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ORIGINAL PAPER

Copula-based multivariate standardized drought index (MSDI) and length, severity, and frequency of hydrological drought in the Upper Sakarya Basin, Turkey

Tugrul Varol[1] · **Ayhan Atesoglu**[1] · **Halil Baris Ozel**[1] · **Mehmet Cetin**[2]

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Abstract
Drought, one of the main factors threatening social life today, is examined and analyzed by its types such as meteorological, agricultural, and hydrological droughts. Thus, decision-makers need advanced methods in monitoring and assessing the drought, which is important for future plans. Multivariate drought indices were developed to allow determining the actual and real level of drought by reducing the deficiencies of current methods. In a region having three different characteristics (BSk: semiarid cold, Csa: dry summer–hot summer, and H: unclassified highland), MSDI was modeled by utilizing the data from Standardized Precipitation Evapotranspiration Index (SPEI) and Standardized Surface Runoff Index (SRI). For the period between 2003 and 2021, the precipitation, evapotranspiration, and surface runoff data were obtained from SPEI Global Drought Monitor and ERA5 databases. Gaussian function was used in establishing the copula-based joint distribution functions according to AIC, BIC, and max-likelihood assessment criteria. The R packages offering a wide range of use for drought modeling and assessment based on the multivariate drought indices were used. The calculations performed for 4 different time scales as MSDI 1-3-6-12 (soil moisture, surface hydrology, and agricultural and hydrological perspectives) showed acceptable performance in multivariate estimation of the drought. It was determined that, for all four time scales (1, 3, 6, and 12 months), MSDI values obtained from modeling were more similar to SPEI values in comparison with SRI values. Considering all the data, it was determined that the years 2007 and 2016 were found to be the driest years for the basin on the 6-month scale, whereas the years 2016 and 2021 were the driest years on the 12-month scale.

Keywords Drought modeling · Copula · Multivariate standardized drought index · Standardized precipitation evapotranspiration Index · Standardized runoff Index

✉ Mehmet Cetin
mehmet.cetin.landscape.architect@gmail.com; mehmet.cetin@omu.edu.tr

[1] Department of Forest Engineering, Faculty of Forestry, Bartin University, 74100 Bartin, Turkey

[2] Department of City and Regional Planning, Faculty of Architecture, Ondokuz Mayis University, Samsun, Turkey

1 Introduction

Drought, to which many factors have effects, especially the natural balance disturbed by the excessive and unplanned use of natural resources in order to meet the increasing needs and demands under the conditions of modern society, is a natural disaster having complex and hard-to-estimate effects on the society, economy, and environment at different levels and variations in ahll the regions throughout the world (Ostad-Ali-Askari 2022; Wilhite and Pulwarty 2005; Keshavarz et al. 2013; Lesk et al. 2016; Schwalm et al. 2017; Wang et al. 2020a, b, c). Rapidly decreasing existence and efficiency of forest areas, damages occurring in natural habitats, and evapotranspiration negatively affect the water resources, which become very insufficient, and the product yield reducing in parallel with the decreasing soil productivity. Besides its effects on the environment, it also threatens the food supply and safety, emerging as a result of the deficiency in natural resources. Insufficient nutrition and consequently occurring health problems accelerate impoverishment, decrease in quality of life, rural-to-urban migration, and even international migration and, as a result, the psychological traumas in family and social order gradually increase the negative economic and social results of droughts (Razmi et al. 2022; Ding et al. 2011; Motamed and Devisti 2012; Daneshmand et al. 2014; Edwards et al. 2015; Freire-González et al. 2017). The fact that drought is related to 22% of all the disasters throughout the world, 33% of individuals being affected, and 3% of deaths suggests a long-term and large-scale capacity of droughts to affect large masses (Rabiei et al. 2022; Wilhite et al. 2007; Keshavarz et al. 2013; Li et al. 2019). Drought is a process that begins with long-term arid periods (meteorological drought) and can continue with a decrease in surface/underground water (hydrological drought). It affects approximately half of the terrestrial area (Stovall et al. 2019; Bento et al. 2020; Grumbine and Xu 2021). Hydrological drought directly affecting the water consumption of humans is measured using various indices such as SPEI (standardized precipitation evapotranspiration Index), PHDI (palmer hydrological drought Index), and SRI (standardized runoff Index) (Wu et al. 2018; Wang et al. 2019; Dikici 2020; Jehanzaib et al. 2020a; Shin et al. 2020; Yisehak and Zenebe 2021). Examining the hydrological drought, Li and Zhou (2016) reported the effects of climate change and humans to be 7–49% and 51–93%, respectively, whereas Jehanzaib et al. (2020b) reported them to be 52.9–99.5% and 0.5–25.6%, respectively. As the results of the present study suggest, it is more necessary to carry out studies aiming to determine the different effects of natural and anthropogenic activities on hydrological drought. Moreover, it is also important to examine the effects of climate change and human activities on the hydrological drought over the course of time, as well as revealing the amplitude of effects (Zhang et al. 2018a, b; Yang et al. 2020).

Managing the risk of drought can be possible only with sustainable and effective risk management strategies (Venton 2012; Dikici 2020). Measures related with preventing the actual and potential effects of the drought and minimizing the results constitute the drought risk management. The first and one of the main measures to be taken in order to reduce the effects of drought is the preparation of drought management plans by considering the basin characteristics (József, 2014; GWP, 2015). Since drought is a slowly progressing event, just like how it begins, it should be carefully observed and analyzed (Aksel and Dikici 2021). Hence, besides the characteristics of a basin, determining the temporal change in aridity in a basin and specifying the indicators and thresholds for the drought are necessary to effectively use the early warning system including the monitorization and estimation of the drought and for the damage reduction activities (Wilhite and Pulwarty 2005; Estrela, and

Vargas, 2012; Svoboda and Fuchs 2016). The present study aims to model and estimate the drought in Upper Sakarya Basin (USB) by modeling the multivariate standardized drought Index (MSDI) depending on the climate and runoff data and to provide important information about water resource management. In this parallel, Bu the best-fit copula family was determined by establishing the SPEI and SRI joint distribution function (JDF) and, in order to better understand the characteristics of hydrological drought, scientific findings were achieved using SPEI and SRI indices for 1, 3, 6, and 12 months of periods.

2 Material and methods

2.1 Material

Upper Sakarya Basin (USB), which incorporates forest, agricultural land, meadowland, and residential areas and thus is one of the effective points of the ecosystem from the industrial, cultural, agricultural, and landscape aspects, was chosen as the study area (Fig. 1). Thanks to its location and characteristics, USB is analyzed in the Global Environment Facility (GEF) project (Contributing to Land Degradation Neutrality (LDN) Target Setting by Demonstrating the LDN Approach in the Upper Sakarya Basin for Scaling up at National Level; http://www.fao.org/gef/projects/detail/en/c/1107403/) within the scope of Land Degradation Neutrality. Mostly (70%) the BSk (semiarid cold), the area has all the raining forms (27% Csa: dry summer-hot summer, 3% H: unclassified highlands).

Considering the long-term average, the highest level of precipitation was in June (127.7 mm), whereas the lowest level was found to be 6.2 mm in August, when the vaporization in the basin was high (maximum vaporization was found to be 60.0 mm in November). The highest difference between vaporization and precipitation was found to be 9.1 mm in May. Considering the long-term average in the basin, the minimum temperature was found in January (−28 °C) and the highest one in August (44 °C). Constituting almost

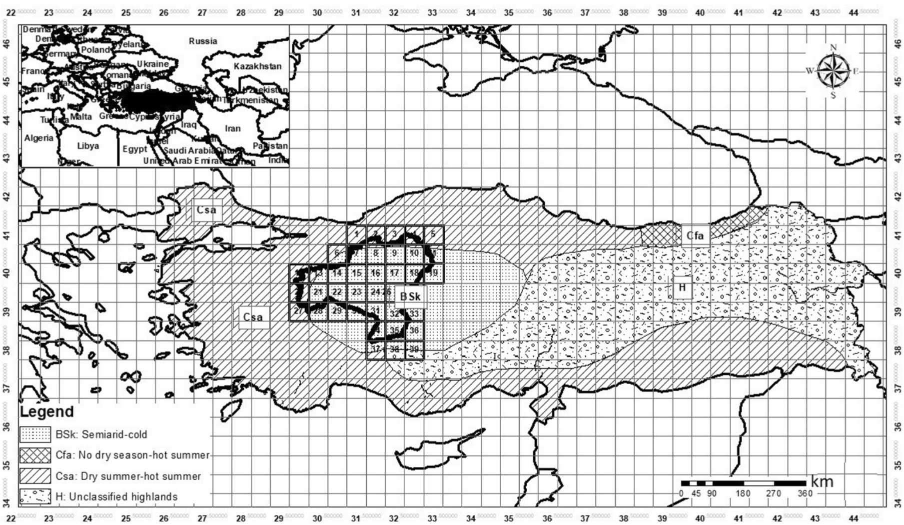

Fig. 1 Study are divided into 39 grid zones (Varol and Ertugrul 2015)

3.4% of all the streams in Turkey, Sakarya River has a mean flow rate of 6.410^9 m^3/year. Having a length of 687 km, 593 km of the river is in the study area. Many streams in the basin deliver their flows to the Black Sea through the Sakarya River, which has Sarıyar and Gökçekaya dams on it (SYGM 2018). Given the TUIK (2021) data, the total of populations of cities in the study area constitutes 13% of Turkey's total population. Moreover, approximately 26% of Turkey's agricultural lands having an area of almost 23 million hectares (BUGEM 2020) are in the Upper Sakarya Basin.

3 Method

The possibly best data for the drought risk estimation and modeling are the homogeneously distributed and actual data obtained at desired frequency and quality. Framed within the Copernicus Climate Change Service (C3S) of the European Commission, the ERA5 database, which is the fifth-generation ECMWF (European Center for Medium Range Weather Forecast) re-analysis for global climate and weather, produces a dataset that will meet the above-mentioned characteristics. (Cucchi et al. 2020; Hersbach et al. 2020). To analyze the trends and anomalies, ERA5-Land supports the hydrological studies on the land and is used in climate models and water resource, land, and environment management practices (Muñoz-Sabater et al. 2021). Since 1950, the ERA5 database includes global-scale data having the standard geometrical resolution of 0.50° × 0.50°. These data have also an hourly resolution. The time series data (Runoff = Sub-surface runoff + Surface runoff) of the sample runoff for the period 2003–2021 corresponding to 39 grids (Fig. 1) constituting the study area at 0.50° × 0.50° scale were obtained from the ERA5 database. Then, they were standardized using runoff Eq. 1. SPEI data having the same resolution were obtained from SPEI Global Drought Monitor (https://spei.csic.es/) at monthly scale. The threshold values for SPEI and SRI values and drought severity classification were obtained as seen in Table 1.

$$\mathrm{SRI} = \frac{x_i - x_j}{\sigma} \tag{1}$$

where x_{i} refers to runoff being examined, x_{j} to the average of series, and σ to the standard deviation of series. At 6- and 12-month scales (SPEI6, SRI6, MSD&, SPEI12, SRI12, MSDI12), length (L), magnitude (M), severity (S), and frequency (F) values of

Table 1 Classification and threshold for SPEI and SRI (Dikici 2020; Zhu et al. 2018)

Threshold values	Drought severity
> 2.00	Extremely humid
1.50–1.99	Very humid
1.00–1.49	Moderately humid
0.50–0.99	Near normal (very little humidity)
− 0.49–0.49	Normal
− 0.5– − 0.99	Near normal (very little arid)
− 1.00– − 1.49	Moderately arid
− 1.50– − 1.99	Severely arid
< − 2.00	Extremely arid

hydrological drought were examined for moderately arid and highly arid classes lasting longer than 6 months as applied by Yisehak and Zenebe (2021).

Copula. Copula was first defined as multivariate joint distribution having uniform marginal distributions (Sklar 1959). For $F_1(x_1)$, …, $F_n(x_n)$ marginal and any $H(x_1,…, x_n)$ point distribution, $H(x_1,…x_n) = C(F_1(x_1),…, F_n(x_n))$, $\forall x \in \overline{R} \times \overline{R}$. And here, if $F_1,…, F_n$ is continuous, copula related with H is unique and it can be stated as follows:

$$C(u_1, \ldots, u_n) = H\left(F_1^{-(1)}(u_1), \ldots, F_n^{(-1)}(u_n)\right) \tag{2}$$

Here, u_1 on the right side of equation is expressed as $u1 = F_1(x_1)$, …, $u_n = F_n(x_n)$.

Because of the second-degree relationships between marginals, copula functions used in various fields such as Gaussian (normal) and Student-t copulas are elliptical (Bhatti and Do 2019). Distribution functions are symmetrical and take values in the range [-1, 1]. The other copula types having the Archimedes structure depending on the functional form of the factor they create might have a dependency level at various variation ranges (Gumbel 1970). Hence, many functional forms can be used as a copula. The equations and parameters for the copula types that are routinely used in forestry and environmental sciences are presented in Table 2, and detailed information can be obtained from Ahsanullah and Bhatti (2010), Tootoonchi et al. (2021), and Wang et al. (2020a, b, c). The five best copula families selected using R software for each grid in the study area are presented in Table 2. In selection of the best copula family, the R software uses AIC, BIC, and max-likelihood eligibility criteria.

4 Results and discussion

4.1 Standardized precipitation evapotranspiration Index (SPEI) and standardized runoff index (SRI).

For the 39 grid areas in the basin, 1-, 3-, 6-, and 12-month values of Standardized Precipitation Evapotranspiration Index (SPEI) were obtained. The data of the basin were

Table 2 Properties of five different copula functions (Buike 2018)

Name of copula	Copula equation	Parameter
Gaussian	$C_{\mathrm{p}}^{\mathrm{Ga}}(u_1 u_2) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left(\frac{-(s_1^2 - 2\rho s_1 s_2 + s_2^2)}{2(1-\rho^2)}\right) \mathrm{d}s_1 \mathrm{d}s_2$	$-1 \le \theta \le 1$
Frank	$C_{\theta}^{\mathrm{F}}(u_1, u_2) = -\frac{1}{\theta} In[\frac{(1-e^{-\theta})-(1-e^{-\theta u1})(1-e^{-\theta u2})}{2}$	$-\infty \le \theta < \infty$
Student-t	$C_{\theta_1,\theta_2}^{t}(u_1 u_2) = \int_{-\infty}^{t_{\theta_1}^{-1}(u_1)} \int_{-\infty}^{t_{\theta_2}^{-1}(u_2)} \frac{\Gamma((\theta_2-2)/2)}{\Gamma(\theta_2/2)2\pi\sqrt{1-\theta_1^2}} \left(\frac{s_1^2 2\theta_1 s_1 s_2 + s_2^2}{\theta_2}\right)^{(\theta_2-2)/2} \mathrm{d}s_1 \mathrm{d}s_2$	$-1 \le \theta_1 \le 1$ and$0 < \theta_2 < \infty$
Gumbel	$C_{\theta}^{\mathrm{Gu}}(u_1, u_2) = \exp\left(-((-Inu_1)^{\theta} + (-Inu_2)^{\theta})^{1/\theta}\right)$	$1 \le \theta < \infty$
Joe-Clayton (BB7)	$C_{\theta,\delta}^{BB7}(u_1, u_2) = 1 - [1 - \left((1 - u_1^{\theta})^{-\delta} + (1 - u_2)^{-\delta} - 1\right)^{-1/\delta}\Big]^{1/\theta}$	$\theta \ge 1, \delta > 0$

translated into areal form by using SPEI values calculated on a grid basis and assigned to the grid center. In order for the SRI values—calculated for 1-, 3-, 6-, and 12-month periods—to be comparable to other indices, the data for the same years were used.

SPEI and SRI values presented for 39 grid areas constituting the USB and at 1-, 3-, 6-, and 12-month periods are presented in Fig. 2. The results obtained showed similarities between mean SPEI and SRI values of the basin. While SPEI6 showed no drought between 2010 and 2011, SRI6 showed that drought lasted for 5 months. For the period between 2015 and 2018, SRI6 showed a recovery in drought, whereas SPEI6 revealed that drought lasted approx. for 13 months. Besides these contrasts and lengths of drought periods, the decreasing and increasing trends in SPEI and SRI values were similar to each other, even different at 4 time scales. This difference might be because USB includes various characteristics (Fig. 1) in it and several precipitation-based drought models such as SPEI are influenced by high variability in precipitation (Mishra et al. 2009; Gidey et al. 2018; King et al. 2020). Since the study area has several climatic characteristics at the same time, the assessments other than the general ones were performed individually for 39 girds.

For the 1-month period, both SPEI and SRI commonly showed years 2007, 2010, and 2021 as the most arid years, whereas the lowest values by SRI were reported to be 2019, 2020, and 2021. For the 3-month scale, the highest drought values were reported for 2007, 2019, and 2020 by SPEI and for 2007, 2013, and 2020 by SRI. For the 6-month scale, the year 2020 was the year with the highest drought value in both SPEI and SRI. For the 12-month scale, the years with the highest drought values were reported to be 2007, 2014, and 2021 by both SPEI and SRI (Fig. 2).

4.2 The Best Copula Family

In the present study using precipitation, evapotranspiration, and runoff as variables, SPEI and SRI were used in modeling the MSDI in determining the hydrological drought. For all the grid areas and on 4 time scales, R packages (VineCopula, drought, copula, VC2copula) selected 5 copula functions seen in Table 1. Constituting the vast majority of 156 options in both grid and time scales, Gaussian Copula was found to be the best copula function for USB. For the basin, AIC, BIC, and max-likelihood eligibility criteria showed that the best model to establish JDF between SPEI and SRI was Gaussian Copula. In many studies such as Hao et al. (2017) and Erhard and Czado (2018), R packages were used for copula function. Besides that, as seen in Sahana et al. (2020), Aghelpour and Varsavian (2021), and Naderi et al. (2022), copula functions used in drought studies were Clayton, Frank, Gaussian, Gumbel, and Student-t.

5 Modeling of multivariate standardized drought index (MSDI)

As in all the grids in the present study and as can be seen in Fig. 3 illustrating all three data in Grid 35 corresponding to Konya province in the study area, MSDI model created showed more similarity to SPEI values (October 2004, June 2010, October 2016, May 2017, November 2021 for 1-month period; December 2004, June 2007, February 2010, October 2020, September 2021 for 3-month period; February 2004, July 2007, February 2010, November 2012, October 2019 for 6-month period; and December 2004, July 2007, October 2014, August 2017, December 2020 for a 12-month period) when compared to SRI values. Estimated using joint probability of precipitation and evapotranspiration, when

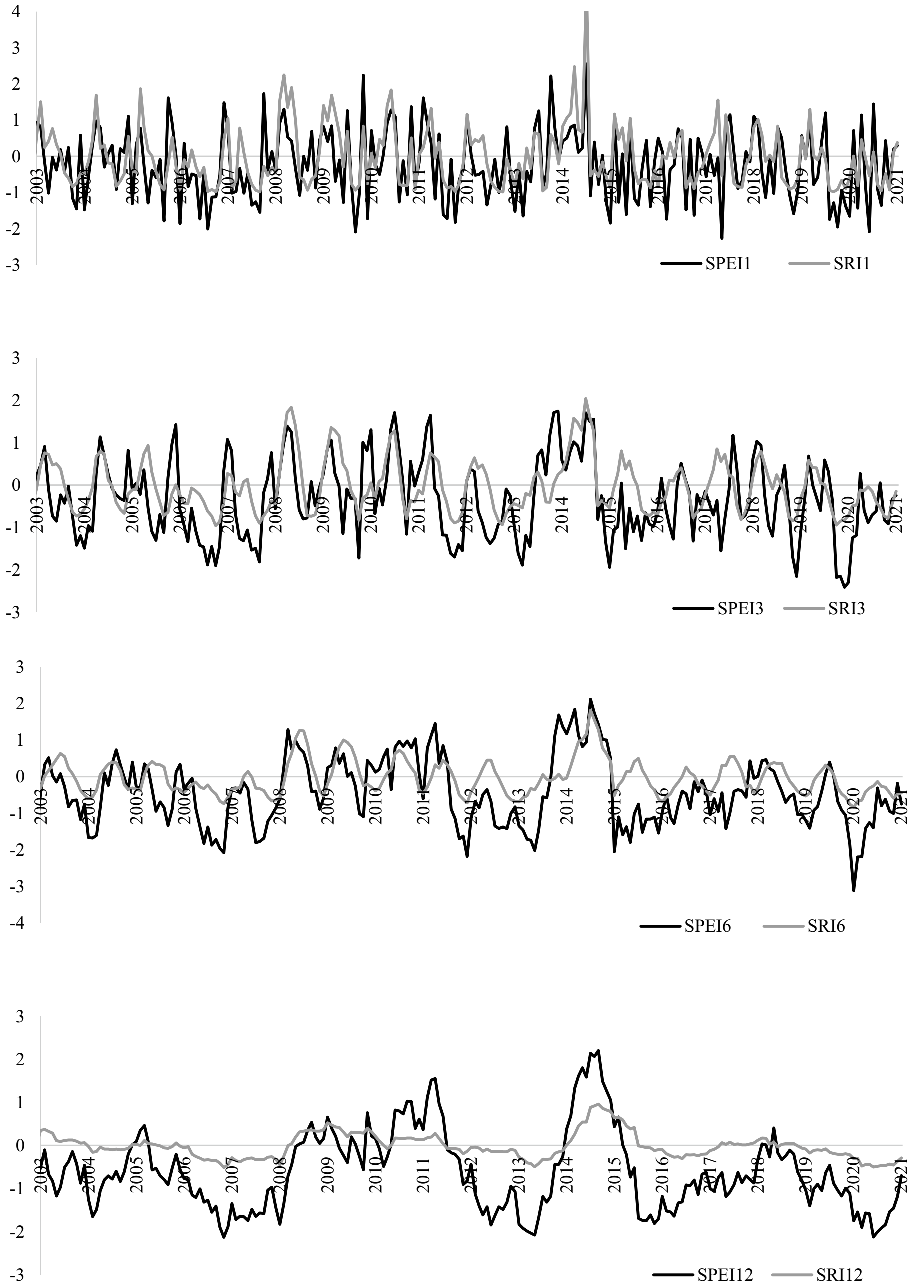

Fig. 2 Long-term SPEI and SRI mean value changes in Upper Sakarya Basin for 4 time periods

compared to many univariate indices, MSDI's JDF-based perspective offers interesting features in determining the severity of drought and the possibility of drought (Hao and AghaKouchak 2014; AghaKouchak, 2015; Dash et al. 2019; Wang et al. 2020a, b, c). For

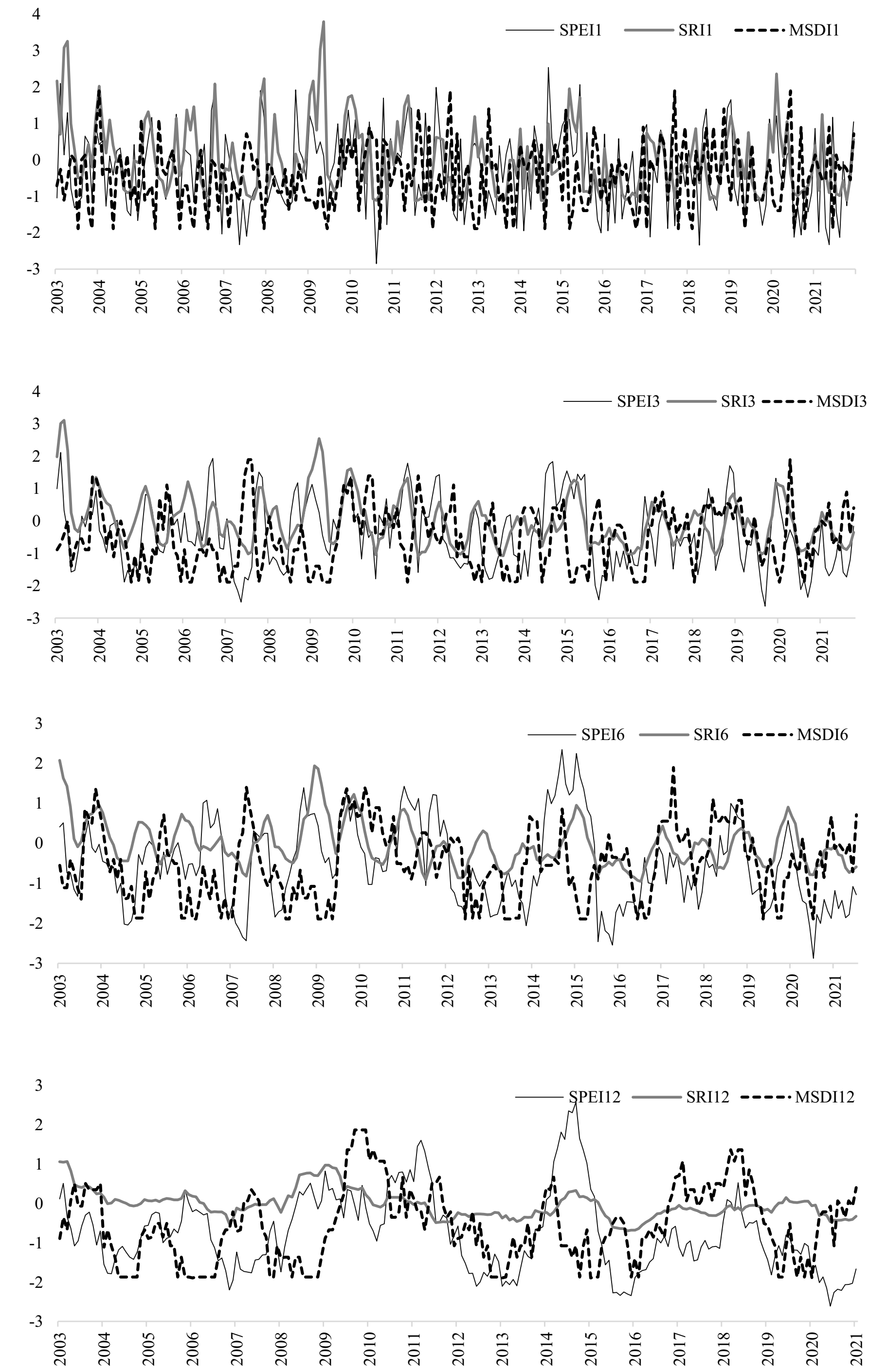

Fig. 3 Comparing SPEI, SRI, and MSDI data for Grid 35 using 4 time scales

the entire basin, the aridest years were 2016 and 2007 in SPEI6 and SRI6, 2016, 2008, 2007, and 2021 in MSDI6, 2021 and 2013 in SPEI12, 2021 in SRI12, and 2021 and 2016 in MSDI12.

As can be seen in Fig. 4 illustrating the drought status of the study area in October 2007 and 2016 for 6- and 12-month scales, MSDI6 data revealed that there was a drought in 47.20% of the period, whereas MSDI12 reported the same percentage to be 29.20%. In October 2007, 42.53% of the area was moderately and severely arid and the same percentage was 15.09% for June 2021. For both 6- and 12-month time scales, the very little humid and moderately humid areas in Eskişehir region are thought to have emerged under the effects of Sakarya River surrounding 3 sides of the area. In the same region, the drought difference between the western and eastern sides of the river was thought to be because of the approx. 300 m altitude difference between the sides. Given the SPEI, SRI, and MSDI diagrams, MSDI showed longer moist and arid periods in comparison with SPEI and SRI. Although arid and moist periods begin 3 months earlier in comparison with MSDI, the periods estimated to be longer cause the next moist or arid period to be estimated later. Hao and AghaKouchak (2014), Farahmand and AghaKouchak (2015), and Yisehak and Zenebe (2021) stated that drought can be estimated earlier using some indices such as MSDI.

6 Determination of hydrological drought change point

On the 6- and 12-month scales, drought length (L), amplitude (M), severity (S), number, and frequency (F) data were summarized using SPEI, SRI, and MSDI. Only one of the examinations performed for each of 39 grid areas constituting the study area is presented in Table 3 (for GRID25). Using SPEI6, the drought was found to last for 8 months between March 07 and October 07 in the entire area except for the area covering Düzce and Bolu provinces (GRID1, GRID2, GRID7, and GRID8), whereas it lasted for 12 months between December 15 and November 16 in the area starting from the middle Eskişehir (GRID15-GRID39). In this period, the amplitude, severity, and frequency values of USB in SPEI6 were 11.89–15.90, 1.48–1.76, and 9.64%-12.50% for March07-October07 and 17.99–23.70, 1.45–1.82, and 14.81%-15.66% for December15-November16. SRI6 values lasting for minimum 7 months and equal to or lower than -0.99 were not observed in the region. Using SPEI12 values, as can be seen in Fig. 4, drought in the region widely lasted between December 20 and August 21 and, when splitting the region as west and east, 9 months in the eastern part. In this time frame, amplitude, severity, and frequency values for SPEI12 ranged between 10.57 and 35.85, 1.32 and 1.79, and 9.78% and 18.34%, respectively. In USB, SPEI12 has higher amplitude and frequency values in comparison with SPEI6. As with SRI6, no values equal to or lower than 0.99 and lasting for minimum 7 months could be found in SRI12.

MSDI data showed that 6-month drought generally occurred between October 05 and April 06 and between December 13 and July 14 at the frequency of 9%-12%. Considering MSDI6, the longest drought lasted for 21 months between June 11 and February 13. Given MSDI12, the longest drought in the region lasted for 24 months between March 13 and February 15 and its amplitude, severity, and frequency values were 40.69, 1.69, and 38.71%. In general, while SPEI6 and SPEI12 values differed for all the GRID areas, MSDI6 and MSDI12 data were more similar to each other. From a general perspective, using the averages of GRID areas, both SPEI and MSDI showed that there were more than 70 drought events having different severity levels throughout the 19-year period.

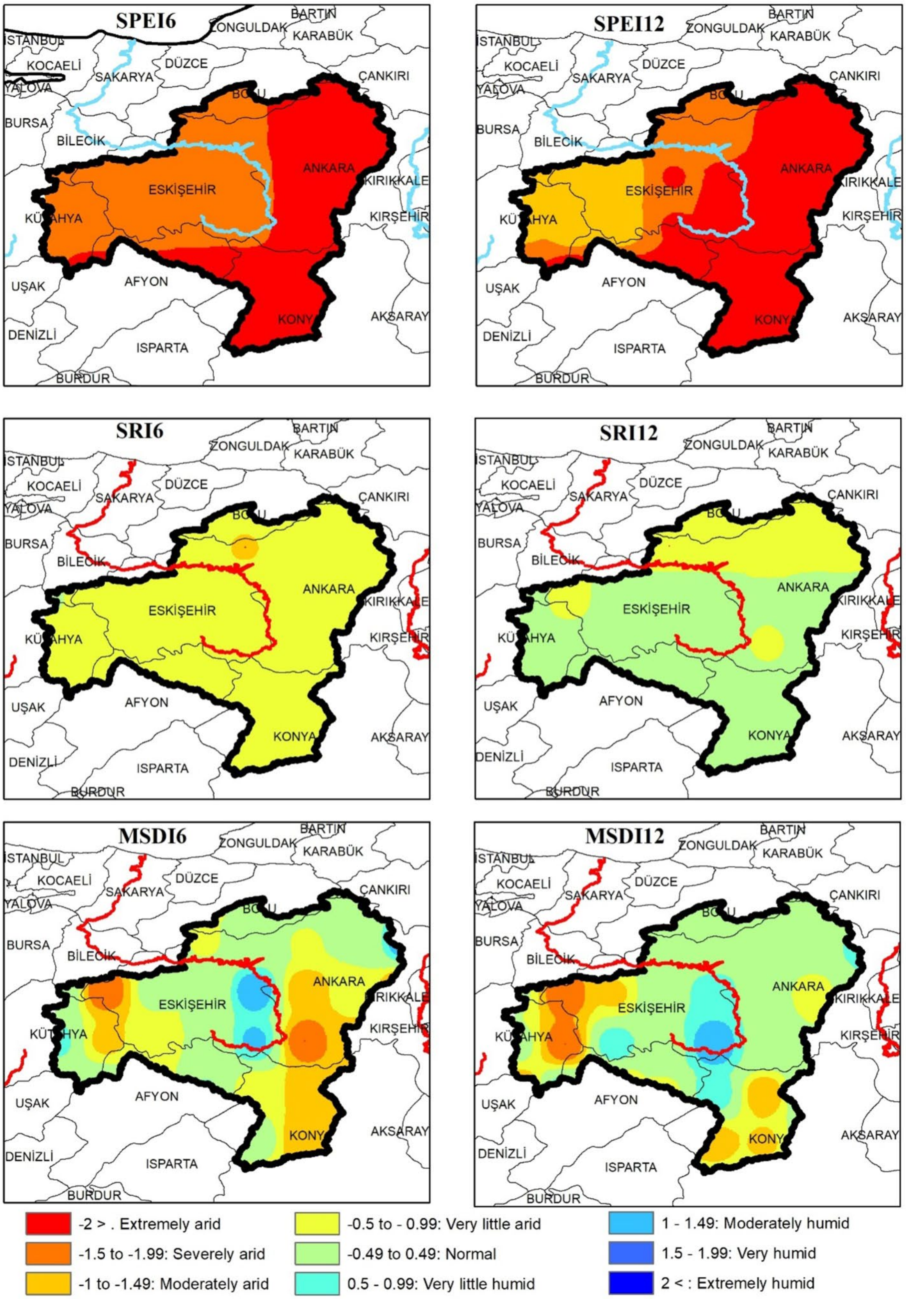

Fig. 4 Hydrological drought status in October 2007 (left) and June 2021 (right) in USB by SPEI, SRI, and MSDI

Table 3 Temporal characteristics of SPEI, SRI, and MSDI values in the period 2003–2021 on 6- and 12-month scales (GRID25)

	Outset	Cessation	*L* (month)	*M* (mm)	*S*	*F* (%)
SPEI6	Mar.07	Oct.07	8	14.66	1.83	9.88
	Jun.13	May.14	12	20.78	1.73	14.81
	Dec.15	Nov.16	12	17.99	1.50	14.81
	Oct.20	May.21	8	17.16	2.15	9.88
SRI6	–	–	–	–	–	–
MSDI6	Jun.06	Dec.06	7	11.96	1.71	9.33
	May.10	Mar.11	11	17.93	1.63	14.67
	Nov.11	Jul.12	9	13.62	1.51	12.00
	Jan.13	Sep.13	9	14.83	1.65	12.00
SPEI12	Sep.04	Mar.05	7	9.97	1.42	6.42
	Feb.07	Jan.09	24	38.88	1.62	22.02
	Jan.13	Aug.14	20	35.85	1.79	18.35
	Jun.16	Jun.18	25	36.92	1.48	22.94
	Jul.20	Dec.21	18	31.88	1.77	16.51
SRI12	–	–	–	–	–	–
MSDI12	Jul.06	Aug.07	14	21.07	1.51	19.44
	Jul.10	Apr.11	10	14.81	1.48	13.89
	Apr.12	Oct.12	7	10.77	1.54	9.72
	Jan.13	Dec.13	12	19.56	1.63	16.67

7 Comparison of three indices

There was a correlation between SPEI and SRI varying between 0.57 and 0.76 for 4 time scales. The same ratio increases to 0.67 and 0.84 between MSDI and SPEI. Similar to SPEI, the correlation between MSDI values and SRI values (0.36–0.79) was higher in comparison with the correlation between SPEI and SRI. Despite the increasing level of correlation, some authors such as Zhang et al. (2018a, b) stated that features of MSDI were overrated in comparison so the other indices. Although there were significant relationships between SPEI and SRI for all 4 time scales, the relationship was at a higher level with MSDI. Ndehedehe et al. (2016) and Yisehak and Zenebe (2021) emphasized that the weak correlation between SPI and SRI increased to a higher level with MSDI. Testing the performance of the relationship between SPEI, SRI, and MSDI by using the R^2 value, as seen in Fig. 5, MSDI had a relationship higher than 0.50 with both SPEI and SRI for 3-month scale.

8 Conclusion

Multivariate drought studies are preferred in preventing the negative effects of drought on water resources. In the present study, the multivariate standardized drought Index (MSDI) was modeled for USB by using the data obtained from SPEI considering the precipitation and evapotranspiration and SRI (surface runoff index). In the modeling process, SPEI obtained from SPEI Global Drought Monitor and SRI values obtained by converting the

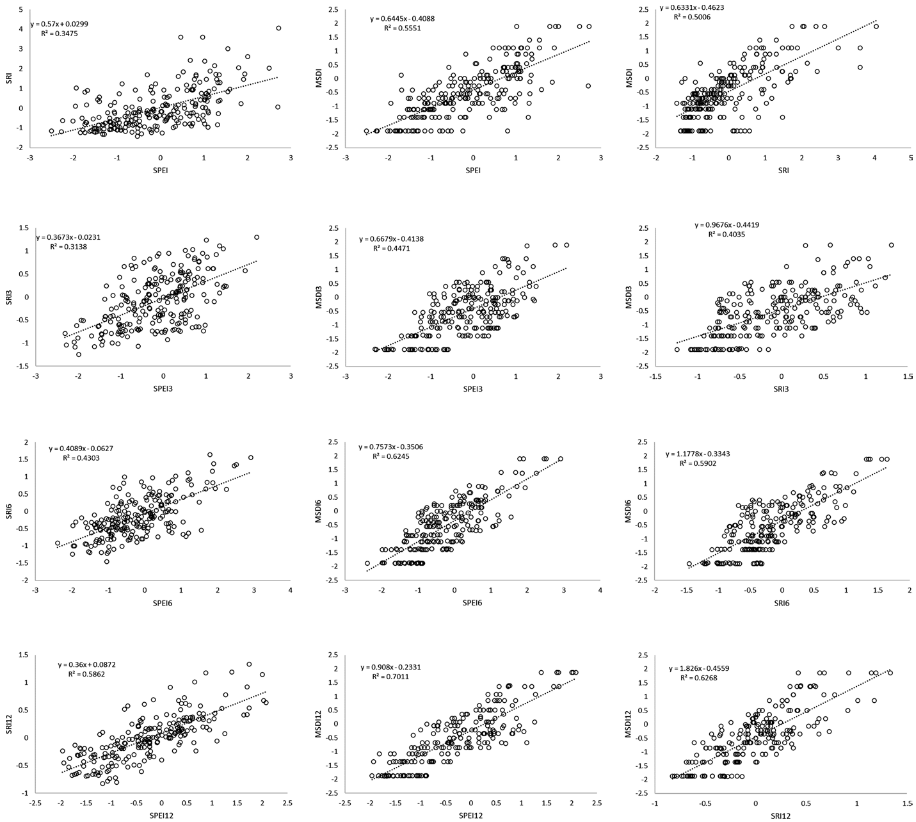

Fig. 5 Regression equations and R^2 values between SPEI, SRI, and MSDI

runoff values obtained from ERA5 into standardized runoff index were used. MSDI was developed by using JFD in selecting the best copula family (such as Gaussian, Frank, Student-t, Gumbel, Joe-Clayton) for SPEI and SRI. Among these five copula families, the Gaussian copula was chosen to be the best model to establish the joint probability distribution. While characterizing the hydrological drought, SPEI, SRI, and MSDI were analyzed at 6- and 12-month scales.

Although MSDI developed for 39 GRID regions constituting the study area was lower than indicated by SPEI (~76 days) for the period 2003–2021 at 6-month scale, it suggests a much longer drought in comparison with the value reported by SRI (~72 days). A similar case applies to the 12-month period (SPEI12 ~ 88 days and MSDI12 ~ 76 days). While the time scale increases from 1 to 12 months for indices, the drought is observed to prolong. The data obtained showed that the aridest years for the basin were 2007 and 2016 for the 6-month scale and 2016 and 2021 for the 12-month scale. MSDI suggested that the longest drought in USB lasted for approx. 13–18 months. Besides Sakarya River coursing a distance of approx. 593 km in the region and the Sarıyar and Gökçekaya dams constructed on the river, also the underground dams aiming to increase the water supply play an important role in reducing the effects of drought with increasing amplitude, severity, and frequency. It can be seen that, considering the criteria such as length and number of drought periods, the regression equations developed as a function of MSDI having a strong correlation with both SPEI and SRI ($R^2 > 0.50$) were more effective in estimating the SPEI. Besides the environmental and ecological effects, also the socioeconomic effects of drought should be examined by analyzing the Upper Sakarya Basin, which incorporates many ecosystems such as agricultural, forest, and meadow lands because of its current natural structure, population density, and gradually increasing drought, at 24–48-month scale.

Authors' contributions Tugrul Varol contributed to conceptualization, methodology, software, validation, visualization, and writing–original draft. Ayhan Atesoglu contributed to data curation, methodology, software, and writing–review & editing. Halil Baris Ozel contributed to methodology, validation, writing–original draft, and writing–review & editing; and Mehmet Cetin contributed to methodology, validation, writing–original draft, and writing–review & editing.

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Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. Data will be made available on request.

Code availability Not applicable.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors declare that they have no conflicts of interest. None of the authors have any competing interests in the manuscript. 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 No potential conflict of interest was reported by the authors.

Ethics approval Not applicable.

Consent for publication Not applicable.

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