Evaluation of the climate change impact on the intensity and return period for drought indices of SPI and SPEI (study area: Varamin plain)

Hamidreza Azizi a and Niloofar Nejatianb,*

a Department of Civil engineering, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran
b Department of Civil engineering, Water and Environmental Engineering, University of Tehran, Tehran, Iran
*Corresponding author. E-mail: niloofar.nejatian@gmail.com

ABSTRACT

In this study, to investigate the climate change effect on meteorological drought in the next three decades of Varamin plain, EC-EARTH model was selected from the (AR5) report with the high performance of temperature and precipitation simulation compared to the base period under RCP scenarios and then by LARS-WG software was downscaled. In addition, (intensity-duration) and the return period of drought indices of SPI and SPEI in annual time series were evaluated. Results illustrated that the seasonal precipitation pattern has changed, and mean temperatures will increase by 1.4 °C compared to the base period. The results of the drought assessment showed that the intensity of drought in the future compared to the base period based on SPI and SPEI index increased by 8 and 28%, respectively, indicating that the SPEI index was more severe in all three scenarios than the SPI index. It can mainly be explained by the contribution and effect of increasing the average temperature along with precipitation in the SPEI index. Also, the return period of severe droughts under RCP8.5 scenario for SPEI index in the base and future periods is 8 and 6 years, respectively, which indicates a decrease in the return period of severe droughts and an increase in dry years in the future.

Key words: climate change, drought, LARS-WG, return period

HIGHLIGHTS

- Evaluation of the effects of rainfall and temperature on the intensity-duration drought of Varamin plain under different climatic scenarios.
- Investigating the effects of climate change on the return period of drought indices in Varamin plain.
- Use long-term data for the base period to increase the accuracy of dry process assessment.

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CLIMATE CHANGE AND ITS IMPACT ON OTHER EXTREME EVENTS SUCH AS DROUGHT HAVE EMERGED AS ONE OF THE MOST CRITICAL CONCERNS OF THE LAST DECADES (LORENZO & ALVAREZ 2020). IN RECENT YEARS, CLIMATE CHANGE AND THE INCREASING TREND OF METEOROLOGICAL DROUGHTS HAVE CAUSED ENVIRONMENTAL, AGRICULTURAL, AND ECONOMIC CRISIS IN ALL WORLD REGIONS, BOTH IN DRY AND WET CLIMATES (LI ET AL. 2013). ACCORDING TO THE FIFTH ASSESSMENT REPORT OF THE INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE (IPCC), GLOBAL TEMPERATURES HAVE Risen 0.85 °C FROM 1880 TO 2012, AND IF GLOBAL GREENHOUSE GAS EMISSIONS GROW AT THE CURRENT RATE BY 2,100, WORLDWIDE AVERAGE TEMPERATURES WILL RISE BY 1.1–4.6 °C (IPCC 2013). CHANGES IN PRECIPITATION PATTERNS AND POSSIBLE INCREASES IN DROUGHT FREQUENCY CAN BE CONSIDERED THE MAIN RESULTS OF CLIMATE CHANGE CAUSED BY GLOBAL WARMING, AND WITH THE INCREASE IN GREENHOUSE GAS EMISSIONS, THE DROUGHT TREND IS LIKELY TO WORSEN IN THE FUTURE (EEA 2020). THEREFORE, THE RISK OF WATER SHORTAGE IN ARID AND SEMI-ARID REGIONS WILL INCREASE DUE TO THE COMBINED EFFECTS OF LOCAL DROUGHTS (NOORISAMELEH ET AL. 2020).

SINCE DROUGHT AFFECTS DIFFERENT SECTORS OF SOCIETY, SUCH AS INDUSTRY AND ECONOMY; THEREFORE, TO PROPERLY PLAN IN DIFFERENT PARTS OF SOCIETY, IT SEEMS CRUCIAL TO MONITOR THIS EVENT IN THE PRESENT AND THE FUTURE. SEVERAL STUDIES HAVE BEEN CONDUCTED ON CONTINENTAL OR REGIONAL SCALES TO EXAMINE CLIMATE CHANGE AND ITS EFFECTS ON TEMPERATURE, PRECIPITATION, AND VARIOUS DROUGHT INDICATORS IN THE PRESENT AND FUTURE PERIODS (DUAN ET AL. 2021). ZAREIAN (2021), USING THE DOWNSCALING LARS-WG MODEL AND UNDER RCP SCENARIOS, STUDIED THE TEMPERATURE CHANGES AND DAILY PRECIPITATION OF THE ZAYANDEHRUD RIVER BASIN, IRAN, DURING THE YEARS 2020–2044. ACCORDING TO THE RESULTS, THE AVERAGE MONTHLY TEMPERATURE INCREASED FROM 0.6 TO 1.3 °C, WHILE THE PRECIPITATION DECREASED BY 6.5 TO 31% ANNUALLY.

DUAN ET AL. (2021) STUDIED CLIMATE CHANGE IN THE PEARL RIVER BASIN IN CHINA OVER THE COMING DECADES BASED ON THE SCP MODEL UNDER TWO RCP SCENARIOS. THEIR RESULTS INDICATED THAT INCREASE IN TEMPERATURE BETWEEN 0.25 AND 0.34 UNDER THE RCP4.5 SCENARIO AND A 0.42–0.6 INCREASE UNDER THE RCP8.5 SCENARIO. IN ADDITION, THEY HAVE FOUND AN INCREASE IN DROUGHT
conditions over the next few decades in the basin. In China, Sun et al. (2019) examined the severity-duration as well as the return period of the SPI meteorological drought-affected by climate change using downscaling of two climate models under RCP scenarios in 2036–2095. Their results revealed that temperature and precipitation would increase in the coming period. Some stations also experience severe drought with less than 10 years of return. Shahvari et al. (2019) investigated the effects of climate change on water resources of the Varamin plain basin using the SWAT model under scenarios A1B, A2, and B1. Their results showed that the minimum and maximum temperatures would increase in future periods, and precipitation level, and its pattern, would change.

Nam et al. (2015) examined the effect of climate change on the drought severity based on SPI and SPEI indices in South Korea during 2011–2012. According to the findings, there will be a significant increase in the drought levels and severity at different timelines for each drought index in the future. Won et al. (2020) examined the severity of future drought in South Korea using the SPI-SPEI and EDDI drought indices and studied these indices’ effectiveness under climate change. They found that drought will be decreased by 11% for SPI4s and SPEI, whereas droughts will be intensified by 17% in EDDI.

Gupta & Jain (2018) evaluated the impact of climate change on the SPI and SPEI drought indices using different RCP scenarios in the coming years in India. The results showed an increase in evaporation due to increasing temperature; subsequently, increased drought in the future, the SPI index also showed the most significant drought compared to another one. In the UK, Vidal & Wade (2009) studied the climate change impact on the future SPI drought index under scenarios A1 and B2. According to their research, there will be an increase in extreme droughts with low persistence in the future.

Hilip et al. (2017) assessed the effect of climate change on climate droughts in the Volta basin in West Africa. They found that the increasing percentage of droughts with the SPEI index is higher than the SPI index. In recent years, droughts have caused extensive damage to agriculture in the study area. Tehran province’s agriculture is heavily dependent on this region, so it is necessary to study climate change, frequency analysis and the return period of drought in the future. So that, managers and planners of water resources in this region can benefit from this study, as some extreme phenomena such as drought are more affected by climate change than others (Quevauviller 2011).

Also, very little research has been carried out regarding drought indices under climate change scenarios in terms of simultaneous analysis of intensity-duration and return period of SPI and SPEI indices, and also evaluate the climate parameters changes trend using a suitable climate model in the scale of study.

Accordingly, in the current study, firstly, the evaluation of 5 climatic models from the fifth IPCC report in Varamin plain was performed, and the appropriate model was selected to simulate climatic elements (temperature and precipitation). Then precipitation and temperature data were simulated under RCP2.6, RCP4.5, and RCP8.5 scenarios for the next three decades, and the temperature and precipitation changes trend were compared to current conditions. Following this, the severity-duration and return period of meteorological droughts in the study area were evaluated by SPI and SPEI indices based on the obtained results, in annual time series under a number of climate change scenarios in the next three decades, which the base period was 1989–2018.

METHODS

Study area

Varamin plain in Tehran province, as a strategic region in terms of agriculture, is located in the south to southeast of Tehran province. This plain is climatically divided into arid to semi-arid climates. As this part of Tehran province has a large agricultural area, paying attention to water management and drought issues in the mentioned region is of vital. Varamin plain catchment area with an area of 1,720 km² is considered as the sub-basin of Namak Lake, located in 35° 7′–35° 39′ north latitude and 51° 26′–51° 55′ east longitude. Meteorological data including precipitation, thermometry, relative humidity, frosty days, sunny days, wind, and evapotranspiration have been collected from Varamin Synoptic Station, representing the plain (Figure 1). Therefore, the daily data of the Varamin meteorological station in the statistical period of 1989–2018 were used as the base period. The average annual temperature in this basin is 16.9 °C, and the average precipitation is 156 mm per year.

Climate models and RCP scenarios

Currently, the most reliable tools for generating climate scenarios are the 3-D models of the Atmospheric-Ocean General Circulation Model (AOGCM) (Wilby & Harris 2006). These models can simulate future global climate conditions in a relatively accurate way. Since 1990, the IPCC has launched a project to standardize AOGCM models and has released six
climate change assessment reports. Since the most critical input of atmospheric circulation models is the greenhouse gas emissions level in future periods, IPCC introduced RCP scenarios in its fifth report (AR5) in 2014 (IPCC 2014). RCP scenarios have been introduced as representing the trajectories of different concentrations of greenhouse gases and the resulting radiative forcing.

These scenarios have four critical trajectories named RCP6.0, RCP4.5, RCP2.6, and RCP8.5, entitled based on their radiative forcing in 2100. Therefore, scenarios used in this study are the fifth report’s new scenarios, including RCP8.5, RCP2.6, and RCP4.5.

According to the aim of this study, which is to evaluate meteorological drought indices under the scenarios of the fifth report, and climate change under RCP emission scenarios in the Plain of Varamin basin, considering the satellite conditions of the models and the climatic conditions of the study area, among 61 AOGCM models of fifth IPCC report, five ones were selected and evaluated. The general information of each of the five models and their research institutes is summarized in Table 1.

These models should be compared with the observational values of the studied station in a common base period to evaluate the performance of their simulations of basin temperature and precipitation variables. According to the study area statistical period, years 1989–2018 due to its complete situation compared to previous research such as 1989–2005, were selected as a common base period.

Table 1 | Specifications of 5 selected models from AR5 collection in the present study

| Model        | Developer          | Spatial Resolution |
|--------------|--------------------|--------------------|
| EC-EARTH     | Netherlands/Ireland| 1.28°x2.5          |
| CCSM4        | USA                | 1.25°x0.9          |
| GFDL-ESM2M   | USA                | 2.5°x2.0           |
| GFDL-ESM2G   | USA                | 2.5°x2.0           |
| GFDL-CM      | USA                | 2.5°x2.0           |
The time series of climatic variables of mean temperature and precipitation related to climatic models were compared with the observed mean temperature and precipitation of the study area. To evaluate the performance of the models, three criteria were used, including determination coefficient ($R^2$), correlation coefficient ($\rho$), and Root Mean Square Error (RMSE).

To understand the drought situation, areas with similar climates, according to some rules, are categorized together known as a drought classification. These classifications can be based on one or more climatic parameters. The precipitation and temperature can be considered the most important ones, used in various drought classifications. Therefore, regarding the research aim and the proposed approach (Figure 2), after evaluating and downscaling the study area climatic models, precipitation and temperature data under the appropriate plain model under the scenarios of RCP2.6 and RCP4.5 and RCP8.5 were simulated. Then, the trend of temperature and precipitation changes rather than the base period were compared.

Finally, the severity-duration and return period of SPI and SPEI meteorological drought indices were determined under climate change scenarios in the future period compared to the base period.

**Downscaling and evaluation of the LARS-WG model in the study area**
AOGCM models require downscaling because of their low resolution. In this study, to produce climate change scenarios by downscaling data, the LARS-WG random climate generator simulated atmospheric data (Rasco et al. 1991; Semenov & Brooks 1999; Semenov & Barrow 2002). Next, the simulation of meteorological data (minimum and maximum temperature and precipitation) for the next three decades will be performed according to the considered climate change scenario (Semenov & Stratonovitch 2010). Also, to ensure the model's ability to provide data in the future, the simulated data by the model were compared with the observations at the Varamin synoptic station. This comparison was performed by Kolmogorov–Smirnov test for probabilistic functions and T-test for downscaled data means.

**Drought indices**
Over the last few decades, researchers have developed various indicators to monitor the drought situation and quantify its effects. The present study used the SPI meteorological drought index to monitor wet and dry periods (McKee et al. 1993). Also, because drought in a region can be affected by various climatic parameters, in addition to the widely used SPI index with a global usage, the important SPEI index was utilized in this study, as this index can consider some important climatic parameters to assess drought in 12-month time series (Vicente-Serrano et al. 2010). This index is calculated based on the time series of precipitation and temperature (Nam et al. 2015). Finally, according to the evaluation of precipitation and temperature changes under climate change scenarios, the changes in these indices can be easily analyzed and evaluated in the future.

**Standard precipitation index (SPI)**
The Standardized Precipitation Index (SPI) was developed in 1993 by Mackie et al. to monitor meteorological drought (McKee et al. 1993). This index is calculated based on the precipitation level with its average difference for a specific time.

![Figure 2](https://example.com/Figure2.png) | The proposed flowchart to assess the drought trend of Varamin plain under climate change conditions.
scale and then divided by standard deviation. A significant benefit of this index is its ability to be calculated at different time scales, enabling it to monitor the effects of both short-term water reserves (including soil moisture) and the long-term water resources (including groundwater reserves and surface water reservoirs) (Mishra & Singh 2010).

**Standardized precipitation-evapotranspiration index (SPEI)**

The SPEI index was developed by Vicente-Serrano (Vicente-Serrano et al. 2010) and revised in 2015 (Vicente-Serrano et al. 2015). This index is determined from the simple water balance equation, i.e. the difference between precipitation and potential evapotranspiration by the Thornthwaite method (Thornthwaite 1948) at different time scales. SPEI values are analyzed similarly to SPI values and indicate the amount of drought and wet conditions. (Table 2) presents the classification of these indices.

**Return period**

Calculating and investigating the probability of occurrence and return period of drought is essential to managing water resources (Cancelliere & Salas 2010). In this study, using drought index data under climate change scenarios, Hyfran plus software (El Adlouni & Bobée 2015; Torres Rojas & Díaz-Granados 2018) was used to determine the return period of droughts from 2 to 1,000 years. Also, to determine the most appropriate statistical distribution, various probability distributions, including GEV, WEIBULL, GAMMA, GUMBEL, and NORMAL, were used. Therefore, the return period of very severe droughts and wet conditions was determined under climate change scenarios.

**RESULTS AND DISCUSSION**

**Investigation of the performance of climate models in simulating temperature and precipitation in the study area**

The performance of selected climate models in the study area in simulating temperature and precipitation values were evaluated. As presented in Table 3, the EC-EARTH model illustrated a high correlation coefficient in temperature and precipitation simulations, with a minor error than other models. Therefore, the performance of the EC-EARTH model was acceptable and selected in this study. In Figures 3 and 4, the model's output and the observed temperature and precipitation values were compared at the Varamin synoptic station in the base period of 1989–2018.

**Evaluation of LARS-WG model in the study area**

The simulated data were compared with the observations at the Varamin synoptic station to verify that the model can provide correct data in future scenarios. The Kolmogorov–Smirnov test results on precipitation parameters and minimum and maximum temperatures in the study area were presented in Table 4. As can be seen from the tables above, in most months, all the parameters mentioned in the study station are at a level of 90% reliability, indicating that they can be the basis for future data production. Also, it should be noted that the Lars model could not provide high performance of daily precipitation in the summer months, which may be attributed to plenty of dry days in this season. Although the model's performance in simulating the precipitation parameter is acceptable, the highest modeling error is related to the precipitation of July and August. As in these months, the simulated precipitation level is estimated to be approximately 20–30% less than the observed values.

| SPI and SPEI value | Class          |
|-------------------|----------------|
| Greater than 2.00 | Extremely wet  |
| 1.50–1.99         | Severely wet   |
| 1.00–1.49         | Moderately wet |
| 0.50–0.99         | Slightly wet   |
| −0.49–0.49        | Near normal    |
| −0.99 to −0.50    | Mild dry       |
| −1.49 to −1.00    | Moderately dry |
| −1.99 to −1.50    | Severely dry   |
| Less than −2.00   | Extremely dry  |
Table 3 | Results of comparison between observational and simulated climatic variables in the period between 1989 and 2018

| Performance benchmark Model | Temperature | Precipitation |
|-----------------------------|-------------|---------------|
|                             | $R^2$ (%)  | $\rho$ (%) | RMSE ($^\circ$C) | $R^2$ (%)  | $\rho$ (%) | RMSE ($^\circ$C) |
| EC-EARTH                   | 98         | 96          | 7.2           | 77         | 87          | 10.3          |
| Can ESM2                   | 68         | 81          | 7.9           | 55         | 69          | 8.3           |
| CCSM4                      | 71         | 89          | 7.2           | 57         | 74          | 18.3          |
| GFDL-CM                    | 79         | 82          | 37.7          | 64         | 81          | 9.8           |
| GFDL-ESM2G                 | 74         | 94          | 7.7           | 59         | 69          | 21.3          |

Note: $R^2$, Determination Coefficient; $\rho$, Correlation Coefficient; RMSE, Root Mean Square Error.

Figure 3 | Mean comparison of monthly observational temperature and different AR5 models in the base period of 1989–2018.

Figure 4 | Mean comparison of monthly observational rainfall and different AR5 models in the base period of 1989–2018.
Based on the poor performance of the Lars model in July in terms of precipitation simulation, we cannot be confident in the amount of precipitation simulated this month.

Generally, evaluation and validation of the LARS-WG model in the Varamin synoptic station indicate the acceptable ability of this model in simulating climatic parameters (precipitation, min and max temperature) of this region. Although the simulation of the precipitation parameter for some months of the year using this model is not significant, the high fit of the simulated values for other climatic parameters is quite evident.

Results of the effect of climate change on temperature and precipitation parameters

The results of temperature and precipitation changes of the Varamin station under the EC-EARTH model are presented in Figures 5 and 6. According to Figure 5, the increasing annual temperature trend is evident under all three emission scenarios until 2050. However, in the study area, the RCP8.5 scenario illustrates a more significant average temperature increase of about 1.4 °C than two others over the next 30 years.
According to Figure 6, the simulated precipitation under the emission scenarios in 2021–2050 does not display constant changes in other months compared to the base period. In other words, the annual precipitation changes trend under all three scenarios of RCP emissions in the future period does not illustrate constant changes compared to the observation period. These alterations can be related to changes in precipitation patterns so that, in the early months of the year to late spring there was an increase in precipitation, while a decrease in precipitation in autumn was observed. Additionally, the RCP4.5 scenario showed a slightly higher annual precipitation increase during the next 30 years than the base period over the two others.

SPI and SPEI values and their changing trends in different RCP scenarios

Both indices were calculated for a 12-month long-term time scale for the base period 1989–2018 and the future period 2021–2050 using the Comprehensive R Archive Network for all three scenarios. Both SPI and SPEI were calculated using Gamma distribution, and log-logistic distribution, respectively. Notably, the Thornthwaite method was used to calculate the evapotranspiration potential in the SPEI index (Vicente-Serrano et al. 2015; Vicente-Serrano & Beguería 2016; Gaitán et al. 2019; Danandeh Mehr et al. 2020). The results are presented in Figures 7 and 8. Additionally, drought heat maps were generated in MATLAB2018b for all three scenarios to understand better and visualize long-term drought events and identify intensity-duration trends for both drought indices in the base period and the future. The severity, time, and duration of drought can be easily determined by analysing these heat maps.

The analysis of Figures 7 and 8 shows that dry and wet periods are repeated alternately for the base and future periods on a long-term time scale. According to both SPI-12 and SPEI-12 indices, it seems that the longest drought in the base period has occurred during 2013–2016. Besides, the most severe droughts according to the SPI-12 and SPEI-12 indices occurred in 1997 and 1989, respectively, as well as the most severe wet seasons, according to both indices have taken place in 1996. According to the analysis of the drought changes trend in the base period, the study area experienced the most prolonged wet period from 2002 to 2007 due to the increasing precipitation trend. SPI and SPEI indices indicated an increase of 8 and 28%, respectively, in drought intensity in the future compared to the base period, indicating that the SPEI index was more severe in all three scenarios than the SPI index. It can be explained by the contribution and effect of increasing the mean temperature and precipitation in the SPEI index. Also, the drought duration (the dry years’ number) in the future has increased by 7.7% in both indices, compared to the base period.

Over the next thirty years, drought trends generally did not display any specific pattern as the base period. In the next four years, both indices begin with a wet season and end with a downward and jumping trend; then, the irregular fluctuations between wet and dry seasons were seen. It should be noted that the highest rate of wet periods intensity will occur in 2044 in both indicators, while in 2024 and 2045–2047, the SPEI-12 index determines that the highest rate of drought periods intensity will take place under all three climate change scenarios. Also, the analysis of the changes trend in drought periods in the future illustrated that the period 2030–2034 is the longest period of drought under all three scenarios in the SPEI-12 index.
Figure 7 | Changes trend and heat map of SPI-12 drought index under the scenarios of RCP8.5, RCP4.5, and RCP2.6 in the period 2050–2021 compared to the base period of 1989–2018 in Varamin plain.

Figure 8 | Changes trend and heat map of SPEI-12 drought index under the scenarios of RCP8.5, RCP4.5, and RCP2.6 in the period 2050–2021 compared to the base period of 2018–1989 in Varamin plain.
However, it is important to note that during the next few years, the most severe drought situation according to the SPI-12 index will occur in 2024 under the RCP8.5 scenario, while according to the SPEI-12 index, under the RCP.26 scenario it will be in 2045. Generally, the results illustrate that drought periods numbers based on both indices and under all three scenarios in the future have increased compared to the base period.

Then, to a better understanding of the relationships between SPI and SPEI indices, they were compared by calculating the Pearson correlation coefficient using SPSS software. The coefficient results of the base period, RCP2.6, RCP4.5, and RCP 8.5 between SPI and SPEI indices were 0.87, 0.9, 0.91, and 0.87, respectively, indicating that there is a high correlation coefficient between these two indices in different climate change scenarios. However, despite the high correlation coefficient between the two indices, the comparison of the time patterns of these indices indicates that wet conditions, wet and drought periods do not necessarily occur in both indices in the same years so that the SPI-12 index compared to SPEI-12 indicates fewer drought years. Thus, since the average temperature increased in the next period, it can be inferred that SPEI results are more realistic and logical than those of the SPI index.

**Drought return results**

According to the definition of the return period, which is the time interval between events of the same magnitude, the results showed that the normal distribution with $P\text{ (value)}=0.9$ is more fit with the SPI and SPEI drought intensity data under climate change scenarios over 30 years, using Hyfran-Plus software, (Figure 9). Due to many graphs, the normal distribution fit for both drought indices was presented under the RCP2.6 scenario.

![Figure 9](image-url)  
*Figure 9* | Fitting of normal distribution on SPI-12 and SPEI-12 drought intensity data under RCP2.6 scenario in 2021–2050.
According to the fit analysis of normal distribution over drought intensity data, the return period for extreme droughts by SPI-12 index under the RCP8.5 scenario for both the base and future period is 15 and 10 years, respectively. However, the same value for the SPEI-12 index is 8 and 6 years, respectively, which indicates a decrease in the return period of extreme droughts, causing an increase in dry years in the future compared to the base period (Table 5).

It should also be noted that the return period of normal droughts by SPEI-12 index in RCP8.5 scenario for the base period and the future is 15 and 5 years, respectively (Table 6), indicating an increase in dry years compared to the base period.

## CONCLUSIONS

Drought is a known natural hazard and a component of climate change. Therefore, it is vital to study the effects of climate change on drought. On the other hand, this study was conducted on the Varamin plain in Iran because it is always susceptible to drought, and climate change affects its water resources considerably. Since the two main components of climate, namely temperature and precipitation, are the inputs of each hydrological model, so to evaluate the effect of climate change on the severity of meteorological drought indicators at Varamin station in the next 30 years, climate simulation is performed using AR5 scenarios in the present study.

The results illustrated that the LARS-WG model considerably could downscale base temperature and precipitation data in the study area. Under all three RCP emission scenarios, the EC-EARTH model predicted a significant trend of moderate temperature increase in the next period. Overall, the mean temperature in the study area under the optimistic and intermediate scenarios of RCP2.6 and RCP4.5, respectively, predicted an increase of 1–1.2 °C compared to the base period. While the same temperature increase based on the most pessimistic scenario, RCP8.5, was predicted on average about 1.4 degrees Celsius compared to the base period in the next period. These results are consistent with (Shahvari et al. 2019).

The most crucial feature of LARS-WG is the lack of coordination between precipitations modeling by the EC-EARTH model for different scenarios in the future period and different months. This model, for example, showed a decrease in rainfall in some months and an increase in others for the period 2021–2050 in the study area during the next 30 years compared to the base period. This may be explained by recognizing the precipitation irregular behavior pattern. Based on the SPI-12 and SPEI-12 indices classification, the drought situation has fluctuated differently from the base period according to all three scenarios. Also, the drought intensity was determined using SPEI-12 index more than SPI-12, which can be concluded that the drought intensity in the SPEI-12 index has increased due to increased temperature and the interaction between temperature and precipitation. According to research findings, the SPEI-12 index has been found to be a more accurate indicator of sequence and fluctuations of drought than the SPI-12 index. Because, in addition to precipitation, temperature, evapotranspiration

### Table 5 | Extreme wet and drought return periods of SPI-12 and SPEI-12 indices under climate change conditions

| YEAR          | SPI (extremely wet) | SPI (extremely drought) | SPEI (extremely wet) | SPEI (extremely drought) |
|---------------|---------------------|-------------------------|----------------------|--------------------------|
| Base (1989–2018) | 15                  | 15                      | 15                   | 8                        |
| RCP 2.6 (2021–2050) | 15                  | 10                      | 10                   | 6                        |
| RCP 4.5 (2021–2050) | 10                  | 10                      | 10                   | 6                        |
| RCP 8.5 (2021–2050) | 10                  | 10                      | 10                   | 6                        |

### Table 6 | Normal wet and drought return periods of SPI-12 and SPEI-12 indices under climate change conditions

| YEAR          | SPI (moderately wet) | SPI (moderately drought) | SPEI (moderately wet) | SPEI (moderately drought) |
|---------------|----------------------|--------------------------|-----------------------|---------------------------|
| Base (1989–2018) | 8                   | 8                        | 10                    | 15                        |
| RCP 2.6 (2021–2050) | 10                  | 15                      | 30                    | 4                         |
| RCP 4.5 (2021–2050) | 15                  | 8                       | 8                     | 4                         |
| RCP 8.5 (2021–2050) | 15                  | 8                       | 8                     | 5                         |
parameters are also taken into account in its calculation. These findings are in accordance with the results of (Vicente-Serrano et al. 2010). Also, the return period of severe droughts in the Varamin plain proved that drought is a reversible phenomenon, and agriculture, surface, and groundwater resources in the study area could be irreparably damaged if the drought occurs again in the future. So, the return period of extreme droughts under the RCP8.5 scenario for the SPEI index showed a decrease in the same parameter and an increase in dry years for the future compared to the base period, which is consistent with the results of (Vidal & Wade 2009).

Nevertheless, due to the semi-arid climate in this study area and the impact of water shortage, this study shows a clear picture of the future with a reasonably accurate forecast that these results can be used by experts and planners associated with water issues. As mentioned before, the present study assesses meteorological drought indicators under the scenarios of the Fifth Climate Change Report in the Varamin Plain for coming years (2021–2050), that for the best estimate of climatic parameters in the future and to consider uncertainty, it is suggested that several AOGCM models be used along with distant future periods. Additionally, other drought indicators such as agricultural drought, groundwater indicators, and their effects on water resources should be evaluated and compared.

**DATA AVAILABILITY STATEMENT**

Data cannot be made publicly available; readers should contact the corresponding author for details.

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