



Modeling, monitoring and forecasting of drought in south and southwestern Iran, Iran

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Abstract

Drought is one of the natural hazards that has hit Iran over the past decades with serious environmental hazards, including those in southern parts of Iran. Researches done in the southern region of Iran in the field of statistical modeling of drought are rare. Therefore, the aim of this study is to fuzzify the SMS index, modeling and forecasting droughts in the southern part of Iran. For this study, 29-year-old temperature and precipitation data were used in 28 synoptic stations in the southern part of Iran during the period 1908–2018. In this study, three drought indexes SPI, MCZI, SET were separately calculated and combined and the fuzzy index SMS was obtained. Then, in ANFIS and RBF neural network models were compared and modelled in MATLAB software and simulated for the next 16 years, and finally, using the TOPSIS multivariate decision-making model, the drought-affected areas for the coming years, 16 next years, they were prioritized. The findings of the study showed that the new fuzzy index of the three indicators reflected drought with acceptable accuracy. In assessing the two models of ANFIS and RBF, the RBF model with a RMSE value of 1.15 and R^2 values of 0.9161 have the highest accuracy than the ANFIS model for prediction. According to the SMS fuzzy index, stations such as Kerman, Yasuj and Abadan with drought of 0.69, 0.97, and 0.89, respectively were exposed more to future drought. Also, based on Topsis model, central and northern stations such as Koohrang and Safashahr with drought of 0.19 and 0.21, respectively, were subjected lower to drought in the following years.

Keywords Statistical analysis · Risk · RBF and ANFIS models · Simulation · Fuzzy

Introduction

The phenomenon of drought can occur due to fluctuations and climate change in different parts of the planet and has many climatic hazards in various parts of human life. However, the drought is characterized by climate disasters with rainfall shortages, humidity and rising temperatures relative to normal conditions (Zeinali and SafarianZingir 2017). Drought monitoring is one of the most important

components of drought management in drought-affected areas (Zeinali et al. 2017). Also, the phenomenon of drought is a clear sign of climate fluctuations that affects human societies more than other natural phenomena (Parasamehr et al. 2018). As a result of drought, low rainfall and subsequently low water flow periods have significant effects on water resource management (Bayazidi 2018). In the other definition, drought is a climatic phenomenon that is formed by precipitation shortage compared to the expected average in the region (Ghorbani et al. 2018). Today, drought is one of the most important natural hazards that has direct and indirect consequences in different parts of the planet (Barqi et al. 2018). However, drought is one of the environmental events and an integral part of climate fluctuations. This phenomenon is one of the main characteristics and recurrence of different climates (Hejazizadeh and Javiyazadeh 2019). Other researchers have investigated in the field of drought in the country and abroad, including: Haddadi and Heidari (2015), Montaseri and Amirataee (2015), Sobhani et al. (2015), Salahi and Mojtabapour (2016), Zolfaghari

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and NouriZamara (2016), Damavandi et al. (2016), Fanni et al. (2016), Gholam Ali et al. (2011), Huang et al. (2015), Jandarmian et al. (2015), Keshtkai (2015), Touma et al. (2015), Spinoni et al. (2015), Kis et al. (2017) and Jinum and Jeonbin (2017). Also, Noroozi et al. (2018) predicted the drought situation during the period of 2018–2037 under a changeable approach in Ilam and Dehloran, and concluded that with increasing statistical period, the continuation of drought and wet periods and their severity will be less. Parasamehr et al. (2018), using RUN theory, studied the severity, duration and period of drought return in Fars province, and concluded that during the last decade, drought severity has increased from the previous decade. Hejabi et al. (2012) moderated the PDSI index based on the ALSIS schema in the Karkheh basin and found that the evaluation of drought indices for the period 1983–2011 indicates the occurrence of more severe droughts for the specified duration by the AL-PDSI index compared to the SC-PDSI index. Bayazidi (2018) conducted a drought assessment of the synoptic stations of the western part of the country using the Herbst method and the comparative neuro-fuzzy model and found that the highest and lowest amount of drought index (I) was occurred at Takab, Sarab, Saqez, Sarpul-Zahab, Lorestan and Ardebil stations.

Ghorbani et al. (2018) investigated the spatial-temporal variations of SPEI index in Iran and found that climate change has occurred in recent years, and Iran has tended toward more dry periods. Barqi et al. (2018) analyzed and identified drought consequences on rural residents, and found that the drought in the studied village reduced income from agricultural and horticultural productions. Babayan et al. (2018) studied the monthly forecast of drought in the southwest basin of the country using the CFSv.2 model and found that, with the frequency of all drought events, observations were made for normal, wet and drought conditions, respectively, 4/76, 12.5% and 8% of total incidence, the overall accuracy of the SPI index was 73.4%. Hejazizadeh and Javiyazadeh (2019). Analyzed the spatial statistics of drought in Iran and concluded that the SPI drought index data has spatial correlation and clustering pattern. James et al. (2015) modelled drought influence based on weather drought indicators in Europe and found that some models (Pseudo- $R^2 = 0.225$ – 0.716) have good ability to predict the possibility of drought. Alam et al. (2017) assessed the drought using the SPEI drought model for different agricultural and ecological regions of India, and found that during the last 24 years, droughts have increased in almost all of the six regions. The findings of the study will greatly help assess the drought effects on primary gross production and develop future possible plans in the same region around the world. Quesada et al. (2008) investigated hydrological changes in a consistent approach to assess flood and drought changes and found that most of the methods used to detect

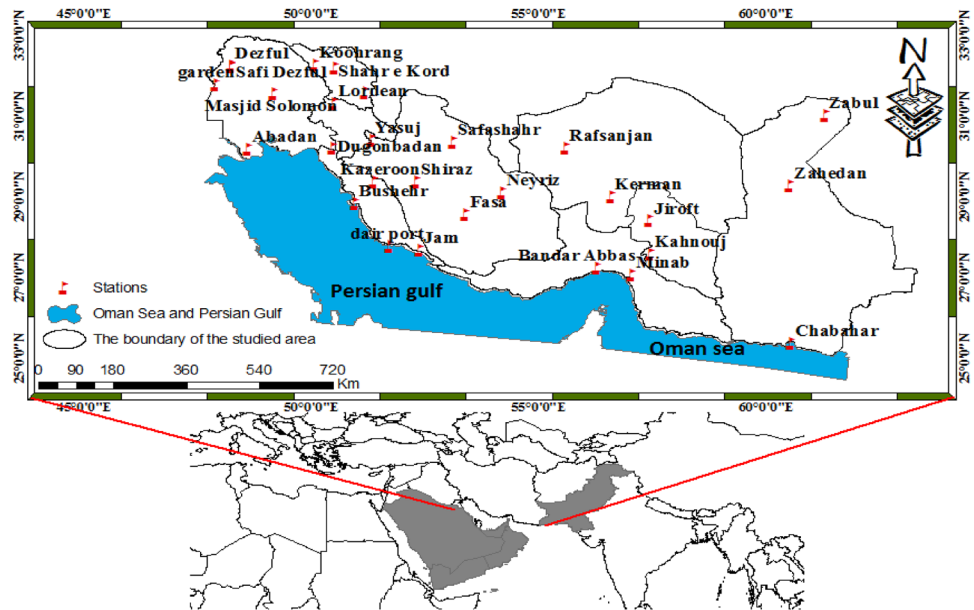
extreme hydrologic trends are not suitable for trend detection and cannot be used in decision making. Modaresirad et al. (2017) conducted a survey of meteorological and hydrological drought and found that the SPI could show two main drought characteristics of meteorology and hydrology in providing accurate estimates during the return period of severe drought. Zelekei et al. (2017) used the Standard Precipitation Index (SPI) and Palmer Drought Index (PDSI) and satellite data to investigate the drought in Ethiopia and concluded that the observed dry and humid periods in the north of the study area mainly focus on the ENSO change in the spring and summer season. Marchanta and Bloomfield (2018) conducted spatial and temporal modeling of underground drought conditions and found that the model has the ability to assess drought and also show that drought has occurred in recent decades. Kay et al. (2012) simulated and predicted drought based on the SPI using the ARMA-GARCH model, and found that the accuracy of the ARMA-GARCH model was much higher than the ARMA model. Gebremeskel et al. (2019) explored the causes, effects and flexibility of drought in eastern Africa, and concluded that a better understanding of the causes and effects of drought, participatory management and local actions is necessary to create drought resistance. Strong cooperation between citizens and the state is also helpful in drought monitoring and management. Wei et al. (2019) modelled the drought loss assessment in southwest China based on a hyperbolic tangible activity and found that the estimated value was very similar to that of real economic losses. Therefore, the regional drought damage assessment model developed in this study and the drought-based assessment model in southwest China is reliable.

According to the researches it is obvious that the phenomenon of drought is of great importance in natural hazards. According to the studies, the existing methods that have been done for studying the drought so far have been general and have not adequately addressed the issue. The purpose of this study was to analyze the temperature and precipitation data first. Then, a model was developed by using ANFIS and RBF comparative models. At last, and the new SMS drought new index was designed. Finally, for better visibility of the drought situation in the future, areas affected by droughts in southern regions of Iran after prediction, the drought of the stations was prioritized using TOPSIS model.

Materials and methods

The southwestern region of Iran, which was studied in this study, has eight provinces, including 28 synoptic stations, which geographically, southeastern of Iran has its own climatic conditions, which has a high environmental risk in terms of drought each year. In Fig. 1, the geographic characteristics of the 28 stations were presented.

Fig. 1 Location of the area and stations studied in the country



In this research, after receiving the 29-year data on temperature and precipitation for 28 stations in the drought areas of Iran, the data were first analyzed and then normalized. After normalizing the temperature and precipitation data, two models were applied for modeling and prediction, namely ANFIS and RBF. After combining three SPI, MCZI, and SET data, the new drought index, called SMS, was created and predicted for the coming years, and eventually, with the use of the TOPSIS model, regions are involved prioritized with drought risk phenomenon and using the ArcGIS software, the output data were mapped.

RBF neural network model

Neural networks with radial-base function are widely used for nonparametric multi-dimensional functions through a limited set of educational information. Radial neural networks with a fast and comprehensive analyzing are very interesting and efficient, and they have received special attention (Hartman et al. 1990). Hartmann and Kepler, in the 1990s proved that radial-base grid networks are very powerful approximation devices, so that by having a sufficient number of neurons in hidden layer they are able to approximate each continuous function with each accurate degree. These networks are often compared to the neural network after propagation of error. The main architecture of the RBF consists of a two-tier network (Khanjani et al. 2016).

ANFIS neural network model

In this step, the possibility of modeling and prediction of dust was studied in the studied area using the ANFIS

model (Ansari and Davar 2010). In this study, the drought phenomenon in a series of time (276 months) was considered in two models of ANFIS and RBF neural networks in each station. The fuzzy system is a system based on the “conditional-result” logical rules that, using the concept of linguistic variables and fuzzy decision making process, depicts the space of input variables on the space of the output variables. In Fig. 2, a SOGNO fuzzy system with three inputs, one output and two laws and an equivalent ANFIS system was presented. This system has two inputs *x* and *y* and one *f* output (Ahmadzadeh et al. 2010). At the end, the error rate of the resulting models is compared and the function that obtains the lowest error rate at the lowest analyzing time was selected as a membership function (Konarkohi et al. 2010).

TOPSIS¹ model

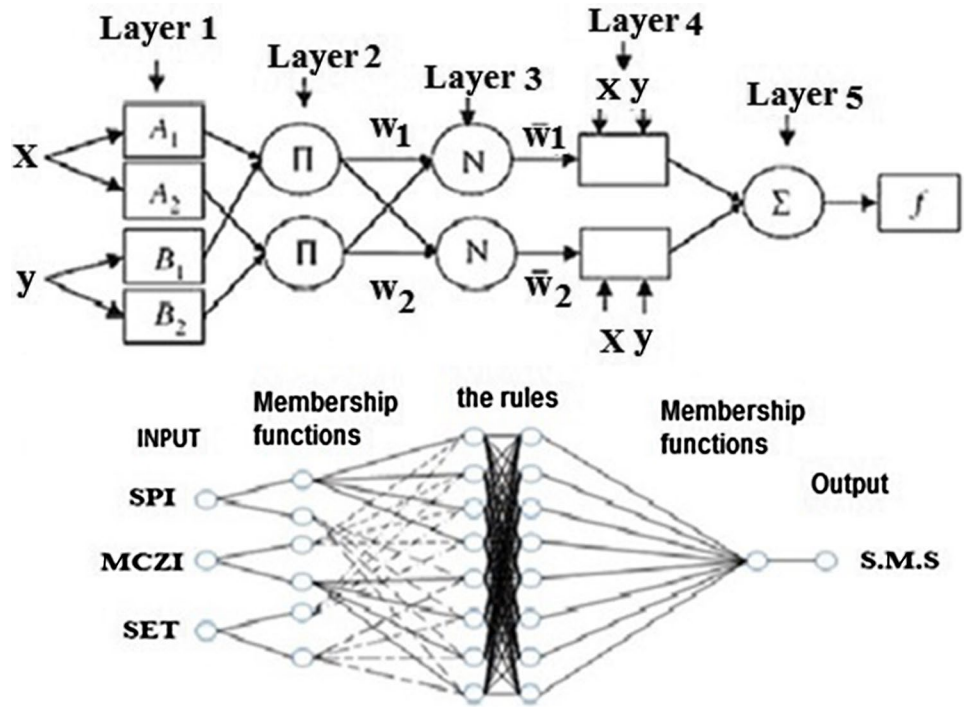
The steps of TOPSIS model are as follows:

Step 1 Formation of data matrix, matrix 1 based on *m* option and *n* index:

$$\text{Matrix (1)} \quad X_{ij} = \begin{bmatrix} x_{11} & x_{22} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix}$$

¹ Technique for order preference by similarity to ideal solution.

Fig. 2 ANFIS model structure



Step 2 Unsealing data and the formation of an unscaled matrix, Eq. (1):

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^m a_{kj}^2}} \tag{1}$$

Step 3 Calculation of a weighted unscaled matrix: Indeed, the matrix (v), the matrix 2 is the multiplication of the unscaled matrix in the weighted matrix:

$$\text{Matrix (2)} \quad V_{ij} = \begin{bmatrix} v_{11} & v_{22} & v_{1n} \\ v_{21} & v_{22} & v_{2n} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ v_{m1} & v_{m2} & v_{mn} \end{bmatrix}$$

Step 4 Determine the positive ideals (the best function of each index), which are indicated by (A^*). Equations (2) and (3):

$$A^* = \left\{ (\max v_{ij} | j \in J), (\min v_{ij} | j \in J') \right\}, \tag{2}$$

$$A^* = \{v_1^*, v_2^*, \dots, v_n^*\}. \tag{3}$$

Step 5 Determine the negative ideals (the worst function of each indicator), which are represented by (A^-). Equations (4) and (5):

$$A^* = \left\{ (\min v_{ij} | j \in J), (\max v_{ij} | j \in J') \right\}, \tag{4}$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\}. \tag{5}$$

Step 6 Determine the distance each option from negative and positive ideals (S_i^+ , S_i^-), Eqs. (6) and (7):

$$d_j^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2}, \tag{6}$$

$$d_j^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}. \tag{7}$$

Step 7 Determine the relative closeness of the options, which is calculated from Eq. (8):

$$C_i = \frac{d^-}{d_i^- + d_i^+}. \tag{8}$$

Step 8 Ranking options by (C_{i+}) value, so that $0 < c_{i+} < 1$. Accordingly, as much as one option approaches the ideal point, c_{i+} trends to 1; it is the best option (Malchovsky 2007: 375)

Table 1 Drought analyzing results for ANFIS model at 28 stations in southern region of Iran

Model	Type of MF	RMSE	R^2	Number of MFs	Type of output function
ANFIS	Trap	12.09	0.4238	222	Linear
		9.76	0.6014	333	Linear
	Trim	12.78	0.3659	222	Linear
		11.42	0.4798	333	Linear
	Gbell	12.39	0.3983	222	Linear
		10.18	0.5708	333	Linear
	Gauss	12.52	0.3881	222	Linear
		9.64	0.6081	333	Linear

Results and discussion

Comparison of two ANFIS and RBF neural network models

According to the comparisons of ANFIS and RBF neural network models, the two models were able to predict the drought. The RMSE value of ANFIS neural network model at best status, was 9.64 and the R^2 value was 0.6081 (Table 1), but The RMSE value of the RBF at best status was equal to 1.15 and the R^2 value was 0.9961 (Table 2). By comparing these two models, finally, Table 3 was obtained, which shows a better performance of the RBF neural network model, Fig. 3. According to the modeling and the results obtained from the comparison of the models, the accuracy and reliability of the model, the RBF neural network was approved for prediction, which the deviation of target value was also presented in Fig. 4, so in the following, the RBF neural network model was used to predict this.

Drought prediction based on RBF neural network model and SMS

After verifying the reliability of neural network models in modeling, RBF neural network model showed more precision for predicting drought phenomena. After the fuzzing of the three SPI, SET, and MCZI indexes, the SMS new drought index has been created. Based on the data obtained from the SMS output, the central and western stations of the studied area were more exposed to drought. Three stations in Kerman, Yasuj and Abadan, with SMS drought percentages of 0.99, 0.97, and 0.89 had the highest percentage of drought and the stations of Jiroft, Rafsanjan, and Safashahr, respectively, with drought percentage (0.19, 0.37, and 0.39), included the lowest amount of drought (Fig. 5). Also to present the reflection of the three drought indicators of SPI, SET, MCZI, in the latest drought index of SMS drought, Abadan Drought Chart, was presented in Fig. 6. Then, after obtaining the SMS index and showing the high reliability of the RBF model compared to the ANFIS model,

Table 2 Drought analyzing results for RBF model in 28 stations in southern region of Iran

Model	RMSE	R^2	Number of neurons
RBF	7.18	0.7742	10
	1.15	0.9961	15
	3.90	0.8856	20
	2.55	0.974	25
	6.01	0.8347	30

Table 3 Comparison of results for RBF and ANFIS models

Model	RMSE	R^2
The best RBF	1.15	0.9961
The best ANFIS	9.64	0.6081

the maximum temperature of the stations based on the RBF model was predicted for the next years which three stations of Zahedan, Abadan and Bandar Abbas with the highest values (53.01, 51.15, and 49.08, respectively), had the most possible maximum temperature for the predicted years, and the station Neyriz, Safashahr, and Jiroft in the central part of the study areas, with the maximum temperature (35.16, 37.22, and 38.19, respectively), had the lowest maximum temperature values (Fig. 7).

Drought severity mapping in southern regions of Iran using TOPSIS

Prioritization of the stations involved in drought in southern regions of Iran was analyzed using Topsis model. First, for calculating and analyzing the statistical data, each of the parameters got a weight and then the rate. The desirability and desirability of each station were studied in terms of climatic indices and, finally, an appropriate option was chosen from an approximate distance to ideal proportions (Sobhani and Safarianzingir 2018). The results of implementing the

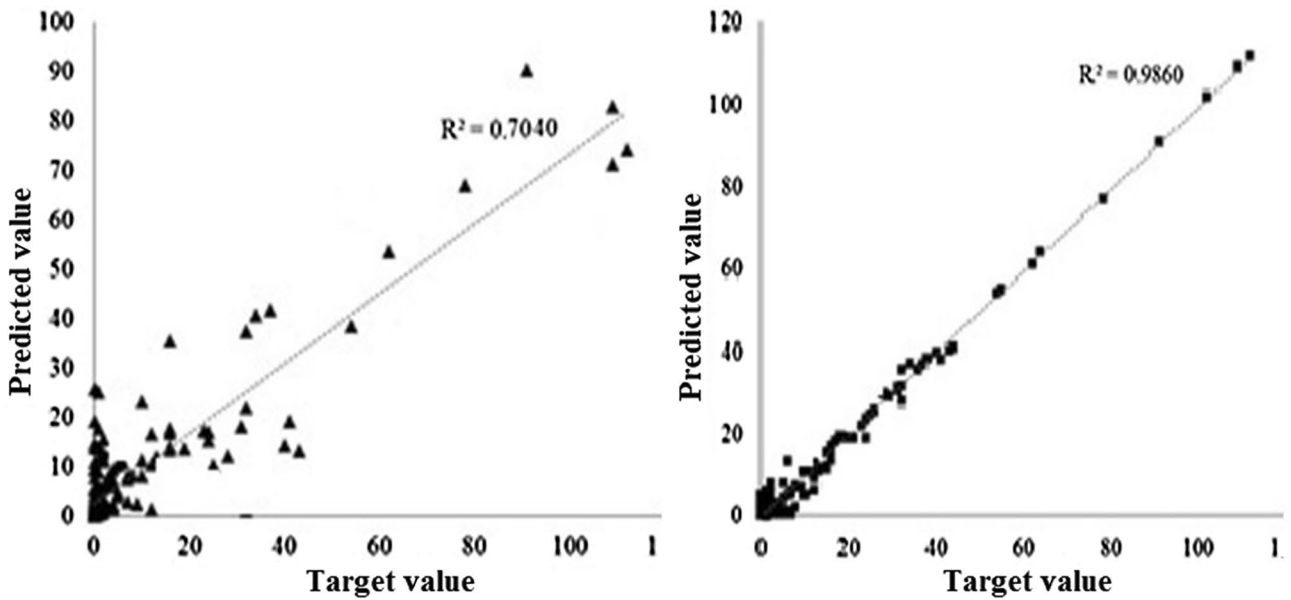


Fig. 3 Diagram for the results, a RBF b ANFIS

Fig. 4 Deviation from target value for RBF and ANFIS models

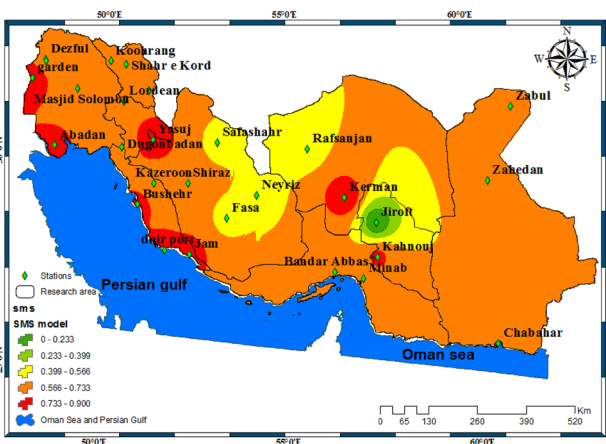
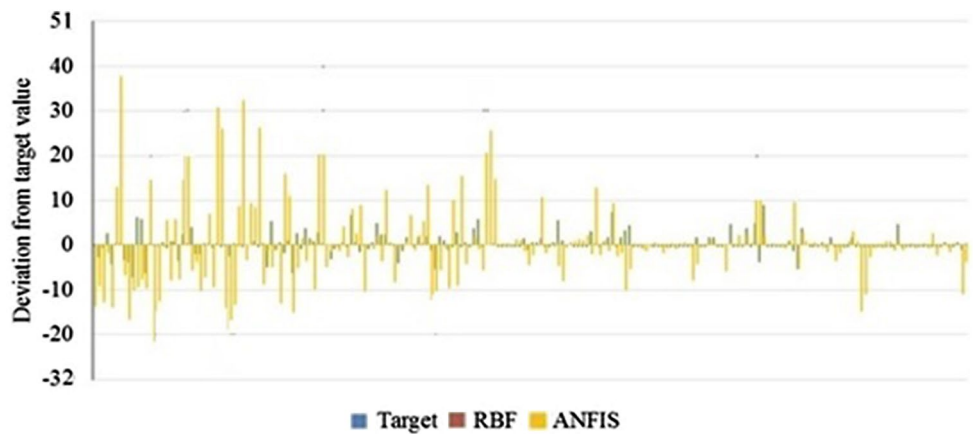


Fig. 5 Drought frequency maps in southern regions of Iran during simulated years based on the new index of SMS

Topsis model using the degree of importance of the criteria derived from the entropy method indicate drought severity and more and less places were affected by drought for the next 16 years in southern regions of Iran. Three stations of Bandar Abbas, Zahedan, and Abadan were subjected to more drought conditions for simulated years with percentages (0.99, 0.90, and 0.87, respectively) and the central and northern stations of the study area Including Koohrang, Safashahr, and Jiroft, respectively, with percentage of 0.19, 0.21, and 0.26 showed a lower drought intensity (Fig. 8). According to the TOPSIS model, South, East and West of Iran were more exposed to drought for simulated years.

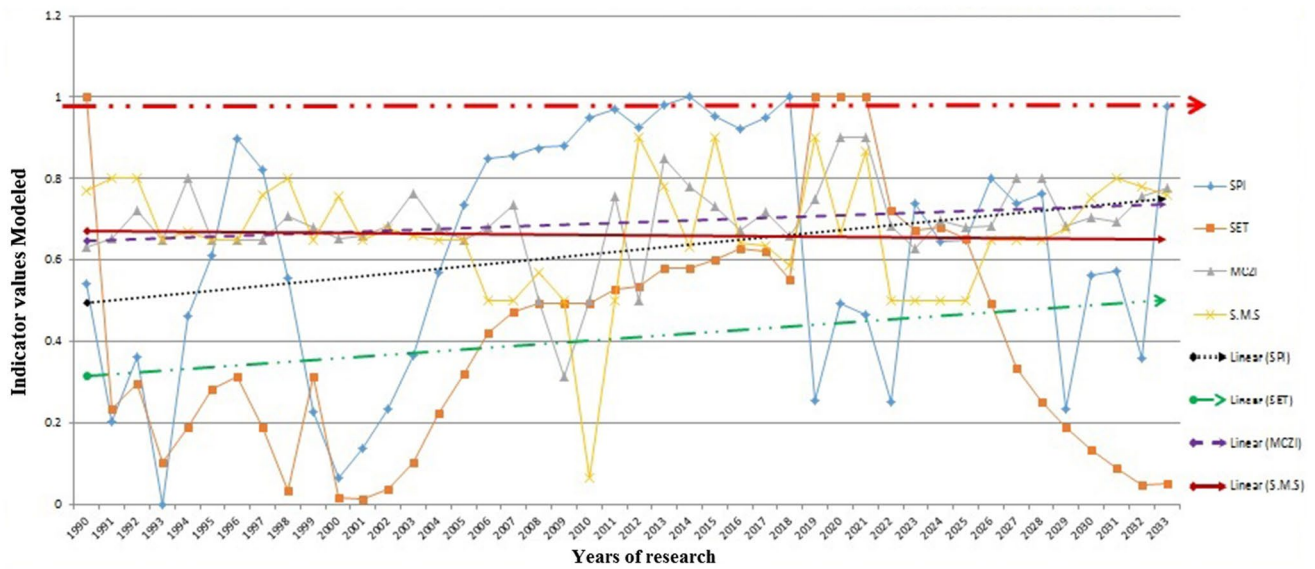


Fig. 6 Drought frequency diagram of Abadan station during simulated years based on the new index of SMS

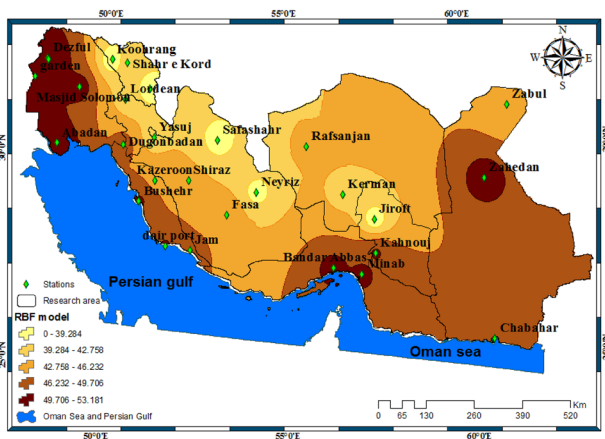


Fig. 7 Drought frequency maps in southern regions of Iran during simulated years based on RBF model

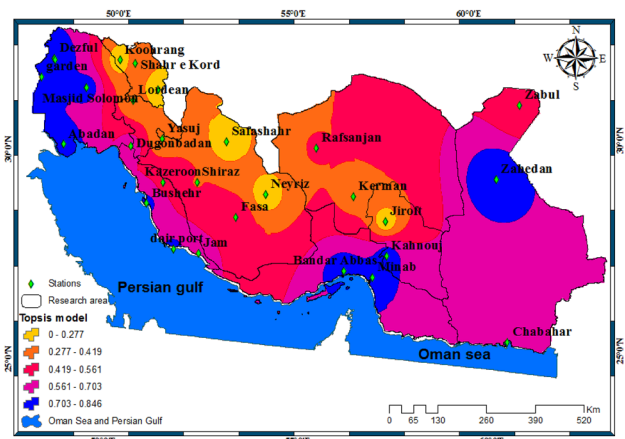


Fig. 8 The final drought severity map of the Iranian southern regions for the next years based on the Topsis model

Conclusion

Drought is one of the natural hazards that has been gradually evolving over the years through the climatic fluctuations and has its effects on different parts of the environment. One of these areas is in Iran, which in recent years has shown drought in its different parts, especially the southern regions with high intensity. Paying attention to these natural hazards (drought) and providing solutions and identifying the affected areas can be a great help to the vulnerable parts affected from the drought. According to the studies carried out abroad and in the country in the field of modeling and predicting of areas susceptible to

drought in the coming years, it will show us more accurate view of the future drought in the southern regions of Iran.

There was no research that could address the accuracy and adequacy of the subject, and if so, it would be very rare. The purpose of this study was to model and investigate the possibility of drought prediction in the southern part of Iran. To do this, the fuzzing of the SMS index, based on the three SPI, MCZI, SET indices, results comparison of two new simulation models (ANFIS and RBF), as well as the TOPSIS multivariate decision-making model. The results showed that the SMS index reflected the three SPI, MCZI, and SET indices. Comparing two models of ANFIS and RBF, the RBF model is more accurate than the ANFIS model.

As a result, for prediction of drought, RBF model was used for future years. The accuracy of the RBF model at best condition was RMSE equal to 1.15 and the R^2 value was 0.9961. The results of the fuzzing of the SMS index showed that the central and western parts of the study areas such as Kerman, Yasuj and Abadan, with the percentage of SMS drought (0.99, 0.97, and 0.89, respectively), were higher exposed to the drought. Also, the results obtained from the prediction of maximum temperature in the studied areas based on the RBF were Zahedan, Abadan and Bandar Abbas stations with 53.01, 51.1, and 49.08 °C respectively.

Based on the RBF model, the northern parts of the Persian Gulf, the Strait of Hormuz and the east of the study area were more exposed to drought in the coming years. Based on the Topsis multivariate decision-making model, the central and northern stations of the study area included Koohrang, Safashahr and Jiroft were subjected to droughts (0.19, 0.21, and 0.26) with lower severity for the coming years. Modeling and predicting of droughts in 28 synoptic stations in southern regions of Iran were compared using the new SMS fuzzy index and ANFIS and RBF models. The methods used in this study like other studies are suitable method in monitoring, modeling and comparison. Among these, studies have been done in Iran including Zeinali and SafarianZingir's (2017) study on drought monitoring in the Lake Urmia basin using fuzzy index; Babayan et al. (2018); by the monthly forecast of drought in the southwestern basin of the country Using CFSv.2 model; Hejazizadeh and Javiyazadeh (2019). By studying the analysis of the spatial statistics of drought in Iran, Hejabi et al. (1997), by modifying the Palmer Drought Extreme Index (PDSI) based on ALSIS scheme in the Karkhe catchment area. Studies conducted abroad include Marchanta and Bloomfield (2018) by spatial and temporal modeling of underground drought conditions; Wei et al. (2019), by studying the modeling of drought loss assessment in southwestern of China based on a hyperbolic tensile activity; Gebremeskel et al. (2019) With the study of the causes, effects and flexibility of droughts in East Africa; Qi et al. (2019) by simulation and prediction of drought based on the SPI index using the ARMA-GARCH model. However, with all the comparisons of different models and indices in these researches, the new SMS fuzzy index and ANFIS and RBF models used in this study, have an acceptable performance in modeling and predicting of drought in the southern regions of Iran.

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Compliance with ethical standards

Conflict of interest The author declares that there is no conflict of interests regarding the publication of this manuscript.

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