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Research Article

Drought Monitoring and Prediction in Kashmar County Using SPI Index and Markov Chain

Bashiri, M.[a], * Esmaeily, Gh.[a]

[a] *Department of Nature Engineering and Medicinal Plants, University of Torbat Heydarieh, Torbat Heydarieh, Iran*

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Abstract

Drought is a natural and mysterious creeping phenomenon, and many believe that it has a complex mechanism and is less known than other natural disasters. Studying drought events is very important for natural and water resource management planning. One strategy to manage drought is to predict drought conditions using a probabilistic tool. The study aimed to predict the probability and severity of meteorological drought in Kashmar. To this aim, the monthly rainfall data of the Kashmar Synoptic Station was used to analyze a 30-year period (2017-1987). The drought status of Kashmar County was considered by drought duration of The Standardized Precipitation Index (SPI) at 1, 3, 6, 9, 12, 18, 24, and 48-month timescales. Next, using the Markov Chain, the transition probability matrix for the study area was carried out, and the probability of meteorological droughts was predicted for severity. The results of this study showed that the severest drought in Kashmar occurred in 2000 and 2009, with an SPI coefficient of greater than -3, while the highest precipitation occurred in 1993, with an SPI coefficient of 2.8. Then, the Markov chain model was used to calculate the balance probabilities for dry, wet, and normal periods at different time scales. The results showed that, on average, the stationary probability of dry, normal, and wet periods is 29, 30, and 41 percent, respectively. Consequently, it means that the region's climate conditions are often normal. As a result, given the critical situation of Kashmar County, the opportunity to reduce water stress and aquifer discharge can be exploited.

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*Corresponding Author:
Bashiri, Mehdi
Email: m.bashiri@torbath.ac.ir
ORCID: 0000-0001-5075-2313

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1-Introduction

Drought is the period of rainfall less than average in a particular area that causes a prolonged lack of surface or underground water, affecting the region's ecosystem and human, agricultural, and economic activities. It can last for months or years and happens in all-weather climates, from very dry to humid areas. Drought can continue for consecutive years and cause food insecurity, malnutrition, the spread of infectious diseases, famine, and human migration. Each drought phenomenon is characterized by three characteristics: duration, intensity, and magnitude (Mosaedi et al., 2017). According to the report of the World Meteorological Organization, climate changes have led to an increase in the frequency, intensity, and duration of droughts, which have had harmful effects on other sectors, especially agriculture, water, energy, and the environment (Muller, 2014) Predictions have shown that due to changing climate conditions, droughts and related social and economic effects will increase in the future (Van Huijgevoort et al., 2014).

Climate change is already affecting water access for people around the world, causing more severe droughts and floods. Drought, like other natural disasters, is not instantaneous and has a creeping nature; it is difficult to determine when it starts and ends. Hence, the need for extensive research in this field seems necessary (Chu et al., 1993). The threshold set as the onset of a drought (e.g., 70% of average precipitation over a given time period) is chosen more by convention than based on a precise relationship to its effects on the environment (Jahangir et al., 2015). Investigation of drought events is essential in natural resources management and water resources planning. One strategy for drought management is to predict its conditions using probabilistic tools (Zarei, 2018). It is not possible to prevent a drought, but it is possible to check its past status by using climate data and drought indicators and predict it by using statistical methods and checking the probability of occurrence to be able to prevent its adverse effects as much as possible by taking the necessary plans.

One of the indices used for this purpose is the Standardized Precipitation Index (SPI). For the first time, (Mckee et al. 1993) used the SPI index in the US state of Colorado and found that the gamma distribution is the most suitable for fitting the rainfall data. SPI is also recommended by the World Meteorological Organization (WMO, 2006, 2012) as a drought indicator (Habibi et al., 2018). SPI can be used in several time scales to investigate different wet or dry classes. Also, SPI is considered to be the most potent and effective index (Capra and Scicolone, 2012). In addition, rainfall data is needed only to evaluate the SPI, so it is easier to calculate. Also, SPI can be used to compare dry or wet conditions in different regions and different time periods.

Autocorrelation and Markov chain models are among the time series models used to predict the probability of rainfall and drought events. The Markov chain model is used to explain and define the random characteristics of random processes (meteorological and hydrological variables). For the first time, Gabriel and Neumann (1962) used a first-order Markov chain model to determine dry and wet days using daily rainfall data. Rahmat et al. (2017) used a Markov chain model to predict short-term drought in Victoria, Australia, using SPI on a 12-month time scale. Szilagyi et al. (2006) used the Markov chain to generate daily discharge data on the Tisza River located in Eastern Europe and emphasized the ability of the Markov chain model. The Markov chain method has a long-term background due to its capabilities in calculating wet and dry periods and simplifying the solution of many problems related to dependent processes (Bonaccorso et al., 2015).

Drought prediction is the most essential solution to deal with and reduce the damages caused by it (Bashari and Vafakhah, 2011). In the science of probability, the primary purpose of Markov chain as a descriptive tool is to predict the future behavior of management systems. For the first time, In 1907, A.A. Markov began to study a new type of stochastic process in which the output of a specific test can affect the output of subsequent tests, which is called a Markov chain (McMahon and Srikanthan, 2001).

In the issue of drought, the Markov chain model is used to estimate the occurrence of different drought severity classes, the expected time for each severity class, the recurrence time of a special drought class, and the expected time for the SPI change of a special class. Markov chain makes it possible to predict the future using probabilistic states and transition probability matrix. The Markov chain is characterized by several states (S) and the probability of transition between states

(Pij). The transition probability Pij is the probability of the Markov chain the next time in state j assuming that it is in state i at present. Thus, if the total states considered for an environmental parameter include drought (D), normal (N), and drought (W), and we are now in a drought state, the state of the environment in the next step can be with a percentage of probability in Each of the states D, N, and W. The mentioned probability is called transition probability. If the transition matrix can be balanced, i.e., the probability of transition from all states to a specific state can be set in a constant number, the system's state can be predicted in the long term, and the resulting matrix is called the stationary matrix.

So far, the Markov chain method has been used in many studies in Iran to predict drought and climate parameters. Alizadeh and Ashgar-Toosi (2008) predicted the climatic conditions of Razavi Khorasan province with the SPI index and Markov chain. The results of the annual prediction showed that the probability of normal weather conditions in most stations of Razavi Khorasan province is higher than the other conditions. Ghamghami and Bazrafshan (2012) investigated the ability of the Markov chain model to monitor and predict the drought conditions of Iran; the results showed that the Markov chain can simulate the probable behavior of drought in Iran. Among the other cases where the Markov chain has been used to predict the drought in Iran can refer to the studies of Taheri and Panahi (2014) at the Qazvin synoptic station, Raziei (2016) in the arid and semi-arid regions of Iran, Siaser and Shahr-Derazi (2015) in the Iranshahr county and Zarei (2018) in the southeast of Iran.

The analysis of monthly rainfall data of 17 stations of North Khorasan province with a statistical period of 22 years to monitor the meteorological drought of the province showed that the DI and SPI indices corresponding to the year of minimum rainfall show the occurrence of severe and very severe drought in all study stations (Hashemi Dovin and Ahangarzadeh, 2013). The drought in Khuzestan province was predicted by the SPI drought index and the Markov chain, and the results showed that in all stations, the normal state (with a six-month time scale) is the most frequent and accounts for 33-44% of the states (Shokrikochak and Behnia, 2013). The Application of SPI and SPEI indices in evaluating the impact of drought on the quality of surface water resources (case study: Kashafrood River) showed that the average of the water quality parameters has changed significantly during drought, and with the decrease in rainfall, increase in temperature and the onset of drought, the quality of water, especially in Downstream stations is reduced) (Helmi and Shahidi, 2023). The effects of climate change on the severity, duration, and amount of drought in the Semnan region were investigated using SPI and RDI indices, and the drought indices showed an increase and decrease in the amount and severity of drought for 3-month and annual time scales, respectively (Delghandi et al., 2023). Simultaneous analysis of meteorological drought characteristics based on the SPI and CRU scenario in the Zarinerood watershed showed an increase in the intensity and duration of droughts in recent years. So, 45% of the studied statistical period had a shortage of rainfall, and 8% of the studied months were faced with severe drought (Samadian et al., 2023).

Abroad, using the precipitation data in the 35 meteorological stations in the Huaihe river basin, an annual analysis of the SPI drought index was conducted over nearly 50 years (1961-2010), and it was concluded that the frequency of drought in the river basin has decreased, but the severity has increased. Most droughts are slight and moderate and severe droughts rarely occur (Yan-jun et al., 2012).

Evaluating Markov chains and Bayesian networks for 1-month SPI drought forecasting in the seasonally dry tropics of Costa Rica showed that these models can predict meteorological drought with a 1-month lead time appropriately (Gutiérrez-García et al., 2023). Probabilistic prediction of drought in Iran using homogenous and nonhomogeneous Markov chains for 35 years showed that the probability of occurrence of various drought classes decreased with the increase of drought severity and, the Markov chain demonstrates that the continuity of the severe drought class more than other classes (Mahmoudi and Rigi, 2023).

Also, the results of Predicting the probability of droughts using the SPI drought index based on the Markov chain model in Sistan and Baluchistan province showed that, on average, the probability of stationary dry, wet, and normal periods in the stations of the province is 29, 5 and 66%, respectively (Siasar and Salari, 2023).

Drought has destructive effects on the

environment, human life, and living beings. Among these effects, we can mention the drying up of rivers, forest fires, and, most importantly, the reduction of the level of wells, underground water, and freshwater. In Kashmar county, due to the growing trend of population and social and economic development and the prosperity of agriculture in the region, the increase in harvest and consumption in urban and rural areas, as well as the development of medium and small industries in the region, the amount of harvest of underground water sources has increased. These conditions have had a noticeable effect on the reduction of underground water resources, and their adverse effects have been manifested in agriculture, drinking water, and industry. The decrease in the agricultural products and following it, the lack of supply to the consumer market and finally the increase in the price of these products, the application of drinking water rationing in the cities and villages of the region, creating problems in the activity of existing industrial units and limiting the establishment of large industrial units that require have reliable and stable water sources, it is one of the most important effects of reduced water resources.

The continued droughts could turn into an economic-social crisis in the future. It is certain that it is necessary to know the periods of drought according to the current conditions. In the study area, drought and its recurrence with different intensities have caused different damages to the social, economic, and political sectors. Since the occurrence of drought has increased in recent years, the investigation and recognition of wet and dry periods and their prediction will reduce damages and improve management plans. In contrast, the study records have paid less attention to the integration and simultaneous analysis of these two methods. So, the questions the present research is seeking to answer include identifying the frequency of short-term to medium-term droughts in the Kashmar region, estimating the probability of drought occurrence in Kashmar County, and prioritizing the future climatic conditions of this region. Therefore, this research aim is to monitor and predict meteorological drought using the SPI and Markov chain in Kashmar County based on the long-term data of its synoptic station in the region.

2- Materials and methods

2-1- Area of the study

Kashmar County is adjacent to Khalilabad county from the west, Neishabur, Sabzevar, and Bardaskan counties from the north and northwest, Torbat Haydarieh from the east and northeast, and Mahwelat from the south and southwest (Fig. 1). Kashmar county, as a part of the Kashmar watershed with longitude coordinates 57˚54′ to 58 ˚39′ E and latitude 34˚ 51′ to 35 ˚ 28′ N, is located in the south of Razavi Khorasan province. This region is located in the northeastern part of the central desert basin of Iran and has an area of 2045.8 square kilometers. About 1221.1 square kilometers of this basin is the Kashmar plain. The Chenarsokhte and Sheshtaraz seasonal rivers are the region's most important rivers. The general slope of the region is from north to south and from east to south and southwest, which decreases from 24 to 7.5 per thousand from the northern highlands to the boundary of the Bajestan desert.

Kashmar county has a semi-arid to arid climate. The calculated average rainfall for this region is 190.6 mm, which is reported as 181.8 mm in the lowlands and 200 mm in the heights. Rainfall in this region is mainly limited to the winter and spring seasons, and it usually occurs in the form of showers with thunder and floods.

In recent decades, the rapid development of agriculture, along with high population growth and the increase in water demand, has caused excessive exploitation and a drop in the underground water level in this county. Extraction from the underground water tables of this region has caused an annual drop of about 0.8 meters in the underground water level, along with a reservoir deficit of 121.4 million cubic meters. The continuous drop in the underground water level has made it among the province's critical plains (Anonymous, 2005). Based on the climate classification of De Martonne and Emberger, Kashmar county has an arid and mild hot desert climate, respectively. The average annual rainfall of the catchment area is reported to be equal to 190.6 mm. The potential of evapotranspiration in the Kashmar synoptic station is 1701 mm per year. The existing hydrometric station in the basin is related to the sub-basin of Irajabad - Sheshtaraz. It has an area of 794.4 square kilometers, an annual runoff volume (MCM) of 7.406, and an average annual runoff volume (MCM) of 22.800 in the water year 2016-2017(Anonymous, 2005). Table 1 and Fig. 2, respectively, show the water balance of Kashmar county and the rainfall graph of the Razavi Khorasan province during the statistical period of 40 years (1977 to 2017).

2-2- Research data

The calculation of the meteorological drought index was done by the monthly rainfall data of the Kashmar synoptic station for 30 years (1987-2017), and then, using the SPI drought index in 1, 3, 6, 9, 12, 18, 24 and 48 months time intervals, the drought condition in the station was investigated. In the next step, using the Markov chain, the transition probability matrix in the station was constructed, and the probability of occurrence for the meteorological droughts was predicted in three different classes of severity.

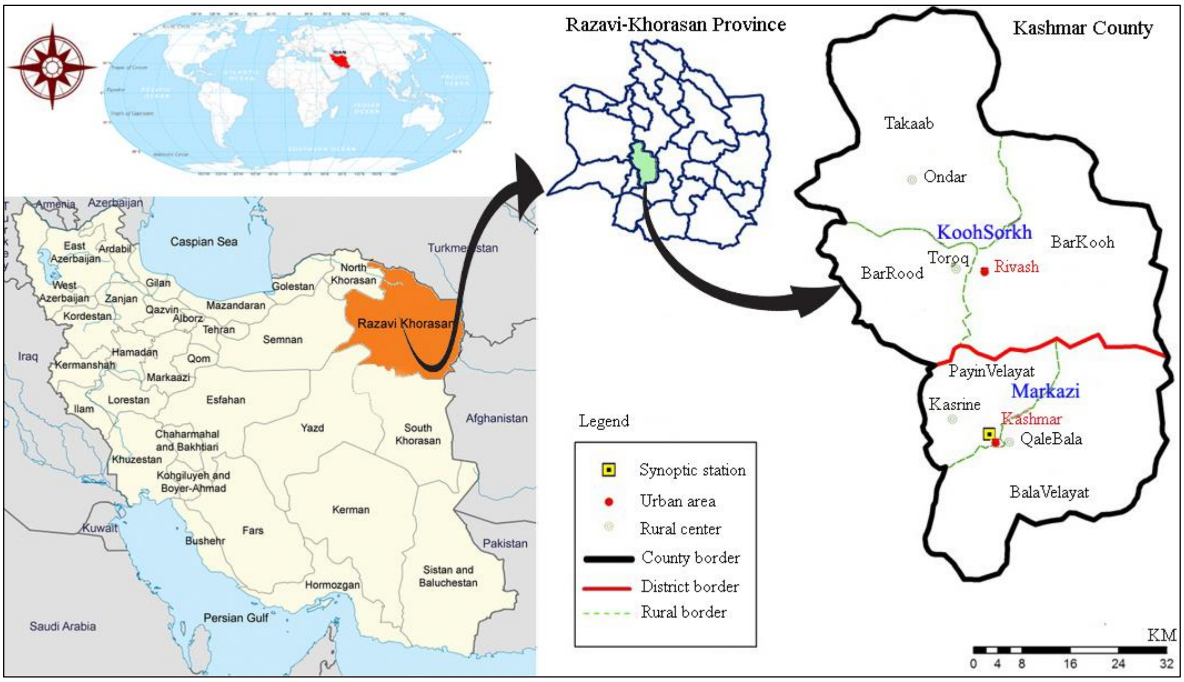

Figure 1. The geographical location of the study area: the left illustrates the international geographical map of IRAN, the mid-above demonstrates the Razavi-Khorasan and its states, and the right map represents the Kashmar county and synoptic station used in this study

Table 1. Water balance of Kashmar county based on reference year (2016-2017)

Parameter	Unit	Value	Details
Precipitation	mm	115.7	Based on the data in the Kashmar station
Rainfall volume		224.1	Based on the square area of the watershed
The volume of evapotranspiration		136.7	-
The Renewable water volume		87.4	caused by precipitation
The return flows to the aquifer		22	Assuming 15% return flows for all types of Consumption
The groundwater recharge by surface flow	MCM	6.1	-
Water Shortage by the reservoir		-36.2	An average of -39.6 in the statistical period
Transition and surface water inflow		6.5	From Rivash watershed
Transition and surface water outflow		0.4	To the Kavir-Namk basin
Groundwater recharge		0.0	-
Groundwater discharge		4.9	To the Bardaskan watershed

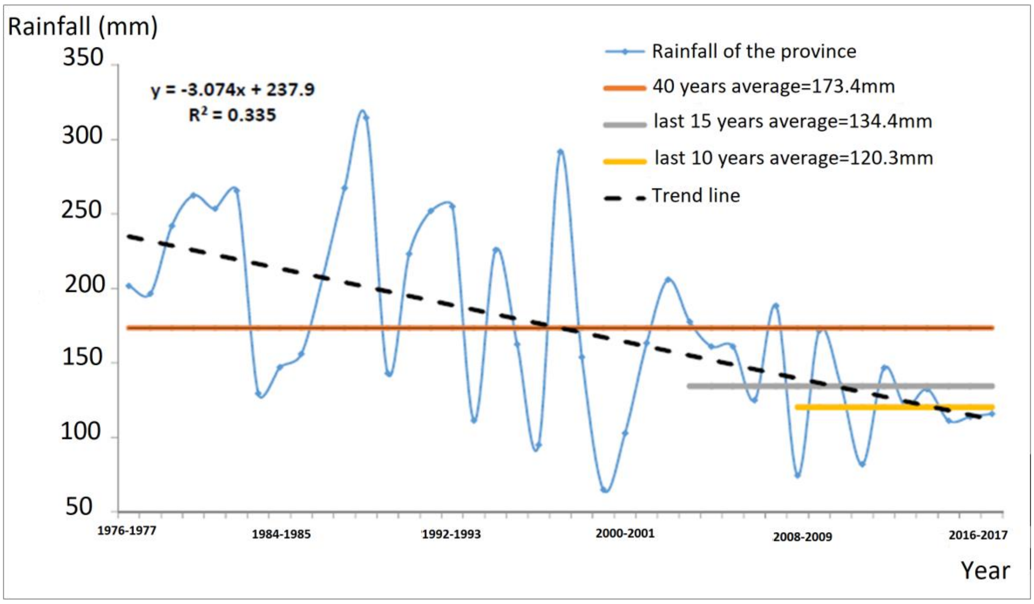

Figure 2. Rainfall characteristics of Razavi Khorasan province during the statistical period of 40 years

In the next step, Markov chain capabilities were used to analyze and predict the possible occurrence of drought in the region. For Markov chain analysis, it is assumed that the amount of precipitation in a given year depends only on the amount of the previous one. Therefore, a 3x3 matrix called the transition probability matrix is formed, and each of its elements is related to the state change from one state to another. Then, to calculate the long-term conditions in the studied station, the stationary probability value (stationary matrix) was calculated for each of the three states according to the matrix multiplication rules. It indicates what part of the time the station stays in a specific state on average in the long term.

2-3- Analysis method

2-3-1- Standardized Precipitation Index (SPI)

In this research, the standardized precipitation index was used to quantify drought. Using SPI, it is possible to determine the phenomenon of drought in a specific time scale and different regions. This index only uses monthly rainfall data and can be calculated in different time scales of 1, 3, 6, 9, 12, 18, 24, and 48 months. The calculation of this index, uses the gamma distribution to fit long-term rainfall data. The Gamma probability density function is defined in Eq. 1:

$$g(X) = x^{(\alpha-1)}\, e^{-x/\beta}\, \frac{1}{\gamma(\alpha)\beta^{\alpha}} \quad (1)$$

where X is the cumulative amount of monthly precipitation, $\gamma(\alpha)$ is the gamma function, and α and β are the shape and scale parameters, respectively, which are calculated by the maximum likelihood method and by Eqs. 2, 3 and, 4:

$$\hat{\alpha} = \frac{1}{4A}\left[1+\sqrt{1+\frac{4A}{3}}\right] \quad (2)$$

$$A = \ln \bar{X} - \frac{\sum \ln(x)}{n} \quad (3)$$

$$\beta = \frac{\bar{x}}{\alpha} \quad (4)$$

where X is the average cumulative rainfall for a month during the statistical period and *n* is the number of rainfall observations. For cumulative probabilities, the amount of standard precipitation index is obtained by Eq. 5 and 6:

$$G(X) = \frac{1}{\gamma(\alpha)}\int_0^x t^{\alpha-1} e^{-t}\, dt \quad (5)$$

$$t = \frac{x}{\beta} \quad (6)$$

Since the gamma function is not defined for *X=0* values and the precipitation distribution may have zero values, the total cumulative probability is obtained by Eq. 7:

$$H(x) = q + (1-q)G(x) \quad (7)$$

In this equation, q is the probability of zero rainfall. If m is the number of zero values in a time series of n, then q is obtained by Eq. 8:

$$q = \frac{m}{n} \tag{8}$$

After calculating the total cumulative probability *H(X)*, the value of the standard normal random variable *(Z)* is calculated using the same probability as the probability with a mean of zero and a variance of one. These values are the SPI index. Drought classification based on the SPI index is shown in Table 2 (Shah et al., 2015).

Table 2. Classification of the standardized precipitation index (SPI) for drought

Drought class	Index Value Range
Extreme wet	2 ≥
Severe wet	1.5 to 1.99
Moderately wet	1 to 1.49
normal	-0.99 to 0.99
Moderate drought	-1.49 to -1
Severe drought	-1.99 to -1.5
Extreme drought	-2≤

According to Table 1, to classify drought based on the SPI index, , whenever SPI values are continuously negative and reach -1 or less, it indicates the occurrence of drought, and its positive values indicate the end of drought (Asiayi, 2006).

2-3-2- Markov chain

Markov chain model is a mathematical technique for modeling random phenomena that shows a sequence of observations over time. The dependence of this chain on time is expressed either through series correlation coefficients or with the help of transition probability matrices (Thompson, 1999).

The first-order Markov chain model is the most basic form of the Markov chain model, which is widely used by users. The first-order Markov chain is a discrete time series in which the behavior of the series in the future time step depends only on the present time and is expressed as Eq. 9 (Wilks, 2011).

$$P_{ij} = P\left\{X_{t+1} = j \;\middle|\; X_t = i\right\} \tag{9}$$

Its transition probability matrix is shown in Eq. 10:

$$p = \left[p_{i.j}\right] = \begin{pmatrix} P_{1.1} & P_{1.2} \cdots & P_{1.S} \\ P_{2.1} & P_{2.2} \cdots & P_{2.S} \\ \vdots & \vdots & \vdots \\ P_{S.1} & P_{S.2} \cdots & \ddots P_{S.S} \end{pmatrix} \tag{10}$$

where P_{ij} is the probability of transition from the *i*-th state at time t to the *j*-th state at the time *t+1*. In this matrix, the sum of the elements for each row equals one. Table 3 shows the transition forms. These nine transfer forms are enumerated separately for each of the 6 SPI time series.

Table 3. The initial conditional transition matrix

	D	N	W
D	N_{dd}	N_{dn}	N_{dw}
N	N_{nd}	N_{nn}	N_{nw}
W	N_{wd}	N_{wn}	N_{ww}

In this matrix, the letter *D* (*X*<-0.99) indicates drought, the letter *W* (*X*>0.99) indicates wet period, and the letter *N* (-0.99 < *X* <0.99) means normal state. For example, N_{dd} means the total number of transitions from drought state to drought state. After counting the number of conditional transition states, the transition probability matrix is calculated by them. Table 4 shows the transition probability matrix for the nine mentioned states.

Table 4. Transition probability matrix

	D	N	W
D	$\hat{P}_{dd}$	$\hat{P}_{dn}$	$\hat{P}_{dw}$
N	$\hat{P}_{nd}$	$\hat{P}_{nn}$	$\hat{P}_{nw}$
W	$\hat{P}_{wd}$	$\hat{P}_{wn}$	$\hat{P}_{ww}$

The matrix must reach the stationary state to predict the climate condition in the future. To obtain this matrix, the transition probability matrix is multiplied by itself until all the rows are equal. This matrix shows the probability of transition from all states to a specific state. This matrix is called the stationary matrix.

Therefore, the probability of occurrence for the dry (wet or normal) periods in the series should be determined first to determine the number of expected dry, wet, or normal periods in the future. Drought occurs if the state is wet or normal and tends to dry. Therefore, the probability of transition to a dry period from a non-dry period can be obtained through the algebraic sum of the multiplication of the probability of transition from that particular state to a dry period in the stationary probability of the same state in the form of Eq. 11:

$$P_D = P^*_N \times P_{nd} + P^*_W \times P_{wd} \quad (11)$$

where P_D is the probability of a drought event (the transition probability from normal and wet to dry state), P_{*N} and P_{*W} are the stationary probability of normal and wet states, and P_{wd} and P_{nd} are the probability of transition from normal and wet states to dry, respectively. The number of times that drought occurs (transition from wet to dry or normal to dry states) is equal to the multiplication of the probability of transition at the threshold level (PD) during the time series under investigation, which is expressed in the form of Eq. 12:

$$E(N) = P_D(L) \quad (12)$$

where *E(N)* is the mathematical expectation of the occurrence for a state or the number of events expected from that state, and *L* is the continuity of a state. The prediction of the average duration of drought (wet or normal) is obtained by Eq. 13, where *E(L)* is the average duration of the desired state (Sadeghinia et al., 2013):

$$E(L) = (P^*_D)/(P_D) \quad (13)$$

Fig. 3 presents the flow chart of the research method.

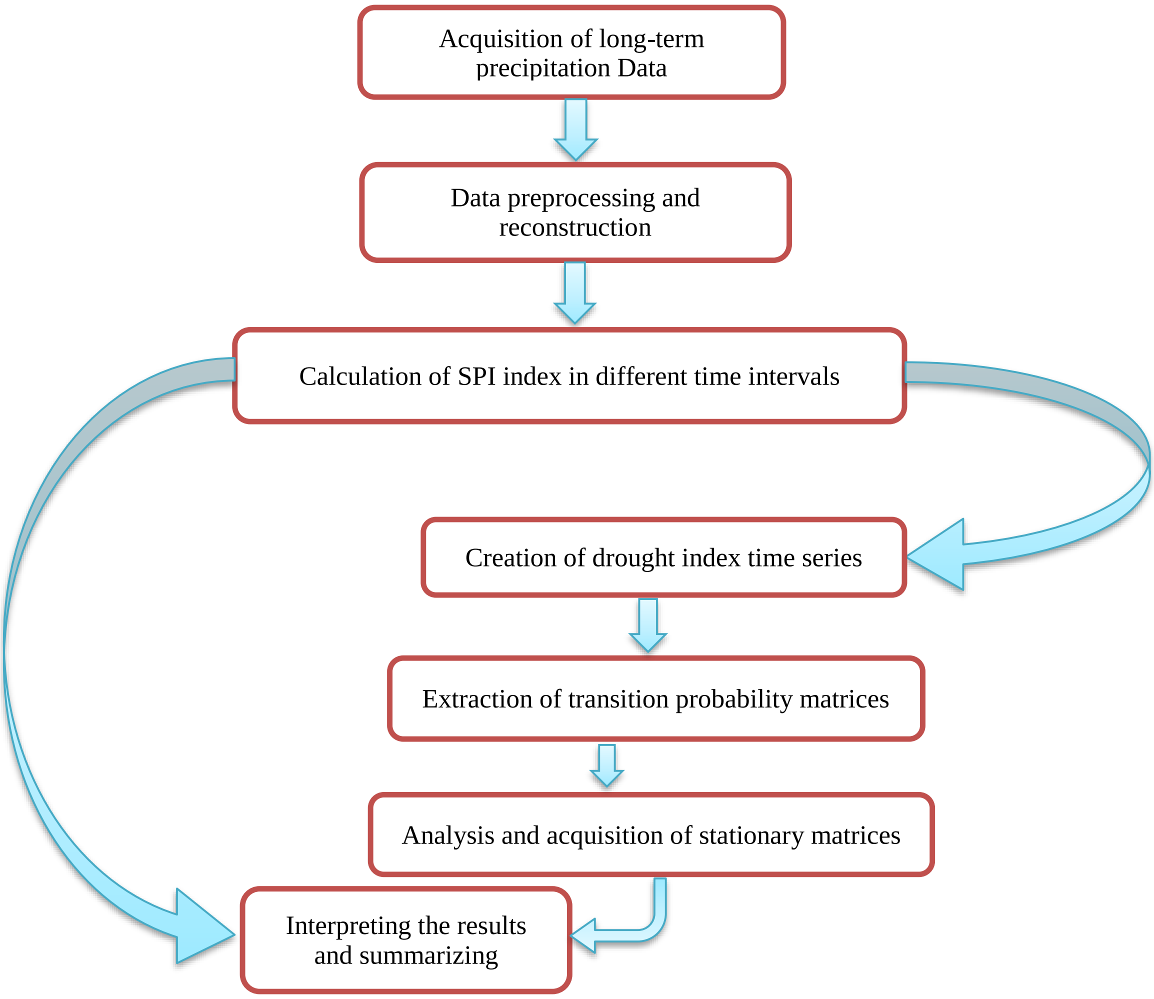

Figure 3: Flowchart of research implementation comprising initial datasets, computation, and outputs.

3- Results and Discussion

The SPI index of Kashmar county was calculated for the periods of 1, 3, 6, 9, 12, 18, 24, and 48 months using the rainfall information of the synoptic station, which had at least thirty years of data, as shown in Fig. 4, the changes of this index since 1987 As of 2017, it has been shown in different time intervals. As we get closer to the end of the time series of drought index values, drought periods and especially long-term droughts have increased, but the severity of droughts has decreased. These findings agree with the results of Delghandi et al. (2023) regarding the intensity and duration of droughts in Semnan and the results of Samadian et al. (2023) Regarding the drought period of the Zarinerood watershed. Also, according to Mahmoudi and Rigi (2023), the duration of drought decreases with increasing intensity of drought.

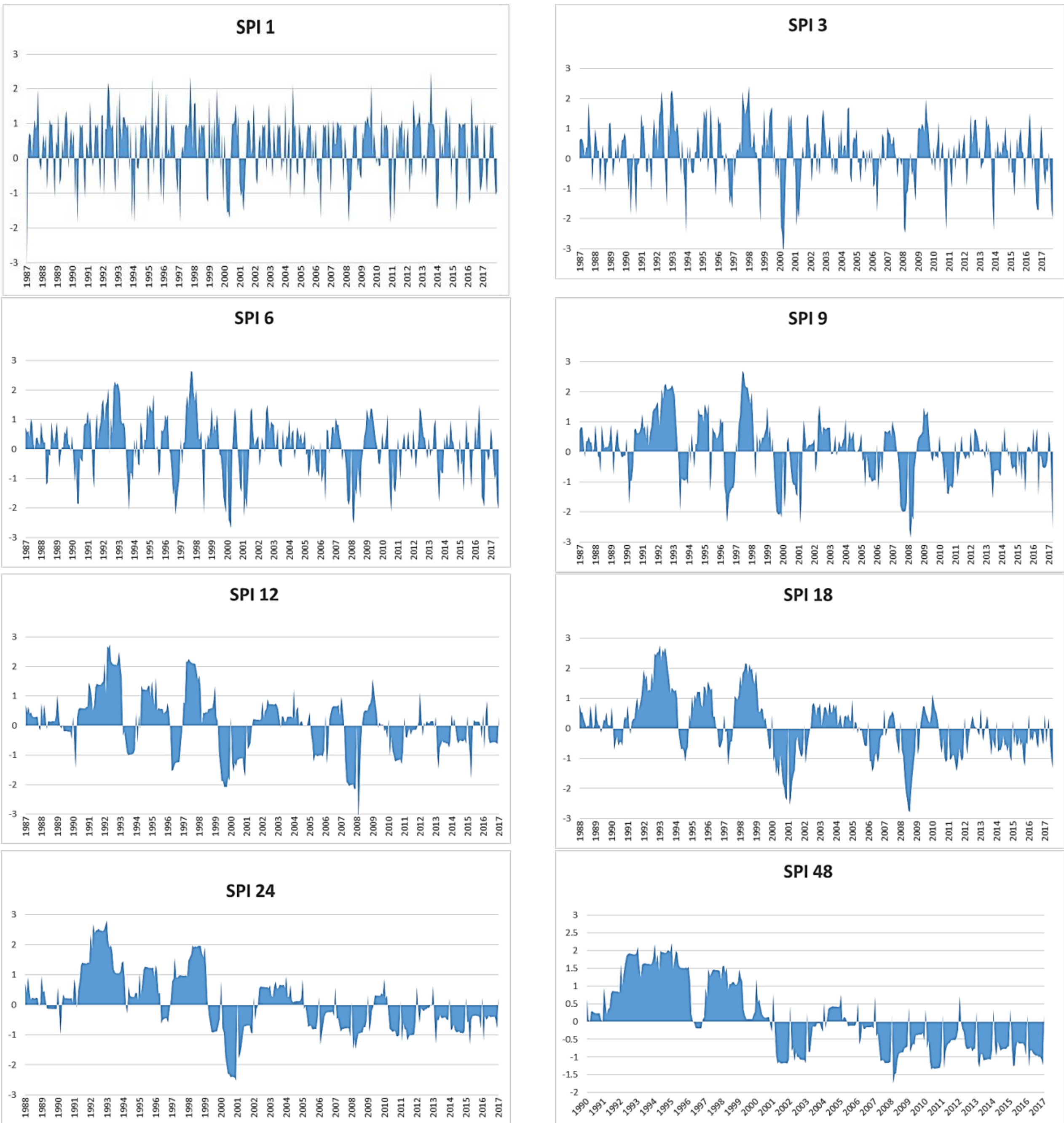

Figure 4. The SPI changes in Kashmar station during the study period (1990-2017) and different time intervals

The drought occurs when the standardized precipitation index has a negative sequence, and when its values are equal to -1 or less, it intensifies. When the standardized precipitation index becomes positive, the drought period ends. Therefore, the duration of drought is defined as the time of its beginning and end, and its intensity is determined for each month of the occurrence of drought (Hosseini et al., 2018). Therefore, according to Fig. 4, the most severe drought in Kashmar was in 2000 and 2009, with an SPI coefficient of less than -3, while the most severe drought occurred in 1993, with an SPI coefficient of 2.8. In addition, according to SPI values in long-term periods (12, 24, and 48 months), it is observed that the behavior of annual rainfall in the first half of the period is entirely different from its behavior in the second half. In the first half of the period, the frequency of positive SPI values, and therefore, wet periods lasts more, but in the second half of the period, the frequency of negative SPI values and dry periods lasts more.

Table 5 shows the transition probability matrix of the Markov chain for the annual rainfall values of Kashmar station, which was determined by examining and counting the corresponding states. The probability of transition from dry to dry state is Pdd, dry to normal Pdn, dry to wet Pdw, wet to wet Pww, wet to normal Pwn, wet to dry Pwd, normal to normal Pnn, normal to dry Pnd and normal to wet Pnw.

Next, to calculate the probabilities of the long-term conditions of the studied location, the stationary probability value (the stationary matrix) was calculated for each of the three states (table 6). This table shows that in the long term, each station, on average, how many percent of the time stays in a specific state. For example, based on the 12-month SPI in Kashmar station, in the long term, the probability of dry, wet, and normal conditions is 16%, 15%, and 69%, respectively. This table shows that the normal state's stationary probability is higher than the other states, which aligns with the results of Alizadeh and Ashgar-Toosi (2008) in Climatic forecasting of Razavi Khorasan province. By moving from the short-term SPI to the 48-month SPI, the values of the probability for normal stationary decrease, and the probability of stationary for the dry state increases, indicating that the probability of staying in drought increases in longer time scales.

Table 5. The transition probability matrix for the precipitation values of the Kashmar synoptic station

Transition states	P_{dd}	P_{dn}	P_{dw}	P_{ww}	P_{wn}	P_{wd}	P_{nn}	P_{nd}	P_{nw}
1-month SPI	0.118	0.794	0.088	0.172	0.810	0.017	0.738	0.100	0.161
3-month SPI	0.444	0.528	0.028	0.500	0.500	0.000	0.801	0.079	0.120
6-month SPI	0.519	0.481	0.000	0.527	0.472	0.000	0.799	0.100	0.100
9-month SPI	0.625	0.375	0.000	0.745	0.216	0.039	0.886	0.064	0.049
12-month SPI	0.759	0.241	0.000	0.811	0.189	0.000	0.904	0.056	0.040
18-month SPI	0.643	0.357	0.000	0.845	0.155	0.000	0.898	0.067	0.035
24-month SPI	0.645	0.355	0.000	0.896	0.103	0.000	0.934	0.042	0.023
48-month SPI	0.765	0.235	0.000	0.947	0.053	0.000	0.919	0.060	0.020

Table 6. The stationary matrix for the precipitation values of the Kashmar synoptic station

State (percent)	48-month SPI	24-month SPI	18-month SPI	12-month SPI	9-month SPI	6-month SPI	3-month SPI	1-month SPI	Average
Dry	16	9	13	16	14	15	10	9	13
Normal	61	74	71	69	72	70	72	75	70
wet	23	17	16	15	14	15	18	16	17

Fig. 5 shows the expected number of dry, wet, and normal events for Kashmar county. This diagram aligns with the findings of Siasar and Salari (2023) in Sistan and Baluchistan shows that the number of normal periods is greater than wet and dry periods. In longer time scales, the number of dry events is greater than the number of wet events.

4- Conclusion

In this research, the drought condition of Kashmar County was investigated by the SPI drought index, and then the drought was predicted using the Markov chain. By examining the severity of the drought in Kashmar, it was found that the most severe drought in Kashmar was in 2000 and 2009, with an SPI coefficient of less than -3, while the most severe wet period occurred in 1993, with an SPI coefficient of 2.8. Also, in long-term periods (12, 24, and 48 months), it is observed that in the first half of the period, the frequency of positive SPI values and, as a result, the wet years is more, and in the second half of the period, the frequency of negative SPI values and dry years is more. In this regard, Vafakhah and Bashari (2012), Ben-Gai et al. (1998), and Szinell et al. (1998) also came to a conclusion in climate studies of different regions that the intensity of short-term drought has increased in recent decades.

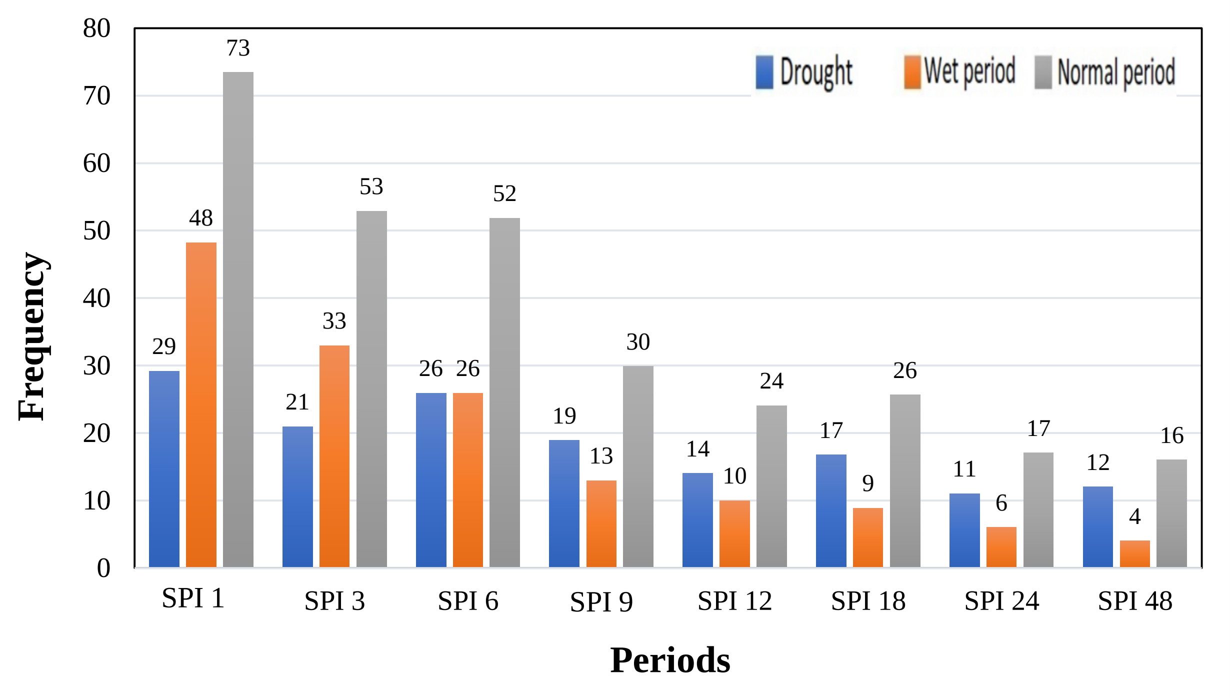

Figure 5. Number of expected events for drought, wet, and normal periods

Next, the stationary probability of the studied station was calculated for three states. The results showed that the probability of normal stationary state is higher than the other two states in all time scales, which means that most of the time, the region will be in normal conditions in terms of climate. While the probability of occurrence of dry and wet conditions is very close to each other, this result is similar to the results obtained by Alizadeh and Ashgar-Toosi (2008).

These results are consistent with the of Eshghi (2014) in the study of drought using the SPI index in the periods of 3, 6, 12, and 24 months, which concluded that the highest frequency of drought conditions in all stations is related to the normal state and the lowest one to the severe drought state. Also, it is consistent with the results of Khalighi Sigaroudi et al. (2009) in evaluating drought in Mazandaran province using SPI, PNPI, and Nietzsche indices. They concluded that the years with a normal state in terms of precipitation have more frequency and continuity than the dry and wet years. The SPI, due to having more capabilities, including more accurate separation of drought and wet periods, is more precise and has more sensitivity to rainfall changes, therefore it is the best model to determine the statistical characteristics of rainfall (intensity and frequency) and to distinguish droughts in Mazandaran province. It is also consistent with the results of Ojaklou-Shahabi (2014) in the investigation of meteorological drought indicators (percentage of normal, deciles, standardized precipitation and Chinese z) in the synoptic stations of West Azerbaijan province, who concluded that the highest rate of frequency is related to the normal state. Also, the lowest frequency percentage is related to very severe drought. The number of expected events for Kashmar county shows that the number of normal periods is higher and in the more extended SPI periods, the number of droughts is higher than wet events.

Due to the intensification of climate change, drought has affected more people in the last 40 years than any other natural disaster. Prediction of hydrological variables is a very efficient tool for managing water resources. On the other hand, using concepts governing time series in forecasting has been evaluated as very appropriate(Bashari and Vafakhah, 2011). Considering that Kashmar lacks water resources, it is necessary to study and predict such expected climatic phenomena as droughts and floods in proper planning and prevent damage. With the aim of better monitoring of the drought in the region, it is suggested that such research should be carried out on a broader level, with more statistical data, and by using spatial and temporal analysis so that it is possible to optimize management and change the perspective from crisis management to risk management and reduce the consequences of drought. Dealing with any destructive natural phenomenon with the aim of preventing or reducing its damages and losses depends on identifying the destructive nature of that phenomenon in the conditions before the occurrence, during, and after it, on the water resources. For this purpose and according to the results of this research, short-term solutions include forming a crisis office, preventing unauthorized water harvesting and pumping, and increasing irrigation efficiency as well as long-term strategies to deal with drought, including Selection of drought-resistant crops, use of treated sewage effluent for agricultural purposes, and study and implementation of flood spreading and artificial recharge are suggested.

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Authors contribution statement

M.B. conceived of the presented idea and developed the theory. G.E. performed the computations. M.B. verified the analytical methods. Also, M.B. and G.E. investigated this work's combined method of SPI and Markov chain. All authors discussed the results and contributed to the final manuscript.

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