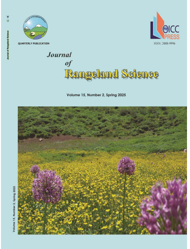

Volume 15, Issue 2, 152518 (1-14)

Journal of Rangeland Science (JRS)

https://doi.org/10.57647/j.jrs.2025.1502.18

Spatio-temporal monitoring of drought indices and their impact on vegetation cover in Zagros region, Iran under climate change scenarios

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Original Research

Received:
3 September 2023
Revised:
11 May 2024
Accepted:
26 June 2024
Published online:
20 April 2025

Abstract:

Climate change has caused major destructive effects across the world. Therefore, it is necessary to conduct studies to evaluate the impact of climate change on weather patterns and drought. In this research, the temporal-spatial monitoring of drought and its impact on the loss of Zagros vegetation under climate change scenarios in 2022 was carried out. For this purpose, four general atmospheric models (BCC-CSM1, CANESM2, HADGEM2-ES, NORESM1-M) were constructed under three representative concentration pathways (RCP 2.6, 4.5, and 8.5) for three future periods 2020 – 2039, 2040 – 2069 and 2070 – 2099 using data from 6 synoptic stations located in the wet and temperate areas in the Zagros region in western Iran. This region was chosen due to its history of droughts and predicted future droughts. Spatial-temporal variations of drought severity and frequency were studied using Standard Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) indices in different periods until 2100. The results showed the area of extremely dry areas will increase by 47.9% in (2020 – 2039) compared to the base period (1984 – 2020). According to SPI results, on average, the frequency of droughts will increase by 1.9% by the end of the century. Analysis of SPEI showed that drought will be more severe in all future periods. Based on SPEI, drought frequency will increase by 2% in (2020 – 2039) relative to the base period, and by 0.3% to 2099. According to the results, the frequency and severity of droughts in the 21th century have become more severe, which is an obvious component of climate change in Zagros. As a result, when the land is damaged and vegetation and forests are destroyed, it will cause instability in all social, economic and ecosystem sectors, so appropriate measures must be taken to control and reduce possible effects.

Keywords: Meteorological drought; Drought severity; Scenarios; SPI and SPEI indices; Desertification

Introduction

Climate change is one of the most important challenges facing humanity and natural ecosystems, bringing about consequences involving the increased atmospheric-climatic hazards such as storms and floods, reduced crop yields and food security, loss of vegetation and ecological migration (Chanapathi and Thatikonda, 2020). Due to the increased production and emission of greenhouse gases, climate change and its destructive impact have become serious concerns across the world (IPCC, 2014). Between 2015 and 2025, climate change is expected to have displaced 22 million people annually through its adverse effects such as floods and droughts (Bower et al., 2015).

The evaluation of the impact of changes in climate parameters on plant communities is crucial for vegetation conservation and assessing climate-related risks (Memarian and Akbari, 2021). Drought, as an important phenomenon affecting plant cover, has a direct correlation with precipitation and an inverse relationship with temperature. With a decrease in precipitation, the impact of drought on the regional vegetation cover is expected to be intensified, particularly with an increase in temperature. Precipitation irregularities are relatively common in the studied provinces, with most rainfall occurring in the cold half of the year and not during the growing season. In many dry inland areas, the majority of annual precipitation occurs in a single day (Naghipour et al., 2019).

The effects of drought on ecosystems are multi-faceted and vary across scales. Studies have shown that climate change has triggered droughts, intensified their damaging effects, or created conditions for subsequent droughts. Although droughts occur naturally, climate change has generally accelerated the contributing hydrological processes, thus making droughts more intense and amplifying their effects such as wildfire risk. The impact of droughts has historically been more severe in developing countries, but developed nations are now experiencing droughts at increased rates as well. It is estimated that more than 75% of the global population will be affected by droughts by 2050. Compared to 1980 – 2000, the frequency and duration of droughts have increased by 29% in the past 20 years (IPCC, 2021). According to the UN's Convention to Combat Desertification, drought has transformed over 70% of natural ecosystems; predictions indicate that this figure could reach 90% by 2050 (D., 2021). Moreover, more than 2.3 million people are currently faced with water stress, and even larger numbers will be at risk in the future. After a drought, irreparable damages are caused in all agricultural, ecosystem, economic and social sectors, and their management becomes very complicated (Squires et al., 2022).

Lack of a unified definition complicates the study of droughts (Tang, 2020; Mukherjee et al., 2018). According to the hydrological definition, droughts are extreme hydrological phenomena characterized by a long-term lack of precipitation in a vast area in any climate (Arzani et al., 2020). The occurrence, persistence, and the intensity of droughts have made them one of the most destructive climatic processes (Pakdin et al., 2021), leading to the development of innovative models and methodologies to evaluate and forecast droughts including drought indices. Drought indices have been widely used across the world (Ndayiragije and Li, 2022), with more than 100 indices being currently available. Among the indices, some have been used to describe drought characteristics in grid maps at the regional or national scale (Shiravand and Hosseini, 2020). Extensive research has been done on the effects of climate change on drought through the use of drought indices (Serrano et al., 2010; Haidarian et al., 2021). **PeltandSwart2011<empty citation>** used Standardized Precipitation Evapotranspiration Index (SPEI) to study drought in the Czech Republic and emphasized the ability of this index to recognize drought severity. Stagge et al. (2015) compared the distribution of Standard Precipitation Index (SPI) and SPEI in Europe. They identified gamma distributions and general limit values for SPI and SPEI, respectively. Lee et al. (2017) used SPEI to study the effects of climate change on drought in North Korea from 1981 to 2100 and found that SPEI increased from -0.9 in 1995 to 1.18 in 2025. Given Iran's geographical location in an arid region, research has been done to predict droughts and their impact on the country (Haile et al., 2020; Lweendo et al., 2017).

Given the important role of greenhouse gas concentrations in atmospheric circulation models, the fifth report published by IPCC in 2014 (AR5) presents several scenarios representing different greenhouse gas levels and radiative forcing values, known as Representative Concentration Pathways (RCPs) (IPCC, 2014). The scenarios include RCP2.6, RCP4.5, RCP6.0, and RCP8.5, named based on the corresponding radiative forcing in 2099. The present study evaluates meteorological drought indicators in western Iran under AR5 scenarios. Of the AOGCMs presented in the IPCC report, four are used in this study. Various scenarios for the increase in greenhouse gasses have been defined in the context of general atmospheric circulation patterns to predict climate change. GCMs have limited applicability because of their very low spatial accuracy and the effects of variations; consequently, these models must be converted to suitable models for smaller spatial scales, known as "scalar" models (Semenov, 2009). In general, scalar models are classified based on the method used for conversion (dynamic, statistical, or a combination of both). Different approaches have been proposed for conversion, the most reliable of which is coupled AOGCM simulations, integrating (coupling) global climate models (GCMs) and regional climate models (RCMs) to enable the study of climate change over time (Fang et al., 2018; Kang et al., 2019). The LARS-WG model is a randomized weather generator that is used to simulate climatic data at a specific station under current and future conditions while accounting for climate change. The LARS-WG model has been applied in a variety of cases (Pakdin et al., 2021).

The forest cover of Zagros is one of the most important components of the Zagros ecosystem, which plays an important role in protecting the water and soil of this region (Alirezaie et al., 2019). With the increase of severe droughts during the last few decades, which occurred due to the decrease of rainfall in many parts of Iran, forests and pastures suffered a lot of damage after enduring a lot of stress (Moradi et al., 2013). The Zagros region (a) large region in western Iran) has experienced ecological and socio-economic pressures due to the lack of precipitation. When the land is damaged and vegetation and forests are destroyed and the type of precipitation changes, it will bring nothing but soil erosion and further destruction of the land. It will follow and eventually, it will lead to economic poverty as we have seen in the areas of Zagros where there is this intensity of instability, the intensity of vegetation loss is increasing day by day. In their investigation of changes in Zagros forests under recent droughts using satellite imagery (2005 – 2016), Goodarzi et al. (2019) found that there is a significant relationship between the loss of vegetation cover and changes in climatic factors.

Although a number of studies have utilized different models to assess climate change and drought in the region, few have combined the models with climate change scenarios for meteorological analysis of drought. Therefore, we assessed the impact of climate change on drought in the Zagros region under three climate change scenarios using four general circulation models. Moreover, SPI and SPEI were calculated for future periods. In this work, (a) we examine the variation in SPI and SPEI to describe the variation in drought characteristics in the Zagros region, (b) evaluate the impact of climate change on drought characteristics, (c) predict drought severity by 2099, (d) investigate the spatial distribution of changes in drought patterns, and (e) analyze the impacts of drought on vegetation cover in the Zagros region.

Materials and methods

Study area

The Zagros climatic zone spans northwestern to southwestern Iran (figure 1). The region has a temperate and humid climate characterized by seasonal precipitation. According to the climatic classification of Heidari and Alijani (1999), the regions consist of three climate classes: sub-humid subtropical, cold, and semi-mountainous areas. The average annual precipitation (P) in the region varies between 250 to 800 mm. Rainfall historically occurs during winter and spring. Summers are hot and dry (mean temperature: 35 °C) and winters are cool (mean temperature: 7 °C) (Fathizadeh et al., 2017).

Droughts in the study area have presented significant threats to rural and urban communities, leading to gradual changes that threaten the environment and the livelihoods of communities in the western provinces of Iran. The negative effects of droughts in the region include unemployment, poverty, the loss of farmlands and rangelands, severe declines in agricultural and livestock production, loss of the only reliable source of income for rural communities, conflicts between local communities over water resources, forced migration, abandonment of villages, formation of security gaps, desertification, drying of river beds and lakes, dust storms, ecosystem degradation, and loss biodiversity (Akbari et al., 2023). Studies show that droughts will intensify under the influence of climate change in many parts of the world, including parts of Iran. Overcoming this challenge and mitigating the associated risks require accurate studies, careful planning, and allocation of financial resources. Climate change has had adverse impact in western Iran; thus, special attention should be paid to this issue to mitigate ecosystem degradation and manage hydrological systems and available water resources. To do so, it is essential to focus on risk management instead of crisis management (Akbari et al., 2019).

Past studies show that only six synoptic stations in the area have data of sufficient quality to be considered for this research. Table 1 shows the location and elevation data for these stations.

Dataset and downscaling statistical data

Daily minimum temperature, maximum temperature, irradiation, and precipitation data were obtained from Iranian Meteorological Organization for the six synoptic stations. A common statistical period was selected between 1984 and 2020, followed by preprocessing. The runs test was used to test homogeneity of the selected synoptic stations and missing data were rectified.

Subsequently, past and future climate at the six stations was simulated. The basic requirement of the model at the calibration stage is a file that identifies past climate at the stations (Semenov and Stratonovitch, 2010). This file was compiled using daily precipitation data, minimum temperature, maximum temperature, and irradiance at the synoptic stations, taking 1984 – 2020 as the base period. According to the latest recommendations by IPCC, the use of multiple models in climatic simulations, instead of running the models individually, can be effective in reducing uncertainties. To that end, we used four General Circulation

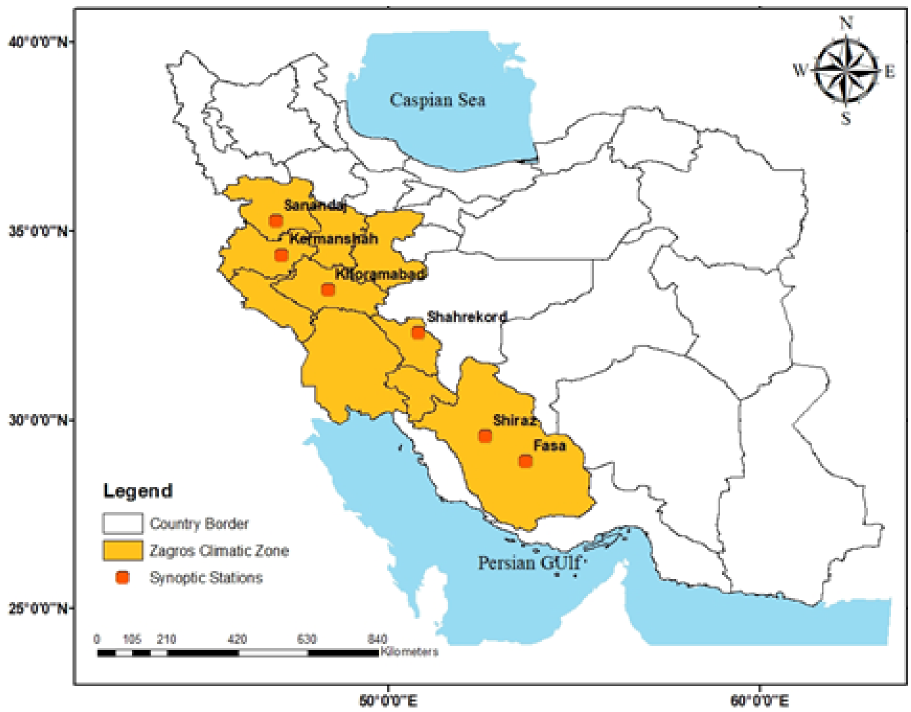

Figure 1. The location of the study area and the synoptic stations.

Table 1. The synoptic stations used in the study (**IranianMeteorologicalOrganization2020**).

Station	Longitude	Latitude	Elevation (m)	Average temperature (°C)	Annual rainfall (mm)
Sanandaj	47.01	35.25	1373.4	13.7	317
Kermanshah	47.15	34.35	1318.5	14.5	457.1
Shahrekord	50.84	32.29	2048.9	11.6	317.4
Shiraz	52.63	29.56	1488	17.8	283.9
Fasa	53.72	28.90	1268	17.4	292
Khorramabad	48.40	33.43	1147.8	17.2	562.5

Models (GCMs) (BCC-CSM1, CANESM2, HADGEM2-ES, NORESM1-M) (Miao et al., 2014), and three representative concentration pathways (RCP 2.6, 4.5, and 8.5), and calculated the arithmetic mean for each group in RStudio Software. Finally, precipitation, minimum temperature, maximum temperature, and irradiance were projected for 2010 – 2039, 2040 – 2069, and 2070 – 2099.

Downscaling

Downscaling was performed using Weather Generators (WGs). WGs modify the statistics obtained from observational time series according to climate change scenarios presented in General Circulation Models (GCMs), and generate future climate scenarios using the modified statistics. Based on the scenarios generated by GCMs, various characteristics of climate variables (including mean, variance, the ratio of rainy days) can change in the future. In the LARS-WG model, future climate scenarios for fine-scale modeling are embedded in such a way that only changes in the means of climate variables are considered for future conditions (Akbari et al., 2016). In this study, changes in other statistical features of climate variables as well as mean values are applied to downscaled scenarios generated by large-scale models to predict future climate in the basin more comprehensively and accurately. Downscaling was conducted as follows: (a) Daily precipitation, minimum temperature, and maximum daily temperature statistics are generated by GCMs for the control period and the future scenario and (b) The ratio of changes for monthly precipitation, lengths of wet and dry periods, standard deviation of daily temperature, and the amount of changes for monthly minimum and maximum temperatures were calculated and applied, respectively, by multiplication and addition to the corresponding observed values to obtain the statistics for downscaled scenarios. Then, based on these statistics, time series are generated for climate variables under future scenarios by LARS-WG.

Model validation

Model validation was conducted using t-test for comparison of means and F-test for comparison of variances between observed and simulated precipitation, minimum temperature, and maximum daily temperature (Table 2) (Ordouni et al., 2021). In these tests, the monthly means of the variables

Table 2. Model validation using t-test, F-test and K-S test for comparison of between observed and simulated Climate data (P values > 0.05 indicated validation of data).

Climate variables	Statistical method	Sanandaj	Kermanshah	Shahrekord	Shiraz	Fasa
Precipitation	t-test	0.99^{ns}	0.59^{ns}	0.76^{ns}	0.83^{ns}	0.39^{ns}
	F-test	0.83^{ns}	0.85^{ns}	0.45^{ns}	0.20^{ns}	0.09^{ns}
	Kolmogorov-Smirnov test	0.20^{ns}	0.004^{*}	0.02^{*}	0.20^{ns}	0.20^{ns}
MIN Temperature	t-test	5.77^{ns}	0.54^{ns}	2.45^{ns}	0.48^{ns}	3.31^{ns}
	F-test	0.83^{ns}	0.96^{ns}	0.94^{ns}	0.98^{ns}	0.96^{ns}
	Kolmogorov-Smirnov test	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}
MAX Temperature	t-test	0.30^{ns}	0.06^{ns}	0.06^{ns}	0.27^{ns}	8.51^{ns}
	F-test	0.99^{ns}	0.96^{ns}	0.83^{ns}	0.94^{ns}	0.92^{ns}
	Kolmogorov-Smirnov test	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}
Radiation	t-test	0.90^{ns}	0.69^{ns}	0.07^{ns}	0.40^{ns}	0.25^{ns}
	F-test	0.83^{ns}	0.95^{ns}	0.70^{ns}	0.92^{ns}	0.97^{ns}
	Kolmogorov-Smirnov test	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}	0.20^{ns}

ns and * represent non-significance and significance at the 5% level, respectively.

were compared with the corresponding values generated by the model. The P-values were generally larger than 0.05, indicating acceptable performance at a 5% significance level. No significant differences were observed between simulated values and observed data for minimum temperature, maximum temperature, solar radiation, and precipitation for most stations, indicating the high accuracy of the model in estimating these parameters. Additionally, P-values in the Kolmogorov-Smirnov test were generally greater than 0.05, indicating that the model has reasonably reproduced the frequency distribution of observed variables at a 5% significance level. Given the acceptable performance of the model in reproducing the statistical characteristics of observed data, the model's validity is confirmed. The performance of the LARS-WG model has been validated in many studies in various regions.

Standardized precipitation index (SPI)

SPI is one of the most important indices in drought monitoring (McKee, 1995). This index is one of the few time-sensitive drought indices. SPI allows for determining the time scale of drought depending on the aspect of drought which has greater importance (e.g., agricultural resources, hydrological features, etc.). SPI can identify droughts lasting from one month to several years. Also, SPI-based indicators for the analysis of drought severity, duration, and frequency outnumber those based on other indices (**Linetal2020**). This study utilized a one-year timescale. SPI is calculated based on precipitation alone, so precipitation was calculated for each station during the selected timescale.

Standardized precipitation evapotranspiration index (SPEI)

SPEI was first introduced by Serrano et al. (2010). This index is a multivariate index in which precipitation data and evapotranspiration data are combined. SPEI is calculated similarly to SPI; however, SPI utilizes monthly precipitation, while SPEI utilizes monthly precipitation difference and potential evapotranspiration (PET), representing water balance. SPEI has been widely used to study meteorological droughts (Chen and Sun, 2015; Zhao et al., 2015). In this study, SPEI was calculated on a one-year time scale in RStudio Software.
SPEI is derived from equations (1) to (7):

$$m = 6.75\times10^{-7}I^3 - 7.71\times10^{-5}I^2 + 1.79\times10^{-2}I \quad (1)$$

$$\mathrm{PET} = 16K\left(\frac{10T}{I}\right)^m \quad (2)$$

$$i = \left(\frac{T}{5}\right)^{1.514} \quad (3)$$

$$K = \left(\frac{N}{12}\right)\left(\frac{NDM}{30}\right) \quad (4)$$

where
T is the average monthly temperature in Celsius,
m is the coefficient of dependence on I,
I is the sum of heat indices for 12 months,
K is the correction factor in terms of month and latitude,
NDM is the number of days in a month, and
N is the maximum number of hours of sunlight.
Thus, the difference (D_i) between precipitation (P) and PET for the month i was calculated as follows:

$$D_i = \mathrm{P}_i - \mathrm{PET}_i \quad (5)$$

The calculation of SPEI requires a three-parameter distribution. The probability distribution function of series D is based on the following equation:

$$F(x) = \left[1+\left(\frac{\alpha}{x-y}\right)^{\beta}\right]^{-1} \quad (6)$$

where, α, β and x are respectively the scale, shape and position parameters for D values (Singh and Narang, 1993). The values of $F(x)$ for series D in different time scales are well-suited to the observed experimental values, so SPEI can be simply calculated from the standard values of $F(x)$.

$$\mathrm{SPEI} = W - (C_0 + C_1W + C_2W^2/1 + d_1w + d_2w^2 + d_3w^2) \quad (7)$$

where
$W = \sqrt{2ln(\mathrm{P})}$ for $\mathrm{P} \leq 0.5$, P being the probability of higher values of D.
C_0, C_1, C_2, d_1, d_2 and d_3 have fixed values.
The mean value of SPEI is zero and the standard deviation is equal to one. SPEI is a standardized variable, so it can be compared with other SPEI values from different times and locations. A SPEI value of zero is equivalent to a cumulative probability of 50% for D (Mavromatis, 2007).

Kernel smoothing

The kernel smoothing method offers promising results for cases involving one real-world and two simulated datasets. At the same time, the method offers a great alternative to Kriging approaches, in particular in cases where the estimation process has failed. This can be the case when there are few samples or the observed data are not suitably designed for computer analyses. In such conditions, the working unit will be a polygon created through Delaunay triangulation. The approach is flexible enough to embed different types of kernels and weight functions. As the method can be easily executed, it is used as a criterion to validate other interpolation methods (Muhlenstadt and Kuhnt, 2011). This method has been used in past studies such as Hessl et al. (2018) and u et al. (2020). Kernel smoothing can be a good option for noisy measurements $x(t_i)$ of processes at irregularly-spaced times t_i. The smoother is a weighted average (equations (8) and (9)).

$$x(t) = \frac{\Sigma_{i=1}^{N} K(t-t_i)\times(t_i)}{\Sigma_{i=1}^{N} K(t-t_i)} \quad (8)$$

$$K(T) = \exp\left(-\frac{T^2}{2\tau^2}\right) \quad (9)$$

Results and discussion

LARS-WG is a common weather generator which generates meteorological data for future periods using temperature and precipitation changes under RCP 2.6, 4.5 and 8.5. Based on SPI values, droughts are expected to intensify in the eastern and northern regions, while the opposite is expected in the western part. SPEI indicates a gradual increase in drought severity from the region's center towards the west. Overall, the entire region will experience an approximately 11 – 15% increase in drought compared to the base period. Overall, we found that droughts would become more frequent in the Zagros region by 2100, which aligned with past studies (Rascon et al., 2021; Haile et al., 2020). SPI and SPEI were also used to study temporal and spatial changes in drought severity and frequency in the Zagros region in different periods between 2020 and 2099. SPI shows that the spatial extent of drought increases significantly (47.9%) in the first period compared to the base period. In the second and third period, dry classes have a much larger area compared with the base period. However, SPEI indicates the dominance of very intense droughts in all periods. A general review of the results indicates an increase in the frequency and severity of drought as well as the emergence of drought-affected areas by the end of the century. Therefore, it is necessary to take appropriate measures to reduce the potential effects of climate change on the ecosystems in the region.

Impact of climate change on drought based on SPI

SPI relies solely on precipitation, while SPEI is calculated based on precipitation and temperature through a simple water balance equation. According to both indicators, droughts will become more frequent in the future compared to the base period; however, the projected impacts depended on the index used in the analysis. Given its reliance on precipitation alone, SPI is a widely applicable indicator. However, it is crucial to exercise caution when using SPI as a drought indicator. According to Table 3, normal dry and normal wet classes were the most common classes in the base period. The extremely wet class had the lowest frequency (17.7 months) while more than 7% of the months in the base period were categorized as severely dry or extremely dry. All stations experienced more dry periods than wet periods, as indicated by the larger percentages and average values for the dry classes (Table 3). This finding is in agreement with Bahrami et al. (2019). In a study spanning the entire country, the researchers found moderately dry and normal dry classes to be the most common classes in 1967 – 2014. The predominance of the moderately dry class in their findings and the absence of the moderately wet class among the most common periods can be justified by the geographical scope of their analysis, which spanned all of Iran. The arid climate of Iran, especially the regions not included in this study, is expected to result in a larger number of dry periods. Similar to our findings, they also report that the very wet and extremely wet classes were the least common.

Changes in the first period compared with the base period

Our analysis showed that the frequency of droughts in the first period will increase by 28% compared to the base period, while the frequency of wet classes will increase by 0.35%. Normal classes (both wet and dry) were unchanged, and the largest difference was observed for the dry classes, with an increase of 9.23% (Tables 3 and 4). In this period, the normal wet class had the largest average and percentage due to the geographical location of the stations. The smallest percentage belonged to the extremely wet class (1.62%). In a similar study in northwestern Iran, Ahmadebrahimpour et al. (2019) found that drought events will become more common in 2011 – 2040 under RCP 8.5 but remain unchanged under RCP 2.6. In another study in the Zagros region, Mirzapour et al. (2023) found that the eastern Zagros region will face severe droughts in 2020 – 2039 under all RCP scenarios. However, the extent of areas affected by different classes of drought severity varied between RCP scenarios.

Changes in the second period compared with the base period

The result showed that the frequency of droughts will increase by 4.78% in the second period compared to the base period while the frequency of wet periods will decrease by 7.7%. Normal classes are predicted to decrease by 1.41% in the second period. Among the stations, Sanandaj shows the largest change in the occurrence of dry periods with an increase of 84.88% compared to the base period (Tables 3 and 5). The majority of the stations were classified as normal wet (36.85%) or normal dry (31.85%) in the second period.

Changes in the third period compared with the base period

Dry periods will increase in the third period by 0.9% compared to the base period while wet months' span 18.8% of

Table 3. Frequency of SPI classes during the base period (1984 – 2020).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	13	11	3	10	12	4	8.83	2.45
Severely dry	17	19	30	16	14	11	17.83	4.95
Moderately dry	22	19	27	47	29	32	29.33	8.15
Normal dry	134	126	127	75	118	163	123.8	34.4
Normal wet	114	137	113	163	122	83	122	33.89
Moderately wet	34	24	39	24	41	21	30.5	8.47
Very wet	16	18	8	25	20	36	20.5	5.69
Extremely wet	10	6	13	0	4	10	17.7	1.99

Table 4. Frequency of SPI classes during the first period (2020 – 2039).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	11	13	5	7	3	11	8.33	2.31
Severely dry	20	14	22	22	2	18	20.67	5.74
Moderately dry	23	25	32	33	40	15	28	7.78
Normal dry	104	130	110	113	98	145	116.6	32.41
Normal wet	156	100	140	119	120	119	125.67	34.91
Moderately wet	24	53	43	41	55	25	40.17	11.16
Very wet	15	20	2	22	13	16	14.6	4.07
Extremely wet	7	5	6	3	3	11	5.83	1.62

the third period. The frequency of dry classes is expected to increase by 56.1%. Fasa station will experience a significant increase in drought indices compared to the base period (Tables 3 and 6). The figures indicate an increase in the percentage and average values of dry periods by 2099. Our findings are consistent with Mesbahzadeh et al. (2019) for future droughts (2017 – 2100) in central Iran. Their results indicate that their study area in central Iran will experience longer and more severe droughts in the future under RCP 2.6, 4.5, and 8.5; the most severe conditions were associated with RCP 8.5.

Spatio-temporal changes in SPI

The frequencies of three levels of drought intensity were calculated and their spatial variations were plotted using kernel smoothing. Figure 3 shows the percentage of the study area covered by each class. In the base period, the northeastern and central parts of the study area experienced the most severe droughts, with all three classes having roughly the same area (figures 2 and 3). As we move from the northeast to the northwest and from north to south, we see an increase in drought at the synoptic stations, which is consistent with the results of past studies (Hasanlo et al., 2020; Bahrami et al., 2019) similarly, the reported worsening drought conditions for the stations were included in this study. The highest drought severity is seen in the eastern part of the region, followed by the western, northern, and southern regions. Projected maps show an increase in droughts in the northern parts and a decrease in the southern parts.
In the first period (2020 – 2039), the most severe droughts are expected in the central and northeastern parts of the region and the least severe droughts in the southeastern parts. In this period, the severity of droughts will increase so that about half of the region will be exposed to very severe drought. In the second period (2040 – 2069), drought is projected to occur in the north whereas the southeastern and southwestern parts are less likely to experience severe drought. The severely dry class will cover more than half of the region in this period. In the third period (2070 – 2099), drought is projected mainly in the northeast. The share of areas in the severely dry class will increase compared to the base period, but coverage will decrease for the moderately dry class.

Impact of climate change on drought based on SPEI

The extremely dry and severely dry conditions identified by SPEI are generally more intense than those identified by SPI in terms of affected area and duration. In a study using CanESM2 and RCP 2.6, 4.5 and 8.5, Mesbahzadeh et al. (2019) found a similar trend in Yazd province, Iran, reporting that droughts identified by SPEI are more severe than those identified based on SPI. As seen in Table 7, the largest percentage and average SPEI belong to the normal wet class (40.37%), and the smallest to the extremely wet class (1.48%).

Table 5. Frequency of SPI classes during the second period (2040 – 2069).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	13	13	7	2	2	12	8.17	2.27
Severely dry	19	13	17	27	21	15	18.67	5.19
Moderately dry	35	20	32	34	41	29	31.83	8.84
Normal dry	84	136	113	114	102	139	114.6	31.85
Normal wet	165	120	146	118	123	124	132.6	36.85
Moderately wet	27	34	26	41	52	13	32.17	8.94
Very wet	10	19	11	21	15	18	15.6	4.35
Extremely wet	7	5	8	3	4	10	6.17	1.71

Table 6. Frequency of SPI classes during the third period (2070 – 2099).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	15	13	5	3	2	11	8.17	2.27
Severely dry	13	13	37	23	25	15	21	5.83
Moderately dry	31	18	14	41	35	25	27.33	7.59
Normal dry	106	138	102	97	107	138	114.67	31.85
Normal wet	150	121	141	144	118	136	135	37.5
Moderately wet	28	33	44	35	57	6	33.83	9.4
Very wet	15	19	16	14	15	18	16.1	4.49
Extremely wet	2	5	1	33	1	11	3.83	1.06

Changes in the first period compared with the base period

Projected SPEI showed that the frequency of droughts will increase by 11.9% in the first period compared to the base period, and that the frequency of wet months will decrease by 6%. This finding is in line with Dehghan et al. (2020). Using Palmer drought severity index (PDSI) and a statistical downscaling model for six weather stations under RCP 4.5 and 8.5, the researchers predict increasing dry periods between 2019 and 2048 in the Fars province, the largest province in our study area. In our analysis, the frequency of normal dry and normal wet months showed a 1% decrease. Shiraz station will experience the greatest increase in dry periods (52%) compared to baseline (Tables 7 and 8).

Changes in the second period compared with the base period

The results showed that the frequency of droughts in the second period will be 12.44% higher than the base period, which is similar to the changes in the first period. Wet periods are predicted to decrease by 1.3%, and the percentage change in the normal dry and normal wet months is expected to be −2.47% (Tables 7 and 9). Ahmadebrahimpour et al. (2019) report similar results for 2041 – 2070 in a nearby basin in northwestern Iran.

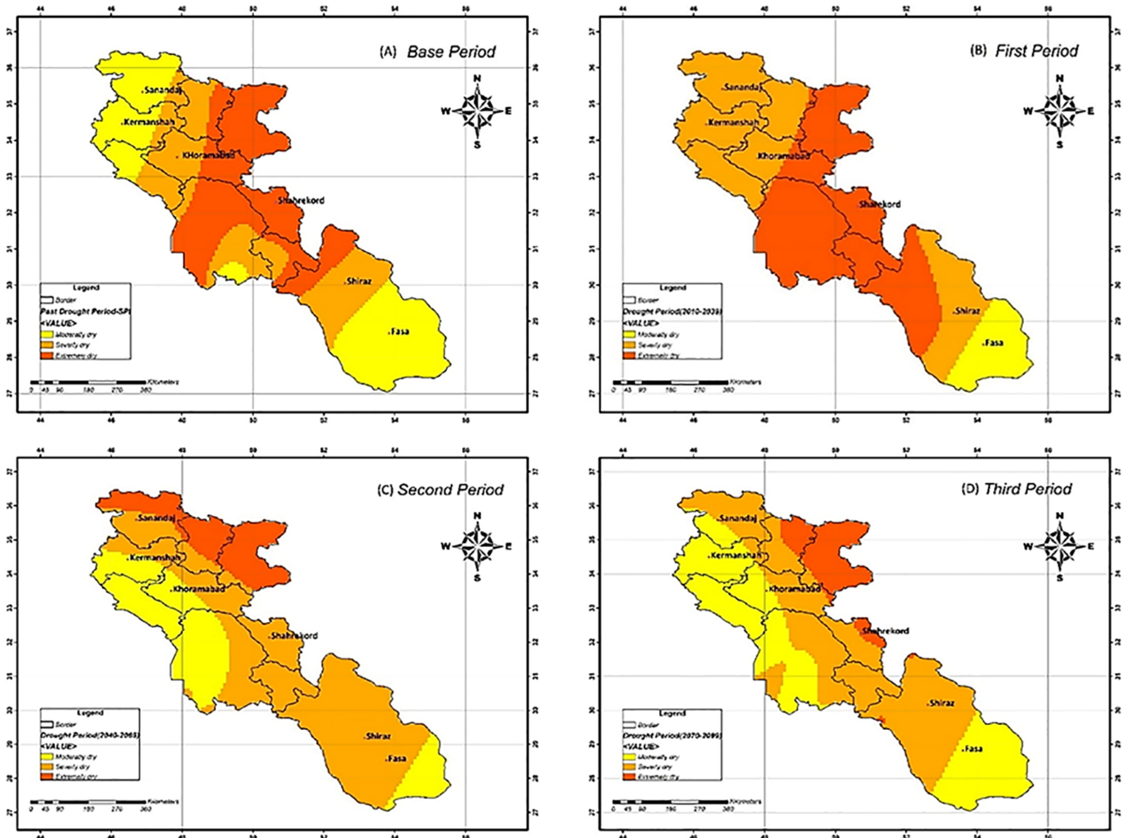

Figure 2. The spatial distribution of three classes of drought severity based on SPI during the base period (A), first period (B), the second period (C), and third period (D).

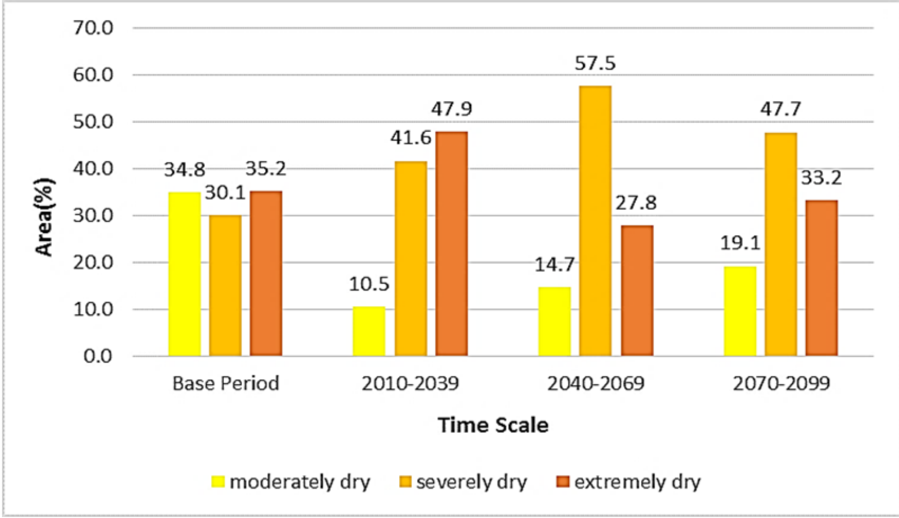

Figure 3. The percentage of drought severity classes in the past and future based on SPI.

Changes in the third period compared with the base period

The frequency of droughts will increase by 22% in the third period compared to the base period and wet periods are projected to decrease by 7%. Normal dry and normal wet periods will experience a decrease of 61.3%. Khorramabad and Sanandaj stations will experience dry periods most frequently due to a significant change in drought months compared to the base period (Tables 7 and 10).

Spatio-temporal changes in SPEI

Investigating the spatial extent of changes in SPEI in the base period revealed that droughts were most frequent in the central and northeastern parts of the region and least frequent in the south (figure 4). A study by Sobhani et al. (2019) on the nearby Lake Urmia basin also found a worsening drought trend in western Iran. The historic downward trend in SPEI is also supported by Nouri and Homaee (2020), who report a drying trend in 85% of their studied sites. In the first period, extreme droughts are predicted to occur to the south of the central areas, and the northern parts will experience less severe droughts. The central part of the area is affected by severely dry conditions. The severely dry class will cover nearly half of the region (47.6%) (Figures 4 and 5). In the second period, extremely dry conditions are expected in the north and south, and severely dry conditions are predicted from the center towards the north. Severely dry conditions will dominate the region with a coverage of 55.4% (figures 4 and 5). In the third period, the northwest will have moderately dry conditions, and the severely dry class will be the most prevalent at 45.25% (Figs. 4 and 5). Using SPEI, we found that the extremely dry class will gradually extend to the northern and southern parts of the Zagros region, which is consistent with the results of similar research in the past (Lee et al., 2017). In this study, SPEI predicted a higher relative frequency for dry conditions compared to SPI. This difference can be attributed to the sensitivity of SPEI to changes in precipitation and the inclusion of temperature parameters, which is consistent with the findings of Polemio and Casarano (2008), and Haile et al. (2020). Similarly, Lotfirad et al. (2022) report that SPEI had better predictive performance than SPI in different regions across Iran, reflected by its higher overall accuracy.

From a time series perspective, there were some similarities in the changes observed in SPI and SPEI across various time scales. Lotfirad et al. (2022) report similar results for the correlation between SPI and SPEI, stating that the cor-

Table 7. Frequency of SPEI classes during the base period (1984 – 2020).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	4	2	5	6	12	12	6.83	1.9
Severely dry	28	27	18	19	9	12	18.83	5.23
Moderately dry	20	23	39	41	25	17	27.5	7.64
Normal dry	147	126	135	132	157	175	145.33	40.37
Normal wet	101	111	98	108	94	70	97	26.94
Moderately wet	28	39	39	26	26	29	31.17	8.66
Very wet	26	28	15	21	35	43	28	7.78
Extremely wet	66	4	11	7	2	2	5.33	1.48

Table 8. Frequency of SPEI classes during the first period (2020 – 2039).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	6	3	2	0	0	8	3.17	0.88
Severely dry	25	21	21	22	24	15	21.33	5.93
Moderately dry	29	25	40	36	46	34	35	9.72
Normal dry	124	136	115	126	107	132	123.33	34.26
Normal wet	125	114	126	108	110	115	116.33	32.31
Moderately wet	23	34	39	43	56	26	36.83	10.23
Very wet	23	24	13	25	16	20	20.17	5.6
Extremely wet	5	3	4	0	1	10	3.83	1.06

relation coefficient for the two indices ranged from 0.94 to 0.81 in temperate climates. However, we also observed differences in the predictions made using SPI and SPEI, which is in line with past studies. Over short timescales, these two indices had the most fluctuation and the differences between them were the largest. The frequency of drought intensity classes predicted based on SPI and SPEI had a disparity of up to 30% when short time frames were selected. Over long timescales, however, the fluctuations in SPI and SPEI were mild and the differences between them decreased. However, these small changes still led to differences in classification. Compared to the classical kriging approach, kernel smoothing shows better performance for data with unstable behavior.

Impact of drought severity on the vegetation cover

The Zagros region has unique climatic conditions and remarkable biodiversity. Over the past years, the average annual temperature has increased in the region, which has led to a decrease in vegetation cover. Our findings show that climate change can have significant impact on habitats and natural vegetation cover in the region. In a study, Estimates from different climate scenarios indicate that 18.72% (RCP 2.6) to 33.69% (RCP 8.5) of the vegetation cover in the region will be lost due to climate change (Asl et al., 2020). Past studies in the same region predict that a large part of the vegetation cover will suffer due to climate change (Naghipour et al., 2019). SPEI and SPI are expected to have decreasing trends due to a decreasing trend in rainfall.

Table 9. Frequency of SPEI classes during the second period (2040 – 2069).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	3	5	1	1	0	7	2.83	0.79
Severely dry	26	20	21	22	21	15	20.83	5.79
Moderately dry	32	29	39	33	51	33	36.17	10.05
Normal dry	109	132	107	125	110	127	118.3	32.87
Normal wet	134	109	139	105	103	119	118.17	32.82
Moderately wet	30	36	33	48	58	30	39.17	10.88
Very wet	17	26	15	26	17	28	21.5	5.97
Extremely wet	9	3	5	0	0	1	3	0.83

Table 10. Frequency of SPEI classes during the third period (2070 – 2099).

Climate variables	Sanandaj	Kermanshah	Khorramabad	Shahrekord	Shiraz	Fasa	Mean	Percentage
Extremely dry	3	5	1	1	0	8	3	0.83
Severely dry	26	21	25	22	27	21	23.67	6.57
Moderately dry	40	26	43	39	45	36	38.17	10.6
Normal dry	101	136	115	117	105	122	115.17	31.99
Normal wet	138	112	118	125	109	116	119.67	33.24
Moderately wet	29	36	34	38	56	28	36.83	10.23
Very wet	22	27	22	17	17	22	21.17	5.88
Extremely wet	1	2	2	1	1	7	2.33	0.65

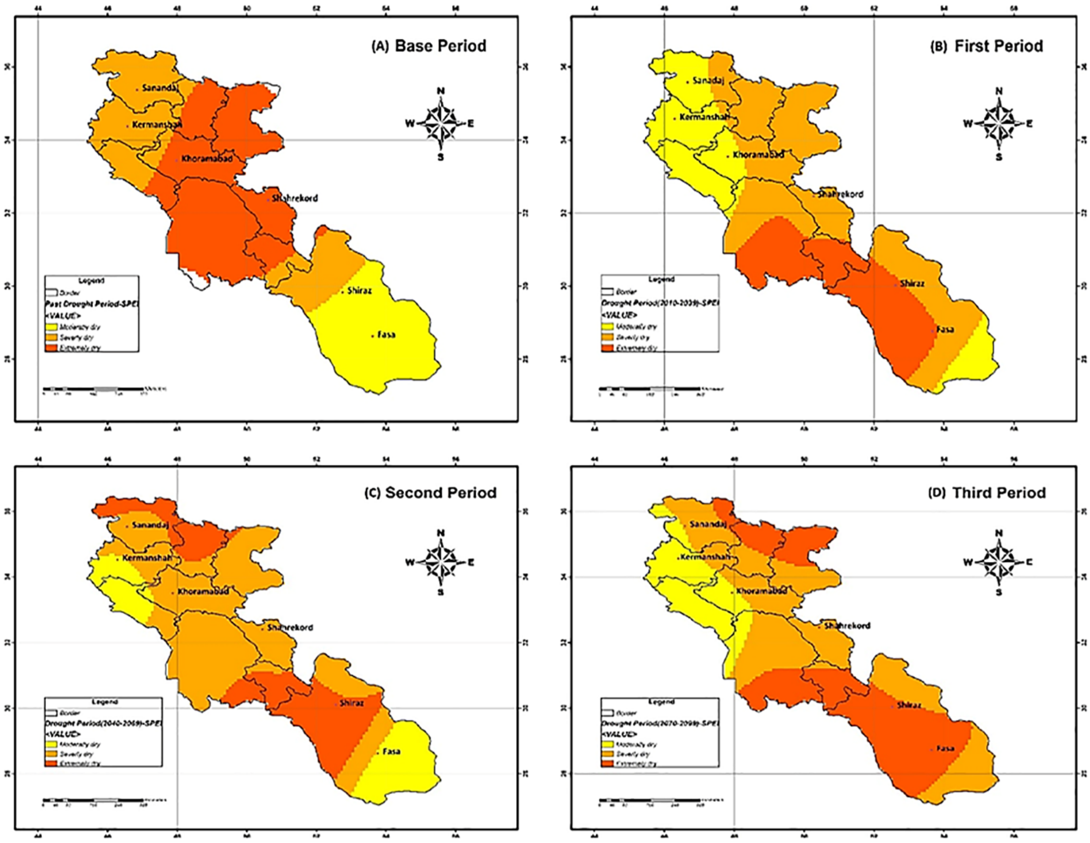

Figure 4. The spatial distribution of three classes of drought severity based on SPEI during the base period (A), first period (B), the second period (C), and third period (D).

Accordingly, the results also indicate that there is a direct relationship between vegetation cover and rainfall during the statistical period, with rainfall contributing to vegetation density and coverage.

Comparing the two indices showed that the average duration of droughts predicted by SPEI is longer than those predicted by SPI in all stations and for all time periods. In general, SPEI predicts more severe drought intensity across classes, which may be due to the sensitivity of the index to changes in precipitation and inclusion of temperature. In light of this fact, it is clear that the expected increase in temperature will have a noticeable effect in the future. Moreover, the average duration of droughts according to SPEI is longer than those predicted based on SPI, which is consistent with the results of previous studies (Berhail and Katipoğlu, 2023; Oksal, 2023).

According to Goodarzi et al. (2019), significant changes have occurred in the density and extent of vegetation in the

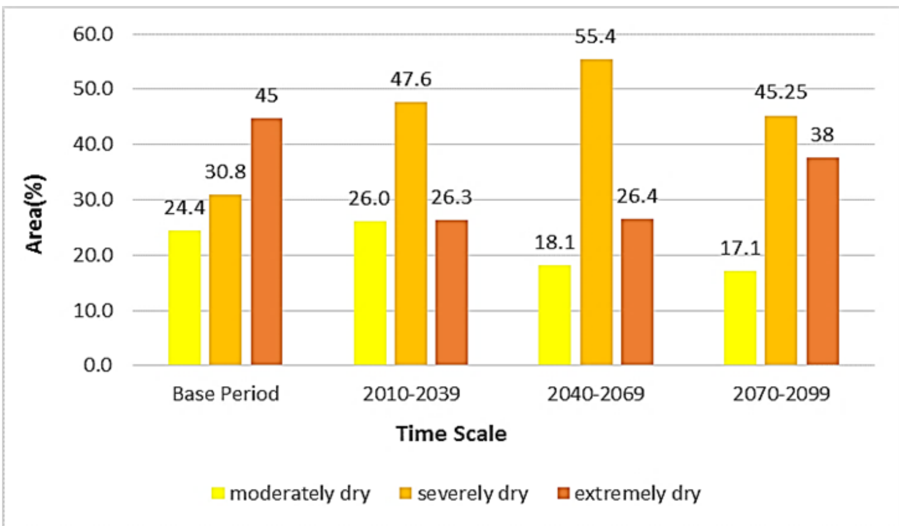

Figure 5. The percentage of drought severity classes in the past and future based on SPEI.

study area during the study period, which confirms the evaluations based on drought indices. Our study also reveals that the two indices used to determine the extent, severity, and frequency of droughts are suitable indicators. Furthermore, the effects of drought on vegetation during the study period are clearly visible.
Analysis using SPI revealed that the central and southern Zagros region experienced extreme drought conditions, while more moderate drought was observed in the northwestern and northeastern sections. However, predictions using SPEI indicated that extreme drought conditions are likely to expand northward and southward, encompassing more of the Zagros region over time.

Conclusion

In this study, SPI and SPEI were used to study past and future droughts in the Zagros region of Iran. SPI analysis revealed that normal classes are predominant across different periods. However, the SPEI index indicates a projected increase of 2% in the frequency of these classes during the first period compared to the base period, followed by a 0.3% increase in the second and third periods. Evaluating the performance of GCMs and simulating future rainfall is important for understanding current climate change and its impact on hydrology, water resources, agriculture, and ecology. The results of this study can provide valuable input for future studies focusing on the entire country. In addition, future studies should combine GCMs using several methods to reduce the uncertainty associated with the predictions.
Drought is the most important environmental challenge in arid and semi-arid regions. One of the most prominent features of this research is the joint implementation of models to predict the geographical and temporal extent of droughts in a semi-humid area. The use of other drought indicators along with other GCMs can be considered in future research. Our findings predict the occurrence of wet and dry periods between 2020 and 2099 in the study area. Based on the results, the increase in droughts will be a serious threat in the region by 2099, particularly in the central and eastern parts of the study area. Reduced precipitation and increased periods of drought diminish soil moisture, which can lead to issues such as dust and reduction of arable land, among other environmental crises. Given the effects of climate and socio-economic change, it is expected that climate risks will increase in the coming years. Extreme drought is among the risks associated with these changes in the Zagros region (and Iran), which can inflict irreparable damage to water resources, agriculture, and rangelands. The severity of droughts investigated in the future period (2100) by the index (SPEI) and SPI, under different climate scenarios (RCP), show that in the future, we will witness very severe droughts with greater intensity and continuity in Zagros and especially in the west of Iran. One of the consequences of the drought that we have seen during the last decade is the drying and reduction of tree reproduction and the quantitative and qualitative reduction of vegetation in the region. Therefore, the trend and intensity of droughts predicted in the future period can be useful for managing water resources in the future in Zagros.
Moreover, the development of a network of stations measuring climate parameters could improve the accuracy, reliability, and coherence of predictions. These predictions can be considered for the formulation of adaptation strategies in the face of drought. The findings of this research can be utilized to effectively manage drought risk in the region and facilitate the coherent development of water-related projects and water supply systems. These results are heavily reliant on simulations derived from a single climate change dataset, which introduces limitations due to the inherent uncertainty in climate change scenarios. However, despite these limitations, this study demonstrates that the Zagros region will be influenced by climate change-induced drought conditions.

Acknowledgment
We would like to express our gratitude toward those who helped us by providing data or improving our analyses.

Authors Contributions
All authors have contributed equally to prepare the paper.

Availability of Data and Materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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

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