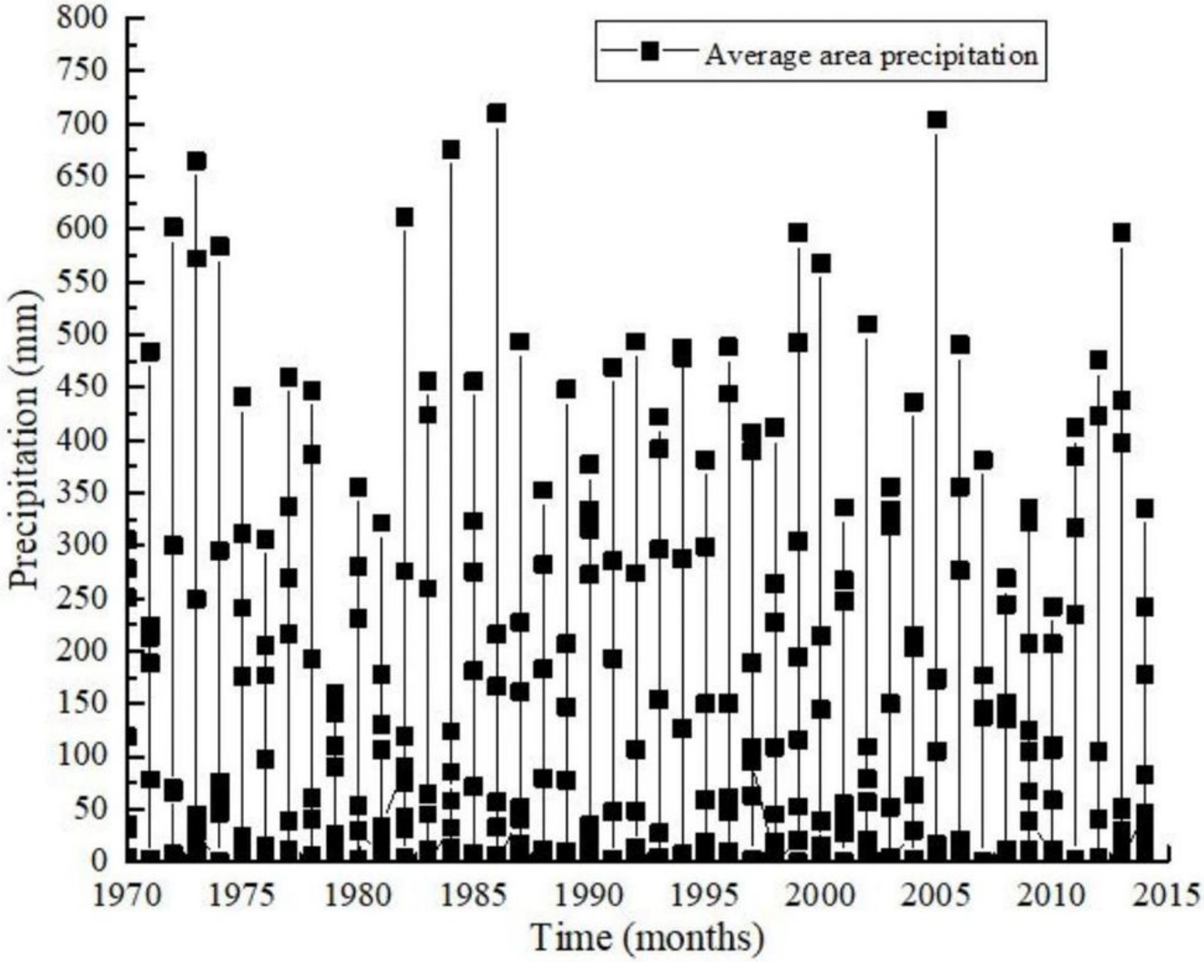

Figure 2

Average area precipitation time series (1970-2014) data of the Betwa river basin.

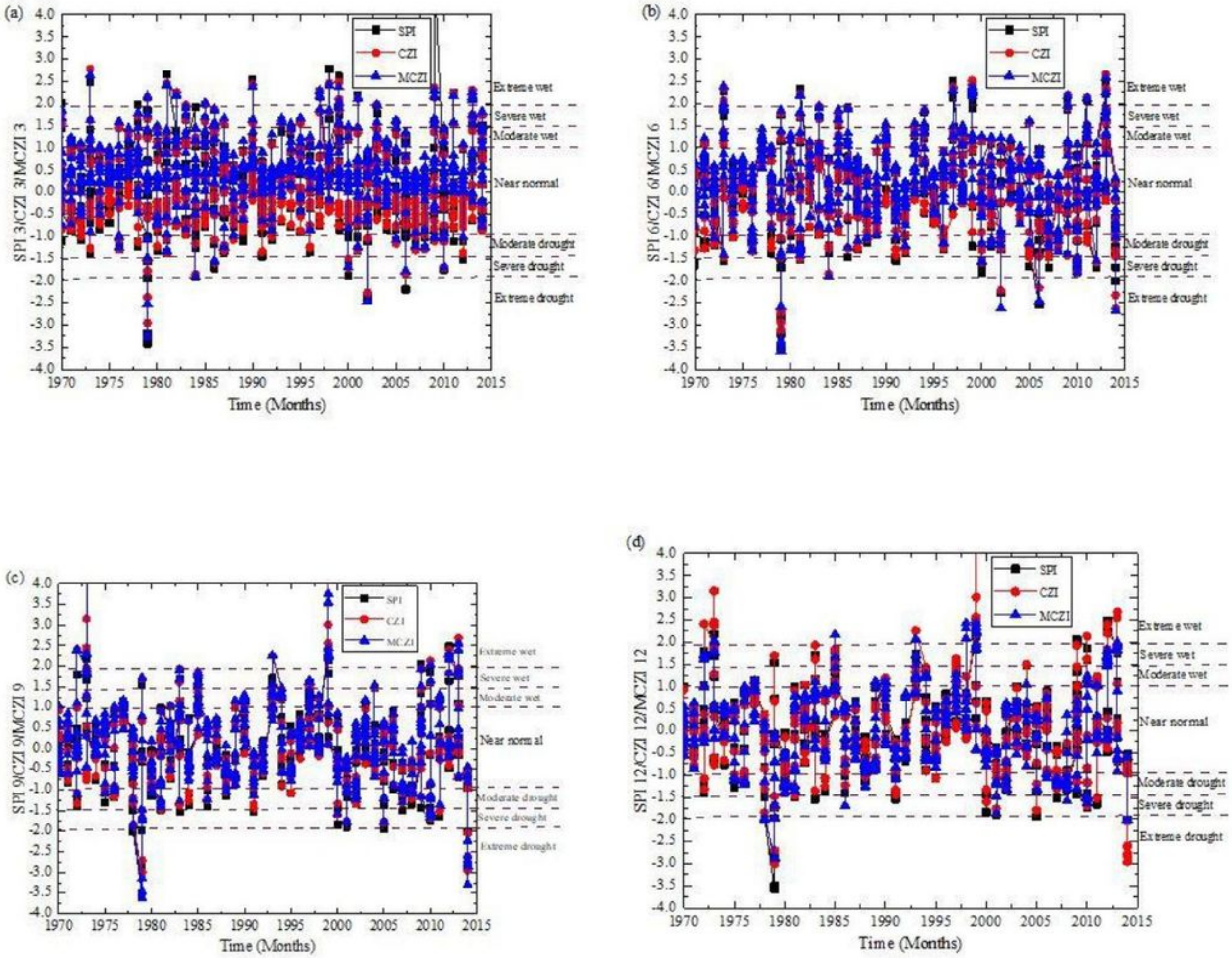

Figure 3

Comparison and drought classification of SPI, CZI, and MCZI at (a) 3-month time-step, (b) 6-month time-step, (c) 9-month time-step, and (d) 12-month time-step.

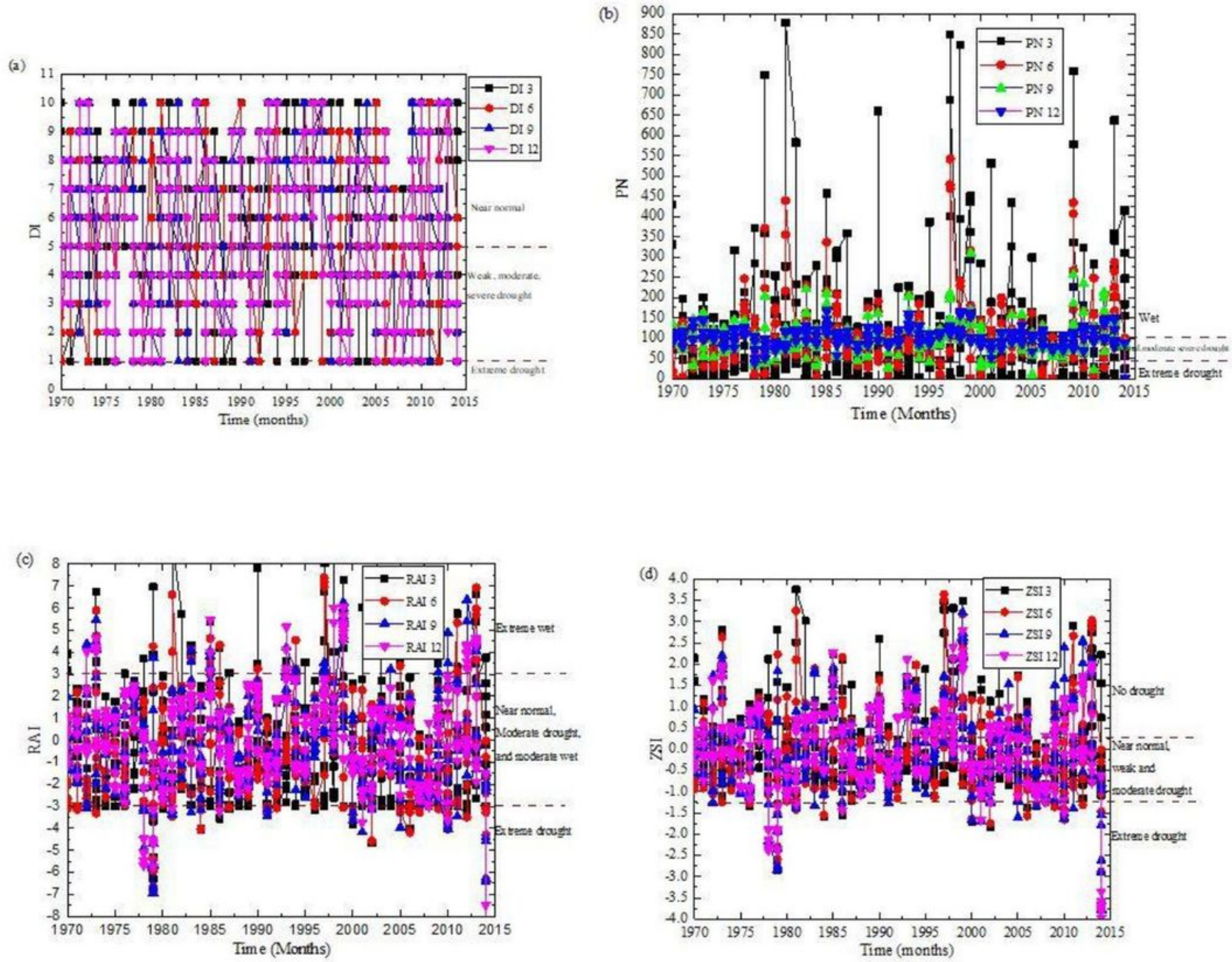

Figure 4

Comparison and drought classification (a) DI, (b) PN, (c) RAI, and (d) ZSI at various time steps.

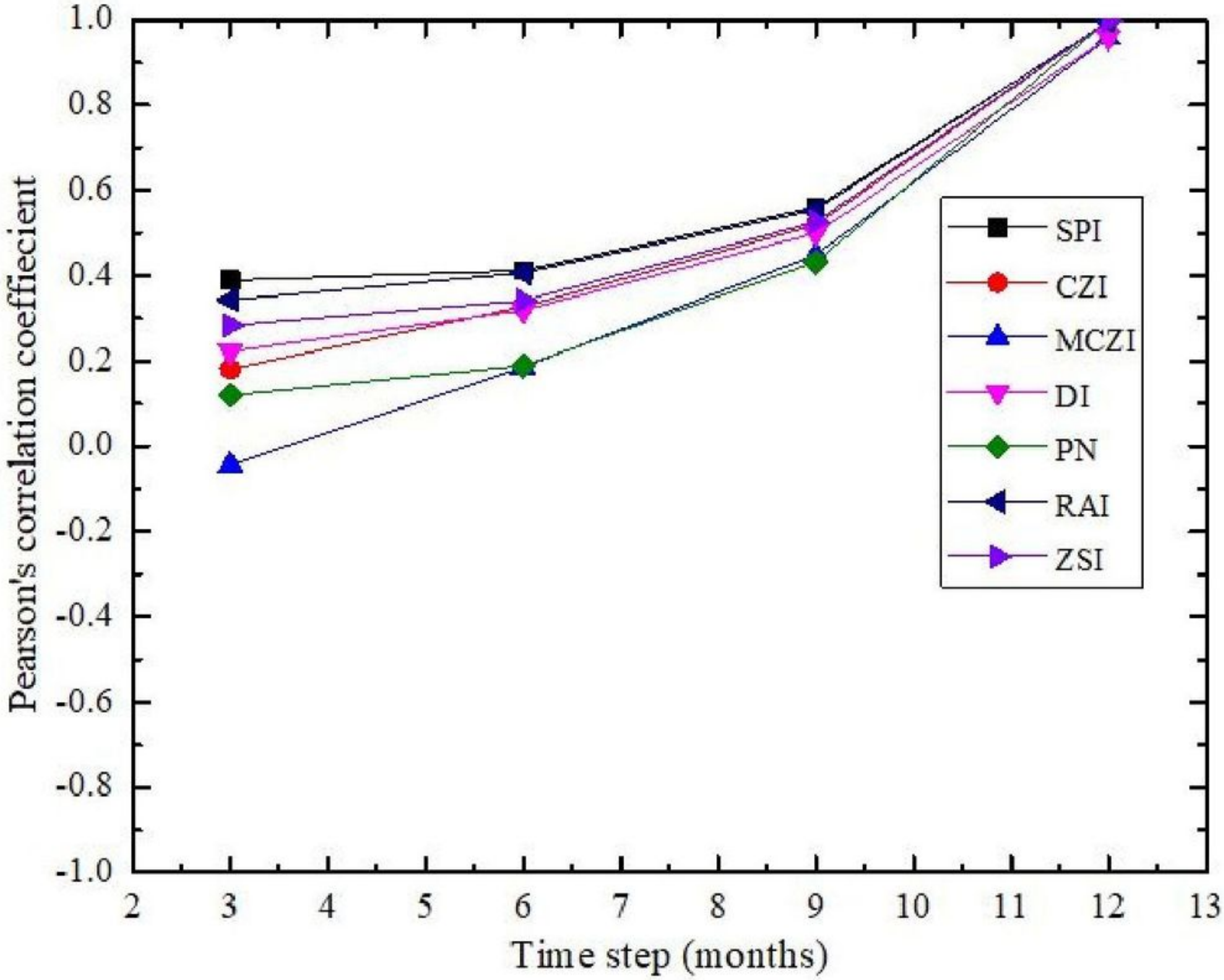

Figure 5

Pearson's correlation coefficient of drought indices of precipitation data at 3,6,9, and 12-month time-step.

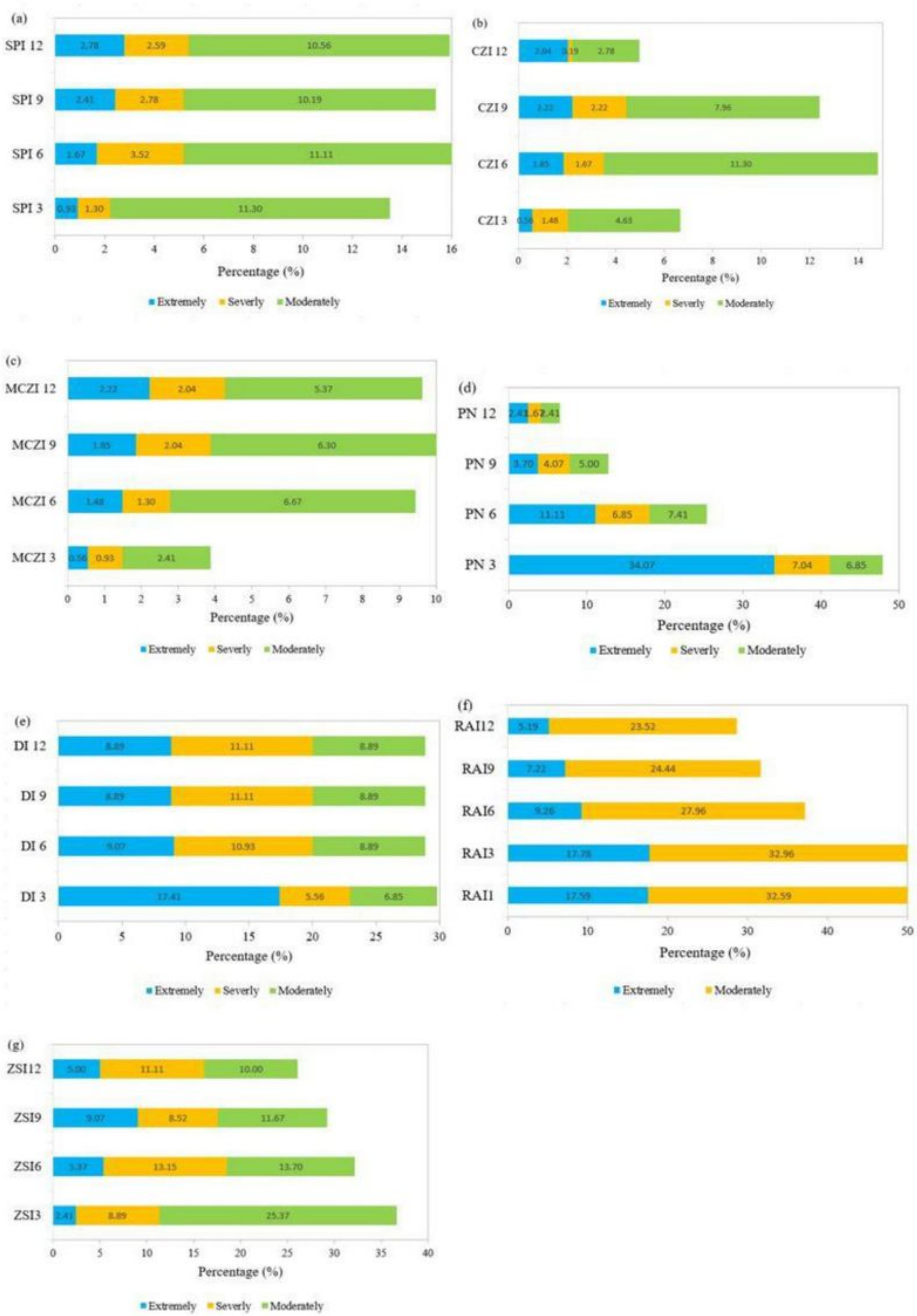

Figure 6

Percentage of drought severities at 3,6,9, and 12-month time step for (a) SPI, (b) CZI, (c) MCZI, (d) PN, (e) DI, (f) RAI, and (g) ZSI.

Supplementary Files

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