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Predicting the probability of transforming different classes of monthly droughts in Iran

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Abstract: The main objective of this study was to predict the transition probability of different drought classes by applying Homogenous and non- Homogenous Markov chain models. The daily precipitation data of 40 synoptic stations in Iran, for a period of 35 years (1983-2018), was used to access the study objectives. The Effective Drought Index (EDI) was applied to categorize Iran's droughts. With the implementation of cluster analysis on the daily values of effective drought index (EDI), it was observed that Iran can be divided into five separate regions based on the behavior of the time series of the studied stations. The spatial mean of the effective drought index (EDI) of each region was also calculated. After forming the transition frequency matrix, the dependent and correlated test of data was conducted via chi-square test. The results of this test confirmed the assumption that the various drought classes are correlated in five studied regions. Eventually, after adjusting the transition probability matrix for the studied regions, the homogenous and non-homogenous Markov chains were modeled and Markov characteristics of droughts were extracted including various class probabilities of drought severity, the average expected residence time in each drought class, the expected first passage time from various classes of droughts to the wet classes, and the short-term prediction of various drought classes. Regarding these climate areas, the results showed that the probability of each category is reduced as the severity of drought increases from poor drought category to severe and very severe drought. In the non-homogeneous Markov chain, the probability of each category of drought for winter, spring, and fall indicated that the probability of weak drought category is more than other categories. Since the obtained anticipating results are dependent on the early months, they were more accurate than those of the homogeneous Markov chain. In general, both Markov chains showed favorable results that can be very useful for water resource planners.

Keywords: Drought; Prediction; Homogenous Markov chain; Non- homogenous Markov chain; Iran

1 Introduction

The vast country of Iran, with about one-third of the world's rainfall, is located in one of the arid and semi-arid regions of the world and drought is its nature and the main characteristic of this climate. In recent years, due to the causes that are often related to global climate change, precipitation anomalies have increased in different parts of the country and severe spatial and temporal fluctuations of drought have caused enormous damage to the country's economy, especially in recent decades. Among the negative effects of drought which threat the sustainable development of this country, reduction in the operation of pastures, reduction in producing the crops, reduction in the number of drinking and agricultural water reservoirs, shortage of surface and groundwater resources, outburst of pests, and animal/plant diseases, migration increase and finally the adverse environmental, economic and social impacts can be mentioned. A study conducted regarding the severity and extent of droughts in Iran during a 40 years statistical period which ended in 2003 showed that in the water year 1999-2000, more than 96% of the country was dominated by drought. Besides, more than two other widespread droughts had happened in 1970-1971 and 1988-1989 which covered 82.21% and 92.05 % of the country, respectively (Bazrafshan 2011).

Drought prediction and determination of its characteristics in the arid and semi-arid areas are some of those fundamental necessities which should be taken into the consideration by environmental and economic planners, specifically by the water reservoir management planners. In many water reservoirs-related programs, it is necessary to have a vision regarding the water condition in the future using which can aid in conducting environmental and executive plans aimed to reduce its negative and harmful effects. Moreover, the drought prediction for the coming months will help farmers to minimize the losses which are related to this phenomenon through changing the date of cultivation or applying drought-resistant crops and varieties.

In recent decades, various statistical and non-statistical methods have been used to predict the droughts, of which the following can be mentioned: Support Vector Machine (Khan and Coulibaly 2006; Shivam et al. 2006; Nikbakht Shahbazi et al. 2012; Dibike et al. 2001; Liong et al. 2002; Chen et al. 2010), Artificial Neural Networks (Crespo and Mora 1993; Dracup and Silverman 2000; Shin and Salas 2000; Kim and Valdes 2003; Mishra and Desai 2006; Mishra et al. 2007), and analysis of time series through Auto Regressive-Integrated Moving Average Model (Han et al. 2013; Mishra and Desai 2005; Abebe and Forch 2007). Additionally, the capability of drought prediction via Tele Connection Patterns has been taken into the consideration (Bradburry et al. 2002; Cordery et al. 2000; Dole 2000; Barlow et al. 2002).

In the current study, the Markov chain model was used to predict the drought. The Markov chain model is a mathematical technique used to evaluate the random events which illustrate the continuity of observations over a period (Alijani et al. 2011). In fact, in the Markov chain model conducted on a series of observations and changes, each observation is evaluated from one state to the other one (Alijani et al. 2010). Using this model has attracted the attention of various experts in different fields, due to its capabilities regarding the calculation of dry and wet periods as well as simplification of many issues which are related to the relevant events (Stern 1982; Moon et al. 1994; Catz 1977; Dahale et al. 1994; Chin 1977; Caskey 1963; Martin Vide and Gomez 1999; Jaafari Behi 2008; Ghader Marzi 2001; Alijani et al. 2005; Hejazizadeh and Shirkhani 2005). Gabriel and Newman (1962) are one of those researchers who used this method to evaluate the characteristics of daily precipitation. By using this method, they illustrated that the daily precipitation in Tel Aviv had the same features as the dual-state first-order Markov chain which means that there is a connection between today's precipitation and yesterday's condition. Afterward, so many other researchers predicted various events by applying the same method. Among these studies, the following can be pointed out: Hopkins and Robillard (1964), Singh and Ibrahim (1996), Feyerherm and Dean Bark (1967), Martin vid and Gomez (1998), Stern (1980), Coenjo et al. (2001), Ochola et al. (2003), Mehorthra and Sharma (2007), Alijani et al. (2011). Besides, some studies carried out on drought prediction applying the same methods are Lohan and Logantan (1996), Lohani et al. (1998), Anagnostopoulou et al. (2003), Allasseur et al. (2004), Tolika and Mahera (2005), Paulo and Pereira (2007), Horvath and Bito (2007), Liu et al. (2009), Daryabari (2006) and Ghamghami et al. (2012).

Drought prediction has always been one of the major concerns of meteorologists and climatologists who used different methods and indicators to achieve this goal; hence, the main objective of this study was to predict the

transition probabilities of the various classes of monthly droughts in Iran through applying Markov chains model which can be very helpful in the development of early warning systems of monthly drought in Iran.

2 Materials and methods

To predict the transition probabilities of the various classes of monthly droughts in Iran, the statistics of daily precipitation of 40 synoptic stations in the country during a period of 35 years (1983-2018) were used. The obtained data involved complete and reliable statistics and the slight statistical gap of data was constructed through applying correlation and regression models. Additionally, to assess the accuracy and reliability of the obtained data in terms of homogeneity a runs test, which is recommended by all meteorological science authorities, was used for all the studied stations, and their homogeneity was highly accepted. The distribution and dispersion of the studied stations are illustrated in Figure 1.

Fig 1 The map of location and dispersion of the studied stations

After providing the required information bank, the Effective Drought Index (EDI) was used to recognize the abundance of various drought classes in Iran. The index was developed in 1999 by Byun and Wilhite to manifest and determine the start and end times of drought. Unlike other drought indexes, the EDI, in its real form, is calculated based on daily data (Akhtari et al. 2009; Kalamaras et al, 2010; Kim and Byun 2009; Kim et al. 2009;

Morid et al. 2006; Roudier and Mahe 2010); however, its principles can generalize monthly precipitation data (Morid et al. 2007; Pandey et al. 2008). Classification of EDI is similar to the classification of Standardized Precipitation Index (SPI) which is illustrated in Table 1.

Table 1 Classification of Effective Drought Index

Condition	Effective precipitation index
Extreme wet	Greater than or equal to 2.5
Severe wet	Greater than or equal to 1.5
Moderate wet	Greater than or equal to 0.7
Normal	Smaller than 0.7 and greater than -0.7
Moderate Drought	Smaller or equal to -0.7
Severe drought	Smaller or equal to – 1.5
Extreme drought	Smaller or equal to -2.5

To gain more information on the counting method of EDI, one can refer to Morid et al. 2006, Kim and Byun 2009, Akhtari et al. 2009, and Kalamaras et al. 2010.

Then, using the hierarchical clustering, the Euclidean distance measure for the observations, and Ward's method for the linkage rule, Iran's droughts were regionalized. Among the various distance measures and linkage rules that can be used in hierarchical cluster analysis, this combination has been shown to yield the most distinctive groups (Darand and Mansouri Daneshvar, 2014).

Because the sample size and the number of states in a series can affect the estimation accuracy of a Markov chain model (Paulo and Pereira 2007 and 2008), the four drought classes or in the other word, the four drought states were redefined: No drought (0), weak drought (1), moderate drought (2), severe and extreme drought (3). The considered thresholds for this classification are the same thresholds that were suggested for EDI. The only difference is that in the recent classification, all classes of the wet year were categorized in one class and severe and extreme classes of drought were categorized in another class.

Finally, after calculation and classification of the Effective Drought Index (EDI), the homogenous and non-homogenous Markov chain was used to predict the short-term droughts in Iran.

2.1 Markov Chain

Markov chain model is one of the mathematics techniques used for the evaluation of random phenomenon which illustrates a continuation of observations during the time. Markov chain is a series of observations and evaluations in which the changes of each observation from one state to another are assessed.

$$P = \{X_{t+1}|X_t, X_{t-1}, X_{t-2}, \dots, X_t\} = P\{X_{t+1}|X_t\} \quad (1)$$

In this relation, X is the stated variable, t stands for time and P is a conditional probability which expresses the concept that each process in $t+1$ time only depends on conditions in t time. In other words, prediction of next month conditions are exclusively conducted through the data of the current month and the previous month's data will not add any additional information to it. Hence, the first step towards using the Markov chain model is providing a transition frequency matrix that calculates the transition frequency. This matrix will be achieved by calculating the number of gained states and is set as follows:

$$N = \begin{bmatrix} N_{00} & N_{01} & \dots \\ N_{10} & N_{11} & \dots \\ \dots & \dots & \dots \\ N_{i1} & N_{i1} & \dots \\ \vdots & \vdots & \vdots \end{bmatrix}$$

In the next step, the transition probability matrix will be calculated through the transition frequency matrix. Equation (2) is used to calculate this matrix.

$$\hat{p}_{ij} = n_{ij} / \sum_j n_{ij} \quad (2)$$

In the above equation, n_{ij} is the number of times that X_t value has changed from state i to state j . Finally, the achieved matrix is as follows.

$$P = \begin{bmatrix} p_{00} & p_{01} & \dots \\ p_{10} & p_{11} & \dots \\ \dots & \dots & \dots \\ p_{i1} & p_{i1} & \dots \\ \vdots & \vdots & \vdots \end{bmatrix}$$

It should be noted that N is the redundancy of the transition from one state to another and P is the probability of transition from one state to another.

After setting the transition probability matrix, the required Markov features – which are presented in the following – can be extracted from the studied time series. The Markov chain model is divided into two types based on its dependency on a certain time.

- Homogenous Markov chain
- Non- homogenous Markov chain

In the Homogenous Markov chain model, the Markov features of the studied time series have no dependency on a certain time. In other words, it is independent of the studied start time. However, in the non-homogenous Markov chain model, the extracted Markov features are strongly dependent on the start time of the calculation which means

it is thoroughly dependent on the studied start time. The modeling and extracted features of homogenous and non-homogenous Markov chains are completely explained below.

2.1.1 Homogenous Markov Chain

As it was mentioned earlier, in the homogenous Markov chain model, the extracted features of the studied time series have no dependency on the time and it is calculated independent of the start time. Therefore, the below features are extracted by applying this model.

- The probability of occurrence of each class of drought severity
- Average expected residence time in each class of drought severity
- The average time of first expected passage from different categories from drought to wet class
- Short-term drought prediction

2.1.1.1 Probability of Occurrence of Each Class of Drought Severity

The first extracted feature in the homogenous Markov chain is the drought probability in each class also known as static probability. It shows the probability of each different drought class during the studied statistical period. In long term, the drought class probability will be independent of the starting state of the Markov chain. Besides, these probabilities, π_j , are pointed to the steady-state probabilities. They are the unique solution of linear equations system:

$$\begin{cases} \pi_j = \sum_{k \in S} \pi_k P_{kj}, j \in S \\ 1 = \sum_{j \in S} \pi_j \end{cases} \quad (3)$$

That π_j is the long-term probability of drought class j which means:

$$\pi_j = \lim_{t \rightarrow \infty} P(X_t = j | X_0 = i), i \wedge j \in S \quad (4)$$

S shows the likelihood of the occurred states.

2.1.1.2 Average Expected Residence Time in Each Class of Drought Severity

The residence time of each drought class refers to the time duration of each drought class. For example if the starting state for a month be the moderate drought class, then this moderate drought would last for how many months. The probability of ongoing sustainability during ‘ m ’ months in a specific ‘ i ’ class is related to the multiplication of consecutive transition probabilities between X_0 and X_m which is illustrated as follows:

$$P(X_1=i|X_0=i)P(X_2 = i|X_1 = i) \dots P(X_{m-2} = i|X_{m-1} = i)P(X_m \neq i|X_{m-1} = i) = P_{ii}^{m-1} (1 - P_{ii}) \quad (5)$$

Therefore, by knowing the probability of ongoing durability in each class of drought 'i' during 'm' months (m=1, 2,..., k,...), the period of expected residence time in each drought class of i, $E(T_i | X_0)$ is calculated as follows:

$$E(T_i | X_0) = \sum_k k P(m = k | X_t = i) \quad (6)$$

2.1.1.3 Average Expected First Passage Time from Each Class of Drought to Wet Year Class

The average period in which the process, for the first time, transits from a starting class (I) to another class j, t_{ij} is called the expected first passage time that is the unique solution for the linear equation system.

$$t_{ij} = 1 + \sum_{k \neq j} P_{ik} t_{kj} \quad \forall i, j \in S \quad (7)$$

The indicators in the above equation are described as below: t_{ij} is the average transition time from class i to class j, P_{ik} stands for the transition probabilities from class i to class k and t_{kj} is the average first passage time via moving from class k to class j.

2.1.1.4 Short-Term Drought Prediction

Short-time prediction of drought is based on a conditional prediction plan which includes the probable estimation of all possible routes from the current state of i in the time t, ($X_t = i$) to all probable future states of j which may happen during m months ($X_{t+m} = j$). Accepting the formulation of homogeneous Markov chain to estimate the most probable 1, 2, and 3 classes of the future month, according to the current month, is presented as follows:

$$P(X_{t+1} = j | X_t = i) \quad (8)$$

$$P(X_{t+2} = j | X_t = i) = \sum_{\forall k \in S} P(X_{t+2} = j | X_{t+1} = k) \cdot P(X_{t+1} = k | X_t = i) \quad (9)$$

$$P(X_{t+3} = j | X_t = i) = \sum_{\forall l \in S} \sum_{\forall k \in S} P(X_{t+3} = j | X_{t+2} = l) \cdot P(X_{t+2} = l | X_{t+1} = k) \cdot P(X_{t+1} = k | X_t = i) \quad (10)$$

The drought predicted class for the m future months would be based on the highest probability of occurrence which means:

$$P(X_{t+m} | X_t = i) \quad (11)$$

2.1.2 Non- Homogenous Markov Chain

In non-homogenous Markov chains –as it was mentioned earlier- the extracted features of the studied time series are thoroughly related to the start time. In non-homogenous Markov chain formulation, the number of months for the transition probabilities matrixes is considered 12 which means the classes are transferring from January to February; February to March; ... and December to January. These matrices are rotation matrixes that are not concerned with the annual changes and their transition probabilities are only related to the month and not the year. The transition probabilities of this type of Markov chain model are defined as follows.

$$P_{i,j}^{(n,n+1)} = P[X_{n+1} = j | X_n = i], \text{ for } i, j = 1, 2, 3, 4 \text{ and } n = 1, 2, \dots, 12 \quad (12)$$

The simplified form of it is:

$$p_{i,j(n,n+1)} = N_{i,j(n,n+1)} / N_i^n \quad (13)$$

In equation (13), $N_{i,j(n,n+1)}$ shows the number of transitions from classes i in month n to class j in month $n+1$, and $N_i^{(n)}$ equals to the number of probabilities in class i during the month n . If the value of $N_i^{(n)}$ for some (i) s be zero, then we define the $p_{i,j(n,n+1)} = 1/4$ for all $j = 0, 1, 2, 3, 4$. In non-homogenous Markov chain formulation, calculation of the following factors is dependent on the starting month which will be resulted from the transition probabilities among various drought classes which are defined for each month. The factors are:

- Drought class probabilities in terms of severity
- Average expected residence time in each class of drought severity
- Average expected first passage time from the various class of drought to wet year
- Short-term drought prediction in various classes

The formulation of each quaternion of the above calculations is thoroughly explained in the following sections (Lohani and Laganatan 1997; Lohani et al. 1998).

2.1.2.1 Drought Class Probabilities in Terms of Severity

Being aware of drought class probabilities for each month can be useful. An area's susceptibility to drought can be reflected in high values of various drought class probabilities.

Assume that $f^{(k)}$ is a probable vector of a class that is formed after k transitions. By using the linear vector of probable starting class, $f^{(0)}$, and monthly transition probable matrixes, we can write:

$$f^{(k)} = [f^{(0)}][P_1][P_2] \dots [P_k] \quad (14)$$

In the equation, $f^{(0)}$ is the linear vector of starting class probable and P_1 is the monthly transition matrix which is related to the starting month and here, the assumption is January to February matrix which means $P_1 = P^{(1,2)} = P^{(Jan.,Feb)}$. However, the starting month can be any of 12 months in a year. Moreover, due to the rotation nature of these matrixes, the transition probably matrix of month 14 to month 15 shown as $P^{(14,15)}$, is, in fact, $P^{(2,3)} = P^{(Feb.,Mar)}$ which is the transition matrix from February to March.

For the long-term probabilities which are illustrated as $k \rightarrow \infty$, we are interested to know if the probabilities of stable class $f^{(\infty)}$, is independent of $f^{(0)}$ or not? This would be true if the multiplication of transitions matrixes $[P_m]$ in $[P_k]$, which is shown as $\phi^{(m,k)}$ and recognized as a combined matrix

$$\phi^{(m,k)} = [P_m][P_{m+1}] \dots [P_k] \quad (15)$$

Be a fixed random matrix with equal lines for capital k for each start m . For such a fixed random matrix, it will follow equation (3-14) where $f_m^{(k)}$ is independent of $f^{(0)}$. However, since the starting month, m , affects the value of $\phi^{(m,k)}$, therefore, the probabilities of the steady class, $f_m^{(k)}$, are functions of m . It shows that the drought behavior of the present month affects the drought pattern of the next month. To implement $f_m^{(k)}$ when $k \rightarrow \infty$, equation (15) is considered as follows. The fixed random matrix (equal lines) for January is defined as the product of a series of 12 consecutive month matrices with the initial matrix as follows:

$$\phi^{(1,\infty)} = \{[Jan] = \{[P_1][P_2] \dots [P_{11}][P_{12}]\} \{[P_1][P_2] \dots [P_{11}][P_{12}]\} \dots \quad (16)$$

Since $[Jan]$ is a fixed random matrix, it yields

$$row[Jan] = f_1^{(\infty)} \quad (17)$$

Now consider

$$\phi^{(2,\infty)} = \{[Feb] = \{[P_2][P_3] \dots [P_{11}][P_{12}][P_1]\} \{[P_2][P_3] \dots [P_{11}][P_{12}][P_1]\} \dots \quad (18)$$

Then

$$[Feb] = [P_2][P_3] \dots [P_{11}][P_{12}][Jan][P_1] \quad (19)$$

Through replacements, it yields

$$[Feb] = [Jan][P_1] \quad (20)$$

Thus

$$row[Feb] = f_2^{(\infty)} = row[Jan][P_1] \quad (21)$$

Similarly, the following could be represented

$$\begin{aligned} row[Mar] &= f_3^{(\infty)} = row[Feb][P_2] \\ row[Apr] &= f_4^{(\infty)} = row[Mar][P_3] \\ &\dots \\ row[Dec] &= f_{12}^{(\infty)} = row[Nov][P_{11}] \\ row[Jan] &= f_1^{(\infty)} = row[Dec][P_{12}] \end{aligned} \quad (22)$$

Equation (22) provides a tool to assess the probabilities of the static class of monthly drought/wet year. It is a system of linear equations in the form of a static class possibilities used to calculate the probabilities for each month and each class for all the regions under study.

2.1.2.2 Average Expected Residence Time in Each Class of Drought Severity

The expected residence time of a particular class of drought shows the drought residence term of that class for the intended area. Drought class, i will remain in the area for time m without being transmitted to another class. The occurrence thereof is formulated as follows:

$$\{X_1 = i = X_2 = \dots = X_{m-1} | X_0 = i\} \quad (23)$$

The expected residence time probabilities for different periods in a specific class of drought, i , can be calculated as follows. For example, the probability of the expected one-month residence probability, shown as $m = 1$, is calculated for January as follows:

$$P[X_{Feb} \neq i | X_{Jan} = i] = P[m = 1 | X_{Jan} = i] = 1 - P_{i,i}^{1,2} \quad (24)$$

Where $P_{i,i}^{1,2}$ denotes the probability of transmission of class i in January to the same class i in February. Equation (24) shows that drought class i has extended for 30 days, that is one month in January and then the extension of this class of drought, i , has stopped from the first day of February via being transmitted to another class $j \neq i$. For the expected two-month residence, $m = 2$, starting from January, the probability can be calculated as follows:

$$P[m = 2 | X_{Jan} = i] = P[X_{Mar} \neq i, X_{Feb} = i] \quad (25)$$

$$= P[X_{\text{Feb}} = i | X_{\text{Jan}} = i] P[X_{\text{Mar}} = i | X_{\text{Feb}} = i] \quad (26)$$

$$= P_{i,i}^{1,2} (1 - P_{i,i}^{2,3}) \quad (27)$$

Besides, the Probability of longer residence times can be calculated as follows. For example, for a 12-month residence time of a class of drought at the beginning of January, it will be as follows:

$$P[m = 12 | X_{\text{Jan}} = i] = P_{i,i}^{1,2} P_{i,i}^{2,3} \dots P_{i,i}^{10,11} P_{i,i}^{11,12} (1 - P_{i,i}^{12,1}) \quad (28)$$

It is easily observed that the calculation of probabilities for various continued residence events on class i contains multiplication of the entries of the i th row by the i th column (diagonal elements) of continuous transition probability matrices. If one of the entries equals zero, the calculation will stop, because all of the remaining probabilities for longer residence times converge into zero. When probabilities for longer continued residence times are calculated for different periods, the expected residence time for class j , $E[R_{uj}]$ will be calculated as follows:

$$E[R_{uj} | \text{starting month}] = \sum_k k P[m = K | \text{starting month}] \quad (29)$$

where R_{uj} denotes the random variable describing the residence time on class j . Equation (29) was calculated for the expected residence time for each month and each starting class in the regions under study.

2.1.2.3 Average Expected First Passage Time from Various Class of Drought to Wet Year

The expected first passage time is defined as the average time that the process spends to pass from a class of drought, i , as a starting point, to other class of drought, j , denoted by m_{ij} . For a heterogeneous chain, the first month, n , is very important in determining the expected first passage time. Thus, let $m_{ij}^{(n)}$ as the expected first passage time for a process to reach class j , starting from class i , in month n . The mathematical form is as follows:

$$m_{ij}^{(n)} = (1) p_{i,j}^{(n,n+1)} + \sum_{k \neq j} p_{i,k}^{(n,n+1)} (m_{kj}^{(n+1)} + 1) \quad (30)$$

Where the first term indicates that class j can continue in the month $(n + 1)$ in a single step. In other words, the process can reach class $k \neq j$ in one step, as shown by 1 in the summation which suggests that to reach class j , step $m_{kj}^{(n+1)}$ shall be passed. Through combining the probability of the first term, $p_{i,j}^{(n,n+1)}$, with the summation of the remaining probabilities, the equation is formulated as follows:

$$m_{i,j}^{(n)} = 1 + \sum_{k \neq j} p_{i,k}^{(n,n+1)} m_{k,j}^{(n+1)} \quad (31)$$

For example, for $n = 1$, it yields:

$$m_{i,j}^{(1)} \equiv m_{i,j}^{\text{Jan}} \equiv 1 + \sum_{k \neq j} p_{i,j}^{(1,2)} m_{k,j}^{\text{Feb}} \quad (32)$$

Where $p_{i,k}^{(1,2)}$ denotes the January-February transmission probability to reach class k from class i . The solution to the systems of linear equations in formula (32) gives the expected first passage times. The average time to return to the same class is called the average return time, m_{ii} which can also be calculated through equation (30) as follows:

$$m_{i,i}^{(n)} = (1) p_{i,i}^{(n,n+1)} + \sum_{k \neq i} p_{i,k}^{(n,n+1)} (m_{k,i}^{(n+1)} + 1) \quad (33)$$

The simplified form is:

$$m_{i,i}^{(n)} \equiv 1 + \sum_{k \neq i} p_{i,k}^{(n,n+1)} m_{k,i}^{(n+1)} \quad (34)$$

Formulas (31) and (34) were used to calculate the expected first passage time and average first return time for all the regions under study.

2-1-2-4- Short-Term Drought Class Prediction

To predict the monthly drought in each class of drought i in the month n , the highest climatic class k in month $(n + 1)$ is expressed as follows:

$$P_{MODE} [X_{n+1} | X_n = i] = K^* \quad (35)$$

Where K^* is the climatic class, with the related equation represented with maximum $p_{i,k}^{(n,n+1)}$ for all k 's given for i .

Likewise

$$P_{MODE} [X_{n+2} | X_{n+1} = K^*] = I^* \quad (36)$$

Where I^* is the maximum $(p_{K^*,I}^{(n+1,n+2)})$ for all i 's given for K^* similarly

$$P_{MODE} [X_{n+3} | X_{n+2} = I^*] = m^* \quad (37)$$

Where m^* is related to the maximum $(p_{I^*,m}^{(n+2,n+3)})$ for all m 's given for I^* .

It is observed that m is the prediction of the climatic class in the month $(n + 3)$ which is given through n^{th} climatic classes given for i .

4 Results and Discussion

Using the Effective Drought Index (EDI), different classes of drought were determined for all the stations. With the implementation of cluster analysis on daily amounts of effective drought index (EDI) of under-study stations have been observed based on which Iran can be divided into five separate clusters according to the behavior of time series of its droughts. Each cluster in this division represents a group of stations where the most similarity is seen in the behavior of the time series of their droughts. The results obtained from such an analysis are presented in the dendrogram. In figure 2, the dendrogram concerning this analysis is shown. This dendrogram clearly shows five selected clusters with five different colors. To continue, by using geo-statistics-nearest neighbor, the clusters obtained were transformed into a regionalization plan titled regionalization of Iran's droughts (figure 3). Five-folded regions obtained can be named as follows: (A) the West-Northern region, (B) the Southern region of the Caspian Sea, (C) the Northern region of Central Iran, (D) the Southern region of Central Iran and finally (E) the South-Eastern region. The spatial mean of the Effective Drought Index (EDI) of each region was also calculated. The Markovian characteristics of each of these five regions have been extracted in the modeling shape of homogenous and non-homogenous chains and finally, the different classes of droughts considering their different states are predicted and presented in different tables.

Fig 2 Dendrogram obtained from cluster analysis on daily values of effective drought index (EDI) of the studied stations

Fig 2 regionalization of Iran based on EDI

Transmission frequency matrices and transmission probabilities were regulated for five regions. 10 matrices were prepared to model homogeneous Markov chains and 120 matrices were created to model non-homogeneous Markov chains. Among this number of matrices, one half belonged to transmission frequency matrices and the other half belonged to transmission probabilities matrices.

4.1 Homogeneous Markov Chain

The first feature of the homogenous Markov chain examined was the drought class probability during the statistical period of the study. The results of the feature showed that the class probability decreased as the severity increased from weak drought to severe drought to extreme drought. For example in the Northern region of Central Iran, the weak drought probability decreased from 0.32 to 0.19 in moderate drought and then to 0.04 in severe and extreme droughts. The weak drought probability had the highest value among different drought classes so that the highest

values were observed in the Northern region of Central Iran and South-Eastern region as 0.32 and 0.3, respectively. Besides, the maximum value of the severe drought probability and extreme drought probability belonged to the West-Northern region and Southern Region of Central Iran (Table 2).

Table 2 Drought class probabilities

Regions	Class			
	0	1	2	3
Northern region of Central Iran	0.46	0.32	0.19	0.03
Southern region of the Caspian Sea	0.51	0.27	0.19	0.03
South-Eastern region	0.47	0.30	0.19	0.04
West-Northern region	0.47	0.29	0.18	0.06
Southern Region of Central Iran	0.46	0.27	0.21	0.06

The expected residence time for each class of drought severity represents the average duration of each class, and the continuation thereof. The residence time of severe drought and extreme drought was higher than that of other drought classes, indicating the tendency of weather to stay in severe and extreme droughts for a longer time. Table 3 reveals the fact well. Most residence in the West-Northern region and the Southern Region of Central Iran. However, these were the highest values for the continuation of drought among different drought classes.

Table 3 Average expected residence time in each class of drought severity

Regions	Class			
	0	1	2	3
Northern region of Central Iran	4.00	1.44	1.78	1.78
Southern region of the Caspian Sea	4.88	1.00	1.94	3.35
South-Eastern region	7.33	3.35	5.25	9.00
West-Northern region	5.67	2.13	2.70	4.00

Southern Region of Central Iran	4.56	1.50	2.57	4.00
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The average expected first passage time in each class of drought to a wet class is helpful for knowing when the period of a drought or a wet year will begin or end. The expected time to reach a class with no drought increased along with the severity of the starting class of drought (Table 4). In general, when the severity of drought classes increases, the expected first passage becomes longer for passing from drought classes to wet classes. The results showed that the beginning of drought seemed slower than its end. For example, the expected time for passage from a class with no drought to moderate drought took 32.38 months in the South-Eastern region, while the passage from moderate drought to a class with no drought took 13.36 months in the same region.

Table 4 Average first passage time from each class of drought severity to wet classes

Regions	μ_{01}	μ_{02}	μ_{03}	μ_{10}	μ_{20}	μ_{30}
Northern region of Central Iran	5	16.94	79.99	5.90	7.89	10.28
Southern region of the Caspian Sea	6.16	16.42	105.22	5.59	8.16	10.83
South-Eastern region	8.33	32.38	146.10	9.58	13.36	23.36
West-Northern region	7.74	20.45	77.93	7.17	10.78	13.97
Southern Region of Central Iran	5.98	18.27	81.48	6.33	9.57	12.18

Prediction of various classes of drought for the next months will be the current state in all regions, especially when the current state suggests the establishment of weak drought conditions, i.e., no change in the state of drought classes could be predicted (Table 5). Nevertheless, when the starting state includes severe or extreme drought, the prediction of drought conditions for the next months will be a moderate drought in all regions except for the South-Eastern region. In the South-Eastern region, the prediction will remain the same class for the next months, when the starting class includes severe drought and extreme drought.

Table 5 Drought prediction for different classes

Regions	Class
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	0	1	2	3
Southern region of the Caspian Sea
South-Eastern region
Northern region of Central Iran
Southern Region of Central Iran
West-Northern region
Drought Classes

	Non-drought	Mild	Moderate	Severe and Extreme

4.2 Non-homogeneous Markov Chain

Since summer precipitation does not occur in most of the regions in Iran, calculation of non-homogeneous Markov chain features was not performed for the three months of July, August and September. The probability of each class of drought severity for the months in winter, spring and autumn was calculated and the results are shown in Table 6. The results showed that the probability of weak drought was higher than that of other classes. The highest weak drought probability belonged to the Northern region of Central Iran in June with a value of 0.49.

Also, the probability of severe and very severe drought category in these regions are noted in the table as the sample and when the initial month is November, the probability is 0.12 in the Southern region of the Caspian Sea and in October is 0.08 in the Southern Region of Central Iran which are the highest percentage of probability in this class.

Table 6 Drought class probability

Regions		Month									
Class		Jan	Feb	Mar	Apr	May	Jun	Oct	Nov	Dec	

Northern region of Central Iran	0	0.38	0.45	0.45	0.39	0.49	0.48	0.49	0.35	0.45
	1	0.49	0.31	0.34	0.45	0.28	0.20	0.28	0.45	0.21
	2	0.10	0.17	0.17	0.13	0.17	0.24	0.20	0.21	0.34
	3	0.03	0.07	0.04	0.03	0.06	0.07	0.03	0.00	0.00
Southern region of the Caspian Sea	0	0.55	0.49	0.41	0.52	0.41	0.61	0.42	0.37	0.55
	1	0.17	0.24	0.38	0.28	0.41	0.25	0.41	0.37	0.17
	2	0.21	0.24	0.17	0.17	0.14	0.15	0.14	0.15	0.24
	3	0.07	0.03	0.04	0.04	0.04	0.00	0.03	0.12	0.03
South-Eastern region	0	0.34	0.45	0.40	0.45	0.49	0.45	0.55	0.45	0.39
	1	0.45	0.27	0.21	0.21	0.21	0.24	0.22	0.32	0.45
	2	0.17	0.24	0.34	0.27	0.24	0.24	0.17	0.17	0.10
	3	0.03	0.03	0.05	0.07	0.07	0.07	0.07	0.07	0.06
West-Northern region	0	0.41	0.41	0.42	0.59	0.51	0.48	0.49	0.38	0.48
	1	0.37	0.34	0.38	0.30	0.25	0.28	0.28	0.38	0.24
	2	0.18	0.22	0.20	0.07	0.20	0.18	0.19	0.24	0.28
	3	0.04	0.03	0.00	0.04	0.05	0.06	0.03	0.00	0.00
Southern Region of Central Iran	0	0.40	0.47	0.33	0.52	0.52	0.54	0.51	0.48	0.51
	1	0.47	0.28	0.46	0.24	0.21	0.18	0.20	0.32	0.29
	2	0.07	0.25	0.21	0.17	0.21	0.21	0.21	0.13	0.14
	3	0.06	0.00	0.00	0.07	0.07	0.07	0.08	0.07	0.07

Residence time shows the average durability of each drought class and then shows the residence for each month, three values are presented which introduce the defined drought classes. When the state 1 or weak drought occurs in January, it is expected to continue 2.12 months in West-Northern region, 1.74 months in the Southern Region of Central Iran, while this state has more continuance in April. The longest residence time for the studied regions in class 3 is in April which indicates climate tends to remain in a severe and very severe state of drought for a relatively long time for the studied regions. Such that its longest time is 9 months in the South-Eastern region and its shortest time is 1 month in Southern region of Central Iran (Table 7). If state 2 (class 2), the moderate drought conditions occur in April in the West-Northern region, it is expected to last 6.44 months on average while in

Southern region of Central Iran the state on average is 0.8 and in Southern region of the Caspian Sea, it is expected to last 2.3 months. The longest residence time in April in studied regions can be due to the fact that the rainy season is over in those areas.

Table 7 Average expected residence time in each class of drought severity

		Starting month								
		Jan			Apr			Oct		
Regions↓	class→	1	2	3	1	2	3	1	2	3
Northern region of Central Iran		1.39	0.83	0	1.67	2.85	4.5	0.33	1.04	0
Southern region of the Caspian Sea		1.01	1.34	4	1.22	2.3	5	0.76	1.59	0
South-Eastern region		1.74	4.52	1	3.74	4.82	9	2.54	2	3
West-Northern region		2.12	1.62	1	2.1	6.44	5.3	1.06	0.8	0
Southern Region of Central Iran		0.74	0	0	3.84	0.8	1	1.54	0.71	1

Table 8 indicates the results of calculating the average expected first passage time in each drought classes to that of wet classes. In this table, the Markovian feature could not be calculated for regions wherein moderate, severe and extreme droughts have not occurred. Therefore, the lack of this type of occurrence for these regions is shown in Table 8 with star marks. Thus, values provided in the table are related to states or classes experienced by the regions during the last 30 years. In most regions under study, the highest first passage time was related to April and weak Drought. For example, in April during a weak drought, the passage from drought to wet classes took 6.89 months in the Northern region of Central Iran and 6.75 months in the South-Eastern region. However, in January, the highest residence time belonged to the Northern region of Central Iran with 1.4 months, and in October, it was 0.4 months for the West-Northern region.

Table 8 Average expected first passage time from each class of drought severity to wet classes

		Jan			Apr			Oct		
Regions		10	20	30	10	20	30	10	20	30
Northern region of Central Iran		1.4	*	*	6.89	*	*	0.04	*	*

Southern region of the Caspian Sea	1.30	*	*	6.72	*	*	0.27	0.39	*
South-Eastern region	1.27	0.79	*	6.75	*	*	0.00	*	*
West-Northern region	0.55	0.16	*	6.28	*	*	0.40	0.68	*
Southern Region of Central Iran	0.58	0.59	*	6.59	*	*	0.11	0.36	*

Table 9 depicts drought prediction for the next 1, 2, and 3 months related to January, April and October. When the current condition suggests the establishment of a state with no drought, the most probable state for the next 1, 2, and 3 months will be the very current state, like that in the Southern region of the Caspian Sea, the South-Eastern region, the West-Northern region and the Southern Region of Central Iran. However, it differs for the Northern region of Central Iran wherein if the starting month is predicted with a wet class, the next two or three months will be predicted with weak drought. When the starting state is weak drought in January, the next two or three months will be predicted with moderate drought in South-Eastern region.

Table 9 Drought prediction for different drought classes

	Month starting									
Regions	Jan				Apr			Oct		
		t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
Northern region of Central Iran	0									
	1									
	2									
	3									
Southern region of the Caspian Sea	0									
	1									
	2									
	3									
South-Eastern region	0									
	1									
	2

5 Conclusions

In the present study, the prediction of drought class transmission probability in Iran was carried out by applying homogeneous and non-homogeneous Markov chains. Homogeneous and non-homogeneous Markov chains allow extracting four features including the occurrence probability of each class, the average residence time of each class, expected first passage time from drought to wet periods and short-term drought prediction.

In the homogeneous Markov chain which is independent of the starting month, the probability of each drought class for homogeneous and non-homogeneous Markov chains showed similar results, such that in both chains, the probability of weak drought is more than other classes of drought. In this chain, the average of expectable residence time in severe and very severe drought is more than that in weak and moderate drought, especially in the South-Eastern region which the severe and very severe drought is predominant in this region due to the climate conditions. The received precipitation in this region is considerable only in winter which is far less than the average precipitation of Iran, the contrary is the case for northern areas of the country in the Southern region of the Caspian Sea, the average time of the first transition from each class of drought severity to wet class, when the gap between the classes is more than wet class, in the homogeneous Markov chain increases which seems logical. For instance the residence time in all studied regions from moderate drought class to wet class is not less than 7 months, while

the average time of first passage from weak drought class to wet class is not less than 5 months which are different in terms of one class. Anticipating drought conditions in the 5 climate region presented in this article which are the samples of regions is the result of that area climate conditions, in Markov chain for example, when severe and very severe drought is predominant in the South-Eastern region, predicting drought class is a severe and very severe drought.

Non-homogeneous Markov chain is dependent on starting month and this dependence can be an advantage for non-homogeneous Markov chain than homogeneous Markov chain because month makes no sense in the homogeneous Markov chain. Therefore, the results in the homogeneous Markov chain are more detailed than those of the homogeneous chain. The probability of weak drought class in all studied months in Iran in most studied regions in weak drought is more than other classes. As noted, this part of the chain is similar to the obtained results of the homogeneous chain. The average residence time in each class of drought in the non-homogeneous Markov chain in starting months of winter, spring, and autumn showed that the predominant climate conditions play important roles in the residence of different classes of drought, such that for example in the South-Eastern region, the dry conditions are more than other areas in June starting month which is the rainy season in Iran and the residence rate of drought class in one month, while as we get further from rainy season, the residence time in starting month of other seasons increases. The average passage time from each drought classes to wet class, is affected by the climate conditions. The transition time from drought class to wet class in the rainy season in Iran is less than 2 months, and this increases by the end of the rainy season such that it does not take less than 6 months in April to go from weak drought class to wet class. Predicting the different classes of drought in the non-homogeneous Markov chain showed the most probable likelihood of anticipating class for 1, 2 and 3 months later and the obtained results are very useful in planning and developing water resources considering the defined starting month.

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Authors' contributions

Conceptualization: Peyman Mahmoudi
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Figures

Figure 1

The map of location and dispersion of the studied stations

Figure 2

Dendrogram obtained from cluster analysis on daily values of effective drought index (EDI) of the studied stations

Figure 3

Regionalization of Iran based on EDI