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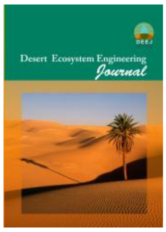

Monitoring meteorological drought with SPI and RDI drought indices and Forecasting Class Transitions Using Markov Chains in southern Iran

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Abstract

The uncertainty found in standard methods of drought monitoring has made it necessary to compare the accuracy of the drought's monitoring methods. This study examined the Standardized Precipitation Index (SPI) and Reconnaissance Drought Index (RDI) to determine drought severity in 12 meteorological stations in southern Iran from 1975-2015 and predict draught transition from one to another class to another, using the Markov Chain model. According to the coefficient correlation analysis results between the precipitation data collected from the meteorological stations and the drought index, it was found that 3-month SPI and RDI have a high correlation with precipitation data. On the other hand, the analysis of the 3-month SPI and RDI index in all stations showed that the highest probability belonged to normal and near-normal classes, with their mean average probability values being 0.73 and 0.27 for SPI and 0.70 and 0.30 for the RDI, respectively. Moreover, based on RDI and SPI, the most probability rate of the drought occurrence in most of the stations belonged to normal and moderate drought classes, confirming a high correlation between meteorological drought and short-term drought index. According to the results, it is recommended that in the analysis of drought features, their characteristics such as vulnerability, resiliency, and reliability should be examined based on the climate type. Furthermore, to reduce the harmful effects of drought, necessary measures must be taken, especially in managing water resources.

Keywords: Meteorological drought, RDI, SPI, Markov Chain Model, Southern Iran.

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1. Introduction

The precipitation changes in humid and arid areas and in wet and dry seasons are predicted to expand further, leading to numerous extreme hydrological consequences such as floods and droughts worldwide (Huang et al., 2017). Due to its adverse effects on the environment, agriculture, economics, and society, drought is considered one of the most destructive natural threats in most climate zones worldwide (Wang et al., 2017).

Drought events cause environmental changes and seriously impact social economies and agricultural development (Habibi et al., 2018). As multiple factors (including precipitation, humidity, wind speed, temperature, heat waves, etc.) are involved in drought (Sheffield et al., 2012; Hao and Singh, 2015), a drought index based on a single climatic variable (Vicente-Serrano et al., 2010) is insufficient for drought monitoring.

Drought indices are commonly employed to monitor drought severity quantitatively. Different scholars have developed different techniques and methods for estimating various types of droughts. For instance, Alizadeh and Nikoo (2018) developed a fusion-based estimation model for meteorological drought using remote sensing data. Feng et al. (2019) integrated remote sensing and machine-learning tools for estimating agricultural drought, Kedzior, Zawadzki (2017) used soil moisture and ocean salinity satellite data to monitor agricultural drought, and Strnad et al. (2020) used an index-flood model to assess hydrological drought.

Drought events can be analyzed in different ways. However, drought indicators are currently the most convenient and effective method in this regard. Many drought indicators have already been developed to assess different types of drought (Liu et al. 2017; Habibi et al. 2018), among which the Standardized Precipitation Index (SPI) and the Reconnaissance Drought Index (RDI) are fast and straightforward indicators to be used for describing drought conditions both in short and long-time scales. Moreover, different drought indices involving different climatic parameters have been developed to detect dry and wet categories of a region for a specified time (Svoboda et al., 2016). The SPI (precipitation) and RDI (precipitation and temperature) have also been used in some studies to analyze the drought's intensity, duration, and frequency trend in Iran's arid and semi-arid regions (Bazrafshan et al., 2019).

Furthermore, different statistical and probabilistic models have been developed to investigate drought characteristics. For instance, copula-based statistical models are used to estimate drought risk (Yu et al., 2018; Nguyen-Huy et al., 2019), Mann–Kendall test-based trend analysis models are employed to classify drought (Santos et al., 2019), Markov chain models are used to find the transition probabilities of drought states (Banik et al., 2002). Moreover, Bayesian network models have recently been developed to assess and forecast drought severity (Madadgar and Moradkhani, 2014; Chen et al., 2018). The theory of Markov chains is a promising approach to develop dynamic model activities with a stochastic factor (Lange, 2010). Since drought events are random, the severity of drought can be analyzed using a stochastic method. A time-series drought index can be used to identify the severity of historical or persistent drought events and predict the drought using a Markov chain, which is widely used to analyze hydro-meteorological conditions (Paulo et al., 2007).

Many studies have already used a Markov chain to identify drought characteristics (Jahangir Alamet al., 2013; Habibi et al., 2018; Tabari et al., 2015). Paulo et al. (2005), Paulo and Pereira (2008), and Paulo et al. (2007) also applied the Markov chain model to study the stochastic characteristics of an SPI drought transition, showing that a stochastic model can be used to monitor the evolution of droughts and generate an early warning system for drought conditions in specific areas. In addition, the Markov chain model is widely used as an agricultural drought index in India to identify proneness to drought (Banik et al., 2002), analyze correlations of rainfall drought (Jahangir Alam et al., 2011), and predict spells of dry and wet conditions. Moreover, Masoudian (2003) studied 27 influential climatic elements at the annual scale in Iran, proving that six factors explain 89% of Iran's climate behavior using the cluster analysis method. Accordingly, it could be argued that in Iran's southern region (ranging from Sistan and Baluchestan province to Khuzestan province), temperature and humidity play significant roles in the regions' climatic behavior.

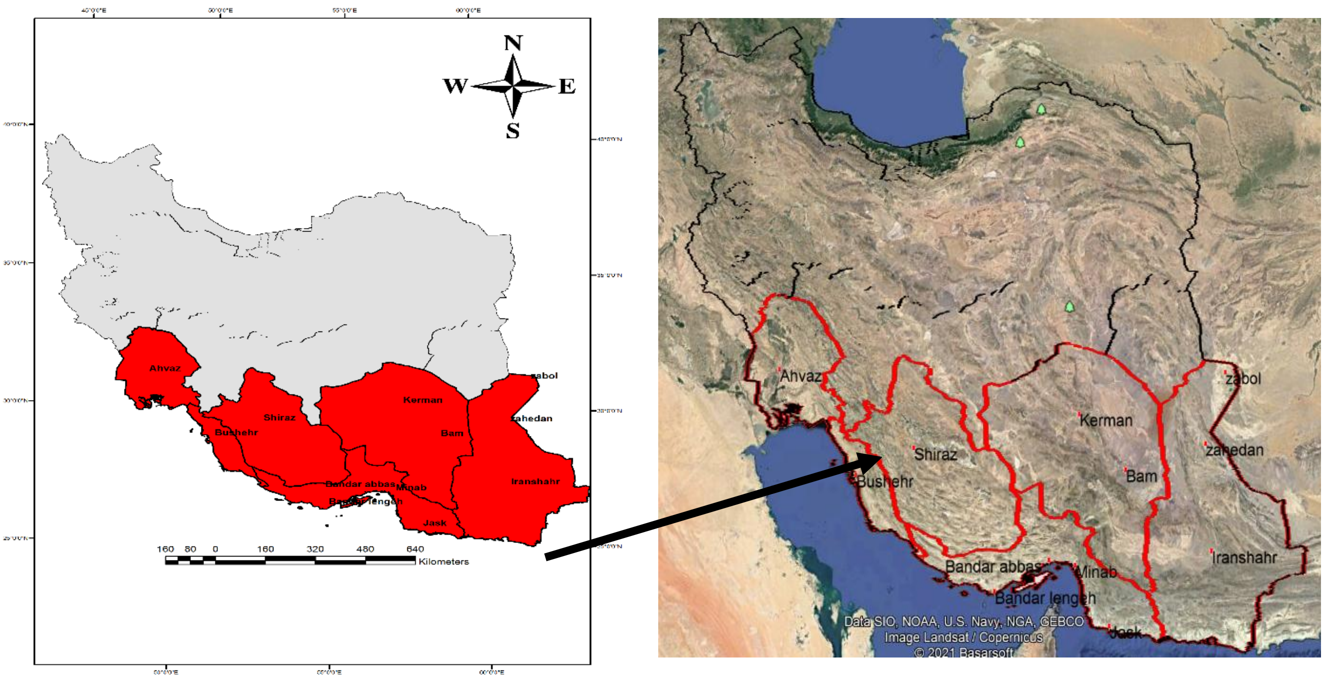
While climatic data is mainly picked up by the station at one point, this study needed the data regarding a zone. Furthermore, the results of climate analysis can be generalized to a wide area when the data is generalized to the area data with the help of interpolation. Therefore, in this study, the SPI and the RDI index were examined to evaluate the drought characteristics in Iran's southern region, and the Markov chain model based on a drought index time series was used to analyze the characteristics of drought events, including the steady-state probability of drought events, the mean duration of the drought, and drought proneness.

2. Material and Methods

2.1. The Study Area

The study area is located in southern Iran, between 25° 0'N to 32° 0'N and 48° 0'E to 64° 0'E, bordering the Persian Gulf and Oman Sea. Fig 1 shows the location of weather stations whose data were utilized in the study.

To study the local and regional characterization of droughts in southern Iran during 3, 12, and 24- month periods, the RDI behavior and SPI series in the selected sites were analyzed with Markov chain Model focusing on the transitions between drought categories.



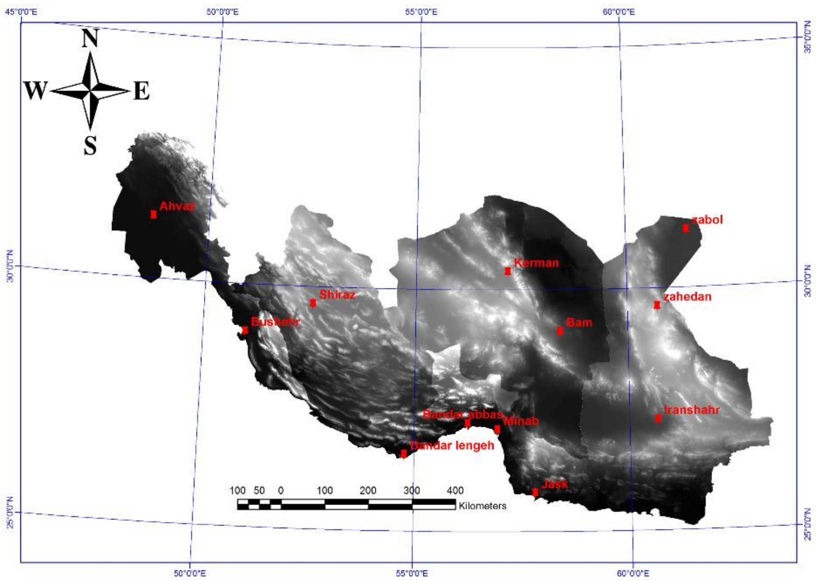


Figure (1): The view of the study area in southern Iran

2.2. Calculation Drought Indices

The SPI index is widely used worldwide to monitor drought (Yihdego et al., 2019). The fundamental advantage of SPI is its simplicity and ability to calculate drought severity at multiple time scales. Due to its multi-scale properties, the SPI can be used to monitor short-term and long-term rainfall deficits and different kinds of drought. To calculate the SPI, daily precipitation data were first aggregated into a specific timescale, and then a gamma distribution was fitted to the data, a method which has been used in many previous studies (Sattar et al., 2018; Sattar et al., 2019; McKee et al., 1993). Then, the data were transformed into a standard normal distribution with a zero mean and a standard deviation of one. The SPI represents the deviation of precipitation values from their mean. Moreover, while positive values indicate surplus precipitation, negative values represent precipitation deficit (Sattar et al., 2020).

A new reconnaissance drought identification and assessment index were first introduced in the MEDROPLAN's coordinating meeting (Tsakiris, 2004), and a more comprehensive description was presented in other publications (Tsakiris and Vangelis 2005; Tsakiris et al. 2006). The index, which is referred to as the Reconnaissance Drought Index (RDI), is calculated by the following equations, where the yearly equations are presented first for illustrative purposes. The first equation is called the initial value of RDI (a_o), which is presented in an aggregated form using a monthly time step and could be calculated for each month of the hydrological year or for an entire year. The a_o is usually calculated for the ***i***th year on an annual basis using the following equation:

$$a_0^{(i)} = \frac{\sum_{j=1}^{12} \mathrm{Pij}}{\sum_{j=1}^{12} \mathrm{PETij}}, i = 1 \text{to N and j} = 1 \text{ to } 12 \qquad (1)$$

Where P_{ij} and PET_{ij} are the precipitation and potential evapotranspiration of the ***j***th month of the ith year, usually starting from October (as it is typical in Mediterranean countries), and N is the total number of years of the available data. The present study estimated the PET rates with the Penman-Monteith equation, which is the most reliable way to estimate PET under various climatic conditions. The Penman-Monteith method reflects changes of all meteorological factors affecting the evaporation and transpiration in the plants. The Normalized RDI (RDIn) is calculated using the following equation:

$$\mathrm{RDI_n} = \frac{a_0^{(i)}}{\bar{\alpha}} - 1 \tag{2}$$

Finally, the Standardized RDI (RDIst) is calculated by a procedure similar to the one used for the calculation of SPI:

$$\mathrm{RDI}_{\mathrm{st(k)}}^{(i)} = \frac{y_k^{(i)} - \bar{y}}{\partial_{\hat{y}k}} \tag{3}$$

Where $\mathbf{y_i}$ is the ln $(\mathbf{a_0^{(i)}})$, $\bar{\boldsymbol{y}}_{\mathbf{k}}$ is its arithmetic mean, and $\partial_{\hat{y}k}$ is its standard deviation. As Standardized RDI behaves similar to the SPI, it is the interpretation of results. Therefore, the RDIst can be compared to the same thresholds as the SPI. (Tsakiris et al., 2007).

The discrete Markov chain is a random process that describes a sequence of events from a set of finite possible states. In contrast, the current event depends only on the preceding event. The discrete Markov is commonly used to model uncertain events in various disciplines. Each discrete Markov chain is characterized by a transition probability matrix that represents the probability of transition from one state to another (Ali et al., 2020; Yeh and Hus, 2019). As a stochastic process, the Markov chain refers to a sequence of random variables X1, X2,… X1, X2, where the probability of the change in each event's state from time t to t + 1 is independent of the previous states:

$$P\{X_{t+1} = j \mid X_0; X_1; \ldots; X_t\} = P\{X_{t+1} = j \mid X_t = i\} \forall i, j \in S; t \in T \tag{4}$$

A Markov chain is characterized by a set of states (**S**) and the transition probability (Pij) between states. The Pij represents the probability when the Markov chain is at the next time point in state ***j***, given that it is present in state ***i***.

For instance, SPI calculates the total transited precipitation and each drought category can be determined for appropriate Markov chain modeling by assigning a unique SPI value. The transition probability matrix is as follows:

$$\boldsymbol{P} = [\boldsymbol{P}_{ij}] = \boldsymbol{P}\{X_{t+1} + \boldsymbol{j} \mid X_t = \boldsymbol{i}\} \tag{5}$$

This matrix is estimated from the sample, counting the number of times ($\boldsymbol{n}_{ij}$) which SPI passes from the state i to the state ***j***, through the following equation:

$$\boldsymbol{P}_{ij} = \boldsymbol{n}_{ij} \Big/ \sum_j \boldsymbol{n}_{ij} \tag{6}$$

The sample size and the number of states influence the accuracy of the estimations. Moreover, the number of the model's parameters depends on the number of states. As the Standardized RDI and SPI perform similarly (McKee et al. 1993), they have the same interpretation. Therefore, the $\mathrm{RDI_{st}}$ values could be compared to the same thresholds through the same technique used for the SPI. In this study, eight drought categories or states were considered (Table 1). The standardized precipitation index (SPI) and Reconnaissance Drought Index (RDI) for each month were calculated using the previous 3-month (SPI-3 and RDI-3), 12-month (SPI-12 and RDI-12), and 24-month (SPI-24 and RDI-24) precipitation data for short-term, intermediate-term, and long- term analysis for management purposes, respectively. As the findings of Guerreiro et al. (2007) study indicated, zero SPI and RDI values mean that there are no deviations between the precipitation rate of the intended period and the mean precipitation of another month. Also, positive values of the SPI and RDI suggest an excess rainfall in proportionate to the mean, and negative values of SPI and RDI indicate a lack of precipitation compared to the mean value. Therefore, dry periods are characterized by negative SPI and RDI values, while wet periods are shown by positive ones. Moreover, as suggested by McKee et al. (1993), the SPI and RDI values are grouped in eight classes from extreme drought (SPI or RDI ≤ −2.0) to extremely wet (SPI or RDI ≥ 2.0), as shown in Table 1.

Table (1): Classification of drought according to the SPI and RDI_{st} values

Range	SPI and RDI_{st} range Drought classes	State
2 or more	Extremely wet	1
1.5 to 1.99	Very wet	2
1 to 1.49	Moderately wet	3
0.99 to 0.0	Normal	4
0.0 to −0.99	Near normal	5
−1 to −1.49	Moderately dry	6
−1.5 to −1.99	Severely dry	7
−2 and less	Extremely dry	8

Monthly and annual RDI and SPI were calculated and organized using the monthly precipitation and evapotranspiration data collected from 12 meteorological stations in southern Iran. RDI and SPI values of 41 periods of hydrological years were calculated from 1975 to 2015 at 3-month, 12-month, and 24-month scales in monthly time scales. Table 2 shows the main characteristics of synoptic stations and their location.

Table (2): General characteristics of 12 surveyed synoptic stations

Row Station name	X coordinate	Y coordinate	Elevation (m)	P (mm)	Climate classification
Ahwaz	321231	3492096	22.5	240.9	Arid
Bam	625967	6495690	66.9	59.3	Hyper-arid
Bandar abbas	522503	6274776	9.8	152.9	Arid
Bandar Lengeh	492608	6137456	22.7	205.6	Arid
Bushehr	683239	5695746	19.6	277.2	Arid
Iranshahr	517934	6781397	591.1	112.4	Arid
Jask	444292	6460648	5.2	139.0	Arid
Kerman	345695	6388972	1753	142.1	Arid
Shiraz	693140	3307538	484	348.0	Semi-arid
Zabol	397206	6853442	489.2	62.6	Hyper-arid
Zahedan	648294	6817934	1370	75.3	Arid
Chabahar	417161	6767470	8	117.5	Arid

Fig 2 shows the 41-year averages of monthly precipitation in the region, indicating a typical Mediterranean precipitation pattern, rainfall concentration during the spring and winter months, and arid summer and autumn.

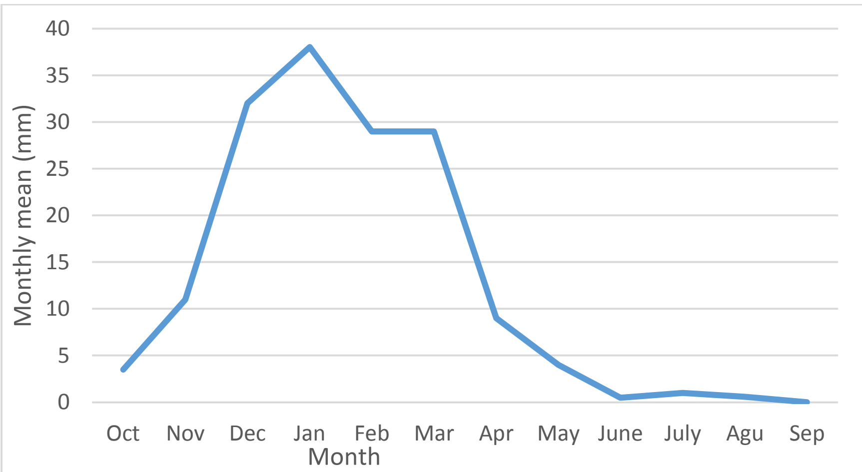


Figure (2): Monthly mean areal precipitation 1975 to 2015 in southern Iran collected from 31 rainfall stations

The results gained from 12 rain gauges distributed in southern Iran revealed that 90.13% of precipitation occurred during the humid season (October to March), and 1.89% occurred from June and September, indicating that April and May were the wettest months of the dry season (Fig 2).

3. Results

The probabilities for the non-drought class were found to be similar in all analyzed locations. However, the relative differences between the sites were higher for more severe drought classes. The expected residence time in each drought severity class indicated the probability of drought in that period. Based on the McKee classification, drought forecasts were prepared for a 41-year data set (1975-2015) in terms of RDI and SPI over a period of 3, 12, and 24 months. Using Markov Chains, the results of which are shown in tables 3 to 8. The SPI and RDI indices were developed by McKee et al. (1993) to identify and monitor local droughts. According to table 3, the probability of the 3-month RDI occurrence is "normal" and 'near normal' for all areas located in the two classes. On average, the probability of the 'normal' and 'near normal' classes was 0.73 and 0.27, respectively.

Table (3): Probability of occurrence based on RDI 3-month over the period of 1975-2015

	RDI 3-month							
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	–	–	–	0.93	0.07	–	–	–
Bandar abbas	–	–	–	0.6	0.4	–	–	–
Iranshahr	–	–	–	0.6	0.4	–	–	–
Bushehr	–	–	–	0.9	0.1	–	–	–
Kerman	–	–	–	0.53	0.47	–	–	–
Zabol	–	–	–	0.9	0.1	–	–	–
Bam	–	–	–	0.63	0.37	–	–	–
Bandar Lengeh	–	–	–	0.83	0.17	–	–	–
Chabahar	–	–	–	0.70	0.30	–	–	–
Jask	–	–	–	0.67	0.33	–	–	–
Shiraz	–	–	–	0.80	0.20	–	–	–
Zahedan	–	–	–	0.67	0.33	–	–	–

Table 4 shows the occurrence probability of different drought classes based on RDI 12-month. Accordingly, normal and near-normal classes are more likely to occur than other drought classes in most stations. The average probability of their occurrence is 0.4 and 0.34, respectively. For instance, in Bushehr station, the probability of the occurrence of all classes from very wet to very dry was observed, but the highest probabilities were related to normal and near-normal classes with values of 0.4 and 0.43, respectively (Table 4).

Table (4): Probability of occurrence based on RDI 12-month, over the period 1975-2015

	RDI 12-month							
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	–	0.07	0.07	0.47	0.23	0.13	0.03	–
Bandar Abbas	–	0.03	0.13	0.30	0.40	0.13	–	–
Iranshahr	–	0.03	0.13	0.47	0.13	0.13	0.10	–
Bushehr	0.03	0.03	0.03	0.40	0.43	–	0.03	0.03
Kerman	–	0.07	0.13	0.33	0.37	0.10	–	–
Zabol	–	–	–	–	–	–	–	–
Bam	–	–	0.23	0.27	0.37	0.10	0.03	–
Bandar Lengeh	–	0.03	0.13	0.33	0.33	0.13	0.03	–
Chabahar	0.03	0.03	0.03	0.47	0.33	0.03	0.03	0.03
Jask	0.03	0.03	0.07	0.37	0.40	–	0.10	–
Shiraz	–	0.07	0.03	0.43	0.37	0.07	–	0.03
Zahedan								

Table 5 shows the occurrence probability of drought classes for RDI 24-month. According to table 5, the probability of the occurrence of a 12-month RDI drought for the "near normal" class shows an increasing trend in Ahvaz, Bushehr, Kerman, Iranshahr, Zabol, and Chabahar stations, indicating a reduction in the probability of continued drought in such areas. At Bandar Abbas, Bam, Bandar Lengeh, Shiraz, and Jask stations, the 'near normal' class showed a decreasing trend, with that Jask station having the lowest occurrence probability with a value of 0.23. On the other hand, the probability of normal class occurrence had increased by 0.1, suggesting an increase in the probability of continued drought in the region. Moreover, the results of Shiraz station showed that the occurrence probability of 'normal' and 'near normal' classes from RDI 12-month to RDI 24- month had a decreasing trend, with their values being 0.43 and 0.37 to 0.37 and 0.33, respectively, and that the very wet class had increased by 5 percent.

Table (5): Probability of occurrence based on RDI 24-month over the period of 1975-2015

RDI 24-month								
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	–	0.03	0.07	0.43	0.30	0.10	0.03	0.03
Bandar abbas	–	0.03	0.07	0.43	0.27	0.17	0.03	–
Iranshahr	–	–	0.07	0.53	0.27	0.03	0.07	0.03
Bushehr	0.07	0.03	0.03	0.27	0.47	0.10	0.03	–
Kerman	–	–	0.20	0.20	0.47	0.10	0.03	–
Zabol	–	–	0.17	0.47	0.20	0.10	0.03	0.03
Bam	–	–	0.13	0.43	0.30	0.03	0.07	0.03
Bandar Lengeh	–	0.03	0.17	0.33	0.30	0.10	0.03	0.03
Chabahar	0.03	0.03	0.10	0.37	0.37	–	0.10	–
Jask	–	0.07	0.10	0.43	0.17	0.20	–	0.03
Shiraz	–	0.13	0.03	0.37	0.33	0.07	0.07	–
Zahedan	0.03	0.03	0.03	0.40	0.37	0.10	–	0.03

According to Table 6, the results of SPI 3-month and RDI 3-month are similar, the highest probabilities belong to normal and near-normal classes, and the normal class bears the highest percentage.

Table (6): Probability of occurrence based on SPI 3-month over the period of 1975-2015

SPI 3-month								
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	–	–	–	0.87	0.13	–	–	–
Bandar abbas	–	–	–	0.67	0.33	–	–	–
Iranshahr	–	–	–	0.63	0.37	–	–	–
Bushehr	–	–	–	0.9	0.1	–	–	–
Kerman	–	–	–	0.53	0.47	–	–	–
Zabol	–	–	–	0.87	0.13	–	–	–
Bam	–	–	–	0.57	0.43	–	–	–
Bandar lengeh	–	–	–	0.83	0.17	–	–	–
Chabahar	–	–	0.03	0.66	0.31	–	–	–
Jask	–	–	–	0.67	0.33	–	–	–
Shiraz	–	–	–	0.73	0.27	–	–	–
Zahedan	–	–	–	0.53	0.47	–	–	–

Table 7 shows the results of occurrence probability based on SPI 12-month. Accordingly, the occurrence probability of the normal class is approximately equal to or more than close to normal except for Ahwaz, Bushehr, and Bandar Lengeh stations (Table 7).

Table (7): Probability of occurrence based on SPI 12-month over the period of 1975-2015

	SPI 12-month							
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	0.03	–	0.03	0.37	0.43	0.10	0.03	–
Bandar abbas	–	–	0.20	0.33	0.27	0.20	–	–
Iranshahr	–	–	0.17	0.43	0.20	0.10	0.10	–
Bushehr	0.03	–	0.07	0.40	0.43	–	0.07	–
Kerman	–	0.07	0.07	0.37	0.37	0.10	0.03	–
Zabol	–	0.03	0.10	0.37	0.37	0.10	0.03	–
Bam	–	–	0.13	0.43	0.27	0.17	–	–
Bandar Lengeh	–	0.03	0.13	0.30	0.37	0.13	–	0.03
Chabahar	0.03	0.03	0.07	0.50	0.27	–	0.07	0.03
Jask	–	0.03	0.10	0.43	0.33	0.03	0.07	–
Shiraz	–	0.03	0.07	0.40	0.33	0.13	0.03	–
Zahedan	0.03	0.03	0.03	0.37	0.40	0.07	0.067	–

On the other hand, the probability of a normal class occurrence has significantly been reduced compared to that of the 3-month SPI, and the probability of other classes has been increased. For instance, at Bandar Abbas station, the occurrence probability of the moderately wet and moderately dry states is 20% (Table 6).

Table 7 shows the results of the occurrence probability based on 24-month SPI, which are similar to those of the. However, the probability of the occurrence of a near-normal class is lower in 12-month than that of the 24-month. Overall, the probability of occurrence of dry classes shows an increasing trend (Table 7).

Table (8): Probability of occurrence based on SPI 24-month over the period of 1975-2015

	SPI 24-month							
	Extremely wet	Very wet	Moderately wet	Normal	Near normal	Moderately dry	Severely dry	Extremely dry
Ahwaz	–	0.10	0.03	0.37	0.37	0.10	0.03	–
Bandar abbas	–	–	0.20	0.37	0.23	0.13	0.07	–
Iranshahr	–	–	0.10	0.53	0.17	0.10	0.03	0.07
Bushehr	0.07	–	0.07	0.37	0.43	0.07	–	–
Kerman	–	0.07	0.07	0.40	0.30	0.13	–	0.03
Zabol	–	–	0.20	0.33	0.33	0.10	–	0.03
Bam	–	–	0.13	0.47	0.27	0.03	0.10	–
Bandar lengeh	–	0.07	0.10	0.33	0.37	0.07	0.03	0.03
Chabahar	0.03	–	0.10	0.40	0.37	–	0.10	–
Jask	–	0.03	0.13	0.43	0.20	0.17	–	0.03
Shiraz	0.03	0.03	0.10	0.40	0.30	0.07	0.07	–
Zahedan	–	0.07	0.07	0.40	0.33	0.10	0.067	0.03

The relationship between rainfall and drought was clarified by examining the relationship between RDI and SPI time- series, frequency of the stations, and correlation analysis. The calculation of the correlation between the indices (SPI 24-month, SPI 12-month, SPI 3-month, RDI 24-month, RDI 12-month, RDI 3-month) and the annual precipitation rate of each station could help identify the more reliable indices for studying the drought in the study area. Table 9 shows the correlation coefficients obtained for each of the 12 stations used during the 41-year statistical period.

Table (9): Calculated correlation coefficients for the stations in the study area

	RDI 3	RDI 12	RDI 24	SPI 3	SPI 12	SPI 24
Ahvaz	0.78	0.67	0.52	0.90	0.68	0.53
Bandar abbas	0.68	0.48	0.495	0.79	0.48	0.49
Iranshahr	0.43	0.71	0.52	0.85	0.692	0.50
Bushehr	0.81	0.512	0.40	0.86	0.52	0.42
Kerman	0.69	0.71	0.54	0.92	0.69	0.53
Zabol	0.86	0.60	0.51	0.88	0.61	0.452
Bam	0.73	0.57	0.43	0.87	0.49	0.39
Bandar Lengeh	0.67	0.64	0.57	0.86	0.63	0.48
Chabahar	0.65	0.54	0.53	0.87	0.58	0.53
Jask	0.87	0.79	0.67	0.91	0.78	0.63
Shiraz	0.83	0.62	0.36	0.87	0.64	0.38
Zahedan	0.45	0.58	0.54	0.90	0.68	0.53

Since only the precipitation parameter directly affects the calculation of the SPI index, there is a significant correlation between the two. The RDI index also shows a good correlation with the precipitation parameters in all stations regardless of the climatic zone. According to Table (9), SPI 3-month and RDI 3-month have the highest correlations with precipitation values in all stations throughout the study period, respectively. The results also indicated that meteorological drought was more correlated with shorter periods of drought indices and that it was better to use short-term indices in meteorological drought studies, which are consistent with the results found by Zarei et al. (2017).

Therefore, Table 6 can be used as a suitable model for classifying the study area's drought, considering that the study area was in a normal and near-normal condition throughout the 41-year statistical period. For instance, according to the SPI 3-month of Ahvaz station, 87% of droughts were normal, and 13% were near normal.

5. Conclusion

This study investigated the probability of transition from one drought class to another in eight cases of extremely dry, severely dry, moderately dry, near normal, normal, moderately wet, very wet, and extremely wet, using SPI and RDI indices and the first-order Markov chain model. It should be noted that among the various methods proposed for drought prediction (such as time-series models), the Markov chain model is compatible with discrete data and allows the prediction of drought classes, and that was why it was preferred over other methods in this study.

The results of predicting the occurrence probability of drought classes showed that according to the quarterly SPI and RDI index in all the studied stations, the highest probability belonged to two normal classes, with average probabilities of 0.73 and 0.27 for SPI, and 0.70 and 0.30 for the RDI index. Therefore, in almost all of the stations surveyed, the Extremely wet and Very wet classes had the lowest frequency. Therefore, based on the SPI index of Bandar Abbas and Iranshahr stations and the RDI index of Bam, Zabol, and Zahedan stations, the stations will never experience extremely wet conditions during the study period. However, the probability of the Extremely wet and Very wet classes was less than 3% in other stations. In all the stations studied, the probability of normal class occurrence is increasing compared to other dry classes according to 12-month RDI 24-month SPI indices. These results are consistent with the findings of the studies carried out by Zarei et al. (2017), Ghaznavi et al. (2020), Azimi et al. (2015), and Doostan (2020).

Therefore, the Markov chain model can be a good instrument for monitoring and forecasting drought (Shokrikochak and Behnia, 2013; Zarei et al., 2017; Maghsoud et al., 2017; Ghaznavi et al., 2020). According to the results of the correlation analysis of drought indices values with each, there was a high correlation between SPI and RDI indices in all climatic zones, which are consistent with results found by Yousefi et al. (2016) and Maleksabet et al. (2015). Based on these results, the most probable states for the next three months could be computed as a predictive tool for the prospective transitions among drought severity classes. The study's results also showed differences in behavior among the locations considered in this study.

The Markov chains modeling could be combined with log-linear models, and the respective probabilities may be better interpreted from an operational perspective. Overall, the combination with other indicators such as those derived from global circulation models and sea temperature anomalies, or just those related to actual and historical soil moisture conditions, streamflow records, and reservoir levels may contribute to support decisions in the context of water management, including those concerning the drought risk management. Predictions may also be used to develop scenarios for 1, 2, and 3 months ahead, which are useful for drought risk management.

Moreover, the findings of Fathizadeh et al. (2017) study showed that the major droughts in Iran have occurred from May to November, and Babaei Fini et al. (2013) found that severe and long-term droughts had occurred mainly in the southern half of Iran. Based on the results found for SPI at 6 and 12-month scales, the southern regions of Iran were more severely affected by drought, necessitating more appropriate water management in these areas (Sharafi et al., 2016; Sobhani and Safarianzengir, 2020). Therefore, according to the study's results, it is recommended that in the analysis of drought characteristics, factors such as vulnerability, resiliency, and reliability be examined according to the climate type. Furthermore, to reduce the harmful effect of drought, some necessary measures need to be taken in this field, the most important of which is the appropriate management of water resources.

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