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Analysis of hydrological drought classes' transition using SPI (A case study: Urmia Lake watershed)

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Abstract

Understanding the drought conditions in space and time is one of the most important issues in water resources management. Drought may occur in all climatic regions; however, its traits significantly vary from a region to another. This phenomenon has considerable effects on economy, environment and water resources. So, drought prediction can have an important role in planning and management of water resources systems, especially in an arid climatic period. Since, analysis based on historical data cannot be a proper criterion to analyze drought, therefore in this research transition of drought classes and its parameters were analyzed in Urmia Lake watershed for 28 hydrometric stations using SPI, Monte Carlo simulation and run theory. The results of this research show that, mean drought severity in Urmia Lake watershed for a 42-year period in the future was moderate and its severity will also be less than current historical data. According to the drought classification in all studied stations, the maximum percentage was related to the number of normal years for both series of historical and produced data. Drought assessment based on theory distribution demonstrated that, historical and produced data have the same trend. Therefore, it can be concluded that, for 42-year period of drought in these areas, we will see the reduction of drought severity, the duration of continuous drought periods, and increase of the interval of drought periods occurrence.

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Introduction

Droughts are hydrological phenomena which are generated by long-term lack of precipitation on a wide area, and may occur in every climatic situation. Drought is a phenomenon not absolute but is relative humidity shortage. This phenomenon is associated with time and the effectiveness of precipitations (intensity, number of precipitation events) (Moradi and Bazrafshan, 2008). Drought as a natural disaster, always cause extensive economic losses. According to the International Centre for Climate Change warnings about global warming and its impact on drought occurrence, determination of time trend of drought occurrence in different periods is much important (IPCC, 2001a). During the last two decades, a lot of reports have been presented about the devastating drought in various parts of the world such as Iran, so that, the frequency and severity of drought in different parts of the world and Iran seems to be increased. Numerous studies have been conducted in various part of the world and Iran which as following: Morid *et al.* evaluated the operation of PNPI, SPI, CZI, DI, MCZ, Z-Score and EDI indices using the statistics of 32 years annual precipitation in Tehran province. They showed that, SPI, CZI and Z-Score had the same operation to identify drought and react slowly to the beginning of drought (Morid *et al.,* 2006). Also, DI Index has inconsistent behavior for temporal and spatial variation of drought. By the way, Morid *et al.* argued that, SPI and EDI are not able to distinguish the beginning of drought and have more stable temporal and spatial variations. Also, EDI index is more capable to distinguish the drought and has more proper operation. Locas *et al.* compared SPI, RAI and Z-Score indices in 28 stations in Greece using 40-year data of precipitation. They concluded that, all three indices have the same trend in 12-month scale to determine wets and droughts, and are consistent with Palmer drought severity (Lokas *et al.,* 2003). Khalili and Bazrafshan (2009) investigated the extent and severity of droughts of Iran during a 40-year statistical period ended in 2003, using precipitation data. They suggested that, in water year 1999-2000, more than 96% of Iran area has been dominated by drought and this pervasive and severe drought is in the midst of a three-year arid period of 1999-1998 to 2001-2000. It should be noted that, two drought years were happened in 1971-1970 and 1998-1989 which have dominated 82.21 and 92.05% respectively (Khalili and Bazrafshan, 2009). Bazrafshan (2010) investigated the application of log-linear models in the analysis of drought classes transition based on time series of SPI index in four old meteorological station of Iran (Isfahan, Boushehr, Tehran and Mashhad) and frequency of various drought classes transition in the first and second half of the twentieth century. Their study was based on a 12-month dynamic time base and the results showed a good fitness of log - linear models on frequency transition matrix at 5% confidence level. Also, it was found that except for Tehran station, the frequency of moderate and severe drought classes transition in the rest of the stations has been significantly increased during the second half of the twentieth century (Bazrafshan, 2010). Also, unconditioned frequency of moderate and severe drought classes in some studied stations in the second half of the twentieth century has risen as three times of the first half. Sabziparvar *et al.* compared seven drought indices by a 35 year precipitation statistics in 22 stations in Hamedan province using cluster analysis, and they showed that, DI, Z, RAI are statistically similar and have the same results in drought assessment under cold and semi-arid climatic conditions of Hamedan province. They also found that, despite capability in distinguishing the beginning of drought, SPI cannot be a suitable index to monitor drought in cold and semi-arid climatic conditions (Sabziparvar and Kazemi, 2010).

There are numerous indices to monitor and warn meteorological and hydrological droughts among which the most famous is Standardized Precipitation Index (SPI). After almost two decades of providing standardized precipitation index by McKee *et al* (2003), it has been used as base index to identify drought periods (McKee *et al.,* 1993). One of these applications is analysis of transition frequency of various drought severity using log-linear models. For the first time, Paolo *et al.* (2005) used the two-dimensional log-linear models to predict the probability of transition from a drought class to another (Paulo *et al.,* 2005). In another study, Moriera *et al.* (2006) applied three-dimensional log-linear models effectively to analyze drought severity classes' transition and to investigate the effect of climate change on drought frequency and class (Moriera *et al.,* 2006). Moriera *et al.* (2008) assessed the possibility of the use of three-dimensional log-linear models to predict various drought severity classes in the rain gauge stations in Portugal. The results showed that, these models have proper efficiency to predict droughts short-time temporal horizons (Moriera *et al.,* 2008). Mishra *et al.* (2007) studied the drought and its prediction using stochastic hybrid models and neural networks using SPI index for 3, 6, 9, 12 and 24-month periods in Kansabati River watershed in India. The results of these researches indicated that, stochastic hybrid models have more suitable results for drought prediction compared with stochastic models ARIMA/SARIMA (Mishra *et al.,* 2007). Moriera *et al.* (2008) predicted the drought using log-linear models based on SPI in Alentejo and Algarve in the southern Portugal. They concluded that, log-linear models are useful to predict short-time periods, and provide the possibility of drought classification as two-month periods, and given that, the maximum precipitation in Portugal occurs in autumn and winter, and spring and summer are often arid, use of these models can be useful to predict short-time periods using 12-month SPI (Moriera *et al.,* 2008). Nafarzadegan and Rezaeian (2012) monitored the drought of Fars province for three decades using different scales of SPI for 3, 6, 9, 12 and 24-month periods for a 30-year period. The results showed that, the highest drought period has been occurred in the last three decades, also, comparison of their results with Mann – Whitney test showed that, there are certain variations in the results using Mann – Whitney test. They also found that, the recent droughts can be as an effective factor on water resources problems but, the role of other factors such as lack of appropriate management about water resources and population growth should not be ignored (Nafarzadegan and Rezaeian, 2012). Barrow *et al.* assessed the drought indices PNPI, SPI, SWSI and ADI for historical data in Yara River in Australia, and produced ADI as the best index according to different concerned criteria in the region (Barua *et al.,* 2011). Moriera *et al.* (2012) used precipitation data of a 67-year period (1932-1999) for risk assessment of drought management in homogenous regions through deductive method of variance analysis along with SPI. They used transition probability table in their work. They divided the study area into eastern and western part based on latitude and longitude, and they concluded that, the amount of drought class in the western part is more severe than the eastern part (Moriera *et al.*, 2012). Antonina & Baldassare (2012) analyzed temporal and spatial pattern of drought in Calabria region, Italia, using short-time temporal scales of Spa 87year (1921-2007) period. The results of their study showed that, half of the region has severely been affected by drought at the interval 1981-1990, and drought fluctuation in wet seasons was 13% and in dry seasons was about 11%. They also indicated that, severe autumn droughts were in the eastern and south-eastern areas of Ionian region. Also, the results of temporal-spatial analysis showed that, drought trend in autumn, winter and spring in ascending while; this trend in the summer was descending (Antonina& Baldassare, 2012). Zhang and Singh (2012) evaluated the drought in Peral River watershed in China using SPI for 42 stations; their results showed that, generally, tendency to dryness was not significant at the confidence level of 95%. Also, in the harsh conditions of drought, high risk of drought can be observed in downstream of the watershed and low risk can be seen in the upstream of the watershed, and this can be considered as an increasing challenge for drought management and water resources management (Zhang and Singh, 2012). Amir Ataei *et al* (2013) compared the operation of seven common drought indices to monitor drought using Monte Carlo simulation, and the results indicated that, application of SPI and SPIo has a relative advantage for an integrated analysis, and Nitzche index also is much suitable for initial or preliminary analysis. PNPI also, was as the most inefficient index for drought analysis which is illusory has high errors (Amir Ataei *et al.,* 2013). Drought is not absolute but also is relative, so, it is defined separately for each features' group.

Weilhite and Glantez (1985) presented four views in investigation of drought including: 1) Meteorological drought: in terms of meteorology, drought is deviation of precipitation from the long-term amount and appears as one of the initial results of drought. 2) Hydrological drought: this kind of drought occurs by dropping the groundwater and surface water reserves from permitted limit. It represents the amount of groundwater and surface water reserves. 3) Agricultural drought: in agricultural view, when the soil moisture is less than the real plant requirement, and agricultural products are damaged, drought occurs. 4) Socioeconomic drought: in this view, drought occurs when the lack of water to supply the water needs of human, causes social and economic abnormalities that affect people's life. In this research, analysis of drought classes' transition has been conducted based on hydrological drought (Weilhite and Glantez., 1985).

Since, drought is considered as one of the rare events, investigation its occurrence frequency variation in a region needs long-term statistics. Awareness about aggravation or attenuation of drought occurrence frequency in Iran during the twentieth century is important in planning to adapt or to cope with drought. Since, analysis based on historical data cannot be a proper criterion to analyze drought, with regard to the results of various studies in which SPI has been found as the best index, a fixed twelve-month scale of SPI, artificial data generation technique were used by applying severity and duration traits of drought and transfer matrix by AR(1) model after producing 1000 samples for 28 studied stations in Urmia Lake watershed and also, Fortran programming language was used in the mentioned model.

The aim of this research is analysis of hydrological drought classes' transition using SPI in Urmia Lake watershed, located in the northwest of Iran.

Materials and methods

Study area

Urmia Lake watershed is located in the northwest of Iran. This watershed has 52700 km² areas which is 21.3% of entire are of Iran, and is located between northern latitude of 35^0 40′- 38^0 29′ and eastern longitude of 44^0 13′- 47^0 53′. The maximum height of the watershed is close to Sabalan mountaintop and by 3850 m, and so, height difference of the watershed is estimated by 2576 m. By investigating the droughts trend, a 42-year statistical period (since water year 1966-1967 till 2007-2008) was selected. The position of stations located in Urmia Lake watershed is presented in Fig.1 and Table 1.

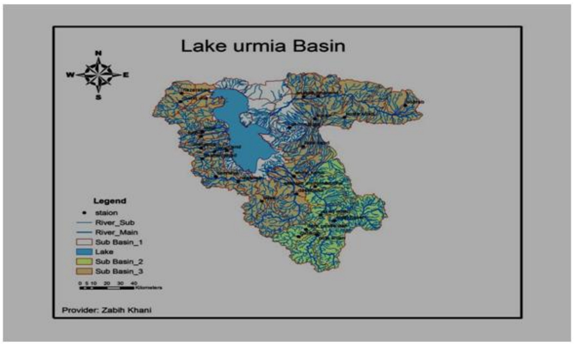

Fig. 1. Position of the studied stations in Urmia Lake watershed.

Testing of randomness and homogeneity of data

Hydrological data usually follow a random state and are not completely non-random. Random data allow us to analyze the data statistically. In order to use probable methods for the data, we should ensure the data are random. Non-random data are due to the method of data collection, and this test show us when the data have been manipulated so, among the reasons of non-random data, we can mention to data making while data collection, data recovery by unusual ways. In hydrology topic, random time series generally means that, these recorded data have been obtained from a series of natural phenomena. In order to ensure about randomness of data, Runtest is used which is based on z-test. If the range of z for the selected stations is 1.96 to -1.96, it can be noted that, precipitation data follow randomness test (Mutreja, 1986). The results of randomness test for the studied stations show that, Pearson distribution type III is the best distribution (Fig. 2, 3).

Transition probability matrix

Conditional probability of Pij, $P[X_{t+1}=j|X_t=i]$ for $i,j\in E$ is called system transition probability from state i to j, which is defined as below:

$$P_{ij}=P\left[X_{t+1}=j\ |X_t=i\right]=\frac{N\left[X_t=i,X_{t+1}=j\right]}{N\left[X_t=i\right]} \quad (1)$$

$$\begin{matrix} P_{00} & P_{01}\ \cdots & P_{0n} \\ P_{10} & P_{11}\ \ldots & P_{1n} \\ \vdots & \vdots & \\ P_n & P_{n1}\ \ldots & P_{nn} \end{matrix} \quad (2)$$

In matrix P, entrance probability of the system from i to state j is greater than or equal to zero (for each $i,j\in E, P_{ij}\geq 0$). Also since, a system is in a set of possible states at any moment of time, sum of the probabilities of each row must be equal to one, it means for each $i\in E$, $\sum_{j=0}^{n}P_{ij}=1$ (Hakimipour, 1997). It is good to be noted that, the main diagonal elements of the matrix P represents the stability and maintenance of each status.

Monte Carlo simulation

Most of conducted studies on analysis and assessment of various drought indices have been based on recorded or historical data. In this kind of study, it is supposed that, precipitations that may occur in the future, have similar behavior with historical data, and precipitation lower and higher than historical data will not occur. In other words, historical precipitations will occur as recurring in the future while, this happening has very low probability. Therefore, in such situations, which do not allow a detailed analysis of historical or recorded data, using Monte Carlo simulation is very important and will be valuable (Douglas, 2000). Precipitation data are a function of time and space that can have random and uncertain behavior (Chow *et al.*, 1988). Therefore, precipitation amount and time cannot be certainly predicted. So, stochastic models are used to generate a series of likely intermittent precipitations in the future, in order to assess various indices in drought prediction. These artificial series describe more realistic the traits of precipitation which may occur in the future (Salas, 1993). In this analysis, discharge data have been used to assess SPI to analyze drought classes' transition. In order to produce discharge data, at first, annual data were produced then, were distributed using Valencia and Shaaki model. The advantage of using distribution models compared with direct models of ARMA (p, q) is that, ARMA models preserve only statistical parameters of monthly data (McMahon and Mein, 1986). Parameters of discharge production are obtained from recorded data. In order to produce monthly discharge data using Valencia and Shaaki model, the discharge data are obtained as below (Valencia and Schaake, 1973).

$$X_{i+1}=\bar{x}+\rho(x_i-\bar{x})+v_i s\sqrt{1-\rho^2} \quad (3)$$

Where xi and xi+1 are produce annual precipitation of year i and i+1 respectively. $\bar{x}$ Is mean discharge or observed annual precipitations, v_i is random variable with standard normal distribution with means zero average and unit variance, ρ is autocorrelation coefficient with a lag of one year, s is the annual standard deviation of the observed data. Valencia and Shaaki model for annual data distribution to monthly as below [26]:

$$X_i=AZ_i+BV_i \quad (4)$$

Where xi is a 12×1 from monthly data from zero mean for year i, Z_i is produced annual data with zero mean for year I, V_i is a 12×1 vector of random variables of standard normal distribution which is independent from Z_i, also, A, B are constant coefficient of the model with dimensions 12×1 and 12×12 respectively and their values are estimated using historical data.

1000 samples of monthly and annual sample data series of discharge were produced with statistical period equal with historical data, or 42-year using equations 3, 4 for each hydrometric stations in the region. Then, each produced data series was used by

SPI using SDSM software package (Montaseri, 2011), and finally, the obtained results were summarized and extracted for all the produced data series (1000 series).

SPI was presented by McKee (1993). SPI is calculated for various temporal scales and is used as primary warning for drought and helping to evaluate its severity [8].

$$SPI = \frac{P_i - \overline{P}}{S_d} \qquad (6)$$

Where SPI is standardized precipitation index, P_i is normalized data, $\overline{P}$ is mean normalized data in the concerned period, S_D is standard deviation of normalized data in the concerned period. Table 2 shows classification of various states based on SPI.

Results and discussion

Studied parameters in drought indices

After producing the artificial precipitation data by the mentioned models as monthly and annual (AR (1) model and Valencia-Shaaki model), drought was analyzed in the produced statistical data and historical data. The considered items are as below:

1) Drought severity. 2) Drought classification. 3) The effect of various months on drought. 4) Comparison of SPI based on the classification of wet year and drought values. 5) Transition probability matrix.

Table 1. Geographical position of the studied stations for two instance stations.

Longitude	Latitude	station	no	Longitude	Latitude	station	no
47° 40′	38° 00′	Sohrab	15	46° 17′	38° 09′	Anakhaton	1
46° 07′	37° 02′	Shirin Kandi	16	45° 05′	37° 02′	Oshnaveyeh	2
46° 40′	36° 24′	Safakhaneh	17	46° 50′	37° 51′	Bostan abad	3
46° 11′	36° 11′	Ghabghloo	18	45° 14′	37° 24′	Babd	4
46° 5′	37° 43	Ghermezigel	19	45° 42′	36° 41′	Beytas	5
46° 17′	38° 18′	Gheshlaghamir	20	45° 02′	37° 00′	Peyghaleh	6
44° 53′	37° 36′	Kalhor	21	46° 16′	37° 43′	Tazehkandeh	7
46° 26′	37° 50′	Leyfvan	22	45° 54′	37° 40′	Tepik	8
46° 26′	38° 07′	Vanyar	23	46° 25′	36° 53′	Chobloch	9
46° 52′	37° 26′	Mirabad	24	44° 36′	38° 05′	Charighe olya	10
45° 23′	36° 58′	Naghadeh	25	46° 17′	36° 17′	Dareh panbedan	11
46° 29′	38° 09′	Nehand	26	46° 10′	36° 47′	Dashband bokan	12
46° 37′	38° 12′	Nazarabad	27	45° 04′	37° 23′	Deyzej	13
44° 54′	37° 17′	Hashemabad	28	46° 29′	36° 29′	Sarifmish	14

Table 2. Characteristics of various wet and drought periods class using SPI.

SPI	Drought classification	Common quantitative index of the class
Higher than +2	Severe wet year	+3
+1.5 to+1.99	Moderate wet year	+2
+1to+1.49	Weak wet year	+1
-0.99 to+0.99	Normal	0
-1 to -1.49	Weak drought	-1
-1.5 to -1.99	Moderate drought	-2
Less than -2	Severe drought	-3

Drought severity

In order to estimate drought severity, SPI was obtained for a 12-month temporal scale for 28 stations for produced data from historical data (1000 produced samples). In this regard, total amount of drought by SPI in each period, has been divided by the number of associated periods. For instance, one-year drought severity is obtained by dividing the total amount of drought by the number of obtained one-year periods. Fig.4 shows an instance of drought severities by SPI for instance stations as two-dimensional. Here it is observed that, drought severity in historical data is abnormal compared with produce data, it is because, analysis in historical data is based on a set of data, so, it will have weak operation for drought analysis based on historical data. As it is found from the results of the study, drought severity in short-term periods is higher than long-term periods, and this is consistent with hydrological analysis basis; because, based on probability basis in hydrology, long-term droughts occurrence probability is less than short-term droughts. This matter shows the accuracy of artificial data production models and Monte Carlo simulation in drought analysis. As it is resulted from the graphs, we will always face with drought in the future periods.

Table 3. Transition probability matrix for 6 instance stations (historical and produced data).

station	Tazehkandeh			station	Tazehkandeh		
Historical	D	N	W	Production	D	N	W
D	0/31	0/16	0/039	D	0/31	0/15	0/055
N	0/63	0/69	0/60	N	0/64	0/69	0/61
W	0/05	0/15	0/36	W	0/06	0/15	0/34
station	Tepik			station	Tepik		
Historical	D	N	W	Production	D	N	W
D	0/29	0/14	0	D	0/31	0/15	0/055
N	0/71	0/75	0/48	N	0/64	0/69	0/61
W	0	0/11	0/53	W	0/06	0/15	0/34
station	Shirin Kandi			station	Shirin Kandi		
Historical	D	N	W	Production	D	N	W
D	0/29	0/16	0/062	D	0/28	0/16	0/057
N	0/65	0/68	0/62	N	0/65	0/68	0/62
W	0/067	0/16	0/32	W	0/08	0/15	0/33

Table 4. Transition probability matrix for 6 instance stations (historical and produced data).

station	Safakhaneh			station	Safakhaneh		
Historical	D	N	W	Production	D	N	W
D	0/23	0/17	0/092	D	0/23	0/17	0/087
N	0/67	0/67	0/66	N	0/67	0/67	0/66
W	0/1	0/17	0/25	W	0/097	0/17	0/25
station	Leyfvan			station	Leyfvan		
Historical	D	N	W	Production	D	N	W
D	0/25	0/05	0/042	D	0/43	0/12	0/013
N	0/61	0/8	0/77	N	0/54	0/75	0/5
W	0/14	0/15	0/19	W	0/02	0/13	0/49
station	Vanyar			station	Vanyar		
Historical	D	N	W	Production	D	N	W
D	0/44	0/11	0/01	D	0/44	0/06	0/01
N	0/54	0/76	0/5	N	0/53	0/82	0/51
W	0/017	0/14	0/48	W	0/03	0/12	0/47

Comparison of SPI based on the classification of wet year and drought values

In order to estimate the probabilities of wet and drought periods to estimate drought classes based on SPI, first, various values of drought indices were calculated from historical and produced data and then, these values were classified as following: (+3) is very severe wet year, (+2) is moderate wet year, (+1) is weak wet year, (0) is normal, (-1) is weak drought, (-2) is moderate drought, and (-3) is severe drought.

Fig. 5 shows the probabilities of wet and drought in the instance stations. Given that, climate change and drought are caused by natural phenomena and processes, it is expected that, they follow a normal distribution; so, comparison of normal state (-1 to +1) with mean state of normal distribution by 68.26%, with (-2 to +2) by 95.44% and with (-3 to +3) by 99% can be used here as the basis of comparison. Considering that, the studied index here is SPI, drought distribution is mostly normal based on this index. Fig. 5 shows drought classification in two-dimensional state, and Fig. 6, 7 show classification of drought periods for all the stations in three-dimensional state for both historical and produced data. As it is found from the graphs, normal year's probability is higher than wet and dry years which are consistent with basis of probability science in hydrology; since, if statistical period is a sample space, it is normal that, normal year's occurrence probability is higher than the other years which clear in the figures.

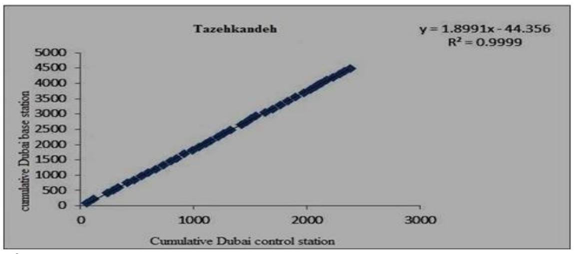

Fig. 2. Homogeneity of the studied stations.

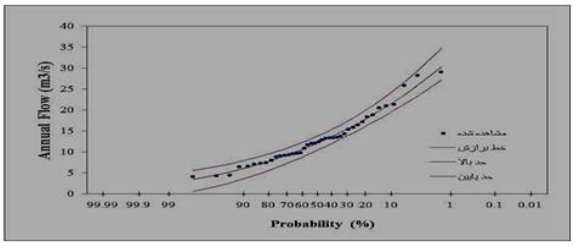

Fig. 3. Probability curve of historical annual data fitting of Tazekand station with Pearson distribution type III.

Evaluation of drought analysis based on historical and produced data and its theoretical distribution

In this section also, after estimation of SPI values for obtained historical and produced data from the average of 1000 samples, the number of one-year, two-year,... and 11-year periods is determined. Then, cumulative failure probability of drought for historical and produced data and theory distribution extracted from transfer matrix are determined using observed data; so that, SPI was calculated based on observed data. In this section, theoretical distribution functions were used to evaluate the model. Fig. 9 shows cumulative failure probability of drought occurrence in various drought periods for all the stations based on historical data and theoretical distribution functions. As it is found from fig. 9, cumulative failure probability of drought occurrence for the studied stations is almost the same for historical and produced data, but, cumulative failure probability of drought occurrence for theoretical distribution is less as it reaches a constant value after three-year periods, and this matter also is consistent with the basis of hydrological analysis because, according to hydrological analysis, by increasing the number of period in the future years, the probability of the existence of wet periods in a long-term period seems obvious. Base on this index, the minimum cumulative probability of one-year periods in most of the stations is about historical data and most of them are related to the theoretical distribution.

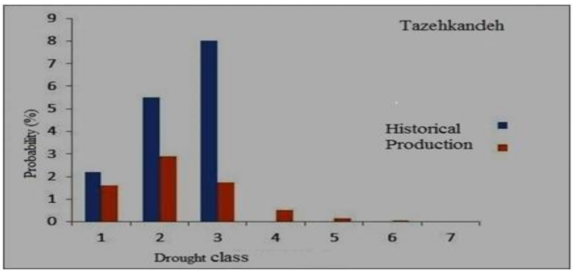

Fig. 4. Drought severity of Tazekand station for historical and produced data.

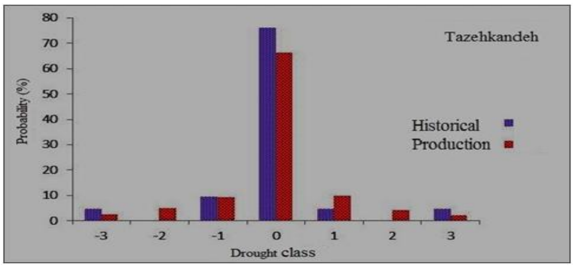

Fig. 5. Drought classification for stations Tazekand and Tepik.

Transition probability matrix

Transition probability can be evaluated for short-term and long-term planning. In this research, SPI values were classified into: (+3) is very severe wet year, (+2) is moderate wet year, (+1) is weak wet year, (0) is normal, (-1) is weak drought, (-2) is moderate drought, and (-3) is severe drought. Determining various states of drought to another state is possible using transition probability matrix which is shown in tables 5, 6. Transition probability from various drought states to other states in various periods has different facts and figures. Probability distribution of normal class in three-month SPI mostly follows normal distribution. Generally, transition probability from drought to wet state and from wet to drought state in all dynamic temporal scales of SPI is zero. Transfer matrix shows various states from various classes to other states. For instance, transfer matrix of historical data for Tepik station, the probability of transition from severe drought state (-3) to severe drought (-3) is 50%, and probability of transition from this state to the normal state is 3%.

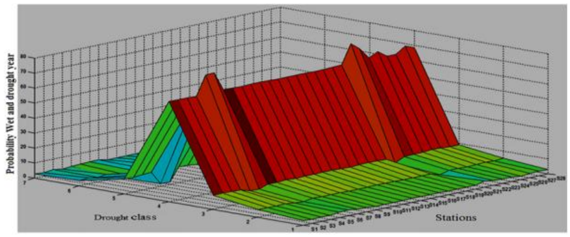

Fig. 6. Drought classification for all the stations for historical data.

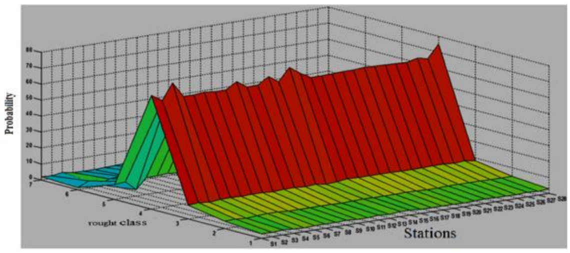

Fig. 7. Drought classification for all the stations for produced data.

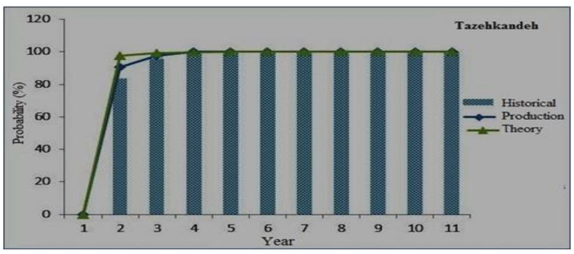

Fig. 8. Cumulative failure probability of drought for historical and produced data and theory.

Conclusion

After studying 28 hydrometric stations in Urmia Lake watershed in which flow regime is real, in order to analyze drought transition using its parameters and transfer matrix for historical and produced data series, artificial data production technique was used by AR (1) model and Fortran programming language was conducted for 1000 samples and the results are as following: 1) artificial data production models for monthly and annual data for statistical years less than 30 years, can acceptably preserve statistical traits such as mean, standard deviation, skewness, and correlation between two consecutive months, while, by increasing the number of statistical years, the model operation is improved which is obvious in this study for most of the stations in which a 42-year period has been used. 2) According to the graphs, it can be concluded that, drought severity in a 42-year period in Urmia Lake watershed in the future will be moderate and its severity is also less than current historical data. According to drought classification in all the studied stations, the maximum percentage of the number of normal years for historical and produced data. Also, based on transition probability matrix, the maximum transition probability is related to the normal periods for both historical and produced data. Also, drought assessment based on theoretical distribution for historical and produced data have the same trend. Therefore, it can be concluded that, in the future 42-year statistical period in this region, we will observe slight reduction of drought severity and the time of drought continuous periods, and along it, increase of the intervals between drought periods occurrence. 3) In terms of monthly drought, SPI shows that, drought severity in produced statistical period is moderate in continuous periods. 4) The number of drought periods is ascending based on 12-years constant SPI for historical and produced states for short-term periods and gradually, the number of these periods decreases, which is consistent with drought analysis basis in hydrology; since, based on hydrological analysis, the occurrence probability of drought with less continuity is more than the droughts with higher continuity, and this matter is true in all the stations. Based on this index, the number of drought periods in the stations located in the east of Urmia Lake is more than the stations located in the west of the Lake.

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