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ORIGINAL PAPER

Analyzing drought history using Fuzzy Integrated Drought Index (FIDI): a case study in the Neyshabour basin, Iran

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Abstract
In arid to semi-arid climates, monitoring drought is very complicated because of different hydrometeorology variables effect on it. It is proposed in this paper to develop Fuzzy Integrated Drought Index (FIDI) which combines most important effective factors in developing drought. At first, Variable Infiltration Capacity (VIC) model calibrated simulated runoff to outlet basin runoff data for years 1993–1995. Results represent high performance of model in simulating runoff of outlet basin. Then, Precipitation Anomaly Percentage Index (PAPI), actual Evapotranspiration Anomaly Percentage Index (EAPI), Runoff Anomaly Percentage Index (RAPI), and Soil Moisture Anomaly Percentage Index (SMAPI) were constructed. FIDI was compared with the PAPI, RAPI and SMAPI for the period of 1985 to 2014. The results indicate that (1) the FIDI has more ability in determining start and persistence of drought event compared with PAPI, RAPI, and SMAPI; (2) in the low time scales, PAPI and SMAPI have high correlation with FIDI, and in the higher time scales, RAPI has the high correlation with FIDI; (3) spatially, the middle, west, and portion of north have higher drought risk in the Neyshabour basin.

Keywords Drought · Fuzzy model · Fuzzy Integrated Drought Index · The Neyshabour basin

Introduction

Drought has been one of the major damaging phenomena in most parts of the world. Iran with arid to semi-arid climate has experienced it often. Thus, there is a need for developing a system to quantify, monitor, and predict droughts (Mishra and Singh 2011). However, given the wide variety of sectors affected by drought and its diverse geographical and temporal distribution, it is difficult to develop a single, precise definition for drought (Rajsekhar et al. 2015).

Drought indices are the best methods which can monitor drought in a proper way. Precipitation data are convenient to access in most regions of the world, so indices based on precipitation have been recommended in recent hydrological studies. However, the meteorological indices mainly consider the influence of precipitation on drought over a period of time, so they have certain limitations reflecting the spatio-temporal variation of drought, and the research time scale tends to be large, usually on the monthly scale (Mao et al. 2017). Therefore, much attention was paid to use other variables affecting the drought. However, the application of drought index based on soil moisture content is limited, because it is difficult to measure soil water content, spatially in situ (Cristi et al. 2016) like runoff data.

For poor-data or non-data regions, the database can be simulated by models, and the simulated data can be used for drought analysis after verification as an alternative to measured data (Mao et al. 2015; Wanders and Van Lanen 2015; Ma et al. 2016). In recent years, a lot of studies have been done by using different kinds of hydrological models for simulating desired variables. In the Neyshabour basin, many researches have utilized Soil and Water Assessment Tool (SWAT) model especially for simulating actual evapotranspiration (Mianabadi et al. 2017; Moazenzadeh et al. 2016; Alizadeh et al. 2013; Shafiei et al. 2013). Shafiei et al. (2013), based on their research suggested because of large number of uncertainty sources in semi-dry to dry regions, SWAT model cannot

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simulate hydrological variables in an accurate way. In this study VIC model has been used a different hydrological model named Variable Infiltration Capacity (VIC). The VIC model (Liang et al. 1994) is a land surface hydrology model that has been well calibrated and used in different parts of the world (Lobmeyr et al. 1999; Te linde et al. 2008; Stephen et al. 2010; Wu et al. 2011; Rajsekhar et al. 2015; Huang et al. 2015; Mao et al. 2017). This model aggregates all information about meteorology, land cover, and soil to simulate long-term runoff, actual evapotranspiration (Et_a), and soil moisture data for hourly to daily time scales.

In recent years, a lot of studies have concentrated on finding new ways to develop high-quality drought indicators. Kao and Govindaraju (2010) presented new drought index which is named Joint Deficit Index (JDI). The results of their studies on meteorological and hydrological droughts in Indiana showed that the JDI has potential to model the complex structure of drought in contrast with previous drought indices. Vicente-serrano and López-Moreno (2010) developed new climate index in which precipitation and temperature data were utilized in it. Climate water balance was the basic theory for constructing Standardized Precipitation Evapotranspiration Index (SPEI). SPEI can distinguish severity of drought properly like Palmer Drought Severity Index (PDSI), because temperature is included in it. Hao and Aghakouchak (2013) proposed Multivariable Drought Index based on copula concept. The suggested drought index was derived from the statistical combination of Standardized Precipitation Index (SPI) and Standardized Soil Moisture Index (SSI). This indicator was used in several parts of northern California. The results revealed that MSDI indicates drought start such as SPI and drought duration such as SSI. Also, MSDI can monitor drought more efficiently than SPI and SSI because of combing impact of precipitation and soil moisture. Rajsekhar et al. (2015) proposed Multivariate Drought Index (MDI) which combines all types of drought by using entropy theory. MDI and PDSI were compared for all climate zones of Texas during 1950–2012. They found that MDI could monitor drought better than PDSI in Texas because of multivariate and multi scale structure of it.

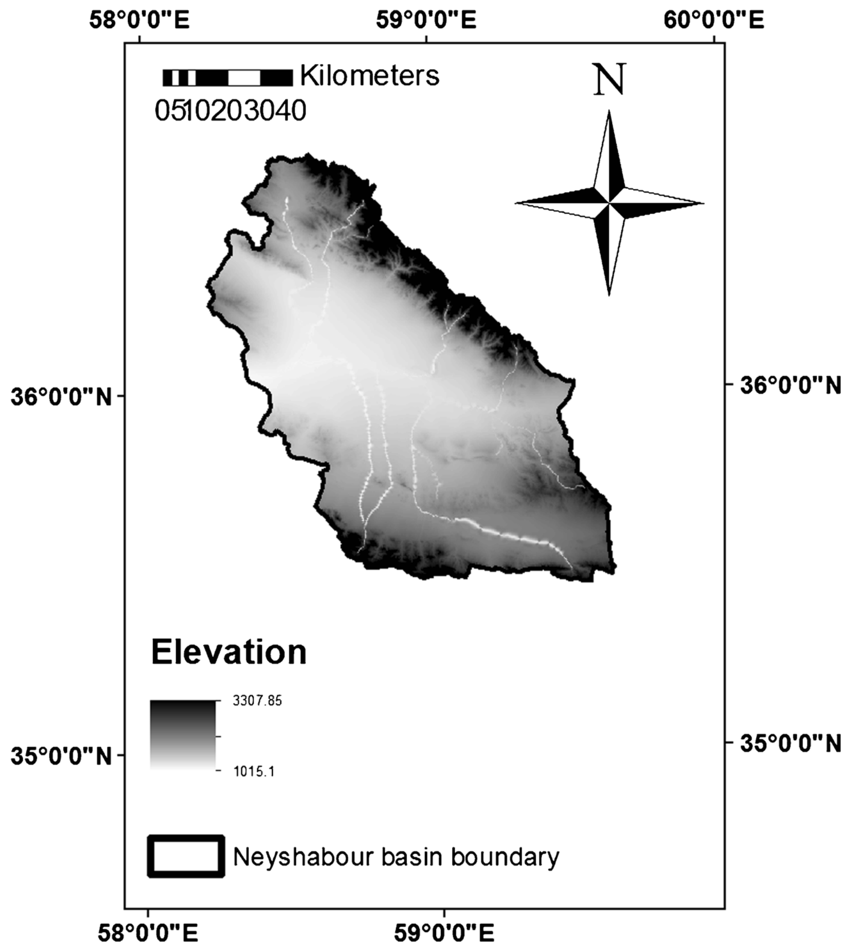
In previous studies, diverse methods were used for monitoring and assessing droughts, while each of them had their own benefits and limitations. For instance, copula was used to access the joint behavior of meteorological and hydrological variables but this does not have any flexibility for more than two dimensions. Due to the fact that many of the phenomena have a fuzzy structure, a lot of attentions have been attracted to use of fuzzy model. For instance, drought and flood season and non-flood season, these concept and phenomena are uncertain (Lei et al. 2014). Pesti et al. (1996) described that there is a strong relation between drought characteristics and general circulation patterns. Therefore, they modeled this relation with fuzzy rule base approach. Results illustrate that constructed model is useful for predicting drought related to atmospheric circulation pattern. Tzimopoulos and Mpallas (2007) used a fuzzy model to extrapolate the data of the recorded precipitation of meteorological stations using adjacent station data. The three stations used in this study are in northern Greece. The results of fuzzy model were compared with linear regression method, which indicate that fuzzy model has priority in producing precipitation data. Ansary et al. (2010) developed Standardized Evapotranspiration Precipitation Index (SEPI) to join the effect of precipitation and temperature to assess drought in Mashhad city in Iran. SEPI was built by combining two fuzzy membership functions related to the SPI and Standardized Evapotranspiration Index (SEI). The results of the model clarified that SEPI has all the benefits of the SPI, including the possibility of calculating different time scales and also the significance of temperature factor especially for dry climates which is considered in it. Furthermore, Huang et al. (2015) suggested an Integrated Drought Index (IDI) combining precipitation, runoff, and soil moisture to monitor drought in the Yellow River basin. Fuzzy model was used to create new multivariate drought index. Then, IDI was compared with SPI and Standardized Streamflow Index (SSFI) and results show that IDI could better reveal onset and persistence of drought in contrast with SPI and SSFI.

Neyshabour basin is one of the major catchments in northeast of Iran and it has experienced drought several times related to its dry climate; therefore, this area was selected as a typical study region. The major goals of this study are as follows: (1) Simulating fundamental factors, which have a great impression on drought (runoff, Et_a, and soil moisture), by running VIC model; (2) Evaluating the performance of the VIC model in producing desired meteorological and hydrological data; (3) Constructing monthly Anomaly Percentage Index of precipitation, runoff, Et_a, and soil moisture variables which have been simulated by VIC model; (4) Accessing the weight of effective variables (precipitation, runoff, Et_a, and soil moisture) on drought using weight method; (5) Establishing new multivariate drought index (Fuzzy Integrated Drought Index) by utilizing Anomaly Percentage Index of precipitation, runoff, Et_a, and soil moisture variables and also fuzzy model; (6) Analyzing the spatial characteristic of drought in the Neyshabour basin by using of the Fuzzy Integrated Drought Index.

Study area

The study area considered is the Neyshabour basin which is located between 58° E–59° E and 35° N–36° N in the Iran country (Fig. 1). Neyshabour basin has an area of 9349 km^2, and plain accounts for 0.55% of the whole basin. The mean annual precipitation and Et_a in the Neyshabour basin are 246 and 250 mm, respectively. Elevation of the Neyshabour basin

Fig. 1 Position of the Neyshabour basin



decreases from east to west with arid to semi-arid climate zone. Neyshabour basin is one of the major areas in Iran which is part of the Markazi catchment area. Neyshabour plain is one of the most prone areas of drought in Iran. It has encountered some of the biggest droughts in the Iran because of its semi-dry to dry climate, for instance, during years 2000–2004. Due to the geographical location of the Neyshabour catchment, this area is cultivated each year, and due to the occurrence of consecutive droughts, the inhabitants of this area have been forced to harvest groundwater abnormally.

This study used daily precipitation and mean temperature data from 13 rain gauge and 7 evaporative stations and the other daily variables (i.e., radiation, air pressure, vapor pressure, and wind speed) from two synoptic stations in the Neyshabour basin during years 1985 to 2014. The Neyshabour basin was divided into 15 cells with spatial resolution of 25 km × 25 km. Meteorological data were calculated in each cell of grid by using the fuzzy method. Unlike previous studies which used Inverse Distance Weighting (IDW) method to interpolate meteorological data (Rajsekhar et al. 2015; Huang et al. 2015; Mao et al. 2017), in this study, the effects of distance and elevation were joined to estimate precipitation and average temperature with fuzzy set theory.

Methods

Simulation of necessary variables with VIC model

The Variable Infiltration Capacity (VIC) model (Liang et al. 1994) is a semi distributed model, which has been specially applied in water resources studies. The overall VIC model framework has been described in detail in literature (Liang et al. 1994; Nijssen et al. 1997). Determining the parameters of hydrological models is the most important step in the process of modeling. The geography, vegetation, and soil parameters of VIC model were achieved with meteorological variables, vegetation types, and soil texture. Meteorological parameters are extracted from data of rain gauge and evaporative and synoptic stations in the Neyshabour basin. VIC model needs 14 vegetation parameters that can be taken from the type of vegetation covers in each cell by utilizing land use map and information which are accessed from MODIS satellite images for considered area. Also, soil parameter file requires 30 parameters which are derived from soil texture for each cell and standard soil tables. Any heterogeneity in soil and vegetation covers can be entered in each cell based on their percentage of the area formed.

In arid to semi-arid regions, because of low runoff (discontinuous flow) in most days of the year, there are difficulties with calibration of hydrological parameters in models like VIC. The effects of infiltration parameter (b_i), the second and third soil layer depths (d_2, d_3), and the three parameters in baseflow scheme (D_m, D_s, W_s) on simulated runoff were considered. Infiltration parameter and second soil layer had the most effect on land surface fluxes. Validation against the observed runoff and Et_a for years 1996 to 1998 was done. The simulations are described by Zhang et al. (2014). Then, the simulated daily precipitation, runoff, Et_a, and soil moisture from 1985 to 2014 were aggregated into monthly scale for calculating new drought index.

Calculating Anomaly Percentage Index

Anomaly percentage index is a way to show how the actual variables differ from multiyear average of them. It is calculated as bellow:

$$\mathrm{API} = \frac{X-\overline{X}}{\overline{X}} \times 100 \tag{1}$$

X represents the monthly simulated variable, and $\bar{X}$ represents the related multiyear average. When the value of the variable is less than its average age, it represents drought in the area. In this research, monthly precipitation, runoff, Et_a, and soil moisture of the Neyshabour basin were used to calculate Anomaly Percentage Index (API) for each variable. The boundary values corresponding to each grade are shown in Table 1. The API values were classified into nine categories based on study of Huang et al. (2015) as shown in Table 1.

Entropy weight method

Information entropy measures the variability time series of considered variable. If the changes of values are obvious, the values give more information and their entropy is small. So variables with low entropy have more weight. In this study, the entropy weight method was used to determine the weights of precipitation, runoff, Et_a, and soil moisture anomaly index for developing a fuzzy drought index. The entropy weight method can be expressed in the series of steps:

(1) Normalize the matrix as follows.

$$f_{ij} = r_{ij}/\sum_{j=1}^{n} r_{ij} \tag{2}$$

where $i = 1, \ldots, m$ is indicators and $j = 1, \ldots, n$ is evaluating objects.

(2) Compute entropy H_i as follows.

$$H_i = -k \sum_{j=1}^{n} f_{ij} \ln f_{ij} \tag{3}$$

where k is entropy constant and is equal to $(\ln n)^{-1}$, and $f_{ij}.\ \ln f_{ij}$ is defined as 0 if $f_{ij} = 0$.

(3) Calculate weight of entropy of ith indicator as follows.

$$W_i = \frac{1-H_i}{m-\sum_{i=1}^{m} H_i} \tag{4}$$

where $0 \le W_i \le 1$, $\sum_{i=1}^{m} W_i = 1$.

Method of fuzzy modeling

Modeling of fuzzy can be described by the procedures of drought development which is developed with low speed in regions. It is very difficult to set a specific boundary for drought, while fuzzy modeling works well to does this. The processes of fuzzy model are organized as follow:

(1) Fuzzification: input variables are made by representing them as fuzzy membership functions suppose x_i of the ith indicator lie in $[y_{ih}, y_{i(h=1)}]$, and relative membership degree of x_i to the hth grade is calculated as follows:

$$\mu_{ih} = \frac{y_{i(h=1)}-x_i}{y_{i(h=1)}-y_{ih}} \tag{5}$$

Table 1 The indicator system of drought assessment in the Neyshabour basin (Huang et al. 2015)

Drought types	Drought indexes	Drought grade				
		ND	LD	MD	SD	ED
Meteorological drought	Monthly precipitation anomaly percentage	> − 25	− 25 to − 50	− 50 to − 70	− 70 to − 80	< − 80
Meteorological drought	Monthly Et_a anomaly percentage	< 25	25 to 50	50 to 70	70 to 80	> 80
Hydrological drought	Monthly runoff anomaly percentage	> − 10	− 10 to − 30	− 30 to − 50	− 50 to − 80	< − 80
Agricultural drought	Monthly soil moisture anomaly percentage	> − 10	− 10 to − 30	− 30 to − 50	− 50 to − 80	< − 80

ED extreme drought, *SD* severe drought, *MD* moderate drought, *LD* light drought, *ND* no drought

Remnants of the grades have one membership degree, where y is the API of each grade and $h = 1, \ldots, 9$ is the grades of percentage index.

(2) Inference modeling: the input variables were applied to build a model made up of linguistic rules. In this study, with four inputs and nine grades, there were 729 rules.
(3) Defuzzification: the consequences from the model in linguistic form were translated into numerical form, by using fuzzy membership functions. The methods applied in fuzzy system are shown in Table 2.

The results of model are the Fuzzy Integrated Drought Index (FIDI) for a specific time scale. The boundary values corresponding to each grade are shown in Table 3.

Results and discussion

At first, it was essential to calibrate and validate the VIC model. The following sections discuss the results of VIC calibration and validation, developing API, calculating entropy weighting method and performance of Fuzzy Integrated Drought Index.

Calibration and validation of VIC model

In the VIC model, some parameters are more sensitive to simulate land surface fluxes. The results of sensitive analysis have shown that b_i and d_2 parameters had the most effect on producing runoff.

Liang et al. (1994) suggested a set of parameters with their suitable range. Figure 2 shows the monthly time series of observed and simulated runoff during 1993–1995. It indicates that the simulation results of VIC were very close to the observations of outlet runoff basin except in peak values that model overestimated runoff. Best values for b_i and d_2 parameters were determined 0.2 and 0.3, respectively. The main reason for this difference can be the construction of artificial tanks especially in the branches of the rivers. Correlation coefficient and NSE values between simulated runoff data and outlet runoff of basin were calculated 0.85 and 0.99, respectively. Hence, from the results, which are shown in Fig. 2, it can be seen the model efficiency is acceptable.

The simulated runoff and actual evapotranspiration (Et_a) both validated against observed data. Average runoff data of 15 cells of the Neyshabour basin were simulated with VIC model which was validated against outlet station runoff data and their statistic values of R^2 and NSE were calculated 0.81 and 0.9 respectively, which is shown in Fig. 3a. ET_a was validated against two types of published data from previous studies which included (1) simulated yearly Et_a from SWAT model for 10 years (2001–2010) by Alizadeh et al. (2013) and (2) estimated Et_a from SEBAL algorithm for the year 2013 by Azadmarzabadi (2014). Results are shown in Fig. 3b, c, which mean that simulated Et_a data with VIC model were much closer to simulated Et_a data with SWAT model. It may be the cause of similarity construction of VIC model with SWAT model. Correlation coefficient and NSE for validation simulated data against SWAT model were calculated 0.76 and 0.70 respectively and against SEBAL algorithm were accessed 0.42 and 0.26, respectively.

Table 2 Operators in fuzzy system

Operators in fuzzy system	Method
Fuzzy inference	Mamdani
Fuzzy implication	Min
Aggregation	Max
DOF[1]	Min
Defuzzification	Centroid of area

[1] Degree of fulfillment

Table 3 FIDI drought classification

FIDI value	Classification
− 16 or less	Extreme drought
− 15.99 to − 12	Severe drought
− 11.99 to − 8	Moderate drought
− 7.99 to − 4	Light drought
− 3.99 to 4	Normal
4.1 to 8	Light wet
8.1 to 12	Moderate wet
12.1 to 16	Severe wet
16 or more	Extreme wet

The impact of precipitation, runoff, Et_a, and soil moisture in the Neyshabour basin

The entropy-weighted method was applied to figure out weight of each affecting variable on drought occurrence in the Neyshabour basin. The computed weight for each cell in the Neyshabour basin is exhibited in Table 4.

It can be obviously seen from Table 4 that the most weight (impact) belongs to monthly runoff anomaly percentage series, whereas the lowest weight is accessed for monthly soil moisture anomaly percentage series in the Neyshabour basin. Variation in time series of precipitation, Et_a, and runoff is more than that of soil moisture in all the cells. For instance, the gained weights of monthly precipitation, Et_a, runoff, and soil moisture series covering

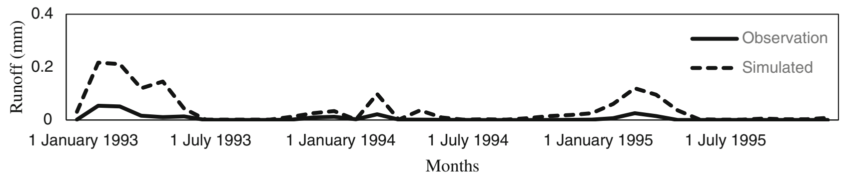


Fig. 2 Comparison of simulated runoff

1985–2014 in cell 1 (58.64° E, 36.54° N) are 0.27, 0.24, 0.42, and 0.05, respectively. So, the new drought index will indicate more features of hydrological drought than of meteorological and agricultural droughts.

Comparison of FIDI with other drought index

After obtaining weights of the desired variables, FIDI for 15 cells in the Neyshabour basin was obtained. To achieve the efficiency of FIDI in quantifying drought event, the 1- and 12-month PAPI, RAPI, SMAPI, and FIDI were computed for the Neyshabour basin. A random location in the Neyshabour basin was selected and FIDI during 1985–2014 in different scales was compared with PAPI, RAPI, and SMAPI in different scales. The selective locations of chosen grid are 58.64° E, 36.54° N (cell 1); 58.41° E, 36.11° N (cell 5); and 59.18° E, 35.87° N (cell 11). Results show a higher correlation between 12-month scale of FIDI and RAPI with the correlation coefficients of 0.94, 0.91, and 0.97 respectively for selected cells because in 12-month scale of FIDI completely shows the characteristics of runoff. But in 1-month scale of FIDI, it has higher correlation coefficient with PAPI and SMAPI which are shown in Table 5.

From Fig. 4, it can be seen that if PAPI is used for drought monitoring, it recognizes the termination of drought, but goes away for a shorter period of time. If RAPI is used for quantifying drought, it follows the trend of FIDI until drought is end. So, RAPI and FIDI can well determine the length of drought occurrence until it ends. Agriculture drought is affected by several factors like soil type, temperature, humidity, and amount of precipitation. The Neyshabour basin with semi-arid to arid climate has higher evapotranspiration and lower precipitation rates. So, if we are quantifying drought PAPI, RAPI, or SMAPI, we might not monitor drought as well as we expect. When we used FIDI, it was seen that it can really recognize the complicated construction of drought with joining the effect of meteorological, hydrological, and agricultural factors. FIDI well predicts the onset of drought and it can also predict durability of drought as well as the onset of drought. The occurrence of dry periods in this index is affected by the lack of rainfall, increase in the value of actual evapotranspiration, and consequently

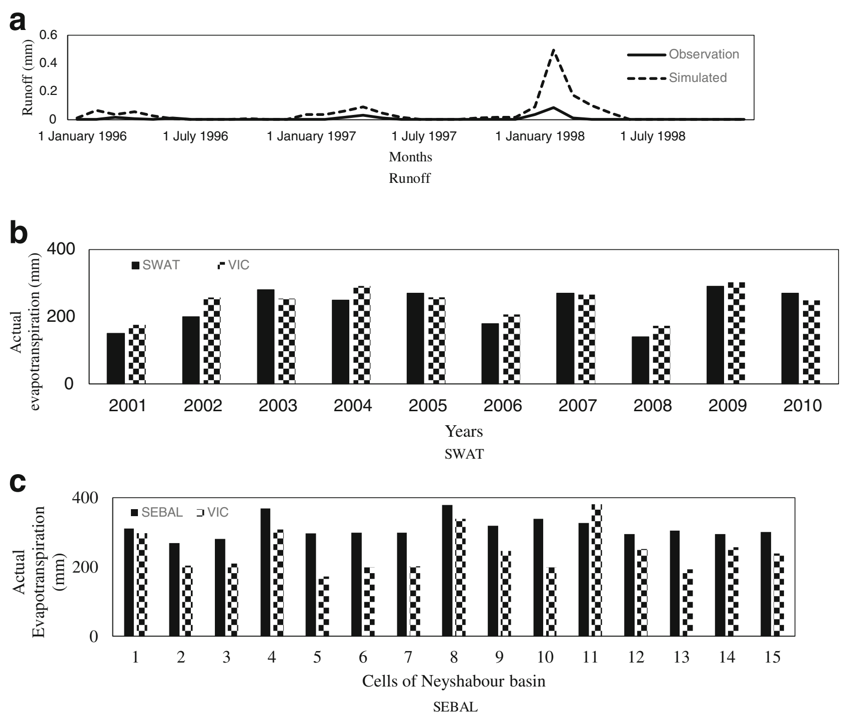


Fig. 3 Comparison of simulated runoff and Et_a with **a** observed runoff (Hosseinabad station), **b** SWAT, and **c** SEBAL algorithm, respectively

Table 4 Computed weights of 15 cells in the Neyshabour basin

Indices	Cells number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PAPI	0.27	0.26	0.27	0.17	0.28	0.25	0.27	0.25	0.24	0.26	0.26	0.25	0.25	0.26	0.34
EAPI	0.24	0.25	0.26	0.24	0.27	0.26	0.27	0.28	0.25	0.26	0.24	0.25	0.25	0.27	0.25
RAPI	0.42	0.37	0.41	0.57	0.38	0.41	0.40	0.38	0.42	0.41	0.41	0.42	0.41	0.41	0.56
SMAPI	0.05	0.10	0.04	0.0005	0.05	0.05	0.04	0.07	0.06	0.06	0.07	0.06	0.07	0.05	0.08

PAPI Precipitation Anomaly Percentage Index, *EAPI* Et_a Anomaly Percentage Index, *RAPI* Runoff Anomaly Percentage Index, *SMAPI* Soil Moisture Anomaly Percentage Index

runoff shortage as the main factors of intensifying drought intensity and also soil moisture with less effect.

Assessment of spatial drought attribute in the Neyshabour basin

FIDI was used to investigate the spatial dispersion of drought in the Neyshabour catchment. The spatial distribution of annual average of FIDI for 30 years is exhibited in Fig. 5. It shows that drought is high in the center, west, and some regions of north in the Neyshabour basin. So these regions are in the danger of drought, because of having lower elevation and also lower precipitation, runoff, and soil moisture. Moreover, higher average temperature intensifies risk of drought in these portions. East and south areas receive more rainfall especially in winter and spring seasons; therefore, they have more vegetation cover, and because of more humid soils, these sections are proper for cultivating. Overall, the trend of drought is increased from east to west areas of the Neyshabour basin.

According to the monthly FIDI, drought duration, severity, and intensity of each cell were calculated and they are shown in Table 6. Drought intensity is higher in the center of the Neyshabour basin. Regions with high intensity have higher average annual temperature, larger evaporation, and fewer precipitation than regions with low intensity values. When intensity and duration of drought increase, the severity of drought also increases. Table 6 shows that regions in middle and west of the basin suffer more severe drought.

Choosing proper scale for FIDI

FIDI is the multiscalar index which can compute different time periods. Typically, shorter time scales are suitable for analyzing the impacts of agricultural and meteorological droughts and larger time series scales are better for hydrological droughts (Mishra and Singh 2011). For selecting the best scale that gives more information to us, entropy method was used. The average results of the entropy for all cells are shown in Table 7.

The method of entropy is discussed in previous sections. Lower value of entropy shows more content of information that can be obtained from that time series. By comparing 1, 3, 6, 9, and 12 time scales of computed FIDI during 1985–2014 for the Neyshabor basin, results are shown that 6-month FIDI gives more information and has the lower value of entropy.

Comparison with other researches

Different researchers studied on drought issue in the Neyshabour basin which has semi-dry to dry climate and has experienced drought many times. Naderianfar et al. (2011) investigated the relationship between level of the groundwater and SPI during years 1993 to 2006 in the Neyshabour basin. The results of low values of FIDI in our research are completely similar to the deficit of groundwater level in this area. Also, FIDI intensively follows the fluctuation trend of groundwater level in the

Table 5 Computed correlation coefficient between FIDI and PAPI, RAPI, and SMAPI at chosen cells in the Neyshabour basin

Latitude (°)	Longitude (°)	Cells number	Scale	PAPI	RAPI	SMAPI
36.54	58.64	1	1	0.84	0.82	0.75
36.54	58.64	1	12	0.70	0.94	0.69
36.11	58.41	5	1	0.79	0.68	0.81
36.11	58.41	5	12	0.75	0.91	0.78
35.87	59.18	11	1	0.76	0.76	0.88
35.87	59.18	11	12	0.59	0.97	0.52

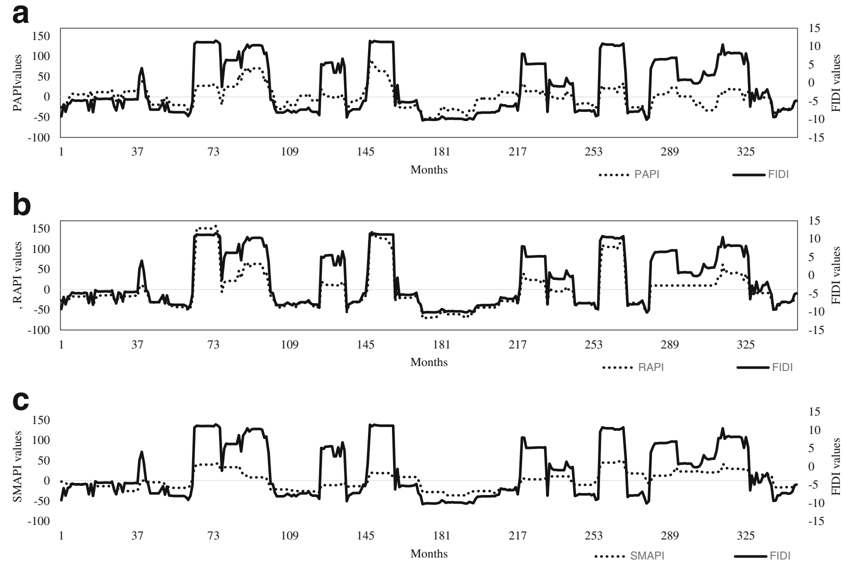


Fig. 4 Comparison of FIDI with PAPI, RAPI, and SMAPI time series for 58.41° E, 36.11° N (cell 5) of the Neyshabor basin during 1985–2014

Neyshabour basin. Ansari and Naderianfar (2012) calculated the values of SEPI and SPI in a 42-month scale for the Neyshabour catchment. Comparison between two studies shows that a greater correlation exists between FIDI and SEPI in contrast with FIDI and SPI for years 1993 to 2008. In the years 2000–2004, SPI did not show the

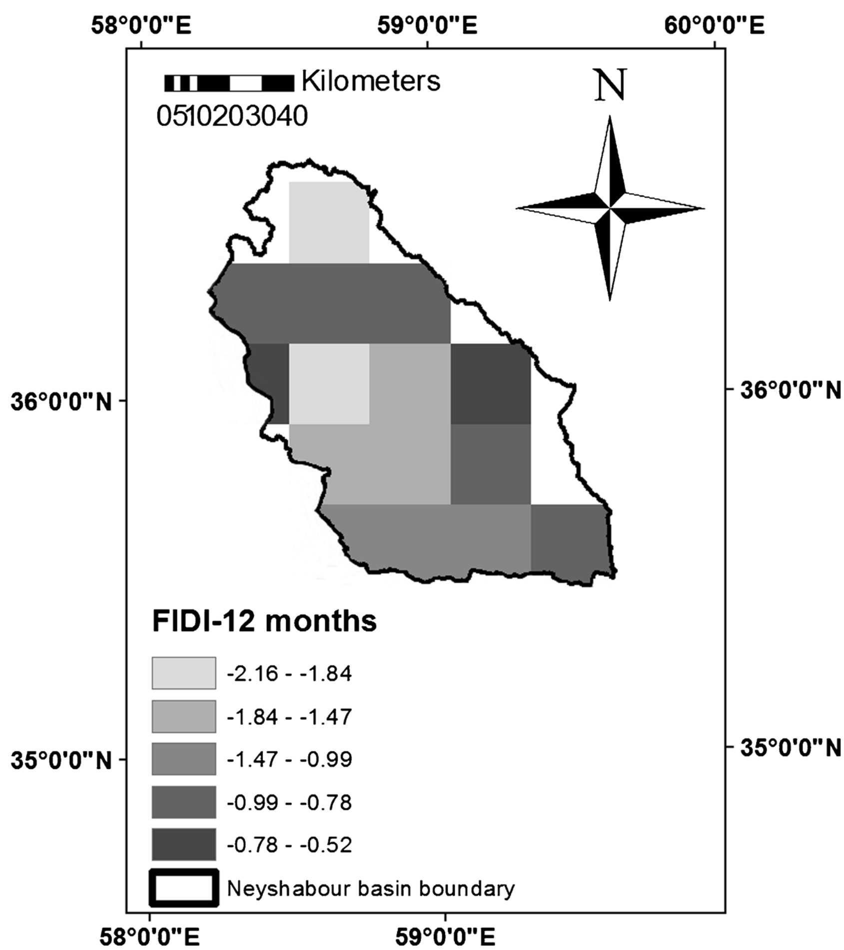


Fig. 5 Spatial dispersion of FIDI in the Neyshabour basin

Table 6 Drought properties in the Neyshabour basin during 1985–2014

Latitude (°)	Longitude (°)	Cells number	Frequency	Duration (average)	Severity	Intensity
36.54	58.64	1	36	8	− 2024.4	− 235.05
36.33	58.36	2	43	6	− 2144.4	− 357.40
36.33	58.63	3	37	7	− 1939.2	− 277.02
36.32	58.50	4	40	8	− 1994.2	− 249.2
36.11	58.41	5	31	8	− 1481.5	− 185.10
36.10	58.63	6	37	7	− 1684.8	− 240.68
36.10	58.91	7	41	6	− 1646.3	− 274.38
36.09	58.19	8	36	7	− 1726.2	− 246.6
35.42	58.63	9	34	7	− 1909.7	− 272.3
35.87	58.91	10	38	7	− 1810.3	− 258.6
35.87	59.18	11	33	8	− 1894.8	− 236.8
35.65	58.72	12	32	8	− 1935.7	− 241.9
35.65	58.90	13	35	7	− 1827.4	− 261.05
35.64	59.17	14	39	7	− 2081.3	− 297.3
35.63	59.45	15	37	7	− 1795.3	− 256.4

continuity of drought in the Neyshabour basin due to considering the only effective factor of rainfall on development of drought, while FIDI recognizes persistence of drought properly. In years 1996–1997, drought occurred in the Neyshabour basin and SEPI shows a lower intensity of drought, while the FIDI has a better ability to determine the severity of drought, taking into account that it considers all factors which affect the occurrence of drought. In another study, Broghani et al. (2015) used SPI, PNI, and ZSI indicators to monitor drought in Khorasan province and determine the best drought index in years 1980–2010. The results showed that SPI, PNI, and ZSI only identified years 2000 and 2001 as dry years in the Neyshabour basin, and normal to wet conditions were obtained in years 2003–2004 in this area. Results indicate that these three indicators did not show the persistence of drought because of utilizing only precipitation factor in their calculation, while FIDI recognized start and period of drought during statistical years 2000–2004.

The present study tries to express the joint effect of major impressive factors on drought based on their weights in a single indicator. Such as SPI, MDI, IDI, and SEPI, suggested drought index in this study has ability to calculate at different time scales. As a result, FIDI can well examine the effects of drought on different water sources and vegetation. The FIDI's preference to the MDI is the use of fuzzy modeling to build this index and also to IDI is the application of actual evapotranspiration, which is a very major factor in creating drought, especially in arid to semi-arid regions. Moreover, the FIDI uses other variables affecting drought (runoff and soil moisture) in comparison with the SEPI, as well as using the entropy method to determine the contribution of each of the indicator variables.

Table 7 Choice of scale for FIDI

	Scales				
	1	3	6	9	12
Entropy values	0.93	0.98	0.91	0.94	0.97
Weights	0.28	0.05	0.34	0.22	0.09

Conclusion

It is found that scarcity of runoff is one of the most important factors in shaping drought and should consider it in providing drought indices. Moreover, temperature is another factor that should be definitely used in monitoring drought of semi-dry to dry regions, although the impact of precipitation, Et_a, runoff, and soil moisture in producing drought indices may vary based on different climates.

In this study, a new feature of drought index is provided which combines the effects of four important variables (precipitation, Et_a, runoff, and soil moisture) that changes in them can construct different types of drought. The study revealed that FIDI has better ability in recognizing different kinds of droughts in contrast with meteorological, hydrological, or agricultural indices.

More specifically, results have shown that remarkable droughts occurred during years 1985–2014. Spatial distribution of FIDI demonstrated that intensity of drought was increased from east to west in the Neyshabour basin. Portions with lower precipitation, runoff, and soil moisture and also higher temperature were prone to more drought.

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