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Applying First-Order Markov Chains and SPI Drought Index to Monitor and Forecast Drought in West Azerbaijan Province of Iran

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Abstract

In this paper by using the data related to the monthly precipitation of 13 stations situated in west Azerbaijan province of Iran in a time period of 34 years, monitoring and forecasting the probability of a drought occurrence is evaluated in next coming months. In this process, first the monthly precipitation amounts for each rainfall station are used in order to calculate the standardized precipitation index (SPI) for a time period of 34 years for each station. Afterwards, by applying this index, 4 drought classes are defined. At the following, based on the changing style of drought classes in the mentioned time period and for each station, the transition matrix related to that station is derived. The transition matrixes are the main concepts of Markov chains for evaluating the studying systems behavior in the future. Afterwards, by applying the mentioned transition matrixes the steady state probabilities, the mean recurrence time of each drought class and the expected residence time in each drought class were obtained. The results obtained from evaluating the related data with various stations indicated that Shahin dezh and Alasaghal Tekab stations remain in none drought class for 6.4 months on average. Therefore, these two stations are less drought-prone in comparison with other stations in the future. On the other hand, it is expected that the two mentioned stations will remain on average 3.3 months in the severe or extreme drought class.

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INTRODUCTION

Drought occurs when the amount of precipitation reduces in a long time period, depending on the type of the regions' climate it may occur in a week, month, year or several years. Drought is an inevitable phenomenon and is amongst disasters that should be considered without the possibility of prevention. This phenomenon can be managed and organized; success in this case depends on the definition of drought and how to quantify the characteristics of drought (Thenkabail and Gamage, 2004). Until now an exact and global definition of the drought phenomenon that is accepted universally has not been presented. Each branch of science has its own definition of the drought phenomenon. In most definitions, drought is defined as a continuous and sustainable period that the amount of water has reduced considerably (Wilhite and Glantz, 1985).

Drought can be classified into four classes of meteorological, agricultural, hydrological and socioeconomic drought (Dracup et al., 1980; Wilhite and Glantz, 1985). Meteorological drought is basically caused by precipitation shortage and if it continues it will lead to hydrological and agricultural drought. One of the important indexes that are applied in previous studies related to drought is the standardized precipitation index; which is applied in this paper in order to derive Markov transition matrixes related to each rainfall station. McKee et al. (1993) applied the SPI for the first time at the Colorado state of America and deduced that the Gama distribution is the most suitable distribution for fitting the precipitation data. Paulo and Pereira (2007) forecasted drought in south of Portugal and they applied the standardized precipitation index (SPI) in their study. Forecasting that when a drought begins and when it ends is very difficult (Cordery and McCall, 2000). Liu et al. (2009) applied Palmer drought severity index and Markov chain in order to forecast drought in north of China. Sharma and Panu (2014) forecasted drought by using the standardized hydrological index and Markov chains in a case study in Canada. Banimahd and Khalili (2013) studied the factors that affect the forecasting capability of Markov chains and in their study they used different types of drought indexes such as SPI, RDI, EDI and SPEI in different climates. Alam et al. (2014) used Markov chains to evaluate and predict agricultural drought occurrence in semiarid regions by using the recent 40 years data related to 12 rainfall stations, and these data included the amount of weekly precipitation related to the 12 stations in the recent 40 years.

Sanusi et al. (2014) used first-order homogeneous Markov chain in order to monitor and forecast drought in Malaysia using the data related to 35 rainfall stations in a time period of 38 years. In their study the SPI drought index and one-month time scale was used in order to derive transition matrixes related to 35 rainfall stations. Afterwards, by using the mentioned matrixes they derived the steady-state probabilities of drought events, the mean residence time for each drought class, the mean recurrence time of drought events and the mean first passage time. Avilés et al. (2015) defined a novel drought index in order to forecast the occurrence time and the residence time of a drought. In their study, first-order Markov chain and second-order Markov chains were applied as a stochastic model and also the frequency of monthly droughts was predicted in this study. Afterwards, two skill scores, the ranked probability score (RPS) and the Gandin-Marphy skill score (GMSS) were applied in order to evaluate the performance of applied models. The results indicated that severe droughts were predicted more accurately. Du et al. (2013) studied the spatial and temporal variation of dry /wet conditions and their annual/seasonal trends by using the standardized precipitation index (SPI) at various time scales. Cancelliere et al. (2007) provided two methodologies by considering the hypothesis of uncorrelated and normally distributed monthly precipitation aggregated at various time scales k, in order to use the SPI for seasonal drought forecasting. Edossa et al. (2010) used meteorological and hydrological variables in order to analyze drought characteristics in the Awash River Basin of Ethiopia. By applying Standardized Precipitation Index, Temporal and spatial analyses of meteorological drought was conducted, also by using the theory of runs and by considering stream flow as the drought indicator the hydrological drought was defined. Khalili et al. (2011) analyzed similarities and differences of the Standardized Precipitation Index (SPI) and the Reconnaissance Drought Index (RDI), respectively, by using precipitation and ratio of precipitation over potential evapotranspiration.

The study area

Lake Urmia is an extensive lake with high salinity and with an area of 5000 square kilometers, located in North West of Iran. It is essential to mention that in recent years due to precipitation reduction and water level drop in the aquifers, the size of the lake has considerably reduced. This lake is situated in North West of Iran and between west Azerbaijan and east Azerbaijan provinces. This Lake subtends a basin with an area of almost 52000 square kilometers which is situated among the provinces of west Azerbaijan, east Azerbaijan and Kurdistan. This water basin is located in an elevation between 1280 and 3600 meters above sea level. The mean precipitation in this region is estimated about 350 mm per year. Most of this precipitation occurs from early autumn until the middle spring. The case study in this research is the south and west part of Lake Urmia (36.48˚_38.07˚ North and 44.6˚_47.04˚ East) that contains 13 rainfall stations with the statistical period of 34 years. In Fig (1), Lake Urmia basin and the location of rain gauges is illustrated (Farajzadeh et al., 2014; Ghajarnia et al., 2015). Furthermore, in Fig (2) the Location of rainfall stations used in this study is shown.

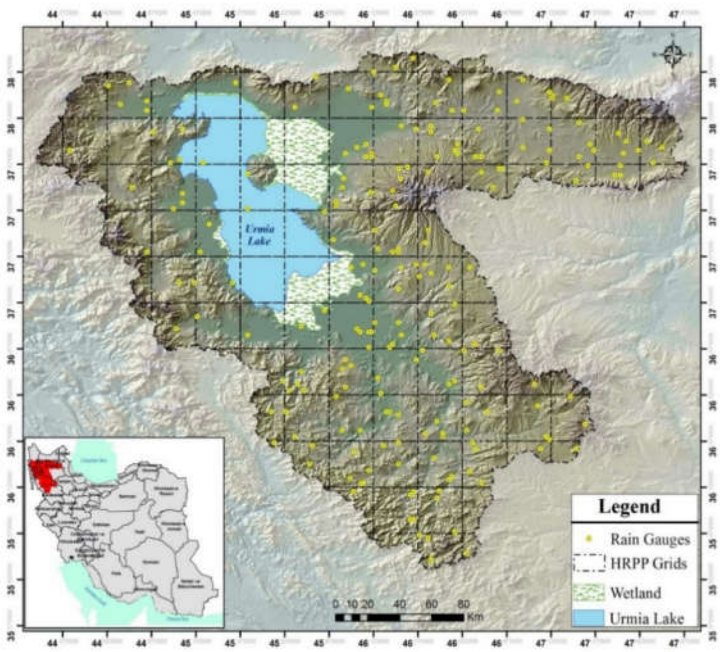

Fig 1. Lake Urmia basin and the location of rain gauges (Ghajarnia et al., 2015)

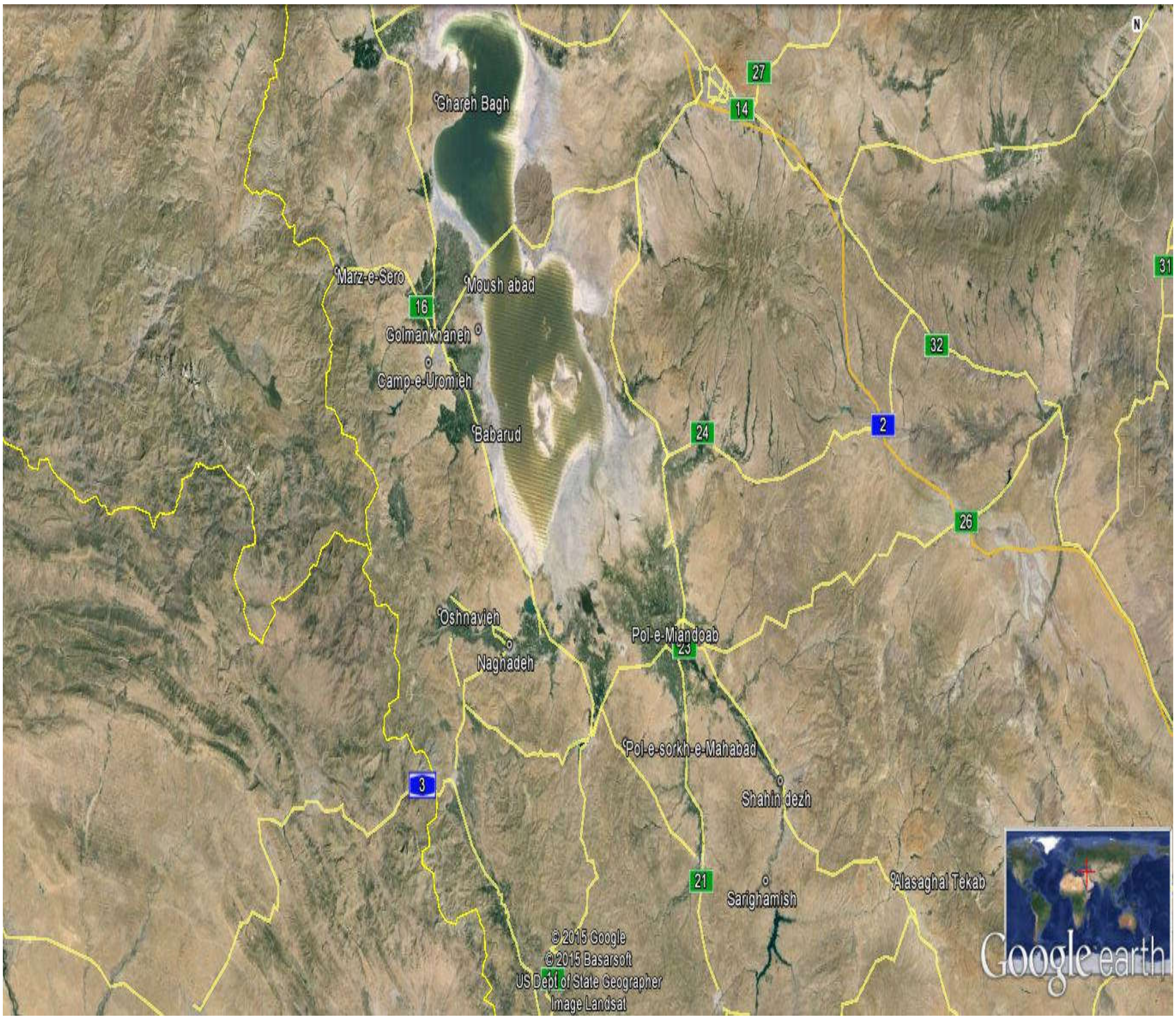

Fig 2. Location of rainfall stations used in this study

Research Methodologies

The data related to the amount of monthly precipitation for 13 stations in a time period of 34 years (1978-2012) is applied in this paper, after the tests of randomness, homogeneity and absence of trend. At the continue, by applying the standardized precipitation index the months among the 34 years were classified in four drought categories and then the transition matrix related to each station was derived. Afterwards, the steady state probabilities, the mean recurrence time of each drought class and the expected residence time in each drought class were calculated and the obtained results were analyzed. The data related to the Name of rainfall stations in this study and their geographic coordinates is gathered in Table (1).

Table 1. Name of rainfall stations in this study and their geographic coordinates

Code	Name of precipitation stations	Latitude	Longitude	Height (ft)	MAP
1	Ghareh Bagh	45.06667º	38.06667º	4862	314.6
2	Camp-e-Uromieh	45.03333º	37.53333º	4568	376.3
3	Golmankhaneh	45.25º	37.6º	4262	253.3
4	Babarud	45.23333º	37.4º	4208	343.6
5	Moush abad	45.2º	37.7º	4192	241.7
6	Marz-e-Sero	44.63333º	37.71667º	5628	359.2
7	Naghadeh	45.38333º	36.96667º	4286	337.6
8	Oshnavieh	45.08333º	37.03333º	4784	432.7
9	Pol-e-sorkh-e-Mahabad	45.88333º	36.76667º	6642	355.8
10	Pol-e-Miandoab	46.11667º	36.96667º	4238	303.3
11	Shahin dezh	46.55º	36.68333º	4427	296
12	Sarighamish	46.48333º	36.48333º	4547	353.6
13	Alasaghal Tekab	47.03333º	36.48333º	5709	362.4

Standardized Precipitation Index

Standardized precipitation index is one of the basic indicators in drought studying and calculating this index requires mean and standard deviation of precipitation amounts in the studied long-term periods. Basically, this index is presented for defining and monitoring drought. This index helps the analyst to identify the number of drought and non-drought events that have occurred in a desired time step. Since this index is dimensionless, by applying it, comparing the information of several regions and deriving the drought range maps are feasible with more accuracy. Another benefit of this index is its capability to identify the regions with severe droughts and severe wets, by fitting the probability density function. To obtain this index first the monthly precipitation amounts for each station are calculated for the intended time scale (1, 3, 6, 9, 12, and 24 months). As an example for the 3 month time scale the sum of precipitations in months May, June and July is considered as the precipitation index for July. Similarly, the sum of precipitations for June, July and August is considered as the index for August and this procedure is continued for the remaining 10 months. Therefore a precipitation time series is obtained for each station in the under study time period. Actually, the precipitation amount for each month is the sum of precipitation amounts in that month and the previous two months. In six-month time-scale the sum of each month's precipitation and the precipitation amount of 5 previous months are considered as the precipitation index of the mentioned month. For other time scales the cumulative precipitation time series are similarly calculated for each month. Afterwards, the amounts of cumulative precipitations for each month are fitted with Gama probability distribution. After calculating the Gama cumulative probability in a time scale for each month of a year, this probability is converted into a standard normal stochastic distribution. Actually, this stochastic variable is the value of the intended SPI. In order to calculate the standardized precipitation index in this paper the DIP software and the six month time scale were applied. In order to classify the drought classes, the limits determined for SPI by McKee et al in 1993 were used which are presented in Table (2). For further information about SPI and the calculation methods it is recommended to study (Du et al., 2013). For instance, Fig (3) illustrates Time evolution of the SPI drought index for the Ghareh Bagh rainfall station.

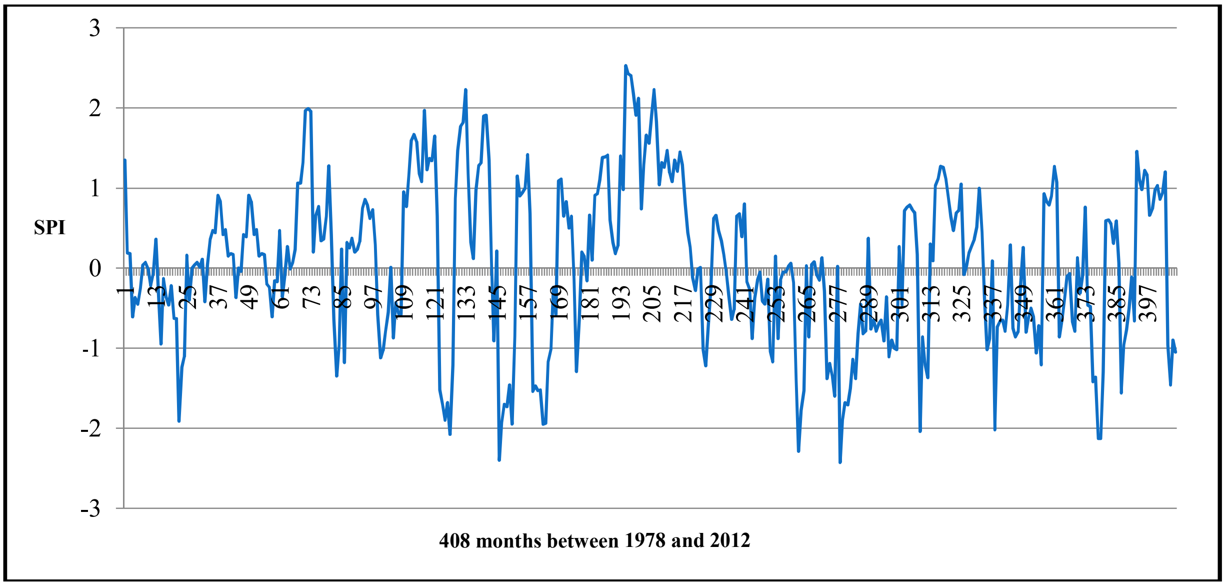

Fig 3. Time evolution of the SPI drought index for the Ghareh Bagh rainfall station

Markov chains

A markov chain (Cinlar, 2013; Paulo et al., 2005; Sirl, 2005) is a stochastic process *X*, such as at any time *t*, X_{t+1} is conditionally independent from $X_0, X_1, X_2, ..., X_{t-1}$, given X_t; the probability that X_{t+1} takes a particular value j depends of the past only through its most recent value X_t:

$$p\{x_{t+1} = j \mid x_0, x_1, ..., x_n\} = p\{x_{t+1} = j \mid x_t = i\}, \quad \forall i, j \in S, t \in T \tag{1}$$

A markov chain is characterized by a set of states, *S*, and by the transition probability matrix, P_{ij}, between states. The transition probability P_{ij} is the probability that the markov chain is at the next time point in state *j*, given that it is at the present time point in state *i*. Then P is the transition matrix, as follows:

$$p = [p_{ij}] = \begin{pmatrix} p_{11} & p_{12} & \dots & \dots & p_{1s} \\ p_{21} & p_{22} & \dots & \dots & p_{2s} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ p_{s1} & p_{s2} & \dots & \dots & p_{ss} \end{pmatrix} \tag{2}$$

Where $0 \le p_{ij} \le 1, \sum_{j=1}^{s} p_{ij} = 1$, $i = 1, ..., S$ and S is the number of states. Estimation of the transition probability is important in markov chain modeling. Different methods have been proposed to estimate the transition probability, namely the maximum likelihood method. In this paper the maximum likelihood estimator (MLE) method has been used because of simplicity. It is recommended to refer to the following references for more information about computing the transition probability (Lohani et al., 1998; Lohani and Loganathan, 1997; Mishra et al., 2009; Sanusi et al., 2014).

$$p = [p_{ij}] = p\{x_{t+1} = j \mid x_t = i\} \tag{3}$$

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}, \quad \forall i, j \in S \tag{4}$$

Table 2. Classification of SPI values

SPI values	Drought categories
SPI > 0	Non drought (N)
- 0.99 < SPI < 0	Mild drought (1)
-1.49 < SPI < -1	Moderate drought (2)
SPI < -1.5	Severe drought (3)

In long term, the steady state probabilities are independent of the initial state of the markov chain. These probabilities, Π_j, could be obtained by the successive multiplication of the first stage markov chains. Also, these probabilities are the unique solution of the system of linear equations:

$$\pi_j = \sum_{k \in S} \pi_k p_{kj}, \quad j \in S \tag{5}$$

$$\sum_{j \in S} \pi_j = 1 \tag{6}$$

t_{ii} is the mean recurrence time of each drought class and represents the average time needed for a specific drought class to return again and is calculated as the following:

$$t_{ii} = \frac{1}{\pi_i} \tag{7}$$

Finally, $E(T_i \mid X_0)$, is the expected residence time in each drought class and indicates the average time the process stays in a particular drought class before migrating to another drought class. In other words, it shows the duration of that particular drought class and is obtained as the following:

$$E(T_i \mid X_0) = \sum_k k.P(m = k \mid X_0 = i) = \frac{1}{1 - p_{ii}} \tag{8}$$

These values are calculated for all of the 13 mentioned rainfall stations and the results are gathered at Table (3) and finally some analysis is done on the obtained results.

Table 3. The transition matrices for the 13 rainfall stations

Ghareh Bagh	N	1	2	3	**Camp-e-Uromieh**	N	1	2	3
N	0.814	0.145	0.010	0.031	N	0.810	0.148	0.019	0.023
1	0.255	0.604	0.129	0.012	1	0.305	0.520	0.137	0.038
2	0.257	0.286	0.314	0.143	2	0.176	0.382	0.265	0.176
3	0.069	0.138	0.241	0.552	3	0.065	0.226	0.194	0.516
Golmankhaneh	N	1	2	3	**Babarud**	N	1	2	3
N	0.808	0.148	0.029	0.015	N	0.803	0.163	0.019	0.015
1	0.276	0.606	0.087	0.031	1	0.262	0.607	0.090	0.041
2	0.059	0.382	0.294	0.265	2	0.281	0.313	0.313	0.094
3	0.160	0.200	0.280	0.360	3	0.074	0.074	0.259	0.593
Moush abad	N	1	2	3	**Marz-e-Sero**	N	1	2	3
N	0.790	0.167	0.024	0.019	N	0.816	0.154	0.024	0.006
1	0.291	0.619	0.072	0.018	1	0.244	0.635	0.096	0.025
2	0.188	0.188	0.375	0.250	2	0.200	0.257	0.343	0.200
3	0.080	0.240	0.240	0.440	3	0.043	0.174	0.261	0.522
Naghadeh	N	1	2	3	**Oshnavieh**	N	1	2	3
N	0.814	0.154	0.012	0.020	N	0.794	0.161	0.031	0.014
1	0.289	0.623	0.079	0.009	1	0.359	0.466	0.117	0.058
2	0.107	0.250	0.464	0.179	2	0.146	0.317	0.415	0.122
3	0.125	0.063	0.125	0.688	3	0.148	0.185	0.185	0.481
Pol-e-sorkh-e-Mahabad	N	1	2	3	**Pol-e-Miandoab**	N	1	2	3
N	0.793	0.160	0.028	0.019	N	0.819	0.154	0.007	0.020
1	0.289	0.614	0.079	0.018	1	0.309	0.567	0.102	0.022
2	0.355	0.226	0.226	0.194	2	0.111	0.185	0.444	0.259
3	0.063	0.031	0.281	0.625	3	0.182	0.091	0.121	0.606
Shahin dezh	N	1	2	3	**Sarighamish**	N	1	2	3
N	0.844	0.112	0.030	0.014	N	0.820	0.141	0.022	0.017
1	0.322	0.574	0.069	0.035	1	0.370	0.550	0.070	0.010
2	0.133	0.333	0.400	0.133	2	0.118	0.235	0.441	0.206
3	0.091	0.061	0.152	0.697	3	0.077	0.115	0.269	0.538
Alasaghal Tekab	N	1	2	3					
N	0.844	0.111	0.030	0.015					
1	0.321	0.574	0.069	0.036					
2	0.133	0.333	0.400	0.133					
3	0.091	0.061	0.152	0.697					

Analysis of the obtained results

Table (3) indicates the transition matrices related to 13 studied rainfall stations. The elements related to each of these matrices represent the transition probability from one state to another state in the next month. As an example the amount of the element related to row 1 and column 1 for the Ghareh Bagh station is 0.814. That means if the drought condition for a region is in none drought class, with a probability of 0.814 next month that regions drought condition is in none drought class either. One of the features of Markov chain transition matrices is that the sum of all elements in a row is equaled one. As observed in all the 13 matrices the repetition probability of none drought class for the next month is almost 80 percent.

Table (4) indicates the steady state probabilities for 13 precipitation stations and it is obtained by the successive multiplication of the first stage transition matrix in itself for many times. Also these long-term values could be obtained by solving the system of equations 5 and 6. In fact, in the long term, drought class probabilities are independent of the initial state of the markov chain. By having a precise look at Table (4) it could be understood that all of the 13 stations will be in non-drought class approximately with the probability of 0.55 and the probability of being in a severe drought category is less and near 0.07 for all stations. Furthermore, among these 13 stations, Shahin dezh station will be in a non-drought category at the future with a higher probability of 0.5989 in comparison with other stations. Besides, Pol-e-Miandoab station will be in a severe drought class with a higher probability in comparison with other stations with 0.0928 in value.

Table (5) indicates the mean recurrence time of each drought class, which is calculated for 13 stations in 4 drought classes. This table represents that the mean recurrence time of none drought class is almost 1.8 months for all of the stations, actually lower values for the first column of the table are desirable or in other words the none drought class will be repeated in a closer future. On the other hand, the forth column in Table (5) is related to mean recurrence time of severe drought, on the contrary, higher values for the fourth column of the table are desirable or in other words the severe drought class will be repeated in a far future. It is obvious that Marz-e-Sero station has gained the highest value in column 4 with 16.4 months and it is a less drought prone area in comparison with other stations. Pol-e-Miandoab station has gained the lowest value in column 4 with 10.8 months.

Table 4. Steady state probabilities

Station	π_1	π_2	π_3	π_4
Ghareh Bagh	0.5475	0.2901	0.0885	0.0739
Camp-e-Uromieh	0.5545	0.278	0.0875	0.0800
Golmankhaneh	0.5341	0.3163	0.0861	0.0635
Babarud	0.5341	0.3163	0.0861	0.0635
Moush abad	0.540	0.315	0.080	0.0650
Marz-e-Sero	0.5323	0.3169	0.0899	0.0609
Naghadeh	0.5522	0.2901	0.0727	0.0850
Oshnavieh	0.5682	0.2572	0.1046	0.0700
Pol-e-Mahabad	0.5569	0.2832	0.0782	0.0817
Pol-e-Miandoab	0.5745	0.2566	0.0761	0.0928
Shahin dezh	0.5989	0.2322	0.0794	0.0895
Sarighamish	0.5959	0.2492	0.0882	0.0667
Alasaghal Tekab	0.5973	0.231	0.0797	0.0920

Table 5. Mean recurrence time of each drought class

Station	t_{11}(N)	t_{22}(1)	t_{33}(2)	t_{44}(3)
Ghareh Bagh	1.8	3.4	11.3	13.5
Camp-e-Uromieh	1.8	3.6	11.4	12.5
Golmankhaneh	1.9	3.2	11.6	15.7
Babarud	1.9	3.2	11.6	15.7
Moush abad	1.9	3.2	12.5	15.4
Marz-e-Sero	1.9	3.2	11.1	16.4
Naghadeh	1.8	3.4	13.8	11.8
Oshnavieh	1.8	3.9	9.6	14.3
Pol-e-Mahabad	1.8	3.5	12.8	12.2
Pol-e-Miandoab	1.7	3.9	13.1	10.8
Shahin dezh	1.7	4.3	12.6	11.2
Sarighamish	1.7	4.0	11.3	15.0
Alasaghal Tekab	1.7	4.3	12.5	10.9

Table (6) indicates the expected residence time in each drought class, which is calculated for 13 stations in 4 drought classes. In this table Alasaghal Tekab station has gained the highest value in column one with 6.4 months, which means in comparison with other stations it has a desirable condition. On the other hand the fourth column in Table (6) is related to expected residence time in severe drought class for each station and lower values for the fourth column are desirable.

Table 6. Expected residence time in each drought class

Station	N	1	2	3
Ghareh Bagh	5.4	2.5	1.5	2.2
Camp-e-Uromieh	5.3	2.1	1.4	2.1
Golmankhaneh	5.2	2.5	1.4	1.6
Babarud	5.1	2.5	1.5	2.5
Moush abad	4.8	2.6	1.6	1.8
Marz-e-Sero	5.4	2.7	1.5	2.1
Naghadeh	5.4	2.7	1.9	3.2
Oshnavieh	4.9	1.9	1.7	1.9
Pol-e-Mahabad	4.8	2.6	1.3	2.7
Pol-e-Miandoab	5.5	2.3	1.8	2.5
Shahin dezh	6.4	2.3	1.7	3.3
Sarighamish	5.6	2.2	1.8	2.2
Alasaghal Tekab	6.4	2.3	1.7	3.3

Conclusion

In this paper in order to monitor and forecast drought in west and south west of Lake Urmia, first the transition matrixes related to 13 rainfall stations were derived using standardized precipitation index. Afterwards, some useful indexes were presented for managers in order to cope with a probable drought by applying these 13 transition matrixes. These useful indexes are steady state probabilities, mean recurrence time of each drought class and expected residence time in each drought class respectively. In this regard, the results obtained for the steady state probability for the Ghareh Bagh station is as following. Π_1 (0.5475), Π_2 (0.2901), Π_3 (0.0885) and Π_4 (0.0739). To clarify, the higher values for the first drought class are more desirable (Π_1); On the other hand, lower values are more desirable for the three other drought classes (Π_2, Π_3 and Π_4), according to Table (4). In addition, the results obtained for the mean recurrence time of each drought class for the Ghareh Bagh station is as following. $t_{11}(N)=1.8$, $t_{22}(1)=3.4$, $t_{33}(2)=11.3$ and $t_{44}(3)=13.5$ months. To better explain, the lower values for the first drought class are more desirable $t_{11}(N)$; On the other hand, higher values are more desirable for the three other drought classes ($t_{22}(1)$, $t_{33}(2)$ and $t_{44}(3)$, according to Table (5). Finally, the results obtained for the expected residence time in each drought class for the Ghareh Bagh station is as following. Non-drought (5.4), Mild drought (2.5), Moderate drought (1.5) and Severe drought (2.2), months. In this regard, the higher values for the first drought class are more desirable (Non drought); On the other hand, lower values are more desirable for the three other drought classes (mild drought, moderate drought and severe drought), according to Table (6). To conclude the mentioned indexes can increase the manager's foresight to better cope with a probable drought in the future.

Suggestions for further studies

- In this research six-month time-scale was applied in order to derive standardized precipitation index, also other time-scales (1, 3, 9 and etc.) can be used according to the situations of the case study.
- In this research the SPI index was used in order to monitor and forecast drought in the case study, other drought indexes such as PALMER and etc. can also be applied.
- The number of the drought classes in order to derive the Markov chains can be increased or decreased according to the situation of the region. (In this study 4 drought classes were considered)
- Second order Markov chains can be applied in further studies instead of first order Markov chains.
- It is recommended to use longer time periods in further researches to achieve more accurate results.

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