

# Comparison of the Calculated Drought Return Periods Using Tri-variate and Bivariate Copula Functions under Climate Change Condition

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## Research Article

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1 **Comparison of the Calculated Drought Return Periods Using Tri-variate and Bivariate**  
2 **Copula Functions under Climate Change Condition**

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12

13 **Abstract**

14 Concerning the various effects of climate change on intensifying extreme weather  
15 phenomena all around the world, studying its possible consequences in the following  
16 years has attracted the attention of researchers. As the drought characteristics identified  
17 by drought indices are highly significant in investigating the possible future drought, the  
18 Copula function is employed in many studies. In this study, the two- and three-variable  
19 Copula functions were employed for calculating the return period of drought events for  
20 the historical, the near future, and the far future periods. The results of considering the  
21 two- and three-variable Copula functions were separately compared with the results of the  
22 calculated Due to the high correlation between drought characteristics, bivariate and  
23 trivariate of Copula functions were applied to evaluate the return periods of the drought.

24 The most severe historical drought was selected as the benchmark, and the drought  
25 zoning map for the GCM models was drawn. The results showed that severe droughts can  
26 be experienced, especially in the upper area of the basin where the primary water resource  
27 is located. Also, the nature of the drought duration plays a decisive role in the results of  
28 calculating the return periods of drought events.

29 **Keywords:** Drought Return Period, Climate Change, Copula Function, Drought Map

### 30 **1. Introduction**

31 Drought occurs for long periods of unusual hydrological conditions resulting in a sharp  
32 decline in rainfall. Fundamentally, drought is an aridity type caused by the decrease in  
33 rainfall. Meteorological measurements are the first sign of a drought (Bazarafshan 2017;  
34 Abdulkadir 2017; Khan et al. 2018). All climate conditions may experience this phenomenon  
35 (Chen et al. 2013). Moreover, extreme weather events, such as drought, are the main causes  
36 of risk to agricultural systems (Ben-Ari et al. 2016; Hernandez-Barrera et al. 2017; Pascoa et  
37 al. 2017; Zampieri et al. 2017; Ribeiro et al. 2018). Drought analysis is mostly done by  
38 calculating its characteristics, such as drought duration and severity, via drought indices  
39 (Yang 2010; Liu et al. 2016). Analyzing drought indices are important for assessing the  
40 drought conditions because the incident provides various methods to determine drought  
41 severity, arrival (Cahng et al. 2016; Hao et al. 2016; Tian et al. 2018; Mukherjee et al. 2018).  
42 Some indices are the Standardized Precipitation Index (SPI), the Reconnaissance Drought  
43 Index (RDI), the modified SPI index, and the Joint Deficit Index (JDI). The values of  
44 modified SPIs are integrated with different time scales through multiple Copula distribution  
45 functions and create the JDI to determine the overall drought situation in the JDI (Kao and  
46 Govindarajo 2010; Ma et al. 2016). The SPI is proper for measuring meteorological drought

47 since it is based on precipitation data. As climate change could cause extreme hydrological  
48 phenomena, investigating its effects is one of the necessities of water resources management  
49 (Ahmadalipour et al. 2017; Oguntunde et al. 2017). In the northern hemisphere, areas  
50 between latitudes 15 and 45 degrees are susceptible to more severe droughts (Mousavi 2005;  
51 Barlow et al. 2016; Gazol et al. 2016).

52 Research has been done for investigating the effects of climate change on the drought via  
53 several drought indices (Mathbout et al. 2018; Thomas and Prasannakumar 2016; Lee2017 et  
54 al. 2017; Bazrafshan et al. 2017). Examples include the SPI and the RDI, the Percent of  
55 Normal Precipitation Index (PNPI), the Agricultural Rainfall Index (ARI), the Multivariate  
56 Standardized Drought Index (MSDI), and JDI Index, having utilized for drought analysis in  
57 different parts of the world including Iran (Bazrafshan et al. 2017; Hoffman et al. 2009,  
58 Kirono et al. 2011, Selvaraju and. Baas 2007, Lee et al. 2013, Serinaldi et al. 2009; Mirabbasi  
59 et al. 2013; MirAbbasi et al. 2013; Madadgar and Moradkhani 2011; Lee et al. 2013; Kirono  
60 et al. 2011; Srinaldi et al. 2009; Hoffman et al. 2009; Selavarajo and Bass 2007).

61 There is a significant correlation between duration and severity of droughts (Ayantobo et al.  
62 2019; Santos et al. 2019; Wu et al. 2017; Ayantobo et al. 2017; Madadgar and Moradkhani  
63 2011). Drought analysis based on just one characteristic can only cause a misunderstanding  
64 of droughts. By calculating the return period only based on one drought characteristic ignores  
65 all other drought characteristics and their relevant characteristics (Ge et al. 2016;  
66 Thilakarathne and Sridhar 2017). Besides, the return period of a drought can be measured as  
67 a sample for the severity larger than a certain value. Nevertheless, the return period cannot  
68 provide information on other drought characteristics, such as drought duration (Taskirirs et al.  
69 2016; Kwon and Lall 2016). Planning for a longer period needs more reflection. Also, it is  
70 crucial to plan for the happening years in advance occasionally. Therefore, knowing about the

71 return period of drought along with paying attention to the drought characteristics for  
72 managing water resources is vital (Zhang et al. 2017). Several trivariate copula functions  
73 were conducted for multivariate frequency analysis of extreme hydrological events such as  
74 droughts (Maddadgar and Moradkhani 2011; Chen et al. 2011; Hao et al. 2017; Hangshing  
75 and Dabral 2018; Zhu et al. 2019). Contrary to conventional methods such as normal  
76 multivariate distribution, the Copula function is independent of marginal distribution  
77 functions, so that any type of marginal distribution function can be considered for each of the  
78 variables (Da Rocha Júnior et al. 2020; Zhang and Singh 2007; Favre et al. 2004). Also, the  
79 current drought index and the copula-based analysis of drought properties present a new  
80 concept for appropriate management practices in the changing environment (Das et al. 2019).  
81 Investigating the use of Copula functions, such as Gumbel, Frank, Clayton, and Gaussian, in  
82 analyzing drought characteristics, Lee et al. (2013) calculated the SPI in four stations of  
83 Canada and Iran and utilized Copula functions for analyzing the drought. Wang et al. (2010)  
84 employed a trivariate Copula to analyze the drought characteristics in the New South Wales  
85 area of Australia. They calculated the SPI to assess the characteristics of the drought. Dashe  
86 et al. (2019) coupled the hydrological Soil Water Assessment Tool (SWAT) with the  
87 multivariate copulas for prediction of the drought years. The results showed that the  
88 developed SWAT-Copula-based method has can be employed in data-scarce regions for  
89 effective drought monitoring with the minimum observed inputs. Daneshkhah et al. (2016)  
90 and Luo et al. (2019) constructed a different flood risk management model via the Copula-  
91 based Bayesian network to analyze the flood risk. Ribeiro et al. (2019) employed the copula  
92 theory for estimating joint probability distributions describing the dependence degree  
93 between drought conditions and crop yield anomalies of two major rainfed portions of cereal.  
94 The Standardized Precipitation Evapotranspiration Index (SPEI), the satellite-derived indices

95 Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) are employed.  
96 The results showed that while TCI is commonly employed in copula models indicating better  
97 probabilities of joint extreme high values of wheat and drought indicators, the VCI and SPEI  
98 are related to copula models illustrating higher probabilities of joint extreme low values.  
99 Balistrocchi and Grossi (2020) predicted the effect of climate change on urban drainage  
100 systems in northwestern Italy via a copula-based approach, finding the seasonal distribution  
101 of storms critical for urban drainage systems. Chatrabgoun et al. (2020) used the copula  
102 functions in a new mathematical framework with nonlinear analysis, investigated the effects  
103 and dangers of frost on the vine. The study revealed that the developed Caspian model is a  
104 proper instrument for predicting the return period of glacial events. Kiafar et al. (2020) used  
105 the copula-based genetic algorithm method to monitor meteorological droughts of Qazvin  
106 station in Iran. The drought characteristics are measured via the monthly SPI. The study  
107 shows that drought probabilistic characteristics could be used for water resources  
108 management and planning.

109 The return periods of drought events has been largely ignored in previous drainage basin  
110 studies and also some basins face some complications, and providing drought zoning maps  
111 will lead to a better understanding of the situation of basins, which has not been sufficiently  
112 discussed in previous studies, especially the Zayandeh Rud basin in Iran. Hence the purpose  
113 of this study was to employ, the Standardized Precipitation Index (SPI) to calculate the  
114 duration, severity, and peak intensity of a drought in the basin throughout history, in the near  
115 future, and far future using data from 15 GCM models obtained from the fifth IPCC report  
116 (AR5).

## 117 **2. Materials and Methods**

### 118 **2.1 The SPI**

119 The SPI was developed by McKee et al. (1993). The SPI value can be positive or negative,  
 120 with positive values indicating periods when precipitation is above the average and negative  
 121 values indicating periods when precipitation is below the average (Shiau 2006). The SPI also  
 122 can be calculated for different time scales (1, 3, 6, 12, 24, and 48 months). While the SPI of  
 123 1-3 months is utilized for meteorological drought study, SPI of 1-6 months is applied for  
 124 agricultural drought study, and the SPI of 6-24 months is employed for hydrological drought  
 125 determination (World Meteorological Organization 2012). In calculating this index, initially,  
 126 the gamma distribution function is adjusted to the precipitation data, then the cumulative  
 127 probability obtained from the gamma distribution is transferred to the normal standard  
 128 cumulative distribution with an average of zero and a mean deviation of one. Equation (1) is  
 129 illustrated as the SPI calculation method.

$$130 \quad F(X) = \int_0^X f(X)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^X X^{\alpha-1} e^{-\frac{X}{\beta}} dx \quad (1)$$

131 The severity, duration, and peak intensity of drought are calculated based on the RUN theory  
 132 proposed by Yevjevich (1967). According to this method, the threshold level for determining  
 133 drought was considered as (-1) to examine more severe drought conditions (Table 1). Since  
 134 the precipitation data were only available for 30 years, the 3-month SPI calculation was  
 135 considered to better comprehend seasonal meteorological drought. According to the  
 136 definition, drought duration means consecutive months in which the SPI value is less than (-  
 137 1). The drought severity is the absolute value of SPI cumulative values in periods when SPI  
 138 values are consistently less than (-1), and the drought peak intensity is the minimum SPI-  
 139 value for every drought event.

140 Distribution functions are utilized to fit drought characteristics including log-normal  
 141 distribution function, exponential distribution function, gamma distribution function, and

142 Weibull distribution function. The most suitable distribution functions for drought severity  
 143 and duration have been determined using the Bayesian information criterion (BIC) method.  
 144 The relation of BIC calculation is used as  $BIC = -2\log\text{likelihood} + d.\log(N)$  in which N is the  
 145 sample size and d is the number of parameters; lower the value, better the fitness (Li et al.  
 146 2013).

147 Table 1- SPI classification

SPI Value	Drought Condi- tion
	Extremely Wet
2.0 and more	Very Wet
1.5 to 1.99	Moderately
1.0 to 1.49	Wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately
-1.5 to -1.99	Dry
-2 and less	Severely Dry
	Extremely Dry

148

149 **2.2 The Multivariate Probabilistic Distribution of a Copula Function**

150 The Copula function is a multivariate joint function applied to connect various probabilistic  
 151 distribution functions. Furthermore, a random vector  $(x_1, x_2, \dots, X_n)$  with continuous marginal  
 152 distribution functions of  $F_i(x) = P [X_i \leq x]$  has been considered. For each member of this  
 153 random vector, uniform margins  $(U_1, U_2, \dots, U_d)$  are available as follows (Nelson 2007):

154  $(U_1, U_2, \dots, U_d) = (F_1(X_1), F_2(X_2), \dots, F_d(X_d))$  (2)

155 Therefore, the C Copula function can be defined as a joint distribution function of  $(U_1, U_2,$   
 156  $\dots, U_d)$  for the vector  $(x_1, x_2, \dots, x_n)$ :

157  $C(U_1, U_2, \dots, U_d) = P[U_1 \leq u_1, U_2 \leq u_2, \dots, U_d \leq u_d]$  (3)

158 The relation is described as follows:

159  $C(U_1, U_2, \dots, U_d) = P$  (4)

160 Scalar theory (1959) showed that C Copula function for each n-dimensional cumulative  
 161 distribution function of H with different margins  $F_1, \dots, F_n$  is defined as follows: (Nelson  
 162 2007)

163  $H(X_1, X_2, \dots, X_n) = C[F_1(X_1), F_2(X_2), \dots, F_n(X_n)] = C(U_1, U_2, \dots, U_n)$  (5)

164 In which  $u_1, \dots, u_n$  is the distribution functions of  $X_1, \dots, X_n$  (Madadgar and. Moradkhani,  
 165 2011).

166 Marginal functions should be uniform in the 0 and 1 range. Copula functions have different  
 167 families, and some of them are increasingly used in hydrological studies (Yan 2007).  
 168 According to the literature review, normal Copula and t Copula were considered to be in the  
 169 family of elliptical Copulas and Gumble, Frank, and Clayton Copulas were considered in the  
 170 family of Archimedes Copulas of the Copula functions that had been used in this study (Chen  
 171 et al. 2013; Yang 2010; Lee et al. 2013; Serinaldi et al. 2009; Mirabbasi et al. ; 2013,  
 172 Madadgar and Moradkhani, 2011 ; Chen et al. 2011; Chen et al. 2011; Chen et al. 2012; Chen  
 173 et al. 2011; Madadgar and Moradkhani 2011; Sarinaldi et al. 2009).

174 **2.3 Return period based on Copula function**

175 It is important to know the frequency of extreme phenomena in hydrological studies. To  
 176 assess the drought, the time between the arrival of a drought phenomenon and the arrival of

177 the next drought is called the inter-arrival time, and the mean inter-arrival time of two  
 178 drought phenomena occurrences is defined as the return period (Srinaldi et al. 2009).

179 In the single variable mode, the return period is calculated as (6) and (7):

$$180 \quad T_d = \frac{E(L)}{P_D(D \geq d)} \quad (6)$$

$$181 \quad T_d = \frac{E(L)}{P_S(S \geq s)} \quad (7)$$

182 Where  $T_d$  is the return period of the drought,  $E(L)$  is the expected value of the drought's inter-  
 183 arrival time,  $D$  indicates the duration of the drought, and  $S$  is the severity of the drought. The  
 184 formula for calculating the return period for a multivariate return period can also be  
 185 developed based on the method of calculating the return period of a single variable.  
 186 According to Xia's (2006) method, the calculation of the return period in multivariate mode is  
 187 done with via two logical operators "and" and "or". The operator "and" indicates the return  
 188 periods in which all variables are greater than or equal to the specified values, and the  
 189 operator "or" indicates a state in which at least one of the variables is greater than or equal to  
 190 the specified values.

191 The return period is calculated for the case of  $D \geq d$  and  $S \geq s$ , as well as for  $D \geq d$  or  $S \geq s$   
 192 mode with the help of relations (8) and (9):

$$193 \quad T_{\text{and}} = \frac{E(L)}{P(D \geq d, S \geq s)} = \frac{E(L)}{1 - F_D(d) - F_S(s) + C[F_D(d), F_S(s)]} \quad (8)$$

$$194 \quad T_{\text{or}} = \frac{E(L)}{P(D \geq d \text{ or } S \geq s)} = \frac{E(L)}{1 - C[F_D(d), F_S(s)]} \quad (9)$$

195 The calculation relations of the return period with the help of trivariate Copula functions for  
 196  $I \geq i$ ,  $S \geq s$  and  $D \geq d$  modes, as well as  $I \geq i$  or  $S \geq s$  or  $D \geq d$  modes, are as described in (10)  
 197 and (11):

198 
$$T_{\text{and}} = \frac{E(L)}{1 - P(D \geq d, S \geq s, I \geq i)} = \frac{E(L)}{1 - F_D(d) - F_S(s) - F_I(i) + C[F_D(d), F_S(s)] + C[F_D(d), F_I(i)] + C[F_S(s), F_I(i)] - C[F_D(d), F_S(s), F_I(i)]}$$

199 (10)

200 
$$T_{\text{or}} = \frac{E(L)}{1 - P(D \geq d \text{ or } S \geq s \text{ or } I \geq i)} = \frac{E(L)}{1 - C[F_D(d), F_S(s), F_I(i)]} \quad (11)$$

201 In the above equations, D indicates the duration of drought, S indicates the severity of  
 202 drought, I indicates the peak intensity of drought in each period, d indicates the duration of  
 203 the determined drought, s indicates the severity of the specified drought and i indicates the  
 204 peak intensity of drought in a period whose value is predetermined.

205 The return period for drought phenomena, where the duration, severity, and peak intensity of  
 206 drought are greater than a certain amount, signals a more severe drought phenomenon.  
 207 Therefore, the  $T_{\text{and}}$  calculation was considered in this study.

## 208 2.4 Climate Change Scenarios

209 Investigating climate change in the future includes several factors, such as greenhouse gas  
 210 emissions, technology development, changes in energy production methods, land use,  
 211 regional economy, population growth, and more. Various groups are examining these issues  
 212 under the supervision of the Intergovernmental Panel on Climate Change (IPCC). The Fifth  
 213 Assessment Report (AR5) was published based on the scenarios of Representative  
 214 Concentration Pathways (RCP), which represent the pathways for emission and concentration  
 215 of gases and the obtained results until 2100 (Wayne, 2013). Since AR5 is the latest report  
 216 released by IPCC, this study employed the data from AR5. The report has defined four RCP  
 217 scenarios: RCP2.6, RCP4.5, RCP6, and RCP8.5. Two RCP4.5 and RCP8.5 scenarios were  
 218 selected for this study. The RCP8.5 scenario includes procedures that along with increasing  
 219 land-use change in agricultural lands and lawns, will also concern the increase in the world's

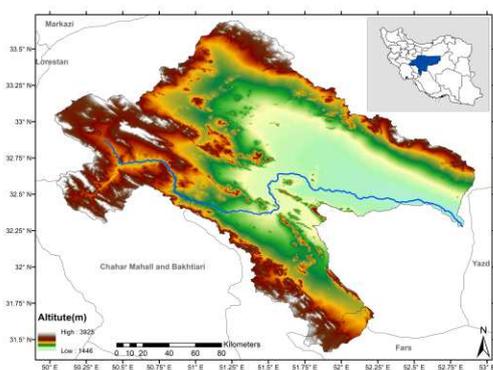
220 population. Therefore, this scenario indicates an increase in greenhouse gas emissions over  
221 time, resulting in a high level of greenhouse gas concentrations (Riahi et al. 2007; Riahi et al.  
222 2011). This scenario is similar to the SRES A1F1 scenario compared to the fourth IPCC  
223 report scenarios. The RCP4.5 scenario is a scenario in which greenhouse gas emissions are  
224 stabilized until 2100 in order not to exceed the desired emission level (Thomson et al. 2011;  
225 Wise et al. 2009; Clark et al. 2007; Smith and Wigley 2006). This scenario is similar to the  
226 SRES B1 scenario compared to climatic scenarios and emission scenarios in the fourth report  
227 (Wayne 2013). NASA has provided researchers with an accuracy of 0.25 degrees and the  
228 predicted data of Earth's global daily exchange on the NASA website named NASA Earth  
229 Exchange Global Daily Downscaled Projections (NEX-GDDP). The data does not require to  
230 be downscaled since it is downscaled for each network on the site (Thrasher et al. 2013). In  
231 this study, daily precipitation data for the 30-year historical period from 1979 to 2008 as well  
232 as daily precipitation data from 15 GCM models under the RCP4.5 and RCP8.5 scenarios for  
233 the next 84-year period of 2016 to 2099 were downloaded from the NASA site.

## 234 **2.5 Study Area**

235 Zayandeh Rud drainage basin is located in Isfahan Province in Iran. The geographical  
236 location of this basin has been shown in Figure 1. The basin is a completely closed basin that  
237 has no access to the sea. The Zayandeh Rud drainage basin covers an area of 26,917 square  
238 kilometers and is located between the latitudes 31°-34° north and longitudes 49°-53° east.  
239 Zayandeh Rud River originates from the Zagros Mountain chain in Western Iran and flows  
240 into the basin, ending up in Gavkhuni Wetland in the southeast of Isfahan Province (Figure1).  
241 The water level of different parts of the basin varies from 1446 meters to 3925 meters, which  
242 leads to different climatic conditions in the basin. In general, the mean annual precipitation in  
243 the basin is 211 mm, widely varying in annual precipitation in various parts of the basin.

244 Also, the mean annual potential evapotranspiration in the basin is 1500 mm. The basin's  
245 mean annual temperature is (14.5) degrees Celsius with the lowest temperature of (-12.5)  
246 degrees Celsius recorded in January and the highest temperature of 42 degrees Celsius  
247 recorded in July. Safavi et al. (2014), in a study on the Zayandeh Rud Basin, reported eleven  
248 dry years, four normal years, and six wet years between 1991-2011. In a study by Gohari et  
249 al. (2013), the effects of climate change on agricultural products and water consumption  
250 efficiency in the Zayandeh Rud drainage basin were investigated from 2015-2044. The  
251 results showed an annual decrease in the precipitation of 11-31 percent, taking into account  
252 changes in precipitation in different months of the year. Furthermore, a study conducted by  
253 Sabzevari (2013) showed that recent droughts in the basin have been very devastating in  
254 reducing surface water and groundwater resources, especially in the western parts.

255



256

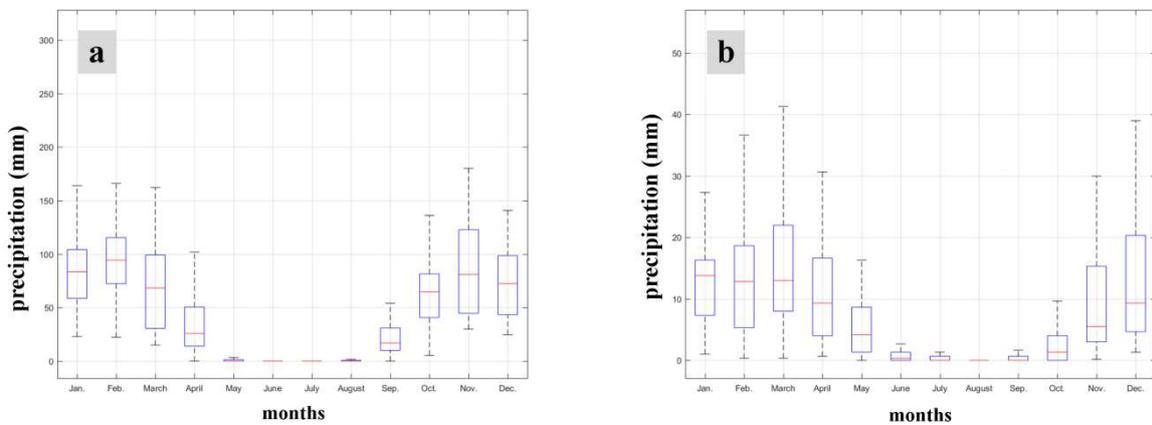
257 Figure 1: Geographic location of the Zayandeh Rud basin

258

## 259 2.6 Data and Information

### 260 2.6.1 Observational Data

261 To better understand the pattern of precipitation in the basin, two specific stations were  
262 selected at two different points in the basin. One of the stations was upstream and the other  
263 was located downstream of the basin. Figure (2) shows the monthly changes in precipitation  
264 at the two selected stations. As can be seen in the figure, the amount of precipitation at the  
265 upstream station was higher than the amount of precipitation at the downstream station.



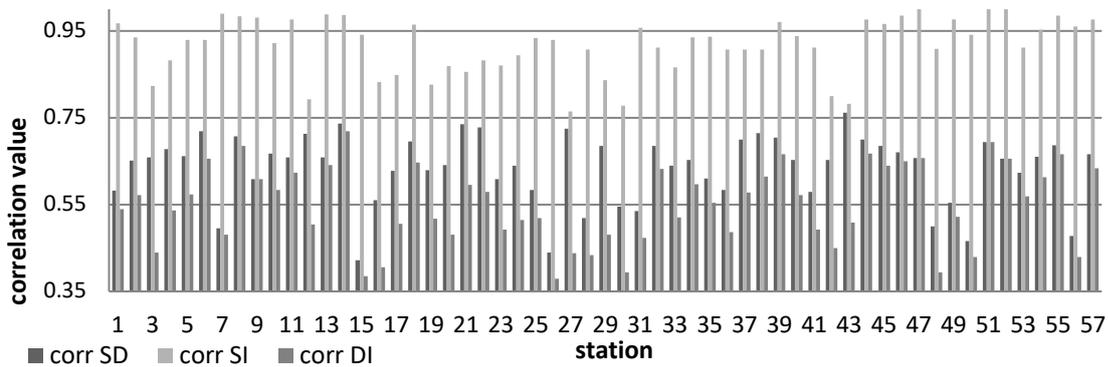
266  
267 Figure 2: Changes in monthly precipitation in the past (1979-2008): a) station located  
268 upstream b) station located downstream

269  
270 **2.6.2 Data Analysis**

271 Zoning of the results on a map is an optimal method to better comprehend the status of the  
272 basin. Using such maps, it is easier to study the general condition of the basin and identify the  
273 more critical parts of the basin. It was decided to use the existing historical data of NEX-  
274 GDDP, which was available for 57 networks within the basin.

275 **2.6.3 Analysis of Historical Drought**

276 The linear correlation between duration parameters, severity, and peak intensity of drought  
 277 has been calculated and almost all obtained values were above 0.5 (Figure 3). The correlation  
 278 range of drought severity and duration was between 0.5 and 0.7. Also, the correlation  
 279 between the severity and peak intensity of drought was between 0.8 and 1, and the correlation  
 280 between the duration and peak intensity of drought was between 0.4 and 0.7.



281  
 282 Figure 3: Linear correlation between drought characteristics (S indicates severity, D indicates  
 283 duration, and I indicates the peak intensity of drought in each period.)

284 According to recent studies, to determine the distribution functions appropriate for each  
 285 drought characteristic (Xu et al. 2015; Shiau 2006), the Exponential, Gamma, Log-normal,  
 286 Weibull distribution functions are appropriate for the duration, severity, and peak intensity of  
 287 the drought. These distribution functions are fitted to calculate drought characteristics in the  
 288 historical period. The most appropriate function is determined for each station in the basin.  
 289 For each marginal distribution function, Table (1) has identified the number of stations, in  
 290 which, the specified distribution function was the best fit for each drought characteristic.  
 291 Table (2) illustrates the selected distribution functions for each drought characteristic. The  
 292 maximum likelihood estimation (MLE) method was utilized to estimate function parameters.  
 293 The BIC method was employed to determine the best function suitable for drought severity,  
 294 duration, and peak intensity. The assigned functions were also used to extract the severity

295 distribution functions, drought duration, and peak intensity of drought in the historical and  
 296 future periods.

297 Table 1: Number of stations with the most appropriate function specified for each drought  
 298 characteristic

<b>Drought characteristics</b>	<b>Exponential function</b>	<b>Gamma function</b>	<b>Log-normal distribution</b>	<b>Weibull distribution</b>
Severity	6	1	41	9
Duration	0	0	57	0
The Peak Intensity of drought	52	0	3	2

299

300 Table 2: Distribution functions selected for each drought characteristics

<b>Drought characteristics</b>	<b>Selected distribution function</b>
Severity	Log-normal
Duration	Log-normal
The Peak Intensity of drought	Exponential

302

303 The most appropriate Copula function for each station in the basin was selected using the  
 304 BIC method. Table 3 shows the number of stations, where the specified Copula function was  
 305 the best-calculated function. Table 4 shows the selected Copula functions for severity-  
 306 duration, the severity-peak intensity of drought, duration-peak intensity of drought, and  
 307 duration-severity-peak intensity of drought.

308 Table 3: The number of stations with the best-specified Copula functions

Copula	t	Normal	Gumbel	Frank	Clayton
<b>severity-duration Copula</b>	<b>0</b>	<b>6</b>	<b>48</b>	<b>3</b>	<b>0</b>
<b>severity-maximum amount of drought</b>	<b>0</b>	<b>25</b>	<b>8</b>	<b>13</b>	<b>11</b>
<b>duration-maximum amount of drought</b>	<b>0</b>	<b>21</b>	<b>29</b>	<b>6</b>	<b>1</b>
<b>duration-severity-maximum amount of drought</b>	<b>21</b>	<b>32</b>	<b>4</b>	<b>0</b>	<b>0</b>

Table 4.

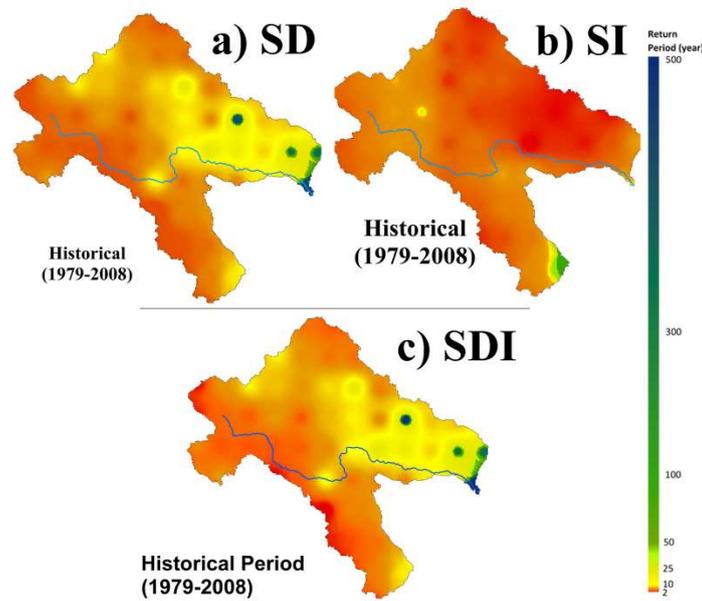
317 Selected Copula functions

Copula marginal function	Selected Copula function
<b>Severity-Duration</b>	<b>Gumbel</b>
<b>Severity-Peak Intensity</b>	<b>Normal</b>
<b>Duration-Peak Intensity</b>	<b>Gumbel</b>
<b>Duration-Severity-Peak Intensity</b>	<b>Normal</b>

320 **3. Results and Discussion**

### 3.1 Effects of Climate Change on the Drought under RCP4.5 S

In this study, 90% of the highest values of severity, duration, and peak intensity of drought in each period of the historical era were considered as the benchmark severe drought in the basin. Accordingly, the characteristics of the most severe historical drought, which was considered as a criterion for measuring droughts, included the severity of drought with an SPI value of (-4.39), the duration of drought equal to 6 months, and the peak intensity in each period with an SPI value of (-1.36). Considering these characteristics, the drought's return period was calculated for all points of the network within the basin for the historical period (1979-2008), the near future (2016-2057), and the distant future (2058-2099). The results were displayed in spatial maps in the GIS software using the inverse distance weighting (IDW) method. Low values indicated more drought occurrence. According to the results of frequency analysis with the help of the bivariate and trivariate Copula function, the return period of the most severe drought in different parts of the basin is based on all three types of bivariate and trivariate Copula varied between 2 to 500 years. Due to the varied topography in different parts of the basin, this range was logical for the return period. According to Figure (4) which shows the results for the historical period (1979-2008), it is clear that most parts of the basin suffered from severe drought in this historical period (drought severity less than (-4.39) and drought duration more than six months and peak intensity less than (-1.36) with a return period of fewer than 10 years.



341

342

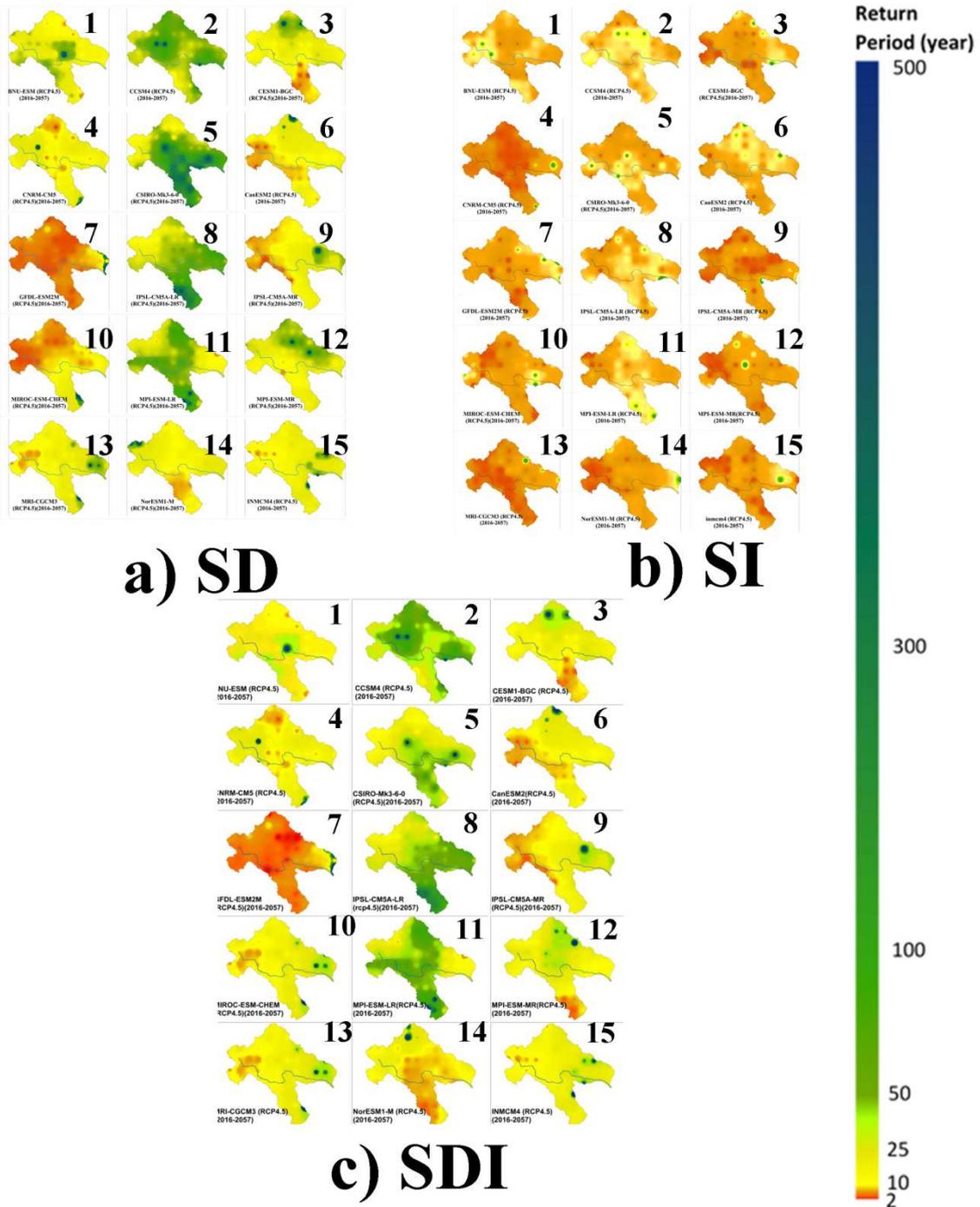
343 Figure 4: Comparison of the calculated return period of the severe drought using tri-variate  
 344 and bivariate copula functions in the historical period (1979-2008) a) SD: bivariate copula of  
 345 Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate  
 346 copula of Severity-Duration-Peak intensity.

### 347 3.2 scenarios

348 According to the Fifth Evaluation Report published by IPCC, the RCP4.5 scenario indicated  
 349 a stabilized emission of greenhouse gases. Using the output data of GCM models under the  
 350 RCP4.5 scenarios, the amount of SPI, as well as the severity and duration and peak intensity  
 351 of drought for all network points within the basin were calculated based on the obtained SPIs.  
 352 Then the Log-normal distribution function was adjusted to the values of severity and duration  
 353 and the Exponential distribution function was adjusted to the values of the peak intensity of  
 354 the drought. Finally, using the bivariate Gumbel Copula function for the severity-duration  
 355 Copula, the bivariate normal Copula function for the severity-peak intensity of the drought

356 and the tri-variate normal Copula function for the severity-duration-peak intensity of the  
357 drought, the return period of the most severe drought in the network points within the basin  
358 was obtained and the zoning map was drawn for each model.

359 The spatial map of the drought return period for GCM models under the RCP4.5 scenario had  
360 been drawn based on the return period calculated with the three mentioned Copulas for the  
361 near future (2016-2057) as shown in Figure (5). In the bivariate severity-duration Copula  
362 during this period, the GFDL-ESM2M model showed almost similar to or a little worse  
363 conditions as the drought conditions during the historical period. Other models showed better  
364 conditions; regarding the intended severe drought, they showed less occurrence frequency  
365 than the historical period. Most of the used GCM models predicted the occurrence frequency  
366 of the intended severe drought to be about 25 years. In some models. the return period of  
367 severe drought in the major part of the basin was about 50 years. In the bivariate Copula of  
368 severity- peak intensity of the drought, the period of intended severe drought was less than 5  
369 years in all models. This means that up to once every 5 years, a severe drought with an SPI  
370 value of less than (-4.39) and a peak intensity of drought with an SPI value of less than (-  
371 1.36) was likely in the basin. During this period, the CNRM-CM5 model showed drought  
372 conditions almost similar to the drought conditions during the historical period. In the tri-  
373 variate Copula of the severity-duration-peak intensity of the drought, the GFDL-ESM2M  
374 model in this period showed the drought conditions almost similar to or a little worse than the  
375 historical period in the basin. Most models predicted the severe drought return period in the  
376 basin to be less than 25 years. In other words, the occurrence frequency of severe droughts  
377 varied from less than 10 years in the past to less than 25 years in the future.



378

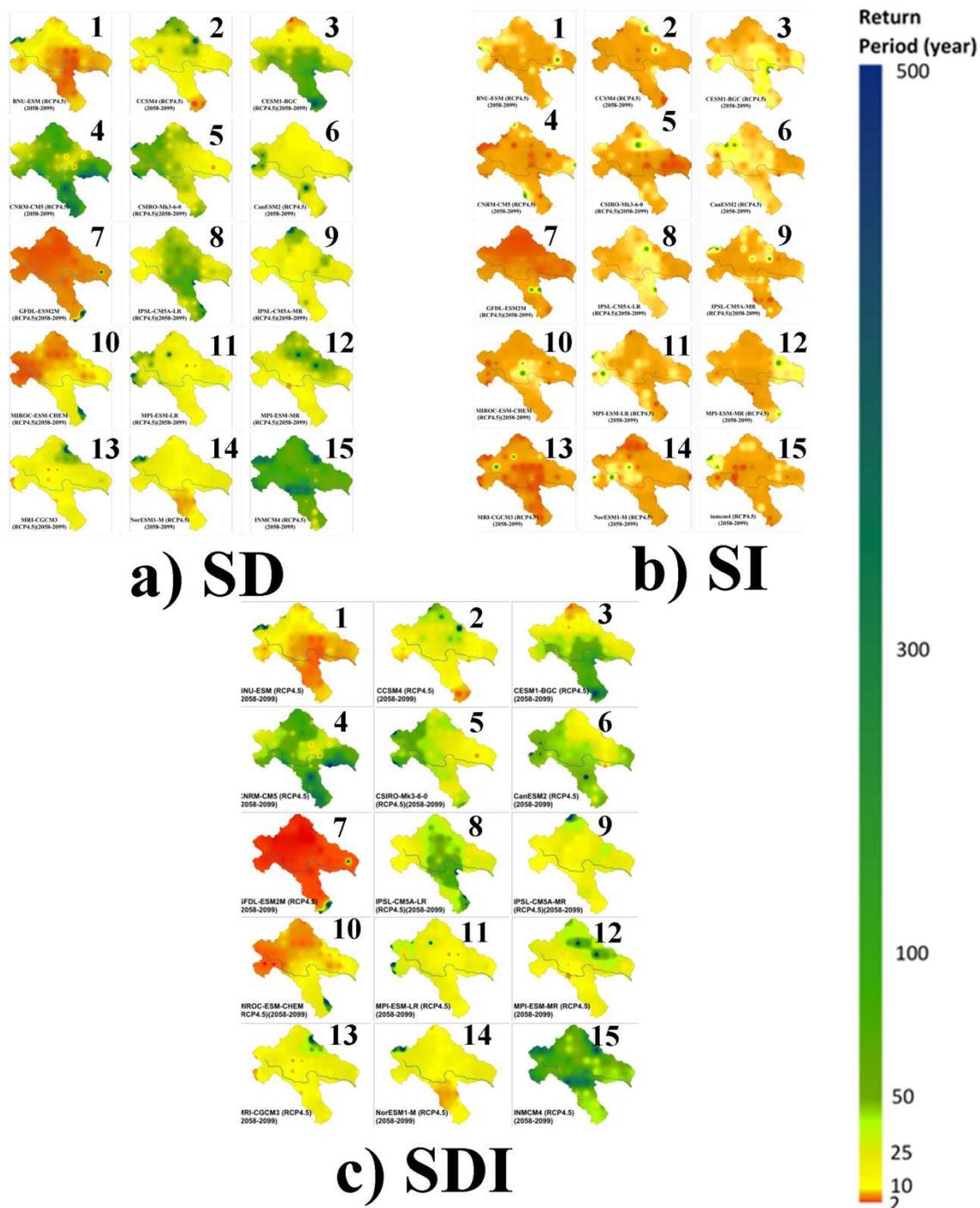
379 Figure5: Comparison of the calculated return period of the severe drought using tri-variate  
 380 and bivariate copula functions in the near future (2016-2057) using 15 GCMs with RCP4.5  
 381 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity  
 382 and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

383 The spatial analysis of the drought return period for GCM models under the RCP4.5 scenario  
384 calculated with the three mentioned Copula for the distant future (2058-2099) is shown in  
385 Figure (6). In the bivariate severity-duration Copula, in the GFDL-ESM2M model, the entire  
386 basin was exposed to severe drought and the frequency of severe drought was less than 5  
387 years. Other GCM models predicted a lower occurrence frequency of the severe drought, and  
388 in some cases, the return period was calculated to be more than 50 years for the severe  
389 drought. In the bivariate Copula of the severity-peak intensity of drought, the results of the  
390 GFDL-ESM2M model indicated similar or a little better conditions to historical conditions.  
391 In this model, the whole basin was exposed to severe drought and the occurrence frequency  
392 of severe drought was less than 3 years. Other GCM models predicted a lower occurrence  
393 frequency of the severe drought, and the probability of intended severe drought has increased  
394 to less than 5 years. As shown in this figure, in the tri-variate Copula of the severity-duration-  
395 peak intensity of the drought, the range of changes in the severe drought frequency from the  
396 15 GCM models under the RCP4.5 scenario in the distant future (2058-2099) was much  
397 greater. The results of the GFDL-ESM2M model showed that the entire basin will be prone to  
398 severe drought with a frequency of fewer than 2 years. Other GCM models predicted a lower  
399 frequency for severe droughts and in some cases, the return period of severe droughts was  
400 extended to more than 50 years.

### 401 **3.3 Effects of Climate Change on the Drought under RCP8.5 Scenario**

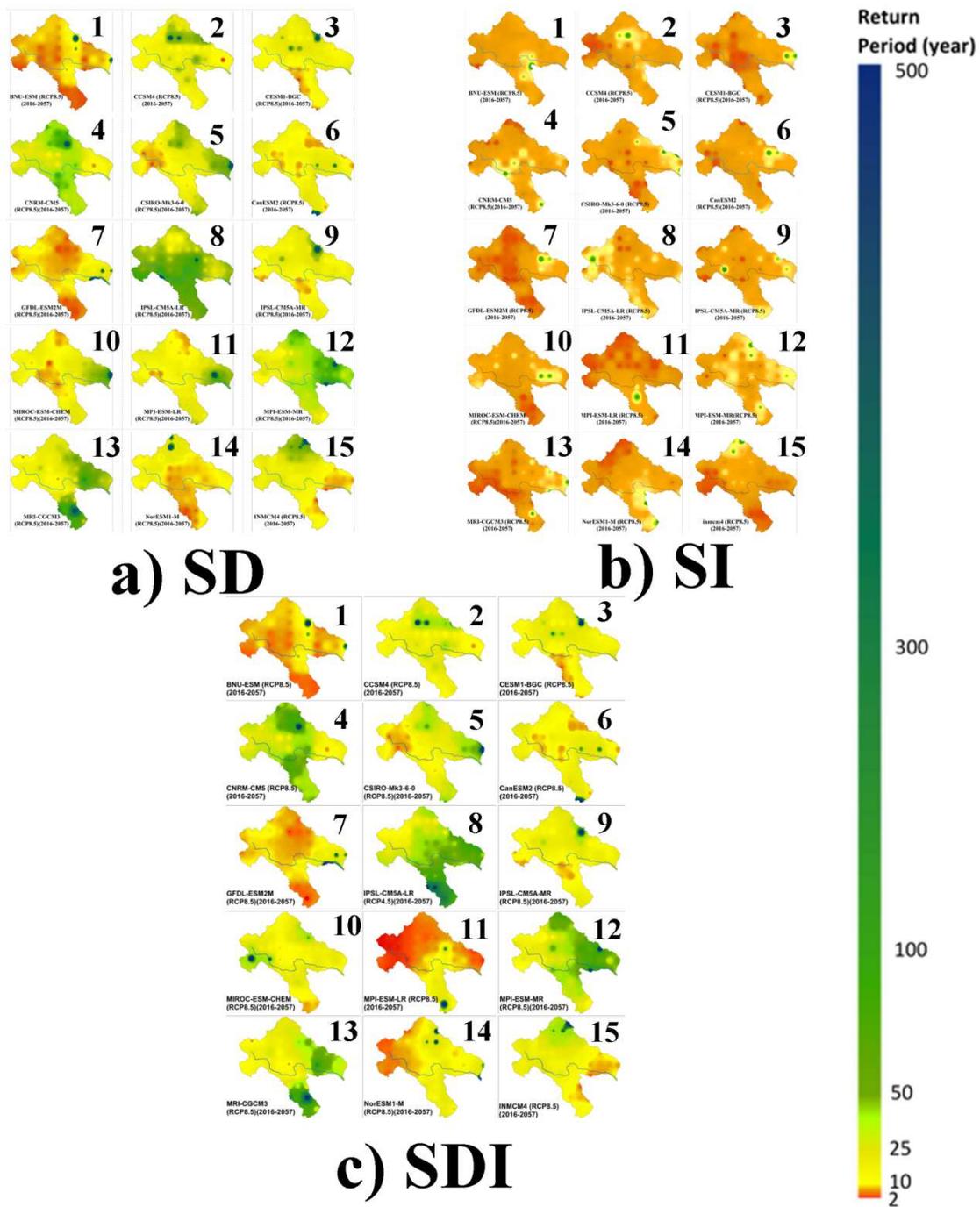
402 According to the previous section, zoning maps from the above calculations were also  
403 prepared based on the RCP8.5 scenario. The effects of climate change on the drought based  
404 on the data from GCM models under the RCP8.5 scenario for the near future (2016-2057) are  
405 shown in Figure (7). In the bivariate Copula of the severity-duration, most GCM models  
406 predicted a longer return period than in the past for possible severe droughts in the near

407 future, which meant less occurrence of the frequency of this drought. In general, according to  
408 the results of the GCM models used under the RCP8.5 scenario in the near future, a return  
409 period of about 25 years is expected for the severe drought in the basin. In the bivariate  
410 Copula of the severity-peak intensity of drought, most GCM models predicted a higher return  
411 period than the past for possible severe droughts in the near future, which meant less  
412 occurrence of the frequency of this drought. In general, according to the results of the GCM  
413 models used under the RCP8.5 scenario in the near future, a return period of about less than  
414 10 years is expected for severe drought in the basin. In the tri-variate Copula of the severity-  
415 duration-peak intensity of the drought, while in the central part of the basin, the severe  
416 drought return period was less than the historical period in this area. Most GCM models  
417 predicted a more severe drought return period for the near future than the historical period,  
418 indicating a lower occurrence frequency of severe drought than the historical period, with  
419 some models even reaching a 50-year return period.



420

421 Figure 6: Comparison of the calculated return period of the severe drought using tri-variate  
 422 and bivariate copula functions in the distant future (2058-2099) using 15 GCMs with RCP4.5  
 423 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity  
 424 and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.



425

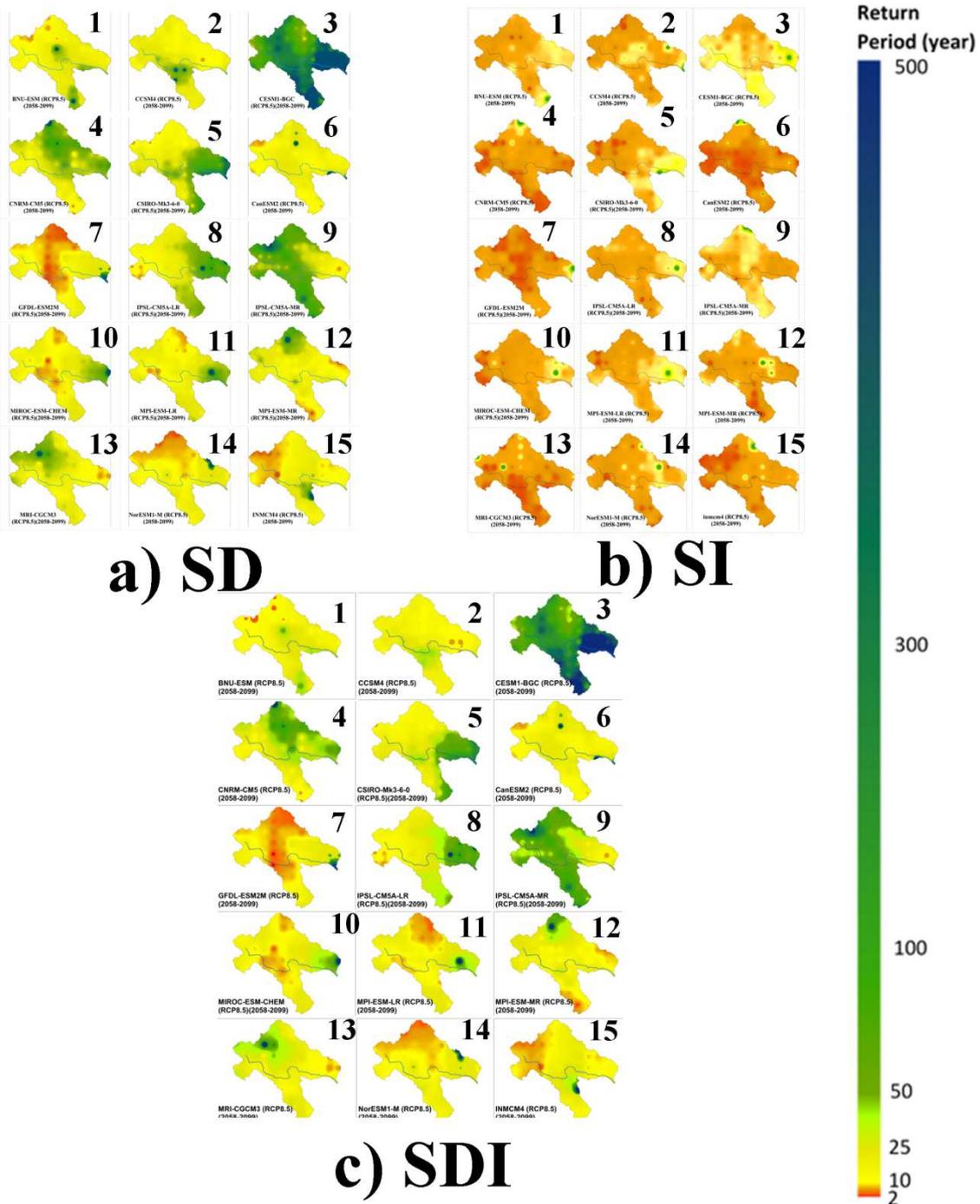
426 Figure 7: Comparison of the calculated return period of the severe drought using tri-variate  
 427 and bivariate copula functions in the near future (2016-2057) using 15 GCMs with RCP8.5 a)  
 428 SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity  
 429 and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

430

431 The effects of climate change on the drought based on the data from GCM models under the  
432 RCP8.5 scenario for the distant future (2058-2099) are shown in Figure (8). In the bivariate  
433 Copula of severity-duration, the range of variations in the return period of the calculation  
434 varied from about less than 10 years to about 400 years. Some models predicted a return  
435 period of more than 100 years. Other models predicted a return period of about 25 years for  
436 the severe drought intended for the basin. In the bivariate Copula of severity - peak intensity  
437 of the drought, the CanESM2 model predicted conditions similar to those of the historical  
438 period. Other models predicted a return period of about 10 years for the intended severe  
439 drought. Depending on the tri-variate Copula of the severity-duration-peak intensity of  
440 drought, the range of return period values in the distant future for the intended basin varies  
441 between 10 years to 400 years. In the CESM1-BGC and the IPSL-CM5A-MR models, the  
442 return period of severe drought has been more than 100 years for almost all parts of the basin,  
443 and the decrease in the occurrence frequency of severe drought in the basin is predicted.  
444 Other GCM models predicted a return period of about 25 years for the severe drought in the  
445 basin.

446 Based on the results of the calculations performed with the help of bivariate Copula of  
447 severity-duration, the drought return period in the near and distant future for the basin  
448 increases from less than 10 years to about 25 years compared to the historical period.  
449 According to the bivariate Copula of the severity-peak intensity of drought, the return period  
450 of the drought in the near and distant future for the basin increases from less than 5 years to  
451 more than 10 years compared to the historical period. The results did not provide information  
452 on the duration and durability of the severe drought. Without the knowledge of the duration  
453 of each drought, planning for water resources is difficult and inaccurate. According to the tri-

454 variate Copula of the severity-duration-peak intensity of the drought in each period, the return  
455 period of the drought in the distant future for the basin increases from less than 10 years to  
456 more than 25 years compared to the historical period. Based on GCM models, despite the  
457 slight increase in precipitation in the future, due to the uncertainty of climate change  
458 forecasts, it is recommended to have a comprehensive water resources management plan in  
459 the basin to deal with long-term severe droughts.



460

461 Figure 8: Comparison of the calculated return period of the severe drought using tri-variate  
 462 and bivariate copula functions in the distant future (2058-2099) using 15 GCMs with RCP8.5

463 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity

464 and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

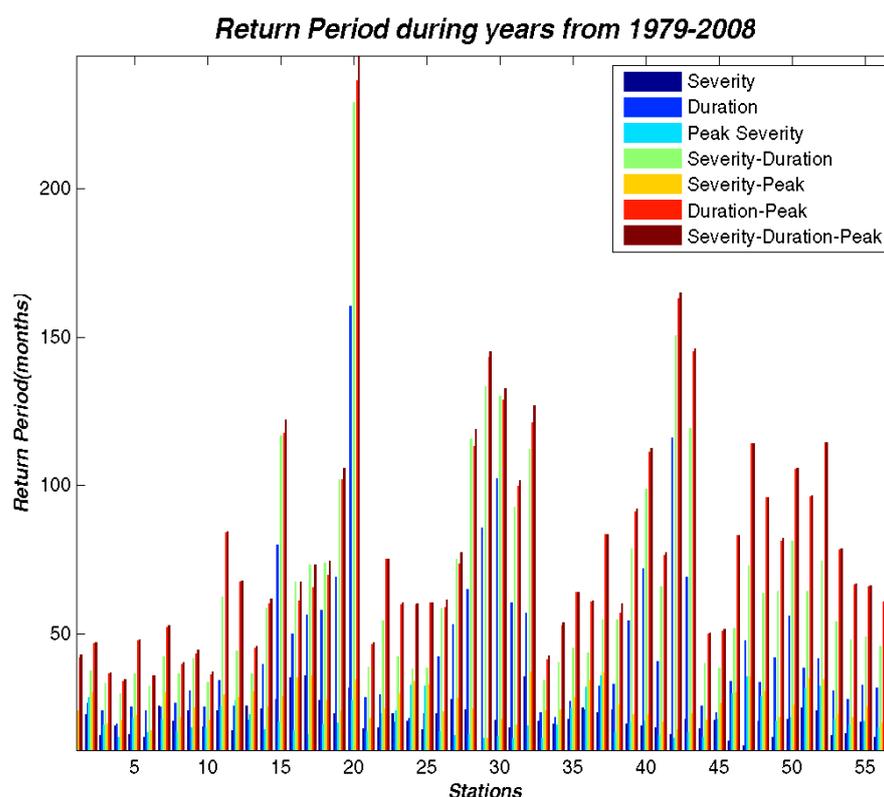
465

466 **3.4 Frequency Analysis of the Most Severe Drought using Bivariate and Tri-variate**  
467 **Copula Functions**

468 According to the results of the drought frequency analysis with the help of bivariate Copula  
469 functions of severity-duration, severity-peak intensity, and the tri-variate Copula of the  
470 severity-duration-peak intensity of the drought, it is quite clear that the results of bivariate  
471 Copula function of severity-duration and tri-variate Copula of the severity-duration-peak  
472 intensity were very close to each other, with similar results for the analysis of historical  
473 drought as well as the drought in the near and distant future. However, the results of drought  
474 analysis with the help of bivariate Copula of severity- peak intensity, was very different from  
475 the results of the previous two Copulas and predicted severe droughts occurring with more  
476 frequency.

477 Figure (9) shows the return period of the severe drought based on different drought  
478 parameters in the historical period (1979-2008). As shown in the figure, the calculated return  
479 period based on the tri-variate Copula was larger. This means that the occurrence frequency  
480 of severe drought with higher values than the specified values of severity, duration, and peak  
481 intensity, was less. After that, the highest value of the return period results was obtained  
482 based on the drought analysis using the bivariate Copula of the duration-peak intensity. Then,  
483 the results of the bivariate Copula of the severity-duration were most similar to the tri-variate  
484 Copula, and three modes obtained the return period of severe drought for the basin more than  
485 other models. The bivariate Copula of severity- peak intensity, showed a lower return period  
486 for the relevant drought, and as shown in the figure, the results were more consistent with the  
487 results of the calculation of the drought return period based on only one of the variables of

488 the severity of peak intensity. The implications of this figure and the results suggest that the  
 489 duration of the drought plays a large role in the drought level return period in the basin, and  
 490 the higher the intended continuity and duration of drought, the higher the return period for  
 491 that drought. While the basin has been exposed to a high frequency of drought occurrences,  
 492 these droughts have not lasted long and have been short-lived.



493  
 494 Figure 9: Return period of severe drought based on various drought parameters in the  
 495 Historical Period (1979-2008)

496 **4 Conclusion**

497 As mentioned, drought is an extreme phenomenon that has far-reaching effects on agriculture  
 498 and water resources. Considering simultaneously the phenomenon of climate change and  
 499 drought, different effects are expected depending on the location and environmental

500 conditions of the region. Therefore, assessing the effects of climate change on the drought is  
501 of particular importance to water resource planners. In this study, three main steps have been  
502 considered, which are: 1) Calculating the duration, severity, and peak intensity of the drought  
503 based on SPI, fitting different distribution functions to them and determining the best  
504 distribution function for each characteristic, determining one of the most severe historical  
505 drought events with the highest value of duration, severity, and peak intensity, and finally  
506 using the appropriate Copula functions to estimate the frequency of drought occurrences with  
507 the predefined highest values, 2 ) Investigating the effects of climate change using general  
508 circulation models (GCM) for future periods, 3) Assessing the return period of the future  
509 drought using Copula functions and calculating the characteristics of drought events in the  
510 future and drawing spatial maps of the return period of future drought.

511 The SPI was used to calculate the duration, severity, and peak intensity of drought in the  
512 basin in the historical period (1979-2008). Among the phenomena that occurred during this  
513 period, 90% of the highest severity, duration, and peak intensity of drought were selected as  
514 the benchmark severe drought in the basin. The values included a drought severity with an  
515 SPI value of less than (-4.39); drought duration more than 6 months, and peak intensity with  
516 an SPI value of less than (-1.36).

517 Due to the high correlation between drought characteristics, bivariate and tri-variate Copula  
518 joint functions were used to analyze the return period of future droughts in the basin. For this  
519 purpose, three types of widely used Copula functions in the Archimedes family (Frank,  
520 Clayton, Gumbel-Hoggard) and two types of the most widely used Copula functions of the  
521 elliptical family (t and normal) were utilized in this study. Then the best Copula function was  
522 selected based on the BIC method. The effects of climate change on the drought were also  
523 investigated using 15 GCM models under RCP4.5 and RCP8.5 scenarios. The future period

524 was divided into two near future (2016-2057) and the distant future (2058-2099) periods to  
525 assess the drought situation.

526 The results of the GCM models under both scenarios for the near and distant future were  
527 almost the same and predicted a longer return period for severe drought than in the past.  
528 Contrary to this prediction for the basin based on GCM models, due to the uncertainties in  
529 climate change forecasting methods, planning for long-term droughts in the basin seems  
530 necessary to manage existing water resources.

531 Also, by examining the calculated return period based on different drought parameters in the  
532 historical period (1979-2008), the results of the bivariate Copula of the severity- peak  
533 intensity can be more compatible with the results of the drought return period based only on  
534 one of the variables of severity or the peak intensity of droughts. It appears that the drought  
535 duration variable plays an important role in the drought return level in the basin; having  
536 increased the continuity of drought duration, the return period of that drought is increased, or  
537 in other words, the occurrence frequency is reduced.

538 It is recommended to compare the results of research using AR4 with the current study to find  
539 the preference of AR5 in comparison with AR4 in the case of a copula. Also, it is worthwhile  
540 to analyze the uncertainty of the prediction by the GCMs and to estimate the probability  
541 levels for each model. Besides, it will be advantageous in future studies to analyze the  
542 uncertainty of calculated past return periods.

543

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547 for providing the authors with the facilities and opportunity to complete this study.

## 548 **Declarations**

549 **Ethics approval and consent to participate** (Approval was obtained from the ethics com-  
550 mittee of Shahid Chamran University. The procedures used in this study adhere to the tenets  
551 of the Declaration of Helsinki)

552 **Consent for publication** (Not applicable)

553 **Availability of data and material** (All data generated or analysed during this study are  
554 available from the corresponding author)

555 **Competing interests** (The authors declare that they have no competing interests)

556 **Funding** (Not applicable)

557 **Authors' contributions:** Material preparation, data collection, study conception, design and  
558 analysis were performed by Dr. Elaheh Motevali Bashi Naeini and then it was involved in  
559 planning and supervised by Dr. Ali Mohammad Akhoond-Ali and Dr. Fereydoun Rad-  
560 manesh. The first draft of the manuscript was written by Elahe Javadi and then Dr. Jahangir  
561 Abedi Koupai commented on previous versions of the manuscript. Dr. Shahrokh Soltaninia  
562 verified the analytical methods and performed some calculations. All authors discussed the  
563 results and contributed to the final manuscript and approved the final manuscript.

564

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# Figures

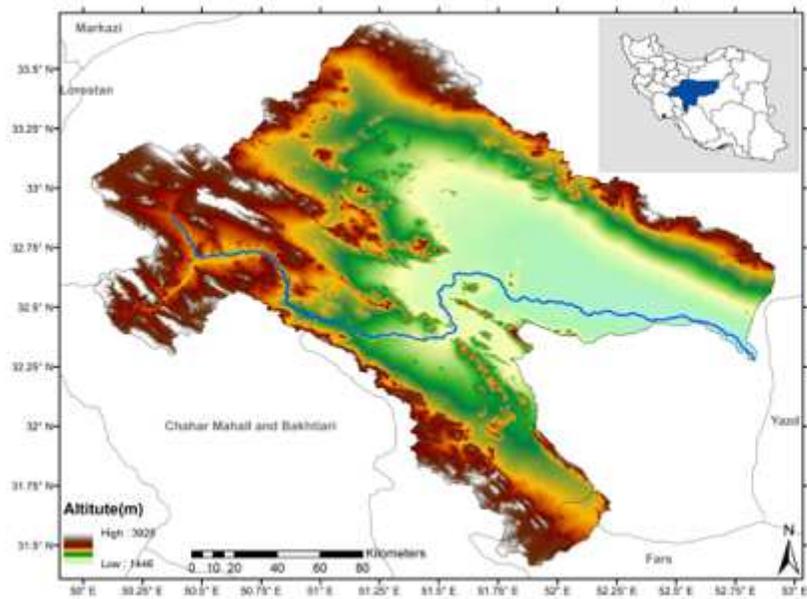


Figure 1

Geographic location of the Zayandeh Rud basin. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

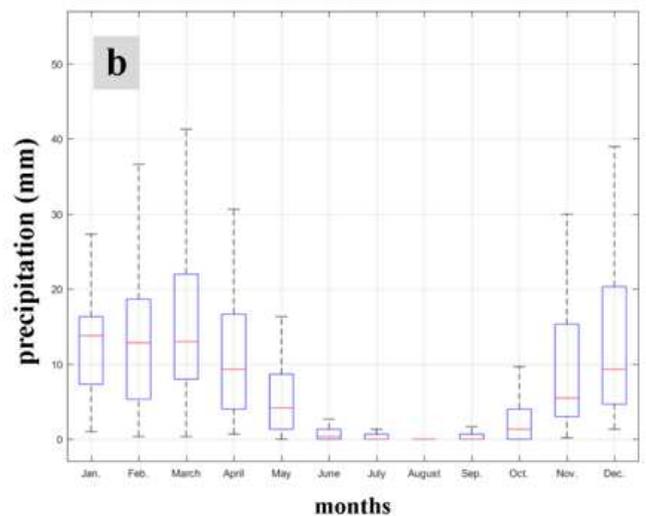
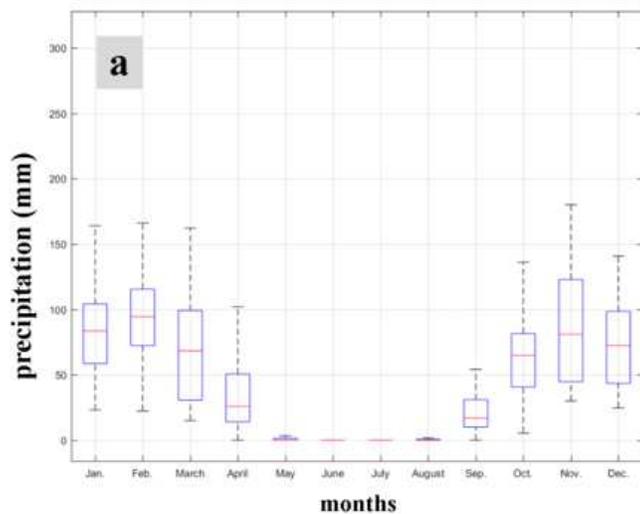


Figure 2

Changes in monthly precipitation in the past (1979-2008): a) station located upstream b) station located downstream

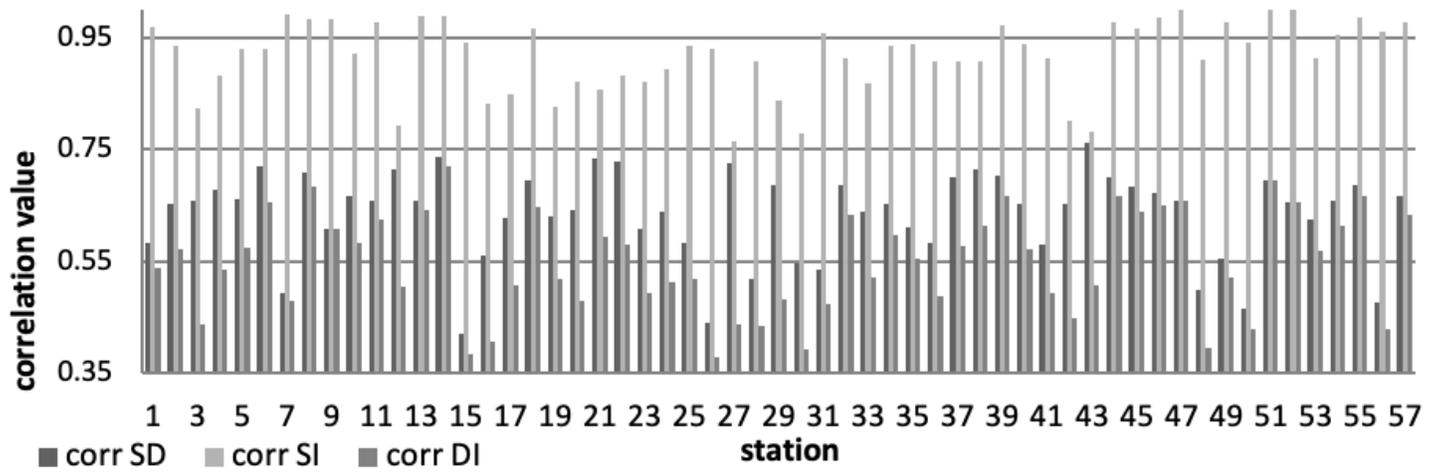
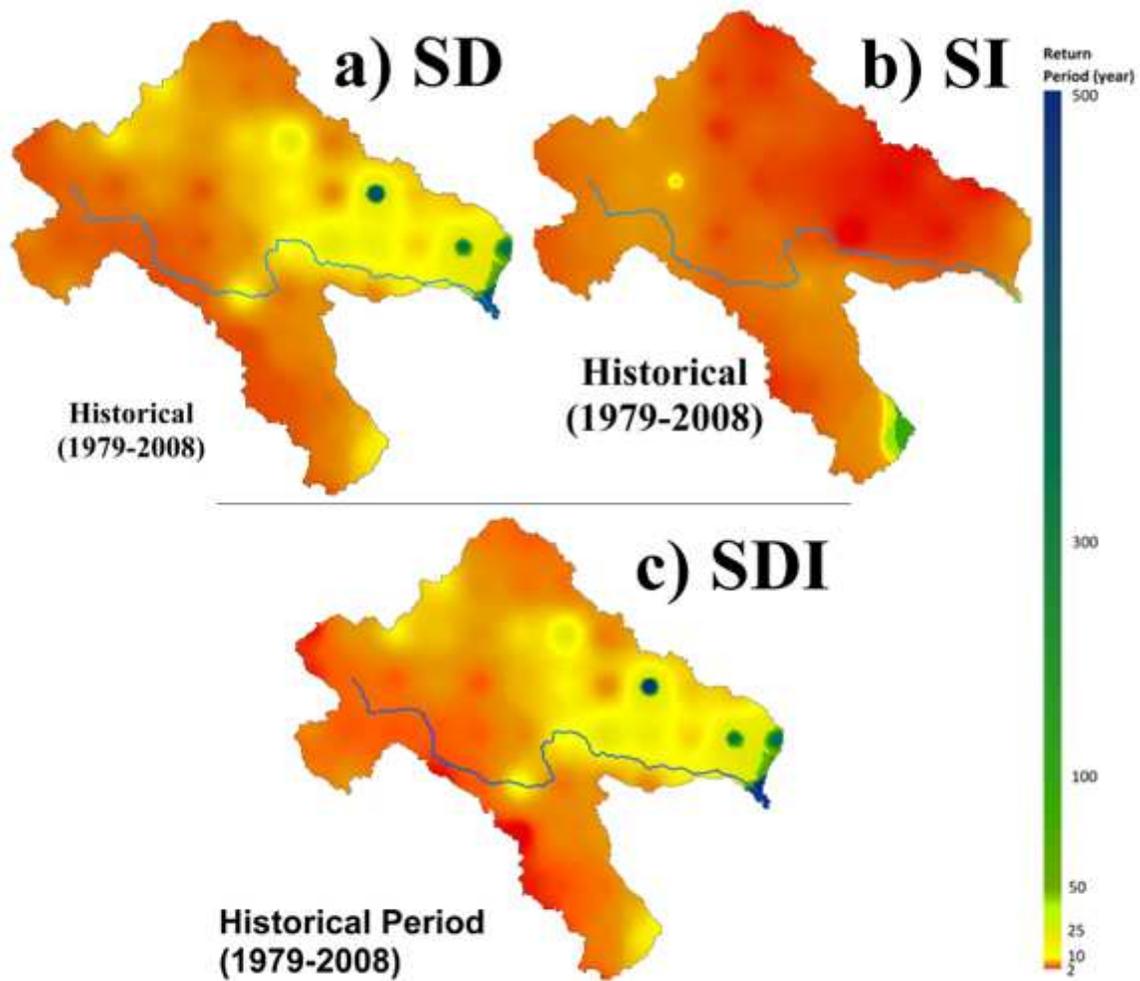


Figure 3

Linear correlation between drought characteristics (S indicates severity, D indicates duration, and I indicates the peak intensity of drought in each period.)



**Figure 4**

Comparison of the calculated return period of the severe drought using tri-variate and bivariate copula functions in the historical period (1979-2008) a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

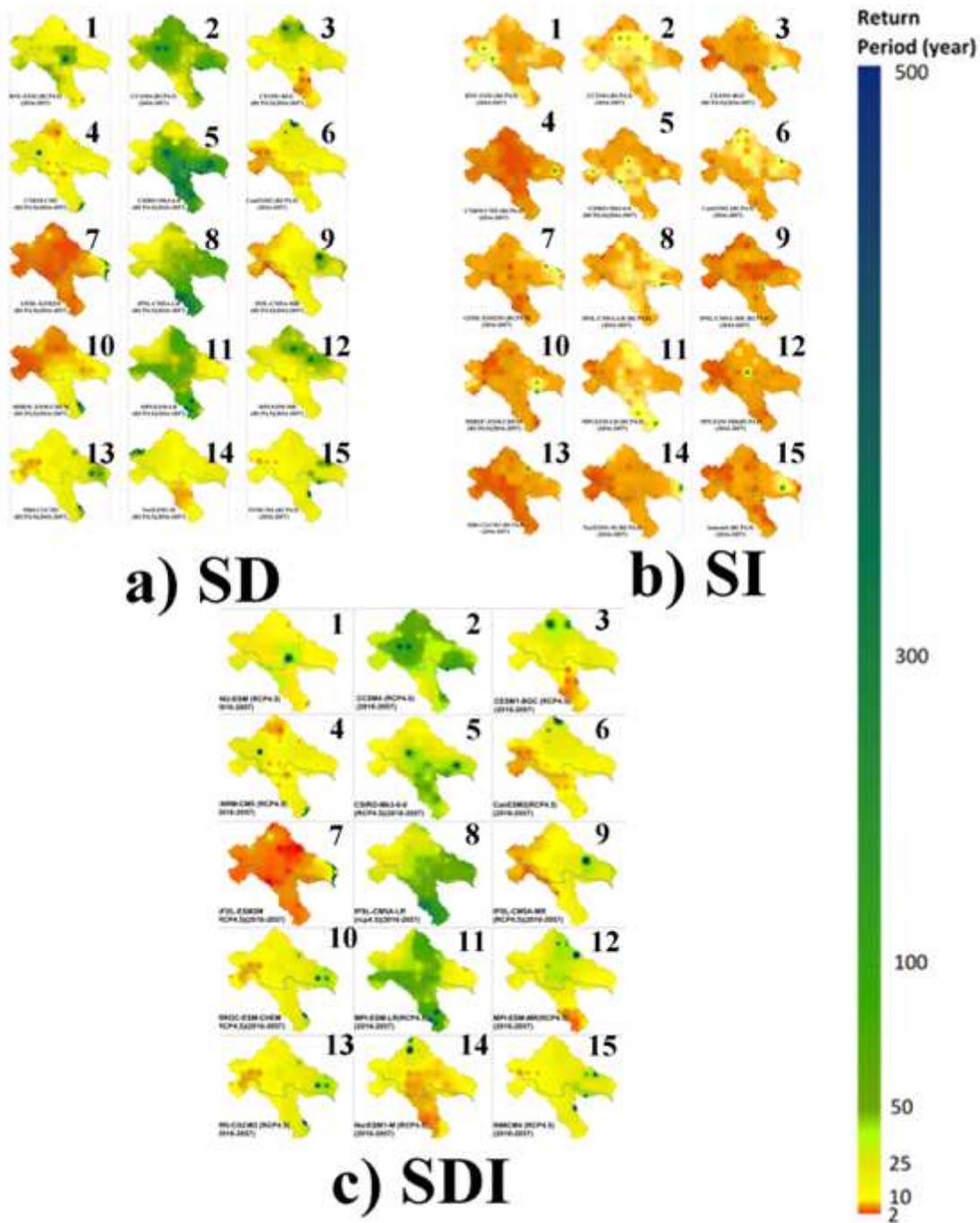


Figure 5

Comparison of the calculated return period of the severe drought using tri-variate and bivariate copula functions in the near future (2016-2057) using 15 GCMs with RCP4.5 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

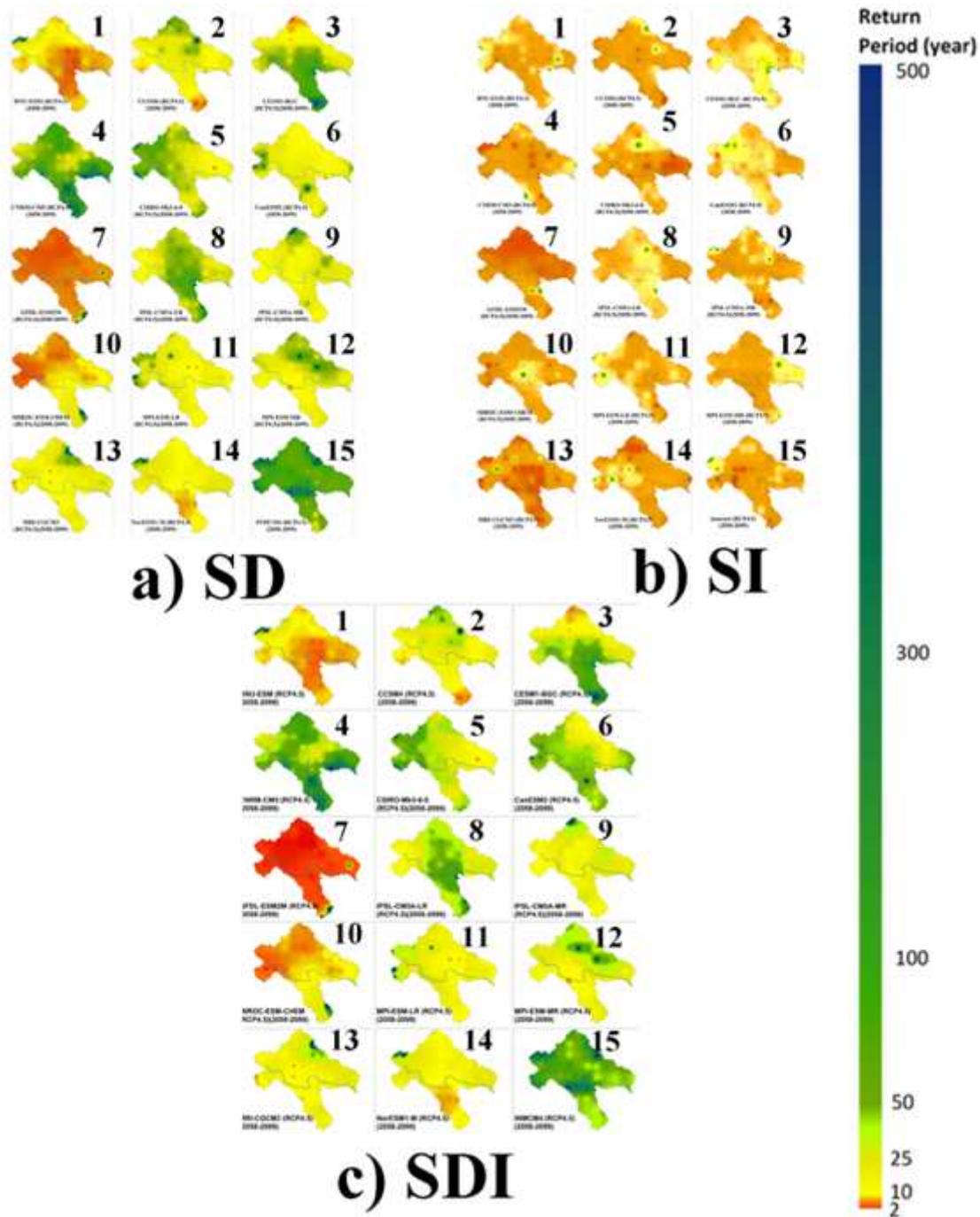
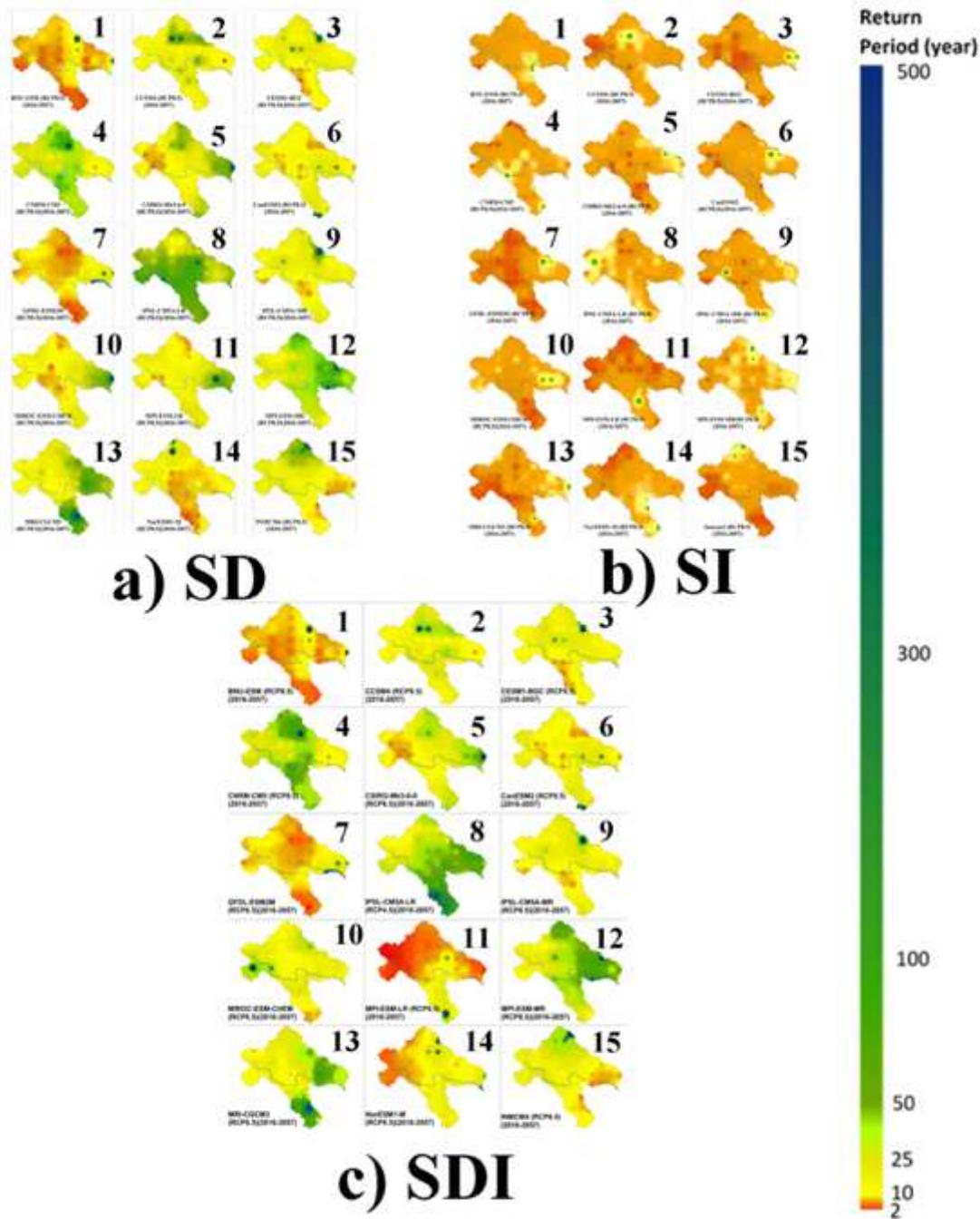


Figure 6

Comparison of the calculated return period of the severe drought using tri-variate and bivariate copula functions in the distant future (2058-2099) using 15 GCMs with RCP4.5 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.



**Figure 7**

Comparison of the calculated return period of the severe drought using tri-variate and bivariate copula functions in the near future (2016-2057) using 15 GCMs with RCP8.5 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.

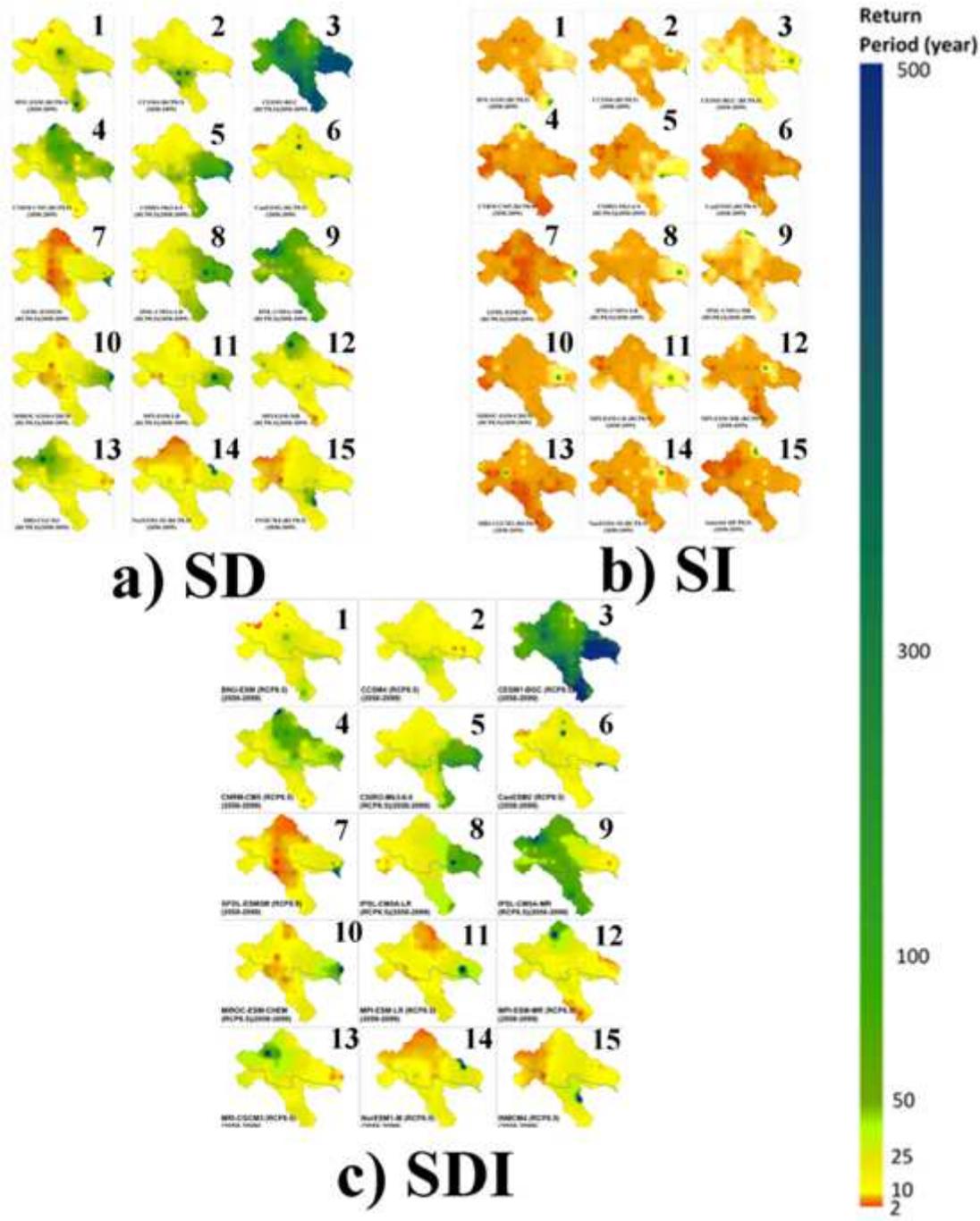
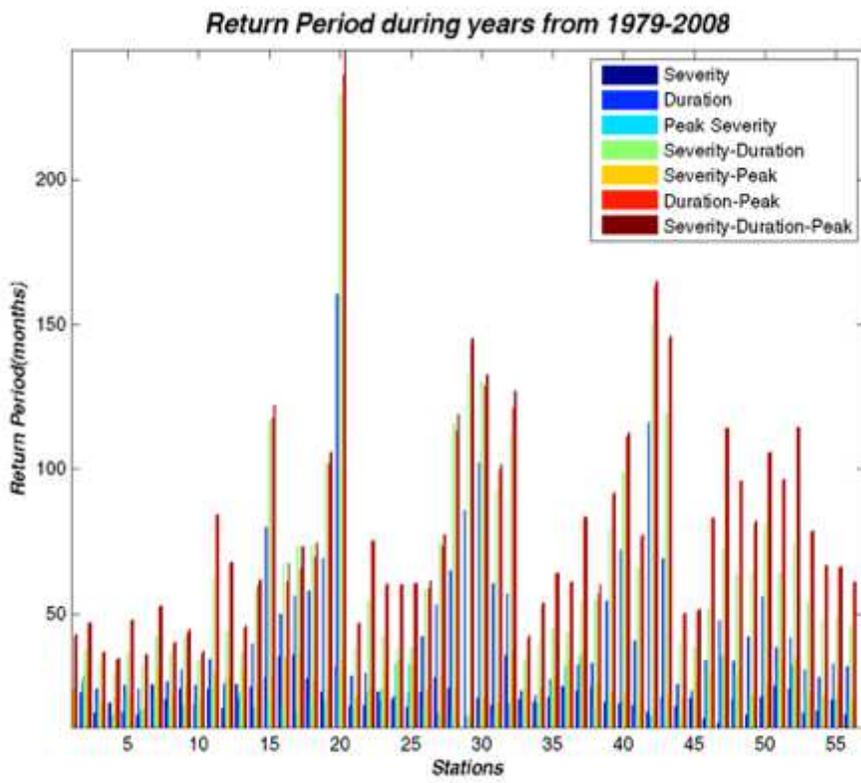


Figure 8

Comparison of the calculated return period of the severe drought using tri-variate and bivariate copula functions in the distant future (2058-2099) using 15 GCMs with RCP8.5 a) SD: bivariate copula of Severity-Duration b) SI: bivariate copula of Severity-Peak intensity and c) SDI: tri-variate copula of Severity-Duration-Peak intensity.



**Figure 9**

Return period of severe drought based on various drought parameters in the Historical Period (1979-2008)