

Hydro-meteorological drought risk assessment using linear and nonlinear multivariate methods

Zahra Azhdari^a, Ommolbanin Bazrafshan^{a,*}, Hossein Zamani^b, Marzieh Shekari^b,
Vijay P. Singh^c

^a Department of Natural Resources Engineering, Faculty of Agriculture and Natural Resources Engineering, University of Hormozgan, P.O. BOX., 3995, Bandar-Abbas, Iran

^b Department of Mathematics and Statistics, Faculty of Science, University of Hormozgan, P.O. BOX., 3995, Bandar-Abbas, Iran

^c Department of Biological and Agricultural Engineering and Zachry Department of Civil & Environmental Engineering, Texas A&M University, College Station, TX 77802, USA

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ABSTRACT

Drought is multivariate, yet several univariate and bivariate indices have been proposed for the evaluation of drought characteristics. However, limited attention has been paid to the mechanisms and performance of these drought indices. This study considered canonical correlation analysis (CCA), principal component analysis (PCA), and copula-based method to construct three composite hydro-meteorological indices, namely, JDHMI-CCA, JDHMI-PCA, and JDHMI-Copula. The main elements of these indices are rainfall and runoff for which historical data for the period of 1986–2016 at a 12-month time scale were collected for Kol-Mehran and Bandar-Sedij basins, Iran. Results demonstrated that the pattern of composite indices reflected the comprehensive moisture status well and was not affected by a single element. Analysis indicated that although the composite, univariate, and multivariate indices followed similar patterns in various parts but the behavior of runoff was the main source of inconsistency in the study region. While PCA and CCA ignored or assigned smaller weights to runoff, the copula method used the information of runoff in constructing the copula-based index. This study investigated the mechanisms of linear and non-linear methods in assessing the drought condition. The methods had a significant effect on the construction of composite indices which can provide useful information for drought monitoring.

1. Introduction

Drought is a natural hazard defined as the reduction of precipitation compared to the long-term average that occurs in all climatic regions (Azhdari et al., 2020; Mishra and Singh 2010). Many indices have been employed for assessing the drought condition. These indices can be classified into single, multiple, and composite indices (Svoboda, 2009). Single drought indices are defined on the basis of only one variable (Waseem et al., 2015), as for instance, SPI is obtained from rainfall, SRI from runoff, and GRI from soil moisture. Multiple drought indices, such as RDI and SPEI, employ more than one variable. However, single or multiple drought indices are able to determine only one type of drought (meteorological, hydrological, agricultural or social-economic). Further, identification of drought events by various indices leads to different conclusions (Yang et al., 2018). Since different drought types may simultaneously occur in one region, it is difficult to distinguish various

drought events (Hao and Singh, 2015). At the same time, single or multiple drought events do not contain enough information to express the relationship between drought variables. To overcome this difficulty, composite indices have been suggested (Yang et al., 2018).

A composite index is considered as an aggregation of several drought indices into one index (Rajsekhar et al., 2015) such that it is capable of explaining the information contained in multivariate drought variables. The composite drought index has been obtained using different methods.

One way of constructing composite drought indices is by combining variables through a linear method, such as principal component analysis (PCA) or canonical correlation analysis (CCA) (Mortensen et al., 2018). The PCA method is able to explain the variance among a large number of variables through a few principal components (Wilks, 2011) and has been used to assess the spatial-temporal pattern of drought events (Soule, 1990; Lana et al., 2001; Bonaccorso et al., 2003; Bordi et al.,

* Corresponding author.

E-mail address: O.Bazrafshan@hormozgan.ac.ir (O. Bazrafshan).

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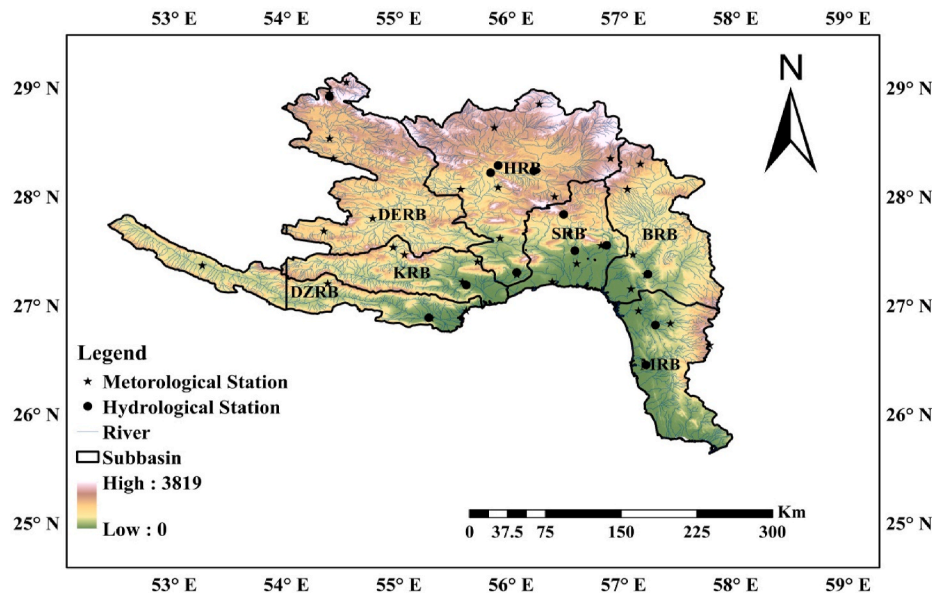


Fig. 1. Elevation and spatial distributions of meteorological and hydrological stations in the study area.

Table 1
Drought classification based on SPI (SRI).

(SPI) SRI range	Category
SPI (SRI) >2	Extremely wet
1.5<SPI (SRI) <2	Severe wet
1<SPI (SRI) <1.5	Moderately wet
0.5<SPI (SRI) <1	Mild wet
-0.5<SPI (SRI) <0.5	Normal
0 < SPI (SRI) < -0.5	Mild drought
-1< SPI (SRI) < -1.5	Moderately drought
-1.5 < SPI (SRI) < -2	Severe drought
SPI (SRI) < -2	Extremely drought

Table 2
List of copulas applied in this study.

Copulas	Bivariate Copula $C_\theta(u, v)$	Parameters θ
Elliptical copulas		
Student's t	$t_{\theta}^{-1}(u) t_{\theta}^{-1}(v) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi\sqrt{1-r^2}} \left\{ 1 + \frac{x^2 - 2rxy + y^2}{\theta(1-r^2)} \right\}^{-\frac{\theta+2}{2}} dx dy$ $t_{\theta}(x) = \int_{-\infty}^x \frac{\Gamma\left(\frac{\theta+1}{2}\right)}{\sqrt{\pi\theta}\Gamma(\theta/2)} (1+y^2/\theta)^{-\frac{\theta+1}{2}} dy$	$\theta > 2, r \in (0, 1]$
Gaussian	$\Phi_2(\Phi^{-1}(u), \Phi^{-1}(v), \rho)$	$-1 \leq \rho \leq 1$
Archimedean copulas		
Clayton	$(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$	$\theta \in [-1, 0) \cup (0, \infty)$
Frank	$-\frac{1}{\theta} \log \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1} \right]$	$\theta \in [-\infty, 0) \cup (0, \infty)$
Joe	$1 - [(1-u)^{\theta} + (1-v)^{\theta} - (1-u)^{\theta}(1-v)^{\theta}]^{1/\theta}$	$\theta \in [1, \infty)$
AMH	$\frac{[1 - \theta(1-u)(1-v)](1-\theta) + 2uv}{[1 - \theta(1-u)(1-v)]^3}$	$\theta \in [-1, 1]$

2004: Vicente-Serrano, 2006: Bordi et al., 2006 : Sigdel and Ikeda, 2010: Raziie et al., 2011).

Keyantash and Dracup (2004), Rajsekher et al. (2015) and Liu et al. (2020) applied meteorological and hydrological variables for constructing a composite index based on the PCA method.

The CCA method considers the highest correlation between two sets of different variables (Wang et al., 2012). However, no study using CCA seems to have been reported for drought events. Copula functions have

been applied to identify the non-linear relationship between variables (Shiau, 2006; Kao and Govindaraju, 2010; Bazrafshan et al., 2020a,b; Hao and AghaKouchak, 2013; Yang et al., 2018; Zhang and Singh, 2019). Salvadori and De Michele (2004) applied copula functions to investigate drought characteristics. Shiau (2006) and Farid (2006) applied copula functions for bivariate drought analysis. Wong et al. (2008) employed a trivariate copula function for monitoring drought severity, duration and magnitude. Chen et al. (2012) used copula functions to compose JDI. .

Drought severity, duration, and magnitude are most important in drought analysis (Yang et al., 2018). Multivariate analysis is therefore needed for characterizing drought. The objectives of this study thus are to: (1) assess the multivariate linear (PCA and CCA) and non-linear (copula) methods compared to univariate analysis in estimating hydro-meteorological drought indices; and (2) compute the drought return period and trivariate hydro-meteorological risk based on the “AND” & “OR” joint functions. It is assumed that the non-linear copula based index has a better performance in the watersheds with climatic and hydrological complexity than the linear indices based on the PCA and CCA methods.

2. Materials and methodology

2.1. Study area and data

The study area is part of Kol-Mehran and Bandar-Sedij watershed (52.45 °E – 57.95°E, 25.75 °N – 29 °N) in the south of Iran. The study area is about 71483.26 km², located in the extra arid region of Iran which includes parts of Hormozgan, Fars, and Bushehr provinces. The spatial and temporal pattern of annual rainfall is irregular and most of the rainfall occurs in May to August and commonly no rainfall event is reported during the rest of the year. The altitude of the area is (1886 m) above sea level and the topography generally decreases from north to south (Fig. 1). This area is located in the middle part of the basin adjacent to the Persian Gulf and the Oman Sea such that surface water and groundwater drain towards the Persian Gulf and the Oman Sea.

Long-term monthly precipitation data and streamflow (1986–2016) were collected from 35 rain gages and 12 hydrological stations from 7 sub-basins, including Darbhgale River Basin (DRB), Kahourestan River Basin (KRB), Dezhgan River Basin (DERB), Sikhoran River Basin (SRB), Hajiabad River Basin (HRB), Mazabi River Basin (MRB), and Berentin

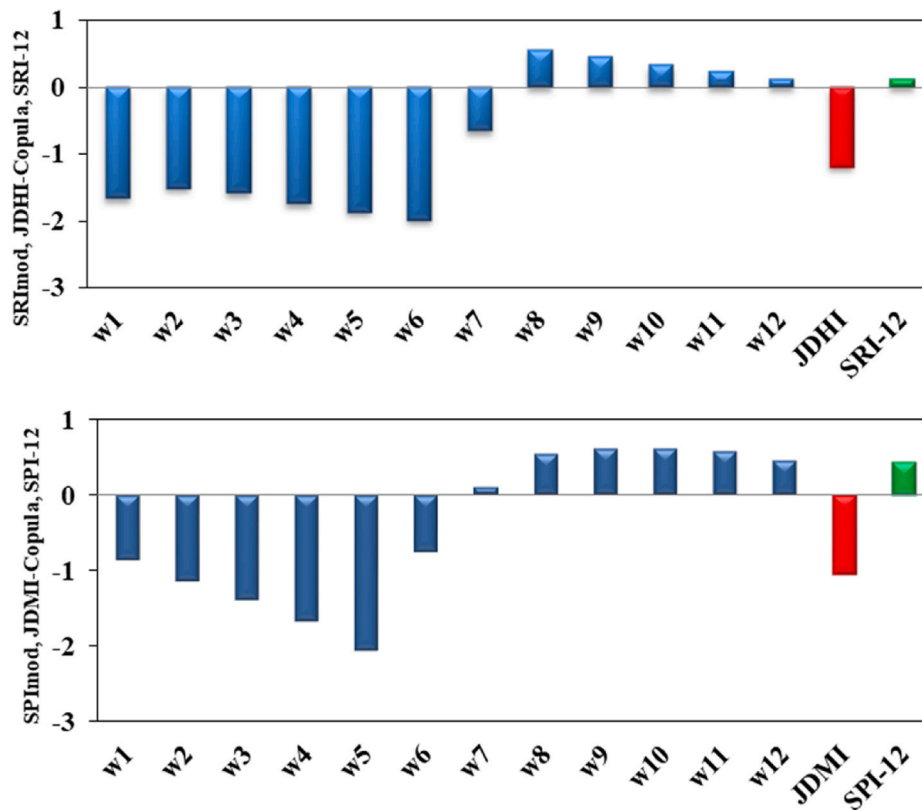


Fig. 2. Comparison of SPI, modified SPI, JDHI-Copula (top) and SRI, modified SRI, JDHI-Copula (bottom) in the BRB for October 2010.

River Basin (BRB). There are various precipitation and runoff regimes in the study area such that in the upstream of BRB, SRB and HRB precipitation is in the snow and rainfall form, while there is an occasional rainfall in the downstream area. The spatial distribution of precipitation is irregular in the downstream part. There were only three perennial rivers (in the HRB, BRB and SRB watershed) but recent droughts have caused the perennial rivers to become the ephemeral.

Bandar-Sedij and Kol-Mehran watershed has an extra-arid warm climate based on the modified De Martone method (Rahimi et al., 2014). Precipitation varies from 1231 mm at SRB, BRB and HRB mountains (north of the basin) to 100 mm at MRB (south of the basin). The average temperature is in the range of 17–28 °C. More than 70% of rainfall occurs during May to August, while there is no rainfall in the rest of the year. The average discharge is 3 m³/s with minimum of 0.01 m³/s and maximum of 12 m³/s in MRB and BRB, respectively.

These data were used to construct the JDHMI index (joint deficit hydro-meteorological index) based on linear (PCA and CCA) and non-linear (copula) methods. Drought characteristics were determined using each method and correlations between them were calculated. Finally, the trivariate return period and joint risk for the 50-year period were obtained using the IDW interpolation method.

2.2. Standardized precipitation (runoff) index

This study applied monthly SPI (McKee et al., 1993) and SRI (Shukla and Wood, 2008) to assess meteorological and hydrological droughts, respectively. Steps for computing SPI and SRI are as follows.

1. Collect precipitation and runoff historical data at specific time scales.
2. Fit probability density functions to given data.
3. Compute cumulative distribution functions (CDF) based on the probability density functions obtained in step 2.
4. Transform the CDFs to the standard normal distribution functions.

2.3. Modified standardized precipitation (runoff) index

Kao and Govindaraju (2010) modified the standardized precipitation index (SPI) for two reasons:

1. The SPI is obtained from a probability function which has the best performance based on historical data, so it is unable to separate precipitation values of wet and dry seasons.
2. Overlapping precipitation values from different time windows (w) produce an autocorrelation between series $X_w(t)$ that results in fitting a biased probability density function. This problem is more common in larger time windows due to more overlapping of larger time scale windows.

To overcome this biasedness, Kao and Govindaraju (2010) suggested that the total precipitation $X_w(t)$ of specific time window t be grouped based on the last months. In other words, for time window t , series $X_w(t)$ should be divided into 12 shorter series on the basis of 12 months of the year. Then, in the modified version of SPI (SRI), series $X_w(t)$ is changed to $X_w^m(y)$ such that m represents the month of time window t (or w) in terms of $m = 1$ (Jan), $m = 2$ (Feb), ..., $m = 12$ (Dec) and $y = 1, 2, \dots, k$ (k is the total number of years) is the year index.

Thus, samples are added yearly in each $X_w^m(y)$ set so they will no longer overlap if $w \leq 12$ and hence the autocorrelation will be reduced between samples. The key in computing the modified SPI(SRI) is fitting a suitable probability distribution to the $X_w^m(y)$ series. By fitting different distributions to each data set i.e. $u_w^m = F_{Y_w^m}(x_w^m)$, $w = 1, 2, \dots, 12$, $m = 1$ (Jan), ..., 12(Jan), the modified SPI can be obtained by transforming u_w^m to the standard normal distribution in terms of $SPI_w^m = \phi^{-1}(u_w^m)$. Table 1 indicates drought classification on the basis of these two indices.

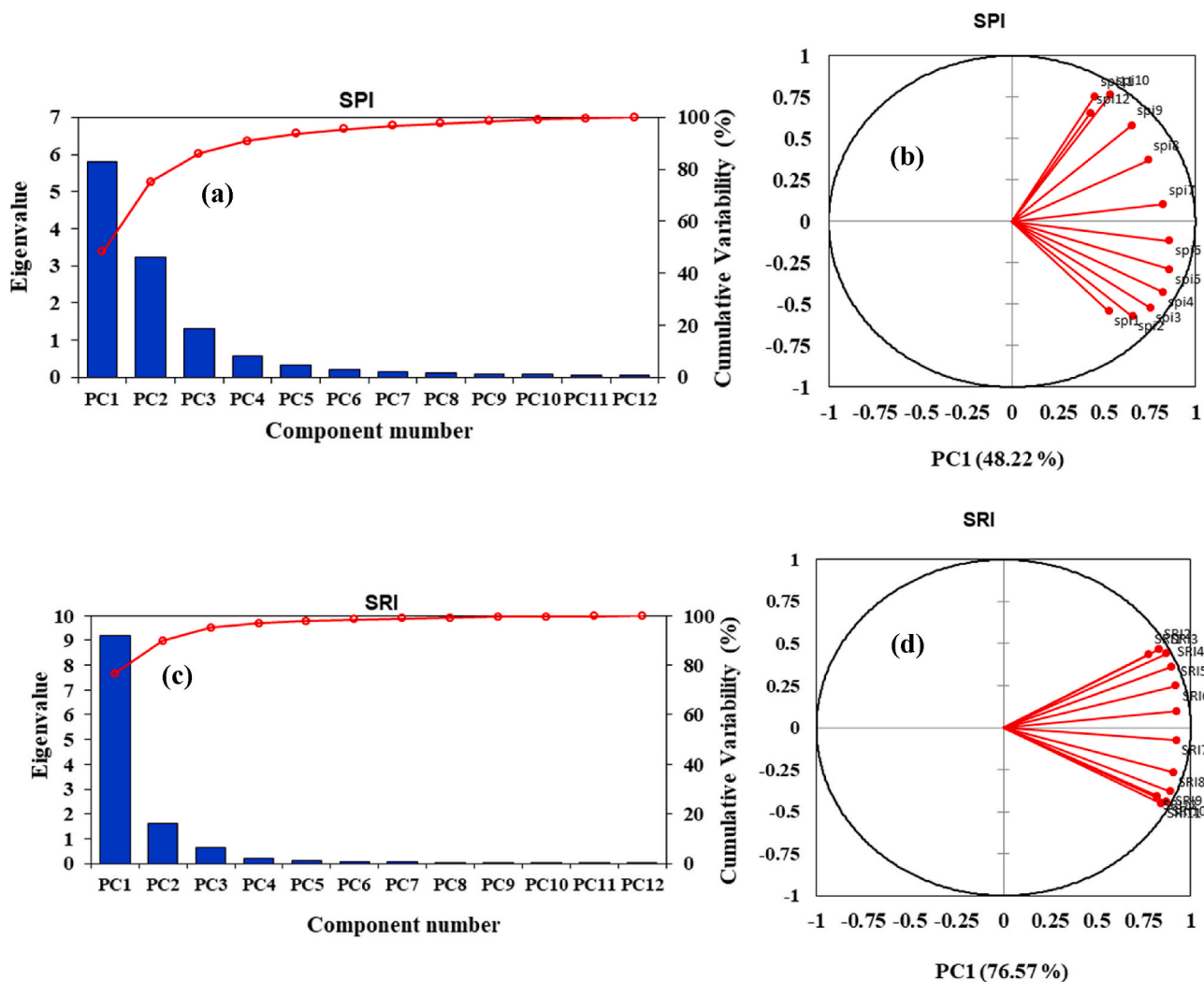


Fig. 3. Scree plot and biplot of PCA obtained from SPI (a,b) and SRI (c,d) variables in BRB subbasin.

2.4. Selecting optimized marginal distributions for meteorological and hydrological indices

To determine the most appropriate copula functions, the best univariate marginal distributions are specified, based on the K-S statistics and the parameters are estimated using the maximum likelihood estimation method (MLM). Six distributions were applied to marginal variables, including Weibull, gamma, log-normal, normal, logistic, and exponential.

2.5. Joint probability distribution based JDI

To investigate the drought condition, the 12-month time scale SPI^{mod} and SRI^{mod} were used. The copula method was applied to obtain the joint distribution of SPI^{mod}.

Theoretically copula functions are defined for any dimension, but they are restricted for high dimensional variables (d ≥ 2). In this situation, the ranked-based empirical copula can be used as an alternative to the theoretical copulas.

For multivariate random vector of sample size n and dimension d, the empirical copula C_n, is given by

$$C_n\left(\frac{k_1}{n}, \frac{k_2}{n}, \dots, \frac{k_d}{n}\right) = \frac{p}{n} \tag{1}$$

where p indicates the number of observations that meet the condition

$x_1 \leq x_{1(k_1)}, \dots, x_d \leq x_{d(k_d)}$ and $x_{1(k_1)}, \dots, x_{d(k_d)}$ is the order statistics. Particularly, the empirical distribution function K_{C_n} (Genest and Rivest, 1993) is given by

$$K_{C_n}\left(\frac{m}{n}\right) = \frac{q}{n} \tag{2}$$

where q represents the number of observations that satisfy the condition $C_n(k_1/n, \dots, k_d/n) \leq m/n$. Another representation of Eq. (6) can be denoted as:

$$K_{C_n}(t) = \frac{1}{n} \sum_{j=1}^n I(e_{jn} \leq t) \tag{3}$$

where e_{jn} is defined as

$$e_{jn} = \frac{1}{n-1} \sum_{i=1}^n I(x_{1(k)} \leq x_{1(j)}, \dots, x_{d(k)} \leq x_{d(j)}) \tag{4}$$

Here, n displays the sample size and I(A) is the indicator function that equals 1 when A is true and zero otherwise. The empirical copula C_n and its empirical cumulative distribution K_{C_n} are efficient for modeling high dimension variables with large sample sizes.

2.6. Theoretical copulas

To investigate the dependence between variables and obtain

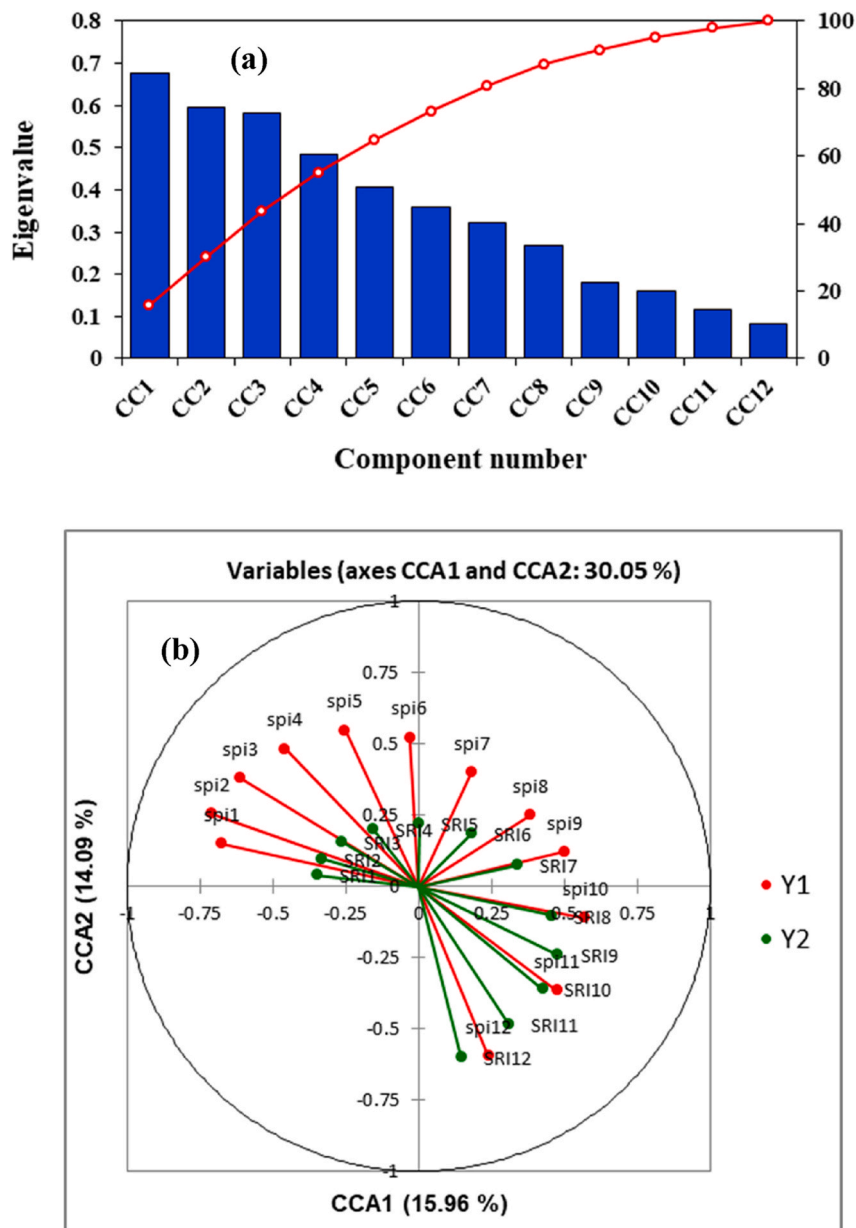


Fig. 4. Scree plot (a) and biplot (b) obtained from CCA for the BRB subbasin.

modified indices, this study used two Bayesian (Gaussian and Student-t) and four of Archimedean copulas (Clayton, Frank, Joe and AMH) (Table 2). The copula parameters were estimated using the MLE method and the best copulas were obtained using the AIC and BIC criteria and Cramer-Von Mises goodness of fit statistic (Genest et al., 2009). For further diagnostic analysis, the Chi and Kendal plots were applied (Hofert et al., 2011).

The study used multidimensional copulas to combine marginal distributions of meteorological and hydrological drought variables and construct multivariate non-linear indices (Kao and Govindaraju, 2010).

2.7. Computing drought variables and fitting marginal distributions

Drought severity, duration, and magnitude were obtained through copula, canonical correlation, and principal components analysis methods. A drought duration (D) begins when several successive SPI (SRI) values become negative or equal zero. This duration ends when SPI (SRI) values return to positive values. Drought severity is defined as the absolute value of cumulative drought in drought duration, while the

drought magnitude is the proportion of drought magnitude over drought duration (Dracup et al., 1980). Correlation coefficients (Pearson, Spearman, and Kendall tau) between these characteristics extracted from indices were obtained. The next step was to determine the probability distributions for drought characteristics using AIC, BIC and L-moment ratio diagrams.

2.8. Principal components and canonical variables

Principal components explain the structure of variance-covariance matrix of a set of multidimensional variables through a few linear combinations of the variables aiming at data reduction and interpretation (Johnson and Wichern, 2002). This study applied the principal component method to SPI-1 to SPI-12 (SRI-1 to SRI-12) to reduce the number of variables and explain the information of SPI-1 to SPI-12 (SRI-1 to SRI-12) through the first two principal components, namely, PC1 and PC2. These two PCs have the largest variances and explain a high percentage of the total population variance.

However, due to different months or places of collected data, the PCs

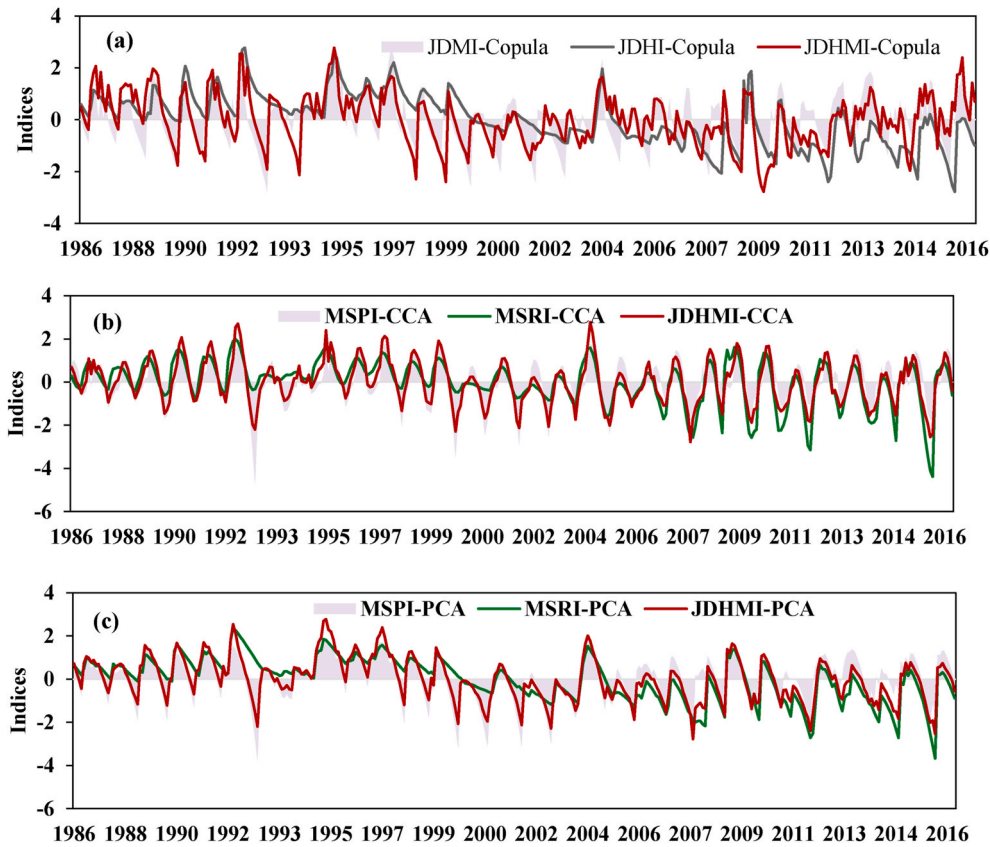


Fig. 5. Time series of nonlinear indices (copula (a)) and linear indices (CCA (b) and PCA (c)) at a 12-month time scale during 1986–2016 for BRB.

are not comparable and need to be standardized in different months of the year. The standardized PC1 was obtained as below (Bazrafshan et al., 2014):

$$Z_{1ym} = \frac{PC_{1ym} - \overline{PC_{1m}}}{SD_{1m}} \approx \frac{PC_{1ym}}{SD_{1m}} \quad (5)$$

Here, Z_{1ym} is the standardized PC1 value in the y th year and m th month, and $\overline{PC_{1m}}$, SD_{1m} , respectively, denote the mean and the standard deviation of the PC1 in the m th month. Thus, Z_{1ym} is considered as a Multivariate Standardized Precipitation Index (MSPI). Statistically, $\overline{PC_{1m}}$ is negligible and close to zero and can be ignored in the numerator of Eq. (3) (Keyantash and Dracup 2004).

The standardized approach applying Eq. (3) should be considered for CCA. In other words, CCA1 should be standardized before constructing indices.

The canonical correlation analysis considers the linear relationship between two sets of variables (Rencher, 2003). It focuses on the corre-

variables is called canonical correlation.

This study considered the canonical variables obtained from two sets of SPI (1–12) and SRI (1–12) variables. The first pair of canonical variables denoted by (U_1, V_1) such that

$$U_1 = \alpha_1(SPI1) + \alpha_2(SPI2) + \dots + \alpha_{12}(SPI12)$$

$$V_1 = \beta_1(SRI1) + \beta_2(SRI2) + \dots + \beta_{12}(SRI12)$$

and $Corr(U_1, V_1)$ is the largest correlation among the canonical pairs.

Similar to PCA, the CCA variables should be standardized due to different scales (month or place) of collected data.

2.9. Computing trivariate return periods

The joint and conditional return periods were obtained from the following equations based on the best fitted copulas:

$$T_{DSM}^{\cap} = \frac{E(L)}{1 - F_D(d) - F_S(s) - F_M(m) + F_{DS}(d, s) + F_{DM}(d, m) + F_{SM}(s, m) - F_{DSM}(d, s, m)}$$

$$= \frac{E(L)}{1 - F_D(d) - F_S(s) - F_M(m) + C_{DS}(u_d, u_s) + C_{DM}(u_d, u_m) + C_{SM}(u_s, u_m) - C_{DSM}(u_d, u_s, u_m)}$$
(6)

lation between two linear combinations of variables from two different but related sets (Johnson and Wichern, 2002). The canonical correlation approach determines the linear combinations of two variables having the largest correlation. The pairs of linear combination are called canonical variables and the largest correlation between canonical

In these equations $E(L)$ is the average of the interval between one beginning drought to the next beginning drought.

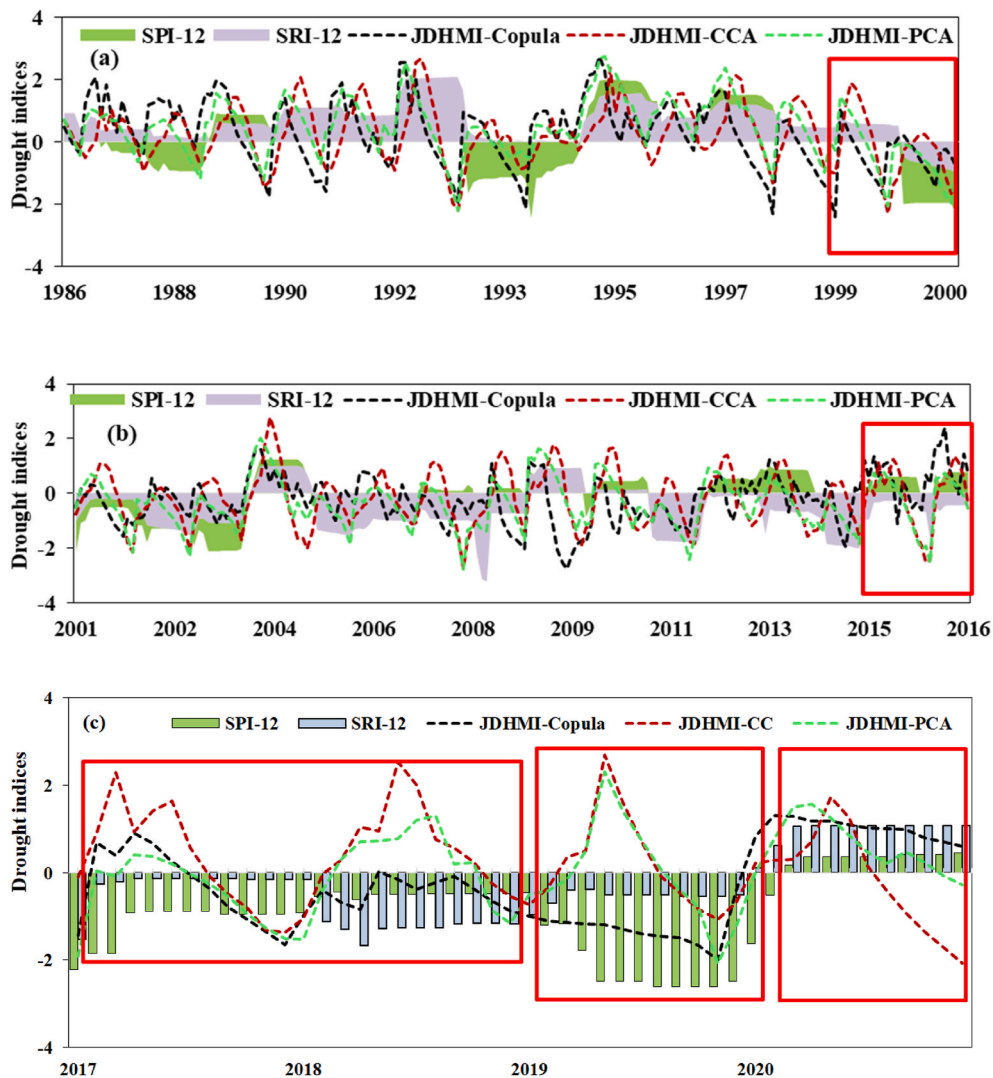


Fig. 6. Time series of 12-month SPI, SRI, JDHMI-Copula, JDHMI-CC and JDHMI-PC during (a) 1968–2000 and (b) 2001–2016 and validation period (2017–2020) (c) in BRB.

2.10. Trivariate drought risk

The joint drought risk was determined using the equation

$$R = 1 - (1 - 1/T)^N \tag{7}$$

where T denotes the trivariate return period and N represents the number of drought years.

Finally, the spatial distribution of risk and return periods were displayed using the Kriging interpolation method.

3. Results

3.1. Hydro-meteorological indices obtained from copula

The JDHMI-Copula and JDHI-Copula were obtained once the

association between variables was assessed. Fig. 2 displays the rainfall (SPI-12, SPImod and JDHMI-Copula) and runoff (SRI-12, SRImod and JDHI-Copula) indices in BRB sub-basin during October of 2010. There was a widespread drought in 2010 in the study area such that it reached a severe situation in October. As described in the methodology the JDHMI (JDHI)-Copula was obtained from the combination of SPImod1-SPImod12 (SRImod1-SRImod12) using the empirical copula function. According to this figure, the SPI-12 was 0.45 in October 2010, while the JDHMI-Copula was -1.1 in the same time.

Interpreting drought in such situations is difficult, because most indices are not able to determine the drought time. But the JDHMI-Copula provides more accurate interpretation because it describes drought situation, based on the dependence structure between the last 12-month precipitation. On the other hand, during the study period (October 2010), while there has been normal rainfall during the last 6 months, but

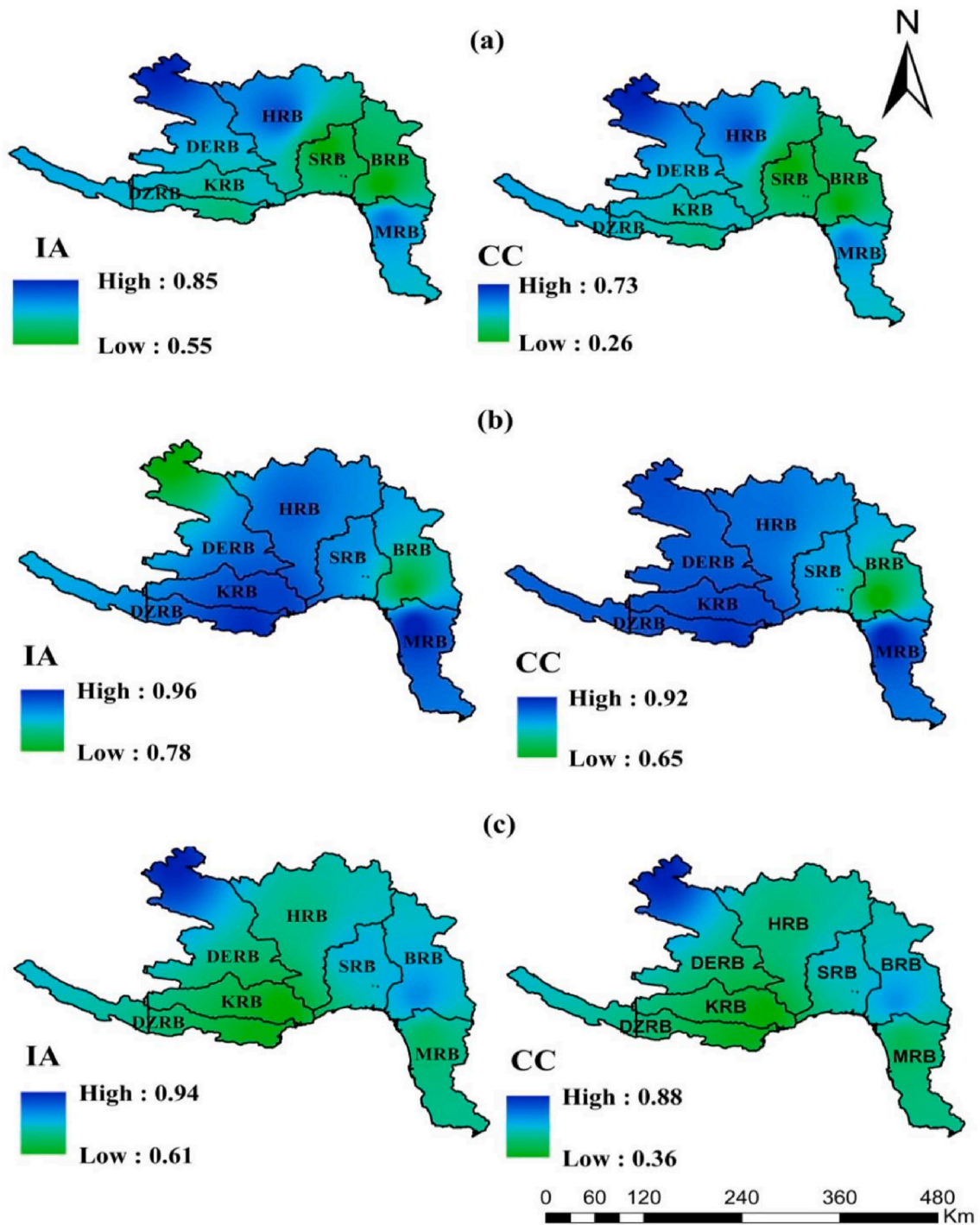


Fig. 7. Spatial distribution of the correlation coefficient (CC) and index of agreement (IA) between JDHMI-Copula and JDHMI-CC (a); JDHMI-Copula and JDHMI-PC (b); JDHMI-CC and JDHMI-PC (c).

the JDHI-Copula indicated a very severe drought situation (negative value) due to a severe deficit rainfall in October 2010. The hydrological drought was similar to the meteorological drought such that the SRI-12 and the JDHI-Copula, respectively, were 0.14 and -1.19 in October of 2010.

3.2. Hydro-meteorological index obtained from PCA

Principal component analysis produces p principal components through a few linear combinations of p variables (for instance in this research, 12 PCs from 12 SPI_{mod} variable and 12 PCs from 12 SR_{mod} variable). These components are uncorrelated and often the k first few components explain much information of initial p measurements. So the

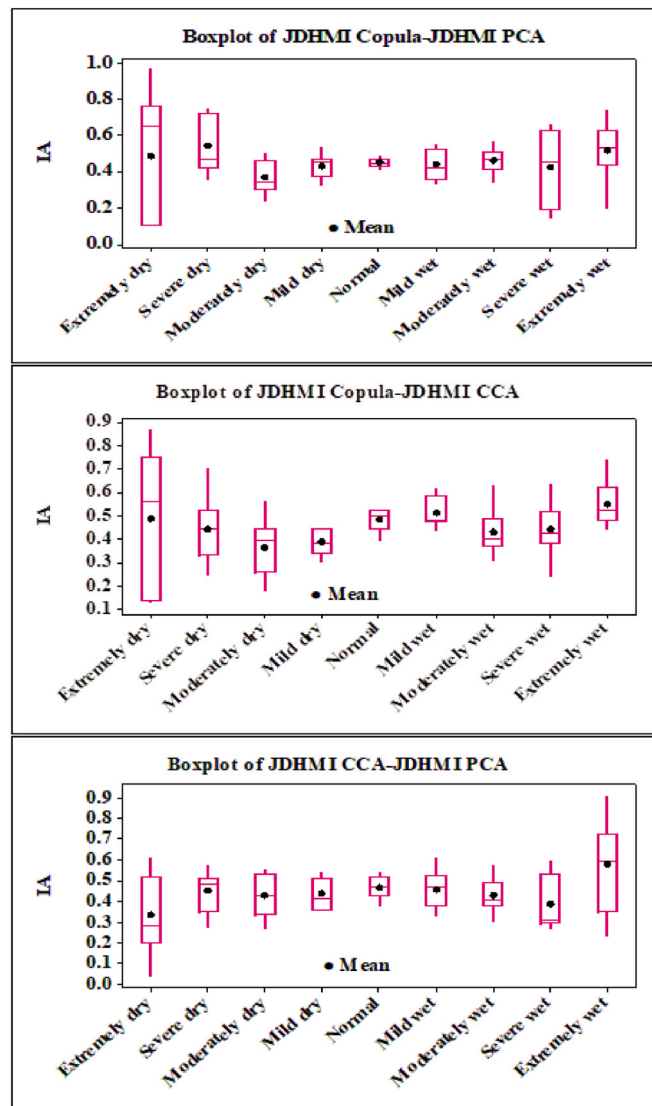


Fig. 8. Boxplot of IA values for nine different dry/wet categories between JDHMI- Copula and JDHMI-CC (a); JDHMI and JDHMI-PC; JDHMI-CC and JDHMI-PC.

k principal components (usually first or two first PCs) can be replaced with initial p variables.

Fig. 3 represents the scree plot and biplot of principal components obtained from 12 SPI (SRI) variables at the BRB station. As the screen plots indicate, PC1 explains high percentage of variability in SPI (48.22%) and SRI (76.57%) variables and the first two principal components explain 73% of SPI and 89% of SRI variables. The variability explained by the third to the end principal component is not noticeable and can be ignored. Similar results were obtained in the other sub-basins. Further, biplots indicated 12 SPI and 12 SRI were in similar direction with PC1 which meant PC1 was a suitable representative of these variables.

3.3. Hydro-meteorological indices obtained from CCA

canonical correlation analysis produces a linear combination from two sets of variables based on the association between these sets. In other words, CCA considers correlation between linear combinations of variables in one set and linear combinations of variables in another set. These linear combinations are such that the first pair of CCA variables have the largest correlation and the second pairs have the second largest correlation and so on. In our study case, we have 12 pairs of CCA variables which was obtained from 24 variables (12 SPI and 12 SRI).

The scree plot and biplot of CCA variables are indicated in Fig. 4. As the scree plot shows (Fig. 4a), the first pair of CCA explained 15.96% of the information in SPI and SRI variables simultaneously, while this

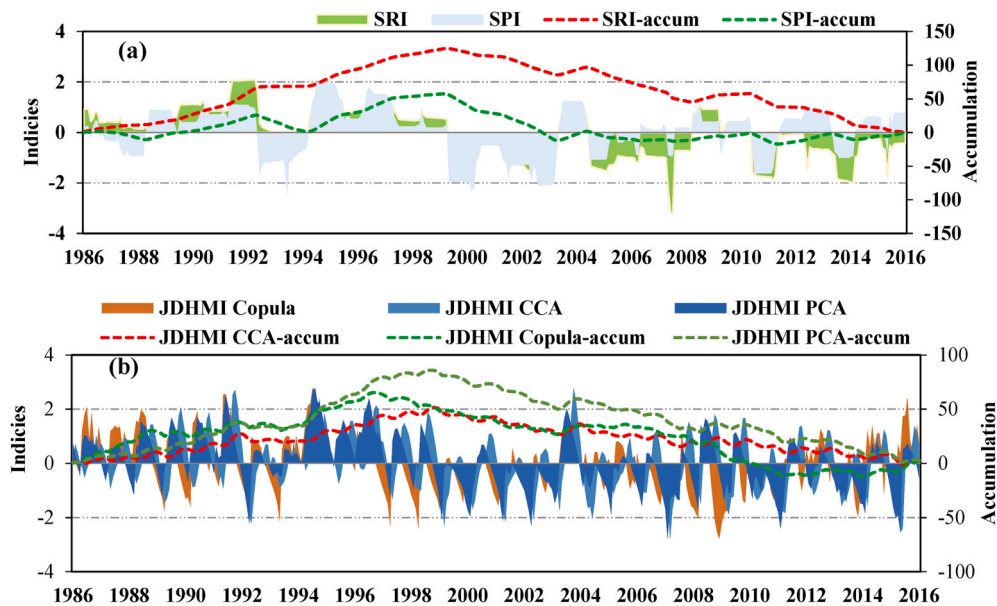


Fig. 9. Time series and cumulative values of (a) SPI and SRI at a 12-month time scale and (b) anomalies of six hydrological variables for the Berentin station.

amount was 36.92% in PCA variables. In this regard, the second pair explained 14.08% and the third pair 13.73% of the variability in the SPI and SRI variables.

For further analysis, the biplot of CCA1 and CCA2 is given in Fig. 4b. The biplot indicates that SPI8, SPI9, SPI10 and SPI11 had the largest positive share and SPI1, SPI2 and SPI3 had the largest negative share with the CCA1 variable. In contrast, SRI7, SRI8 and SRI9 had the largest positive and SRI1, SRI2 and SRI3 had the largest negative share with the CCA1 variables. Generally, SPI10 and SRI8 had the largest positive share with the CCA1 variable. For the pair of CCA2, SPI6 and the SRI4 had the largest positive share and SPI12 and the SRI12 had the largest negative share with the CCA2 variables.

3.4. Comparison of multivariate indices with linear and nonlinear methods

To evaluate the performance of linear and non-linear drought assessment, meteorological and hydrological multivariate indices were compared with hydro-meteorological composite index which was obtained using the copula, PCA and CCA methods. Fig. 5a displays the multivariate indices obtained from the copula functions. As is seen, the JDHMI-copula changed similarly to the JDHI and JDMI indices. Fig. 5b and c obtained from the CCA and PCA methods represented the same trend. It can thus be concluded that all of the three indices represented the historical drought well. Evaluation of these three indices indicated that the hydro-meteorological index obtained from both linear and non-linear methods reflected the simultaneous behavior of hydrological and meteorological droughts well but generally the linear approaches had less variability than did the non-linear method.

In addition, five commonly used standardized drought indices were

selected for further assessment. Specifically, SPI can represent the climatic moisture anomaly caused by precipitation deficit and the runoff-based SRI is a hydrological drought index. As an example, Fig. 6 presents the time series of five drought indices at a 12-month time scale for the BRB station. From Fig. 6a and b, it can be seen that the variations of JDHMI-CC, JDHMI-PC and JDHMI-Copula basically fell within the ranges of two reference indices, implying the integrated features of these two composite indices in drought characterization. To have a better understanding on the combination mechanisms of composite indices, two dry spells were amplified for more detailed analysis.

As shown in Fig. 6a, a similar evolution pattern was observed between composite indices during 1986–2000, especially for the marked period (1999–2000), when SRI presented persistent and enhanced dry status, both composite indices were little influenced by this anomaly signal but indicated weakened drought intensity as the other three standardized drought indices. This suggests composite drought indices would not be easily influenced by the behavior of a single variable. Fig. 6b revealed another phenomenon where some disagreements were found between non-linear and linear indices during 2015–2016.

Before starting this period, all indices represented a wet period but runoff decreased at once. Due to linear structure, both linear indices were affected by a severe change in SRI and represented a very severe drought situation, while the JDHM-Copula was not under this effect.

This different behavior of linear and non-linear indices can also be seen from the validation data (2017–2020) at the BRB station (Fig. 6c). While the copula index was very close to the observed data, the linear indices provided an over- or under-estimation for drought situation during this period. For instance, linear indices indicated a persistent drought situation during the 2017–2019. In other words, linear indices contained more oscillation range than did the copula index. Further, as

Table 3
Descriptive statistics of drought characteristics obtained from JDHMI-Copula, JDHMI-CC and JDHMI-PC in the sub basins of the study region.

JDHMI-Copula	DZRB	KRB	DERB	HRB	SRB	BRB	MRB
Number of drought	111	111	111	111	111	111	111
Maximum drought severity	13.40	17.31	31.86	32.72	29.57	17.56	35.24
Maximum drought duration	15.00	18.00	32.00	34.00	27.00	18.00	33.00
Maximum drought magnitude	1.54	1.73	1.28	1.30	1.34	1.76	1.41
Average drought severity	5.30	5.79	6.45	6.63	6.33	5.80	6.73
Average drought duration	6.50	6.81	7.69	7.81	7.23	6.81	7.85
Average drought magnitude	0.74	0.82	0.68	0.72	0.72	0.82	0.69
Minimum drought severity	0.37	0.32	0.51	0.63	0.74	0.28	0.10
Minimum drought duration	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Minimum drought magnitude	0.18	0.16	0.20	0.21	0.25	0.14	0.05
JDHMI-CC	DZRB	KRB	DERB	HRB	SRB	BRB	MRB
Number of drought	111	111	111	111	111	111	111
Maximum drought severity	13.90	14.75	12.59	10.49	14.23	10.75	10.76
Maximum drought duration	9.00	10.00	19.00	9.00	18.00	10.00	12.00
Maximum drought magnitude	1.99	1.64	1.56	1.75	1.67	1.46	1.56
Average drought severity	4.90	4.73	4.91	3.39	4.83	4.73	4.55
Average drought duration	6.07	5.90	6.17	4.05	6.00	5.87	5.55
Average drought magnitude	0.77	0.69	0.75	0.78	0.75	0.74	0.79
Minimum drought severity	0.90	0.12	0.60	0.17	0.17	0.29	0.42
Minimum drought duration	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Minimum drought magnitude	0.18	0.06	0.17	0.09	0.08	0.15	0.21
JDHMI-PC	DZRB	KRB	DERB	HRB	SRB	BRB	MRB
Number of drought	111	111	111	111	111	111	111
Maximum drought severity	17.37	17.98	30.80	34.50	32.64	23.35	57.56
Maximum drought duration	21.00	24.00	31.00	41.00	27.00	29.00	56.00
Maximum drought magnitude	1.29	1.60	1.23	1.35	1.21	1.43	1.20

Table 3 (continued)

JDHMI-Copula	DZRB	KRB	DERB	HRB	SRB	BRB	MRB
Average drought severity	7.10	6.15	7.08	7.11	6.41	6.74	6.16
Average drought duration	8.75	7.52	8.80	8.80	7.95	8.38	7.48
Average drought magnitude	0.73	0.74	0.69	0.64	0.69	0.71	0.62
Minimum drought severity	0.24	0.34	0.64	0.26	0.37	0.46	0.50
Minimum drought duration	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Minimum drought magnitude	0.12	0.17	0.16	0.13	0.12	0.23	0.25

Dependence structure and marginal distributions of drought variables.

shown, from the beginning of 2020, SPI and SRI entered a wet period. While the copula index estimated the situation well, the linear indices provided an under-estimation for this wet situation.

The above analysis suggested that drought characterization from a multivariate perspective tended to provide a comprehensive reflection of moisture status, which to some extent could avoid overestimating or underestimating moisture conditions when limited drought information was considered. Meanwhile, as two different combination approaches, some disagreements were apparent between JDHMI-Copula with JDHMI-PC and JDHMI-CC.

3.5. Correlation and concordance index between multivariate linear and non-linear indices

To assess the correlation between linear and non-linear hydro-meteorological indices, the CC and IA evaluation criteria were applied. The CC coefficient was used to measure linearity between two time series, while IA described the degree of concordance between drought indices due to drought classes. As Fig. 7 shows, large values of CC and IA indicated close agreement between multivariate indices. JDHMI-CC and JDHMI-PCA had the highest degree of agreement, while the lowest degree of agreement belonged to the JDHMI-Copula and JDHMI-CCA indices. Generally, the agreement indices had larger values than did the correlation coefficient. Since, in linear methods (CCA and PCA), a pair of linear combination was used as the representative of original data which contained only a percentage of information of the original data. For instance, in this study the first pair of both CCA and PCA contained less than 50% of the information of original data. So they have a lower correlation between linear methods than the copula method which used original data.

Generally, lower correlation was observed between linear and nonlinear methods in BRB, SRB, and HRB than the other sub-basins. This is due to different rainfall-runoff regimes in these watersheds as there is snow in winter and snowmelt in spring.

This indicates that linear and nonlinear methods have low similarity in estimating hydro-meteorological indices in areas with complex rainfall and runoff behavior.

Fig. 8 displays the degree of agreement between drought classes (9 dry/wet classes) based on hydro-meteorological composite indices on a 12-month time scale. Further investigation indicated that there existed a W-shape pattern between JDHMI-Copula and JDHMI-PCA and JDHMI-CCA where values for normal and extremely dry/wet levels were generally high (with the average values ranging between 0.7 and 0.9) and lower values were intensively distributed in the mild and moderate categories (between 0.33 and 0.37) which can be considered as the main source of inconsistency. The largest and the lowest agreement was

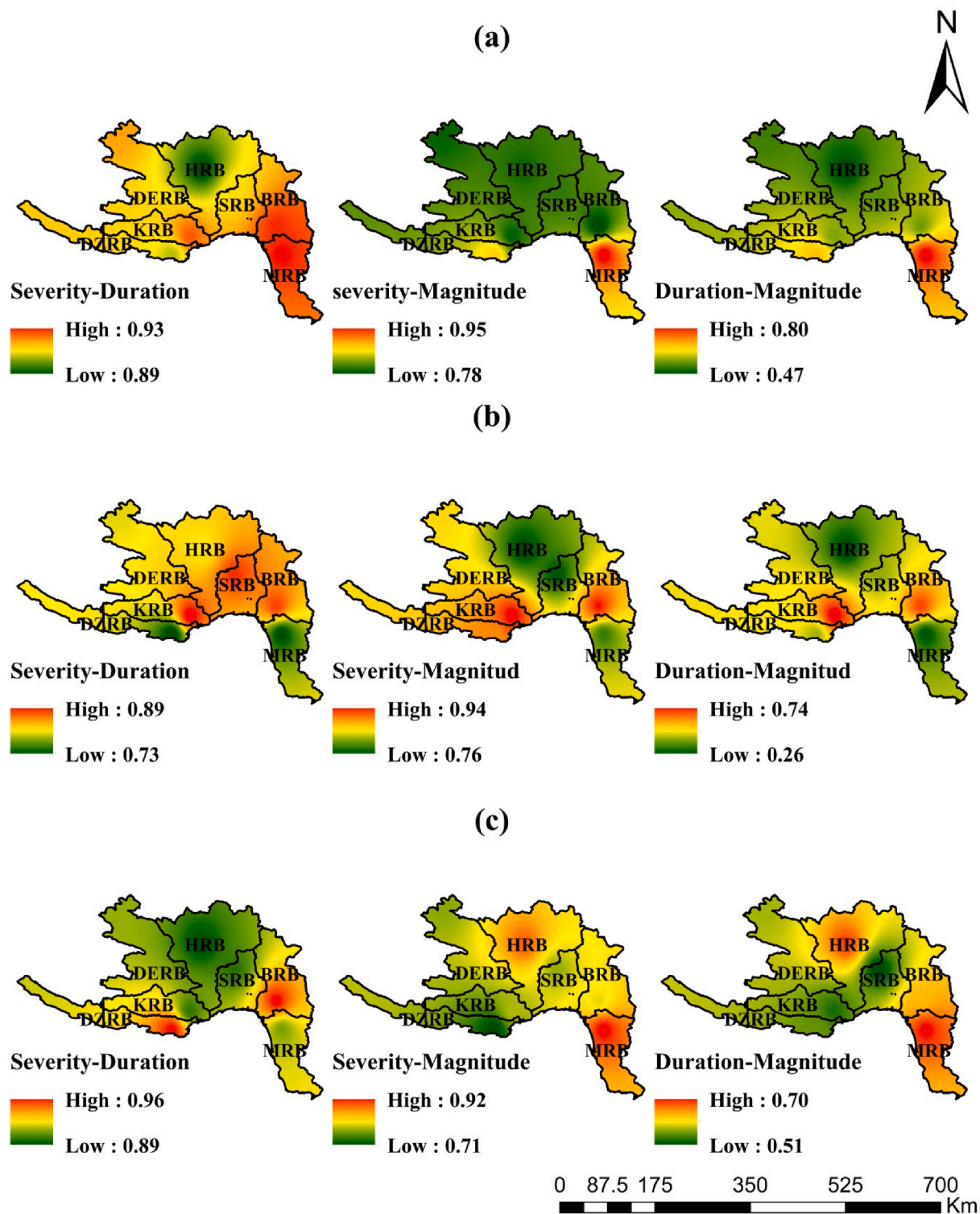


Fig. 10. Spatial distribution of pairwise correlations between drought characteristics in the whole basin (a) JDHMI-Copula, (b) JDHMI_CCA, and (c) JDHMI_PCA using rho-Spearman.

obtained, respectively, for extremely wet and extremely dry classes. According to Liu et al. (2020), the W-shaped pattern in estimating drought classes can be due to three factor, including 1) mathematical structure of linear and non-linear methods, 2) nature of data such as sequence of drought and wet period in the study area, and 3) a combination of two previous reasons.

3.6. Role of hydrological and meteorological variables in the formation of a composite drought index

The aim was to investigate the mechanism of PCA, CCA and Copula in combining hydrological and meteorological drought variables, and then to determine the reasons of similarity between hydro-

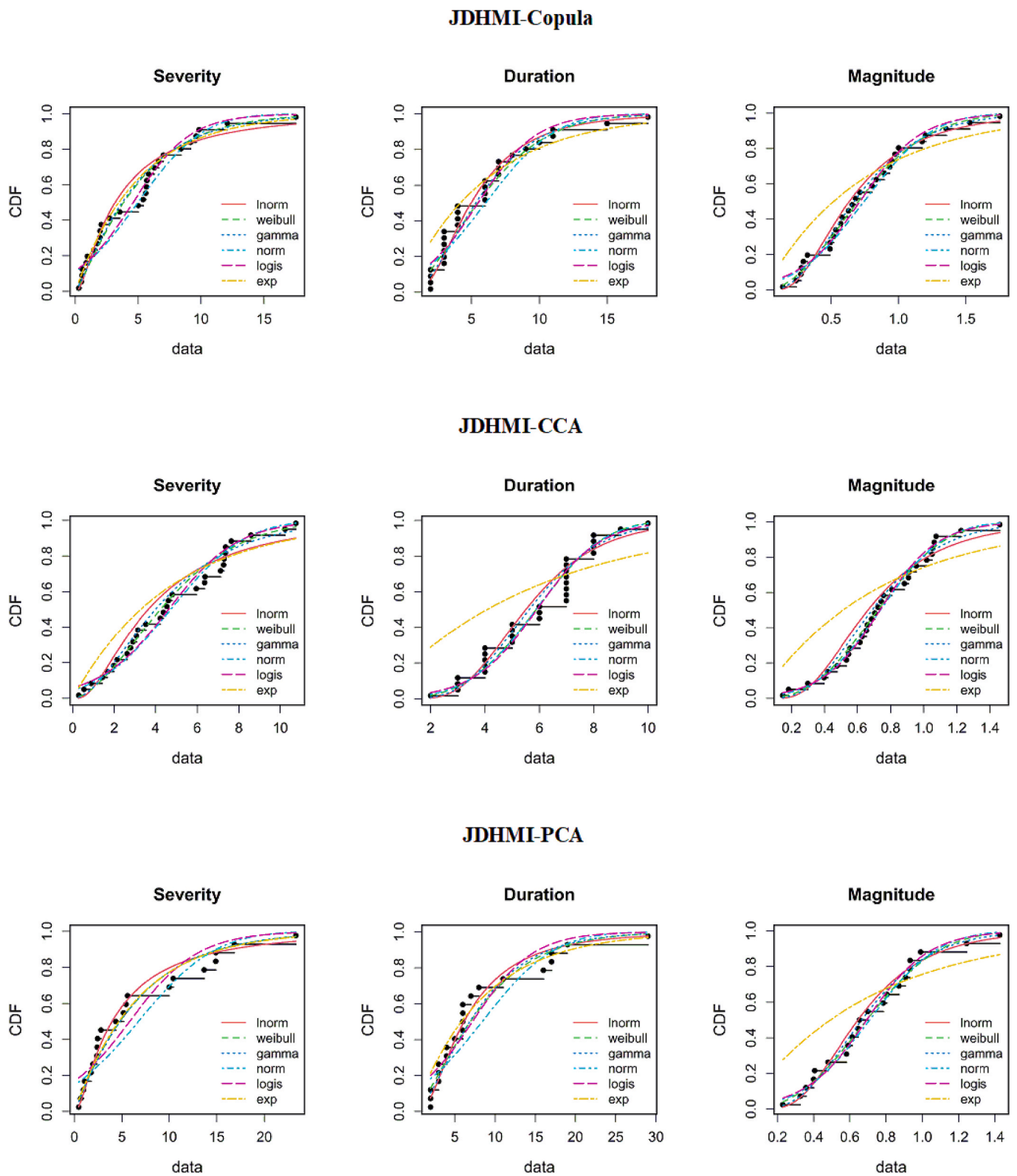


Fig. 11. CDF plot of the fitted distributions versus empirical distributions of drought variables for JDHMI-Copula (a); JDHMI-CCA(b) and JDHMI-PCA (c) in BRB.

meteorological composite indices. Fig. 9 (a) shows that the SPI and SRI series and their cumulative series followed increasing trends during 1986–1999 (wet period) and decreased after 2000. This figure indicates the standardized runoff was inconsistent in some years. As Fig. 9b indicates, the patterns of variation of JDHMI-Copula, JDHMI-CCA and

JDHMI-PCA series and their cumulative series were similar to those of the univariate indices such that they followed increasing and decreasing patterns, respectively, during 1986–1999 and 2000–2016. Thus, the three composite indices behaved similarly to the hydrological and meteorological univariate indices.

Table 4
Goodness of fit statistics for drought severity, duration and magnitude obtained from composite indices.

JDHMI-Copula					
Variables	Sub-basin	Copula Function	Sn	Parameter	P-value
S-D-M	DZRB	Clayton	0.027	5.28	0.72
	KRB	Clayton	0.037	4.16	0.46
	DERB	Frank	0.04	10.09	0.24
	HRB	Frank	0.062	9.31	0.06
	SRB	Joe	0.029	5.27	0.55
	BRB	Clayton	0.037	4.13	0.43
	MRB	Frank	0.03	18.54	0.38
JDHMI-CCA					
S-D-M	DZRB	Frank	0.04	8.36	0.24
	KRB	Clayton	0.03	6.14	0.21
	DERB	Frank	0.04	8.62	0.33
	HRB	Clayton	0.05	2.47	0.11
	SRB	Frank	0.04	8.16	0.35
	BRB	Clayton	0.02	5.30	0.82
	MRB	Clayton	0.02	2.19	0.83
JDHMI-PCA					
S-D-M	DZRB	Clayton	0.01	6.17	0.99
	KRB	Clayton	0.04	3.70	0.43
	DERB	Frank	0.04	9.85	0.49
	HRB	Frank	0.04	10.76	0.55
	SRB	Frank	0.037	8.75	0.62
	BRB	Clayton	0.02	6.11	0.93
	MRB	Joe	0.04	5.73	0.17

3.7. Drought characteristics based on composite indices

Drought severity, magnitude, and duration were extracted from JDHMI-Copula, JDHMI-CCA, JDHMI-PCA for all sub basins. Table 3 shows the descriptive statistics of these indices. Particularly, 111 drought events were recorded in all sub basins based on the three indices.

The maximum drought duration from JDHMI-Copula was 34 months which was recorded in HRB with severity and magnitude equal to 32.72 and 1.3, respectively. The ranges of drought characteristics were 2–34 months for duration, 1–35.24 for severity, and 0.05–1.76 for magnitude.

The JDHMI-CCA index estimated lower values of drought characteristics than did the other two composite indices. This index estimated the maximum drought duration in DERB equal to 19 months with severity and magnitude equal to 13 and 1.56, respectively. The ranges of drought characteristics were 9–10 months for duration, 10.49–14.75 for severity, and 1.99–4.46 for magnitude. Further, the largest values of characteristics were estimated, respectively, by the JDHMI-Copula, JDHMI-PCA and JDHMI-CCA methods.

The maximum drought duration based on the JDHMI-PCA was 56 months which had been recorded in MRB with severity and magnitude equal to 57.56 and 1.2, respectively. From this index, the ranges of duration, severity, and magnitude, respectively, were 21–56 months, 17.37–57.56, and 1.20–1.60.

It can be concluded that the linear and non-linear methods had performed differently in estimating drought situations. According to the results, PCA and CCA provided an over-estimation of the drought situation. This was due to the structure of linear combinations that were affected by high fluctuations of a few variables, while the JDHMI-Copula

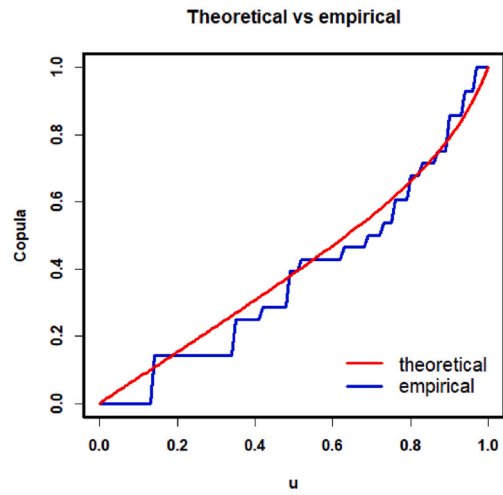
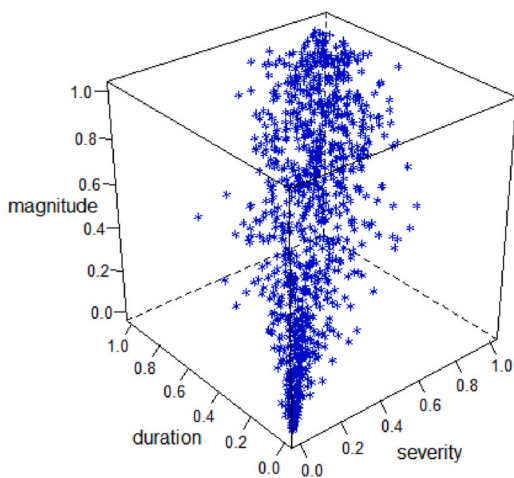
was not influenced by the anomaly of one or a few variables. Generally, linear methods, such as PCA, are greatly influenced by the magnitude of variables. In other words, variables with larger numerical values, have more effect and role in calculating the PCA or CCA values, although they are not theoretically important variables (Johnson and Wichern, 2002; Cheraghalizade et al., 2018). But the copula instead considers the probability of variables and is not affected by the magnitude of variables.

The Pearson, Spearman, and Kendall-tau correlation coefficients between drought characteristics (SDM) indicated that the Spearman correlation had the best performance in determining the dependence structure between drought characteristics (SDM) and was used to obtain the spatial distribution of pairwise correlations (Fig. 10).

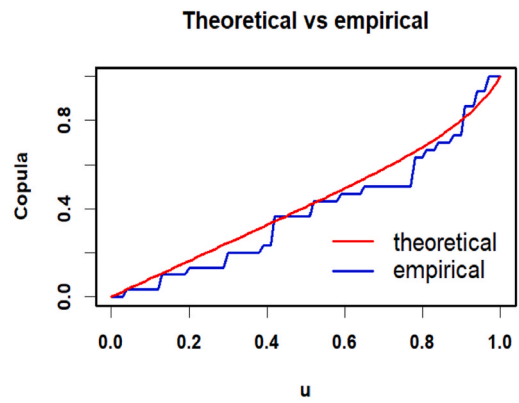
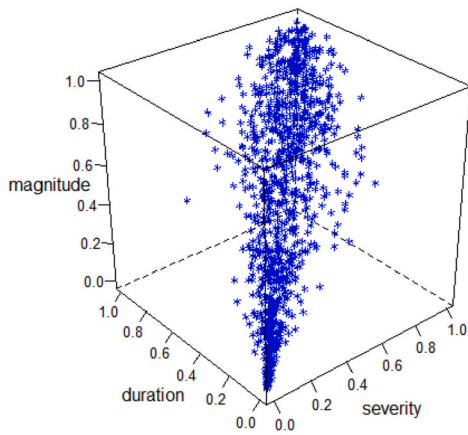
The JDHMI-Copula demonstrated a larger correlation between S-M and S-D (Fig. 10a). The smallest correlation was observed in the north part of the study region, while the largest correlation was obtained in the east and south of the region. This pattern was also followed by other composite indices.

Once the correlation between characteristics was determined, the marginal distributions of drought characteristics were obtained in each of the sub-basins. We used log-normal, gamma, Weibull, normal, log-logistic and exponential distributions to obtain the best fitted model for each characteristic. The log-normal distribution had the best performance for severity and duration for all three methods, while the Weibull distribution was the best for fitting the drought magnitude. Fig. 11 displays the goodness of fit at the BRB station.

IDHMI-Copula



IDHMI-CCA



IDHMI-PCA

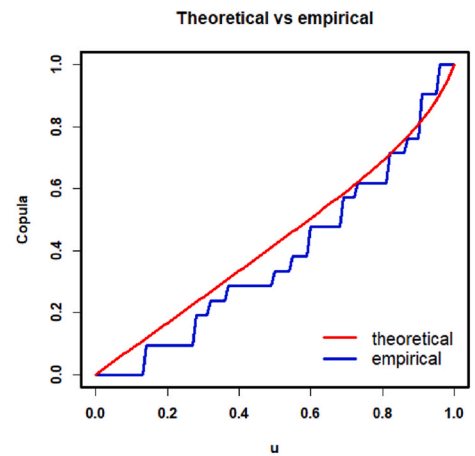
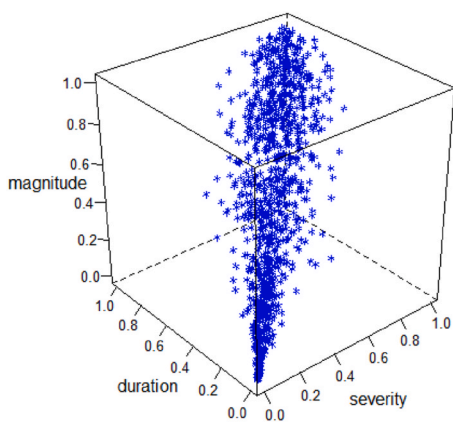


Fig. 12. Goodness of fit plots for assessing Clayton copula fitted to composite characteristics.

Table 5
Return periods of univariate and trivariate of composite indices.

Return period		HRB	KRB	BRB	DZRB	MRB	SRB	DERB
JDHMI-Copula	S	64.31	63.13	61.80	29.28	21.72	68.75	81.61
	D	52.00	51.95	77.01	33.08	21.66	86.74	72.81
	M	1.33	1.74	1.52	1.75	1.48	2.36	1.39
	T_{SMD}^{\square}	93.15	49.05	151.58	59.58	29.57	827.77	71.18
JDHMI-CCA	Risk	0.42	0.64	0.28	0.57	0.82	0.06	0.51
	S	11.18	18.45	11.90	12.96	10.74	18.90	14.43
	D	10.23	10.95	9.82	8.86	10.33	16.88	12.71
	M	1.65	1.62	1.38	1.69	1.54	1.56	1.59
JDHMI-PCA	T_{SMD}^{\square}	47.45	86.02	78.82	39.29	97.62	84.03	42.46
	Risk	0.66	0.44	0.47	0.72	0.40	0.45	0.70
	S	48.93	24.00	26.43	27.74	27.75	25.08	41.78
	D	34.87	21.99	30.57	24.93	24.69	29.21	33.68
	M	1.42	1.51	1.46	1.35	1.41	1.39	1.35
	T_{SMD}^{\square}	105.64	78.60	109.02	125.71	92.12	67.94	111.90
	Risk	0.38	0.47	0.37	0.33	0.42	0.49	0.36

3.8. Fitting copula function for characteristics obtained from composite indices

The Archimedean and elliptical copulas were applied for trivariate frequency analysis of drought characteristics. The inversion of Spearman's correlation rho (irho) method was used to estimate the parameters and the best fitted copula was identified using S_n statistics. Results demonstrated that the Clayton, Frank, and Joe copulas were identified as the best fitted copulas at most of the stations (Table 4). Fig. 12 illustrates the goodness of fit assessing the plot of Clayton copula for three composite indices at the BRB station.

3.9. Return period and trivariate risk analysis in the sub-basin

The joint return period of AND case at 0.95 probability was computed using equation (4). Equation (5) was applied to estimate the trivariate drought risk for the basin and results are illustrated in Table 5 and Fig. 13. For instance, considering 0.95 probability of the AND case at the BRB station, the trivariate return period was 151.58 using JDHMI-Copula with the $\{S \leq 61.8, D \leq 77.01, M \leq 1.52\}$ threshold. Under a similar condition, the trivariate return periods were 78.82 and 109, respectively, using JDHMI-CCA with the $\{S \leq 11.9, D \leq 9.82, M \leq 1.38\}$ threshold and JDHMI-PCA with the $\{S \leq 26.43, D \leq 30.57, M \leq 1.46\}$ threshold.

Thus, for a particular probability, the JDHMI-Copula, JDHMI-PCA and JDHMI-CCA indices displayed larger thresholds and hence larger return periods.

The larger return periods result in lower risk and lower probability of occurrence. The spatial variation in drought risks was investigated at the sub-basin level regarding the low (<0.4), moderate (0.4–0.7), and high (>0.7) categorical classes.

Therefore, based on copula method, areas with complex hydrological and climatic regimes such as HRB, BRB, SRB are classified in low risk category and other sub-basins with ephemeral rivers and almost homogeneous climatic and hydrological conditions were categorized into medium and high risk classes. This means that the risk and the return period were separable in a certain range. But it can not be observed as a regular variation based on linear methods due to the climatic and hydrological complexity.

4. Conclusion

This study first constructed linear (PCA and CCA) and non-linear (Copula) multivariate hydro-meteorological indices from SPI and SRI and then investigated their ability in drought monitoring.

Comparing univariate indices (SPI and SRI), hydrological and meteorological copula indices (JDHI and JDMI), linear PCA and CCA indices (MSPI, MSRI) and hydro-meteorological composite indices (JDGMI-Copula, JDHMI-CCA, JDHMI-PCA) indicated that they generally followed similar patterns in the study period.

Analysis of drought characteristics indicated that the maximum values of drought severity, duration, and magnitude were, respectively, extracted from the JDHMI-Copula, JDHMI-PCA and JDHMI-CCA indices. In most cases, the composite indices obtained from linear CCA and PCA methods underestimated the drought condition.

In constructing drought composite indices, the information displayed by runoff is discarded by linear methods while it is included by the copula method. The specific behavior of runoff variable was the main reason for inconsistency. It seems the most important factor for runoff incompatibility in perennial rivers in BRB, HRB and SRB is the upstream snow cover.

Thus, the JDHMI-Copula was superior to JDHMI-CCA and JDHMI-PCA in multivariate drought analysis. While the JDHMI-PCA and JDHMI-CCA methods supposed the marginal characteristics had linear behavior over the area, the JDHMI-Copula considered the nonlinear behavior of candidate variables.

Generally, the linear method uses a pair of linear combinations as the representative of the SPI and SRI data sets. These linear combinations often contain a percentage of information of the original data sets. Thus, the indices obtained from linear methods contain more uncertainties than the index obtained from the copula method, since the copula approach applies the original data and includes the observation in the analysis.

This study assumes that linear methods evaluate drought conditions well in the areas with less climatic and hydrological complexity, while nonlinear methods has better performance in more complex areas. In this research, the non-linear model was preferred due to the climatic and hydrological diversity in BRB, HRB and SRB sub-basins.

This study provides a better understanding of the mechanisms of combined methods for constructing composite drought indices and helps develop drought monitoring.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

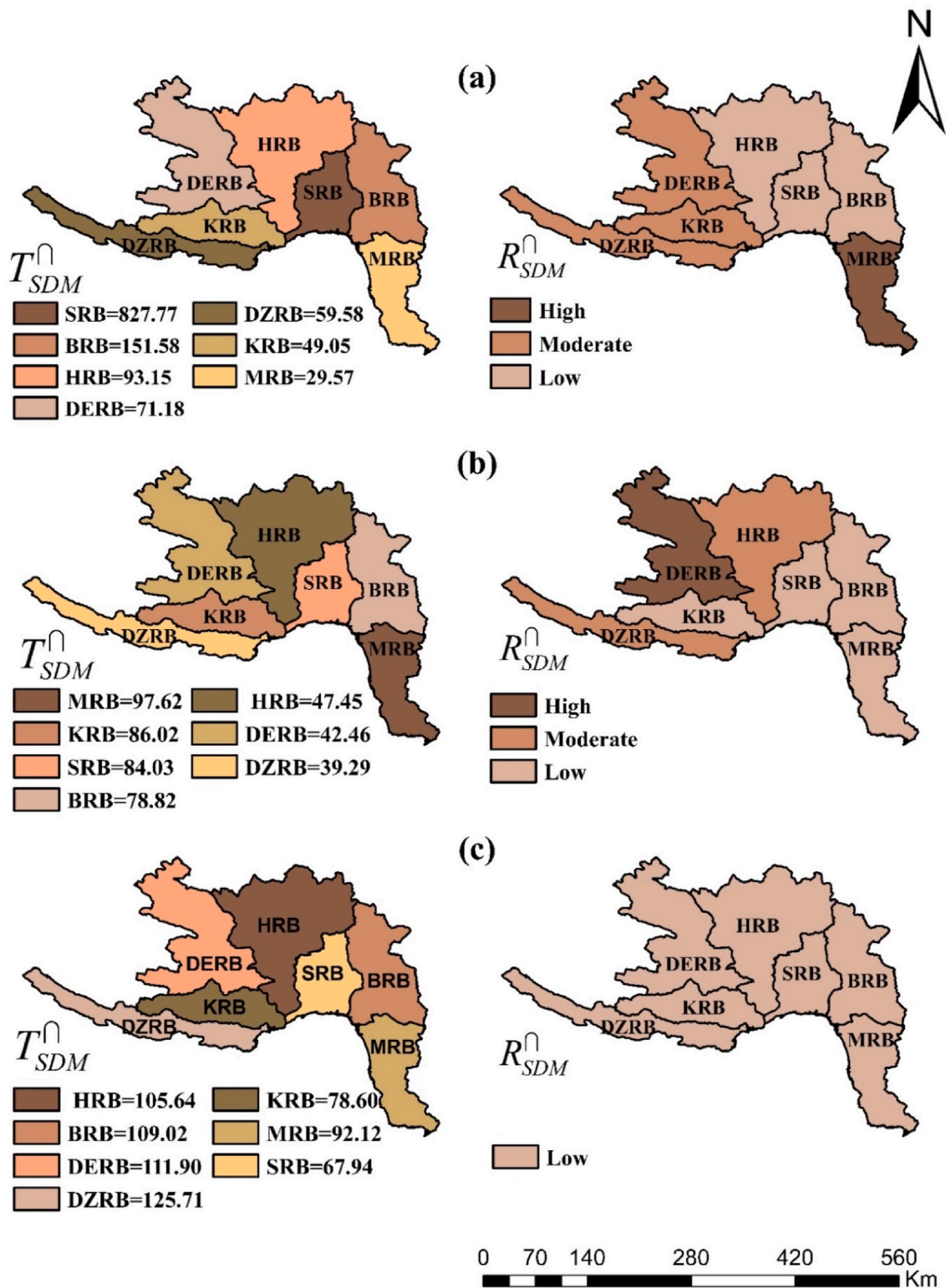


Fig. 13. Spatial analysis of trivariate return periods and risk analysis (a) JDHMI-Copula (b) JDHMI-CCA (c) JDHMI-PCA.

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