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Modelling, evaluation and simulation of drought in Iran, southwest Asia

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The drought phenomenon is not specific to a region and it affects different parts of the world. One of these areas is Iran in southwest Asia, which suffered from this phenomenon in recent years. The purpose of this study is to model, analyze and predict the drought in Iran. To do this, climatic parameters (precipitation, temperature, sunshine, minimum relative humidity and wind speed) were used at 30 stations for a period of 29 years (1990–2018). For modelling of the Combined Indicateurs based on four indices, Standardized Evapotranspiration Torrent White Index (SET), Standardized Precipitation Index (SPI), Standardized Evapotranspiration Blanney Creedal FAO Index (SEB) and Modified CZI Index (MCZI) were fuzzy in Matlab software. Then the indices were compared and the Topsis model was used for prioritizing areas involved with drought. Finally, Anfis adaptive artificial neural network model was used to predict. Results showed that the new fuzzy index TIBI for classifying drought reflected above four indicators with high accuracy. Of these five climatic parameters: (precipitation, temperature, sunshine, minimum relative humidity and wind speed) used in this study, the temperature and precipitation parameters had the most effect on the fluctuation of drought severity. The severity of the drought was more based on 6-month scale modelling than 12 months. The highest percentage of drought occurrence was at Bandar Abbas station with a value of 24.30 on a 12-month scale and the lowest was in Shahrekord station with a percentage of 0.36% on a 6-month scale. Based on Anfis model and TIBI fuzzy index, Bandar Abbas, Bushehr and Zahedan stations were more exposed 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 months scale, the southern regions of Iran were more severely affected by drought, which requires suitable water management in these areas.

Keywords. Simulation; fuzzy; drought; artificial neural network; southwest Asia.

1. Introduction

Drought is one of the natural hazards that are dominated by climate change. Drought is also one of the most important natural disasters affecting agriculture and water resources (Shamsniya *et al.* 2008). In recent years, different regions of the world have experienced more severe drought (Mirzaee *et al.* 2015). In addition, drought is a natural phenomenon that occurs in all climatic conditions and in all parts of the planet (Samidianfard and Asadi 2018). Drought is caused by the lack of atmospheric rainfall such as rain and snow (Jinum and Jeonbin 2017; Quesada *et al.* 2017; Jonilda *et al.* 2019; Kinga *et al.* 2019). Also, drought as a climatic phenomenon greatly affects all aspects of human activity (Zeinali and Safarian Zengir 2017). Drought in recent decades has become more pronounced in various arid and semi-arid regions (Bappa and Kalach 2019; Indirarani *et al.* 2019;

Mahmoudin *et al.* 2019; Zilong *et al.* 2019). Drought is a common hydrometeorological phenomenon and a pervasive global risk (Harry *et al.* 2019; Olusola and Jiahua 2019; Xiao *et al.* 2019).

Other internal and external researchers have investigated various models in the field of drought, including Hartman *et al.* (1990), Salajeghe and Fath-Abadi (2009), Ansari *et al.* (2010), Gholamali *et al.* (2011), Haddadin and Hideri (2015), Huanga *et al.* (2015), James *et al.* (2015), John Darmian *et al.* (2015), Montaseri and Amirataee (2015), Sobhani *et al.* (2015), Spinoni *et al.* (2015), Touma *et al.* (2015), Damavandi *et al.* (2016), Fanni *et al.* (2016), Hao *et al.* (2016), Salahi and Mojtabapour (2016), Zolfaghari and Nourizamara (2016), Alam *et al.* (2017), Alizadeh *et al.* (2017), Liu *et al.* (2017), Zeinali *et al.* (2017), Ghorbani *et al.* (2018), Jafari *et al.* (2018), Gebremeskel *et al.* (2019), Marchanta and Bloomfield (2018), Montaseri *et al.* (2018), Qi *et al.* (2019), Wei *et al.* (2019), Sobhani et al (2018), Sobhani and Safarianzengir (2019), Sobhani *et al.* (2019), Safarianzengir *et al.* (2019) and Safarianzengir and Sobhani (2020).

The results of Alizadeh *et al.* (2017), in a research named, the modelling of dispersion of drought caused by climate change in Iran using dynamic system, conclude that in all stations, the values of evapotranspiration of the Evaporation and transpiration Reference Plant recourse plant) increased from January to July, then decreased to December, and all stations reached their maximum levels in July.

Kamasi *et al.* (2016) conducted a drought prediction with Standardized Precipitation Index (SPI) and Effective drought index (EDI) indices using Adaptive network-based fuzzy inference system (ANFIS) modelling method in Kohgiluyeh and Boyer-Ahmad province. They concluded that clustering increases the accuracy of modelling at the stage of calibration. Bayazidi (2018) evaluated the drought of synoptic stations in the west of the country using Artificial Neural Network (ANN) method and comparative neuro-fuzzy model. They concluded that the coefficient of determination and the error rate of the model were not better than those of Kermanshah, Mianeh and Piranshahr stations. Torabipour *et al.* (2018) estimated droughts using smart grids and showed that the use of wavelet neural network model could be effective in drought estimation. Akhtari and Dinpazhoh (2018) applied EDI to study drought periods. The results showed that the years of 2002–2003, 2004–2005 and 2006–2007 are the driest years for Tabriz, Bandar Anzali and Zahedan stations, respectively, during the 60-year statistical period.

Zelekei *et al.* (2017) have used the Standard Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) and satellite data to investigate the drought in Ethiopia. The results showed 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 season, 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. Precipitation anomalies reflect variability in surface water (Martha *et al.* 2013; Cammalleri *et al.* 2015; Huiqian *et al.* 2019). Monitoring and forecasting of drought in the agricultural sector are very important (Zexi *et al.* 2019; Zengchao *et al.* 2017). Runping *et al.* (2019), in a study, developed a drought monitoring model using deep learning based on remote sensing data and concluded that the correlation coefficient between the model drought index and soil relative humidity at 10 cm depth was greater than 0.550 ($P < 0.01$). Bandyopadhyay *et al.* (2019) In research into critical analysis and suggestion of new drought policy made special reference to Gujarat (India) and they concluded that the evolution of drought policies at the national and state levels should have an ongoing trend. Modaresirad *et al.* (2017) studied meteorological and hydrological drought in the west of Iran. The results showed that the SPI index can show two main characteristics of meteorological and hydrological droughts and also provide accurate estimation for recurrence of a severe drought. Kis *et al.* (2017) in their research, analyzed the dry and wet conditions using RCM and concluded that uncertainty exists in weather forecasts. However, according to their results, probably dryer summers will occur in the southern regions and more severe precipitation will occur in the winter and autumn in the northern regions of the study area in the future.

According to the present study, many researchers have conducted researches on drought monitoring and prediction, but an investigation that can show the drought phenomenon with a more accurate future vision is not done; even if it is done, not adequately to address the issue. Accordingly, the researchers conducted this research to model, monitor and predict the drought with the new method in Iran.

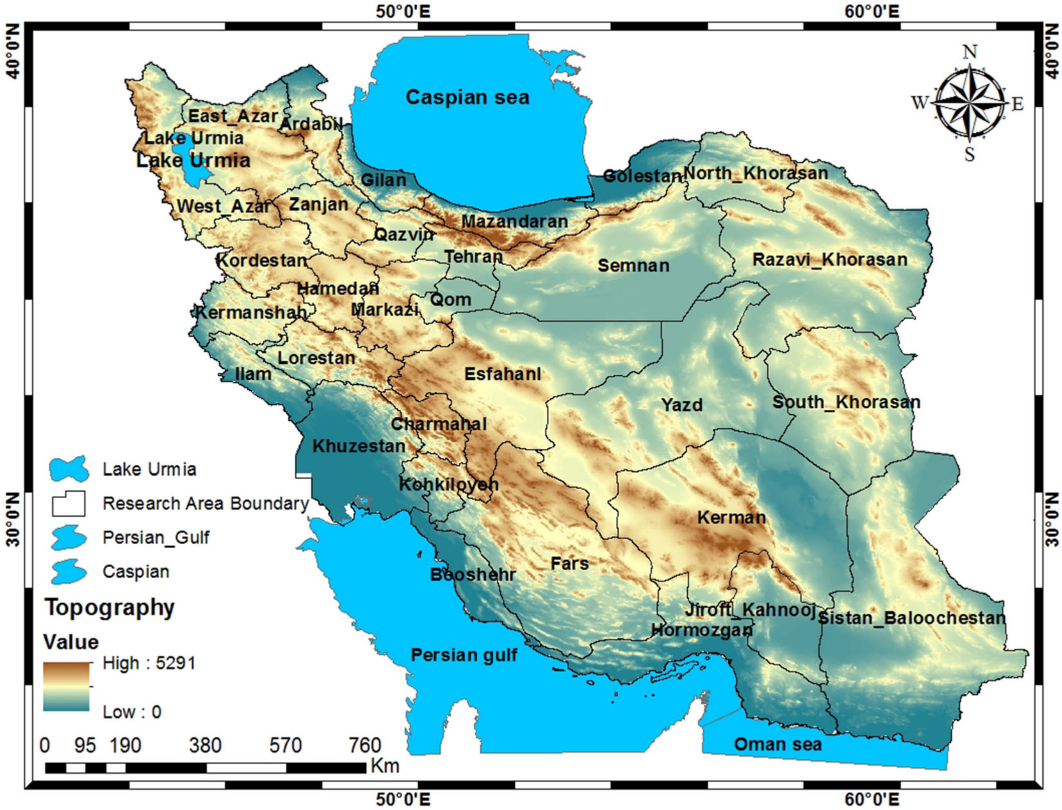

Figure 1. Geographic location of the study area.

2. 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 months' scale) for the time period 1990–2018 (29 yrs) for 30 stations by implication of TIBI new index (calculated by four valid indicators of WMO including SET, SPI, SEB and MCZI). The position of the study area is presented in figure 1.

For modelling of the new TIBI index, the climatic data were first normalized, then four indices of SET, SPI, SEB, and MCZI were calculated separately and the fuzzy modelling of the four indices was performed in the Matlab software and eventually to prioritize the drought-affected areas, Topsis model was used. For the standardization of the SET, SPI indicators, it was used in equation (1) and SEB MCZI indices were used in equation (2).

$$x_{ij} = \frac{x_j \max - x_j}{x_j \max - x_j \min}, \qquad (1)$$

Table 1. *Linguistic variables and fuzzy values of input indices (SET, SPI, SEB, and 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 to 0.39
DS	−0.99 to −0.5
DA	−1 to −1.39
DH	−1.5 to −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

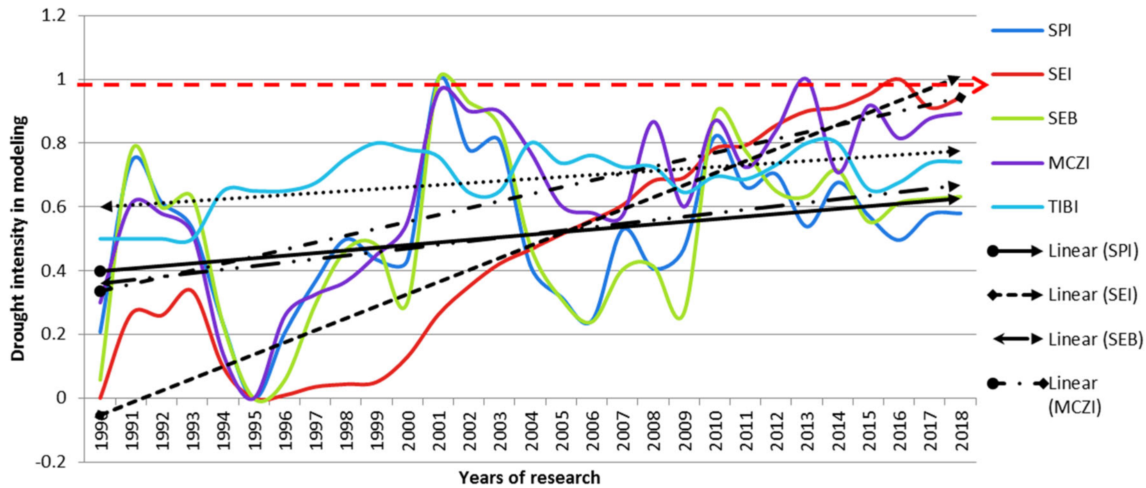

Figure 2. The fluctuation of the indices at the Bojnourd station at the 6-month scale and statistical period (1990–2018).

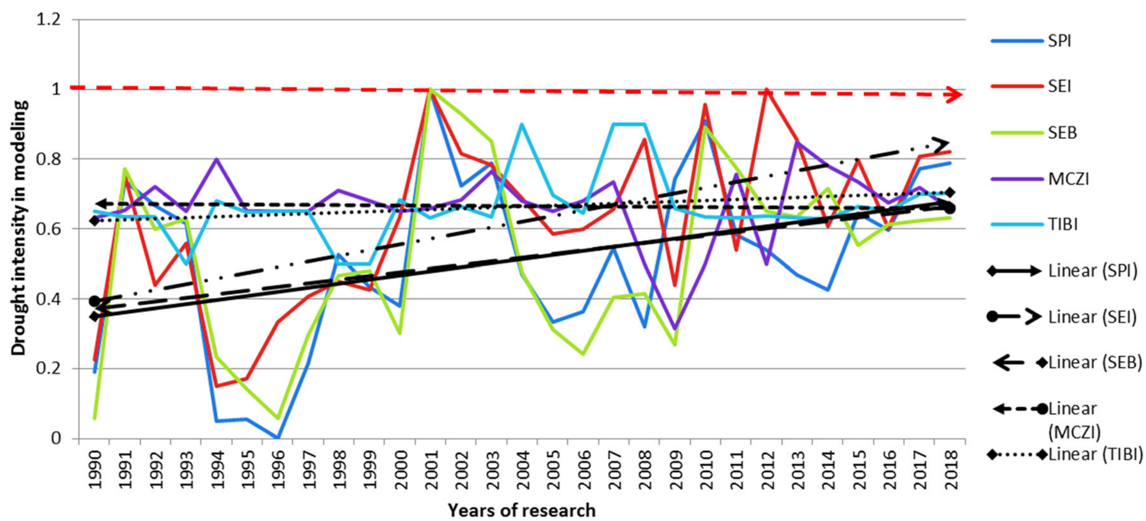

Figure 3. The fluctuation of the indices at the Bojnourd station at the 12-month scale and statistical period of (1990–2018).

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

Drought classes	Index value of TIBI
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
Very severe wet season	0.0–0.06

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

In these relationships, x_{ij} represents the standardized value, x_j the desired index value, $x_{j\max}$ the maximum value in the number series, and $x_{j\min}$ represents the lowest value in the numeric series (Mulchsfaki 2006). One of the ways in which linguistic expressions in regular words can be converted to their corresponding fuzzy numbers is to use 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).

After the modelling of the TIBI fuzzy index, the effect of climate parameters on the drought of the studied stations was investigated. Then drought was monitored. In drought monitoring based on TIBI, trend, the severity of persistence and frequency of drought occurrence were studied and the trend of the indices was determined by linear trend method. Frequency relationship was used to obtain the percentage of drought occurrence in different classes.

Table 4. *The frequency per cent of drought incidence in different classes in the 6-month time scale and statistical period (1990–2018).*

No.	Station name	Very severe wet season	Severe wet season	Moderate wet season	Mild wet season	Normal	Mild drought	Moderate drought	Severe drought	Very severe drought	Very severe wet season	Total
1	Ormia	0	0.5	0.19	0.14	0.03	1.19	0.15	0.82	0.13	0	1.10
2	Tabriz	0.01	0	0.23	0.19	1.41	0.47	1.04	1.09	0.07	0.01	2.20
3	Ardabil	0.03	0	0.39	0.39	3.25	0.36	1.21	0.58	0.09	0.03	1.88
4	Esfahan	0	0.09	0.01	0.01	0.56	1.25	0.26	0.19	0.47	0	0.92
5	Ilam	0	0	0	0.05	1.64	0.08	1.5	0.11	0	0	1.61
6	Boushehr	0	0	0	0.01	3.99	7.89	4.54	6.11	0.59	0	11.24
7	Tehran	0	0.06	0	0.61	1.74	2.41	1.3	2.23	0.02	0	3.55
8	Shahrekord	0	0	0.08	0.32	1.21	1.54	0.23	0.11	0.02	0	0.36
9	Birjand	0	0	0	0	2.34	3.87	0.45	0.02	0	0	0.47
10	Mashhad	0	0	0.14	0.11	1.4	4.41	1	1.57	0.11	0	2.68
11	Bojnord	0	0	0.04	0	1.5	1.15	3.09	2.12	0.04	0	5.25
12	Ahvaz	0	0	0	0.09	4.54	9.12	6.47	7.15	0.51	0	14.13
13	Zanjan	0	0	0.12	0.41	1.18	4.12	2.74	3.3	0	0	6.04
14	Semnan	0	0	0.01	0.01	2.14	5.18	3.13	0.95	0	0	4.08
15	Zahedan	0	0	0	0.09	1.44	3.19	1.48	5.10	0.04	0	6.62
16	Shiraz	0	0	0.05	1.14	1.10	4.71	1.09	0.64	0.14	0	1.87
17	Ghazvin	0	0	0.03	0.11	2	2.23	2.11	1.45	0	0	3.56
18	Ghom	0	0	0.09	0.16	1.45	1.17	1.23	4.87	0	0	6.10
19	Sanandaj	0	0	0	0.29	2.36	2.09	1.85	3.58	0.05	0	5.48
20	Kerman	0	0	0	0.15	1.31	3.07	3.87	1.89	0.03	0	5.79
21	Kermanshah	0	0	0.01	0.18	0.64	4.48	1.25	2.85	0	0	4.10
22	Yasouj	0	0	0.04	0.25	1.41	1	1.65	0.26	0.10	0	2.01
23	Gorgan	0	0	0.28	0.36	1.41	1.43	0.12	0.75	0	0	0.87
24	Rasht	0	0	0.69	0.48	0.74	3.74	0.12	1.14	0	0	1.26
25	Khorramabad	0	0.09	0	0	0.54	2.28	1.31	0.12	0.09	0	1.52
26	Sari	0	0	0.03	0.06	0.14	2.74	1.08	0.45	0.18	0	1.71
27	Arak	0	0	0.01	0.07	1.47	1.68	2.74	2.18	0.23	0	5.15
28	Bandarabbas	0	0	0	0.21	5.18	12.58	8.07	8.19	0.36	0	16.62
29	Hamedan	0	0	0.09	0.09	0.32	1.10	3.85	0.08	0	0	3.93
30	Yazd	0	0	0	0	0.87	3.86	1.35	0.79	0.02	0	2.16

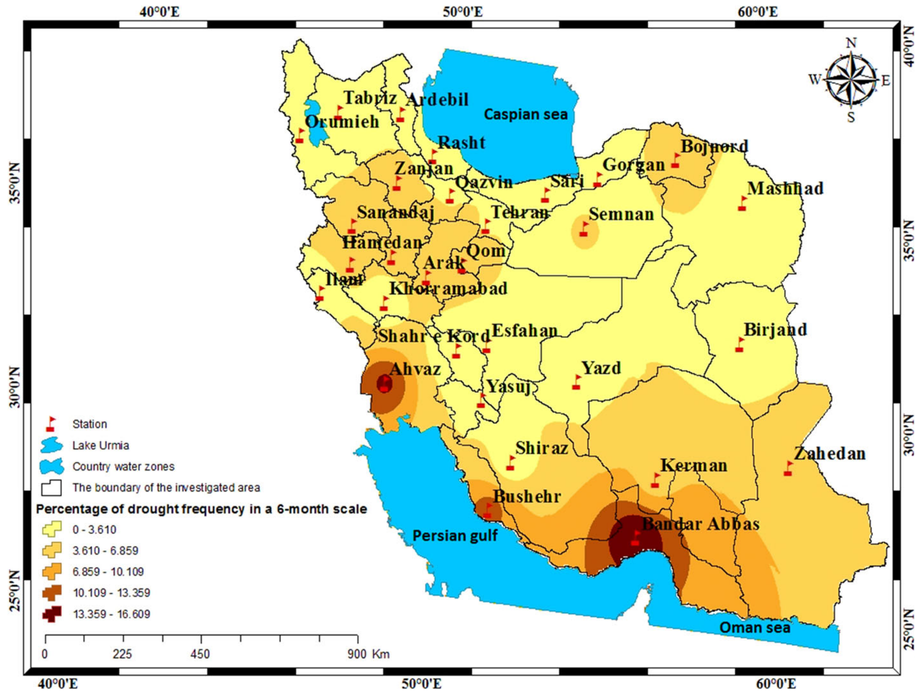

Figure 4. The zoning of the frequency per cent of drought occurrence in the studied stations in a 6-month scale and statistical period (1990–2018).

3. Results and discussion

3.1 *Monitoring of drought fluctuations based on four integrated indicators in TIBI*

In order to investigate the effect of indices on drought fluctuations in drought conditions of stations, it is possible to analyze the changes in the indicators (SET, SPI, SEB, and MCZI) as appeared in the TIBI index. Considering the 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 scale in figures 2 and 3. In these figures, the cross-sectional red line shows drought margin on a 6-month and more scale with the amount of 0.74 and on a 12-month and more scale with the amount of 0.76.

The analysis of these figures shows that at the 6- and 12-month scale at Bojnourd station, the amount of evapotranspiration was similar in drought conditions, which decreased from April 1994 to February 1999, and after this month an increase was observed, while the impact of rainfall on a 6-month scale is weaker than the 12-month scale. It means that from May 1993 to November 1997, an increasing trend occurred and after that followed by the same pattern. The indicators (SET, SPI, SEB, MCZI) affect the TIBI index and show 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 shows a sharper shape than the 12-month scale.

According to the results obtained from the frequency of drought in the 6 and 12-month scales, the total percentage of drought at 12-months was more than 6-months scale, but drought severity at 6-months scale was more than 12-months scale. In the study area at 6-months scale, the severity of the drought was more pronounced in the south, west and centre of Iran. The stations of Bandar Abbas, Bushehr in the south and Ahwaz in the southwest and Zahedan in the south-east of the study area had most percentages of drought (16.62, 11.24, 14.13 and 6.62, respectively). Stations with a lower percentage of drought severity were more frequently in north-west, north and west parts of the region including the stations of Urmia and Ardebil in northwest of Iran with frequency percentage of 1.10 and 1.88, Ilam and Yasuj with percentage of 1.61 and 2.01) in west of Iran, Rasht and Gorgan, with percentage of 1.26 and 0.87 in the north of the study area (table 4 and figure 4).

According to the model, at 12-month scale, semi-southern regions of Iran were more exposed to drought. The stations of Bandar Abbas and Bushehr in the south of the study area with

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

No.	Station name	Severe wet season	Moderate wet season	Mild wet season	Normal	Mild drought	Moderate drought	Severe drought	Very severe drought	Very severe wet season	Total
1	Ormia	0	0.32	0.09	0.11	0.69	1.12	0.12	0.91	0.14	1.17
2	Tabriz	0	0	0.26	0.12	1.96	3.59	2.16	0.41	0.09	2.66
3	Ardabil	0.01	0.03	0.42	0.40	2.37	0.76	2.28	0.49	0.011	2.781
4	Esfahan	0	0	0.04	0.13	1.89	1.59	0.48	0.99	0.39	1.86
5	Ilam	0	0.02	0.06	0.09	2.99	2.98	2.69	0.39	0.10	3.18
6	Boushehr	0	0	0	0	8.38	8.02	5.69	7.79	1.35	14.83
7	Tehran	0	0	0	0.17	3.84	3.12	2.78	1.63	0.16	4.57
8	Shahrekord	0	0	0.02	0.14	2.84	1.78	0.47	0.98	0.18	1.63
9	Birjand	0	0	0	0.09	2.89	1.81	0.87	0.79	0.04	1.70
10	Mashhad	0	0	0	0.08	4.49	3.51	2.01	2.61	0.13	4.75
11	Bojnord	0	0	0.02	0.07	2.69	2.39	2.14	1.49	0.03	3.66
12	Ahvaz	0	0	0	0	10.96	10.66	7.14	9.89	1.44	18.47
13	Zanjan	0	0	0.04	0.06	5.98	5.41	3.89	2.76	0	6.65
14	Semnan	0	0	0.02	0.04	3.47	4.13	2.93	0.84	0.01	3.78
15	Zahedan	0	0	0	0	3.81	2.79	2.56	3.08	0.24	5.88
16	Shiraz	0	0	0.03	0.07	2.58	2.49	1.74	0.44	0.29	2.47
17	Ghazvin	0	0	0.02	0.01	1.78	4.69	3.36	2.38	0.13	5.87
18	Ghom	0	0	0.07	0.12	3.84	2.96	2.76	3.79	0.01	6.56
19	Sanandaj	0	0	0	0.19	4.87	3.85	3.69	2.45	0.09	6.23
20	Kerman	0	0	0	0	2.98	2.51	1.69	4.63	0.69	6.74
21	Kermanshah	0	0	0.08	0.13	1.87	4.04	3.13	1.71	0.04	4.88
22	Yasouj	0	0	0.09	0.14	2.96	3.36	2.28	2.37	0.15	4.80
23	Gorgan	0	0	0.18	0.24	2.57	1.36	0.29	0.81	0	1.10
24	Rasht	0	0.24	0.51	0.63	1.68	1.71	0.49	0.09	0	0.58
25	Khorramabad	0	0	0	0.11	1.41	3.36	2.56	0.99	1.94	5.49
26	Sari	0	0.08	0.28	0.67	3.89	1.14	0.07	0.14	0.85	0.79
27	Arak	0	0	0.29	0.41	3.52	2.14	1.98	1.11	0.17	3.26
28	Bandarabbas	0	0	0	0	14.46	13.19	10.42	11.89	1.99	24.30
29	Hamedan	0	0.02	0.13	0.18	0.76	2.81	2.74	0.09	0	2.83
30	Yazd	0	0	0	0	0.98	2.91	2.51	0.47	0.08	3.06

drought frequency per cent of 24.30 and 14.83, Ahvaz with 18.47 in the southwest of the study area, Kerman with the amount 6.74 in southeastern of Iran had the highest percentage of drought occurrence in the 12-month scale, but stations of Birjand (1.70) and Bojnurd (3.66) in the northeast, Urmia (1.17) and Tabriz (2.66) in northwestern of Iran, Rasht (0.58) and Sari (0.78) in north of Iran had the lowest percentage of drought frequency at the 12-month scale (table 5 and figure 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 modelling of the TIBI fuzzy index, the severity of drought at 6-month scale was more than the 12-month scale. Based on the results, the annual drought severity at 6-month and 12-month scale began since 1994 and 1996, respectively, and it has continued ascending.

3.2 *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 a weight and then the desirability and the lack of desirability of each of the studied stations was investigated in terms of climatic indices and, finally, an appropriate option was selected from an approximate approach to ideal proportions (Sobhani and Safarian Zengir 2018).

The results of the implementation of the TOPSIS model using the degree of importance of

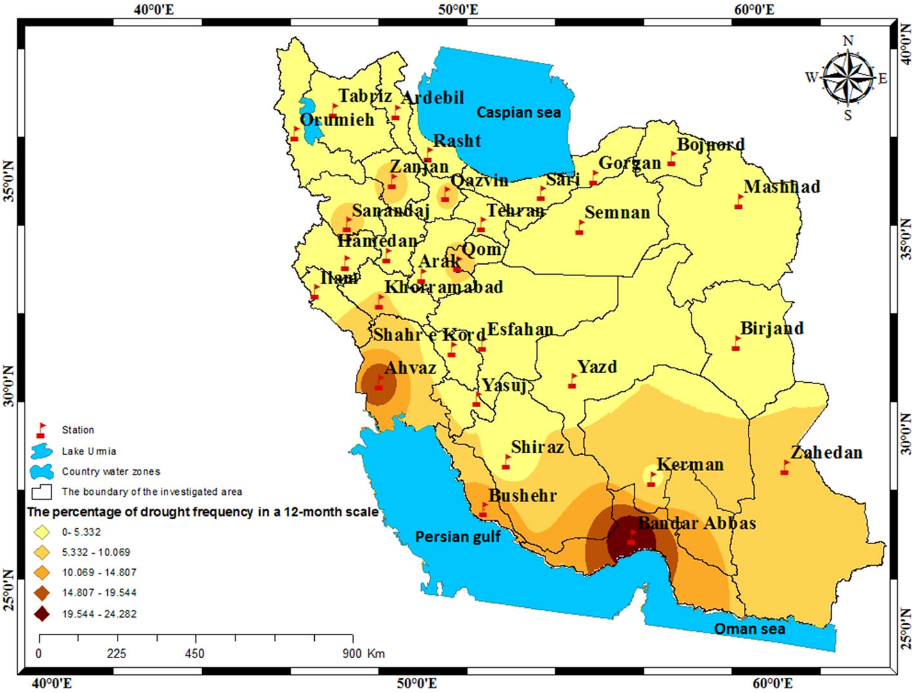

Figure 5. The zoning of the frequency per cent of drought occurrence in the studied stations in a 12-month scale and statistical period (1990–2018).

Table 6. *Prioritization of drought-infected stations based on the Topsis model during the statistical period (1990–2018).*

Station name	Topsis value	Topsis rating score	Station name	Topsis value	Topsis rating score	Station name	Topsis value	Topsis rating score
Kermanshah	0.203	12	Bojnord	0.2147	9	Ormia	0.0351	28
Yasouj	0.1495	18	Ahvaz	0.7898	2	Tabriz	0.0992	20
Gorgan	0.0263	30	Zanjan	0.2976	5	Ardabil	0.0931	22
Rasht	0.0356	27	Semnan	0.1795	14	Esfahan	0.0466	25
Khorramabad	0.1611	16	Zahedan	0.2982	4	Ilam	0.0969	21
Sari	0.0537	24	Shiraz	0.0855	23	Boushehr	0.6291	3
Arak	0.205	11	Ghazvin	0.2122	10	Tehran	0.1805	13
Bandarabbas	1	1	Ghom	0.2973	6	Shahrekord	0.0333	29
Hamedan	0.1578	17	Sanandaj	0.2724	7	Birjand	0.0359	26
Yazd	0.1072	19	Kerman	0.2509	8	Mashhad	0.1624	15

the criteria derived from the entropy method indicate that, in terms of drought, more and fewer places are involved with drought by combining the two 6- and 12-month scale were identified according to the TOPSIS model. The three stations of Bandar Abbas, Ahvaz and Bushehr in the south and southwest of Iran with priority values of 1, 0.78, and 0.62 were most affected, respectively, by the drought, based on the TOPSIS model and three stations of Gorgan, Shahr-e-Kord and Urmia in the north and west regions of Iran were rated as 0.026, 0.033, 0.03 and 0.035, respectively, had less priority for drought occurrence (table 6 and figure 6).

3.3 *Drought prediction based on ANFIS model*

After modelling of drought indices and reassurance, TIBI index was predicted for the next 16 yrs using the ANFIS adaptive neural network model. After verifying the validity of neural network models in modelling, ANFIS Neural Network model showed more precision for predicting drought phenomena. Drought index data of TIBI was estimated for the time period 2019–2033. Based on the results of predictions, stations of Bandar Abbas, Bushehr and Zahedan, with the TIBI index of 0.62, 0.96 and 0.97 in southern of Iran, were more exposed to drought for the coming

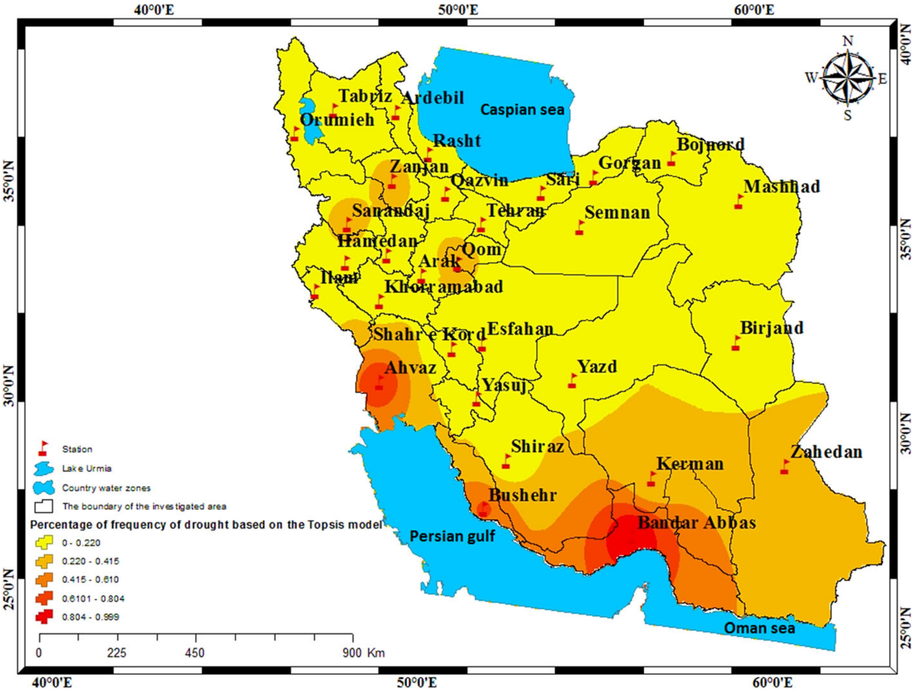

Figure 6. Final maps of areas affected by drought in Iran based on the Topsis model during the statistical period (1990–2018).

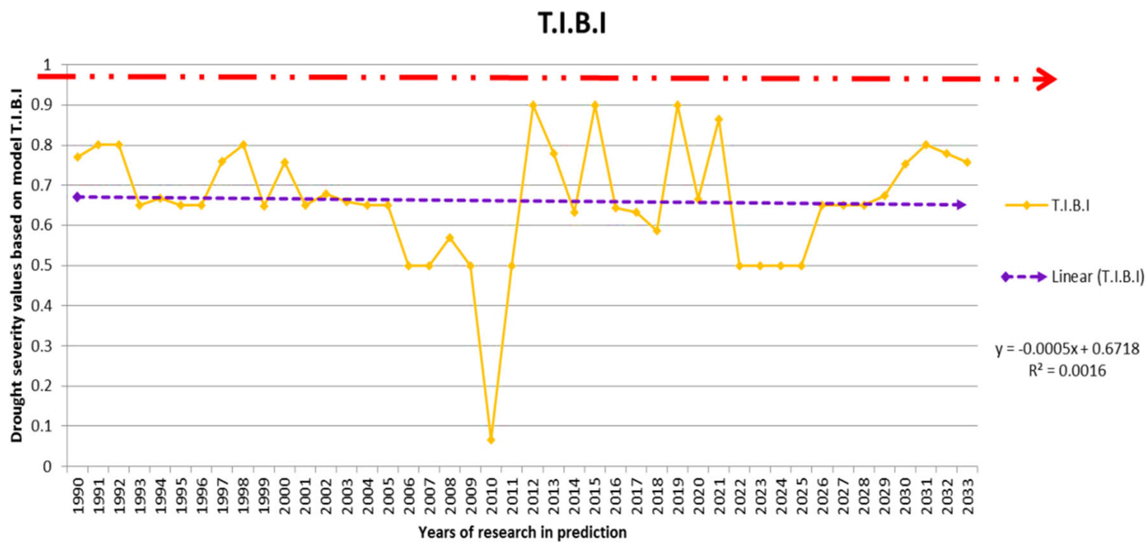

Figure 7. Final maps of areas affected by drought in Iran based on the Topsis model during the statistical period (1990–2018).

years, but stations of Urmia, Tabriz and Shahr-e-Kord, respectively, had the lowest amount of drought based on the TIBI index with the amount of 0.17, 0.15 and 0.12, respectively (figures 7 and 8).

4. Conclusion

Drought is a natural disaster that is gradually evolving under the influence of climatic abnormalities over a long period of time. In recent years, various parts of the Middle East have faced drought, including Iran in southwest Asia. In this study, the drought phenomenon was predicted in two 6-months and 12-months scales, using TIBI's new fuzzy index. The results of the study showed that the total frequency of drought was more at 12-months than those of at 6-months, but the severity of the 6-months drought is more than those of at 12 months. On a 12-months scale, drought repetitions and its continuity are more than 6 months. The drought was less continuous in

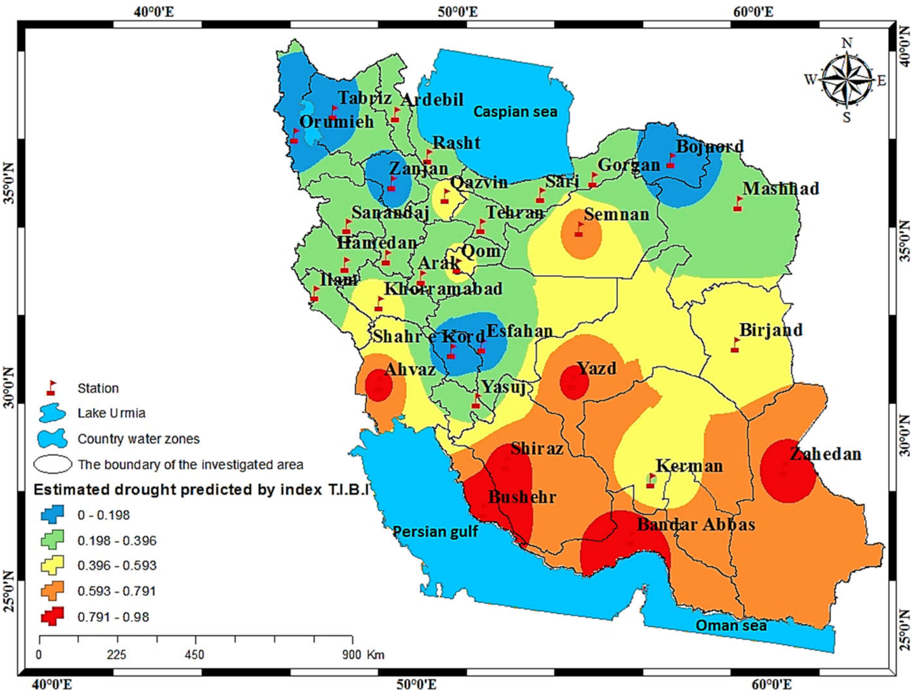

Figure 8. Drought mapping in simulated years based on TIBI model during the statistical period (2019–2033).

short-run time scale and affected by temperature parameter, while the severity of drought in the long periods of time was less responsive to rainfall variations. The highest percentage of drought incidence in 6-months scale was for Bandar Abbas, Bushehr, Ahvaz and Zahedan stations in the southern section of the study area with the frequency of drought of 16.62, 11.24, 14.13 and 6.62, respectively, and the lowest at 6-month scale was for Urmia, Ardabil, Ilam and Yasuj stations with frequency per cent of 1.10, 1.88, 1.61 and 2.01, respectively. Also, Rasht and Gorgan had a drought severity of 1.26 and 0.87 in the north and west of Iran. The highest frequency of drought incidence in 12-months scale was for Bandar Abbas and Bushehr stations, respectively, with drought frequency percentage of 24.30 and 14.83, Ahvaz with drought severity of 18.47 and Kerman with drought frequency of 6.74 in the south and southwest of Iran and the lowest at the 6-month scale were stations of Birjand (1.70), Bojnurd (3.66), Urmia (1.17) and Tabriz (2.66) in the northwest of Iran, Rasht (0.58) and Sari (0.78) in the northern part of Iran. Also, based on Topsis model, Bandar Abbas, Ahwaz and Bushehr stations in the south and southwestern 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 indicates that Bandar Abbas, Bushehr and Zahedan stations with the TIBI index of 0.62, 0.96 and 0.97, respectively, in southern regions of Iran were mostly exposed to drought for the coming years.

In this research, we studied modelling, monitoring and prediction of drought phenomenon in Iran. This method has been used in few studies and has been considered as a suitable method for monitoring, analysis and comparison. For example, Alizadeh *et al.* (2017) in their research on the modelling of dispersion of droughts due to climate change in Iran by using a dynamical system; Zeinali and Safarian Zengir (2017) in their study on drought monitoring in the Lake Urmia Basin using fuzzy index that it had an acceptable performance. Fathi-Zadeh *et al.* (2017) in research on the relationship between meteorological drought and solar variables in some of Iran's interconnected stations, and finally Parsa-Mehr and Khosravani (2017) in research, they used Topsis model and verified the efficiency of the models. Also, models in the present study were useful in modelling, monitoring and predicting the drought phenomenon in Iran.

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