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Spatial and Temporal Displacements in Wet and Dry Periods in the Southeast of the Caspian Sea: Golestan Province in Iran

Yelghei, A.[1], Ghanghermeh, A.[2*] and Roshan, Gh.[3]

1. M.Sc. Graduated, Department of Geography, Golestan University, Gorgan, Iran
2. Assistant Professor, Department of Geography, Golestan University, Gorgan, Iran
3. Associate Professor, Department of Geography, Golestan University, Gorgan, Iran

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Abstract

The global warming phenomenon has had a great impact not only on the temperature patterns of the regions, but also on the spatial-temporal patterns of the occurrence of wet and dry days. As some areas have increased (decreased) the number of dry days, the result of these changes requires new approaches to water management in these areas. Golestan province in northern Iran is one of the provinces in south of Caspian Sea, where evidence suggests a decrease in precipitation days as well as the temporal displacement of precipitation days from the cold period to the warm period of the year. Therefore, the present study investigates the probability of occurrence of wet and dry days based on the one-time Markov chain method, as a change of decade. Thus, in this research, precipitation data from 197 precipitation stations for a period of 40 years from 1971 to 2010 was used. In this study, based on the most internal consistency of different regions in terms of the occurrence of wet and dry days, eight different spatial zones were identified. The results of this study indicate that the continuity of the wetter periods in the eight-cluster zones of Golestan province indication that the length of the wetter period has decreased in most months. The highest decrease in July was on average 0.20 days per decade. However, in August, September, and October, it reached its lowest level. In August and September, clustered zones in the eastern regions of the province show an increase in the longer period. This indicates that during the last decades throughout the second half of the summer, rainfall has increased in the province.

Keywords: Climatic variability, Multidecadal variation, precipitation pattern, Markov chain, Golestan province.

1. Introduction

In recent years, due to the global warming phenomenon and regional and local changes in climate, in addition to rising average temperatures, several components of climate, including rainfall properties have gone under considerable changes (Alexander and Arblaster, 2009). In many areas, the annual rainfall may have not been much affected, but its consequences are the observed increase in evaporation due to warming and lack of access to water resources or temporal displacements (from one month to another). Most of the time, extreme climate phenomena such as the occurrence of wet and dry days cannot be determined. From the statistical point of view, they are considered as part of random processes. However, the prediction of the occurrence of such atmospheric phenomena is not easy and possible (Orosa et al., 2014). It needs to be explained that access to correct data and past periods of atmospheric factors is an effective factor in the prediction of these atmospheric events. For this purpose, the prediction of dry (wet) periods based on the identification of historical temperature data of a station can provide an example for understanding climate change. Overall, it is possible to predict climatic phenomena based on both statistical and dynamic methods. The other set of predictive models is statistical models that do not explicitly focus on the physics of the underlying phenomenon and only emphasize the relationship between inputs and outputs. These batch models excel in the ease of use of previous models. Although the general impression is that the results of dynamic models are superior to statistical models, this proposition is not always correct, and it depends on the recognition of the governing physical laws, the model's perception and the resolution of the model.

*Corresponding author: a.ghangherme@gu.ac.ir

For this reason, the use of second-generation models is inevitable in some cases. In general, because of the complexity, timeliness, economical considerations and sometimes their need for supercomputers to implement dynamic models, researchers have welcomed the use of statistical methods due to the ease and requiring less time and costs (Wilby and Dawson, 2007; Kallache et al., 2011; Yang et al., 2012; Roshan et al., 2013a; Roshan et al., 2013b; Sillmann et al., 2013; Farajzadeh et al., 2014). According to probability rules, some random phenomena have a greater chance of occurring, while the odds of occurring are somewhat lower. In addition, sometimes only one of the modes can occur in the *n* mode, while none of the modes can take precedence over other modes (Mandal et al., 2015; Sonnadara and Jayewardene, 2015; Cindrić et al., 2010). A proper model is required to calculate the chance of occurrence of the events. Examining these uncertain states is probability knowledge. Time-series methods, especially the Markov chain, are among the probabilistic prediction methods (Privault, 2013). The Markov chain, with a simple mathematical method (such as multiplication of arrays), makes solving the probabilities associated with dependent processes very easy. The Markov chain model (MCM) has two advantages over other methods: first, predictions are immediately available after observation; second, they require minimal computing procedure after processing the meteorological data (Cindrić et al., 2010; Mandal et al. 2015; Sonnadara and Jayewardene 2015).

MCM is one of the most suitable and practical models of statistical forecasting in atmospheric sciences, which has attracted the attention of researchers in recent years. Various studies have been performed on the use of McMinn determining the probability of rainfall and droughts both around the world and in Iran. Among them, the results of the research by Hejazizadeh and Shirkhani (2005) have predicted the droughts and short-term dry periods of Khorasan province. They concluded that most of the monthly differences and differences among stations could be identified in the study of the return periods of long-term dry periods, because the occurrence of short-term periods in almost all parts of the province shows similar trends. Daryabari (2006), using a matrix model for the probability of experimental transfer, predicted drought in 26 meteorological stations in Iran and stated that by using the base year's rainfall, it was possible to predict up to 5 years. Asakereh (2008) examined the persistence and continuity of rainy days in Tabriz city using MCM and then estimated persistent probability and daily return period of each of the two rainfall-drought states. Asakereh et al. (2010) studied the probability of occurrence of dry days in Golestan province using the MCM in 51 weather stations within a 20-year statistical period and concluded that spatial variations of the probability of occurrence of dry day in the province were not significant. Moreover, with the increase of precipitation thresholds for the dry day, the probability of occurrence of dry day increased and its spatial differences decreased. Eyvazi et al. (2012) examined the drought in Golestan province using seven stations in 30 years in a probabilistic framework, which included the evaluation of the statistical behavior of the SPI drought index using the first-order, three-mode Markov model, for wet, normal and drought years. Their results indicated that the persistent probability, the average continuous-time and the frequency of drought were different in different regions of the province. Khadr (2015) predicted the meteorological drought of the Neil Blue watershed in Ethiopia using the MCM, and the result of the model performance showed that predicted and observational data had similar characteristics in terms of time series in different states. Moreover, the relative performance of the prediction model showed that in the developed state, it was able to detect events and non-events. Khorshiddoost and Fakhari (2016) worked on the probability of continuity and persistence of rainy days in southwestern Iran using the MCM and showed that the lowest probability of precipitation was in the flat areas and the highest probability was in Mountainous areas. He postulated that the most probable occurrence of rainy days was in the spring. Javan (2016) studied the persistence of rainy days in the Urmia Lake basin using the Markov chain for seven stations in 20 years and concluded that the average daily precipitation duration in the studied basin was about 2 days. Tan et al. (2014) studied the multidecadal variability of daily monsoon rainfall of the northeastern Malaysian Peninsula using the hidden Markov model and concluded that the Markov model was able to identify the behavior of the large-scale rainfall phenomena. Yoo et al. (2016) examined the effect of climate change on daily rainfall, especially on the average number of wet days and average rainfall intensity, and concluded that increasing or decreasing the number of rainfall days to justify changes in the amount of monthly precipitation alone was not justifiable. However, it was justifiable by changes in precipitation severity. At Seoul's sampling station, it was determined that rainy days account for 30% and rainfall intensity accounted for 70% of the total variation. In recent years, in Golestan province, given the bulk of studies conducted, it is shown that the changes in the intensity of precipitation were not significant relative to temperature or evaporation increases. On the other hand, there is evidences that rainy days are decreasing and the temporal displacement of rainy days from the cold period to the warm period of the year is raised (Ghanghermeh et al., 2016). Mostafazadeh et al. (2016) studied monthly wet and dry spell using power laws in Golestan province and their results show that the number of low rainfall periods is higher than the high rainfall in all stations studied. In addition, in periods of three consecutive months and longer, the number of low rainfall periods at stations northwest and north of the province is higher than the rainy season. Mostafazdeh et al. (2017) analyzed spatial and temporal variations of monthly precipitation in Golestan province using fractal dimensions. They concluded that the number of consecutive dry-wet months has decreased over a longer time scale (months). The analysis of fractal dimension showed that the dry periods have a lower frequency. Besides, the intensity of wet durations is higher in central and eastern parts of the study area, while the western part of the Golestan province had experienced more persistent wet periods.

Therefore, the purpose of this study is to evaluate the spatial-temporal variations of Markov rainfall characteristics in Golestan province for 40 years with a decade scale. It has to be explained that despite various climatic studies that have used the Markov chain model throughout Iran, the perspective of studying the decade-long variations of the one-time Markov chain probability is done for first time in Iran.

2. Data and methods

Golestan province, due to its location in the southeast of the Caspian Sea, neighboring the Karakum desert (in Turkmenistan), as well as the west-east extension of the Alborz Mountains in the southern part of the province has a diverse climate. According to these conditions, the annual rainfall in Golestan province varies between 150 and 750 mm. In this study, the data of 197 stations were used to accomplish the research objectives, of which 110 stations data were extracted from the Meteorological Organization and 89 ones from the Ministry of Energy (Figure 1). The length of the study period included the daily rainfall data for a period of 40 years, which was selected from 1971 to 2010.

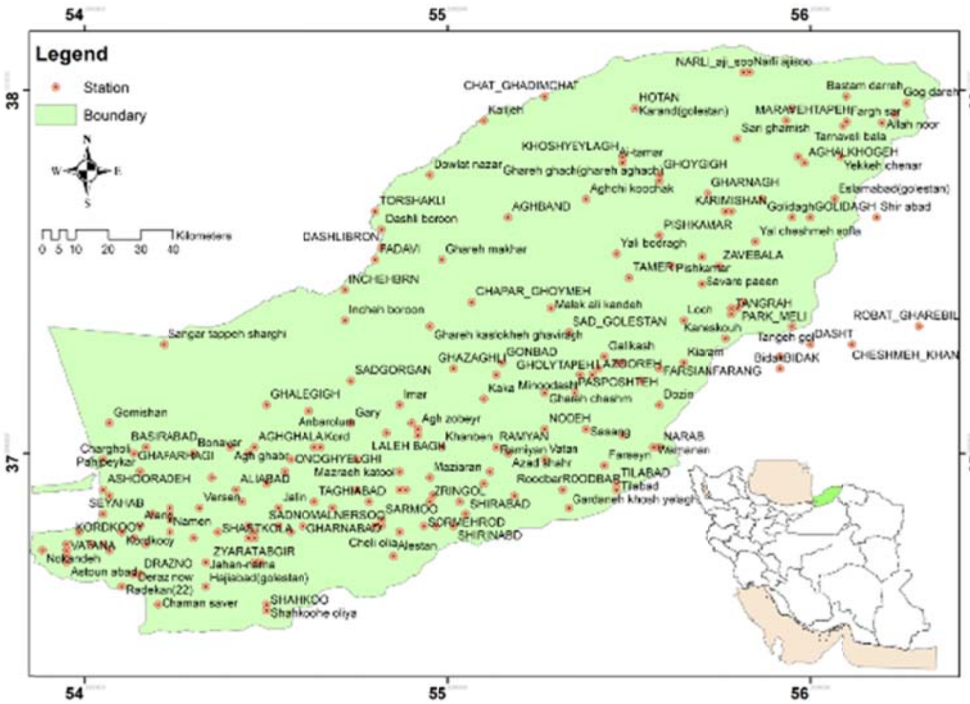


Figure 1. Distribution map of Golestan province rain gauge stations.

In this research, random analysis of Markov chain was run to investigate rainfall variability in Golestan province in temporal and spatial terms. Therefore, for this study and use of first-order Markov chain, four conditions were taken into account. However, it must be explained that the characteristics of the rainy days were first described tentatively, and then Markov components were calculated. The first step in this task is to determine the probability value from one to all possible modes. The probability matrix of the Markov chain can be written for the first order: in this matrix, dry day is shown with (0) and the wet day with (1). The symbol P11 means the probability of a wet day after another wet day and the P00 indicates the probability of a dry day after a dry day. In order to use the above matrix in the subsequent calculations, p and q were replacing as follows (Hejazizadeh and Shirkhani, 2005):

$$P = \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} p = p_{01} \quad , q = q_{10} \qquad (1)$$

By identifying the matrix elements, the probability of transferring some of the important characteristics of the observation series, such as climatic probability, wetness and dryness, the expected wet and dry periods in each month, and the simple probabilities of dryness and wetness were obtained. Then the Markov features in four decades of 1970s, 1980s, 1990s, and 2000s were estimated in Golestan province. In order to analyze these probabilities and to compare the time and place of it, according to the calculations carried out with regard to the most internal consistency, the zoning was done. To do this, in ArcGIS software, Multivariate function and ISO Cluster Unsupervised Classification sub-function were used.

It should be noted that in this research, two different temporal perspectives have been used to study wet and dry periods. In the first method, for the whole 40-year period, the components of the Markov chain were studied. In the second method, to determine the changes in wet and dry periods, the statistical data were divided into four periods of ten years, and then Markov changes were studied for dry to wet (the constant probability of the occurrence of wet day) and wet to dry (the probability of the occurrence of dry day) conditions (Hejazizadeh and Shirkhani, 2005; Daryabari, 2006; Asakereh, 2008). The Flowchart of the method is shown in Figure 2.

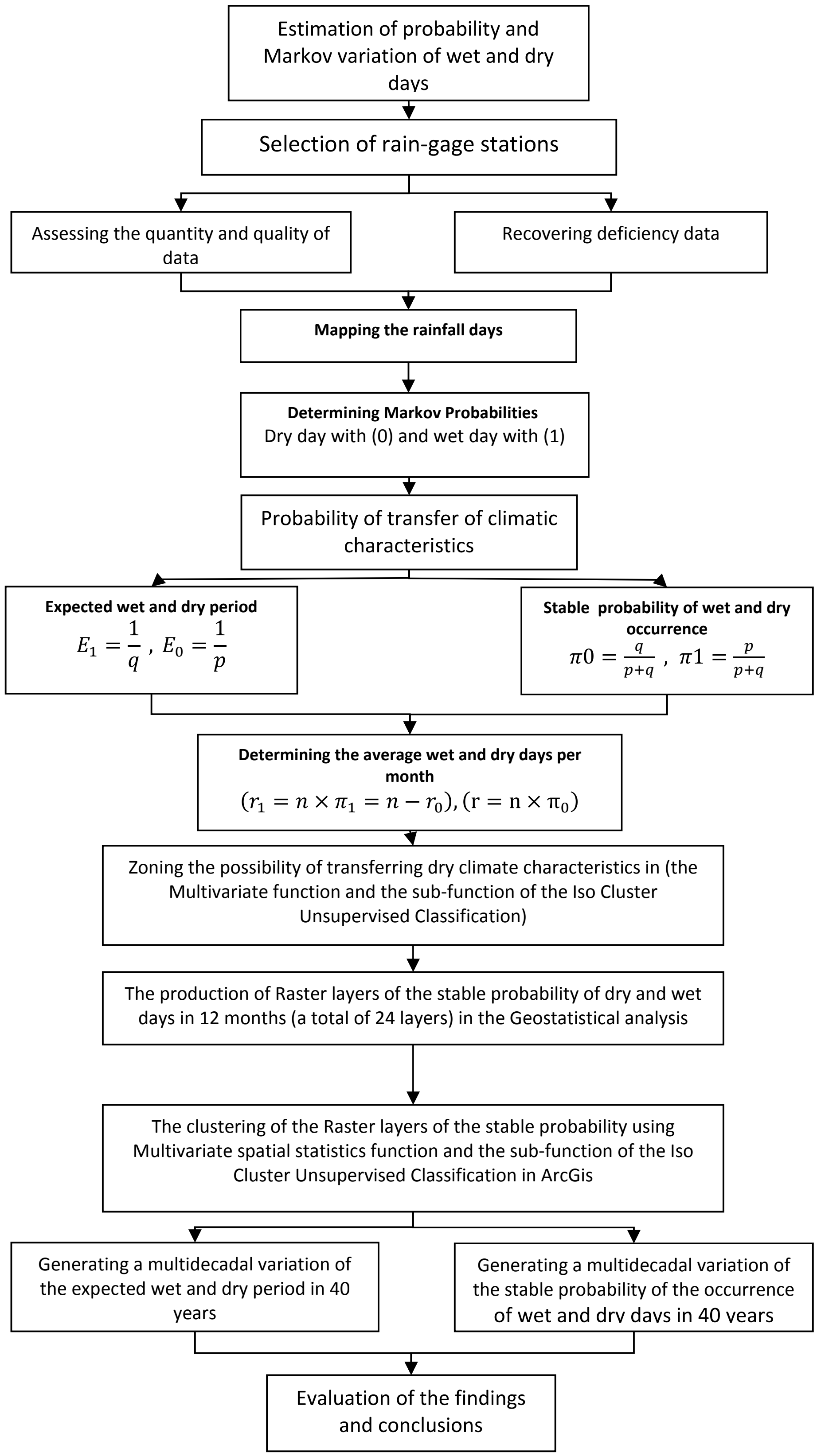


Figure 2. Flowchart of research methodology.

3. Results

3-1. Frequency of occurrence of precipitation days and its 40-year variability percentage

In this part of the research, the average frequency of the occurrence of rainfall days for each month in the province is shown and, on the other hand, its variability is monitored based on the CV index. However, the average daily rainfall in Golestan province, as shown in Fig. 3, indicates that most of the precipitation days occur in the highlands, and the lowest in the northern areas of the province adjacent to the Turkmen desert. The investigation of rainy days in monthly time scale shows that, the average precipitation days are more than 6 to 9 days and even more than 9 from December to April, while in other months, the trend of precipitation days is reduced. Interestingly, no month of the years had the non-rainy days. The study of the 40-year variability of precipitation days shows that from December to April, the average precipitation days in the province are more than 30 to 50 percent, while in the other months it is between 50 percent and 70 percent in most areas of the province.

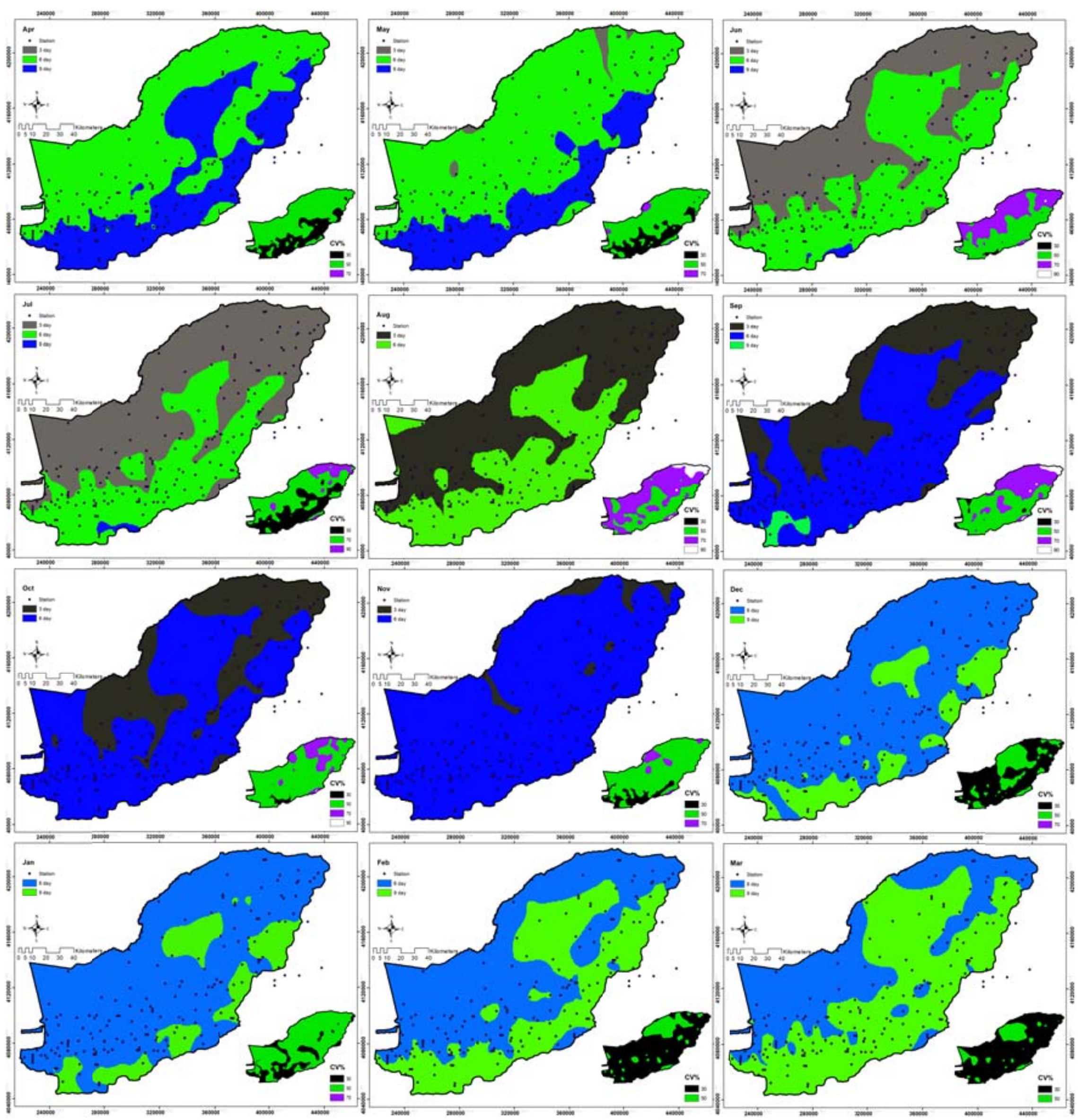
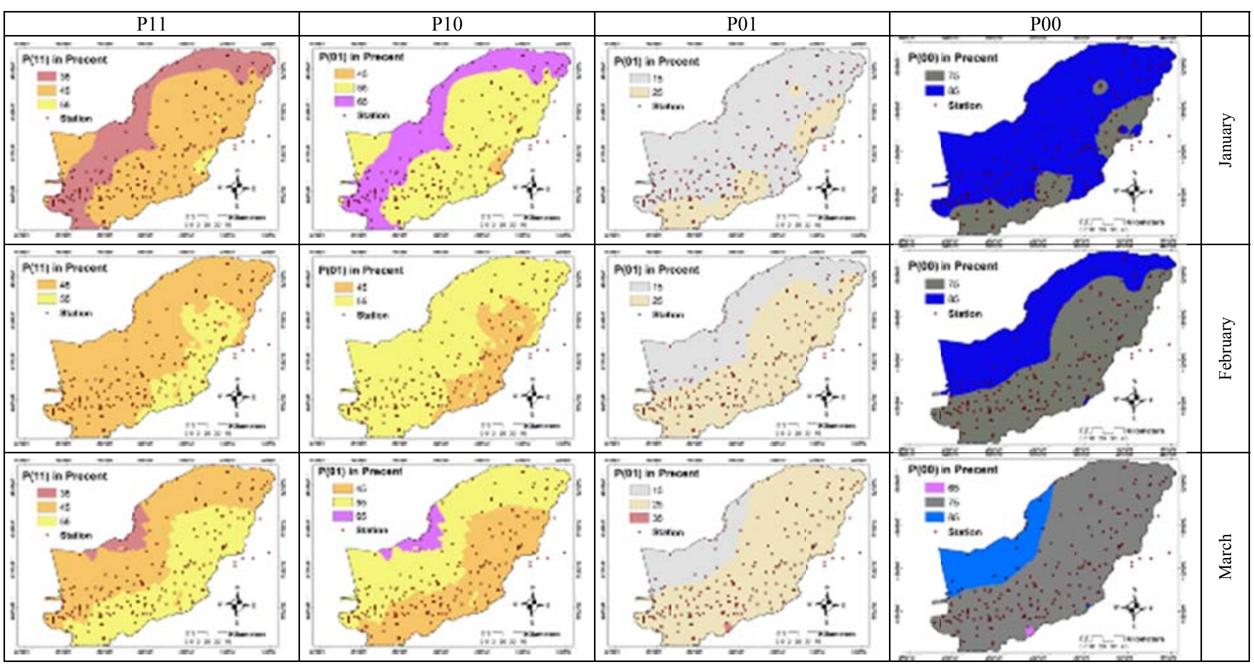
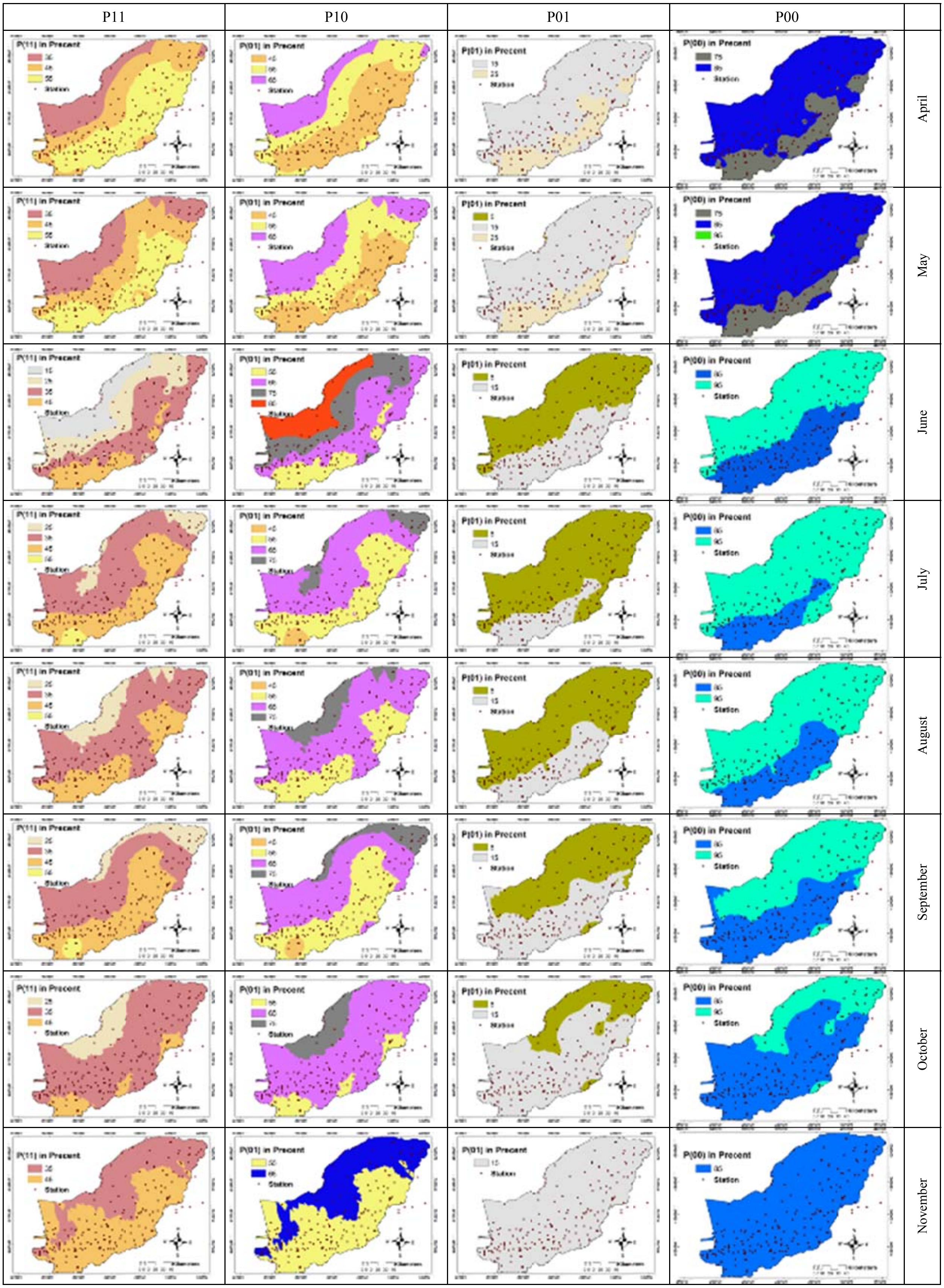


Figure 3. Maps of rainy days and coefficient of variability of rainy days.

3-2. The results of Markov chain conditional probability states

The conditional probability of a first-order Markov chain for P00 and P01 modes is assessed based on 100 1-p and p modes and for P10 and P11 based on 100 q and 1-q modes. Accordingly, each P00 and P01 are expected to be 100% and P10 and P11 to be 100% as well. As shown in Fig. 4, different conditions of the Markov conditional probabilities are illustrated on a monthly basis. In this interpretation, only two P00 and P11 states are considered, although the other two modes are inverse of their previous states. It should be noted that the zoning map of the events of each of the four scenarios has been generated for different months of the year, so that every zone shows that in what percent of the months, one of the four modes has been experienced. At P00 condition in different months, the area of different regions of Golestan province varies according to the probability of occurrence, as can be seen from Fig. 4, in January, April and May the 85% probability of occurrence is 16321.2, 15301.1 and 16525.2 km^2 with the highest area, respectively. Whereas February, March, and December accounted for 75% of the probability of occurrence, with the largest area of the province being 12444.9, 16525.2 and 10608.8 km^2, respectively. Whereas, in June, July, August, and September, the 95% probability of occurrence, with 12648.9, 16321.2, 14485.1 and 11220.8 km^2 covers the largest area of the province. In condition P11, January, February, March, May, November and December accounted for 45% of the probability of occurrence in the Golestan province with the highest area of 12929.1, 16199.3, 10689.0, 7295.4, 11581.1 and 16259.5 km^2, respectively. Whereas in June, July, August, September and October, 35% of the probability of occurrence was 7383.9, 10447.1, 11920.8, 9380.8 and 15504.4 km^2 respectively. In total, the results of the above study indicate that the conditional probability of the P00 state, dry to dry, is likely to occur spatially with the highest incidence in the northern regions and has decreased to the mountainous areas, and in temporal terms, during the warm season, it has the highest frequency and the frequency of its occurrence in the cold season decreases. This conditional probability also shows that the phenomenon of drought intensifies when precipitation decreases. While P11 mode, i.e. wet-to-wet mode, is the exact opposite of the previous state. Because both in spatial terms, in the southern regions and in mountainous areas, and in temporal terms in the cold periods of the year, the probability of its occurrence increases due to the arrival of the precipitation systems.




P11
P10
P01
P00
April
May
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October
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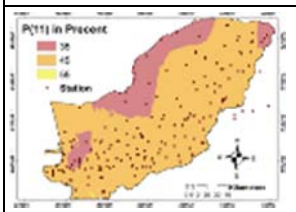
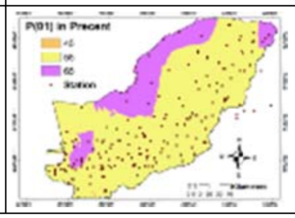
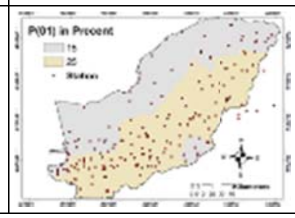
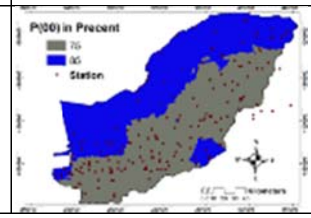
P11	P10	P01	P00	
				December

Figure 4. Markov quadratic conditional probability maps for different months of the year..

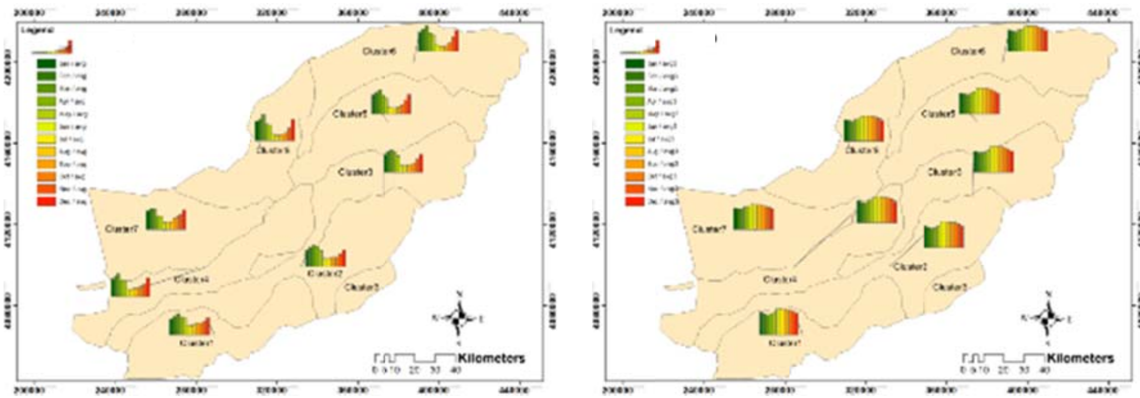
3-3. Climatic probability

In this study, climatic probabilities are defined to determine the stable probability of the occurrence of wet day and the stable probability of the occurrence of dry day. In order to analyze this probability and compare its spatial and temporal terms with respect to the calculations performed, first, spatial zoning with the highest internal consistency was determined, then spatial and temporal comparisons of Markov components in the province based on it were evaluated. Based on the zoning, eight zones in Golestan province were identified in terms of precipitation characteristics, which are some of the major geographical features of each zone: The highest number of days with 139 days in eighth cluster, 1730 m high and lowest the number of rainy days, with 82 days a year, is in the lowest zone, the seventh cluster. However, the highest annual precipitation is in the second cluster zone and the lowest in the eighth cluster (Fig. 5).

Accordingly, the map of constant probability of wet days is shown in Figure 6. As can be seen, the highest probability is seen in April, May, December, January, February and March. On the other hand, the probability of occurrence is very low during the warm period. The constant probability of the occurrence of wet days is determined at the province level according to Fig. 6. Geographically, the lowest probability is seen in cluster 8 and the highest in clusters 1 and 2. However, according to this diagram, the probability values for each month are different in different clusters, as in April, the highest frequency is observed in cluster 2 and the lowest in cluster 7, while in May, the highest is in cluster 1 and the lowest is in cluster 7.

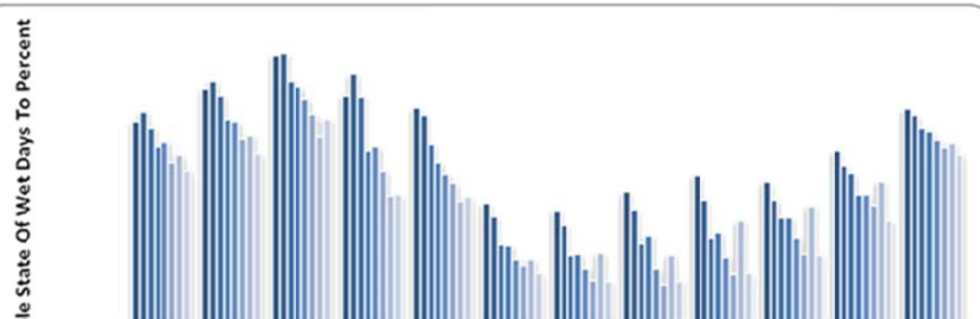
Table 1. Major geographic features of clustered zones in Golestan province.

Zoning	Elevation (m)	Rain (mm)	CV%-Rain	Number of rainy days	CV%- day
Cluster 1	1730.06	674.23	35.97	139.11	5.13
Cluster 2	714.05	708.53	40.33	120.17	4.78
Cluster 3	722.82	576.96	37.02	115.27	5.19
Cluster 4	45.88	500.45	30.24	99.91	4.38
Cluster 5	434.74	445.88	29.79	106.06	5.41
Cluster 6	296.63	339.09	24.81	85.91	4.72
Cluster 7	2.03	412.99	28.30	82.06	3.92
Cluster 8	40.90	297.70	21.04	91.17	4.65



(a) (b)

Figure 5. a) The stable probability of the occurrence of wet days in a 40-year period. b) The stable probability of the occurrence of dry days in a 40-year period.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	27.6	32.0	36.5	31.0	29.4	16.4	15.4	18.0	20.2	19.3	23.5	29.3
Cluster2	28.9	33.0	36.7	34.0	28.4	14.6	13.5	15.5	16.9	16.9	21.5	28.4
Cluster3	26.6	31.1	33.0	30.9	24.5	10.9	9.3	11.0	11.6	14.5	20.5	26.7
Cluster4	24.1	27.9	32.3	23.6	21.9	10.7	9.5	12.0	12.4	14.5	17.5	26.3
Cluster5	24.7	27.5	30.6	24.2	20.3	8.8	7.6	7.6	9.1	11.7	17.5	25.1
Cluster6	21.9	25.2	28.6	20.8	19.2	8.0	6.0	5.4	6.8	9.5	16.0	24.0
Cluster7	23.0	25.7	25.5	17.3	16.7	8.7	9.6	9.4	14.0	16.0	19.4	24.5
Cluster8	20.9	23.1	27.8	17.5	17.2	7.0	5.9	5.9	6.9	9.3	14.0	23.0

Figure 6. Climatic probabilities of stable probability of the occurrence of wet days in Golestan province.

As shown in Fig. 5b, the stable probability map of the dry day occurrence shows that the highest frequency is in the warm months of the year, while it is less likely to occur in cold weather. According to Fig. 7, the table diagram of the stable probability of the occurrence of the dry day shows that in cluster 1 and 2, there is the lowest probability of occurrence and in clusters 6 and 8, there are the highest probability of occurrence of dry day. Like the stable wet mode, in the stable dry state, however, according to this chart, probability values vary in different clusters per month. As an example, in April, the lowest frequency is observed in cluster 2 and the highest is in cluster 7, while in May, the lowest is in cluster 1 and the highest is in cluster 7.

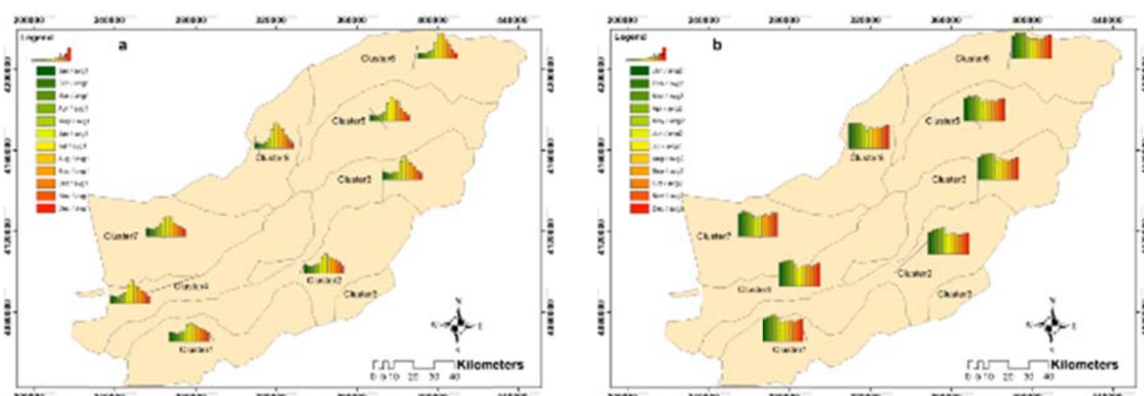
3-4. Monthly dry and wet periods

The dry and wet periods of each month, or the expected dry and wet periods, include the number of dry or wet days, or the duration of the period. According to Fig. 8a, the diagram map shows that the longest dry periods occur in summer months, and during cold and precipitation periods of the year, the length of dry periods is very short. According to Fig. 9, the diagram shows that the highest continuity in the occurrence of dry days is in clusters 6 and 8. In these clusters, especially in July and August, the length of the dry period lasts more than 20 days per month, and the slightest continuation in the occurrence of dry days is observed in mountainous clusters 1 and 2. In the warm times of the year, namely July and August, the average continuity is less than 11.5 days. In conclusion, as we move towards the cluster areas in the northeast of the province, the length of dry period increases, and as we move towards the southern and western mountainous regions, the length of dry period reduces for all months.

Also, Fig. 8b chart map shows the longest periods occur during the colder months of the year. According to this figure, in almost all cluster zones in April, May, February and March, the wet period is longer than other months. Fig. 10 also shows that the highest duration of occurrence of more days occurs in clusters 1 and 2, with an average rainfall of more than two days estimated in April, May, February and March.

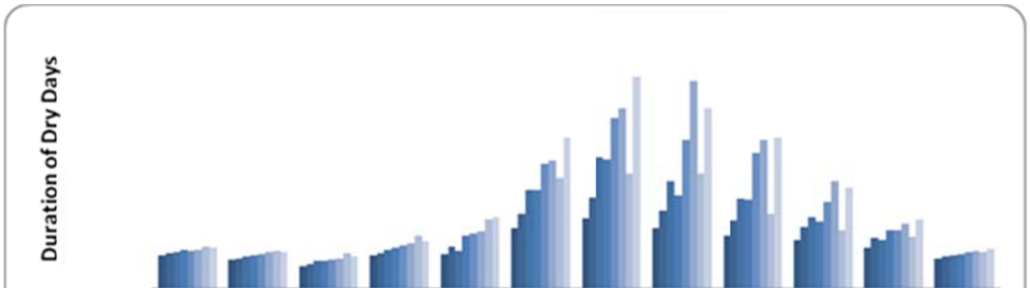
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	72.4	68.0	63.5	69.0	70.6	83.6	84.6	82.0	79.8	80.7	76.5	70.7
Cluster2	71.1	67.0	63.3	66.0	71.6	85.4	86.5	84.5	83.1	83.1	78.5	71.6
Cluster3	73.4	68.9	67.0	69.1	75.5	89.1	90.7	89.0	88.4	85.5	79.5	73.3
Cluster4	75.9	72.1	67.7	76.4	78.1	89.3	90.5	88.0	87.6	85.5	82.5	73.7
Cluster5	75.3	72.5	69.4	75.8	79.7	91.2	92.4	92.4	90.9	88.3	82.5	74.9
Cluster6	78.1	74.8	71.4	79.2	80.8	92.0	94.0	94.6	93.2	90.5	84.0	76.0
Cluster7	77.0	74.3	74.5	82.7	83.3	91.3	90.4	90.6	86.0	84.0	80.6	75.5
Cluster8	79.1	76.9	72.2	82.5	82.8	93.0	94.1	94.1	93.1	90.7	86.0	77.0

Figure 7. Climatic probability of the stable probability of the occurrence of dry day in Golestan province.



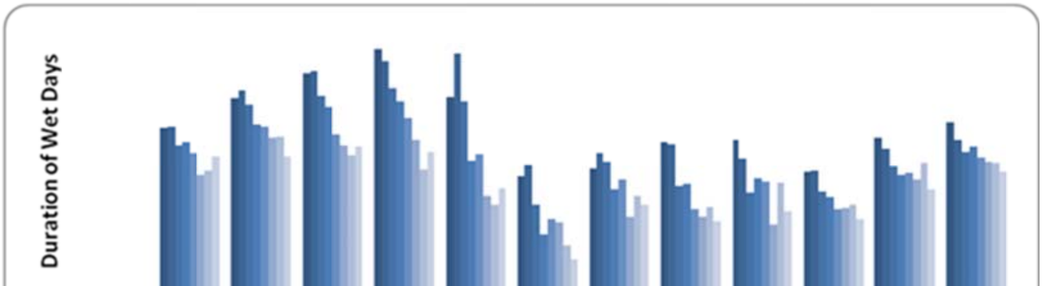
(a) (b)

Figure 8. a) The length of dry period in each month or the expected length of dry period in 12 months; b) The length of wet period in each month or the expected length of wet period in 12 months.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	4.8	4.3	3.6	4.8	5.0	8.1	9.1	8.0	7.1	6.6	5.8	4.5
Cluster2	5.1	4.4	3.9	5.2	5.8	9.6	11.5	10.0	8.8	8.1	6.9	4.7
Cluster3	5.3	4.7	4.2	5.4	5.4	12.4	16.2	13.5	11.4	9.2	6.7	4.9
Cluster4	5.5	4.8	4.2	5.8	7.2	12.4	16.0	11.8	11.2	8.8	7.7	5.0
Cluster5	5.3	5.0	4.3	6.0	7.3	15.4	20.7	18.2	16.8	11.0	7.7	5.2
Cluster6	5.5	5.2	4.5	6.2	7.7	15.9	21.9	25.1	18.3	13.4	8.5	5.4
Cluster7	5.8	5.3	5.1	7.2	9.1	13.8	14.3	14.3	9.7	7.8	7.1	5.2
Cluster8	5.7	5.3	4.7	6.5	9.2	18.5	25.5	21.8	18.5	12.7	9.0	5.6

Figure 9. The continuity of dry period per month or the expected length of dry period in 12 months and for the study clusters.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	1.9	2.0	2.2	2.3	2.0	1.6	1.7	1.8	1.8	1.6	1.8	1.9
Cluster2	1.9	2.1	2.2	2.2	2.3	1.7	1.7	1.8	1.7	1.7	1.8	1.8
Cluster3	1.8	2.0	2.0	2.1	2.0	1.5	1.7	1.6	1.5	1.5	1.7	1.8
Cluster4	1.8	1.9	2.0	2.0	1.7	1.3	1.5	1.6	1.6	1.5	1.6	1.8
Cluster5	1.7	1.9	1.8	1.9	1.7	1.4	1.6	1.4	1.6	1.4	1.6	1.7
Cluster6	1.6	1.8	1.8	1.8	1.5	1.4	1.4	1.4	1.4	1.5	1.6	1.7
Cluster7	1.6	1.8	1.7	1.7	1.5	1.2	1.5	1.5	1.6	1.5	1.7	1.7
Cluster8	1.7	1.7	1.8	1.8	1.6	1.2	1.5	1.4	1.4	1.4	1.5	1.6

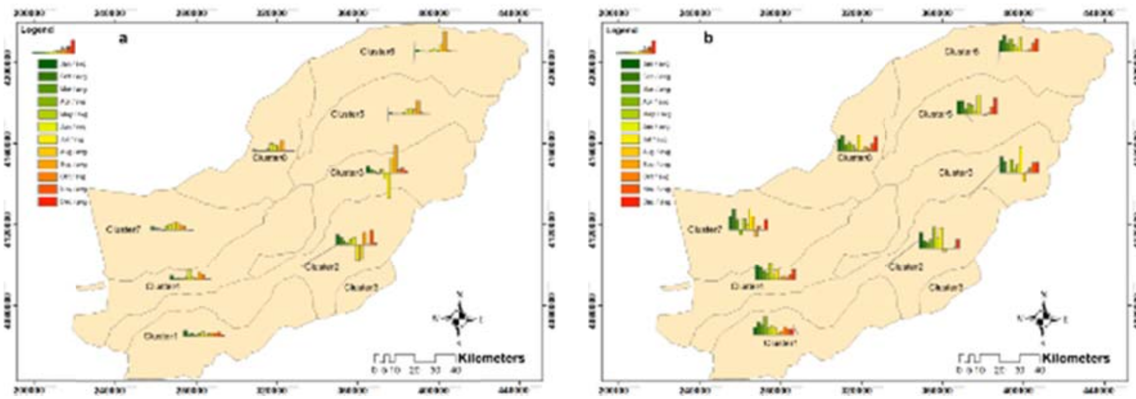
Figure 10. The diagram of the continuity of wet period per month or the expected length of wet period in 12 months and for the study clusters

3-5. Temporal and spatial variations of dry and wet days

We investigated the continuity variations of dry and wet days in the four decades of 1970s, 1980s, 1990s, and 2000s in Golestan province. It seems that the temporal continuity of dry days and the temporal continuity of wet days are considered to be the best criteria for the Markov chain to determine the variation of the precipitation cycle in temporal-spatial terms. On the one hand, it shows the temporal continuity for an average dry cycle with precipitation, and on the other hand, its spatial variability in the province, according to the cluster maps can be investigated. Therefore, at this stage of the research, the continuity of dry and wet days calculated with the Markov chain has been compared for decades. In this study, multidecadal variations are in fact the mean of ten years of change over the past 40 years.

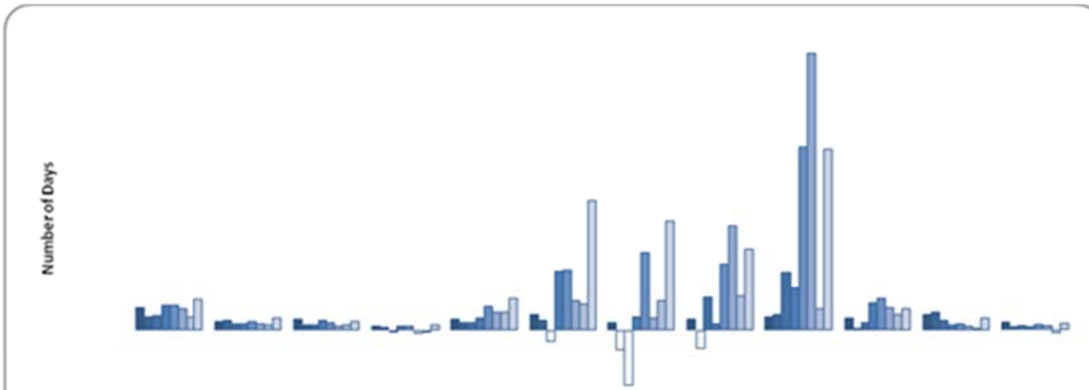
3-6. Multidecadal variations of temporal continuity in dry and wet periods in Golestan province

Figures 11a and 12 show that the four decades of dry period continuity across the eight cluster zones indicate the least changes in April, December, February, and March. However, from June to September, changes in the persistence of the dry period are most pronounced. These changes in July in clusters 2 and 3 resulted in a decrease of 1.05 and 2.89 days, respectively. In the same month, cluster 8 increased to 5.84 days. In June, clusters 4, 5, and 6 increased 3.14, 3.21, and 6.92 days, respectively, during the dry period.



(a) (b)

Figure 11. a) Average multidecadal variations of the length of dry periods in Golestan province in the last 40 years. b) Average multidecadal variations of the length of wet periods in Golestan province in the last 40 years



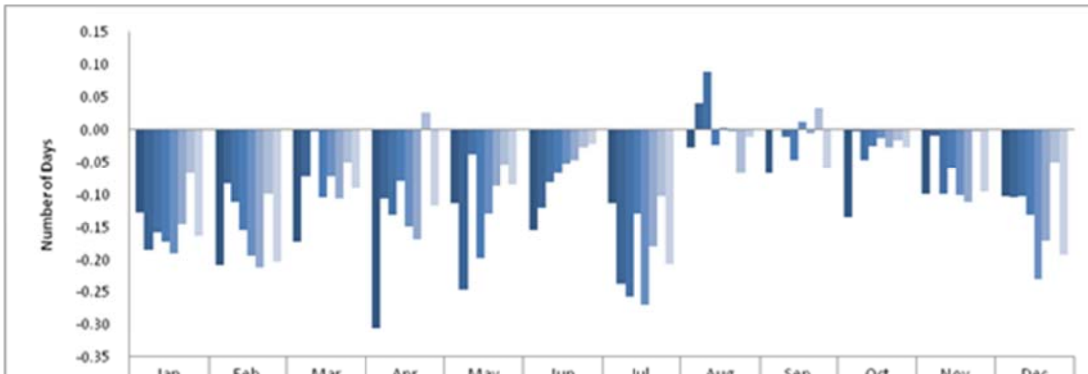
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	1.21	0.44	0.59	0.20	0.57	0.85	0.37	0.60	0.68	0.66	0.84	0.36
Cluster2	0.71	0.50	0.25	0.15	0.38	0.52	-1.05	-0.98	0.82	0.06	0.98	0.12
Cluster3	0.75	0.33	0.25	-0.08	0.40	-0.61	-2.89	1.75	3.10	0.37	0.53	0.21
Cluster4	1.30	0.31	0.50	0.22	0.64	3.14	0.71	0.34	2.26	1.43	0.25	0.15
Cluster5	1.30	0.43	0.39	0.19	1.24	3.21	4.16	3.52	9.79	1.73	0.35	0.27
Cluster6	1.17	0.31	0.18	-0.17	0.97	1.56	0.62	5.60	14.81	1.23	0.22	0.20
Cluster7	0.71	0.27	0.28	-0.10	0.94	1.37	1.57	1.82	1.12	0.82	0.10	-0.14
Cluster8	1.62	0.64	0.43	0.27	1.69	6.92	5.84	4.32	9.70	1.14	0.66	0.35

Figure 12. Table diagram of the features of multidecadal variations of the dry periods in Golestan province in the last 40 years

It is also shown in Figures 11b and 13 that in April, all the clusters but cluster 7 had a decrease in the wet period, with an average of 0.15 days and the highest decrease in cluster 1 being 0.31 days. In May, the average decrease in the wet period was 0.13 days per decade and the highest was observed in cluster 2 equal to 0.25 days. In June and July, the average wet period decline is 0.08 and 0.20 days per decade, respectively. Whereas in August and September, the duration of the wet period in clusters 2, 3, 5 and 6 shows an increase. This indicates that in the last decades during the second half of the summer, the rainfall in the province has increased. In summary, it can be concluded that in August, September and October, there are only slight changes in the length of the wet season but also in the eastern part of the province, indicating the temporal shift of precipitation from cold months to warm months.

4. Discussion and conclusion

The present research sought to detect spatial and temporal variations in the occurrence of wet and dry days in Golestan province using a one-order Markov chain method. An examination of the 40-year variability of precipitation days suggests that the coefficient of variation for this component varies between 30% and 50% for December to May, while in other months this figure is between 50% and 70% in most areas of the province. The results of this study showed that the highest frequency of dry conditions is related to dry to dry condition (P00), so that the frequency of its occurrence is even more than 90% in June to September for some areas of the province. While in December to March, the maximum frequency is up to 70%, that is, in the cold months of the year, the frequency of occurrence of this condition decreases. Also, the probability of wet-to-wet event (P11) in some areas of the province is even reaching 30% for the months of February to May, while in other months of the year, the probability of its occurrence is low. In the following, the results of the present study on the conditional probability of the Markov chain showed that the maximum spatial probability of occurrence of the P00 condition belongs to the northern areas of the province, whose value decreases to the mountainous areas. This is in line with the research results of Khorshiddoost and Fakhari, (2016) in southwestern Iran, in the way that they concluded that moving to mountainous areas reduces the probability of occurrence of the P00 condition.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cluster1	-0.13	-0.21	-0.17	-0.31	-0.11	-0.16	-0.11	-0.03	-0.07	-0.13	-0.10	-0.10
Cluster2	-0.18	-0.08	-0.07	-0.11	-0.25	-0.12	-0.24	0.04	0.00	0.00	-0.01	-0.10
Cluster3	-0.16	-0.11	0.00	-0.13	-0.04	-0.08	-0.26	0.09	-0.01	-0.05	-0.10	-0.10
Cluster4	-0.17	-0.15	-0.10	-0.08	-0.20	-0.07	-0.13	-0.02	-0.05	-0.02	-0.06	-0.13
Cluster5	-0.19	-0.19	-0.07	-0.15	-0.13	-0.05	-0.27	0.00	0.01	-0.01	-0.10	-0.23
Cluster6	-0.15	-0.21	-0.11	-0.17	-0.09	-0.05	-0.18	0.00	-0.01	-0.03	-0.11	-0.17
Cluster7	-0.07	-0.10	-0.05	0.03	-0.05	-0.03	-0.10	-0.07	0.03	-0.02	0.00	-0.05
Cluster8	-0.16	-0.20	-0.09	-0.12	-0.09	-0.02	-0.21	-0.01	-0.06	-0.03	-0.10	-0.19

Figure 13. Table diagram of multidecadal variations of the length of wet periods in Golestan province in the last 40 years.

In addition, the temporal pattern of the P00 condition is the highest in the warm period of the year and with the lowest probability of occurrence in the cold period. This state of conditional probability shows that the phenomenon of dryness intensifies when precipitation decreases. While in the P11 condition, wet to wet mode, is the exact opposite of the previous state, so that both in spatial terms, in the southern regions and in mountainous regions, is high in its occurrence, and also in temporal terms, during the cold period due to the arrival of the precipitation systems, the probability of occurrence increases.

In this study, the maximum constant probability of occurrence of wet days is more likely to occur in April and May, as well as in December, January, February, and March, and that the probability of occurrence is very low during the warm period. Geographically, the least likely occurrence of this probability is seen in cluster 8 and the highest in clusters 1 and 2. However, the constant probability of the occurrence of a dry day also indicates that the highest frequency is in the warm months of the year, while it is less likely to occur in cold periods. In clusters 1 and 2, the lowest probability of occurrence and in clusters 6 and 8, the highest probability of occurring of the dry day are observed. However, the results showed that the maximum duration of the dry period in the warm months of the year and its minimum occurrence for the cold period of the year is due to the arrival of the precipitation systems. The decrease in summer precipitation chiefly depends on retreating Westerly's (Alijani, 1996). In general, as we move towards cluster areas in the northeastern part of the province, the length of dry period increases, and as we move towards the southern and western mountainous regions, the dry period is reduced throughout the months. This result is different from those of the study by Asakareh and Mazini (2010), because the results of their study showed that spatial variations of the probability of occurrence of dry day in the province are not significant. However, perhaps one of the factors in the inconsistencies of the results of this research with the present study is the lack of fit and consistency during the statistical period and the number of study stations. Because in the study conducted by Asakareh and Mazini (2010), the length of the study period was merely 20 years and only on 51 stations. However, many studies for Iran and the various regions of the world show the temporal-spatial variability of rainfall for recent decades.

Based on the overall conclusion of this study, it was found that the Markov chain has properly been able to provide reasonable estimates of the probabilities and spatial-temporal variability of the wet and dry days according to the region's reality.

Similar to the results obtained in this study, for many other studies using the Markov method, the validity and acceptability of the results of this method are apparent (Hejazizadeh and Shirkhani, 2005; Daryabari, 2006; Asakereh, 2008; Asadah et al., 2010; Javan, 2016; Roshan and Nastos, 2018). Multidecadal variations of the temporal continuity of dry periods at the eight cluster areas indicate considerable spatial-temporal variations at the provincial level. In general, during the last 40 years, almost all months and clusters have grown over the dry period, but the slightest changes are in the months of April, December, February, March, and the most changes are from June to September. On the other hand, the findings showed that the length of dry periods is more pronounced for northern areas of the province. Also, the multidecadal variability of temporal continuity period of wet periods in Golestan province indicates that in most months and most study clusters, the length of wet period is declining. Therefore, it can be concluded that in August, September and October, the lowest variability in the decline of the length of wet period, but its increase in eastern regions is seen. This suggests a shift in precipitation from cold months to hot months.

The variability of the precipitation model is not concentrated solely for the southern Caspian Sea, but for the northern parts of the Caspian Sea, spatial and temporal variations in the pattern of extreme precipitation occurrences indicate that these patterns have changed for the recent decades.

The most important solutions to mitigate the effects of atmospheric hazards, such as drought, are to develop early warning systems. Although there are differences in drought alert systems due to the variety of data used, but similar to all these alert systems, drought monitoring is an essential first step in their design. Therefore, in order to develop drought-warning systems, a good understanding of the temporal-spatial distribution of precipitation events plays an important role in this process. So the results of this study can be used as a preliminary study in designing drought-warning systems in Golestan province.

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