International Journal of Plant Production 11 (2), April 2017
ISSN: 1735-6814 (Print), 1735-8043 (Online)
www.ijpp.info

GUASNR

Regionalization of dryland farming potential as influenced by droughts in western Iran

M. Nazari[a], F. Razzaghi[b,d,*], D. Khalili[c,d], A.A. Kamgar-Haghighi[c,d], S.M. Tahami Zarandi[a]

[a]*Graduated Master Student, Water Engineering Department, College of Agriculture, Shiraz University, Iran (Postal code: 7144165186).*
[b]*Assistant Professor, Water Engineering Department, College of Agriculture, Shiraz University, Shiraz, Iran (Postal code: 7144165186).*
[c]*Professor, Water Engineering Department, College of Agriculture, Shiraz University, Shiraz, Iran (Postal code: 7144165186).*
[d]*Drought Research Center, Shiraz University, Shiraz, Iran (Postal code: 7144165186).*
*Corresponding author. E-mail: razzaghi@shirazu.ac.ir

Received 6 October 2016; Accepted after revision 23 February 2017; Published online 20 March 2017

Abstract

Clustering was used to divide dryland farming areas in western Iran into homogeneous sub-regions to identify dryland farming potential, considering drought impacts. Clustering utilized eight algorithms/four indices to detect optimal number of clusters. Ward's algorithm validated by Silhouette index, produced the best result by detecting 7 dryland farming clusters. Based on similar P/ET_o values, four sub-regions were recognized among 7 clusters. Northwestern sub-region was ranked first, followed by central, northeastern and southern sub-regions. Drought impact analysis led to 6 optimal clusters by Ward's algorithm, validated by Silhouette index. Ranking criteria utilized drought characteristics, obtained from 3- to 12-months SPI analysis. Northwestern sub-region and parts of central sub-region, with respectively first and second rankings for dryland farming, are also least affected by droughts. Areas in central sub-region with good dryland farming potential can be strongly impacted by droughts. Northeastern and southern sub-regions respectively ranked third and fourth for dryland farming, were severely affected by droughts. In conclusion, areas with highest dryland farming potential were impacted minimally by drought, while areas with lowest potential were strongly affected by droughts. However, sub-regions with good dryland farming potential were be severely influenced by drought. Therefore, drought analysis should be considered for dryland farming management.

Keywords: Dryland Farming; Drought Events; Drought Indices; Clustering Analysis.

Highlights

- Applicability of P/ET_o as an agroclimatological index for dry land farming classification.
- Cluster analysis as an appropriate tool for regionalization of dryland farming.
- Drought affected dryland farming.

Introduction

Dryland farming is a major agricultural practice in western Iran (Yavari, 1987). At the same time, the rather vast area associated with dryland farming exhibits a variety of climatic conditions, which require analysis for dryland farming potential on regional and sub-regional basis. Furthermore, occurrence of frequent droughts during the past decade in many parts of Iran (including the western parts), has turned into a major issue for farmers and agricultural planners (Madani et al., 2016). Establishment of dryland farming potential based on sub-regional land suitability classification and realistic understanding of drought impacts should provide information, which can be used for planning and management purposes.

Considering the fact that dryland agriculture covers vast areas of land in many areas of the world, it would be necessary to assess the spatio-temporal variability of such large areas. For this purpose, by applying available regionalization procedures (algorithms), it is possible to breakdown (classify) the region of interest into sub-regions with homogeneous (similar behaviour) and common characteristics for dryland farming. Among the many available classification techniques, clustering can be used for such purposes (Halkidi et al., 2001). Clustering techniques have the capability to find similar behaviour among the objects (represented by selective data) for formation of individual clusters (sub-regions).

Drought is considered to be a natural phenomenon with reoccurrence tendency, causing deficiencies in water resources over a large area (Rossi et al., 1992) for a long period of time (Rossi et al., 1992). For the purposes of water resources management, a drought event can be characterized by severity (intensity), duration and areal extent (Rossi et al., 1992). Drought intensity is viewed to be the most important one among the drought characteristics. Drought intensity refers to significant reduction of available water, compared to a pre-established threshold level or what is commonly called the “normal conditions”. As a common practice, normal condition is defined to represent the mean/ median of data on water availability, considering a relatively long period of historical record (Tsakiris and Vangelis, 2005).

Drought events are usually very difficult to analyze, because they are the result of several complicated relationships between climate and climate-related parameters. As an alternative, drought indices are used as simplified yet representative procedure for drought monitoring and assessment (Tsakiris and Vangelis, 2005). Drought indices provide the medium for exchange of information on drought related issues among different interest groups (Wilhelmi and Wilhite, 2002). Over the years numerous drought indices have been proposed, which can be used to evaluate different aspects of water resources availability. Palmer (1965), proposed the Palmer’s Drought Severity Index (PDSI), as the pioneering work on drought studies. The PDSI requires data on precipitation, evapotranspiration and soil moisture. While the PDSI procedure is scientifically sound and popular, it cannot readily be applied to different areas due to lack of data availability. McKee et al. (1993) introduced the standardized precipitation index (SPI), which has gained popularity for the years due to its effectiveness and simplicity of application. The only required data for the SPI is precipitation, which makes it easy to study drought in many regions.

Droughts have been a major problem over the past decades for many areas worldwide. For example, the percentage of global land affected by drought has doubled from 1970s to 2000s (Dai et al., 2004). As drought extended, more lands have been converted to dryland, whereas drylands covers 40-41% of Earth's land area (Safriel and Adeel, 2005). UNESCO (1979) introduced a term as aridity index, which is based on the ratio of annual precipitation (P) and reference evapotranspiration (ET_o) rates. It was pointed out by Salem (1989) that the semi-arid areas with aridity index of 0.20-0.50 can support rain-fed agriculture with more or less sustained levels of production. Drylands are defined as areas with aridity indices of below 0.65, indicating that mean ET_o is at least 1.5 greater than annual mean precipitation.

Iran, with an area of 165 million hectares, is located in arid and semi-arid regions of the world. Due to low rainfall and high potential evapotranspiration, Iran has an average annual precipitation of 252 mm (less than one third of the world average), whereas 179 mm of rainfall is directly evaporated (Tabari and Aghajanloo, 2013). Out of the 165 million ha of the country's land area, about 20 Mha are considered for irrigated land and about 17 Mha considered for dryland agriculture. Rainfed agriculture and dry farming are most successful in western and northwestern parts of Iran, as well as the sloping lands in the Caspian coast (Statistical Center of Iran, 1998).

Although, wheat and barley are the main crops cultivated in Iran, wheat is the dominant crop, accounting for 35% of the food grain production of the country. Rainfed wheat produced 30-35% of wheat production in the country. Nassiri et al. (2006) studied the potential impact of climate change on rainfed wheat production in West and North West of Iran and stated that rainfed wheat yield reduced by 8.3-17.7% due to a rainfall deficit and the growth period also declined by 8-36 days. Further, Sadeghi et al. (2002) used the ratio of annual and fall rainfall over reference evapotranspiration as a agroclimatological indices and found out that area with P/ET_o of at least 0.2 were suitable for dryland agriculture in southern Iran.

In the present study dryland farming potential is evaluated for the western part of Iran. For this purpose, the concept of aridity index (P/ET_o) proposed by UNESCO (1979), is used as a means to establish dryland farming potential in the study area. The motivation for employing this type of approach stems from the fact that while precipitation is considered as an important parameter in dryland farming applications, utilization of P and ET_o values as ratio allows for proper combination of precipitation and potential evapotranspiration, which can effectively evaluate dryland farming potentials. This type of approach has been previously applied by other researchers, i.e., Sadeghi et al. (2002). Using the P/ET_o values of individual climatic stations, along with longitude, latitude and elevation attributes and within the framework of cluster analysis, sub-regional classification for dryland agricultural potential can be defined.

In the present research, possibility of breaking down large areas of land into homogeneous clusters (sub-regions) was investigated. The main purpose was identification of sub-regional areas according to dryland farming potential and as influenced by drought impacts. The study area is western Iran, which has been known as a major dryland farming zone.

Materials and Methods

Study area

The study area is located in western Iran within the longitude of 31^o to 38^o North and latitude of 45^o to 49^o East. The elevation of study areas are between 22 m and 3140 m above mean sea level. It includes southern Azarbayjan gharbi, southern Azarbayjan sharghi, southern Ardabil, Ilam, northwestern Khoozeston, Zanjan, Kordestan, Kermanshah, western Loreston and western Hamedan provinces and exhibits a highly diverse combination of climatic conditions. The location of study area is shown in Figure 1. The southern parts of the study area, are characterized as semi-arid with mild winters and long and hot summers. On the other hand, the northern areas are mostly mountainous with cold winters and mild summers. Maximum annual temperature of the study area varies between 15 ^{o}C and 33.5 ^{o}C and the minimum temperature changes between -0.3 ^{o}C and 17.3 ^{o}C. In the study area, mean annual precipitation (based on a 21-year record period, 1998 – 2009) is varied between 169.9 mm and 692.3 mm. About half of the annual precipitation occurs during the winter season, with the remaining half during fall and spring seasons. Provided geographic/climatological information was provided from the Iran Water Resources Mangement Company by personal communication.

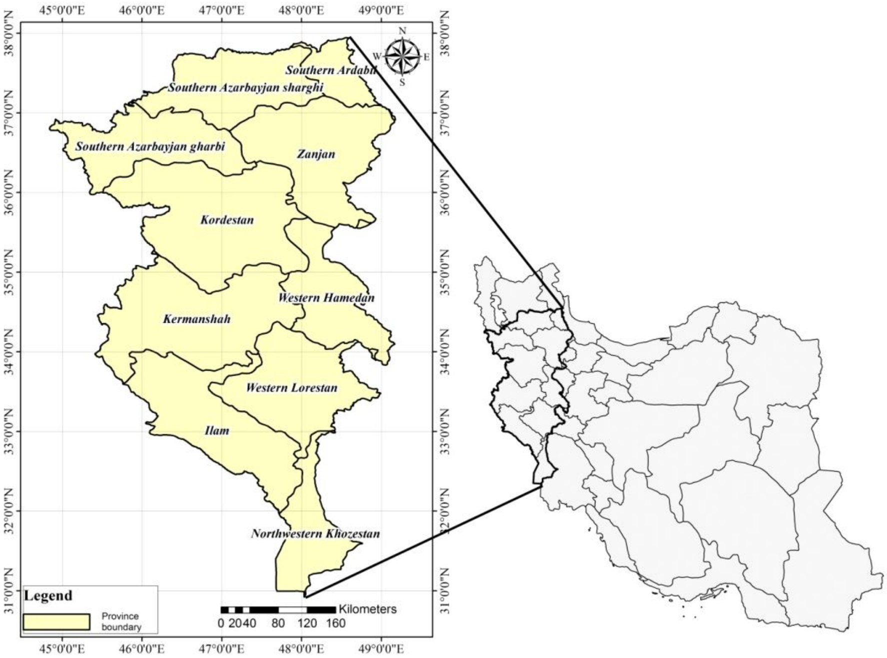

Figure 1. Study area location.

Data from more than 170 weather stations were available from archives of Regional Water Resources Organizations and National Iranian Climatic Organization. However, only monthly precipitation and temperature data from 32 stations were either complete or worthy of reconstruction for a study period of 21 years (1988 – 2009). At the same time, since drought analysis requires at least 30 years of data, monthly precipitation data were collected from 39 stations for a study period of 31 years (1977 – 2009). Data from stations with minor data deficiency were reconstructed using the data from nearby stations. The employed reconstruction procedures included linear regression equations and interpolation techniques.

The P/ET$_o$ bioclimatic index

In the present study the concept of P/ET$_o$ is used as a means to establish the potential of dryland farming in the study area (Sadeghi et al., 2002). Estimation of ET$_o$, usually requires application of available mathematical relationships, which usually relate ET$_o$ to climatic variables. One of the widely accepted methods is the Penman-Montieth procedure, which requires extensive data availability. As discussed by Allen et al.

(1998), it is possible to apply the Hargreaves-Samani formula (Hargreaves and Samani, 1985), which requires minimal data and provides reasonable estimation for ET_o. The Hargreaves-Samani procedure was used in the present study.

The standardized precipitation index (SPI)

In the present research, among available drought indices, the standardized precipitation index (SPI) was used to analyze drought impact. According to McKee et al. (1993), the SPI is presented as (Eq. 1).

$$SPI = \frac{x_i - \bar{x}}{\sigma} \tag{1}$$

where x_i represents precipitation values and $\bar{x}$, σ are average value and standard deviation of the "normalized precipitation", respectively. Available precipitation data (usually on a monthly basis), represented by x_i, was fitted to the gamma distribution. Then, at different probability levels, data are transformed into standard Normal distribution, represented by Eq. 1. The SPI values are in fact normalized values, representing dimensionless precipitation amounts with respect to zero precipitation as a reference point. SPI values above and below zero respectively indicate non-drought and drought events. McKee et al. (1993) indicated that for the SPI analysis, it is necessary to have months with sufficient amounts of precipitation for statistical analysis.

Establishment of precipitation sufficiency can be achieved by identifying the rainy season, using boxplots (Tukey, 1977). Previously, the boxplot approach has been used in several applications (Banimahd and Khalili, 2013; Khalili et al., 2011; Modaresi Rad et al., 2016; Modaresi Rad and Khalili, 2015; Saadat et al., 2013; Tabrizi et al., 2010). Boxplots are graphical representations of data variability, based on the 50^{th} (mediam), 25^{th}, 75^{th} percentiles, the minimum and maximum values, an also outlier data. By graphically inspecting the boxplot, it is possible to distinguish between the dry- and the wet seasons. More information on boxplots are available from several text books and publications (Tukey, 1977; Wilks, 2011).

Clustering procedures

In order to divide the study area into sub-regions with homogeneious characterstics, it is necessary to apply one of the available regionalization techniques. Clustering is one of the popular techniques, since it has the capability of utilizing several evaluation algorthims to achieve the best combination of sub-regions. It is necessary to first identify appropriate objects (attribute) for cluster analysis from available data. The selected attributes for the present study included, longitude and latitude, elevation above mean sea level and seasonal/annual P/ET_o values.

Furthermore, three clustering approaches, i.e., Hierarchical Clustering (HC), K-means and Self Organizing Maps (SOM) and eight combinations of these approaches are utilized for cluster analysis, as described below:

Hierarchical clustering

In hierarchical clustering (HC), selected attributes such as longitude, latitude, etc. are grouped based on a hierarchy (dendrogram), which explains the relation among data without the need to define cluster numbers prior to the analysis. The distance between clusters can be computed by utilizing four algorithms, as will be explained.

The first algorithm is the Ward's method (Ward Jr, 1963), as shown by Eq. 2:

$$d(r,s)=\sqrt{\frac{2n_r n_s}{(n_r+n_s)}}\left\|\bar{x}_r-\bar{x}_s\right\|_2 \qquad (2)$$

where, $\bar{x}_r$ and $\bar{x}_s$ represent the centroid of cluster r and s, $\| \quad \|_2$ is the Euclidean distance and n_r, n_s indicate the corresponding clusters.

In the second algorithm, an average distance between objects pairs is calculated for each pair of clusters:

$$d(r,s)=\frac{1}{n_r n_s}\sum_{i=1}^{n_r}\sum_{j=1}^{n_s} dist(x_{r,i},x_{s,j}) \qquad (3)$$

The third algorithm is based on the maximum distance between objects in the pair of clusters:

$$d(r,s)=\max(dist(x_{r,i},x_{s,j})),\ \ i\in(1,...,n_r),\ \ j\in(1,...,n_s) \qquad (4)$$

The forth algorithm is based on the minimum distance between objects in the pair of clusters:

$$d(r,s)=\min(dist(x_{r,i},x_{s,j})),\ \ i\in(1,...,n_r),\ \ j\in(1,...,n_s) \qquad (5)$$

The K-Means

MacQueen (1967) introduced the K-means clustering procedure as a simple, unsupervised learning algorithm by minimizing the sum of squares of distances between the data and the associated cluster centroid. To use this algorithm, different attributes such as longitude, latitude, mean annual precipitation and mean elevation above sea level can be applied as the required data. This algorithm uses a five-step approach. Additional details can be found in Chang et al. (2008).

Self Organizing Map (SOM)

A self-organizing map (SOM), was proposed by Kohonen (1982). It is an unsupervised neural network model, which is very popular. It has been applied for hydrology and water resources applications (Chang et al., 2007; Lin and Wu, 2007). SOM is made up of an n×m nodes network, whereby every node has its own topological position (an x, y coordinate in the lattice), along with a vector of weights with same dimension as the input vectors. Application of SOM requires training and execution of several steps with iterations (Chang et al., 2007).

It may be difficult to detect cluster boundaries, especially with large number of clusters. In such cases, the problem can be resolved by applying the K-means and HC to the best matching units (BMUs) of the SOM.

Evaluation of clustering algorithms

In the present research, eight clustering algorithms will be evaluated, which either directly use the above mentioned algorithms or are combinations of the above algorithms, i.e., Hierarchical (Ward, Average, Single and Complete) K-means, SOM-Ward, SOM-Average and SOM-Kmeans. Clustering algorithms can either be applied individually or as combinations of the two algorithms. By combining two clustering algorithms, i.e., Ward and K-means, clustering procedures (discussed in sub-section 2.5) are performed respectively by the corresponding algorithms.

Cluster validation

Clustering is done with the main objective of finding partitioning with the best fitting of the available data. As suggested by Berry and Linoff (1997), the following criteria can be used to evaluate clusters and also select the optimal clustering index:

i. Compactness, the members of each cluster should be as close to each other as possible. A common measure of compactness is the variance (within cluster), which should be minimized.

ii. Separation, the clusters themselves should be widely spaced.

The Silhouette validation index (Rousseeuw, 1987), C-index (Hubert and Schultz, 1976), the CH index (Caliński and Harabasz, 1974) and Davis-Bouldin (DB) index (Davies and Bouldin, 1979) can be utilized for optimization of the number of clusters. In the present study, the Cluster Validity Analysis Platform (CVAP) package, in Matlab® was used to perform cluster analysis procedures. Table 1 shows individual index interval and index optimization status.

Table 1. Optimal number of clusters and index interval.

Index	Optimal number of clusters	Computation interval
Caliński- Harabasz (CH)	Largest value	[0, ∞]
C – Index	Smallest value	[0, 1]
Davies- Bouldin (DB)	Smallest value	[0, ∞]
Silhouette	Largest value	[-1, 1]

Results and Discussion

Cluster analysis for dryland farming

In the present study, number of clusters suggested by eight algorithms were optimized (validated) by four different indices and the best possible number of clusters was identified. While algorithms are based on minimum distance analysis, the indices indicate algorithm performance, considering either minimization or maximization procedures.

For dryland farming cluster analysis, information on P/ET_o, latitude, longitude and elevation were used as clustering attributes. Results showed that the C-index as well as CH and DB indices were deficient in providing reasonable validation results for the algorithms (results not shown). The main problem was lack of sensitivity of these indices to different number of clusters. On the other hand, the Silhouette index was able to provide reasonable results, which was used to detect optimal number of clusters (Figure 2).

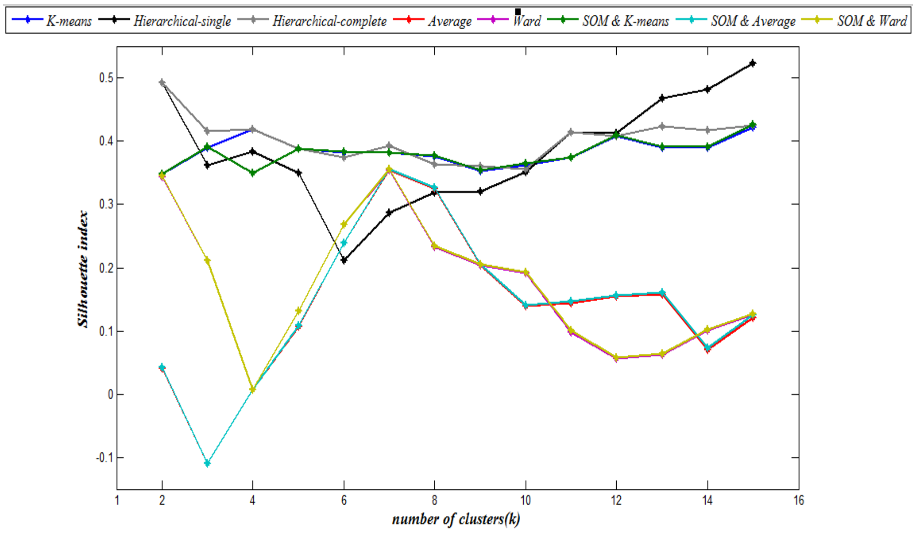

Figure 2. Results of cluster validation by the Silhouette index for dryland farming analyses.

Since the Silhouette index is a maximization procedure, an algorithm with the highest index value is regarded as having the best validation results. According to Figure 2, SOM & K-mean, K-mean and Hierarchical-complete algorithms did not show much sensitivity to different cluster numbers and as a result could not be considered. The Hierarchical-single algorithm produced a minimum index value; however, since the Silhouette index is a maximization procedure, the results would not be valid. As Figure 2 shows, the remaining four algorithms were able to identify the optimal number of clusters as 7. However, the Ward's algorithm by detecting the maximum distance from both 6 and 8 clusters was selected as the preferred algorithm.

Cluster analysis for drought impact analysis

For drought impact cluster analysis, information on precipitation, latitude, longitude and elevation were used as clustering attributes. Similar to the results of dryland farming cluster analysis, the C-index, CH and DB indices were not able to provide reasonable validation results for the algorithms (results not shown). The results by the Silhouette index are shown in Figure 3, illustrating validation of the eight algorithms. Considering that the Silhouette index is a maximization index, the Ward's algorithm produced the maximum validation among the eight algorithms, which corresponded to 6 clusters. The results of clustering for dryland farming and drought impacts were further evaluated to respectively select clusters with higher potential and also clusters which are minimally impacted by drought events, as discussed next.

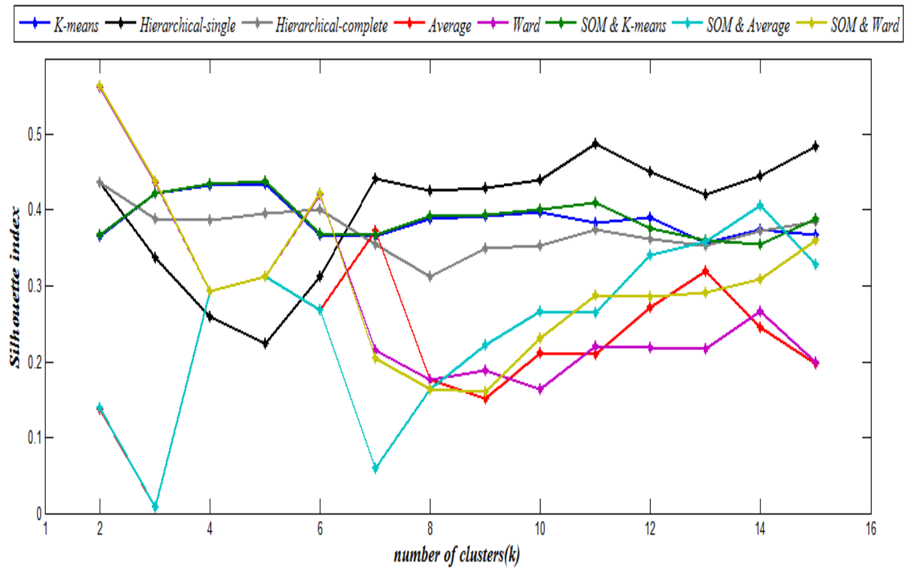

Figure 3. Results of cluster validation by the Silhouette index for drought analyses.

Cluster ranking for dryland farming potential

Figure 4 illustrates the 7 clusters for dryland farming, which are ranked according to achieved P/ET_o values as measure of dryland farming potential. For this purpose, P/ET_o values for each station and within each cluster were calculated and the ISO-P/ET_o lines were plotted in the geographic information systems (GIS) environment. The ISO-P/ET_o lines identify spaces with designated ranges of P/ET_o values in each cluster (Figures 4a to 4g).

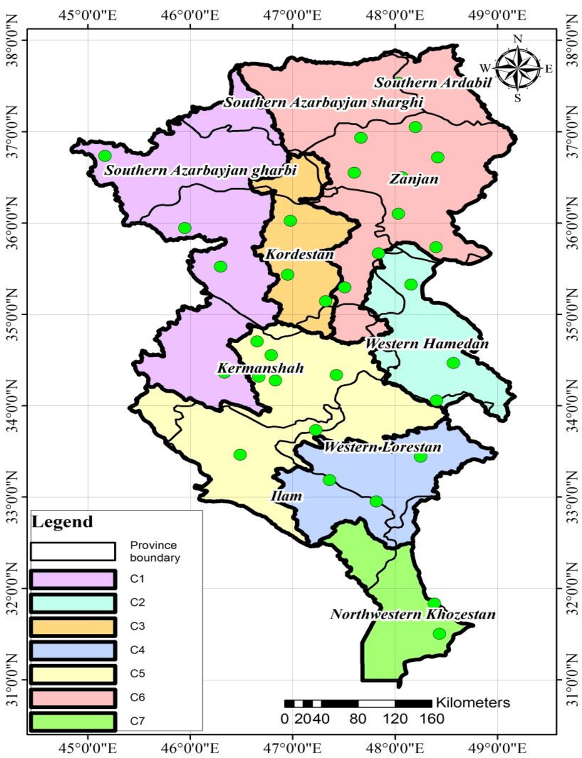

Figure 4. Final clusters for dryland farming.

The cluster identified in Figure 4 as C1 and with P/ET_o values in the range of 0.520 – o.667 (Figure 4a), is ranked first, i.e., the cluster with the highest range of achieved P/ET_o values has the highest potential for dryland farming. The designated area includes southern Azarbayjan gharbi, Southwestern Azarbayjan sharghi, Western Kordestan and Western Kermanshah.

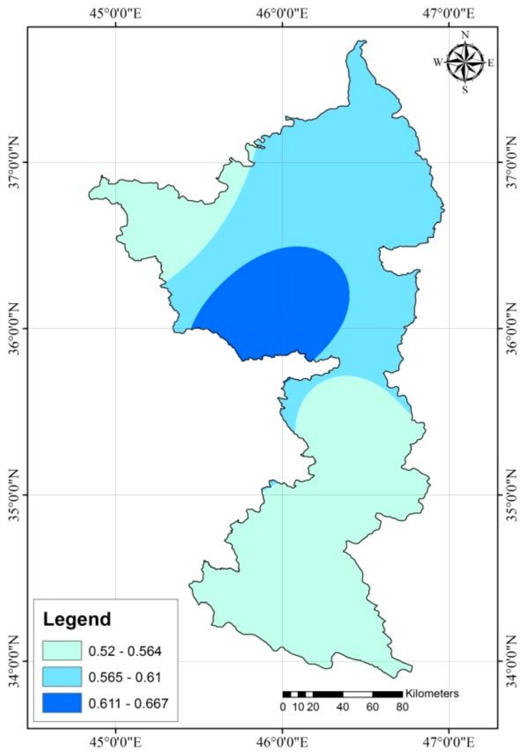

Figure 4a. ISO-P/ET_o lines for the C1 cluster.

Group of clusters identified as C2 to C5 in Figure 4 with combined P/ET_o values in the range of 0.233 – o.432 (Figures 4b to 4e), are ranked as second. The corresponding sub-region includes areas in Western Hamedan, Central Kordestan, Eastern Kermanshah, Ilam & Western Lorestan and exhibit rather similar P/ET_o values. The area in cluster C5 (Figure 4e), representing Northwestern Lorestan with P/ET_o values in the range of 0.233 – 0.299 appears to have the poorest dryland potential among clusters C2 to C5.

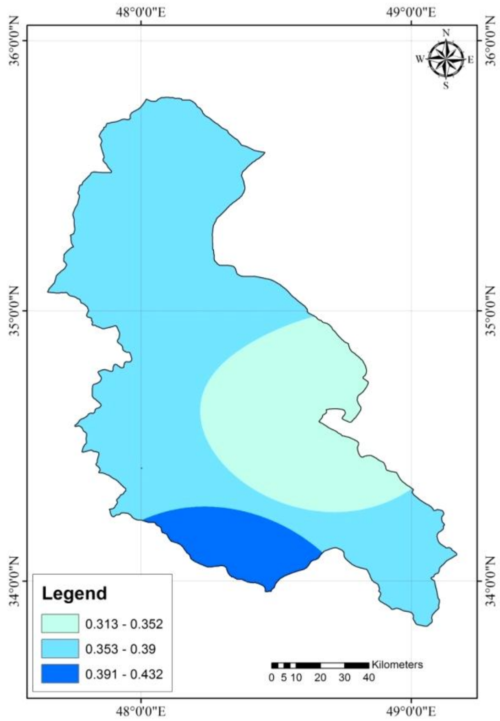

Figure 4b. ISO-P/ET_o lines for the C2 cluster.

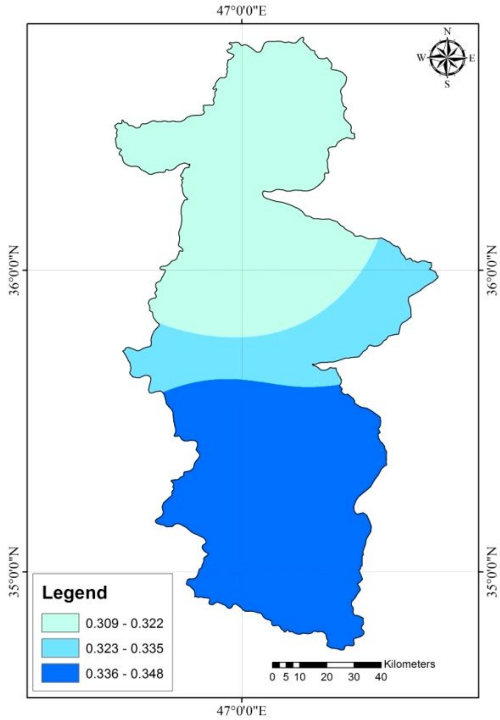

Figure 4c. ISO-P/ET_o lines for the C3 cluster.

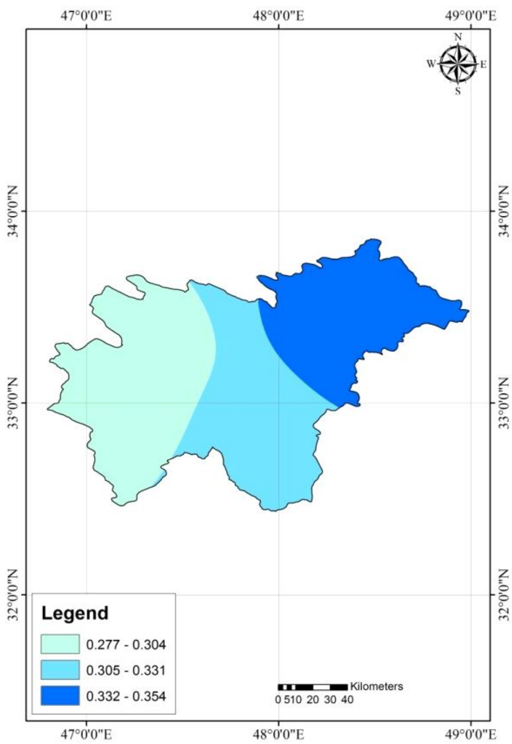

Figure 4d. ISO-P/ET_o lines for the C4 cluster.

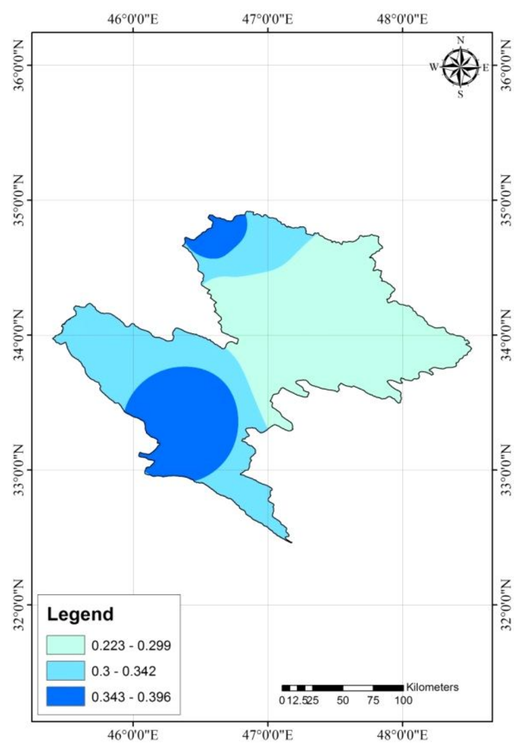

Figure 4e. ISO-P/ET_o lines for the C5 cluster.

The C6 cluster in Figure 4 is ranked third with P/ET_o values in the range of 0.163 – 0.324 (Figure 4f), representing areas in Southern Azarbayjan Sharghi, Southern Ardabil, Zangan & Eastern Kordestan. The C7 cluster (Figure 4) is ranked forth with P/ET_o values in the range of 0.129 – 0.139 (Figure 4g), representing Northwestern Khozestan and small part in Southern Ilam.

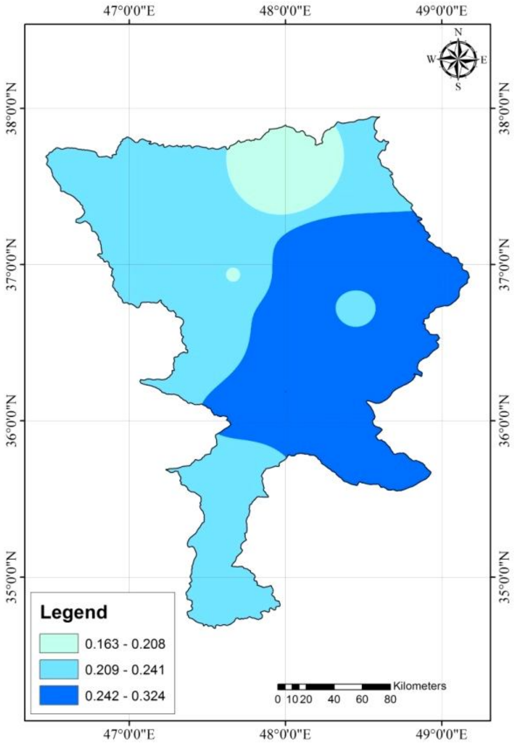

Figure 4f. ISO-P/ET_o lines for the C6 cluster.

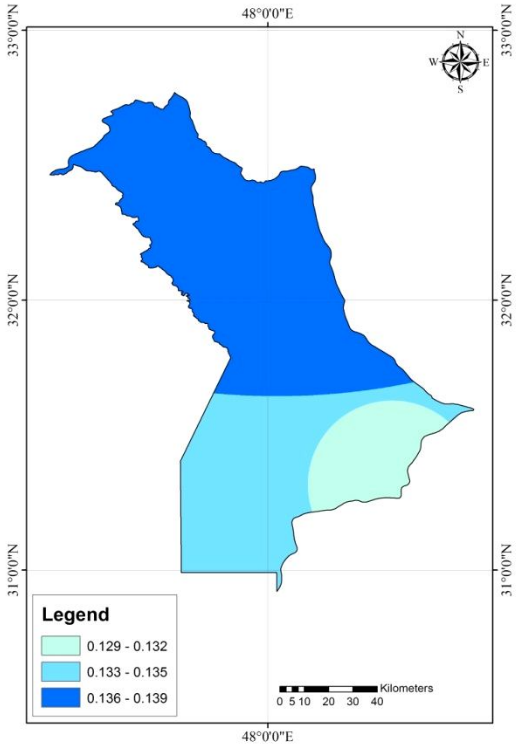

Figure 4g. ISO-P/ET_o lines for the C7 cluster.

Cluster ranking for drought impact

Figure 5 illustrates the 6 clusters for drought impact analysis, which are ranked according to their responses to the occurrence of droughts during the study period. For this purpose, the SPI results for 3-, 6-, 9- and 12-month timescales were used for cluster ranking. For each cluster the most severe drought event, the number of droughts and mean drought resident time were calculated as selection criteria. The results of ranked clusters are shown in Table 2. As Table 2 shows, clusters identified as D1 to D6, respectively represent sub-regional areas with lowest to highest sensitivity to occurrence of severe drought events.

In Figure 5, the D1 cluster is identified as the sub-region with the least danger of occurrence of drought events. The D1 cluster is essentially identical to the C1 cluster of Figure 4, representing the sub-region with the highest potential for dryland farming. As the results have indicated, the C1 cluster is ranked the highest considering P/ET_o values as well as the area with minimum drought impacts.

The D2 cluster in Figure 5 is ranked second, representing areas in Southern Azarbayjan sharghi, Southern Ardabil, Zanjan, Western Kordestan, Western Hamedan and Western Kermanshah. In comparison with the second ranked sub-region of C2 to

C5 clusters (Figure 4), only partial correspondence exists between results of Figure 4 and Figure 5, i.e., areas of Western Hamedan, Eastern Kordestan and Northeastern Kermanshah. Consequently, Southern Azarbayjan sharghi, Southern Ardabil and Zanjan while not strongly impacted by droughts, should not be considered for dryland farming, because of low dryland farming potential.

Table 2. Drought information obtained from the SPI analyses.

Cluster	SPI	Most intense drought event	Intense droughts details	
			Number of droughts	Duration average (months)
D1	3- month	-2.37	5	-2.13
	6- month	-1.85	0	0
	9- month	-2.07	0	0
	12-month	-2.50	5	-2.05
D2	3-month	-2.25	1	-2.25
	6- month	-1.93	0	0
	9- month	-2.05	1	-2.05
	12-month	-1.96	0	0
D3	3-month	-3.04	2	-2.62
	6-month	-2.59	3	-2.22
	9-month	-2.59	1	-2.25
	12-month	-2.45	8	-2.17
D4	3-month	-2.80	5	-2.40
	6-month	-2.50	3	-2.29
	9-month	-3.29	17	-2.15
	12-month	-2.67	12	-2.16
D5	3-month	-3.17	4	-2.49
	6-month	-2.39	5	-2.02
	9-month	-2.69	8	-2.27
	12-month	-2.86	7	-2.31
D6	3-month	-3.17	11	-2.48
	6-month	-3.50	5	-2.52
	9-month	-2.92	10	-2.29
	12-month	-2.58	11	-2.09

The D3 cluster (Figure 5) is ranked third, representing areas of Western Lorestan and Southern Ilam. The impact of drought events for D3 cluster is not very strong, which corresponds to parts of sub-regional C2 to C5 clusters (Figure 4) for dryland farming.

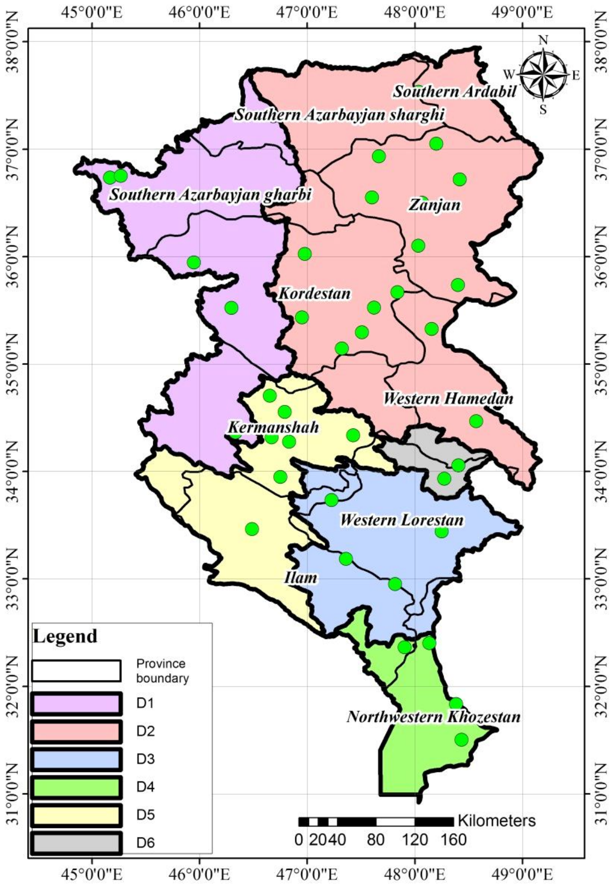

Figure 5. Final clusters for drought analyses.

The D4 cluster (Figure 5) is ranked forth, representing areas of Northwestern Khozestan and the Southern tip of Ilam. The impact of drought events for D4 cluster is rather strong as indicated in Table 2. The D4 cluster corresponds to C7 cluster (Figure 4), which produced the lowest potential for dryland farming.

The D5 and the D6 clusters (Figure 5) are respectively ranked fifth and sixth, representing areas of Eastern/Southern Kermanshah & Northern half (D5) and an small area bordering Western Hamedan & Western Lorestan (D6). The impact of drought events for D5 and D6 clusters are extremely strong (Table 2), requiring special attention with respect to dryland farming practices. For example as also practiced in the African dryland farming (Amjath-Babu et al., 2016), groundwater resources can be applied in form of supplemental irrigation, when possible. The D5 and D6 clusters correspond to parts of sub-regional C2 to C5 clusters (Figure 4), which were ranked second for dryland farming practices. As a result, despite the rather good ranking for dryland farming, possible impacts of severe drought event should also be considered.

Discussion of research findings in the context of available literature

The results of the present research has shown that proper investigation of dryland farming in western Iran should be based on results of regionalization techniques such as clustering algorithms. In this respect, attributes such as local information on geographical longitude and latitude strongly influenced regionalization results.

Furthermore, the results have indicated that parts of the study area can be strongly impacted by occurrence of drought events. These results highlight the need for utilization of regionalization techniques as well as the types of analysis, i.e., drought impacts, which can be used as a measure of dryland vulnerability. This issue has been cover extensively in the literature, addressing insight gained from global socio-ecological patterns of dryland vulnerability (Kok et al., 2016). In a separate study in northeast Brazil, measures for reduction of regional socio-ecological vulnerability under dryland conditions were investigated (Sietz, 2014).

Conclusions

In the present research, possibility of breaking down large areas of land into homogeneous clusters (sub-regions) was investigated. The main purpose was identification of sub-regional areas according to dryland farming potential and as influenced by drought impacts. The study area is western Iran, which has been known as a major dryland farming zone.

Among the eight available clustering algorithms and four validation indices, optimal number of clusters for dryland farming evaluation was seven, based on the results of the Ward's algorithm, validated by the Silhouette index. Although three other algorithms provided similar results, the Ward's algorithm results were selected as optimal because of providing stronger validation. Sub-regional analysis for drought impact evaluation suggested six clusters as optimal.

The northwestern sub-region with highest potential for dryland farming is also minimally impacted by drought events. However, only some parts of the central sub-region (ranked second for dryland farming) showed minimum drought impact, i.e., there are areas in the central sub-region which have good dryland farming potential, but can be strongly impacted by drought events. This is an issue which should be considered in planning and decision making processes for dryland farming applications.

References

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome, 300p.

Amjath-Babu, T., Krupnik, T.J., Kaechele, H., Aravindakshan, S., Sietz, D., 2016. Transitioning to groundwater irrigated intensified agriculture in Sub-Saharan Africa: An indicator based assessment. Agr. Water Manage. 168, 125-135.

Banimahd, S.A., Khalili, D., 2013. Factors influencing Markov chains predictability characteristics, utilizing SPI, RDI, EDI and SPEI drought indices in different climatic zones. Water Resour. Manage. 27, 3911-3928.

Berry, M.J., Linoff, G., 1997. Data mining techniques: for marketing, sales and customer support. John Wiley & Sons, Inc. 444p.

Caliński, T., Harabasz, J., 1974. A dendrite method for cluster analysis. Commun. Stat.-Theor. M. 3, 1-27.

Chang, F.-J., Chiang, Y.-M., Chang, L.-C., 2007. Multi-step-ahead neural networks for flood forecasting. Hydrolog. Sci. J. 52, 114-130.

Chang, F.-J., Tsai, M.-J., Tsai, W.-P., Herricks, E.E., 2008. Assessing the ecological hydrology of natural flow conditions in Taiwan. J. Hydrol. 354, 75-89.

Dai, A., Trenberth, K.E., Qian, T., 2004. A global dataset of Palmer Drought Severity Index for 1870-2002: Relationship with soil moisture and effects of surface warming. J. Hydrometeorol. 5, 1117-1130.

Davies, D.L., Bouldin, D.W., 1979. A cluster separation measure. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-1, 224-227.

Halkidi, M., Batistakis, Y., Vazirgiannis, M., 2001. On clustering validation techniques. J. Intel. Inf. Syst. 17, 107-145.
Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96-99.
Hubert, L., Schultz, J., 1976. Quadratic assignment as a general data analysis strategy. Brit. J. Math. Stat. Psy. 29, 190-241.
Khalili, D., Farnoud, T., Jamshidi, H., Kamgar-Haghighi, A.A., Zand-Parsa, S., 2011. Comparability analyses of the SPI and RDI meteorological drought indices in different climatic zones. Water Resour. Manage. 25, 1737-1757.
Kohonen, T., 1982. Self-organized formation of topologically correct feature maps. Biol. Cybern. 43, 59-69.
Kok, M., Lüdeke, M., Lucas, P., Sterzel, T., Walther, C., Janssen, P., Sietz, D., de Soysa, I., 2016. A new method for analysing socio-ecological patterns of vulnerability. Reg. Environ. Change. 16, 229-243.
Lin, G.-F., Wu, M.-C., 2007. A SOM-based approach to estimating design hyetographs of ungauged sites. J. Hydrol. 339, 216-226.
MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations, Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. Oakland, CA, USA., 281-297.
Madani, K., AghaKouchak, A., Mirchi, A., 2016. Iran's Socio-economic Drought: Challenges of a Water-Bankrupt Nation. Iranian Studies. 49, 997-1016.
McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales, Proceedings of the 8th Conference on Applied Climatology. American Meteorological Society Boston, MA, pp. 179-183.
Modaresi Rad, A., Khalili, D., Kamgar-Haghighi, A.A., Zand-Parsa, S., Banimahd, S.A., 2016. Assessment of seasonal characteristics of streamflow droughts under semiarid conditions. Nat. Hazards. 82, 1-24.
Modaresi Rad, A.M., Khalili, D., 2015. Appropriateness of clustered raingauge stations for spatio-temporal meteorological drought applications. Water Resour. Manage. 29, 4157-4171.
Nassiri, M., Koocheki, A., Kamali, G., Shahandeh, H., 2006. Potential impact of climate change on rainfed wheat production in Iran. Arch. Agron. Soil Sci. 52, 113-124.
Palmer, W.C., 1965. Meteorological drought. US Department of Commerce, Weather Bureau Washington, DC. 58p.
Rossi, G., Benedini, M., Tsakiris, G., Giakoumakis, S., 1992. On regional drought estimation and analysis. Water Resour. Manage. 6, 249-277.
Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 20, 53-65.
Saadat, S., Khalili, D., Kamgar-Haghighi, A.A., Zand-Parsa, S., 2013. Investigation of spatio-temporal patterns of seasonal streamflow droughts in a semi-arid region. Nat. Hazards. 69, 1697-1720.
Sadeghi, A., Kamgar-Haghighi, A., Sepaskhah, A., Khalili, D., Zand-Parsa, S., 2002. Regional classification for dryland agriculture in southern Iran. J. Arid Environ. 50, 333-341.
Safriel, U., Adeel, Z., 2005. Dryland systems. Ecosystems and Human Well-Being, Current State and Trends, eds Hassan R, Scholes R, Ash N. Island Press, Washington. 1, 625-658.
Salem, B., 1989. Arid zone forestry: a guide for field technicians. Food and Agriculture Organization (FAO) Conservation Guide 20, 143p.
Sietz, D., 2014. Regionalisation of global insights into dryland vulnerability: Better reflecting smallholders' vulnerability in Northeast Brazil. Global Environ. Change. 25, 173-185.
Statistical Center of Iran, 1998. The 1993 General Census of Agriculture: Detailed Results for the Entire Country, Plan and Budget Organization. Publication No. 3217, Tehran, Iran, 124p. (In Persian)
Tabari, H., Aghajanloo, M.B., 2013. Temporal pattern of aridity index in Iran with considering precipitation and evapotranspiration trends. Int. J. Climatol. 33, 396-409.
Tabrizi, A.A., Khalili, D., Kamgar-Haghighi, A.A., Zand-Parsa, S., 2010. Utilization of time-based meteorological droughts to investigate occurrence of streamflow droughts. Water Resour. Manage. 24, 4287-4306.
Tsakiris, G., Vangelis, H., 2005. Establishing a drought index incorporating evapotranspiration. European Water. 9, 3-11.
Tukey, J.W., 1977. Exploratory data analysis. Reading, PA: Addison-Wesley.
UNESCO, 1979. Map of the world distribution of arid regions: Map at scale 1:25,000,000 with explanatory note. MAB Technical Notes 7, UNESCO, Paris, 55p.

Ward Jr, J.H., 1963. Hierarchical grouping to optimize an objective function. J. Am. Stat. Assoc. 58, 236-244.

Wilhelmi, O.V., Wilhite, D.A., 2002. Assessing vulnerability to agricultural drought: a Nebraska case study. Nat. Hazards. 25, 37-58.

Wilks, D.S., 2011. Statistical methods in the atmospheric sciences. Academic press, 676p.

Yavari, M., 1987. Dryland Farming in Iran. M.Sc. thesis. College of Literature and Humanities, Isfahan University, 270p. (In Farsi)