DESERT

DESERT
Online at http://jdesert.ut.ac.ir

DESERT 18 (2013) 79-87

Assessment of Severity of Droughts Using Geostatistics Method (Case Study: Southern Iran)

A. Nohegar[a*], M. Heydarzadeh[b], A. Malekian[c]

[a] *University of Tehran, Tehran, Iran*
[b] *Hormozgan University, Bandar Abbas, Iran*
[c] *Faculty of Natural Resources, University of Tehran, Karaj, Iran*

Received: 25 February 2013; Received in revised form: 6 May 2013; Accepted: 27 May 2013

Abstract

Drought monitoring is a fundamental component of drought risk management. It is normally performed using various drought indices that are effectively continuous functions of rainfall and other hydrometeorological variables. In many instances, drought indices are used for monitoring purposes. Geostatistical methods allow the interpolation of spatially referenced data and the prediction of values for arbitrary points in the area of interest. In this research, several geostatistical methods, including ordinary kriging (OK), indicator kriging (IK), residual kriging (RK), probability kriging (Pk), simple kriging (SK), universal kriging (UK), and inverse distance weighted (IDW) methods were assessed for the derivation of maps of drought indices at 12 climatic stations in southern Iran. Data regarding monthly rainfall, temperature, wind, relative humidity, and sunshine of three periods (1985, 1995, and 2005) were taken from 12 meteorological synoptic stations and distributed areas. Based on the used error criteria, kriging methods were used for spatial analysis of the drought indexes and were selected as the best method**.** Results also showed that the lowest error (RMSE) is related to the kriging method. The results indicated that IK with tree frequency is more appropriate for the spatial analysis of the RDI index, and the Pk and SK methods are more appropriate for the spatial analysis of the SPI index. The kriging methods mean errors (RMSE) selected years for RDI and SPI index respectively are 0.85 and 0.84. In several cases, the "moderately dry" class received a more critical value by RDI. The results showed that by utilizing the ET0, the RDI can be very sensitive to climatic variability.

Keywords: Drought; RDI; SPI; Geostatistics Method; South of Iran

1. Introduction

Drought is a complex natural phenomenon and has significant impacts on effective water resource management. In general, drought gives an impression of water scarcity due to insufficient precipitation, high evapotranspiration, and overexploitation of water resources, or a combination of all the above (Bhuiyan, 2004). Nevertheless, Beran and Rodier (1985) and Panu and Sharma (2002) suggested that it may be possible to forecast well the probable timing of drought inception and termination reasonably over a short period, such as a month or a season. The impacts of drought depend largely on social vulnerability at the time the drought occurs. Blaikie *et al.* (1994) showed that the risk of possible disaster is a combination of a hazard and social vulnerability. In the last two decades, losses from drought have significantly increased without documented evidence of increased number or severity of droughts (Wilhite, 2000b).The aim of regionalizing the displayed data is to provide a map to demarcate growth areas (Jansen et al., 2002). Contour line graphics are a feasible method for this purpose. Among a large number of interpolation algorithms, geostatistical methods are widely used. Geostatistical theory is based on a stochastic model which allows the derivation of optimal predictions at arbitrary points in the considered region (Wamling, 2003). The kriging method was originally developed by Matheron

* Corresponding author. Tel.: +98 21 61113165, Fax: +98 21 66407719.
E-mail address: ahmad.nohegar@gmail.com

(Matheron, 1971). It was first applied to mining engineering in South Africa (Journel and Huijbregts,1978) and then to subsurface hydrology, e.g. to the estimation of parameters (Delhomme, 1978), and the network design of wells (Hughes and Lettenmaier, 1981; Bastin et al., 1984). Tabios and Salas (Tabios et al., 1985) compared the kriging method with other available interpolation methods and concluded that the kriging method is an effective alternative. For spatial drought monitoring, some authors applied the WMA technique (Smakhtin et al., 2007;.Svoboda, 2004). Others have suggested using simple multiple linear regression-based models (Loukas et al., 2004; Livada and Assimakopoulos, 2007). In this study, kriging (K) and inverse distance weighted (IDW) geostatistical methods were assessed to identify the optimum method for SPI and RDI indices. The main aims of this study were to determine drought occurrence periods and intensities across southern Iran by different drought indices (1), to compare different drought indices (2), and to develop a drought zone scheme of southern Iran with IDW and kriging methods (3).

2. Materials and Methods

2.1. Drought Indices

The Standardized Precipitation Index (SPI), one of the most widely used drought indices, was designed by McKee et al., (1993). Quantities and descriptive situations of this index are shown in Table 1. SPI was calculated by GIS software (Rossi et al., 2007). Some recent studies on drought evaluation include those by Edossa et al. (2010), Pandey et al. (2010), Vasiliades et al. (2010), and Vangelis et al. (2010). Some more recent research efforts on the SPI in Iran include but are not limited to Morid et al. (2006), Raziei et al. (2009), Modarres (2010), Abolverdi and Khalili (2010), and Tabrizi et al. (2010). Another widely used meteorological index is the rainfall deciles, developed by Gibbs and Maher (1967).

As an alternative meteorological drought index, the reconnaissance drought index (RDI) was proposed by Tsakiris and Vangelis (2005). It utilizes the ratios of precipitation to reference crop evapotranspiration (ET0) for different time scales to be representative of the region of interest. In the expression value of RDI (a_o), a_o is usually calculated for the i_{th} year on an annual basis using the following equation:

$$a_0^{(i)} = \frac{\sum_{j=1}^{12} \mathrm{Pij}}{\sum_{j=1}^{12} \mathrm{PETij}}, \mathrm{i} = 1\mathrm{to}\ \mathrm{N}\ \mathrm{and}\ \mathrm{j} = 1\mathrm{to}\ 12 \quad (1)$$

where P_{ij} and PET_{ij} are the precipitation and potential evapotranspiration of the jth month of the *i*th year, starting usually in October as is customary for Mediterranean countries, and N is the total number of years of available data. During the present study, PET rates were estimated using the Penman-Monteith equation (Monteith, 1965), which is the most reliable way to estimate PET under various climatic conditions (Jensen et al., 1990). During the current analysis, RDI calculations were performed using MATLAB. Since the standardized RDI and SPI are performed in similar manners (McKee et al., 1993), they have similar interpretations of results. Therefore, the RDI values could be compared with the same thresholds as that of the SPI technique (Table 1).

Table 1. Classification of drought according to the SPI and RDI_{st} values

State	Range	SPI and RDI_{st} range Drought classes
1	2 or more	Extremely wet
2	1.5 to 1.99	Very wet
3	1 to 1.49	Moderately wet
4	0.99 to 0.0	Normal
5	0.0 to −0.99	Near normal
6	−1 to −1.49	Moderately dry
7	−1.5 to −1.99	Severely dry
8	−2 and less	Extremely dry

2.2. Interpolation Method

Comparison of interpolation techniques

Geostatistics started in mineral mining and is currently applied in many disciplines such as hydrogeology, hydrology, meteorology, and epidemiology. The prefix *geo* is usually associated with geology, owing to its having originated from mining (Majani. B.S., 2007). Two methods for drought index mapping at different spatial units are outlined in the next section.

A spatial distribution map was generated by geostatistics methods in Arc GIS. Kriging and IDW (inverse distance weighting) methods were used to analyze the spatial variation of main factor values and to generate the contour map of key water quality factors. The best geostatistical methods were selected by RMSE and MSE indices, and the final contour maps were generated using them.

The IDW method estimates the values of unsampled locations by weighting observations based on their distance from unsampled locations (Shepard, 1968). To predict a value for any unmeasured location, the IDW method uses the measured values surrounding the prediction location. The IDW formula gives data points close to the interpolation point relatively large weights, but those far away exert little influence.

The presence of a spatial structure where observations close to each other are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics (Goovaerts, 1999). The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value (Deutsch et al., 1998) and thus can depict autocorrelation at various distances. In this case, ordinary and simple kriging models can be stated as follows (Attorre et al., 2006):

$$Z\ (si) = m + e\ (si)$$

where Z (si) is an intrinsic stationary process and m is an unknown (locally) constant trend in ordinary kriging; rather, Z (si) is a second-order stationary process and m is known in simple kriging (Ver Hoef JM, 1993). In particular, in the UK (Ver Hoef, 1993), such a trend can be modeled as a linear function in p explanatory variables (say climatic, geographical, and topographical covariates) and p unknown constants βj, which yield for the observation at Si:

$$Z(si) = \sum_{j=1}^{p} Xj(si)\beta j + e(si) \tag{2}$$

Here, Xj (si), j = 1. .. P represents covariates values measured at the i-th point in the grid. This model resembles a standard linear regression model with the addition of an error term, e(si), which is no longer assumed to be independent on e(sj), i ≠ j =1, . . , n.

While kriging is well known as the best linear unbiased (spatial) predictor (BLUP), there are problems of non-stationarity in real-world data-sets which could limit its applications. Rather than using the UK with a trend function modeled via a set of covariates, some authors (e.g., Agnew and Palutikof, 2000; Ninyerola et al., 2000; Antonic et al., 2001) have proposed a simpler approach based on RK, i.e. 'kriging after de-trending' where the trend function and estimated residuals are modeled separately.

Indicator variograms were computed and indicator kriging performed using the Auto-IK approach of Goovaerts, (2009).

Evaluation Criteria

Various methods of interpolation based on cross-validation were investigated and evaluated. In this method, one point was temporarily removed and, by applying the desired interpolation, the value for that point was estimated, so the deleted amount return instead of itself and for the rest of points is done this estimated. With survey amounts and drought intensity estimated through RDI and SPI, the best zoning and spread drought by assist ones of geostatistics methods with minor errors accomplished for during three periods time 1985, 1995, and 2005.

Results were shown in a table with two columns demonstrating real and estimated values. With these two values, the Mean Square Error (MSE) and Root Mean Squared Error (RMSE) of the model could be estimated.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}[z^*(xi) - Z(xi)]^2}{n} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[z^*(xi) - Z(xi)]^2}{n}} \tag{4}$$

Where $Z^*(x)$ is the estimated value of the desired variable, Z (x) is the measured amounts of desired variable, and N is number of data.

2.3. Study Area

The study area encompassed most of southern Iran, with an approximate area of 59.705236 km^2 between 25° 0′ N to 32° 0′ N and 48° 0′ E 64° 0′ E (Fig.1).

Table 2 shows the characters of the studied synoptic stations. Precipitation and potential evapotranspiration were used to classify the bioclimatic aridity in a globally comparable way.

3. Results

Comparisons of various interpolation techniques in order to interpolate SPI and RDI

All the interpolators used for SPI were compared on the basis of root mean squared (RMS) and root mean squared error (RMSE). The errors for all interpolation techniques i.e. ordinary kriging (OK) indicator kriging (IK), residual kriging (RK), probability kriging (Pk), simple kriging (SK), universal kriging (UK), and inverse distance weighted (IDW) methods, were calculated using optimal power function. Tables 4 and 5 show the ranking of all interpolation techniques during the three times periods of 1985, 1995, and 2005. Among the various criteria of spatial interpolation, the extent of the study area also played an important role. The area of southern Iran is very large, 59.705236 km^2. Similar results were obtained in a study by Collins (2000), where various interpolation techniques for different regions (region 1 had large spatial extent and region 2 was small) were compared. Kriging using optimal power consistently gave better results than other techniques. The correlation coefficients of SPI and RDI for each station and each time scale are described in Table 3.

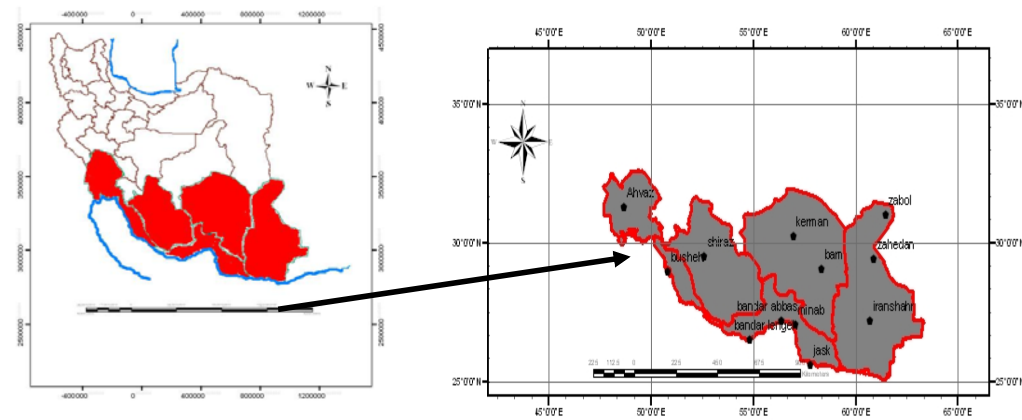

Fig. 1. Geographic location of the south Iran (case study). Weather stations are marked as black points

Table 2. General characteristics of the studied synoptic stations

Station	X coordinate m	Y coordinate m	Elevationa.s.l. (m)	P (mm)	Climatic classification
Ahvaz	321231	3492096	22.5	240.9	Arid
Bam	625967	6495690	66.9	59.3	Hyper- arid
Bandar abbas	522503	6274776	9.8	152.9	Arid
Bandar lengeh	492608	6137456	22.7	205.6	Arid
Bushehr	683239	5695746	19.6	277.2	Arid
Iranshahr	517934	6781397	591.1	112.4	Arid
Jask	444292	6460648	5.2	139.0	Arid
Kerman	345695	6388972	1753	142.1	Arid
Shiraz	693140	3307538	484	348.0	Semi-arid
Zabol	397206	6853442	489.2	62.6	Hyper-arid
Zahedan	648294	6817934	1370	75.3	Arid
Minab	509911	2999361	27	214	Arid

Table 3. Correlation coefficient of SPI and RDI in the stations for different time scales

Station		Time scales					
		3 month	6 month	9 month	12 month	18 month	24 month
1	Ahvaz	0.98	0.98	0.95	0.91	0.93	0.88
2	Bam	0.95	0.94	0.90	0.90	0.89	0.88
3	Bandar abbes	0.99	0.99	0.98	0.97	0.97	0.96
4	Bandar lengeh	0.99	0.99	0.99	0.99	0.99	0.99
5	Bushehr	0.99	0.99	0.99	0.98	0.98	0.98
6	Iranshahr	0.96	0.95	0.94	0.95	0.95	0.96
7	Jask	0.99	0.99	0.99	0.99	0.99	0.99
8	Kerman	0.97	0.96	0.91	0.88	0.89	0.86
9	Shiraz	0.99	0.98	0.96	0.96	0.95	0.93
10	Zabol	0.97	0.97	0.95	0.95	0.95	0.96
11	Zahedan	0.97	0.97	0.96	0.96	0.97	0.98
12	Minab	0.996	0.995	0.99	0.99	0.992	0.99

Considering Tables 4 and 5, the best zoning was determined for years with drought intensity in which of periods. Table 6 shows the numerical amount of any year with the most droughts in any time span.

Table 4. The Assessment of geostatistical methods for spatial analysis of RDI drought indices during 1985, 1995 and 2005

RDI	Year	Model	MODEL	RMS	RMSE
3 Month	1985	SK	GAUSSEAN	0.1298	0.9189
	1995	SK	GAUSSEAN	*0.1295*	*0.9166*
	2005	SK	exponential	0.2	0.9592
6 Month	1985	IK	GUASSEAN	0.5435	0.9957
	1995	IK	GUASSEAN	*0.635*	*0.8744*
	2005	UK	GUASSEAN	0.3442	0.9735
9 Month	1985	PK	GUASSEAN	*0.6163*	*0.854*
	1995	OK	SPRICAL	0.754	0.9755
	2005	PK	HOLE EFFECT	0.4946	0.97
12 Month	1985	OK=UK	HOLE EFFECT	0.659	0.9036
	1995	IK	HOLE EFFECT	*0.5058*	*0.8613*
	2005	IK	HOLE EFFECT	0.5789	1.066
18 Month	1985	OK	HOLE EFFECT	*0.6306*	*0.7682*
	1995	SK	HOLE EFFECT	0.5717	0.9418
	2005	IK	EXPONENTIAL	0.5007	0.9464
24 Month	1985	OK	HOLE EFFECT	0.6599	0.9036
	1995	IK	HOLE EFFECT	*0.5058*	*0.8613*
	2005	PK	HOLE EFFECT	0.5606	1.028

Table 5. Assessment of geostatistical methods for spatial analysis of SPI drought indices during 1985, 1995 and 2005

SPI	Year	Model	MODEL	RMS	RMSE
3 Month	1985	SK	HOLE EFFECT	0.1805	0.8733
	1995	SK	HOLE EFFECT	0.282	0.9951
	2005	OK	EXPONENTIAL	0.1853	0.9846
6 Month	1985	PK	GUASSEAN	0.3547	0.7487
	1995	OK	GUASSEAN	0.4959	0.9932
	2005	OK	GUASSEAN	0.2707	0.9229
9 Month	1985	SK	EXPONENTIAL	0.4966	0.9515
	1995	PK	HOLE EFFECT	0.5083	0.9729
	2005	OK	EXPONENTIAL	0.4609	0.9571
12 Month	1985	UK	CIRCRULAR	0.5672	0.887
	1995	IK	HOLE EFFECT	0.5058	0.8613
	2005	IK	GUASSEAN	0.4915	0.946
18 Month	1985	SK	EXPONENTIAL	0.5742	0.8937
	1995	PK	HOLE EFFECT	0.4922	0.9456
	2005	SK	EXPONENTIAL	0.4768	0.8794
24 Month	1985	PK	GUASSEAN	0.3514	0.7432
	1995	SK	HOLE EFFECT	0.5139	0.97
	2005	OK	CIRCRULAR	0.3834	0.9397

Table 6. the driest year's based RDI and SPI

RDI		Range Drought	Drought classes	SPI		Range Drought	Drought classes
3 Months	1995	-0.132	Near normal	3 Months	1985	-0.6702	Near normal
6 Months	1995	-0.323	Near normal	6 Months	1985	-0.9855	Near normal
9 Months	1985	-1.765	Moderately dry	9 Months	2005	-0.09283	Near normal
12 Months	1995	-1.1612	Moderately dry	12 Months	1995	-1.0560	Moderately dry
18 Months	1985	-1.565	Moderately dry	18 Months	2005	-0.4680	Moderately dry
24 Months	1995	-1.0774	Moderately dry	24 Months	1985	-1.840	Moderately dry

Table 6 that shows the years dries with the best zoning and less errors. According to Table 6, in order and based on RDI and SPI index, figures 2 and 3 are given for every specific time. Classifications for each of the driest year's values for best zoning are based on McKee classification (Table 1),with the mean of each of value trend of 2 value, (the) area is very wet and each of value trend of 0 and negative value, (the) area is drought.

After spatial analysis of the geostatistics methods, these methods were assessed in two ways. The evaluation criteria in the first method are the error criteria RMSE and MSE. Table 6 shows the estimated amount of error and deviation values of the methods than the real values. As seen in this table, for SPI and RDI indices, the lowest error (RMSE) was related to the kriging method. In all periods, this method was more accurate in its calculations for other years. The highest volatility of MSE was related to the IDW method. Therefore, if MSE is considered a major factor for selecting methods, the kriging method can be introduced as the better method. Even if the same time to be consider the both error criteria for optimization method, kriging method are known as the best method again. For methods analysis of RDI index was determined that Kriging method can be a good estimated of this index in unknown points with least error (MSE).

In Figure 2, part **a** for RDI 3 month and part **c** for RDI 9 month with forest green color, part **e** for RDI 18 month with dark blue color display spread severity of drought in south of case area. While part **b** for RDI 6 month on piece of North West area and part **f** for RDI 24 month with pea green in region North and North West area shows intensity drought. On base part **d** for RDI 12 month drought spread (extend) shows in small region of center and west and east area with pink color.

According to Figure 3, the driest area in parts **a** and **b** are shown in red in the southern part of the case study. On part **c** in the south and west area, part **d** in the center and east area, part **f** in the center and east area, and part **e, a** small area in the south of the area, are indicated in red.

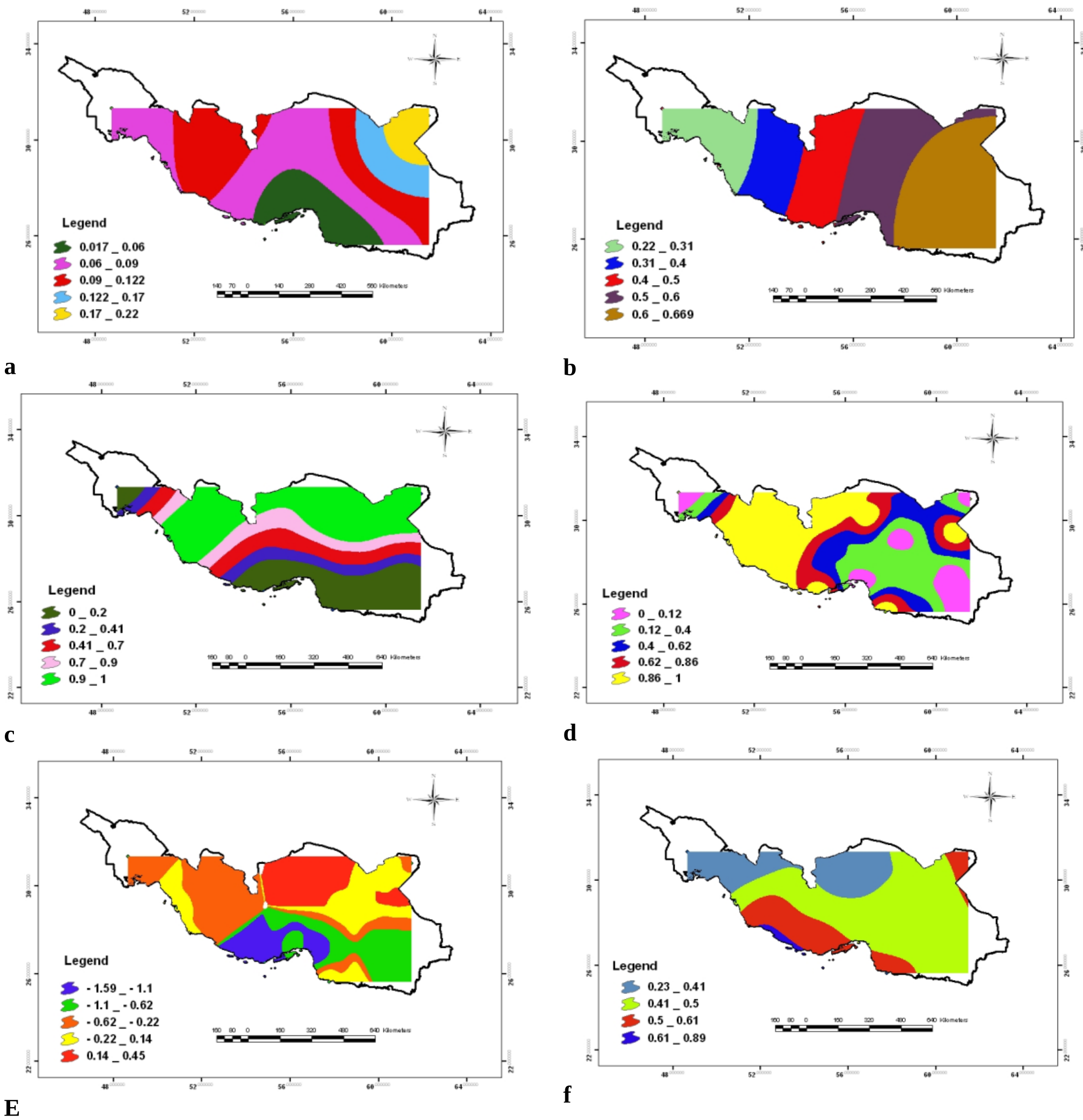

Fig. 2. The best zoning based on RDI index for case study
a= RDI 3 Month(for 1995 year), b= RDI 6 Month(for 1995 year), C= RDI 9 Month(for 1985 year), d= RDI 12 Month(for 1995 year) , e = RDI 18 Month(for 1985 year), f= RDI 24 Month(for 1995 year)

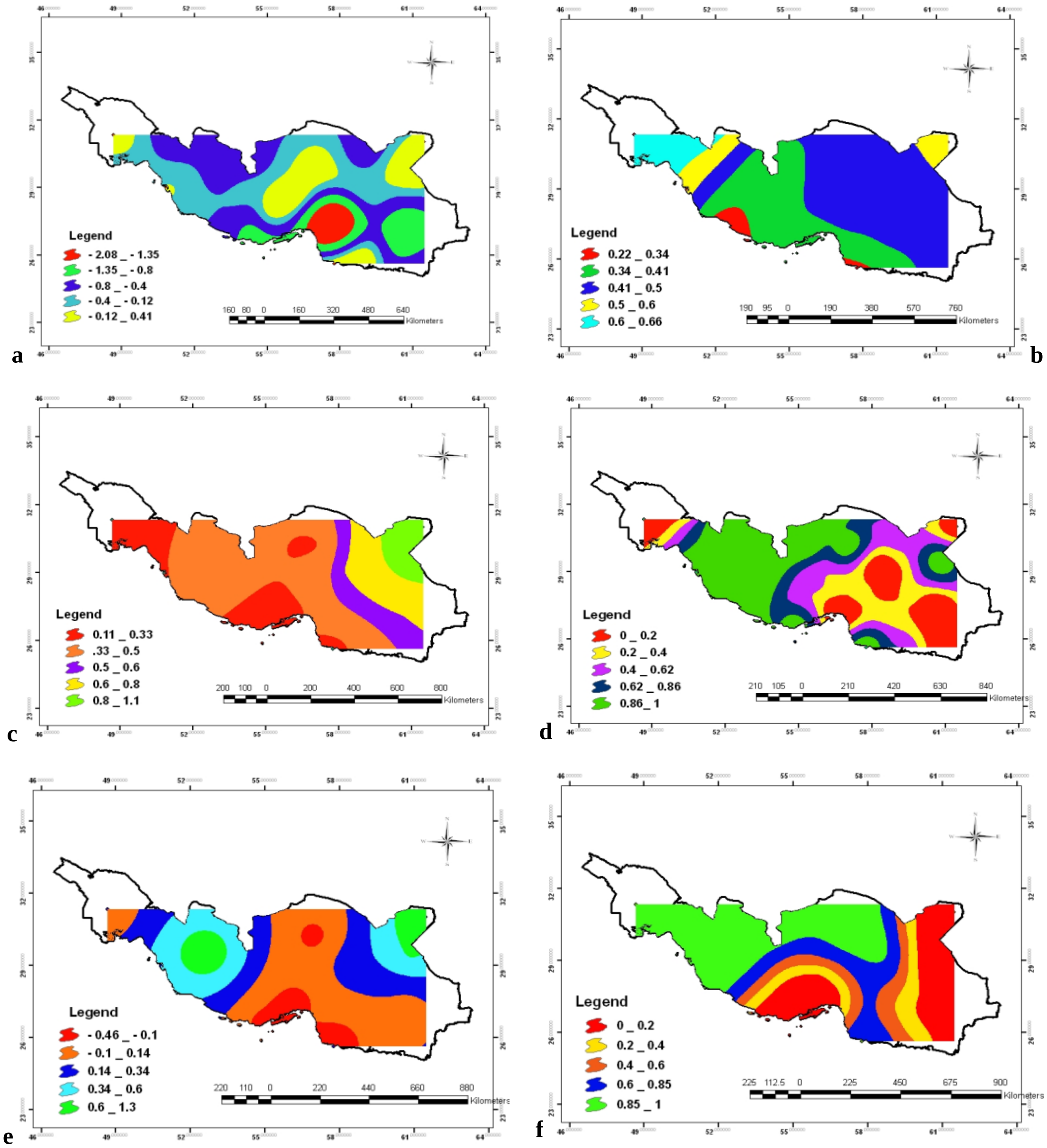

Fig. 3. the best zoning based on SPI index for case study
a= SPI 3 Month(for 1985 year), b= SPI 6 Month(for 1985 year), c=SPI 9 Month(for 2005 year)
d= SPI 12 Month(for 1995 year), e= SPI 18 Month(for 2005 year), f=SPI 24 Month(for 1985 year)

4. Conclusion

From this case study, the following can be concluded:
Rainfall varies spatially and temporally throughout all of southern Iran. An analysis of rainfall at all 12 stations in the state from 1985, 1995, and 2005 revealed a large variation in rainfall, especially in the months of July through October in all years. The minimum and maximum mean rainfall observed during this time period affected the RDI and SPI indices, and minimum and maximum means observed during this time period was about -1.76 to 2.32 for RDI, and -1.92 to 2.13for SPI, and indicates a large variation in distribution of drought at all stations.

Occurrence of drought cannot be monitored by comparing the relative rainfall observed in various stations. To overcome these limitations, the use of SPI and RDI for drought monitoring were highlighted. RDI and SPI were computed

at time-scale 3 for all stations. Further interpolations of SPI and RDI were carried out using various interpolation techniques in order to visualize it spatially. Among all the techniques, i.e. ordinary kriging, simple kriging, indicator kriging, probability kriging, and completely regularized kriging using optimal power function, kriging proved to be best as it gave the least error.
Based on the used error criteria, kriging methods were used for spatial analysis of the drought indices and were selected as the best methods. Adequate and appropriate numbers, the accurate and principled distribution of meteorological stations, and evaluation and assessment have determining roles in the interpolation operation. Thus regions that do not have appropriate distribution or a sufficient number of stations should be the priority for construction of new stations. In several cases, the "moderately dry" class received a more critical value by RDI. The results show that by utilizing the ET0, RDI can be very sensitive to climatic variability. This is rather important, since if the drought analyses are for use in agricultural applications, utilization of the RDI would seem to serve a better purpose.

As the results indicated, the indicator kriging (IK) method with tree frequency is more appropriate for spatial analysis of the RDI index, and probability kriging (Pk) and simple Kriging(SK) methods are more appropriate for spatial analysis of the SPI index. Kriging method mean errors (RMSE) for the selected years for RDI and SPI index are 0.85 and 0.84, respectively. These results are consistent with the findings of other researchers, such as Khalili et al., 2011 in Iran and Diodato, 2005 in southern Italy, and Rusoo et al., 2005 in central Italy.

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