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Monitoring and prediction of drought using TIBI fuzzy index in Iran

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ABSTRACT

The drought phenomenon is not specific to the region, affecting different parts of the world. One of these areas is Iran in Southwest Asia, suffering from this phenomenon in recent years. The purpose of this study was to model, analyze and predict the drought in Iran. So that, climatic parameters (precipitation, temperature, sunshine, minimum relative humidity and wind speed) were used at 30 stations during 29 years (1990-2018). For modelling the TIBI fuzzy index, at first, four indicators (SET, SPI, SEB, and MCZI) were been fuzzy in MATLAB software. Then the indices were compared and the TOPSIS model was used for prioritizing areas involved drought, followed by employing ANFIS adaptive artificial neural network model for predicting drought. Results showed that the new fuzzy index TIBI for classifying drought reflected four above indicators with high accuracy. Of these five climatic parameters used in this study, the temperature and precipitation exhibited the most impact on the fluctuation of drought severity. The severity of drought was more based on 6-month scale modelling than on 12-month one. The highest rate of drought occurrence was found at the Bandar Abbas station with 24.30% on a 12-month scale, and while the lowest was at the Shahrekord station with 0.36% on a six-month scale. Based on ANFIS model and TIBI fuzzy index, Bandar Abbas, Bushehr and Zahedan stations were more encountered ones to drought due to the TIBI index of 0.62, 0.96 and 0.97 respectively. According to the results in both 6- and 12-month scales, the southern regions of Iran were more severely affected by drought, which requires suitable water management in these areas.

Key words: Statistical evaluation, *TIBI index, Fuzzy, Drought, ANFIS.*

INTRODUCTION

Drought is one of the natural hazards that is dominated by climate change. Drought is also one of the most important natural disasters affecting agriculture and water resources (Shamsniya *et al.* 2008; Sobhani & Safarianzengir 2020; Sobhani *et al.* 2020a; Amazzal *et al.* 2020; Azizi *et al.* 2020). In recent years, different regions of the world have experienced more severe drought (Mirzaee *et al.* 2015). Also, drought is a natural phenomenon that occurs in all climatic conditions and all parts of the planet (Samidianfard & Asadi 2018; Safarianzengir *et al.* 2019; Mdehheb *et al.* 2020; Safarianzengir & Sobhani 2020; Zolfagharpour *et al.* 2020). Moreover, drought as a climatic phenomenon greatly affects all aspects of human activity (Zeinali & Safarianzengir 2017). Other authors have investigated various models in the field of droughtn(Haddadi & Heidari 2015; Montaseri & Amir Ataee 2015; Sobhani *et al.* 2015; Huanga *et al.* 2015; John Jan Darmian *et al.* 2015; Spinoni *et al.* 2015; Salahi & Mojtabapour 2016; Zolfaghari & Nouri Zamara 2016; Damavandi *et al.* 2016; Fanni *et al.* 2016; Alizadeh 2017; Zeinali *et al.* 2017; Jafari *et al.* 2018; Sobhani *et al.* 2018; Sobhani & Safarianzengir 2019a; Sobhani *et al.* 2019b; Sobhani *et al.* 2019a). Alizadeh *et al.* (2017) in a study about the modelling of dispersion of drought caused by climate change in Iran using dynamic system concluded that at all stations, the evapotranspiration rates of the reference plant increased from January through July, then decreased through December, and all stations reached their maximum levels in July. Kamasi *et al.* (2016) predicted drought with SPI

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and EDI indices using ANFIS modelling method in Kohgiluyeh and Boyer-Ahmad Province, Iran concluding that clustering increases the accuracy of modelling at the stage of calibration. Bayazidi (2018) evaluated the drought of synoptic stations in the west of Iran using HERBST method and comparative neuro-fuzzy model reporting that the coefficient of determination and also the error rate of the model were not better than those of Kermanshah, Mianeh and Piranshahr cities (stations). Torabipour *et al*. (2018) estimated droughts using smart grids suggesting that the use of wavelet neural network model could be effective in drought estimation. Ekhtiari khajeh & Dinpazhoh (2018) applied the effective drought index (EDI) to study drought periods. Their results exhibited that during a 60-year statistical period, the years of 2005-2007, 2005-2007 and 2002-2003 were the driest years in Tabriz, Anzali and Zahedan cities respectively. Zelki *et al*. (2017) used the standard precipitation index (SPI), Palmer drought index (PDSI) and satellite data to investigate the drought in Ethiopia. Their results revealed that the observed dry and wet periods in the north of the study area mainly depend on the change of the ENSO in the spring and summer seasons, while the drying trend in the south and southwest is associated with the warming of the Atlantic and the surface water temperature in the western Pacific Ocean. Kossada *et al*. (2017) studied hydrological alterations in a consistent approach to assess flood and drought changes, concluding that most of the methods used to detect extreme hydrologic trends are not suitable for trend detection, hence cannot be used in decision making. Therefore, they proposed a method based on the theory of implementation and threshold level. To study the regional climatic models (RCMS), Guinnium *et al.* (2017) examined the observed drought characteristics based on the SPEL in Central Asia, suggesting that employing RCMs are appropriate in humid areas, but not in arid areas, thus this model cannot achieve drought events for large spatial scales. Modaresirad *et al*. (2017) studied the meteorological and hydrological droughts in the west of Iran reporting that the SPI index can reveal two main characteristics of meteorological and hydrological droughts and also provide accurate estimation for recurrence of a severe drought. Kis *et al*. (2017) analyzed the dry and wet conditions using RCM concluding that uncertainty exists in weather forecasts. However, they suggested that probably dryer summers will occur in the southern regions, while more severe precipitation will occur during the winter and autumn in the northern regions of the study Carpatian area in the future. As a whole, Many authors have studied drought monitoring and prediction to date. However, no study was found about the drought phenomenon with a more accurate future vision, and if found, not adequately addressed this issue. So, we conducted this study to provide modeling, monitoring and predicting the drought using a new method in Iran.

MATERIALS AND METHODS

The present study conducts modelling, monitoring and prediction of drought in Iran using climatic data including precipitation, temperature, sunshine, relative humidity and wind speed (as monthly and yearly and in 6- and 12-month scales) for a 29-year period (1990-2018) at 30 stations by implication of TIBI new index (that calculated by four valid indicators of WMO including SET, SPI, SEB, MCZI). The location of the study area was presented in Fig. 1.

For modelling the new TIBI index, the climatic data were first normalized, then four indices including SET, SPI, SEB, MCZI were calculated separately. Moreover, the fuzzy modelling of the four indices was performed in the MATLAB software and eventually to prioritize the drought-affected areas, TOPSIS model was employed (Sobhani *et al.* 2020b). The Equation 1 was used for the standardization of the SET and SPI indicators, while SEB and MCZI indices were calculated using Equation 2.

$$x_{ij} = \frac{x_j max - x_j}{x_j max - x_j min} \quad \textbf{(1)}$$

$$x_{ij} = \frac{x_j - x_j min}{x_j max - x_j min} \quad \textbf{(2)}$$

In these equations, xij represents the standardized value, xj the desired index value, xjmax the maximum value in the number series, and xjmin the lowest value in the numeric series (Malchovsky 2007; Sobhani *et al.* 2019c; Sobhani & Safarianzengir 2019b). For converting the corresponding fuzzy numbers to linguistic expressions in regular words, we used membership functions in the MATLAB software, with the range of four inputs between 2 ± (Table 1) and the output index domain is between 0 and 1 (Table 2).

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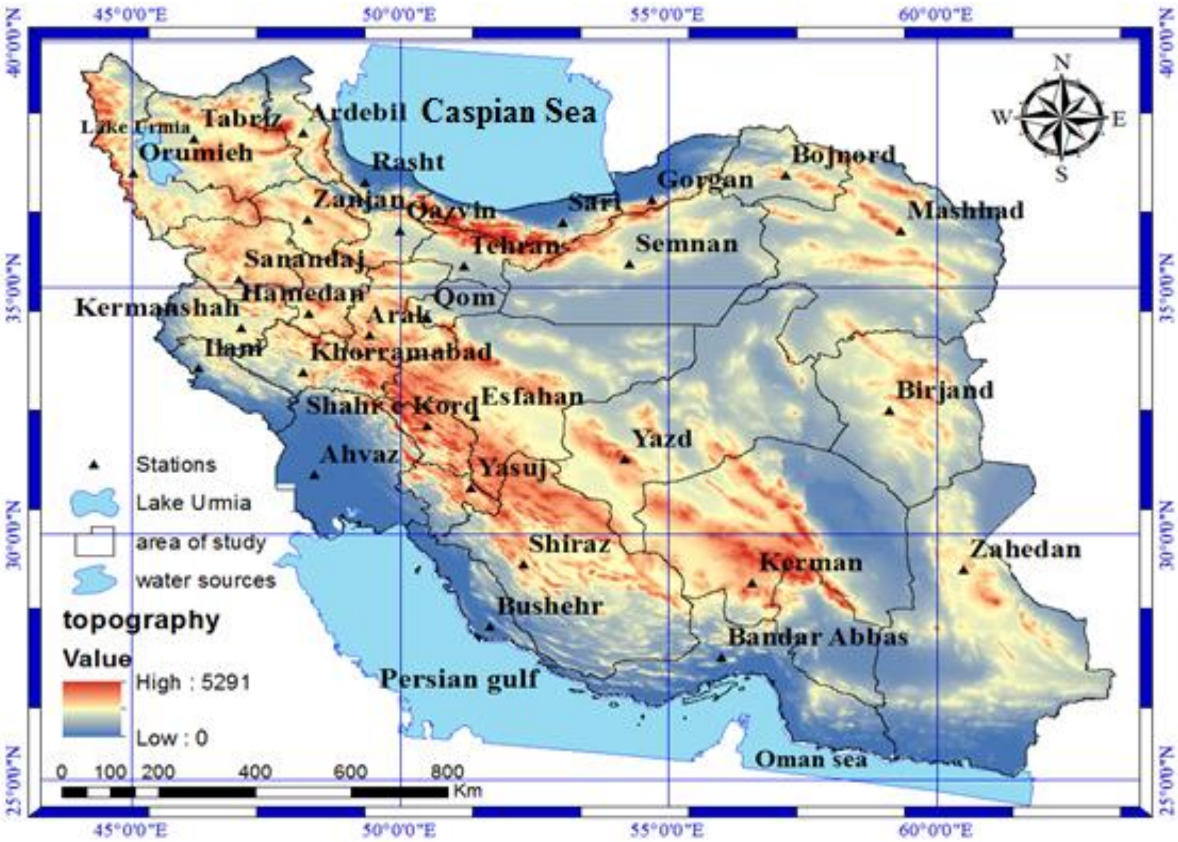

Fig. 1. Geographic location of the study area.

Table 1. Linguistic variables and fuzzy values of input indices (SET, SPI, SEB, MCZI).

Language variables	Fuzzy value
WVH	≥ 2
WH	1.5 - 1.99
WA	0.99 - 1.39
WS	0.5 - 0.99
N	-0.39 - 0.39
DS	-0.99 - 0.5
DA	-1 - 1.39
DH	-1.5 - 1.99
DVH	≤- 2

Table 2. Linguistic variables and fuzzy values of the new index derived from the modelling of TIBI.

Language variables	Fuzzy value
WVH	0, 0, 0, 0.1
WH	0, 0.1, 0.1, 0.2
WA	0, 0.2, 0.2, 0.4
WS	0.2, 0.35, 0.35, 0.5
N	0.3, 0.5, 0.5, 0.7
DS	0.5, 0.65, 0.65, 0.8
DA	0.6, 0.8, 0.8, 1
DH	0.8, 0.9, 0.9, 1
DVH	0.9, 1, 1 , 1

After the modelling of the TIBI fuzzy index, the effects of climate parameters on the drought in the studied stations were investigated, followed by drought monitoring. In the monitoring based on TIBI, we studied trend, the severity of persistence and frequency of drought occurrence. Then, the indices trends were determined using linear trend method. Frequency relationship was used to obtain the rate (%) of drought occurrence in different classes.

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TOPSIS model

The steps of TOPSIS Model are as follows:

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

$$X_{ij} = \begin{bmatrix} x_{11} & x_{22} & x_{1\,n} \\ x_{21} & x_{22} & x_{2\,n} \\ \vdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ x_{m\,1} & x_{m\,2} & \ldots x_{m\,n} \end{bmatrix}$$ **Matrix (1)**

Step 2: Unsealing data and the formation of an unscaled matrix, equation 3.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \qquad \textbf{(3)}$$

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.

$$V_{ij} = \begin{bmatrix} v_{11} & v_{22} & v_{1\,n} \\ v_{21} & v_{22} & v_{2\,n} \\ \vdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ v_{m\,1} & v_{m\,2} & \ldots v_{m\,n} \end{bmatrix}$$ **Matrix (2)**

Stage 4: Determining the positive ideals (the best function of each index), which are indicated by (A^*). Equations 4 and 5.

$$A^* = \left\{ (\max_i v_{ij} \mid j\epsilon J), (\min_i v_{ij} \mid j\epsilon J' \right\} \qquad \textbf{(4)}$$

$$A^* = \{v_1^*, v_2^*, \ldots v_n^*\} \qquad \textbf{(5)}$$

Step 5: Determining the negative ideals (the worst function of each indicator), which are represented by (A^-). Equations 6 and 7.

$$A^* = \left\{ (\min_i v_{ij} \mid j\epsilon J), (\max_i v_{ij} \mid j\epsilon J' \right\} \qquad \textbf{(6)}$$

$$A^- = \{v_1^-, v_2^-, \ldots v_n^-\} \qquad \textbf{(7)}$$

Step 6: Determining the distance of each option from negative and positive ideals (Si^+, Si^-), Equations 8 and 9.

$$d_j^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \qquad \textbf{(8)}$$

$$d_j^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \qquad \textbf{(9)}$$

Step 7: Determining the relative closeness of the options, which is calculated from equation 10.

$$C_i = \frac{d^-}{d_i^- + d_i^+} \qquad \textbf{(10)}$$

Step 8: Ranking options by (Ci+) value. So that $0 < c_{i+} < 1$. Accordingly, if as much as one option approaches the ideal point, c_{i+} trends to 1.

Hence, it will be the best option (Malchovsky 2007).

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ANFIS Neural Network Model

In this step, the possibility of modelling and prediction of dust was studied in the studied area using the ANFIS model, (Ansari 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. Fig. 2 presents a SOGNO fuzzy system with four inputs, one output and two laws as well as an equivalent ANFIS system. This system has two inputs including x and y and one output (Ahmadzade *et al.* 2010). At the end, the error rates of the resulting models were compared together and the function obtaining the lowest error rate at the lowest analyzing time, was selected as a membership function (Konarkuhi 2010).

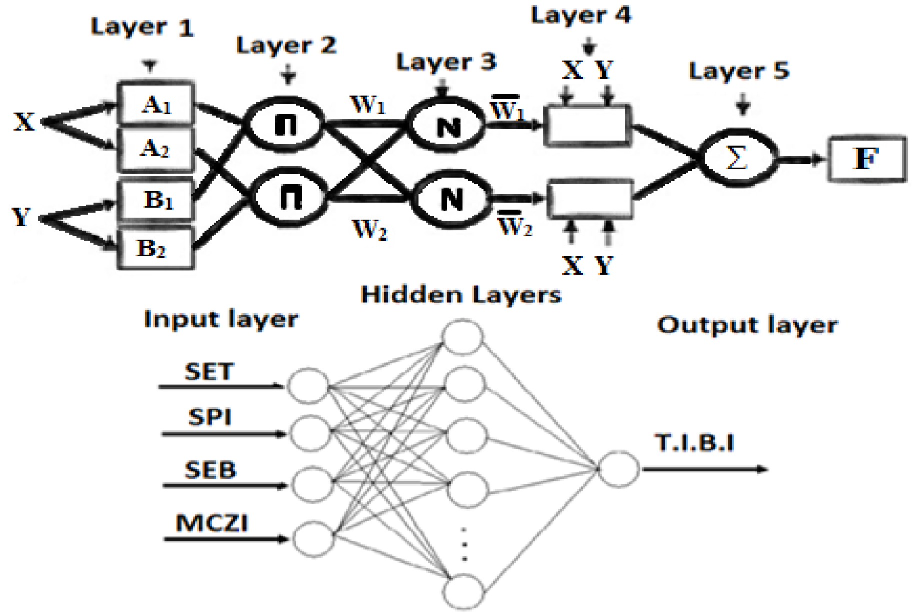

Fig. 2. ANFIS model structure.

RESULTS

Monitoring of drought fluctuations based on four integrated indicators in TIBI

In order to investigate the effects of drought fluctuation indices in drought conditions of stations, it is possible to analyze the alterations in the indicators (SET, SPI, SEB, and MCZI) as appeared in the TIBI index. Given a large number of stations, for the sake of better understanding, only the drought series graph of Bojnord station was presented in both 6- and 12-month scales (Figs. 3 and 4). In these Figs., the cross-sectional red line shows drought margin on a 6-month and more scales with 0.74 as well as a 12-month and more scales with 0.76.

The analyses of these figs. exhibit that at the 6- and 12-month scales in Bojnourd station, the amount of evapotranspiration was similar in drought conditions, decreasing from April 1994 through February 1999, though elevated after this month. However, the impact of rainfall at a 6-month scale was weaker than at a 12-month one. It means that from May 1993 through November 1997, an increasing trend occurred, there after followed by the same pattern. The indicators such as SET, SPI, SEB, and MCZI affected the TIBI index and displayed somehow a trend, indicating that the new TIBI fuzzy index reflects the four indicators well.

The scale of its drought classes was presented in Table 3. The TIBI index at the 6-month scale revealed a sharper figure than at the 12-month one.

According to the results obtained from the frequency of drought in the 6- and 12-month scales, the total drought rate (%) at 12-month scale was higher than at 6-month one. However, drought severity at 6-month scale was higher than at 12-month scale. In the study area at 6-month scale, the drought severity in Iran was more pronounced in the south, west and center than in the other parts. Bandar Abbas and Bushehr in the south, Ahwaz in the southwest and Zahedan in the south-east of the study area exhibited the most drought rate (16.62%, 11.24%, 14.13% and 6.62% respectively).

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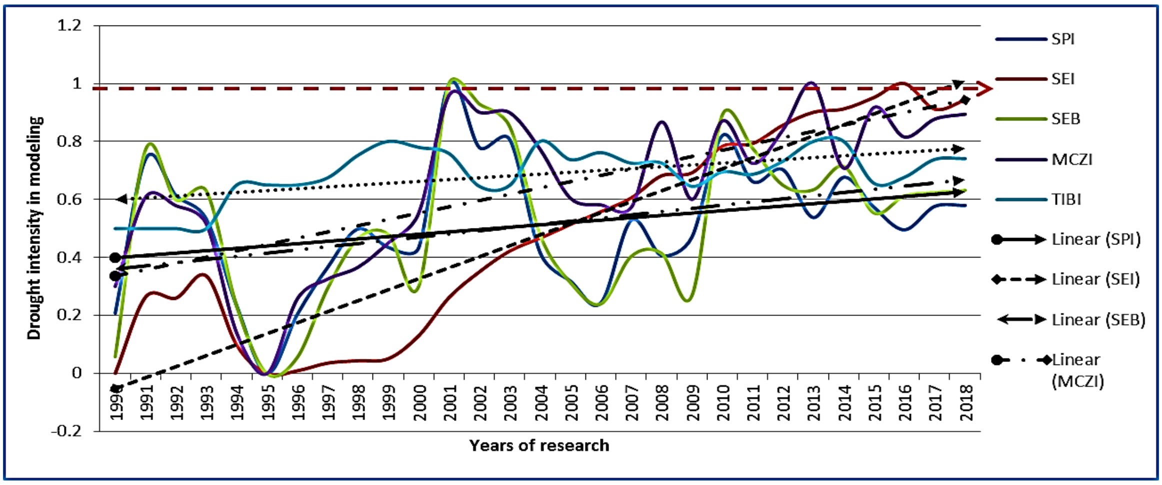

Fig. 3. The fluctuation of the indices at the Bojnourd station at a 6-month scale and period of 1990-2018.

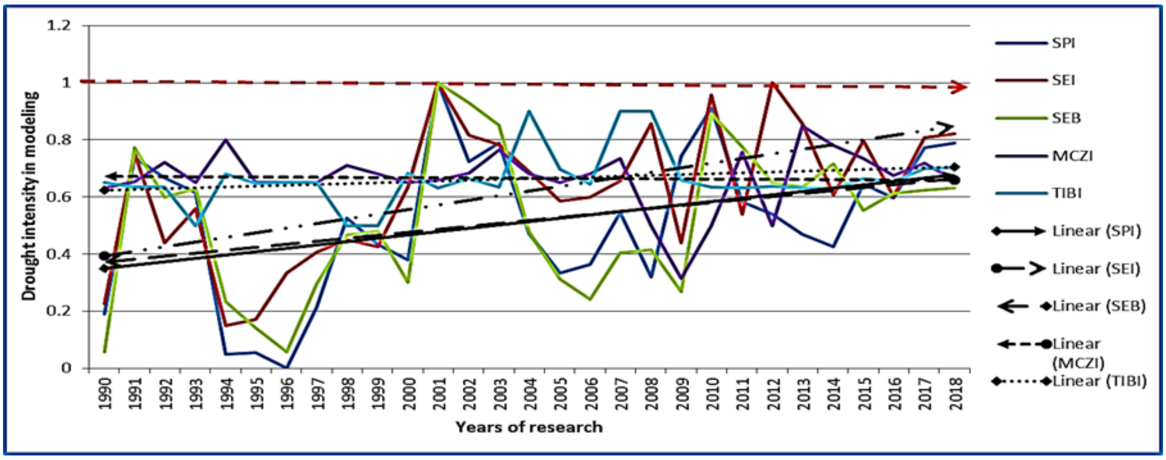

Fig. 4. The fluctuation of the indices at the Bojnourd station at the 12-month scale and period of 1990-2018.

Table 3. Drought severity classification based on fuzzy modelling of TIBI.

Drought classes	The index value of T.I.B.I
Very severe drought	0.96-1
severe drought	0.87-0.96
moderate drought	0.74-0.87
mild drought	0.59-0.74
Normal drought	0.44-0.59
Mild wet season	0.29-0.44
Moderate wet season	0.15-0.29
Severe wet season	0.06-0.15
The very severe wet season	0.-0.06

Stations with a lower drought severity were located more frequently in the north-west, north and west parts of the region including Urmia and Ardebil with 1.10% and 1.88%; in the west including Ilam and Yasuj with 1.61% and 2.01%; and finally in the north including Rasht and Gorgan with 1.26% and 0.87% respectively (Table 4). According to the model, in the 12-month scale, semi-southern regions of Iran were more exposed to drought. Bandar Abbas and Bushehr in the south of Iran with drought frequency of 24.30% and 14.83%, Ahvaz with 18.47% in the southwest, Kerman with 6.74% in southeast exhibited the highest drought occurrence in the 12-month scale, while Birjand (1.70%) and Bojnurd (3.66%) in the northeast, Urmia (1.17) and Tabriz (2.66%) in northwest, Rasht (0.58%) and Sari 0.78%) in the north displayed the lowest drought frequency (Table 5). Depending on the definition of drought based on the TIBI index, values of 0.74 and higher, or from a mild drought class to higher, are raised as dry conditions. Accordingly, in the modeling of the TIBI fuzzy index, the drought

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severity at the 6-month scale was higher than at the 12-month one. Based on the results, the annual drought severity at the 6- and 12-month scales began since 1994 and 1996 respectively, continuing ascending.

Assessment of drought-affected areas based on the TOPSIS model

Prioritization of the stations involved in drought in Iran was analyzed using TOPSIS model. To calculate and analyze the statistical data, each of the parameters took weight. Then the desirability and non-desirability of each of the studied stations were investigated in terms of climatic indices. Finally, an appropriate option was selected from an approximate approach to ideal proportions (Sobhani & Safarianzengir 2018). The results of the implementation of the TOPSIS model using the degree of importance of the criteria derived from the entropy method indicated that in terms of drought, by combining the two 6 and 12-month scales, more and fewer places involved with drought. Based on the TOPSIS model, Bandar Abbas, Ahvaz and Bushehr in the south and southwest of Iran with priority values of 1, 0.78, and 0.62 were the most affected stations by the drought respectively, while Gorgan, Shahre-Kord and Urmia in the north and west regions with 0.026, 0.033, 0.03 and 0.035, respectively had less priority for drought occurrence (Table 6) (Fig. 5).

Table 4. The frequency (%) of drought incidence in different classes in the 6-month time scale and study period (1990-2018).

No.	Station	Normal	mild drought	moderate drought	severe drought	Very severe drought	very severe wet season	total
1	Ormia	0.03	1.19	0.15	0.82	0.13	0	1.10
0	Tabriz	1.41	0.47	1.04	1.09	0.07	0.01	2.20
3	Ardebil	3.25	0.36	1.21	0.58	0.09	0.03	1.88
4	Esfahan	0.56	1.25	0.26	0.19	0.47	0	0.92
5	Ilam	1.64	0.08	1.5	0.11	0	0	1.61
6	Boushehr	3.99	7.89	4.54	6.11	0.59	0	11.24
7	Tehran	1.74	2.41	1.3	2.23	0.02	0	3.55
8	Shahrekord	1.21	1.54	0.23	0.11	0.02	0	0.36
9	Birjand	2.34	3.87	0.45	0.02	0	0	0.47
10	Mashhad	1.4	4.41	1	1.57	0.11	0	2.68
11	Bojnord	1.5	1.15	3.09	2.12	0.04	0	5.25
12	Ahvaz	4.54	9.12	6.47	7.15	0.51	0	14.13
13	Zanjan	1.18	4.12	2.74	3.3	0	0	6.04
14	Semnan	2.14	5.18	3.13	0.95	0	0	4.08
15	Zahedan	1.44	3.19	1.48	5.10	0.04	0	6.62
16	Shiraz	1.10	4.71	1.09	0.64	0.14	0	1.87
17	Ghazvin	2	2.23	2.11	1.45	0	0	3.56
18	Ghom	1.45	1.17	1.23	4.87	0	0	6.10
19	Sanandaj	2.36	2.09	1.85	3.58	0.05	0	5.48
20	Kerman	1.31	3.07	3.87	1.89	0.03	0	5.79
21	Kermanshah	0.64	4.48	1.25	2.85	0	0	4.10
22	Yasouj	1.41	1	1.65	0.26	0.10	0	2.01
23	Gorgan	1.41	1.43	0.12	0.75	0	0	0.87
24	Rasht	0.74	3.74	0.12	1.14	0	0	1.26
25	Khorramabad	0.54	2.28	1.31	0.12	0.09	0	1.52
26	Sari	0.14	2.74	1.08	0.45	0.18	0	1.71
27	Arak	1.47	1.68	2.74	2.18	0.23	0	5.15
28	Bandarabbas	5.18	12.58	8.07	8.19	0.36	0	16.62
29	Hamedan	0.32	1.10	3.85	0.08	0	0	3.93
30	Yazd	0.87	3.86	1.35	0.79	0.02	0	2.16

Drought prediction based on ANFIS model

After modelling drought indices and reassurance, TIBI index was predicted for the next 16 years using the ANFIS adaptive neural network model. After verifying the validity of neural network models in modelling, ANFIS neural network model revealed more precision for predicting drought phenomena. Drought index data of TIBI was estimated for the period of 2019-2033. Based on the results of predictions, Bandar Abbas, Bushehr and Zahedan, with the TIBI index of 0.62, 0.96 and 0.97 in southern Iran, were more exposed to drought for the coming years while the Urmia, Tabriz and Shahr-e-Kord displayed the lowest rate of drought based on the TIBI index with 0.17, 0.15 and 0.12 respectively (Fig. 6). In this study, we performed modelling, monitoring and prediction of drought phenomenon in Iran.

Table 5. The frequency percent of drought incidence in different classes in the 12-month scale and statistical period (1990-2018).

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No.	Station	Normal	Mild drought	Moderate drought	Severe drought	Very severe drought	Very severe wet season	total
1	Ormia	0.11	0.69	1.12	0.12	0.91	0.14	1.17
0	Tabriz	0.12	1.96	3.59	2.16	0.41	0.09	2.66
3	Ardebil	0.40	2.37	0.76	2.28	0.49	0.011	2.781
4	Esfahan	0.13	1.89	1.59	0.48	0.99	0.39	1.86
5	Ilam	0.09	2.99	2.98	2.69	0.39	0.10	3.18
6	Boushehr	0	8.38	8.02	5.69	7.79	1.35	14.83
7	Tehran	0.17	3.84	3.12	2.78	1.63	0.16	4.57
8	0	0.14	2.84	1.78	0.47	0.98	0.18	1.63
9	Birjand	0.09	2.89	1.81	0.87	0.79	0.04	1.70
10	Mashhad	0.08	4.49	3.51	2.01	2.61	0.13	4.75
11	Bojnord	0.07	2.69	2.39	2.14	1.49	0.03	3.66
12	Ahvaz	0	10.96	10.66	7.14	9.89	1.44	18.47
13	Zanjan	0.06	5.98	5.41	3.89	2.76	0	6.65
14	Semnan	0.04	3.47	4.13	2.93	0.84	0.01	3.78
15	Zahedan	0	3.81	2.79	2.56	3.08	0.24	5.88
16	Shiraz	0.07	2.58	2.49	1.74	0.44	0.29	2.47
17	Ghazvin	0.01	1.78	4.69	3.36	2.38	0.13	5.87
18	Ghom	0.12	3.84	2.96	2.76	3.79	0.01	6.56
19	Sanandaj	0.19	4.87	3.85	3.69	2.45	0.09	6.23
20	Kerman	0	2.98	2.51	1.69	4.63	0.69	6.74
21	Kermanshah	0.13	1.87	4.04	3.13	1.71	0.04	4.88
22	Yasouj	0.14	2.96	3.36	2.28	2.37	0.15	4.80
23	Gorgan	0.24	2.57	1.36	0.29	0.81	0	1.10
24	Rasht	0.63	1.68	1.71	0.49	0.09	0	0.58
25	Khorramabad	0.11	1.41	3.36	2.56	0.99	1.94	5.49
26	Sari	0.67	3.89	1.14	0.07	0.14	0.85	0.79
27	Arak	0.41	3.52	2.14	1.98	1.11	0.17	3.26
28	Bandarabbas	0	14.46	13.19	10.42	11.89	1.99	24.30
29	Hamedan	0.18	0.76	2.81	2.74	0.09	0	2.83
30	Yazd	0	0.98	2.91	2.51	0.47	0.08	3.06

Table 6. Prioritization of drought-influenced stations based on the TOPSIS model during the study period (1990-2018).

Station	TOPSIS value	Station	TOPSIS value	Station	TOPSIS value
Kermanshah	0.203	Bojnord	0.2147	Ormia	0.0351
Yasouj	0.1495	Ahvaz	0.7898	Tabriz	0.0992
Gorgan	0.0263	Zanjan	0.2976	Ardebil	0.0931
Rasht	0.0356	Semnan	0.1795	Esfahan	0.0466
Khorramabad	0.1611	Zahedan	0.2982	Ilam	0.0969
Sari	0.0537	Shiraz	0.0855	Boushehr	0.6291
Arak	0.205	Ghazvin	0.2122	Tehran	0.1805
Bandarabbas	1	Ghom	0.2973	Shahrekord	0.0333
Hamedan	0.1578	Sanandaj	0.2724	Birjand	0.0359
Yazd	0.1072	Kerman	0.2509	Mashhad	0.1624

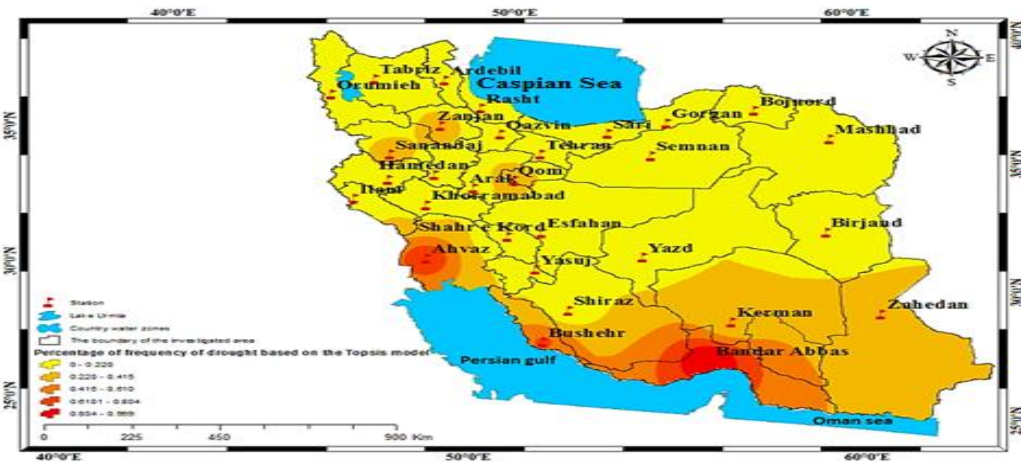

Fig. 5. The final map of areas affected by drought in Iran based on the TOPSIS model during the study period (1990-2018).

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This method has been used in a few studies and considered as a suitable method for monitoring, analysis and comparison. Alizadeh *et al*. (2017), e.g. once working on the modelling dispersion of droughts due to climate change in Iran using a dynamical system and also Zeinali & Safarianzengir (2017) on drought monitoring in the Lake Urmia Basin using the fuzzy index concluded that this method exhibits acceptable performance. Fathi-Zadeh *et al.* (2017) once working on the relationship between meteorological drought and solar variables in some of interconnection stations in Iran, and finally, Parsamehr & Khosravani (2017) used TOPSIS model and verified the efficiency of the models. Models presented in the current study are also useful in modelling, monitoring and predicting the drought phenomenon in Iran.

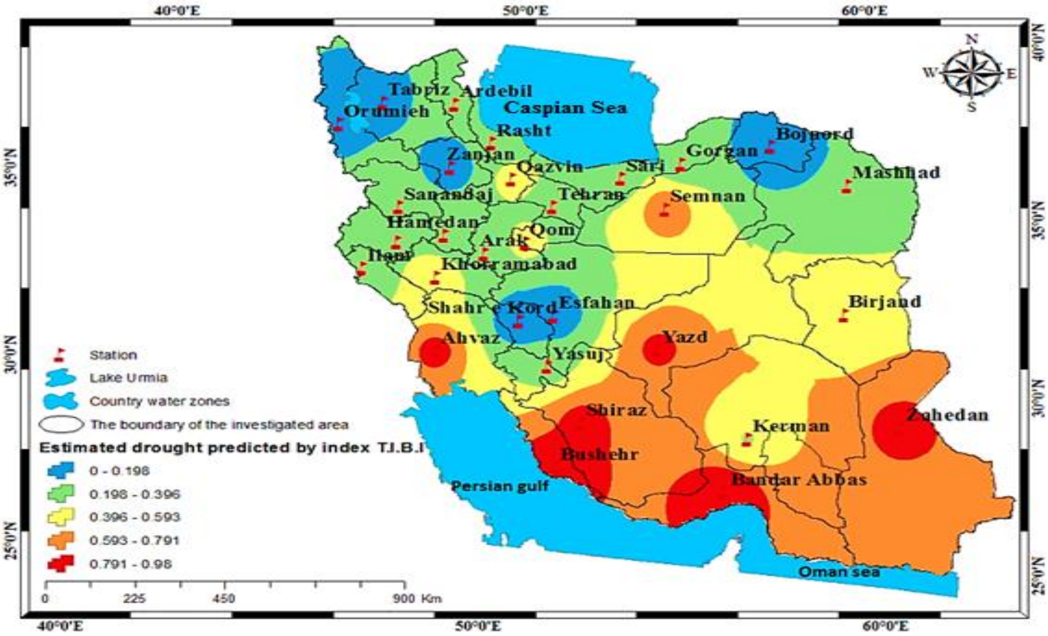

Fig. 6. Drought mapping in simulated years based on TIBI model during statistical period (2019-2033).

DISCUSSION

Drought is a natural disaster that is gradually evolving under the influence of climatic abnormalities over a long period. In recent years, various parts of the Middle East have faced drought, including Iran in Southwest Asia. Drought is one of the natural hazards that has been gradually evolving over the years through the climatic fluctuations and has its effects on the different parts of the environment. One of these areas is in Iran, which in recent years has been encountered drought in its different parts, especially the southern regions with high intensity. In this study, the drought phenomenon was predicted in two 6- and 12-month scales using the TIBI new fuzzy index. The results of the study revealed that the total frequencies of drought were higher at 12- month scale than at 6-month one. However, the severity of the 6-month drought was higher than that of 12-month one. At a 12-months scale, drought repetitions and its continuity were higher than at 6-month one. The drought was less continuous in short-run time scale and affected by temperature, while the severity of drought in the long periods was less responsive to rainfall variations. The highest rates (%) of drought incidence in a 6-month scale were found in Bandar Abbas, Bushehr, Ahvaz and Zahedan in the southern part of the study area with the frequency of drought of 16.62%, 11.24%, 14.13% and 6.62% respectively, while the lowest at 6-month scale were in Urmia, Ardebil, Ilam and Yasuj with frequency of 1.10%, 1.88%, 1.61% and 2.01% respectively. Moreover, Rasht and Gorgan exhibited a drought severity of 1.26 and 0.87 in the north and west of Iran. The highest frequency of drought incidence in a 12-months scale were found in Bandar Abbas and Bushehr with drought frequency of 24.30% and 14.83%, Ahvaz with 18.47% and Kerman with 6.74% in the south and southwest of Iran respectively. The lowest frequencies at the 6-month scale were found in Birjand (1.70%), Bojnurd (3.66%), Urmia (1.17%) and Tabriz (2.66%) in the northwest as well as Rasht (0.58%) and Sari (0.78%) in the northern part of Iran. Also, based on TOPSIS model, Bandar Abbas, Ahwaz and Bushehr in the south and southwest of Iran were prioritized with high drought severity (1, 0.78, and 0.62 respectively). The prediction of drought based on the ANFIS comparative neural network model indicate that Bandar Abbas, Bushehr and Zahedan with the TIBI index of 0.62, 0.96 and 0.97 respectively in southern parts of Iran will be mostly encountered to drought for the coming years.

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پایش و پیش بینی خشکسالی با استفاده از شاخص فازی TIBI در ایران

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چکیده

پدیده خشکسالی مختص ناحیه‌ای خاص نبوده و مناطق مختلف جهان از آن متأثر است. یکی از این مناطق، ایران در جنوب غرب آسیا است که در چند سال اخیر از این پدیده رنج می‌برد. هدف پژوهش حاضر مدل‌سازی، تحلیل و پیش‌بینی خشکسالی در ایران است. برای این کار ابتدا فراسنجه‌های اقلیمی: بارش، دما، ساعات آفتابی، کمینه رطوبت نسبی و سرعت باد در بازه زمانی ۲۹ ساله (۲۰۱۸- ۱۹۹۰) در ۳۰ ایستگاه ایران استفاده شد. برای مدل‌سازی، شاخص فازی TIBI ابتدا چهار شاخص (SET, SPI, SEB, MCZI) با استفاده از منطق فازی در نرم‌افزار MATLAB فازی‌سازی شدند و در نهایت برای پیش‌بینی از مدل شبکه عصبی مصنوعی تطبیقی ANFIS بهره گرفته شد. یافته‌های پژوهش نشان داد شاخص فازی نوین TIBI طبقات خشکسالی، چهار شاخص مذکور را با دقت بالا در خود منعکس کرد. از بین ۵ فراسنجه اقلیمی مورد استفاده در این پژوهش، دما و بارش در نوسان شدت خشکسالی بیش‌ترین تأثیر را داشت. شدت خشکسالی براساس مدل‌سازی انجام شده در مقیاس ۶ ماهه بیش‌تر از ۱۲ ماهه بود، بیش‌ترین درصد رخداد خشکسالی در ایستگاه بندرعباس با مقدار (۲۴/۳۰) در مقیاس ۱۲ ماهه و کم‌ترین آن در ایستگاه شهرکرد با مقدار درصد فراوانی خشکسالی ۰/۳۶٪ در مقیاس ۶ ماهه اتفاق افتاد. پیش‌بینی خشکسالی شاخص فازی TIBI براساس مدل ANFIS ایستگاه‌های بندرعباس، بوشهر و زاهدان به ترتیب با مقدار شاخص TIBI (۰/۶۲، ۰/۹۶ و ۰/۹۷) در نیمه جنوبی ایران بیش‌تر در معرض خشکسالی قرار گرفتند. براساس نتایج کلی پژوهش در هر دو مقیاس ۶ و ۱۲ ماهه مناطق نیمه جنوبی ایران از شدت بیش‌تر خشکسالی برخوردار بود که نیازمند مدیریت دقیق و کارآمد در مدیریت منابع آبی در این مناطق است.

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