



A Comparative Evaluation of Drought Indices Using CMIP6 Climate Model Simulations: A Case Study of Semnan Province, Iran

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Article Info	ABSTRACT	
Article type: Research Article	Global warming has led to an increased incidence of drought in many parts of the world. This study monitors and projects future drought characteristics in Semnan Province using the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). We utilized outputs from 12 CMIP6 models to project temperature and precipitation across the study area. These General Circulation Models (GCMs) were Bias correction using the empirical Quantile Mapping (QM) method. To reduce GCM uncertainty, an ensemble model was developed using the Bayesian Model Averaging (BMA) approach. Using these projected precipitation and temperature values, we computed the 12-month SPI and SPEI indices for a baseline period and the near-future (2031–2054). Drought characteristics (duration, intensity, and magnitude) were then extracted using Run Theory and compared between these periods. Multi-model ensemble projections indicate that the average temperature across the province will increase by approximately 1.1 to 2.1 °C under both scenarios compared to the baseline. Mean annual precipitation is projected to increase by 3% to 8% across all stations in the province, except for Shahrud. The SPI and SPEI values showed a significant positive correlation and relatively similar performance, despite minor discrepancies. Both indices indicated a distinct upward trend in drought duration and intensity towards the end of the 2031–2054 horizon compared to the baseline. This increase was most pronounced in the SPEI index under the SSP585 scenario. Specifically, SPEI-based drought duration increased from 6.6 months in the baseline to 9.8 and 16 months per year under the SSP245 and SSP585 scenarios, respectively. For the SPI index, these values ranged from 6.3 to 6.5 and 8.7 months per year, respectively.	
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1 Introduction

Drought is considered a periodic climatic anomaly, whose most important characteristics include slow development, long duration, and widespread impacts (Rahman et al., 2025; Li et al., 2021). This phenomenon is one of the most costly and least understood natural hazards, which alone led to economic losses of \$7.5 billion worldwide in 2020 (Zheng et al., 2023). According to the Sixth Assessment Report (AR6), climate change alters precipitation and temperature patterns, and these alterations, by increasing evapotranspiration and decreasing soil moisture, can provide the conditions for drought intensification. One of the primary impacts of climate change is the occurrence of more severe and frequent hydrological hazards, such as droughts and floods (Bolan et al., 2024).

. Under the influence of drought, the agricultural sector, water resources, environment, and socio-economic activities suffer damage, which leads to increased human migration, wind and water soil erosion, alterations in water and soil quality, increased exploitation of groundwater, and land subsidence (IPCC, 2022). Due to its specific geographical location relative to general atmospheric circulation patterns and its topographical characteristics, Iran is situated in the world's arid belt and possesses an arid and semi-arid climate; consequently, it has grappled with severe and extreme droughts in most years (Asadi-RahimBeygi et al., 2025). Therefore, evaluating this phenomenon in the current period and upcoming decades appears essential to mitigate its destructive impacts.

To quantify drought, various indices are employed, most of which are based on measuring the deviation of calculated values from their long-term mean. The Standardized Precipitation Index (SPI) is one of the most efficient and widely used indices for drought monitoring and studies, largely due to its limited data requirements and ease of calculation. However, the SPI relies solely on precipitation and does not account for the effects of temperature variations and atmospheric evaporative demand on drought.

Considering that approximately 80% of precipitation is lost through evapotranspiration (McKee et al., 1993), and that incorporating variables like temperature and evapotranspiration can provide a more comprehensive understanding of dryness, especially under climate change (Hu and Willson, 2000), a more robust index is often needed. The Standardized Precipitation Evapotranspiration Index (SPEI), introduced by Vicente-Serrano (2010), addresses this by incorporating both precipitation and evapotranspiration. This allows the SPEI to evaluate drought sensitivity to temperature variations and atmospheric evaporative demand. Therefore, a comparative analysis of SPI and SPEI can reveal the extent to which temperature variations and atmospheric evaporative demand influence drought characteristics beyond just changes in precipitation.

The significance of this issue has also been addressed in various international studies. For instance, Wubneh et al. (2023) compared the SPI, RDI, and SDI indices in Ethiopia's Lake Tana basin, demonstrating their differential performance in identifying droughts. Similarly, Montes-Vega et al. (2023) investigated future drought variations using SPI, SPEI, and GRDI under various climate change scenarios. Other studies comparing the SPI and SPEI have revealed that incorporating temperature and evapotranspiration can lead to different estimations of drought characteristics, including frequency, severity, and duration (Gumus, 2023; Bouabdelli et al., 2022). Overall, these studies indicate that the choice of index can

influence the assessment of drought characteristics. Therefore, employing precipitation-based indices alongside those that account for temperature variations and atmospheric evaporative demand provides a more comprehensive understanding of drought behavior under changing climate conditions.

The importance of this matter becomes more pronounced in regions with arid climates and limited water resources, such as Semnan Province. Semnan Province, with its arid and semi-arid climatic conditions, low precipitation, and high evapotranspiration, is among the regions where drought variations can have substantial consequences for water resources and their dependent activities. Despite this significance, studies conducted in this province have predominantly investigated drought characteristics or related factors using a single drought index, notably the SPI. Kianian et al. (2018), utilizing the SPI and examining dynamic-synoptic patterns, investigated the role of atmospheric anticyclones in the formation of pervasive droughts in Semnan Province. Their results indicated that the establishment of a strong ridge, negative vorticity, dynamic air subsidence, moisture reduction, and the weakening of ascending currents are among the most important synoptic mechanisms associated with drought occurrence in the province. Additionally, the intrusion of Siberian high-pressure ridges into central Iran was accompanied by a reduction in atmospheric disturbances and the restriction of precipitation conditions. In another study, Yousefi Mobarhan and Khaleghi (2024), by simultaneously examining the Dust Storm Index (DSI) and the Standardized Precipitation Index (SPI) at five synoptic stations during the 2003–2017 period, demonstrated that the annual variations of DSI lack a specific trend, although it generally increases during drought periods and decreases during wet periods. However, the statistical relationship between DSI and SPI was not significant, indicating that dust variations in the region cannot be exclusively explained by meteorological drought.

Despite numerous studies, the simultaneous investigation of SPI and SPEI to elucidate differences in drought characteristic estimations and the role of temperature variations and atmospheric evaporative demand in Semnan Province, particularly under future climatic conditions, has received less attention. This gap is critical because rising temperatures can exacerbate drought variations by increasing atmospheric evaporative demand, an effect not directly reflected in precipitation-only based indices. Therefore, this study employed a comparative approach to investigate drought variations in Semnan Province using SPI and SPEI under the SSP245 and SSP585 climate scenarios. For this purpose, outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6) climate models were utilized after bias correction and combination via the Bayesian Model Averaging (BMA) method, and drought characteristics were compared between baseline and future periods. Furthermore, the primary characteristics of drought events, including frequency, severity, duration, and magnitude, were evaluated based on both indices. The results of this research can provide a more accurate understanding of the differential drought estimations based on the two index approaches and the role of temperature variations in future drought dynamics in Semnan Province, thereby serving as a foundation for adaptation planning and water resources management under future climate conditions.

2 Materials and Methods

2.1 Study Area

Semnan Province, spanning approximately 98,000 square kilometers, is situated between 51°58' and 57°58' East longitude and 34°17' to 37°30' North latitude. Located on the southern slopes of the Alborz mountain range, the province also encompasses a portion of the Dasht-e Kavir. Its average elevation is 1,113 meters above sea level, and its diverse geography can be divided into three distinct zones: mountainous, foothill, and the low-lying areas of the Dasht-e Kavir. The province experiences an average annual precipitation of approximately 125.8 mm and an average annual temperature of 17.3 °C. Figure 1 illustrates the geographical location of the study area and the spatial distribution of synoptic stations within the province.

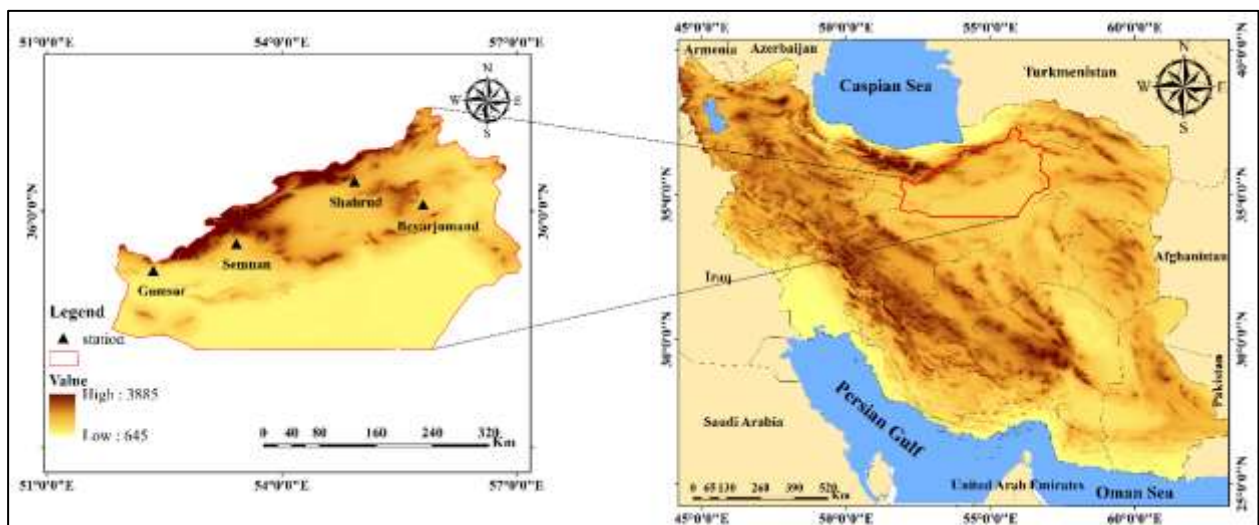


Fig 1. Location of the study area

2.2 Methodology

2.2.1 Data

To conduct this research, daily precipitation and temperature data from the Beyarjmand, Garmsar, Semnan, and Shahrud synoptic stations for the period 1990–2014 were obtained from the Iran Meteorological Organization. The characteristics of the selected stations are presented in Table 1. Furthermore, to investigate the impacts of climate change on droughts in the study area, the outputs of 12 Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) were utilized (Table 2). To assess drought, two scenarios were employed: the intermediate scenario (SSP245) and the pessimistic scenario (SSP585). The projection was executed for a 25-year near-future period (2031–2054) in the twenty-first century. The outputs of the GCMs were bias correction using the Quantile Mapping method, and the accuracy of the models was evaluated using the RMSE, R^2 , and MAE indices.

Table 1. Locations of Weather Stations and Climate Models Utilized in the Study

Data	Station	Longitude	Latitude	Elevation (m)
Observed	Beyarjmand	55° 08'	36° 08'	1099.3
	Garmsar	52° 21'	35° 14'	899.9

	Semnan	53° 25′	35° 35′	1127
	Shahrud	54° 57′	36° 25′	1325.2
	Name	Description		Resolution spatial
GCMs simulated	CMCC-ESM2	Center Euro-Mediterraneo Sui Cambiament Climatici		1.875° × 1.25°
	EC-Earth3-Veg-LR	The EC-Earth-Consortium team of European institutions and organizations		0.7° × 0.7°
	INM-CM5-0	Institute for numerical mathematics, Russian Academy of Science/Russia		1.5° × 2°
	INM-CM4-8	Institute for Numerical Mathematics, Russian Academy of Science/Russia		1.5° × 2°
	MRI-ESM2-0	Meteorological Research Institute (MRI)/ Japan		1.1° × 1.1°
	NESM3	NUIST Earth System Model / China		1.9° × 1.9°
	MIROC6	Institute for Environmental Studies, RIKEN Center for Computational Science /Japan		1.4° × 1.4°
	CNRM-ESM2	Centre National de Recherches Meteorologiques/France		1.4° × 1.4°
	ACCESS-CM2	Australian Community Climate and Earth System Simulator/Australian		1.2° × 1.8°
	FGOALS-g3	Flexible Global Ocean-Atmosphere-Land System Model /China /Beijing		0.9375° × 1.25°
	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory/ USA		1.0° × 1.3°
	MPI-ESM1-2-LR	Max Planck Institute Earth System Model / Germany		1.875° × 1.875°

2.3 Bias Correction Method and Ensemble Model Generation from GCM Outputs

Bias correction is a crucial technique for enhancing the quality of General Circulation Model (GCM) outputs by eliminating systematic errors. Various methods exist for bias correction, each with its own advantages and limitations. The effectiveness of these methods is influenced by factors such as the choice of GCMs, the study region, the season, and the specific climate variable being analyzed (Asgari et al. 2024).

2.3.1 Quantile Mapping Method

The Quantile Mapping (QM) method, introduced by Panofsky and Brier in 1968, is a widely used technique for bias correction. The QM algorithm has demonstrated superior performance compared to simpler methods that only adjust the mean or both the mean and variance of precipitation time series (Cannon et al. 2015). This method employs a transfer function to construct cumulative distribution functions (CDFs) for both model simulations and observations. This transfer function enables the transformation of raw model outputs into corrected values, ensuring that the CDF of the corrected model aligns with that of the observational dataset (Teutschbein and Seibert 2012). Mathematically, the Quantile Mapping can be implemented using the following equation:

$$Y = F_{obs}^{-1}(F_{GCM}(x)) \quad (1)$$

In this context, Y represents the corrected value, while x is the value that needs correction. In addition, F_{obs}^{-1} denotes the inverse of the observational CDF, while F_{GCM} represents the CDF of the GCM used.

2.3.2 Bayesian Method Averaging

Bayesian model averaging is a technique used to combine forecasts from various models, resulting in a new probability density function (PDF) that predicts the desired climate variable for the upcoming period. The output of BMA is a weighted average of the probability density functions (PDFs) centered on the bias-corrected forecasts. The weights assigned by BMA indicate the relative contribution of each model component in predicting the training samples, allowing for an assessment of the usefulness of each ensemble member. For a variable y that must be predicted based on the training data y^T using K models $M_1, \dots, M_K$, the predictive PDF $P(y | y^T)$ can be expressed as follows (Wang et al., 2018):

$$P(y|y^T) = \sum_{k=1}^K P(y|M_k y^T) P(M_k|y^T) \quad (2)$$

In this equation, $P(y | M_k, y^T)$ is the predictive PDF based on model M_k ; K is the number of models; and $P(M_k | y^T)$ is the posterior probability that model M_k is correct given the training data, indicating how well model M_k represents the training data. The sum of the posterior model probabilities is equal to one, i.e., $\sum_{k=1}^K P(M_k | y^T) = 1$. Therefore, they can be considered as weights. In the study by Raftery et al. (2005), more detailed information about the BMA model is provided, and the method for estimating the weight of each model M_k in BMA is described. In the present study, the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) were used to monitor and forecast drought in Semnan Province.

2.4 Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index was first introduced by Vicente-Serrano et al. (2010). The advantage of this multivariable index compared to the SPI is that it accounts for the effect of evapotranspiration on drought. In the SPEI index, the values of the difference between precipitation and potential evapotranspiration (PET), based on the climatic water balance, are used. This index is obtained using the following equations:

$$PET = 16K \left(\frac{10^T}{I} \right)^m \quad (3)$$

$$m = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.79 \times 10^{-2} \quad (4)$$

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

(5)

$$K = \left(\frac{N}{12} \right) \left(\frac{NDM}{31} \right)$$

(6)

In these equations, T represents the mean monthly temperature in degrees Celsius; m is a coefficient dependent on I ; I is the thermal index, or the annual sum of the 12 monthly i values; K is a correction factor based on the month and latitude; NDM is the number of days in a month; and N is the maximum possible sunshine duration in hours.

Accordingly, once the potential evapotranspiration is determined, the difference between precipitation P and PET for the i -th month can be calculated.

$$D_i = R_i - PET_i \quad (7)$$

Since the values of D_i range from the lower bound to negative values, two-parameter probability functions are not suitable for this purpose. Vicente-Serrano et al. (2010) examined various three-parameter functions and found that the three-parameter log-logistic probability density function provides the best fit for these values. The general form of the probability density function of this distribution is presented in Equation (8).

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} \left[1 + \left(\frac{x-\gamma}{\alpha}\right)^\beta\right]^{-2} \quad (8)$$

In this equation, the parameters α , β , and γ represent the scale, shape, and location, respectively, for the values of D_i within the range $\gamma < D < \infty$. The probability distribution function of the D series is calculated using Equation (9):

$$F(X) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^\beta\right]^{-1} \quad (9)$$

The SPEI index can easily calculate the standardized values of $F(X)$.

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (10)$$

In this equation, $W = \sqrt{-2\ln(p)}$ for $P \leq 0.5$, where P represents the probability of exceeding the specified values of D . The coefficients C_0 , C_1 , C_2 , as well as d_1 , d_2 , and d_3 , are constants.

The standardized index can be compared with other SPEI values across different locations and time periods. An SPEI value of zero corresponds to a cumulative probability of 50% for D (Vicente-Serrano et al., 2010).

2.5 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI), developed by McKee et al. (1993), is a tool for identifying and monitoring droughts and their intensity over various time scales. It functions as a Z-score, indicating how much an event deviates from the average, measured in standard deviation units. This characteristic enables the comparison of SPI values across different locations and time periods. A drought event is deemed to occur when the index values drop below -1 , and it concludes when the values become positive again. The index is calculated using the following equation:

$$SPI = \frac{X_i - \bar{x}}{\delta} \quad (11)$$

Where SPI is the standardized precipitation index for a given period, X_i represents precipitation, $\bar{x}$ is the mean precipitation, and δ denotes the standard deviation of precipitation. The classification of the two indices mentioned above is presented in Table 2.

Table 2. Classification scale of SPEI and SPI Drought Indices

Drought/Wetness Class	Index Value
Extremely wet	≥ 2
Very wet	1.5 to 1.99
Moderately wet	1.0 to 1.49
Near normal	-0.99 to 0.99
Moderate drought	-1.0 to -1.49
Severe drought	-1.5 to -1.99
Extreme drought	≤ -2

2.6 Drought Characteristics (Run Theory)

One widely used method for analyzing drought is the Run Theory. This approach defines three key characteristics of drought: duration, severity, and intensity. In this study, we assessed these characteristics by calculating the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) on a monthly basis for both current and future periods. According to this method, the duration of a drought period is determined by the sequence of negative values (Drought Duration). Drought severity (Severity, D) is measured by the sum of negative deviations within each sequence, while drought intensity reflects the average precipitation deficit during a specific drought period (Guerrero-Salazar, & Yevjevich, 1975).

2.7 Wavelet Coherence

The concept of wavelet coherence in signal processing focuses on measuring the relationship between two signals or their representations. When examining two continuous signals with finite energy, $x(t)$ and $y(t)$, the classical cross-correlation can be considered as the relationship between these signals. By examining the Fourier transform of the signals, the spectral correlation of the signals $x(t)$ and $y(t)$ is defined according to relation (12):

$$p(f) = \frac{S_{xy}(f)}{\sqrt{|S_{xx}(f)S_{yy}(f)|}} \quad (12)$$

Here, $S_{xy}(f)$ represents the cross-spectral density between the two signals $x(t)$ and $y(t)$. It is defined under the assumption of stationarity in the cross Fourier spectrum.

$$S_{xy} = \int_{-\infty}^{+\infty} R_{xy}(\tau) \exp(-i2\pi f\tau) d\tau \quad (13)$$

$p(f)$ takes a value between zero and one. If $p(f)$ is close to one for every frequency, then $y(t)$ can be approximated as a linear time-invariant function of $x(t)$. In climatological and hydrological time series, which are often non-stationary, it has been suggested to use time-frequency representations of the signals. The coherence analysis reveals the temporal variations in the relationship between the two signals and allows for the identification of transitional covariance values. To address the challenges posed by non-stationary signals, wavelet coherence has been introduced. A key issue arises when applying analog formulas to equation (13), resulting in a coherence value of one at all times, despite the absence of a genuine relationship between the signals. To mitigate this problem, efforts have been made to utilize a smoothed estimate of the wavelet spectrum, leading to the recommendation of

wavelet coherence. The definitions for the smoothed wavelet spectrum and the smoothed cross-spectrum are provided in relations (14) and (15).

$$Sw_{xy}(a, \tau) = \int_{t-\frac{\delta}{2}}^{t+\frac{\delta}{2}} W_{xx}^*(a, \tau) W_{xy}(a, \tau) da d\tau$$

(14)

$$Sw_{xy}(a, \tau) = \int_{t-\frac{\delta}{2}}^{t+\frac{\delta}{2}} W_{xx}^*(a, \tau) W_{yy}(a, \tau) da d\tau$$

(15)

In these relationships, the scalar indicates the size of the two-dimensional smoothing filter (Luterbacher et al., 2001). This is a crucial parameter for wavelet coherence, and it must be sufficiently large to yield an accurate estimate. Consequently, the Fourier coherence is defined as follows:

$$Wc(a, \tau) = \frac{|SW_{xy}(a, \tau)|}{\sqrt{[|W_{xx}(a, \tau)| |W_{yy}(a, \tau)|]}} \quad (16)$$

W_c takes a value between zero and one. Wavelet coherence, by identifying existing periodicities, can provide a comparison between phenomena and reveal the relationships between them. In climatological studies focused on identifying similar structures within time series, the Morlet mother wavelet is commonly employed for time-frequency analysis (Mirzayi Hasanloo et al., 2020). This study utilized continuous wavelet analysis to assess the coherence between the two indices, SPI and SPEI.

3 Results

3.1 Validation of CMIP6 models

Projected precipitation and temperature data from 12 Global Climate Models (GCMs) and an ensemble model were compared with observational data from 4 synoptic stations in Semnan Province for the period 1990–2014. The results, presented in Figure 2, indicate that individual climate models show higher capability for temperature prediction compared to precipitation, as evidenced by statistical metrics (RMSE, MBE, and R^2). This difference is attributed to the highly variable nature of precipitation.

The BMA ensemble model significantly improved accuracy for both parameters, substantially reducing the error margin. This reduction was particularly notable for precipitation, as shown by the RMSE and MAD metrics. Consequently, all subsequent analyses for drought monitoring and projection in the study area will be based on the BMA ensemble model, thus confirming the superior performance of the multi-model ensemble over individual models.

Following the selection of the ensemble model, projected future temperature and precipitation data for the near-future period (2031–2054) were analyzed under the SSP245 and SSP585 scenarios. Table 3 presents the percentage changes in temperature and precipitation for Semnan Province during this period. The table indicates that the projected mean temperature at all studied stations is expected to rise in the coming decades under both scenarios, with the most significant increase occurring in the pessimistic SSP585 scenario. The average temperature increases across the province range from approximately 1.1 to 1.5 °C under the intermediate SSP245 scenario and from 1.21 to 2.12 °C under the SSP585 scenario.

Table 3 also shows that the spatial patterns of annual precipitation changes across the studied stations exhibit significant variability in response to different climate scenarios. Most stations in Semnan Province are projected to experience an increase in total annual precipitation in the future, suggesting a potential improvement in moisture conditions in certain areas of the province. In contrast, Shahrud station, which has a baseline precipitation of 175.2 mm, is expected to follow a different trend. It is forecasted to see a decrease in annual precipitation under both the SSP245 and SSP585 scenarios, with estimated reductions of approximately 11.8% and 9.9%, respectively.

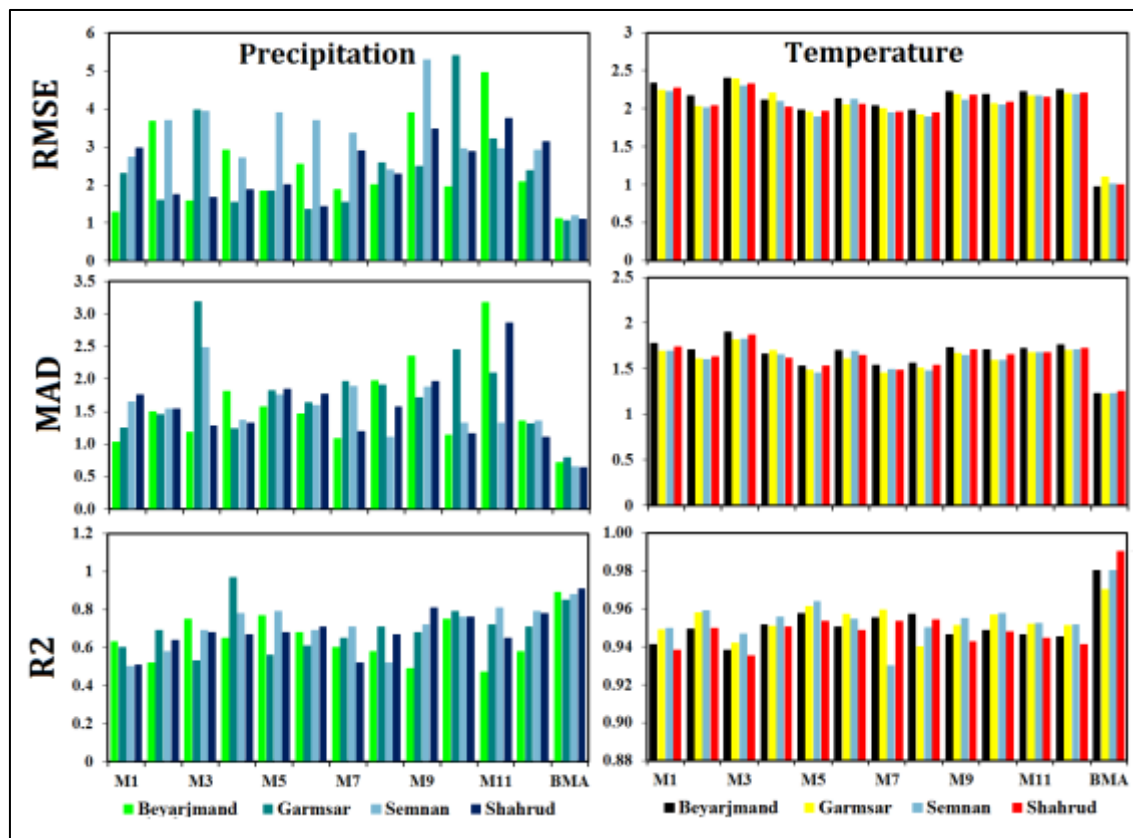


Fig. 2. Statistical evaluation of error correction: Individual CMIP6 models vs. BMA ensemble for precipitation and temperature.

Table 3. Percentage changes in temperature and precipitation in Semnan Province under future climate conditions

station	Baseline Mean Temperature (°C)	Mean Temperature (°C)		Baseline Precipitation (mm)	Precipitation Change (%)	
		SSP245	SSP585		SSP245	SSP585
		(2040s)			(2040s)	
Beyarjmand	16.1	1.2	1.4	125.7	6.1	8
Garmsar	18.9	1.1	1.2	117.2	3.7	5.3
Semnan	18.5	1.1	1.3	140.3	3.2	3
Shahrud	15.4	1.5	2.1	175.2	-11.8	-9.9

3.2 Assessment of SPI and SPEI Drought Indices under Historical and Future Climate Conditions

To investigate the temporal variations and severity of dry and wet periods, the SPI and SPEI drought indices were calculated and analyzed at a 12-month timescale for the Beyarjmand, Garmsar, Semnan, and Shahrud synoptic stations during the observation period (1990–2014). Figure 3 illustrates the temporal variations of these two indices for the studied stations.

The results from both indices indicate a regular alternation of drought and wet periods in the region. However, the severity, duration, and timing of these periods differ among the stations and between the two indices, reflecting spatial heterogeneity and the differential sensitivity of the indices to climatic components.

Based on the SPEI, the water balance in all studied stations was predominantly positive during the 1990–1997 period. In some years, index values exceeded +1, indicating significant wet periods across the province. The coincidence of this period with the positive phase of the North Atlantic Oscillation (NAO), as reported in previous studies (Yousefizadeh and Jalali, 2014), may suggest the role of large-scale atmospheric systems in amplifying the region's moist conditions.

Conversely, during the 1998–2002 period, the SPEI indicates moderate drought in the Semnan and Beyarjmand stations. This period coincided with the strong El Niño event of 1997–1998 and, according to national reports, led to a severe decline in surface and groundwater resources and a drop in agricultural production across a vast portion of Iran (Zareabyaneh et al., 2015). During the same period, the Garmsar and Shahrud stations predominantly experienced normal conditions, highlighting the differential climatic response of the stations to synoptic fluctuations.

The temporal trend analysis of the SPEI reveals that the Garmsar station was primarily affected by moderate to severe droughts from 2006 to 2014 (except for 2012). Similar conditions are observed at the Semnan station from 2007 to the end of the study period, although two short-term wet periods in 2010 and 2012 temporarily disrupted the drought's continuity. Among the studied stations, Shahrud experienced relatively wetter conditions and, with the exception of 2008, was mostly in a normal or wet state.

An examination of the SPI also reveals a similar alternating pattern of dry and wet periods in the region. The results of this index indicate a relatively prolonged wet period from 2006 to 2009 across all stations, which intensified in 2008. The SPI time series analysis shows that droughts in the Beyarjmand, Garmsar, and Semnan stations were nearly simultaneous in timing, with the most severe drought occurring in 1998, reaching an index value of approximately -2.5. In contrast, the Shahrud station was in normal or wet conditions during most years of the 1990–2014 period based on the SPI.

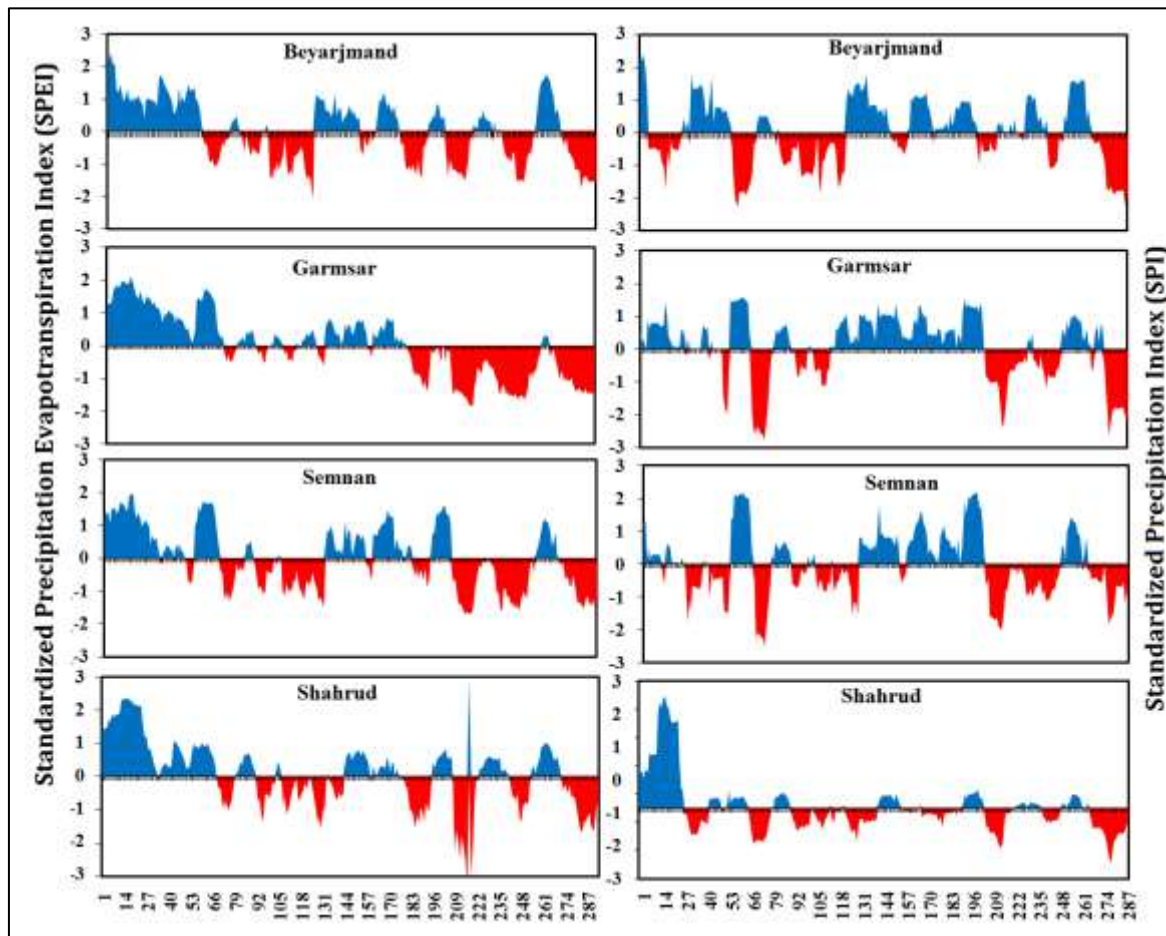


Fig 3. Dry and wet period variations based on SPI and SPEI (1990–2014)

Figure 4 presents the status of drought indices under the SSP245 scenario in near-future conditions. According to the SPEI, during the 2031–2054 period, the studied stations experience normal to severe wet conditions, with the maximum intensity occurring at the beginning of the investigated period. From 2046 onwards, the drought phenomenon dominates the region, causing the entire province to be uniformly affected by this hazard. It is noteworthy that in the early 2050s, the SPEI values in all stations exceed -2, and they will experience the most severe droughts of the last half-century. These conditions exhibit more fluctuations in the SPI. In the SPI, the selected stations display an alternation of wet, normal, and dry periods. Despite minor differences between the two investigated indices, the SPI, similar to the Standardized Precipitation Evapotranspiration Index, is dominated by wet periods at the beginning of the period, while an alternation of drought and wetness is observed towards the end. Although the observed differences are not highly conspicuous, this issue in the SPI stems from the lack of influence of the temperature parameter, which, according to previous results, demonstrates a more pronounced increasing trend in the future climate.

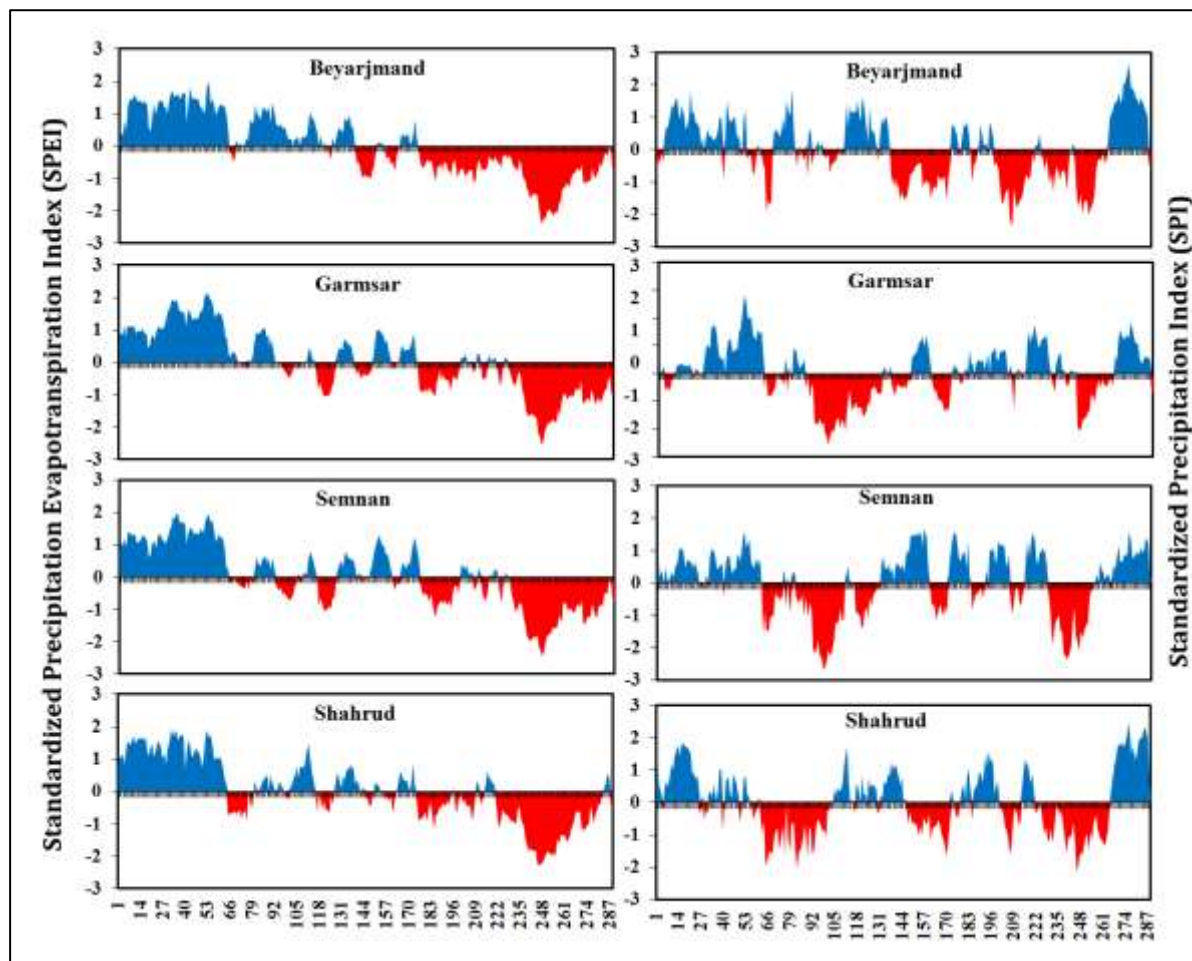


Fig 4. Variations in dry and wet periods based on the SPI and SPEI indices under the SSP245 scenario

The increasing trend of future precipitation, particularly intense daily precipitation, manifests its effect more distinctly in precipitation-driven phenomena. The aforementioned issue is observed in both studied indices under the pessimistic SSP585 scenario in province. In fact, despite the more severe temperature increase in this scenario, the highly variable and uncertain precipitation trends have caused the drought indices in the charts to lean towards less extreme values, seemingly reducing the severity of the phenomenon in question. In other words, the maximum Standardized Precipitation Evapotranspiration Index in this scenario was -1.95, observed in 2048 at the Beyarjmand station; this value does not reach -2 in the other stations either, whereas under SSP245, the drought severity varied from -2.28 to -2.54 in the selected stations. However, unlike drought severity, the alternation of wet and dry periods was identical in both scenarios, and the study area will uniformly experience more severe droughts in the final years of the 2031–2054 horizon (Figure 5).

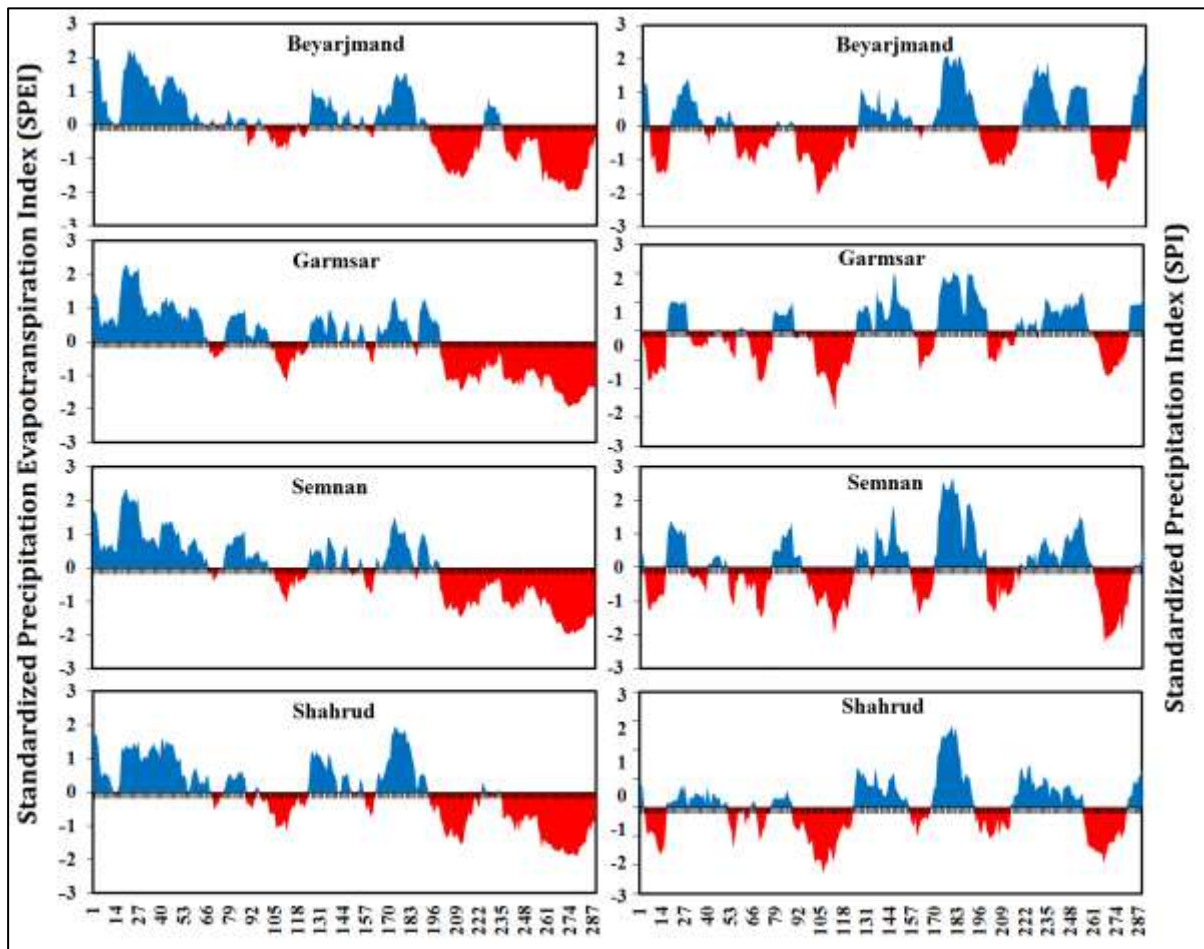


Fig 5. Variations in dry and wet periods based on the SPI and SPEI indices under the SSP585 scenario

3.3 Continuous Wavelet Analysis

In this study, the cross-wavelet transform (XWT) algorithm was utilized to assess whether a statistically significant relationship exists between the SPI and SPEI indices at the 95% confidence level. The cross-wavelet analysis reveals the distribution of covariance between these indices across various time scales.

The coherence results between the two aforementioned indices for the study area, as depicted in Figure 6, reveal several key findings. At the Beyarjmand station, a significant positive correlation is observed at the 16 to 32-month timescale during the baseline period (1991–2008). Additionally, a significant positive correlation is present at the 2 to 8-month scale during 1993–2004, 2008, and 2011. For the Garmsar station, a significant positive correlation at the 95% confidence level is evident at the 16 to 32-month timescale from 1991 to 2006. This coherence trend continues at the 32-month scale from 2007 to 2014. Furthermore, sporadic significant correlation is observed at the 2 to 8-month scale throughout the studied years at this station. Based on the wavelet transform findings, the Semnan station exhibits the highest level of significant correlation between the SPI and SPEI in the province. A significant positive correlation is observed from 1991 to 2014 at long-term scales (16 to 64 months) and at the 2 to 8-month scale in most of the investigated years. At the Shahrud station, wavelet analysis indicates a positive and significant correlation at

the 16 to 64-month timescale during 1993–2011, and at the 8 to 16-month scale during 1996–2005 and 2008–2010.

Overall, the wavelet coherence analysis in Semnan Province demonstrates a significant correlation between these two indices across all studied stations at long-term timescales (13 to 32 months). This finding suggests that the SPI can be reliably utilized in regions lacking temperature data, where the SPEI would otherwise be precluded, given the observed significance and correlation coefficient.

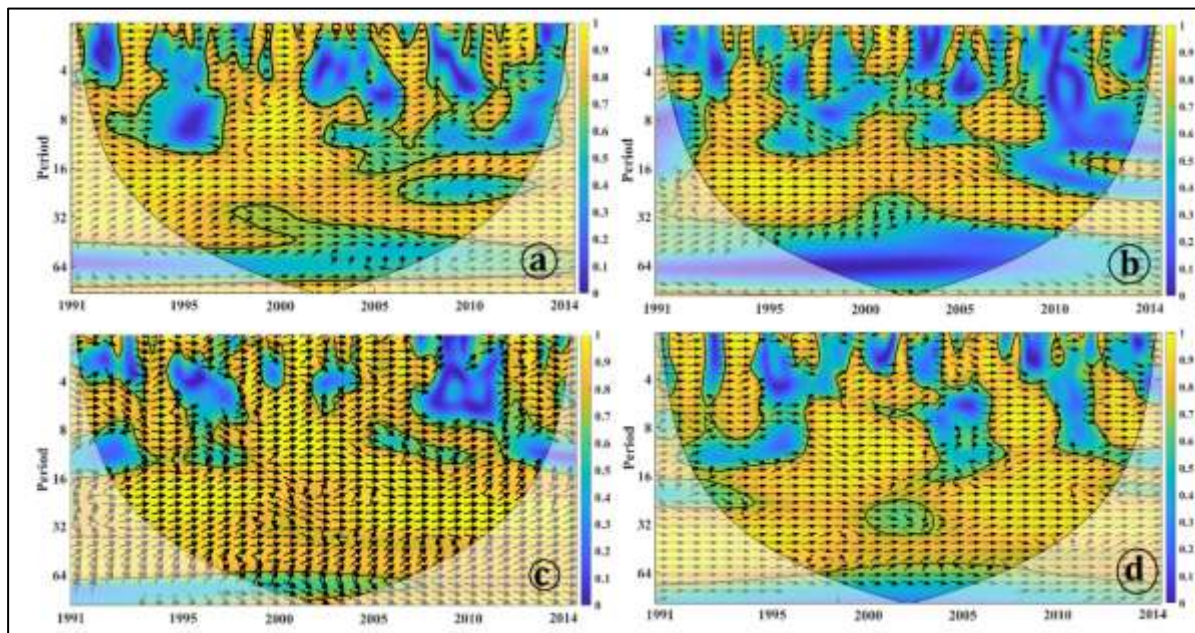


Fig. 6. Continuous wavelet analysis of the SPI and SPEI indices from 1991 to 2014: (a) Beyarjmand, (b) Garmsar, (c) Semnan, and (d) Shahrud.

3.4 Temporal variations in drought characteristics

Drought characteristics, including severity, duration, and magnitude, were calculated according to the Run theory for the SPI and SPEI time series for the current and near-future periods under the SSP245 and SSP585 scenarios in Semnan Province. Table 3 presents the temporal variations of the average drought duration, severity, and magnitude. The projections derived from the SPEI values under the SSP245 scenario, compared to the baseline period, indicate that in the future, the duration and severity indices of drought will increase across all stations, while the magnitude will decrease. With the upward temperature trends in the pessimistic SSP585 scenario, a substantial difference is observed in the duration and severity indices compared to the 1990–2014 period. For instance, the most significant increase observed in drought duration is at the Garmsar and Shahrud stations, where the duration increased from 8.7 and 4 months to 20 and 15.2 months per year, respectively, under the SSP585 scenario. Furthermore, based on the obtained results, the most extreme drought, with a severity of 9.6, corresponds to the Shahrud station under the SSP585 scenario.

The drought characteristics derived from the SPI, generated by the Shared Socioeconomic Pathways (SSP) scenarios, slightly differ from the SPEI metrics. Although the duration and severity of droughts in this index will also increase in the coming decades, they exhibit lower

severity and duration compared to the Standardized Precipitation Evapotranspiration Index (SPEI). This discrepancy arises from the incorporation of temperature and evapotranspiration parameters in the calculation of the latter index, which consequently alters the drought characteristics. Overall, based on both indices, Semnan Province will face more severe and prolonged droughts in the future under both scenarios.

Table 3. Temporal Changes in Drought Characteristics During the Observational and Projected Periods

Station	Index	Baseline	SPEI		Baseline	SPI	
			SSP585	SSP245		SSP585	SSP245
			(2040s)			(2040s)	
Beyarjmand	Duration	7.7	7.8	13	5.8	5.6	11.7
	Severity	4.5	4.2	8.1	4.2	3.5	7
	Magnitude	0.5	0.2	0.4	0.5	0.4	0.4
Garmsar	Duration	8.7	16.7	20	7.3	7.4	7.5
	Severity	5.1	5.6	8.6	4.5	3.4	4.7
	Magnitude	0.5	0.3	0.3	0.4	0.3	0.4
Semnan	Duration	6.9	9.7	15.7	6.4	6.6	7.5
	Severity	4.7	5.5	7.1	3.6	4.5	4.4
	Magnitude	0.4	0.2	0.3	0.4	0.4	0.4
Shahrud	Duration	4.1	5.1	15.2	5.6	6.6	7.7
	Severity	6.1	3.5	9.6	2.2	3.6	4.6
	Magnitude	0.6	0.2	0.3	0.2	0.3	0.4

4 Discussion

Climate change and its subsequent consequences are considered among the most critical challenges of water resources management in the twenty-first century. The rise in global temperatures and alterations in precipitation patterns have led to an increase in the frequency and severity of extreme events, including droughts, in many regions of the world. Therefore, assessing the potential changes in drought under future climate conditions can play a crucial role in long-term water resources planning and climate hazard risk management. In the present study, to investigate the future status of drought in Semnan Province, the outputs of 12 CMIP6 General Circulation Models under two Shared Socioeconomic Pathways (SSP245 and SSP585) were utilized. Following downscaling via the Quantile Mapping method and combining the models using the Bayesian Model Averaging (BMA) approach, variations in temperature, precipitation, and the SPI and SPEI drought indices were analyzed for the 2031–2054 horizon.

The climate projection results indicated that the mean temperature of Semnan Province exhibits an increasing trend under both investigated scenarios compared to the baseline period, such that the highest magnitude of increase corresponds to the pessimistic SSP585 scenario. Furthermore, the examination of annual precipitation changes indicates a relative increase in precipitation at most studied stations, except for the Shahrud station. Such a pattern of temperature and precipitation changes is consistent with the results of the study

Joorabloo et al. (2018) in the Semnan region, who reported an increase in temperature and precipitation variability in future periods. Furthermore, research by El-Rawy et al. (2023) suggests that rising temperatures due to climate change may lead to higher reference evapotranspiration, exacerbating water stress in various areas, which significantly contributes to the worsening of climatic droughts.

The analysis of drought indices in this research revealed that both the SPI and SPEI exhibit a relatively similar pattern of drought variations in the study area, such that in the future horizon, particularly in the final years of the 2031–2054 period, the frequency and severity of drought events will increase. This increase is more pronounced under the SSP585 scenario, indicating the high sensitivity of arid and semi-arid climate systems to increased greenhouse gas emissions. Similar results have been reported in the study by Ghaemi et al. (2024) on a national scale, where they predicted an increase in drought severity in many regions of Iran, especially under higher emission scenarios. This indicates that climate change can significantly alter the temporal pattern and severity of droughts in the arid regions of Iran.

On the other hand, the results of this research demonstrated that the severity and duration of drought are not identical across the investigated indices. The SPI operates primarily based on precipitation changes and, consequently, is more capable of reflecting short-term moisture fluctuations; hence, short-term drought periods and rapid transitions between normal and dry conditions are more prominently observed in this index. In contrast, the SPEI, by incorporating potential evapotranspiration, is sensitive to temperature changes in addition to precipitation, thereby reflecting the moisture balance status more comprehensively. For this reason, this index possesses a greater capability in revealing the persistence and continuity of droughts. The observed difference between these two indices highlights the growing role of temperature rise in exacerbating climatic droughts and reducing the efficiency of precipitation in compensating for moisture deficits; an issue that gains greater significance under climate change conditions.

The present findings are consistent with the results of Ahrari and Raja (2025), as well as Nikbakht and Hadeli (2021). Nikbakht and Hadeli (2021) demonstrated that evapotranspiration-based indices, including SPEI and RDI, are more sensitive to climate change compared to the SPI, and under rising temperature conditions, they are capable of depicting the severity and extent of drought more realistically. Accordingly, it can be inferred that in arid and semi-arid regions, such as Semnan Province, employing indices that incorporate the effects of temperature and evapotranspiration in assessing the moisture balance can provide a more accurate picture of the actual drought status and facilitate a better understanding of arid climate dynamics.

The results of the wavelet coherence analysis in Semnan Province revealed a significant correlation between the SPI and SPEI indices across all studied stations at long-term timescales (13 to 32 months). This high correlation indicates that at long-term timescales, the behavior of these two indices is largely convergent, reflecting the region's moisture variations in a similar manner. Consequently, in regions where temperature data is unavailable, the SPI can be utilized as a reliable alternative for drought monitoring. The

results of this section are also in agreement with the findings of Mostafazadeh and Zabihi (2016) in Kurdistan Province.

Furthermore, the examination of drought characteristics based on the Run theory indicated that in the future period, the duration and severity of droughts will increase in most stations across the province. Such a pattern of increasing drought characteristics is consistent with the results of Delghandi et al. (2023), who reported an elevated risk of drought due to global warming and changing climatic conditions. In addition, recent research in other regions of the world demonstrates that temperature rise and land-use changes can exacerbate the severity and duration of hydrological droughts by increasing evapotranspiration and altering runoff regimes (Lu et al., 2025; Chen et al., 2025; Li et al., 2024). These studies suggest that drought is a multidimensional phenomenon influenced simultaneously by climatic and anthropogenic factors.

Overall, the results of the present study indicate that climate warming and precipitation variability can lead to an increase in the frequency, severity, and duration of droughts in Semnan Province. Given that this region falls within the arid and semi-arid zones of Iran, the intensification of droughts will entail widespread consequences for water resources, agriculture, and the sustainability of the region's ecosystems. Therefore, continuous drought monitoring using composite indices and leveraging future climate scenarios can play a vital role in formulating adaptation strategies and sustainable water resources management in this region.

5 Conclusion

The present study evaluated future drought changes in Semnan Province. Results indicate that from 2031 to 2054, the region's mean temperature will increase under both climate scenarios, with a more pronounced rise in the higher emission scenario. Conversely, annual precipitation in most studied stations shows only a limited relative increase. Despite this rise, the region's water conditions may not improve due to the concurrent increase in temperature and potential evapotranspiration.

Analysis of drought indices revealed that both indices effectively identify dry and wet periods. However, the SPEI, by incorporating temperature and evapotranspiration effects, demonstrates greater sensitivity to climate change. In many cases, it estimates higher drought severity and duration compared to the SPI. Thus, climate change will likely exert greater pressure on Semnan Province's limited water resources in the coming decades. Since a substantial portion of the region's economic activities, particularly agriculture, depends on water resources, increased drought frequency and severity could significantly impact food security, ecosystem sustainability, and regional development. Therefore, this research highlights the necessity of prioritizing climate change adaptation approaches and integrated water resources management.

Several key strategies can reduce the region's vulnerability to future droughts. First, developing drought monitoring and early warning systems based on multivariate indices like the SPEI, coupled with climate predictions, will improve risk management and decision-making. Second, enhancing water use efficiency in agriculture through modern irrigation methods, modified cropping patterns, and drought-tolerant cultivars can significantly

alleviate pressure on water resources. Finally, integrated water resources management, emphasizing groundwater extraction control, artificial aquifer recharge, and using unconventional water resources like wastewater recycling, will increase the resilience of the region's water systems. Additionally, integrating climate study results with developmental planning and land management policies can facilitate long-term decisions compatible with future climate conditions.

Based on these findings, future research should investigate the impacts of climate change on other drought dimensions, including hydrological and agricultural droughts, using a larger ensemble of climate models and emission scenarios. Furthermore, coupling climate models with hydrological models and evaluating uncertainty at various simulation stages will provide a more accurate and comprehensive picture of drought risk under future climate conditions. Such approaches can establish a sound scientific foundation for formulating climate change adaptation policies and sustainable water resources management in Iran's arid and semi-arid regions.

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