



# Assessment of hydrological drought return periods with bivariate copulas in the Tigris river basin, Turkey

Yavuz Avsaroglu<sup>1</sup> · Veysel Gumus<sup>1</sup>

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## Abstract

Drought basically consists of four main components: duration, severity, intensity, and frequency. The fact that these different components having impact on drought are related to each other brings some difficulties in drought research. These parameters are generally evaluated univariate in drought analyses, however, a “joint multivariate distribution” of these parameters is required for a realistic drought assessment. Joint multivariate evaluation of drought parameters can be determined with Copula functions. In this study, hydrological drought analysis is conducted for 16 streamflow gauging stations in the Tigris Basin, Turkey, with the Streamflow Drought Index (SDI). The drought duration and severity values are extracted using Run Theory, and the best fitted marginal distribution functions of each parameter are determined among 13 distribution functions. The joint probabilities of drought duration and severity are evaluated using six different copulas (Ali-Mikhail-Haq, Clayton, Frank, Galambos, Gumbel-Hougaard and Joe), and the best representing copula is found as Galambos according to Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Univariate return periods and bivariate return periods calculated with Galambos copula are compared and the results are evaluated spatially. It is seen that the difference between univariate return periods and bivariate return periods is in the range of 5–10% in most of the stations. As a result of the spatial analysis of the drought duration and severity in the Tigris basin with bivariate copula, it is seen that the central and western parts of the basin have a high risk.

## 1 Introduction

Natural disasters cause serious hydrological imbalances and create a water deficit when the natural water availability used by different systems in the world falls below its long-term average or normal values in a certain time period. On a regional scale, this phenomenon is defined as “drought”. It is generally grouped into four classes as meteorological, hydrological, agricultural, and socio-economic droughts (Nabaei et al. 2019; Park et al. 2017; Van Loon 2015). Precipitation that falls less than average occurs as a “meteorological drought”. Drought in dry agricultural areas manifests itself as “agricultural drought” with the lack of soil moisture.

“Hydrological drought” is described as a lack of groundwater and surface water in lakes or rivers (Mishra and Singh 2010; Yüceerim et al. 2019). Socio-economic drought can be defined as the inability of the supply of an economically good (water) to meet the demand of droughts that occur due to the inadequacy of water resources systems (precipitation, irrigation, storage, etc.). Although there is a direct relation between meteorological and hydrological drought, hydrological measurements cannot be considered one of the first drought indicators. There will be a time interval between the precipitation deficit and the occurrence of water deficiency in reservoirs. The hydrological drought situation may still be ongoing even long after the meteorological drought is over (Gumus and Algin 2017). Therefore, since it is difficult to obtain realistic information about hydrological drought by evaluating only meteorological drought, it is essential to consider hydrological drought separately using streamflow or groundwater data for the water resources management.

The drought event consists of four main components as duration, severity, intensity, and frequency. These features affect drought characteristics and make drought a stochastic and complex natural disaster. A single variable cannot

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✉ Veysel Gumus  
gumus@harran.edu.tr  
Yavuz Avsaroglu  
yavsaroglu@harran.edu.tr

<sup>1</sup> Department of Civil Engineering, Harran University, 63050 Şanlıurfa, Turkey

provide a comprehensive assessment of droughts, as all these interdependent components have an impact on drought (Mishra and Singh 2010; Shiau et al. 2007). Therefore, the multivariate properties of drought should be considered in drought analysis and different drought characteristics should be analysed collaboratively. To evaluate different components jointly, the best approach is to use probability theories, such as Copula (Ayantobo et al. 2018; Shiau 2006).

Copula functions have been used in hydrology to evaluate the multivariate probability distribution in recent years. Copulas do not need assumptions for equality, normality, or independence for the marginal distribution of variables. Since they take into account the probabilistic nature of each variable, copula-based joint distributions have more advantages than the other multivariate distributions (da Rocha Júnior et al. 2020; Nabaei et al. 2019; Zhang and Singh 2007). In short, it can jointly model two different variables, even though they have different distributions. Copula functions were proposed by Sklar (1959) to generate multivariate distributions and were first used in the finance and insurance industry. In hydro-meteorological studies, it is first used by De Michele and Salvadori (2003) to create a bivariate model describing the intensity and duration of rainfall. It is also commonly used to analyse the joint distribution of features of various hydro-meteorological events such as precipitation (Hangshing and Dabral 2018; Sajeev et al. 2021; Wee and Shitan 2013), flood (Balistrocchi et al. 2017; Li et al. 2013b; Luo et al. 2021) and drought (Dehghani et al. 2019; Pathak and Dodamani 2021; Shiau 2006).

Although there are many drought studies based on copula globally, these studies have generally been about the meteorological drought calculated by the Standardized Precipitation Index (SPI) method. For example, Bivariate (Duration-Severity) drought analyses are performed for Bangladesh by testing the data obtained from the SPI-3 time scale with three copula functions by Mortuza et al. (2019), for the Eastern Cape Province of South Africa by testing the data obtained from the SPI-3 and SPI-6 time scales with ten copula functions by Botai et al. (2020), for the Northeast Brazil by testing the data obtained from SPI-12 time scale with five copula functions by Pontes Filho et al. (2020). Contrary to meteorological drought, which is studied using precipitation data, studies in the form of joint modelling of hydrological drought with multiple components using streamflow data are limited worldwide. For example, using the streamflow or runoff data with various copula functions, Zhang et al. (2015) in the East River basin in China, Zhao et al. (2017) in the Weihe River in China, Vaziri et al. (2018) in the Tajan River in Iran studied bivariate (Duration-Severity) drought analyses of the hydrological drought.

Studies about the research on drought and planning to reduce its impacts are especially important for regions such as Turkey, where agricultural activities are intense, and the

economy of millions of people depends on it. Since 51 million hectares corresponding to 37.3% of Turkey's area is arid and semi-arid under climate conditions, drought is a critical issue that needs to be carefully handled (MGM 2019).

There are many studies on the temporal and spatial analysis of meteorological (Dabanlı et al. 2017; Keskin et al. 2011; Tonkaz 2006; Umran Komuscu 1999; Yerdelen et al. 2021) and hydrological (Altın et al. 2019; Gumus and Algin 2017; Özcan et al. 2019) drought in different regions of Turkey, which is vulnerable to drought. However, there are limited studies in evaluating of multivariate drought using the copula method in Turkey. For example, Tosunoglu and Can (2016) calculated monthly SPI values (a time series for each region) for seven regions by Principal Component Analysis with precipitation data from 173 precipitation observation stations in Turkey. After obtaining the drought duration and severity parameters from the calculated SPI values by the Run Theory, they determined the best fitted marginal distribution and the best fitted copula among four different copulas. As a result of comparing the univariate return periods with the bivariate return periods, it is seen that the joint return periods in some regions exceeded the univariate return periods by more than 50%. Tosunoglu and Kisi (2016) evaluated the hydrological drought of 5 streamflow gauging stations in the Çoruh Basin in northern Turkey with a threshold value. Their study compared the univariate return periods of annual maximum drought severity (the largest value of the computed severity series for each year), and corresponding duration (length of maximum drought severity) parameters and calculated the bivariate return periods of these parameters with the copula. As a result of the study, it is determined that the difference between the univariate and the joint return periods varied between 23 and 29%. Tosunoglu and Onof (2017) performed a bivariate analysis of SPI values calculated with historical and synthetic data of five stations in the Çoruh basin in the north of Turkey using copula. As a result of the study, when evaluating the duration and severity of drought for univariate 50- and 100-year return periods obtained in historical data as a bivariate, it is showed that the return periods increased to 83.2 and 168 years, respectively. As the past studies are examined, there is no study in which the components of hydrological drought (duration, severity, peak, etc.) are evaluated jointly with the copula using streamflow data in the Tigris basin of Turkey. This basin originates from the Tigris-Euphrates River basin, which is the largest water basin in the Middle East. Especially analysing the drought return periods, which are calculated as univariate, with two variables together and determining the change in the return periods will help the effective planning and use of water resources in the region.

In this study, hydrological droughts of 16 streamflow gauging stations covering the entire Tigris Basin, Turkey, are calculated with the Streamflow Drought Index (SDI), and

**Table 1** Geographical characteristics and observation periods of the stations

Station no	Station name	Longitude (E)	Latitude (N)	Drainage area (km <sup>2</sup> )	Elevation (m)	Observation period	Long-term mean streamflow (m <sup>3</sup> /s)
D26A008	Pamukluk River-Dilaver Bridge	40.2333	37.6667	648	702	1974–2015	1.88
D26A012	Başnik Stream-Salat	40.8833	37.8500	1060	525	1980–2015	4.00
D26A032	Pamuk Stream-Karahan Bridge	40.5697	38.0667	305	738	1980–2010	1.88
D26A040	Mehmediyan Stream-Tepecik	40.5667	38.2667	79	800	1979–2015	0.48
D26A054	Kızılsu-Kasrik Strait	42.1781	37.3969	650	400	1981–2015	10.36
D26A060	Başköy Stream-Kıbrıs	40.9167	38.0167	157.9	594	1989–2015	0.62
D26A062	Sallar Stream-Yolköprü Village	39.7044	38.2433	51.6	852	1989–2015	0.76
E26A003	Garzan Stream-Beşiri	41.3458	37.9650	2450.4	545	1946–2002	48.5
E26A005	Tigris River-Diyarbakır	40.2297	37.8800	5655.2	570	1956–1997	71.3
E26A010	Bitlis Stream-Baykan	41.7825	38.1614	640.4	910	1955–2016	18.23
E26A012	Batman Stream-Malabadi Bridge	41.2044	38.1544	4105.2	597	1965–2016	116.64
E26A018	Ambar Stream-Köprübaşı	40.3842	37.9919	976	595	1969–1998	7.68
E26A020	Zap Stream-Üzümcü	43.5656	37.4864	5270.3	1072	1971–2012	56.28
E26A024	Kezer Stream-Pınarca	41.8572	37.9614	1169.6	530	1972–2016	19.73
E26A030	Zap Stream-Teknisyenler	43.9883	37.6986	4161.5	1425	1986–2011	35.35
E26A031	Çatak Stream-Tüliran	43.0544	37.9983	2455	1482	1988–2011	25.44

the drought properties are evaluated. The drought duration and severity values are extracted with the Run Theory, and marginal distribution functions of each parameter are determined. To evaluate the joint probabilities of these two variables in the basin, the copula that best represents the joint bivariate at each station is determined by testing the performances among six different copulas. First, the univariate return periods are calculated and the bivariate return periods corresponding to the drought duration and severity values of the univariate return periods are determined for these variables. Afterwards, the univariate return periods and bivariate return periods calculated with the copula that best represents (fitted) the region are spatially given and discussed.

## 2 Materials and methods

### 2.1 The study area

The Tigris-Euphrates River Basin (TERB) is one of the largest basins in the Middle East, and the size of this basin is 879,790 km<sup>2</sup>. This river basin is located in Iraq, Turkey (22%), Iran, Syria, Saudi Arabia, and Jordan (Bozkurt and Sen 2013). Euphrates and Tigris rivers are the two main rivers in this basin. The Tigris River is a river with a total length of approximately 1900 km, 523 km of which is within Turkey boundaries, born in the southeast of Turkey. The total area of the Tigris basin is 54,145 km<sup>2</sup>, which corresponds to 6.9% of Turkey's acreage. It also has 13.6% of the total water potential of the country with a water potential of 25,183 km<sup>3</sup>

(DSI 2018). The geographical characteristics and observation periods of streamflow values for the stations are given in Table 1.

Anthropological impacts are considered when choosing the stations, and in this study drought analysis is carried out using monthly mean streamflow data from 16 streamflow gauge sites in the Tigris Basin, as shown in Fig. 1. Elevation values reach above 4000 m in the east of the Tigris basin, but it drops to 263 m in the west. The altitudes of the stations E26A020, E26A030 and E26A031 located in the east of the basin are above 1000 m, while the remaining stations are 400–910 m. The minimum long-term mean streamflow is observed 0.48 m<sup>3</sup>/s at station D26A040. The maximum long-term mean streamflow is observed 116.64 m<sup>3</sup>/s at station E26A012. Stations with high streamflow are generally found on the Tigris River's main tributaries, whereas stations with low streamflow are found on its side tributaries.

### 2.2 Methodology

#### 2.2.1 Streamflow Drought Index (SDI)

The Streamflow Drought Index (SDI) method, developed by Nalbantis (2008), includes a similar calculation to the Standardized Precipitation Index (SPI) method (McKee et al. 1993), which is widely used to calculate the meteorological severity of drought. One of the main advantages of SDI is that it depends on streamflow data directly related to hydrological drought and can be easily calculated with this data. In this method, the onset and duration of drought are

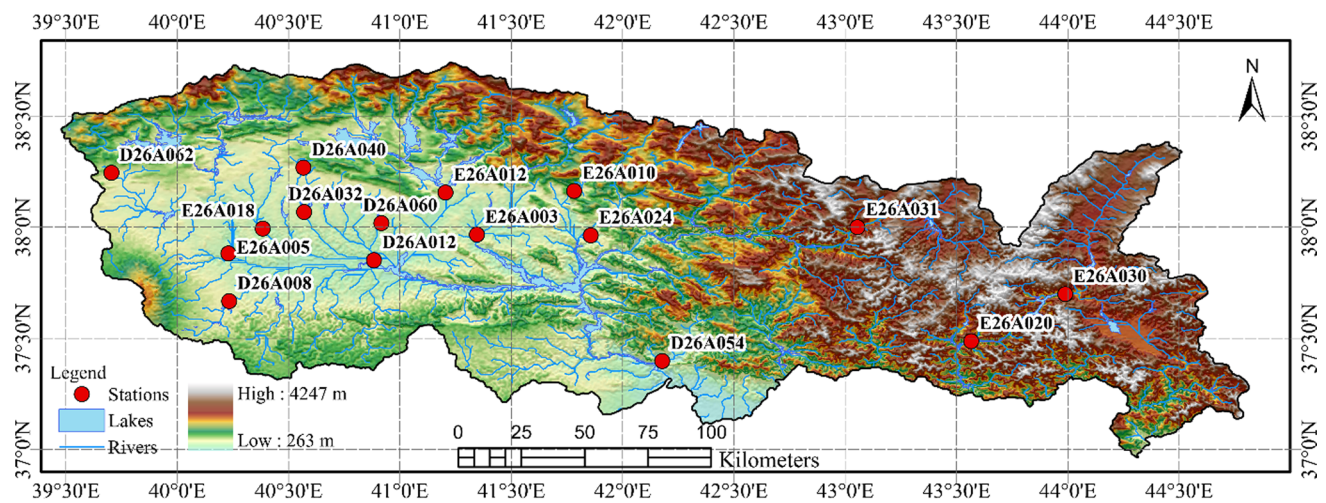


Fig. 1 Tigris River Basin of Turkey

determined using the cumulative streamflow amount of the river, which were used to evaluate and monitor hydrological droughts and obtain water balance indicators for hydrological drought (Jahangir and Yarahmadi 2020; Tigkas et al. 2012). The relevant references can obtain more information about the SDI method and its application to hydrological drought analysis (Nalbantis 2008; Nalbantis and Tsakiris 2009). The SDI is defined as Eq. 1:

$$SDI_{i,k} = \frac{V_{i,k} - \bar{V}_k}{S_k} \quad i = 1, 2, \dots, k = 1, 2, 3, 4, \dots \quad (1)$$

In Eq. 1,  $SDI_{i,k}$  is the value of streamflow drought index for  $k$ th month in  $i$ th hydrological year,  $V_{i,k}$  is streamflow volume for  $k$ th month in  $i$ th hydrological year,  $\bar{V}_k$  and  $S_k$  are the mean and the standard deviation of streamflow volumes in  $k$ th month over the study period. The time period between October–September is chosen as the hydrological year within the scope of this study. In this study, a 3-months SDI (SDI-3) is used for a short-term drought identification, and SDI values are calculated using the gamma distribution. In this method, the severity of drought for a wet and drought condition is categorized in eight classifications as shown in Table 2 (Gumus and Algin 2017).

### 2.2.2 Run theory

This approach, proposed by Yevjevich (1967), is known as the threshold level method or Run Theory and many researchers use it, because it can be applied to daily, monthly and annual data (Nam et al. 2015; Wu et al. 2020). As seen in Fig. 2, hydrological droughts are divided into drought components and can be characterized for a chosen threshold level. Drought event is based on SDI values (a threshold

Table 2 Classification for wet and drought conditions according to calculated SDI values

SDI values	Classification
$SDI \geq 2$	Extremely wet
$1.5 \leq SDI < 2.0$	Severely wet
$1.0 \leq SDI < 1.5$	Moderately wet
$0 \leq SDI < 1.0$	Mildly wet
$-1.0 \leq SDI < 0$	Mild drought
$-1.5 \leq SDI < -1.0$	Moderate drought
$-2.0 \leq SDI < -1.5$	Severe drought
$SDI \leq -2$	Extreme drought

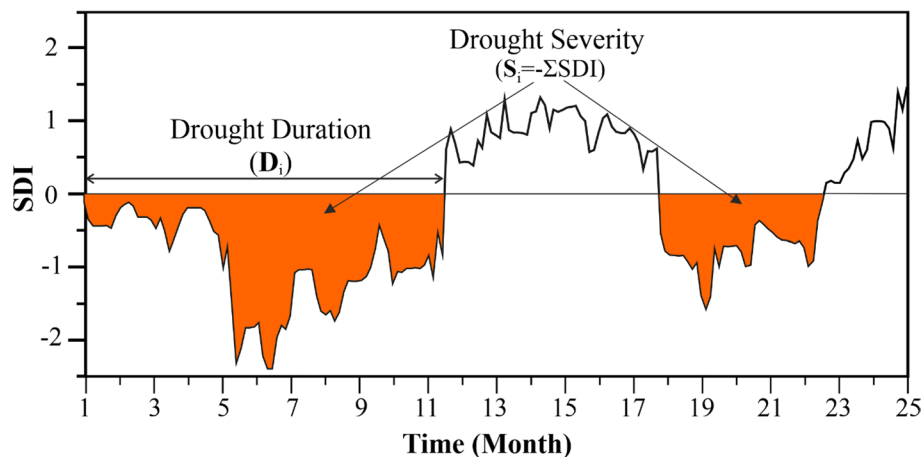
value of below 0) is selected to identify drought using Run Theory in this study. Important drought parameters, such as duration and severity, can be simply calculated after identifying drought occurrences in accordance with the chosen threshold value with the Run Theory. According to the graph, a drought occurs if the values are negative, and the drought continues until the values become zero.

Figure 2 shows drought characteristics using the Run Theory for a threshold value of below 0, the  $D_i$  represents the drought duration (the sum of consecutive months with the negative SDI values, the unit of duration is month), and  $S_i$  represents the unitless drought severity (the sum of the negative SDI values of the consecutive dry period).

### 2.2.3 Univariate marginal distributions for drought duration and severity

It is necessary to determine the best fitted distribution function of the drought duration and severity variables to calculate the joint probability function in copula. The best

Fig. 2 The Run Theory



fitted distribution function of input variables will increase the accuracy of the joint distribution function to be calculated (Kavianpour et al. 2020). In this study, the Exponential, Extreme Value, Gamma, Inverse Gaussian, Logistic, Log-logistic, Lognormal, Nakagami, Normal, Rayleigh, Rician,  $t$  location-scale and Weibull marginal distributions are used. The best fitted marginal distributions for each variable are determined according to the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The details are given in the following section (see Sect. 2.2.6). Finally, the best fitted distributions for drought duration and severity are used to calculate the joint probability function in the copula.

#### 2.2.4 Copulas

Although researchers have performed studies on the drought's probability characteristics since the 1960s, most of these studies have been conducted as univariate analysis of drought. However, as it is well known, drought is a complex natural phenomenon that can be expounded with severity, duration, and intensity parameters. Moreover, there is a significant correlation between these parameters. For this reason, "joint modelling" of drought variables is necessary to interpret the effects of drought in a region more realistically and this would be only possible with the use of multivariate methods.

The probability distribution types of different variables must be the same in traditional methods to apply multivariate distributions (Shiau 2006). However, as the related drought parameters such as duration and severity generally fit different probability distributions, it creates difficulties in multivariate modelling (Azam et al. 2018; Pontes Filho et al. 2020). On the other hand, the copula functions method, which is introduced by Sklar (1959), successfully performs the calculations of the multivariate probability distribution and it has the feature of overcoming many disadvantages

inherent in traditional methods (Wu et al. 2020; Zhang et al. 2015).

Sklar's theorem explains the role of copulas in the relation between univariate distribution functions and their marginal distribution functions. For instance, let  $x_1, x_2, \dots, x_n$  be the univariate cumulative distribution functions (CDF) of random vectors  $F_1, F_2, F_n$ . Then, according to Sklar's theorem, these random vectors have an  $n$ -dimensional copula function that defines joint univariate cumulative distribution functions. This function is calculated as in Eq. 2:

$$H(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)), \quad (2)$$

where  $C$  is the  $n$ -dimensional copula with parameter  $\theta$ .

Copula functions have advantages such as retaining the correlation between random variables and carrying different distribution properties of the variables. This feature provides excellent convenience to researchers in determining the marginal distributions of random variables. Drought analysis with copula theory takes into account dependencies among drought variables (Mesbahzadeh et al. 2020).

#### 2.2.5 Copula family

There are many copula types and families in the literature to determine joint distributions (Sadegh et al. 2017). However, copulas used for the analysis of hydro-meteorological data are divided into four classes as the Archimedean (Ali-Mikhail-Haq-AMH, Clayton, Frank, Gumbel-Hougaard and Joe), elliptical (normal and student  $t$ ), extreme value (Galambos, Husler-Reiss, Tawn and  $t$ -EV) and miscellaneous (Farlie-Gumbel-Morgenstern and Plackett) copulas (Ayantobo et al. 2019). The Archimedean class copulas are frequently used in hydrological studies due to their simple structure and strong representation features (Mellak and Souag-Gamane 2020; Mortuza et al. 2019). In addition, it is known that the Galambos copula, which is in the extreme value class, has proven

**Table 3** Used Copulas and their mathematical formulations

Copula Name (Reference)	Mathematical formulation	Parameter range
Ali-Mikhail-Haq (AMH) (Ali et al. 1978)	$\frac{uv}{1-\theta(1-u)(1-v)}$	$\theta \in [-1, 1)$
Clayton (Clayton 1978)	$\max(u^{-\theta} + v^{-\theta} - 1, 0)^{-1/\theta}$	$\theta \in [-1, \infty) \setminus 0$
Frank (Li et al. 2013a)	$-\frac{1}{\theta} \ln \left[ 1 + \frac{(\exp(-\theta u)-1)(\exp(-\theta v)-1)}{\exp(-\theta)-1} \right]$	$\theta \in \mathbb{R} \setminus 0$
Galambos (Huyh et al. 2014)	$uv \exp \left\{ (-\ln(u))^{-\theta} + (-\ln(v))^{-\theta} \right\}^{-1/\theta}$	$\theta \in [0, \infty)$
Gumbel-Hougaard (Li et al. 2013a)	$\exp \left\{ -\left[ (-\ln(u))^\theta + (-\ln(v))^\theta \right]^{1/\theta} \right\}$	$\theta \in [1, \infty)$
Joe (Li et al. 2013a)	$1 - \left[ (1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta \right]^{1/\theta}$	$\theta \in [1, \infty)$

its success in evaluating the drought duration and severity together (Kiafar et al. 2020; Mirabbasi et al. 2012). Botai et al. (2020) analysed the univariate and bivariate return periods for SPI values in Eastern Cape Province, South Africa. Three copulas (Joe, Tawn and BB1) are tested for bivariate analysis and Joe copula is found successful and selected for bivariate joint return periods.

Therefore, in this study, AMH, Clayton, Frank, Gumbel-Hougaard and Joe copulas from the Archimedean class and Galambos copula from the extreme value class are used for evaluating the joint modelling of drought duration and severity. The mathematical expressions of the bivariate copulas used in the study are given in Table 3.  $u$  and  $v$  are random variables with uniform distribution, and  $\theta$  is the copula parameter in the equations in Table 3. More detailed information about the copulas used can be obtained from the references given in the table.

**2.2.6 The choice of the best fitted distributions and copulas**

The selection of the best fitted marginal distribution of the drought duration and severity is required to determine the joint distributions with the copula. In addition, as the copula function to be selected directly affects the results of the analysis and calculations, it is essential to choose the copula function that will best represent the variables in the performed analyses. Using only a single selection criterion for copula selection presents some disadvantages and determining the most suitable parameter set with a single criterion is not entirely satisfactory due to the limitations in comparing distributions (Huang et al. 2014; Huard et al. 2006). In this study, Akaike Information Criterion (AIC) (Akaike 1974) and Bayesian Information Criterion (BIC) (Schwarz 1978) are used as selection criteria when choosing the best fitted univariate marginal distributions and bivariate copula function that models the data. In both selection criteria methods, the lower the value indicates better performance. The formulas of AIC and BIC are given in Eqs. 3 and 4, respectively.

$$AIC = 2D - 2\ell \tag{3}$$

$$BIC = D \ln n - 2\ell, \tag{4}$$

where  $D$  is the number of parameters of the statistical model and  $\ell$  is the log-likelihood value of the best parameter set.

**2.2.7 Univariate and bivariate return periods**

The return period for a univariate variable is calculated separately for drought duration and severity as per Eq. 5.

$$T_S = \frac{E(L)}{1 - F_S(s)}, T_D = \frac{E(L)}{1 - F_D(d)}, \tag{5}$$

where  $T_D$  and  $T_S$  represent univariate return period of duration and severity,  $L$  is the drought interarrival time,  $E(L)$  expected interarrival drought time which can be estimated from observed droughts,  $F_S(s)$  and  $F_D(d)$  are CDF of drought severity and duration.

There are two types of bivariate return periods calculated with the copula functions; “ $T_{DS}^{AND}$ ” which is the co-occurrence return period for the condition of  $D \geq d$  and  $S \geq s$ , and “ $T_{DS}^{OR}$ ” which is the joint return period for  $D \geq d$  or  $S \geq s$ . The formulation of  $T_{DS}^{AND}$  and  $T_{DS}^{OR}$  are given in Eqs. 6 and 7, respectively.

$$T_{DS}^{AND} = \frac{E(L)}{P(D \geq d, S \geq s)} = \frac{E(L)}{1 - F_D(d) - F_S(s) + C(F_D(d), F_S(s))} \tag{6}$$

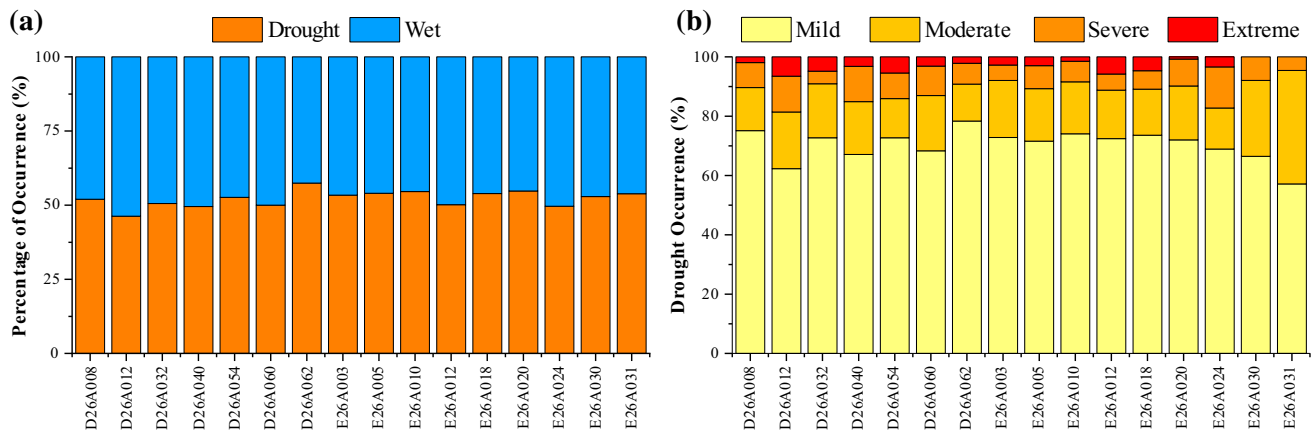
$$T_{DS}^{OR} = \frac{E(L)}{P(D \geq d \text{ or } S \geq s)} = \frac{E(L)}{1 - C(F_D(d), F_S(s))}, \tag{7}$$

where  $C$  is the copula function in the bivariate return period.

**3 Results and discussion**

**3.1 Drought analysis**

The percentages of dry and wet occurrences of calculated SDI values using the streamflow data of 16 streamflow



**Fig. 3** a Percentage of drought/wet occurrence. b Percentage of occurrence for different drought classifications

gauging stations in the Tigris basin are given in Fig. 3a. According to the SDI values, it is observed that the dry period is more than the wet period in 11 of the 16 stations. The dry period is equal in four of them (D26A040, D26A060, E26A012, E26A024). In only one station (D26A012), the dry period is less than the wet period. The highest rate of dry period is seen at station D26A062 with 57%. The distribution of the dry periods according to the classification at Table 2 is given in Fig. 3b. It is determined that the most common drought class at all stations is mild drought, and this event occurred at a maximum of 78% at station D26A062 and minimum of 57% at station E26A031. The highest moderate drought occurrence rate is 38% at station E26A031, while the highest severe drought is 14% at station E26A024. The rate of occurrence of extreme drought, which creates devastating impacts is calculated as 7% at station D26A012, which is the station where the least dry period occurs. There are no extreme drought conditions observed in stations E26A030 and E26A031 throughout the basin, and the maximum dry event (over 90%) at these two stations is mild and moderate drought.

The drought duration and severity parameters of the separately calculated SDI values for 16 stations in the Tigris basin are determined using the Run Theory. The scatter plots of the drought duration and severity values of all stations and the histograms of the value ranges are given in Fig. 4. Drought duration (month) and severity (sum of negative SDI) values are mostly 0–10 at all stations. The maximum drought duration value at stations varies from 17 (D26A008) to 50 months (E26A031), and the mean of the highest dry period values of all stations occurs as 33.5 months. The mean of the dry periods occurring at all stations is 6.43 months. The maximum drought severity value at the stations varies from 18.2 (D26A008) to 56.92 (E26A024), and the mean of the highest drought severity of all stations

is 38.35. The mean value of drought severity occurring at all stations is 4.87.

Figure 5 shows the relationship between drought duration and severity spatially according to Kendall's tau, Spearman's rho and Pearson correlation coefficients. Correlation coefficients obtained at all stations showed a significant relationship between drought duration and drought severity for 0.01 level (two-tailed). According to all correlation coefficients, the highest correlation occurred at station D26A012, and the lowest correlation; according to Kendall's tau and Spearman's rho occurred at station D26A060, and according to Pearson at station D26A062. Although Kendall's tau value is relatively low compared to other coefficients, it can be said that there is a strong relationship between drought duration and severity throughout the basin when the correlation coefficients are evaluated in generality.

### 3.2 Univariate marginal distribution

To calculate the joint probability of copula functions and drought characteristics, it is first necessary to determine the optimal marginal distributions of these variables (duration and severity of drought for this study) that affect drought characteristics. Therefore, in this study, the most suitable ones are determined among Exponential, Extreme value, Gamma, Inverse Gaussian, Logistic, Log-logistic, Lognormal, Nakagami, Normal, Rayleigh, Rician, t location-scale and Weibull marginal distributions for drought duration and severity, according to AIC and BIC. The marginal distribution functions that the best fit for the drought's duration and severity according to the stations are given in the radar graph in Fig. 6. For example, for the drought duration variable in the Tigris basin, the best fitted marginal distribution is determined by the Inverse Gaussian for 15 of the 16 stations, and the Exponential distribution only at station D26A040. The best fitted distribution for the drought severity variable

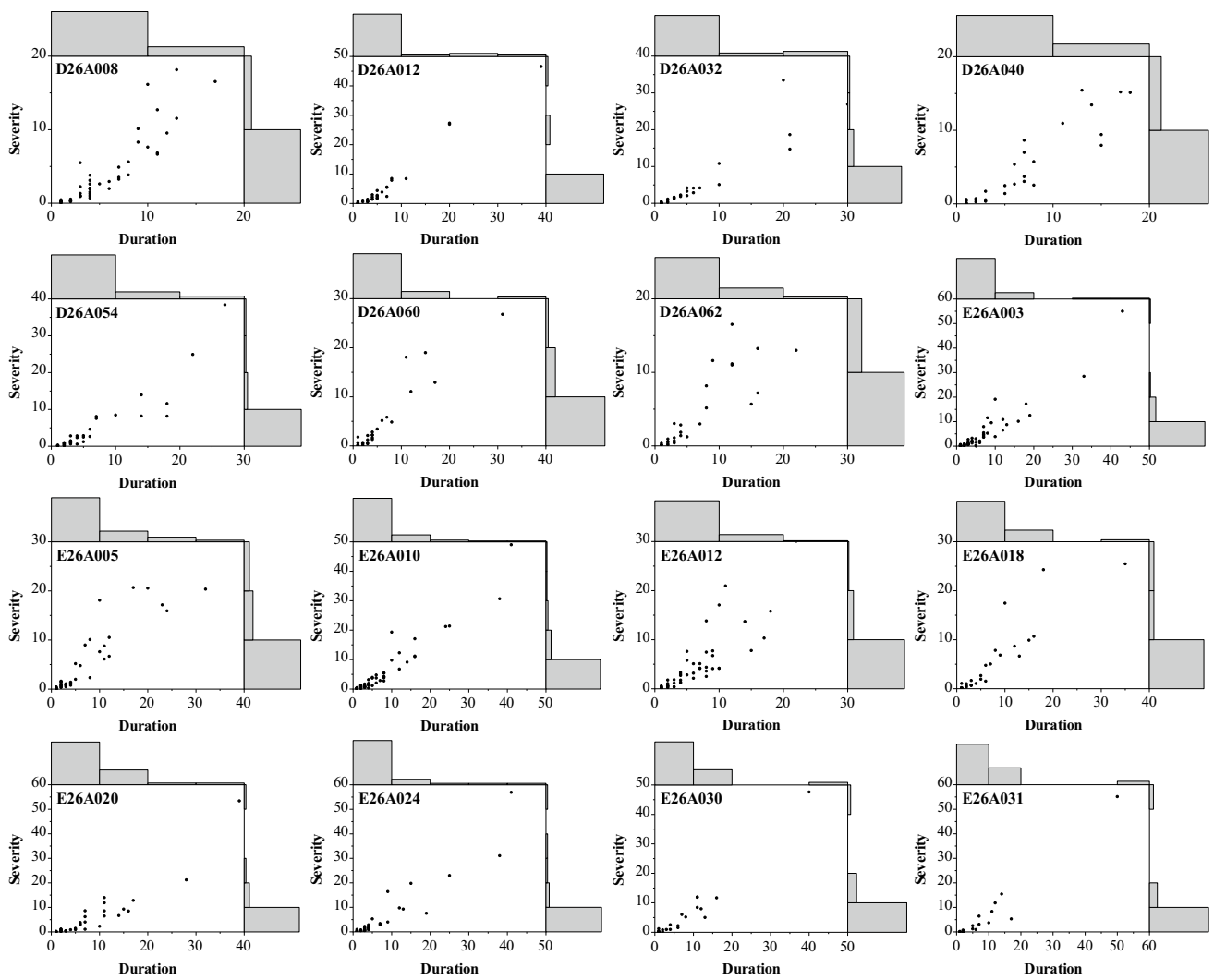


Fig. 4 Scatter plot of drought duration and severity

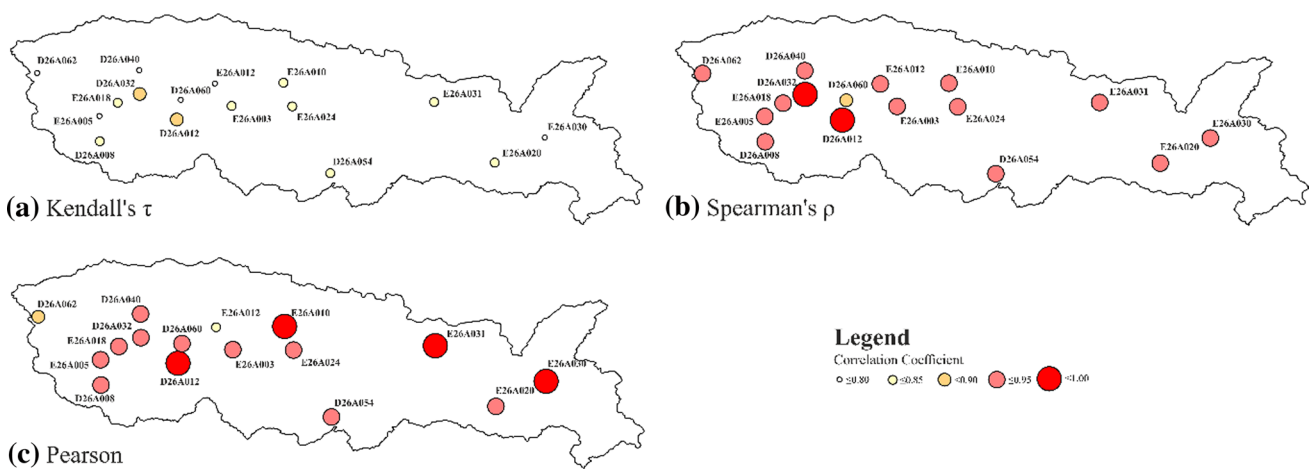
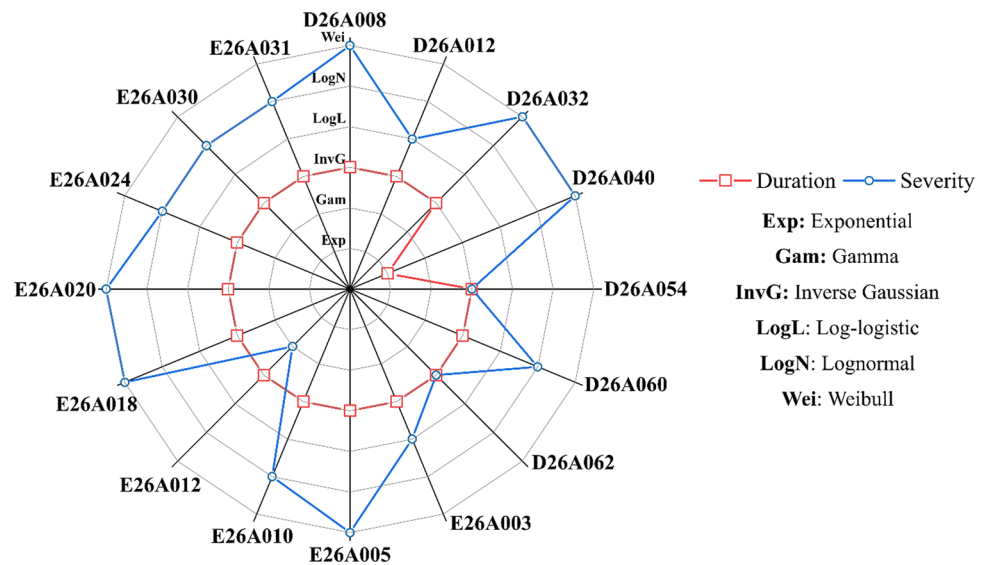


Fig. 5 Spatial distribution of correlation coefficient for drought duration and severity (a Kendall's  $\tau$ , b Spearman's  $\rho$ , c Pearson)



**Fig. 6** The best fit result of the univariate marginal distribution of the duration and severity



is found as Weibull for six stations, Lognormal at five stations, Log-logistics and Inverse Gaussian at two stations, and gamma distribution at one station.

### 3.3 Copula

AMH, Clayton, Frank, Galambos, Gumbel-Hougaard and Joe copulas are used to define the bivariate joint probability of the calculated drought duration and severity of the 16 stations in the Tigris basin. The copula that best fits the data set is determined according to the AIC and BIC parameters using the best performance marginal distributions of drought duration and severity values. The numerical results obtained, and the parameters of the evaluated copulas are given in Table 4. The copulas with the best results are marked in bold and italics in the table. Among the copulas used, the Galambos copula, which is from the extreme value family, showed the best fit at 13 of 16 stations (approximately 81%). The stations, the best fitted copula of the Galambos, are *D26A008*, *D26A012*, *D26A032*, *D26A040*, *D26A054*, *D26A062*, *E26A003*, *E26A005*, *E26A010*, *E26A018*, *E26A024*, *E26A030* and *E26A031*. The Frank copula from the Archimedean family is the best fitted copula in the basin at two stations (*E26A012* and *E26A020*), and the Joe copula is designated as the best fitted in a single station (*D26A062*). The Archimedean copulas (AMH, Frank, Clayton, Gumbel-Hougaard, and Joe) are generally successful in representing hydrological variables in the literature (Mellak and Souag-Gamane 2020; Mortuza et al. 2019). However, within the scope of this study using streamflow data, it is seen that the Galambos copula is pretty successful compared to other copula types in jointly evaluating the drought duration and severity in the majority of the stations. Mirabbasi et al. (2012) and Kiafar et al. (2020) found the Galambos copula

to be successful in evaluating jointly the drought duration and severity of monthly SPI values. It is determined that the Galambos copula, which is successful in different hydro-meteorological studies, is successful in 13 stations in this study area. Although it did not yield the most successful result in the other three stations, it gave approximate results to the best fitted copulas. For this reason, the Galambos copula is applied to all stations for comparing the bivariate return periods in the basin with each other.

### 3.4 Univariate return periods

Univariate return periods for 20, 50, 100 and 200 years are calculated using Eq. 5 in the basin and spatial distributions are given in Fig. 7. For the 20-year and 50-year univariate return periods, the highest drought duration and severity occurred at station *E26A031* and the lowest at station *D26A008*. For the return periods of 100 and 200 years, the highest drought duration is also determined at the station *E26A031* with 57.51 and 73.36 months, while the highest drought severity is calculated at the station *D26A012* with 169.74 and 340.34 months. For the return periods of 100 and 200 years, the lowest drought duration and severity values are calculated at station *D26A008*. The drought duration variable also indicated similar characteristics in the basin for different return periods. However, it is observed that only at the stations *E26A020*, *E26A030* and *E26A031* in the east of the basin, the drought duration values for the return periods of 50, 100 and 200 years are mostly higher than the other parts of the basin. According to the drought severity values, it is observed that the drought severity for all return periods is quite low in the western part of the basin compared to other places.

**Table 4** The result of AIC, BIC values and parameters for selected copulas (The bold and italics values represent the best successful copula)

Station	Criteria	AMH	Clayton	Frank	Galambos	Gumbel-Hougaard	Joe
D26A008	AIC	-253.68	-305.78	-311.37	<b>-312.13</b>	-311.24	-305.84
	BIC	-251.73	-303.83	-309.42	<b>-310.18</b>	-309.29	-303.89
	Parameter	1.0000	3.1084	16.914	<b>4.9098</b>	4.4530	34.9996
D26A012	AIC	-129.58	-162.19	-183.58	<b>-192.38</b>	-185.89	-192.06
	BIC	-128.11	-160.72	-182.11	<b>-190.92</b>	-184.42	-190.60
	Parameter	1.0000	4.2783	19.806	<b>34.9829</b>	5.6316	34.9997
D26A032	AIC	-131.63	-157.45	-177.56	<b>-184.45</b>	-175.51	-183.19
	BIC	-130.17	-155.98	-176.09	<b>-182.98</b>	-174.05	-181.73
	Parameter	1.0000	3.1018	18.693	<b>34.9988</b>	4.5199	34.9999
D26A040	AIC	-143.87	-183.33	-205.42	<b>-208.34</b>	-194.67	-208.32
	BIC	-142.43	-181.89	-203.99	<b>-206.90</b>	-193.24	-206.88
	Parameter	1.0000	3.4191	16.284	<b>10.7922</b>	4.0222	34.9972
D26A054	AIC	-155.98	-195.65	-211.11	<b>-222.39</b>	-206.66	-222.03
	BIC	-154.35	-194.02	-209.48	<b>-220.75</b>	-205.02	-220.39
	Parameter	1.0000	3.8949	15.475	<b>8.1420</b>	4.3480	34.9998
D26A060	AIC	-124.08	-141.61	-166.72	-179.26	-163.26	<b>-179.56</b>
	BIC	-122.67	-140.21	-165.32	-177.85	-161.86	<b>-178.16</b>
	Parameter	1.0000	2.4140	13.570	34.9896	3.8193	<b>15.5127</b>
D26A062	AIC	-134.92	-163.82	-167.23	<b>-168.69</b>	-158.53	-168.37
	BIC	-133.52	-162.42	-165.83	<b>-167.28</b>	-157.13	-166.97
	Parameter	1.0000	3.2450	14.303	<b>6.8059</b>	3.6033	34.9998
E26A003	AIC	-272.93	-306.56	-381.66	<b>-394.54</b>	-370.25	-392.63
	BIC	-270.82	-304.45	-379.55	<b>-392.43</b>	-368.14	-390.51
	Parameter	1.0000	1.9892	15.220	<b>21.2937</b>	3.5967	21.2735
E26A005	AIC	-173.98	-209.02	-218.70	<b>-221.00</b>	-209.88	-220.84
	BIC	-172.29	-207.33	-217.01	<b>-219.31</b>	-208.19	-219.15
	Parameter	1.0000	3.1435	14.262	<b>12.7610</b>	3.7544	34.9958
E26A010	AIC	-274.35	-339.30	-385.90	<b>-404.35</b>	-377.65	-402.94
	BIC	-272.22	-337.17	-383.77	<b>-402.22</b>	-375.52	-400.82
	Parameter	1.0000	3.3007	17.191	<b>34.9960</b>	4.4025	34.9999
E26A012	AIC	-278.90	-319.39	<b>-330.37</b>	-329.10	-322.87	-326.40
	BIC	-276.87	-317.36	<b>-328.34</b>	-327.08	-320.84	-324.37
	Parameter	1.0000	2.2481	<b>13.444</b>	5.2686	3.2280	34.9998
E26A018	AIC	-122.37	-148.77	-158.48	<b>-163.95</b>	-153.90	-163.60
	BIC	-121.03	-147.44	-157.15	<b>-162.62</b>	-152.57	-162.27
	Parameter	1.0000	3.2834	14.625	<b>12.0171</b>	3.7601	34.9997
E26A020	AIC	-178.97	-214.69	<b>-225.16</b>	-225.05	-223.24	-221.50
	BIC	-177.36	-213.08	<b>-223.55</b>	-223.44	-221.63	-219.89
	Parameter	1.0000	2.8877	<b>15.047</b>	4.9139	3.9996	34.9984
E26A024	AIC	-157.74	-183.39	-208.39	<b>-219.80</b>	-200.78	-219.64
	BIC	-156.07	-181.73	-206.73	<b>-218.14</b>	-199.12	-217.97
	Parameter	1.0000	2.5575	13.280	<b>34.9880</b>	3.5015	34.9995
E26A030	AIC	-104.77	-120.46	-120.99	<b>-123.12</b>	-118.97	-120.13
	BIC	-103.59	-119.28	-119.81	<b>-121.95</b>	-117.79	-118.95
	Parameter	1.0000	4.0148	15.498	<b>9.6406</b>	4.3473	34.9997
E26A031	AIC	-83.42	-99.53	-105.14	<b>-106.44</b>	-105.02	-105.34
	BIC	-82.53	-98.64	-104.25	<b>-105.54</b>	-104.13	-104.45
	Parameter	1.0000	3.1184	14.843	<b>6.0855</b>	4.1340	26.2232

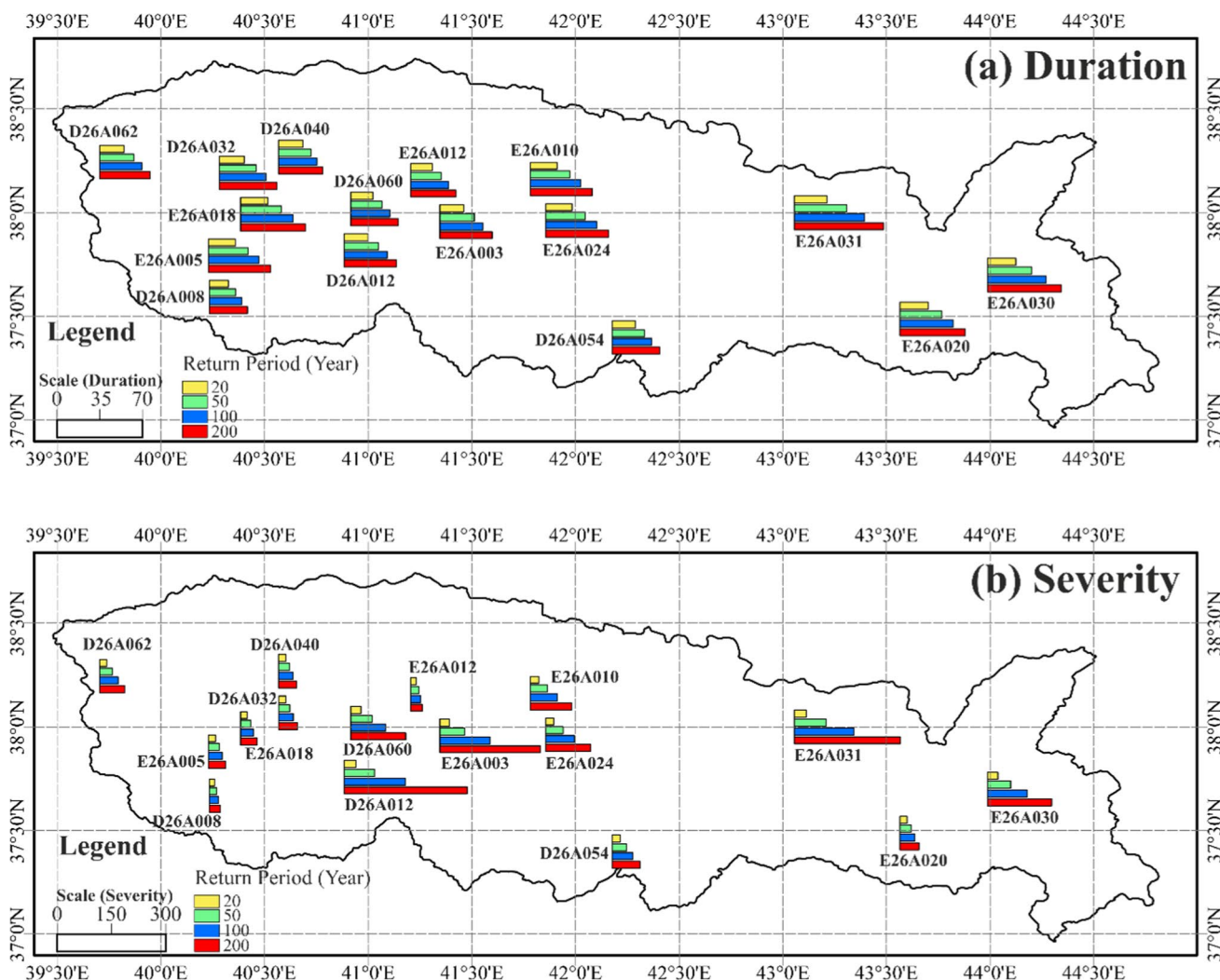
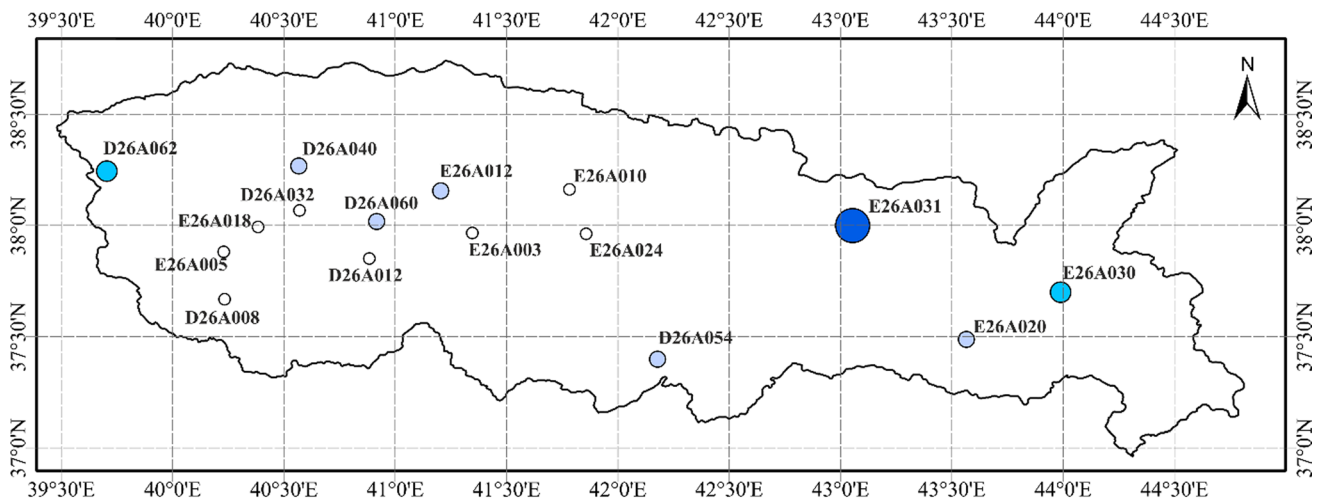


Fig. 7 Drought events for the univariate return period of 20, 50, 100 and 200 years (a Duration, b Severity)

### 3.5 Bivariate return periods

With the help of copula functions, it is possible to determine the  $T_{DS}^{and}$  (the probability that two variables exceed specific values) and  $T_{DS}^{or}$  (the probability that one of two variables exceeded specific values) return periods as calculated in Eqs. 6 and 7. In this section, the return periods in the case of drought duration and severity variables simultaneously or separately will be evaluated. Bivariate return periods are determined with the help of copula functions using the drought duration and severity values determined with univariate 20-, 50-, 100- and 200-year return periods. For this purpose, the Galambos copula, which showed the most successful performance in the basin, is used at all stations. Using the Galambos copula, the return periods in case of simultaneously ( $T_{DS}^{and}$ ) and separately ( $T_{DS}^{or}$ ) drought duration and severity are given in Figs. 8 and 9, respectively. As the  $T_{DS}^{and}$  graph given in Fig. 8 is

examined, it is seen that the bivariate return periods are approximately 5–10% higher than the univariate return periods in most of the stations in the basin. At station E26A031 located in the east of the basin, the bivariate return period is approximately 20% higher than the univariate return period compared to other stations. For example, at station E26A031, the drought duration for the univariate 20-year return period is 26.69 months and its severity is 34. According to these drought duration and severity values, the co-occurrence return period calculated with the Galambos copula functions is 24.3 years. There may be a difference of more than 20% between the probability of the univariate return period and the bivariate return period co-occurring. The same station's 50-, 100- and 200-year return periods are 61.1, 122.6 and 245.4 years, respectively. At the stations E26A003, E26A010, E26A024, D26A008, D26A012 and D26A032 located in the middle region of the basin, in case of simultaneous occurrence



**Bivariate Return Period**

$T_{DS}^{and}$	200 Year	100 Year	50 Year	20 Year
○	210.0-212.3	105.0-106.1	52.3-53.0	20.50-21.17
○	212.2-220.6	106.2-110.2	53.1-55.1	21.18-21.97
○	220.5-228.9	110.1-114.3	55.2-57.1	21.98-22.76
○	229.0-237.1	114.4-118.5	57.2-59.1	22.77-23.55
○	237.0-245.5	118.6-122.5	59.2-61.2	23.56-24.34

**Fig. 8** Spatial distribution of the co-occurrence return period ( $T_{DS}^{and}$ ) corresponding to various univariate risks of return periods

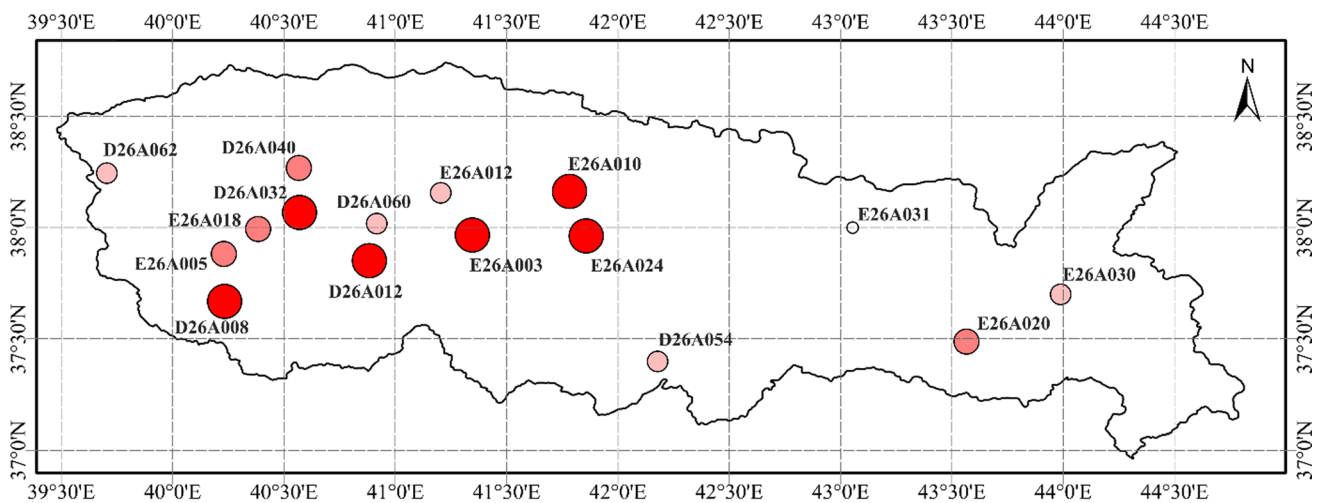
of drought duration and severity values corresponding to univariate return periods, the bivariate return periods of 20, 50, 100 and 200 years are approximately 20.5, 51, 102 and 204 years, respectively. In other words, it turns out that there is no significant difference between univariate return periods and bivariate return periods at the central point of the basin. It has been observed that the difference between univariate return periods and bivariate return periods ( $T_{DS}^{and}$ ) is in the range of 5–10% at stations E26A005, E26A012, E26A018, E26A020, E26A030, D26A040, D26A054, D26A060 and D26A062 which are located outward the central parts of the basin.

As the  $T_{DS}^{or}$  graph given in Fig. 9 is examined, it can be interpreted that the results are similar to the  $T_{DS}^{and}$  results. It is seen that the highest difference occurred again at station E26A031, located in the eastern part of the basin, and the occurrence of both drought duration and severity variables separately decreased to 168 years for a 200-year univariate return period. In other stations, it can be said that the univariate return period of 200 years varies between 181 and 196 years. Therefore, it can be reached that the univariate return periods of a significant part of the basin are in parallel with the results of  $T_{DS}^{or}$ .

It can be said that stations D26A008, D26A012, D26A032, E26A010 and E26A024, located in the middle

and western part of the Tigris basin, are at high risk of drought according to  $T_{DS}^{and}$  compared to other stations.

There are studies about the bivariate return periods calculated according to the drought duration and severity values of univariate return periods. For instance, Botai et al. (2020) analysed the bivariate return periods in Eastern Cape Province, South Africa with using Joe copula. The maximum change of the univariate 100-year return period is 128.6 years for  $T_{DS}^{and}$ , (increased 28.6%), and is 84.4 years for  $T_{DS}^{or}$ . The minimum change is 106.8 years for  $T_{DS}^{and}$  and 94 years for  $T_{DS}^{or}$  for 100 years. Tosunoglu and Can (2016) made a bivariate (drought duration and severity) frequency analysis of monthly SPI values using the precipitation values of 173 meteorological stations covering the whole of Turkey, including the Tigris basin with Copula functions. Univariate and bivariate joint return periods are investigated in the region where the Tigris basin is also located (named the fourth region in the related study). Although their study is made with monthly SPI values, it is known that meteorological drought eventually causes hydrological drought (Gumus and Algin 2017). In the study, the joint return periods of drought duration and severity ( $T_{DS}^{and}$ ) corresponding to univariate return periods of 10, 50-, 100-, 200- and 500-year, in the region where the Tigris basin is located are 15.5, 78.0, 156.1, 312.9 and 781.6, respectively. For  $T_{DS}^{or}$ , the common



**Bivariate Return Period**

$T_{DS}^{or}$	200 Year	100 Year	50 Year	20 Year
○	170.0-174.2	85.0-87.2	42.5-43.6	17.0-17.5
○	174.3-179.7	87.3-89.9	43.7-44.9	17.6-18.0
○	179.7-185.2	90.0-92.6	45.0-46.3	18.1-18.5
○	185.3-190.7	92.7-95.4	46.4-47.7	18.6-19.1
●	190.7-196.2	95.5-98.1	47.8-49.1	19.0-19.6

**Fig. 9** Spatial distribution of the joint return period ( $T_{DS}^{or}$ ) corresponding to various univariate risks of return periods

return periods corresponding to 10-, 50-, 100-, 200- and 500-year return periods are determined as 7.4, 36.8, 73.6, 147.3 and 367.8 years, respectively. For the monthly SPI at bivariate return periods, there is a difference of over 50% compared to the univariate return periods. However, the difference is lower at the 3 months SDI values for the current study. It can be interpreted that this result is due to the SDI values calculated with the 3-month cumulative totals.

### 4 Conclusions

In this study, hydrological droughts of 16 streamflow gauging stations of the Tigris Basin, Turkey are calculated with the Streamflow Drought Index (SDI). The drought duration and severity values are extracted. The univariate and bivariate return periods of these two variables in the basin are evaluated with the copula functions.

The main conclusions of the present study are:

- SDI values of the basin show that the percentage of dry period is significantly higher than the wet period at 69% of stations.

- A strong relationship is determined between drought duration and severity throughout the basin according to Pearson and Spearman's rho correlation coefficients.
- The best fitted marginal distributions of drought duration are found out that Inverse Gaussian for 15 of the 16 stations. For the drought severity variable, Weibull and Lognormal distributions are determined the best fitted marginal distribution at six and five stations, respectively.
- It is found that the Galambos copula is the most successful copula function compared to other used copula types in the majority (81%) of the stations for the bivariate analysis.
- Univariate analysis of return periods shows that for only three stations in the east of the basin the drought duration for the return periods is mostly higher than the other parts of the basin. Additionally, the drought severity return periods is quite low in the western part of the basin.
- It has been observed that the difference between univariate return periods and bivariate return periods ( $T_{DS}^{and}$ ) is in the range of 5–10% at stations that are located outward the central parts of the basin.  $T_{DS}^{or}$  results are found to be similar to the  $T_{DS}^{and}$  results.
- As a result of the spatial analysis of the drought duration and severity in the Tigris basin with the bivariate copula,

it is seen that the central and western parts of the basin have a high risk in terms of return periods.

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**Author contributions** YA: performing analysis, interpreting results, and writing the manuscript; VG: conceptualisation, coding, writing the manuscript.

**Data availability** The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Conflict of interest** The authors declare no competing interests.

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** All the co-authors are familiar and agree with the content of this paper.

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