Modeling and Monitoring of Drought for forecasting it, to Reduce Natural hazards Atmosphere in western and north western part of Iran, Iran

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Abstract

The phenomenon of drought has a lot of damage every year in different parts of human life. The drought is not specific to the region, and it affects different parts of the world. One of these areas is Northwest of Iran, which suffered from this phenomenon in recent years. The purpose of this study is to model, analyze, and predict the drought in Northwest of Iran. To do this, climatic parameters (precipitation, temperature, sunshine, minimum relative humidity, and wind speed) of 21 stations were used in the period of 32 years (1987–2018). For modeling of the TIBI fuzzy index, 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 with drought. Results showed that the new fuzzy index of T.I.B.I. for classifying drought reflected four above indicators with high accuracy. Of these five climatic parameters used in this study, the temperature parameter had the most effect on the fluctuation of drought severity. The severity of the drought was more based on a 12-month scale modeling than 6 months. The longest drought persistence in the study area occurred in Urmia Station in the 12-month period from July 2003 to December 2004. The highest percentage of drought occurrence was at Urmia station on a 12-month scale and the lowest was in Sanandaj station on a 6-month scale.

Keywords Fuzzy logic · Drought monitoring · T.I.B.I. · Northwest · Iran

Introduction

Drought is one of the natural hazards that during the period of its occurrence results in damage in various sectors of agriculture, economy, etc. In recent years, there has been a severe drought in different parts of the world. Also, drought is one of the most important natural disasters affecting water resources, which is abundant especially in arid and semi-arid regions of Iran. Drought analysis and monitoring are one of the most important principles in managing drought and risk. Drought

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is a natural phenomenon that has a complex process due to the interactions of various meteorological factors and occurs in all climatic conditions and in all parts of the planet. Drought is a clear indication of climate fluctuations and has a major impact on human societies. The study of drought condition is very important for planning and management of water resources (Shamsniya et al. [2008;](#page-10-0) Mirzaee et al. [2015](#page-10-0); Alizadeh 2017; Zeinali and Safarianzengir [2017](#page-11-0); Zeinali et al. [2017;](#page-11-0) Fathi-Zadeh et al. [2017](#page-9-0); Parsa-Mehr and Khosravani [2017;](#page-10-0) Samidianfard and Asadi [2018;](#page-10-0) Jafari et al. [2018](#page-10-0)). Drought is a common hydrometeorological phenomenon and a pervasive global Risk (Harry et al. [2019;](#page-9-0) Olusola and Jiahua [2019](#page-10-0); Xiao et al. [2019\)](#page-11-0). Remote sensing data are often used in drought indices, which are widely used by researchers to monitor and detect current and historical drought events (Wenzhe et al. [2019a,](#page-10-0) [b](#page-10-0)). Precipitation anomalies reflect variability in surface water (Martha et al. [2013;](#page-10-0) Cammalleri et al. [2015;](#page-9-0) Huiqian et al. [2019\)](#page-9-0). Droughts are caused by the lack of rainfall in different areas. The Middle East has been severely affected by drought in recent decades (Armando & Santos, [2015;](#page-9-0) Jinum & Jeonbin, [2017;](#page-10-0) Montaseri & Amirataee, [2015;](#page-10-0) Yarahmadi, [2014](#page-11-0)). Monitoring and forecasting of drought in

the agricultural sector are very important (Zexi et al. [2019](#page-11-0); Zengchao et al. [2017](#page-11-0)). Yunjun et al. [\(2011](#page-11-0)), in a research of ground-based drought monitoring based on the combined evapotranspiration model, concluded that the patterns of monthly EDI anomalies correlated well with the Palmer Drought Severity Index (PDSI) anomalies from January 1984 to December 2002. Qamasi et al. ([2016](#page-10-0)) conducted a drought prediction with SPI and EDI indexes using ANFIS modeling method in Kohgiluyeh and Boyer-Ahmad Province. They concluded that clustering increases the accuracy of modeling at the stage of calibration. In the study, Junfang et al. ([2016\)](#page-10-0) monitored the drought in the Huaihe River in China and found that the trend of drought calculated using soil moisture and depth of soil water deficit was similar. Alizadeh et al. [\(2017\)](#page-9-0), in a research named at the modeling of dispersion of drought caused by climate change in Iran using dynamic system, conclude that at all stations, the values of evapotranspiration of the reference plant, increased from January to July, then fell to December, and all stations reached their maximum levels in July. In the investigative, Nourani and Amir [\(2017\)](#page-10-0) examined drought indices and concluded that there was a relative correlation between sea Mediterranean, Red, and Black SST. Zeinali et al. [\(2017\)](#page-11-0) studied the drought and its prediction in the stations of Lake Urmia

Basin. The highest percentage of drought occurred in Urmia station and the lowest in Mahabad. Bayazidi [\(2018\)](#page-9-0) evaluated the drought of synoptic stations in the west of the country using HERBST 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. Torabipodeh et al. ([2018\)](#page-10-0) estimated droughts using smart grids and showed that the use of wavelet neural network model could be effective in drought estimation. Ekhtiari khajeh and Dinpazhoh [\(2018](#page-9-0)) applied the Effective Drought Index (EDI) to study drought periods. The results showed that the years of 2005–2007, 2005–2007, and 2002–2003 are the driest year for Tabriz, Bandar Anzali, and Zahedan stations respectively during the 60-year statistical period. Moradi et al. ([2008](#page-10-0)) simulated and analyzed the relationship between aquatic and climatic droughts using probabilistic models in Babol plain and concluded that the occurrence of droughts and wet-years in the Babol River is affected more by wetyears and drought of Ghaemshahr station. Montaseri et al. [\(2018](#page-10-0)) applied to the application of the Effective Drought Index (EDI) for the study of dry periods. They concluded that the years 2003–2007 and 2005–2008, Tabriz, Bandar Anzali, and Zahedan stations, are the driest dry year during the 60-

Fig. 1 Geographical location of the study area in Iran

year statistical period. Liu et al. ([2017\)](#page-10-0) examined drought changes in southwest China and showed that the dangers and severity of droughts in the past decades have increased dramatically throughout the studied region. Hao et al. [\(2016\)](#page-9-0) presented a drought theory method for multivariate drought index based on a linear hybrid index. Based on the standard index of drought, theoretical distribution of linear combination index (LDI) is derived which can be used for drought classification using percent method. The results of comparing this method with experimental methods show its satisfactory performance for drought classification. Huanga et al. [\(2016\)](#page-9-0) investigate the relationship between hydrological drought, climate indicators, and human activity in the Columbia River Basin. The results show that the use of maximum and minimum annual is not a suitable way to check characteristics of volume and duration of flood and drought and in order to assess drought, other methods, such as the standard index, should be widely used. Quesada et al. [\(2017\)](#page-10-0) have studied hydrological changes in a consistent approach to assessing flood and drought changes and concluded that most of the methods used to detect extreme hydrologic trends are not suitable for trend detection and cannot be used in decision making. Therefore, they proposed a method based on the theory of implementation and threshold level. Modaresirad et al. ([2017\)](#page-10-0) studied the drought of meteorological and hydrological 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. Zelekei et al. ([2017](#page-11-0)) have used the Standard Precipitation Index (SPI) and Palmer Drought 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. Kis et al. [\(2017\)](#page-10-0), 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. Jinum and Jeonbin [\(2017\)](#page-10-0), in an attempt to investigate the regional climate models (RCMS), examined the observed drought characteristics based on SPEL in Central Asia, and the results showed that RCMs in wet areas are accurate, but in irregular areas, and this model cannot produce drought events for large spatial scales. In a study, Runping et al. [\(2019\)](#page-10-0) 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 $(P < 0.01)$. In research into critical analysis and suggestion of new drought policy, Bandyopadhyay et al. [\(2019\)](#page-9-0) 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. Other internal and external researchers have investigated various models in the field of drought, including Salajeghe and Fathabadi [\(2009\)](#page-10-0), Jafar Nejad ([2010\)](#page-9-0), Gholam Ali et al. ([2011](#page-9-0)), Makvandi et al. [\(2012](#page-10-0)), Shokri-kouchak and Behnia [\(2013\)](#page-10-0), Nazmfar and Amina [\(2014\)](#page-10-0), Zahiri et al. [\(2014\)](#page-11-0), Yarahmadi et al. (2014), Jan Darmian et al. [\(2015](#page-10-0)), Touma et al. [\(2015\)](#page-10-0), Spinoni et al. [\(2015\)](#page-10-0), Armando et al. (2015), Haddadi

and Heidari [\(2015\)](#page-9-0), Montaseri and Amir Ataee (2015), Sobhani et al. [\(2015](#page-10-0)), Salahi and Mojtabapour [\(2016](#page-10-0)) Zolfaghari and

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

Table 2 Linguistic variables and fuzzy values of the new index derived from the modeling of T.I.B.I.

Nouri [\(2016\)](#page-11-0), Damavandi et al. [\(2016\)](#page-9-0), Fanni et al. [\(2016\)](#page-9-0), Huanga et al. [\(2016\)](#page-9-0), Keshtkarisani [\(2015\)](#page-10-0), Alizadeh et al. [\(2017\)](#page-9-0), Zeinali et al. [\(2017\)](#page-11-0), Jafari et al. [\(2018\)](#page-10-0), Alirreza et al. [\(2019\)](#page-9-0), Jonilda et al. ([2019](#page-10-0)), and Kinga et al. [\(2019](#page-10-0)). According to the studies done inside and outside the country, this study was conducted to model and monitor the drought phenomenon in northwestern of Iran using the new fuzzy index T.I.B.I.

Materials and methods

The present study conducts modeling, monitoring, and prediction of drought in northwest of Iran using climatic data including precipitation, temperature, sunshine, relative humidity,

For modeling 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 modeling of the four indices was performed in the MATLAB software (Fig. [2](#page-2-0)), and eventually to prioritize the drought-affected areas, Topsis model was used. For the standardization of the SET, SPI indicators, it was used the Eq. [1](#page-4-0) and SEB MCZI indices were used from Eq. [2.](#page-4-0)

Fig. 5 The fluctuation of the indices at Tabriz station in the 6-month scale and statistical period of 1987–2018

$$
x_{ij} = \frac{x_j \max - x_j}{x_j \max - x_j \min} \tag{1}
$$

$$
x_{ij} = \frac{x_j - x_j \text{min}}{x_j \text{max} - x_j \text{min}}\tag{2}
$$

In these relationships, x_{ii} represents the standardized value, x_i 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\)](#page-10-0). 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 $2\pm$ (Table [1](#page-2-0)) and the output index domain is between 0 and 1 (Table [2](#page-2-0)). Considering the spoken word scale values of 9 unique, these four fuzzy model inputs, and the T.I.B.I. output index for measuring drought status statement, it is as follows: Wet Very hard, Wet hard, Wet Average, Wet small, Normal conditions, Drought small, Drought Average, Drought hard, and Drought Very hard.

After the modeling of the T.I.B.I. 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 T.I.B.I. 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.

$ANFIS¹$ 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 et al. [2010\)](#page-9-0). 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. [3\)](#page-3-0), a SOGNO fuzzy system with four inputs, one output, and two laws, and an equivalent ANFIS system were presented. This system has two inputs x and y , and one output (Ahmadzadeh et al. [2010\)](#page-9-0). In 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 (Konarkuhi et al. [2010](#page-10-0)). After creating the FIS, the model structure can be shown in Fig. [3](#page-3-0). The branches of this graph are encoded with circles. These circles specify the type of rules (or and or). The last node on the left is the input, and the last node on the right is the output. The five-layer ANFIS structure described above is visible in this structure.

In the Surface Viewer, different modes of output index in the form of fuzzy membership functions are displayed in the Surface Viewer as well as changes in the values of the input index classes and can give more details of the level of changes in the new index between 0 and 1. According to the classification and changes of the matching eight octaves, the four inputs are aggregated and output one image using MATLAB software (Fig. [4\)](#page-3-0).

Results and discussion

Monitoring of drought fluctuations based on four integrated indices in T.I.B.I

In order to investigate the effect of index drought fluctuations ¹ Adaptive Neuro-Fuzzy Inference System in drought conditions of stations, it is possible to analyze the

Fig. 6 The fluctuation of the indices at Tabriz station in the 12-month scale and statistical period of 1987–2018

changes in the indicators (SET, SPI, SEB, 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 Tabriz station was presented in both 6- and 12-month scale (Figs. [5](#page-4-0) and 6) (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 0.74). The analysis of these figures shows that at the 6- and 12-month scale at Tabriz station, the amount of evapotranspiration was similar in drought conditions, which decreased from Mars 1994 to July 1998, 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 April 1996 to December 2004, 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 is presented in Table 3. The T.I.B.I. index at the 12-month scale shows a sharper shape than the 6-month scale.

Table 3 Classification of drought and wet year severity based on fuzzy modeling of T.I.B.I. index

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	$0.06 - 0.15$		
Very severe wet season	$0 - 0.06$		

According to the results obtained from the frequency of drought in the 6- and 12-month scale, the total percentages of drought were at 6 months of West and Northwest stations were more than 12-month scale. The stations of Urmia, Jolfa, and Mako had most percentages of drought (15.26, 9.10, and 10.70, respectively). Stations with a lower percentage of drought severity were more frequently in east parts of the region including the stations of Sanandaj, Maraghe, and Tabriz with frequency percentage of 1.39, 2.01, and 2.20 (Table [4](#page-6-0) and Fig. [7](#page-6-0)). At the 12-month scale, west of the study area was most exposed to drought, with the most drought-affected stations in Urmia, Jolfa, and Maku with drought frequency obtained (13.90, 11.82, and 12.18, respectively) from four integrated indices (SET, SPI, SEB, and MCZI). In the new TIBI fuzzy model, central and southern stations of the study area were less exposed to drought, including Khorramdareh, Tabriz, and Maragheh with drought frequency percentages (4.15, 4.34, and 4.19, respectively) (Table [5](#page-7-0) and Fig. [8](#page-7-0)).

According to the definition of drought based on the T.I.B.I. index, values of 0.74 or higher or mild to higher drought are considered as arid conditions. Accordingly, in the modeling of the new T.I.B.I. fuzzy index, the drought intensity at the 12-month scale was higher than the 6-month scale. Based on the results of the present study, the annual drought intensity at the 6 month scale started in 1998 and at the 12-month scale since 1996 began mildly and continued upward.

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

Fig. 7 Mapping of frequency percent of drought occurrence in studied stations in a 6-month scale and statistical period of 1987– 2018

Station names	Normal	Mild drought	Mediocre drought	Severe drought	Very severe drought	Total
Ardebil	2.47	6.39	6.09	1.10	1.12	8.31
Khalkhal	4.52	9.05	2.12	3.19	0.32	5.63
Parsabad	3.85	10	6.02	2.12	$\overline{0}$	8.14
Tabriz	3.29	8.03	2.36	1.09	0.89	4.34
Ahar	1.87	13.74	4.85	2.21	$\mathbf{0}$	7.06
Jolfa	2.74	12	6	5.11	0.71	11.82
Sarab	3.32	5.36	3	2.26	$\mathbf{0}$	5.26
Maraghe	5	4.12	2.68	1.15	0.36	4.19
Miane	$\overline{4}$	5.06	3.60	2.09	$\overline{0}$	5.69
Oromieh	4	4.83	7	5.96	0.94	13.9
Khoy	3	14	4.75	1.30	$\mathbf{0}$	6.05
Mahabad	3	12.11	1.32	3.36	0.65	5.33
Mako	0.87	13.45	7.12	5.6	$\mathbf{0}$	12.18
Sardasht	4.89	14.63	3.08	0.98	0.73	4.79
Takab	3.08	7.56	6.87	3.09	$\mathbf{0}$	9.96
Sanandaj	\overline{c}	9.86	4	0.92	0.76	5.68
Bijar	3	15.10	4.18	2.49	0.98	7.65
Saghghez	1.08	13.87	5.86	4.28	0.16	10.30
Zanjan	4	8.65	7	1.89	$\mathbf{0}$	8.89
Khorramdarreh	6	9.68	3	0.86	0.29	4.15
Khodabandeh	2.8	13.55	6.12	2.98	$\mathbf{0}$	9.10

Table 5 Frequency percentage of drought incidence in different classes in the 12-month time scale and statistical period of 1987–2018

appropriate option was selected from an approximate approach to ideal proportions (Sobhani and Safarianzengir [2018\)](#page-10-0). The results of the implementation of the TOPSIS model using the degree of importance of

Fig. 8 Mapping of frequency percent of drought occurrence in studied stations in a 12-month scale, in the statistical period of 1987–2018

Table 6 Prioritization of stations involved with drought based on the Topsis model during the statistical period of 1987–2018

Station names	Topsis values	Station names	Topsis values
Ardebil	0.11	Mahahad	0.34
Khalkhal	0.34	Mako	0.67
Parsabad	0.18	Sardasht	0.27
Tabriz	0.05	Takab	0.43
Ahar	0.16	Sanandaj	0.03
Jolfa	0.56	Bijar	0.36
Sarab	0.14	Saghghez	0.35
Maraghe	0.04	Zanjan	0.50
Miane	0.08	Khorramdarreh	0.10
Oromieh	1	Khodabandeh	0.18
Khoy	0.51		

the criteria derived from the entropy method indicate that, in terms of drought, more and fewer places that are involved with drought by combining the two 6- and 12-month scale were identified according to the TOPSIS model. The three stations of Urmia, Mako, and Jolfa with priority values of 1, 0.67, and 0.56 were most affected respectively by the drought, and three stations of Sanandaj, Maraghe, and Tabriz were rated as 0.03, 0.04, and 0.05, respectively, and had less priority for drought occurrence (Table 6) (Fig. 9).

Conclusion

In recent years, drought has been one of the most important issues in causing damages in various sectors such as agriculture, economy, and so on in different regions of Iran including northwest of Iran. Researchers have done a lot of research on drought monitoring with different models, but not enough on the issue. The purpose of the present study is to model and investigate the drought phenomenon in northwestern Iran at 6 and 12-month scale. The results of the study showed that the drought severity, drought repetitions, and its continuity were more at 12 months than those of at 6 months. The drought was less continuous in 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. Drought trend in northwestern Iran showed an increase, and temperature trend was mildly upward. The highest percentage of drought incidence in 6- and 12-month scale was for Urmia station and the lowest was for Sanandaj. The frequency percentage of drought in the Jolfa, Mako, and Urmia stations in 12-month scale was higher than the 6 months. According to the results, modeling was highly reliable and the new T.I.B.I. fuzzy index outperformed the SPEI fuzzy index. Also, according to the results of the new T.I.B.I. index modeling, drought was more intense at the 12-month scale than the 6-month scale. Based on the results of the 6-month modeling, the highest percent of droughts occurred in the northwest of the study area (Mako, west of Urmia Lake and the Urmia stations)

and in the 12-month scale, the semi-western scale of the study area (south and west of Urmia Lake). Finally, based on TOPSIS multivariate decision-making model, Urmia station with a score of 1 was given the highest priority by drought conflict and Sanandaj station with a score of 0.03% was the last priority with a drought conflict.

In this research, we studied modeling, monitoring, and prediction of drought phenomenon in Northwest of Iran. This method has been used in many studies, and it has been considered as a suitable method for monitoring, analysis, and comparison, for example, Shamsniya et al. ([2008](#page-10-0)), by study on drought modeling in Fars Province using time series analysis; Mirzaee et al. ([2015](#page-10-0)) by research on the development of WEAP integrated water resource model for modeling drought conditions; Perovi et al. ([2015](#page-10-0)) in their study on the modeling of the drought effect on the total hardness and solids of groundwater solution in Mashhad plain; Adib and Georgian (2016) by drought monitoring using drought indices; Zolfaghari and Nouri [\(2016\)](#page-11-0) by study on application of the Drought Index (CPEL) in determining the appropriate variables for the analysis of drought in Iran; Alizadeh et al. (2017) in their research on the modeling of dispersion of droughts due to climate change in Iran by using a dynamical system; and Parsa-Mehr and Khosravani [\(2017\)](#page-10-0) in a research used Topsis model. Zeinali and Safarian-Zengir [\(2017\)](#page-11-0) in study on drought monitoring in the Lake Urmia Basin using the fuzzy index that it had an acceptable performance and finally Fathi-Zadeh et al. (2017) in a research on relationship between meteorological drought and solar variables in some of Iran's interconnection stations and verified the efficiency of the models. However, models in the present study were useful in modeling, monitoring, and predicting the drought phenomenon in Northwest of Iran.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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