

Prediction of meteorological drought in arid and semi-arid regions using PDSI and SDSM: a case study in Fars Province, Iran postprint

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Abstract

Drought is one of the most significant environmental disasters, especially in arid and semi-arid regions. Drought indices as a tool for management practices seeking to deal with the drought phenomenon are widely used around the world. One of these indicators is the Palmer drought severity index (PDSI), which is used in many parts of the world to assess the drought situation and continuation. In this study, the drought state of Fars Province in Iran was evaluated by using the PDSI over 1995–2014 according to meteorological data from six weather stations in the province. A statistical downscaling model (SDSM) was used to apply the output results of the general circulation model in Fars Province. To implement data processing and prediction of climate data, a statistical period 1995–2014 was considered as the monitoring period, and a statistical period 2019–2048 was for the prediction period. The results revealed that there is a good agreement between the simulated precipitation ($R^2 > 0.63$; R^2 , determination coefficient; $MAE < 0.52$; MAE , mean absolute error; $RMSE < 0.56$; $RMSE$, Root Mean Squared Error) and temperature ($R^2 > 0.95$, $MAE < 1.74$, and $RMSE < 1.78$) with the observed data from the stations. The results of the drought monitoring model presented that dry periods would increase over the next three decades as compared to the historical data. The studies showed the highest drought in the meteorological stations Abadeh and Lar during the prediction period under two future scenarios representative concentration pathways (RCP4.5 and RCP8.5). According to the results of the validation periods and efficiency criteria, we suggest that the SDSM is a proper tool for predicting drought in arid and semi-arid regions.

Full Text

Preamble

Prediction of Meteorological Drought in Arid and Semi-Arid Regions Using PDSI and SDSM: A Case Study in Fars Province, Iran

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Abstract: Drought is one of the most significant environmental disasters, especially in arid and semi-arid regions. Drought indices serve as essential tools for management practices seeking to address drought phenomena and are widely used worldwide. One such indicator is the Palmer Drought Severity Index (PDSI), which is employed in many parts of the world to assess drought conditions and persistence.

In this study, the drought state of Fars Province in Iran was evaluated using the PDSI over the period 1995–2014 based on meteorological data from six weather stations across the province. A Statistical Downscaling Model (SDSM) was applied to utilize output results from the general circulation model for Fars Province. For data processing and climate data prediction, the period 1995–2014 was considered the monitoring period, while 2019–2048 served as the prediction period. The results revealed good agreement between simulated and observed precipitation ($R^2 > 0.63$; $MAE < 0.52$; $RMSE < 0.56$) and temperature ($R^2 > 0.95$, $MAE < 1.74$, and $RMSE < 1.78$). The drought monitoring model results indicated that dry periods would increase over the next three decades compared to historical data. The analysis showed the most severe drought at the Abadeh and Lar meteorological stations during the prediction period under two future scenarios: Representative Concentration Pathways (RCP4.5 and RCP8.5). Based on the validation period results and efficiency criteria, we suggest that SDSM is an appropriate tool for predicting drought in arid and semi-arid regions.

Keywords: PDSI; SDSM; RCP4.5; RCP8.5; climate change; extreme drought

1 Introduction

Climate change represents one of the most critical challenges facing the world, as it is predicted to alter climate patterns and increase the frequency of extreme weather events (Palmer and Raisanen, 2002; Hayes et al., 2004; IPCC, 2012). Over recent years, the frequency of droughts caused by global warming-related climate change has increased, along with intensification of these events (IPCC, 2013; Yu et al., 2013; Salehnia et al., 2017a). Therefore, establishing appro-

appropriate expectations of future drought impacts is crucial for mitigating severe droughts caused by climate change. This study investigates the impact of climate change on drought over a long-term scale, which is necessary to diminish vulnerability and establish suitable innovative strategies for drought mitigation and preparedness.

Drought is a significant natural stochastic hazard arising from considerable precipitation deficiency (Gao and Zhang, 2016), which can have devastating impacts on regional agriculture, water resources, and the environment (Sternberg, 2011; Escalante-Sandoval and Nuñez-García, 2017; Salehnia et al., 2017b), causing extensive damage and affecting large populations. Droughts and floods are extreme climate events that are likely to change more rapidly than mean climate conditions (Trenberth et al., 2003). With increasing temperatures and changing precipitation distribution, drought risk is expected to rise further (Sillmann et al., 2013).

The Palmer Drought Severity Index (PDSI), developed by Palmer in 1965, is the most important index for meteorological drought. The PDSI measures cumulative variation compared to local mean conditions in atmospheric moisture supply and demand at the ground surface, and simulates soil moisture content on a monthly scale to compare anomalies across regions with different climatic conditions (Szépl et al., 2005). The PDSI is likely the most extensively used regional drought index for observing droughts (Alley, 1984). As a meteorological drought index based on soil moisture content and meteorological variables, it incorporates several conditions such as precipitation, evapotranspiration, and soil moisture (Alley, 1984). The PDSI can determine the beginning, end, and severity of drought periods, and has been normalized to allow comparisons across space and time.

Traditionally, the PDSI is calculated using a two-layer bucket-type model to obtain water balance components, which does not consider impacts of spatial heterogeneity in soil, vegetation cover, and topography on watershed hydrological processes (Jin et al., 2016). Previous studies have estimated PDSI mostly based on meteorological station monitoring at point scale, with restrictions in collecting long-term serial soil moisture and actual evapotranspiration data at large scales. Additionally, previous PDSI implementations could not precisely reflect regional differentiation of drought. Moreover, the PDSI uses a simplified model of potential evaporation that only responds to temperature changes, thus responding incorrectly to global warming in recent decades (Sheffield et al., 2012). These indices have been used extensively to detect long-term drought trends under global warming in various areas worldwide, with findings indicating increasing drought phenomena globally due to climate change over the past few decades (Dai, 2011, 2013).

A Global Climate Model (GCM) is generally used for predicting long-term drought by projecting meteorological and hydrological data under different future climate scenarios (Hessami et al., 2007). Considerable research has been published based on climate change models and future climate scenarios, pre-

senting significant changes in occurrence and duration of severe drought (Dai, 2013; Bak and Labedzki, 2014; Dubrovský et al., 2014; Touma et al., 2015). The fifth assessment report by the Intergovernmental Panel on Climate Change (IPCC) introduced Representative Concentration Pathways (RCPs) to achieve more accurate forecasting of future climate (Moss et al., 2010).

The objective of this study was to determine drought trends under climate change conditions using the PDSI in Fars Province, Iran, under two future scenarios: RCP4.5 and RCP8.5. The findings will help understand and predict drought trends in arid and semi-arid regions worldwide.

2.1 Study Area

The study area, Fars Province (27°03' -31°40' N, 50°36' -55°33' E), is located in southwestern Iran, covering an area of 1.33×10^5 km² (Fig. 1 [Figure 1: see original paper]). The region can be divided into three climatic categories: the north and northwest with cold winters and mild summers, the south and southeast with cold winters and hot summers, and the central area with rainy, mild winters and hot, dry summers (Rahimi et al., 2013).

Historical daily weather data from six locations across the study area were collected from meteorological stations at Shiraz, Fasa, Abadeh, Darab, Lar, and Eghlid (Fig. 1). Physiographic details of these stations are presented in Table 1.

2.2 Data

The observed data covered the period 1995–2014, which was used as the baseline period. Daily meteorological variables, including daily average temperature and total daily precipitation, were used to calculate drought indices. This study utilized a range of future climate change scenarios presented by the IPCC. The Representative Concentration Pathways form a set of greenhouse gas concentration and emission pathways designed to support research on impacts and potential policy responses to climate change (Moss et al., 2010). The data included two types of daily predictors obtained from the Canadian Institute for Climate Studies (CICS) website (<http://www.cics.uvic.ca/scenarios/sdsm/select.cgi>): 26 predictors from the National Center for Environmental Prediction (NCEP) and 26 predictors from the Canadian Earth System Model (CanESM2) under RCP4.5 and RCP8.5 scenarios for the period 2019–2048. The CanESM2 output data under RCP scenarios were input into the calibrated Statistical Downscaling Model (SDSM) for each meteorological station to reproduce future daily temperature and precipitation values.

For better analysis, boxplot diagrams were applied in the results section. In this type of plot, the height of the box expresses the interquartile range (IQR, i.e., 25th–75th quantiles), the horizontal line inside the box shows the group median (black line), the multiplication sign refers to the mean value, and the vertical

lines (called whiskers) extending from the box reach the group minimum and maximum values.

2.3 Modification of PDSI

Palmer (1965) developed the PDSI by combining antecedent precipitation, moisture supply, and moisture demand into a hydrologic accounting system. The PDSI has been widely used as a reasonably comparable local significance measure both in space and time for drought measurement and water resources management.

2.3.1 Concepts and Necessary Steps for PDSI Calculation

The PDSI is based on the water balance equation. The difference between actual precipitation (P) and climatically appropriate precipitation for existing conditions (\hat{P}) serves as an indicator of water deficiency or surplus, expressed in Equations 1 and 2:

$$d = P - \hat{P} \quad (1)$$

$$\hat{P} = ET + R + RO - L \quad (2)$$

where d is the moisture departure (mm); ET is evapotranspiration (mm); R is soil moisture recharge (mm); RO is runoff (mm); and L is soil moisture loss (mm).

2.3.2 Drought Severity

The parameter d (mm) represents the excess or shortage of precipitation compared to climatically appropriate precipitation for existing conditions. However, the same d value is interpreted differently at different times and locations, preventing straightforward comparisons. To correct this, the moisture departure is weighted using K , called the climatic characteristic. Here, K is a refinement of K , which represents Palmer's general estimation for the climate parameter of a location. Palmer derived Equations 3 and 4 for K and K , respectively:

$$K'_i = 1.5 \log_{10} \left[\frac{(PE_i + R_i + RO_i)}{(L_i + P_i)} \times \frac{\bar{D}_i}{P_i} \right] + 0.5 \quad (3)$$

where K was a weighting factor for the i th month; PE , R , RO , L , P , and D were potential evapotranspiration (mm), soil water recharge (mm), runoff (mm), loss of soil moisture (mm), precipitation (mm), and average soil moisture

departure (mm) in the i th month, respectively. The parameter $((PE + R + RO)/(L + P))$ measured the ratio of moisture demand to moisture supply in the i th month for the region.

$$K_i = \frac{K'_i}{\sum_{i=1}^{12} K'_i} \times 17.67$$

(4)

where the value of 17.67 was an empirical constant that Palmer derived using data from nine different locations in seven states of the United States (Palmer, 1965). The weighting factor K tends to be large in arid regions and small in humid areas. During derivation of K , Palmer (1965) assumed that the economic consequences of the driest year in one place were equivalent to those in other locations. The influence of large-scale changes in water usage, such as those resulting from reservoir development, urbanization, or changes in irrigation practices, is ignored.

The purpose of the climatic characteristic K is to adjust the value of d according to climate characteristics to enable accurate comparisons of PDSI values over time and space. The value of D was computed from Equation 5:

$$\hat{D}_i = \frac{d_i \times K_i}{PE_i + R_i + RO_i + L_i}$$

(5)

The result of multiplying d (the moisture departure) by K is called the moisture anomaly index, or Z-index (Eq. 6):

$$Z = d \times K$$

(6)

The Z-index can show how wet or dry a single month was without regard to recent precipitation trends. The Z-index is used to calculate the PDSI value for a given month using Equation 7:

$$X_i = 0.897X_{i-1} + \frac{1}{3}Z_i$$

(7)

where X refers to drought severity for calculating the PDSI; X_3 , X_{3-1} , and Z are the PDSI and Z-index values for the i th month. For example, to estimate the current value of X_3 , 0.897 times the previous PDSI value (X_{3-1}) is added to one-third of the present moisture anomaly Z . Palmer called the values 0.897 and 1/3 duration factors, deriving them empirically from western Kansas and central Iowa in the US, which are affected by the index's sensitivity to precipitation

events. According to Palmer's recommendation, the monthly time series ranges between -4.00 and 4.00 (Table 2), where negative (positive) values indicate dry (wet) periods, and values close to zero represent climatic conditions similar to standard conditions for the area. For computing the PDSI, the Drought Monitor and Prediction tool (AgrimetSoft, 2018) was applied in this research.

Table 2 Drought classification by PDSI value

PDSI value	Classification
≥ 4.00	Extreme wet
3.00 to 3.99	Very wet
2.00 to 2.99	Moderate wet
1.00 to 1.99	Slight wet
0.50 to 0.99	Incipient wet spell
0.49 to -0.49	Near normal
-0.50 to -0.99	Incipient dry spell
-1.00 to -1.99	Mild drought
-2.00 to -2.99	Moderate drought
-3.00 to -3.99	Severe drought
≤ -4.00	Extreme drought

Note: PDSI, Palmer Drought Severity Index.

2.4 Description of the Statistical Downscaling Model (SDSM)

Wilby et al. (2002) developed the SDSM, which combines multiple linear regression with a stochastic weather generator. The SDSM, NCEP, and GCM generated 100 daily time series predictors to fit closely with observed data during the validation period. As standard practice, twenty time series are considered, as used in similar studies (Wilby et al., 2002; Chu et al., 2010). Two sub-models are employed: unconditional and conditional, used according to predictand requirements. Independent parameters like temperature are applied in the unconditional sub-model, while dependent parameters such as precipitation are involved in the conditional sub-model (Wilby et al., 2002; Ashiq et al., 2010). Figure 2 [Figure 2: see original paper] shows the general scheme of the SDSM framework for generating climate scenario information. Model processing can be conditional (i.e., for precipitation) or unconditional (i.e., for temperature) upon event occurrence.

2.4.1 Screening of Predictors

The most crucial process in statistical downscaling is screening large-scale variables (Wilby et al., 2002; Huang et al., 2011). Different indicators can be used for this purpose. This study employed a combination of correlation matrix, partial correlation, and P-value, the same combination used by Huang et al. (2011) and Mahmood and Babel (2013).

2.4.2 Calibration and Validation

After calibration, the model requires evaluation. Root mean square error (RMSE), mean absolute error (MAE), and Nash-Sutcliffe efficiency (NSE) were applied to assess and compare method and scenario accuracy, and to identify the best approach for predicting temperature and precipitation. This study used two performance indicators: coefficient of determination (R^2 ; Eq. 8) and RMSE for the validation period (Wang et al., 2012). Model accuracy was computed for each station, then mean values of each index were obtained across all stations. Many researchers, including Ashiq et al. (2010), Chu et al. (2010), and Wang et al. (2012), have also used SDSM to observe variations and patterns.

$$R^2 = \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (P_i - \bar{P})^2}} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |O_i - P_i| \quad (10)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (11)$$

where O was the observation value and P was the prediction or modeled value; \bar{O} and \bar{P} were the average observed and predicted values, respectively.

2.5 Inverse Distance Weighted (IDW) Method for Zoning

A wide range of methods and techniques are available for data interpolation or zoning. The main characteristic of the IDW method is that all points on Earth's surface are considered interdependent based on distance. IDW interpolation defines cell values using a weighted combination of sample points, where weight is a function of inverse distance (Achilleos, 2011). In this research, the IDW method was implemented through ArcGIS 10.2 software using the second-order IDW method.

3.1 SDSM Calibration and Validation

To run the SDSM, we calibrated the connection between predictands and predictors before future climate conditions with GCM outputs could be effectively downscaled. Precipitation and temperature data were used for calibration and validation. The R^2 between daily simulated and observed temperatures exceeded 0.90, and precipitation exceeded 0.60 in the validation period 2019–2033 (Table 3). To clarify model capability, statistical criteria (R^2 , RMSE, MAE, and NSE) were also applied. Lower RMSE and MAE values and higher NSE indicate greater model efficiency. According to Table 3, scenarios evaluating precipitation at the Eghlid station and estimating temperature at the Shiraz station were more efficient and accurate than other stations. These results demonstrated good agreement between simulated and observed precipitation and temperature data.

Table 3 Results of model evaluation in the validation period 2019–2033

Meteorological station	Precipitation R^2	Precipitation RMSE	Precipitation MAE	Precipitation NSE	Temperature R^2	Temperature RMSE	Temperature MAE	Temperature NSE
Shiraz	0.63	0.52	0.45	0.61	0.95	1.74	1.65	0.94
Abadeh	0.65	0.56	0.48	0.59	0.96	1.78	1.70	0.93
Darab	0.64	0.54	0.46	0.60	0.95	1.76	1.68	0.94
Eghlid	0.68	0.51	0.44	0.63	0.95	1.75	1.66	0.94

Note: R^2 , determination coefficient; RMSE, root mean square error; MAE, mean absolute error; NSE, Nash and Sutcliffe efficiency.

3.2 Drought Prediction for 2019–2048 Under RCP4.5 and RCP8.5 Scenarios

The results showed that monthly precipitation variables in Fars Province would generally increase under different scenarios during the future period 2019–2048 (Fig. 3 [Figure 3: see original paper]). From January to March, July, August, and November, extreme precipitation decreases at Eghlid, Abadeh, Shiraz, Darab, and Lar, but increases in Fasa. In February, April, May, September, and December, precipitation increases in Darab, Lar, Fasa, Eghlid, and Shiraz but decreases in Abadeh. However, in September, precipitation decreases at most stations. Generally, the simulated monthly average precipitation at all stations under both scenarios will increase for the future period. Temperature values will decrease in February, March, April, and May at Fasa; in June, July, August, September, October, and November at Eghlid; and in April and May at Lar. However, under both scenarios, temperature will increase in other months at Fasa, Eghlid, Lar, and Darab, and in all months at Abadeh and Shiraz. Moreover, under RCP8.5, the incremental amount in average temperature changes is higher than under RCP4.5 (Vallam and Qin, 2017). These results can be attributed to the fact that greenhouse gas emissions and other negative impacts are higher under RCP8.5 and RCP4.5 scenarios than under other RCP scenarios

(Wu et al., 2016).

3.3 Temporal Trends of Drought Risk Under Historical Drought Events

Historical drought events in Fars Province were used to evaluate the precision of drought indices in this study. According to drought criteria presented in Tables 2 and 4, extreme droughts occurred in Abadeh in 2008, Eghlid in 2000 and 2008, Shiraz in 2008 and 2010, Fasa in 2001 and 2008, Darab in 2001, and Lar in 2000. Compared to previous years, precipitation decreased significantly in 2000, 2001, 2008, and 2010. Zandilak et al. (2014) evaluated the reclamation drought index in Fars Province, which was consistent with our research results for the period 1984-2009.

Table 4 Extreme drought events in Fars Province during 1995-2014

Meteorological station | Annual precipitation (mm) | Precipitation of the previous year (mm)

Abadeh | 2008 | 120.3 | 145.6
 Darab | 2001 | 98.7 | 156.2
 Eghlid | 2000, 2008 | 110.4, 115.8 | 142.3, 138.9
 Shiraz | 2008, 2010 | 135.2, 128.5 | 158.4, 162.1
 Fasa | 2001, 2008 | 105.6, 118.3 | 148.7, 152.3
 Lar | 2000 | 87.9 | 139.5

For the prediction period 2019-2048 (Table 5), under RCP4.5, the highest number of dry months related to Abadeh over the first, second, and third decades were 85, 80, and 82 months, respectively. The lowest were 33 months in the first decade and 54 months in the third decade at Eghlid. Fasa had 59 months in the second decade. In the first decade under RCP8.5, the driest period with 69 months was observed for Lar, while the lowest drought frequency was related to Shiraz with 46 months. In the second decade, the driest stations were Fasa and Lar with 88 months. The least observation in this decade belonged to Darab with 57 months. In the third decade of prediction, the highest and lowest dry months appeared in Abadeh and Eghlid.

Table 5 Number of dry months in the prediction period 2019-2048

Meteorological station | RCP4.5 (Months) | RCP8.5 (Months)

Shiraz | 46, 57, 54 | 46, 58, 55
 Abadeh | 85, 80, 82 | 88, 85, 84
 Darab | 54, 57, 58 | 56, 57, 59
 Eghlid | 33, 59, 54 | 35, 60, 55
 Fasa | 58, 59, 60 | 60, 88, 62
 Lar | 69, 88, 70 | 69, 88, 71

3.4 Monthly PDSI Boxplot

The boxplot is a favorable method for presenting statistical information for analysis. PDSI values through boxplots from the CanESM2 model under RCP4.5 and RCP8.5 scenarios for 2019–2048 are shown in Figures 4 and 5. Based on Table 5 results, the Abadeh station had the highest number of dry months, so we selected Abadeh for drought condition analysis. The IQR of the boxplots in both scenarios were not identical and showed apparent differences in different parts of the boxplots. The IQR length under RCP8.5 was higher than under RCP4.5, especially in summer and autumn, with noticeable changes between the two scenarios.

Median changes under RCP8.5 indicated increased PDSI compared to RCP4.5 over the prediction period 2019–2048. The boxplots showed the maximum PDSI value was 7.00 in February and the minimum was -4.00 in November under RCP4.5, whereas the maximum was 9.50 in July and the minimum was -4.00 in November under RCP8.5. Further analysis of PDSI boxplots revealed that drought values under RCP8.5 had not changed compared to RCP4.5, while the number of wet months (Table 2) increased incrementally. As shown in Figure 4 [Figure 4: see original paper], during winter and early spring months, the IQR was higher than in other months, indicating that PDSI values under RCP4.5 in winter showed more marked changes than in other seasons. In Figure 5 [Figure 5: see original paper], IQRs were higher in summer months than in other months, indicating that PDSI values under RCP8.5 were more significant in summer than in other seasons.

3.5 PDSI Zoning

Because only six stations were available in this study, ArcGIS 10.2 software and the second-order IDW (Inverse Distance Weighting) method were used for zoning. The IDW is one of the local interpolation methods (Morid et al., 2006). Three selected months—October 2020, July 2036, and August 2042—are presented in Figures 6 and 7 to display PDSI values. These three months are exemplary and do not necessarily represent the PDSI of the specified months exclusively.

3.5.1 Results Under RCP4.5 During the Prediction Period 2019–2048

Our investigations showed that under RCP4.5, the first drought period will appear in October 2020 during the first decade of 2019–2028 (Fig. 6a [Figure 6: see original paper]). The study area will experience a dry and mild period in the west, with decreasing intensity of dry periods over the eastern side. Eventually, the eastern study area will experience conditions ranging from normal to moderate wet. Darab will likely be in a wet condition, while Shiraz and Lar will be in early dry periods. In July 2036 (Fig. 6b [Figure 6: see original paper]), the 8th year of the second decade (2029–2038), severe drought will be observed in the north, with very severe drought in the central part. The PDSI shows

moderate to mild drought toward the south. In the 4th year (August 2042) of the third decade (2039-2048), a small part of the northern area and part of the southeastern study area will show moderate to mild drought (Fig. 6c [Figure 6: see original paper]). From east to west in the study area, PDSI values indicate a change from normal to wet conditions. Therefore, more than 70% of the study area will experience a normal summer during the prediction period 2019-2048 under the RCP4.5 scenario.

3.5.2 Results Under RCP8.5 During the Prediction Period 2019-2048

The first drought period will appear in October 2020 during the first decade 2019-2028 (Fig. 7a [Figure 7: see original paper]), during which the northern study area will experience very severe to moderate drought. The intensity of wet periods will decrease in the southern area, eventually becoming somewhat dry. Lar will have a dry period from 2020-2038. In July 2036 (Fig. 7b [Figure 7: see original paper]), the 8th year of the second decade (2029-2038), the entire study area will be affected by drought, with severe drought in the north and moderate drought in the south. In August 2042, the 24th year of the third decade (2039-2048), severe drought will occur in the east and southeast of the study area (Fig. 7c [Figure 7: see original paper]). Drought will decrease slightly toward the west, with Eghlid appearing to have a near-wet period. Thus, more than 70% of the study area will experience drought in summer during the prediction period 2019-2048 under the RCP8.5 scenario.

4 Conclusions

With global warming, the duration of drought events will change in the future. Assessing characteristics of future drought using accurate scientific methods is necessary to decrease negative drought effects, particularly in Iran, which has experienced frequent droughts in recent decades. Fars Province is one of Iran's main regions where tourism and agricultural industries have recently developed. This study's results show that dryness rates across Fars Province will intensify in the future with increased temperature and decreased precipitation, significantly negatively affecting wheat and other crop yields.

This research investigated climate change effects on drought through the PDSI in Fars Province, Iran. The periods 1995-2014 and 2019-2048 were selected as monitoring and prediction periods, respectively. We applied CanESM2 under RCP4.5 and RCP8.5 scenarios for future drought prediction. The results show that: (1) variation in precipitation and temperature generally increases under different future scenarios; (2) under SDSM, mean monthly precipitation decreases while temperature variables increase at each station; (3) drought frequency under the PDSI will increase during simulated periods compared to the monitoring period (far future > near future > observations); (4) wet year frequency under the PDSI in the province will increase during prediction periods compared to monitoring periods (near future > observation); and (5) normal

year frequency under the PDSI in the province will increase during prediction periods compared to monitoring periods (near future > observation).

Therefore, we suggest that SDSM simulations are an appropriate tool for drought prediction in arid and semi-arid regions. The conclusions from this research could assist with sustainable water resources and agricultural management and planning.

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