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RESEARCH PAPER

Assessment of spatial interpolation techniques for drought severity analysis in Iran's Salt Lake Basin

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Abstract

Drought risk management requires drought monitoring which is usually carried out by applying different drought indices which are, effectively, continuous functions of precipitation and other meteorological data. However, these indices are estimated at specific locations, and the spatial distribution of drought must be calculated in the form of maps. Geostatistical and deterministic techniques make it possible to interpolate spatially-referenced data. These methods are able to estimate values for arbitrary locations in regions of interest. The current study applied five spatial interpolation methods (inverse distance weighted, global polynomial interpolation, local polynomial interpolation, radial basis function, and kriging [with 4 sub-types]) to extract maps of SPI at 60 rain-gauge stations in the Salt Lake Basin of Iran. Based on the root mean square error, mean absolute error, and mean bias error values of estimations made using sampled data from 1969 to 2009, RBF and kriging techniques were the best and most suitable methods for the spatial analysis of SPI in the study area.

Keywords: Drought monitoring, Standard precipitation index, Geostatistical techniques, Deterministic methods, Salt Lake Basin.

Introduction

Drought as a creeping hazard and reappearing phenomenon is the consequence of a reduction in rainfall and an increase in temperature which begins slowly and may be observed in any climatology condition (Morid, 2006; Shamsipour et al., 2008; Kirono et al., 2011; Azarakhshi et al., 2011; Capra et al., 2013; Zehtabian et al., 2013; Asefjah et al., 2015). In arid and semi-arid regions of the world, such as Iran, precipitation spatio-temporal variability is significant (Dastorani et al., 2011; Naserzadeh and Ahmadi, 2012; Bazrafshan and Khalili, 2013; Shahabfar and Eitzinger, 2013; *Zarei* et al., 2013; Asefjah et al., 2015). Therefore, precipitation pattern changes may cause severe natural disasters such as drought or floods which could influence all parts of an ecosystem and environment. Compared with other natural hazards, many scientists consider drought to be the most complex but least understood phenomenon, which influences the largest number of people (Hagman, 1984; Morid, 2007; Gumus and Algin, 2017). There is no global definition for drought for various reasons, such as large-scale variability both in space and time in the duration of drought consequences. Although, drought have classified by Wilhite and Glantz (1985) into four groups as meteorological (shortage of precipitation); hydrological (decreasing of surface water storage); agricultural (shortage of root zone soil moisture) and socio-economic (shortage of water supply for socio-economic aims).

Drought survey systems allow the monitoring and tracking of various drought effects and can be applied to prepare plans for reducing the consequences of drought. Normally, drought

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monitoring can be done by applying drought indices with time scales. Many indices for monitoring different drought conditions have been developed to characterize drought. Among drought indices, some are most often applied and well-known around the world such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the Deciles Index (Gibbs, 1967), the China-Z Index (CZI) (Wu et al., 2001), the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Aridity Index (Gore et al., 2002), and the Percent of Normal, using Deciles (Gibbs and Maher, 1967). Generally, these indices allow the tracking and evaluation of the beginning and severity of drought events; therefore, it is essential that the spatial and temporal characteristics in different areas are determined and compared (Alley, 1984). Also, the data required by most of these indices is measured at meteorological stations; the values are point measurements, which, of course, are not adequate for studying geographical development and identifying the extent of regions influenced by drought. Thus, for discovery and monitoring purposes, the maps of drought severity must be produced from point measurements to trace geographical drought expansion in the total area. Spatial prediction and uncertainty quantification can be provided by geostatistics, which supplies a coherent structure for this. Spatial prediction or interpolation considers how to evaluate the variable under investigation at a place without observations using data from observations at nearby places. This process of spatial evaluation purposes to discover a single number at the unmeasured site (Jingxiong et al., 2009). Geostatistical assumption is based on a field of statistics which makes possible the derivation of suitable estimations at selected sites in a study area (Wamwling, 2003).

There are a number of geostatistical methods which have been suggested and applied for spatial interpolation of climate parameters, like mapping the drought severity of the region. The oldest and simplest method known as the Thiessen Polygon (TP) method was suggested by Thiessen (1911) and is currently being widely applied (Driks et al., 1998; McCuen, 1998; Goovaerts, 2000). Weighted Moving Average (WMA) (Bedient and Huber, 1992) and geostatistical methods have also been applied for spatial interpolation. Geostatistical approaches are important because of the structure and correlation of spatial data. There is a group of methods such as kriging, co-kriging, kriging with an external drift, Thin Plate Smoothing Spline (TPSS), Radial Basis Functions (RBF), Inverse Distance Weighted (IDW) (Zheng and Basher, 1995), and others that belong to the family of geostatistical approaches.

Many related researches have been done about using geostatistical approaches for interpolation such as Tobies (1985), Pohlman (1993), Price et al. (2000), Goovaerts (2000), Hargrove (2001), Apaydin et al. (2004), Russo et al. (2005), Banejad et al. (2006), Eivazi and Mosaedi (2011), Eyshi Rezaei et al. (2011), Alijani and Yousefi Ramandi (2015). In many studies which have been done the main purpose was comparison between these spatial interpolations.

Matheron (1971) developed the kriging approach. It was used in different areas such as mining engineering (Journel and Huijbregts, 1978), subsurface hydrology, (Delhomme, 1978) and network design of wells (Hughes and Lettenmaier, 1981; Bastin et al., 1984). Tabios and Salas (1985) compared kriging and other available interpolation approaches and introduced the kriging method as the most suitable option. The WMA technique has been applied by other researchers for spatial drought monitoring (Svoboda, 2004; Smakhtin and Hughes, 2007). Some researchers suggest applying a simple multiple linear regression-based model (Loukas and Vasiliades, 2004; Livada and Assimakopoulos, 2007). Vankuienber et al. (1982) applied and compared kriging approaches with weighted average methods to determine the soil moisture in the Netherlands and concluded that kriging was the most suitable alternative. Nalder and Wein (1998) interpolated the monthly spatial and temporal distribution of precipitation in the northern forest of Canada. Their comparison of these methods indicated that the GIDS technique is a more optimal approach than the others.

Durao et al. (2010) applied a direct sequential simulation algorithm to evaluate relationships between spatial and temporal variations of events of extreme precipitation in southern Portugal. The results indicated an increase in the spatial continuity of extreme rainfall patterns in the last 40 years and also explained that spatial variability has decreased. This indicates that extreme rainfall events have a tendency to be more spatially homogeneous. Mozafari et al. (2011) applied Ordinary Kriging, Inverse Distance Weighted and Thin Plate Smoothing Spline to derive maps of drought indices in the south of Iran (Persian Gulf shore) and concluded that the IDW approach is most suitable for the spatial interpolation of SPI and ordinary kriging is most suitable for the spatial interpolation of EDI.

Nohegar et al. (2013) evaluated the severity of droughts applying the kriging and IDW methods in southern Iran. Their results indicated that kriging was the best method. Sadat Noori et al. (2013) determined wet, normal, and dry climatic periods in the study area during 1993–2003 applying SIAP and SPI drought indices. Also, four different geostatistical methods were applied for the interpolation of groundwater levels. The results showed that among the geostatistical methods applied, co-kriging was the best method for interpolation. Alijani and Yousefi Ramandi (2015) indicated that the circle simple kriging model is the best approach for spatial interpolation of drought and wet regions for PNPI, MPNPI, RAI, DRI, MDRI, NICHE, and MNICHE indices in central and northwestern Iran.

The main purpose of the current study was to compare several interpolation approaches, including the Inverse Distance Weighted (IDW), Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI), Radial Basic Function (RBF), and various kriging techniques to determine the most suitable method for interpolating SPI values.

Materials and Methods

The study area

The Salt Lake Basin with a total area of 89650 km2 is one of the major arid and semi-arid watersheds of Iran. It is located in the northwestern part of the Iranian Central Plateau (Figure 1), where the capital of Iran (Tehran) is also located. The geographic situation of this basin is about 48 to 53 °E longitude and 32 to 37 °N latitude. Precipitation varies from about 700 mm in the northern parts to 130 mm in the southern parts of this area (Ensafi Moghadam, 2007). Absolute maximum and minimum temperatures of about 44 °C and -21.5 °C, respectively, have been reported. The study area included both arid and semi-arid climates. In the current study, precipitation data from 60 rain-gauge stations in the basin between the years 1969 to 2009 was applied. Regression equations were applied to fill in the missing data.

Methods

Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is a tool for drought monitoring and can be estimated for several time periods (e.g., one, three, and 24 months) (McKee et al., 1993). Research results have shown that applying SPI to longer time ranges is not recommended as the sample size decreases even with long-term records (Asefjah et al., 2015). Using different timescales provides an evaluation of the consequences of a precipitation shortage on various components of water resources such as stream flow, groundwater, reservoir storage, and soil moisture. Positive and negative values indicate more and less than average precipitation, respectively. This index can be used for monitoring both dry and wet conditions. The "drought" part of the SPI range is divided into "near normal" ($0.99 > SPI > -0.99$), "moderately dry" (−1.0 > SPI > −1.49), "severely dry" (−1.5 > SPI > −1.99), and "extremely dry" (SPI < −2.0) conditions.

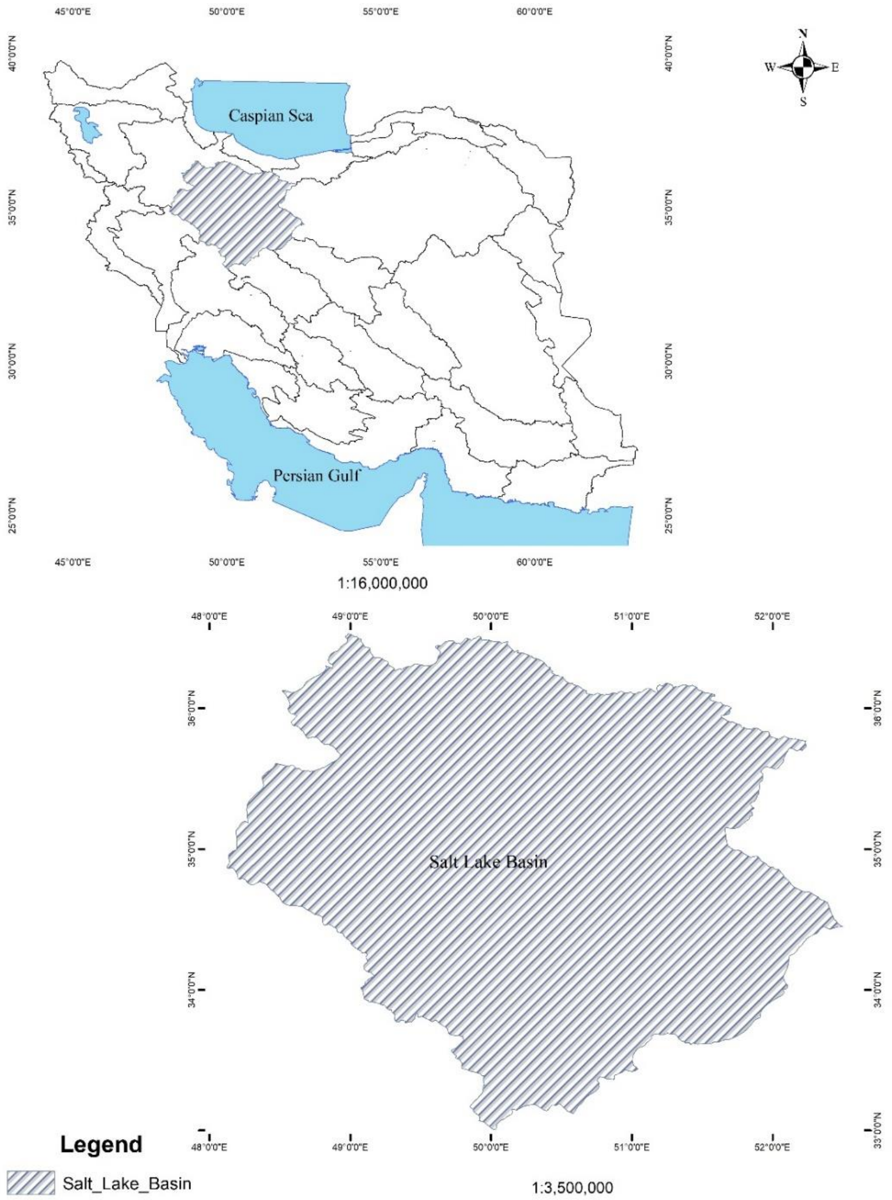


Figure 1. Geographic location of the Salt Lake Basin in Iran

The start and end points of a drought event are when the SPI values become negative and positive again, respectively. There must be no gap in the time series data when calculating SPI. It is recommended that data records should not be less than at least 30 years (Wu et al., 2001), because the drought index ranges are fitted to that period and are also intercomparable with other sites of various climates. Recently, SPI has been widely applied in various drought-related studies for assessing the consequences of climate change on agriculture, hydrology, water resources, and ecosystems (Capra et al., 2013).

Spatial Interpolation Procedures

Interpolation methods are categorized into the two main groups of deterministic and geostatistical methods. Deterministic interpolation methods use either the extent of similarity (e.g., IDW) or the degree of smoothing (e.g., CRS) to prepare maps from sampled locations. An exact interpolator technique, such as IDW and CRS, predicts a value identical to the sampled value at a measured site, while inexact techniques, such as GPI and LPI, predict values that differ from the sampled values and should be applied to avoid sharp peaks or troughs in the output map (Johnston et al., 2001).

Geostatistical interpolation methods apply the statistical characteristics of sampled locations. Geostatistical methods allow for the quantification of spatial autocorrelations among sampled locations and the calculation of the spatial configuration of sample locations near the prediction site (Borga and Vizzaccaro, 1997; Campling et al., 2001; Johnston et al., 2001; Isaaks and Srivastava, 1989; Cressie, 1993; Rivoirard, 1994; Kitanidis, 1997; Chiles and Delfiner, 1999). In this study, spatial interpolation was carried out by applying the following deterministic and geostatistical methods.

- Inverse Distance Weighted (IDW)

The assumption which is implemented in the Inverse Distance Weighted interpolation method is that close objects are more similar than those which are farther. Therefore, based on this assumption, every sampled site has a spatial effect which decreases with distance (Ashraf et al., 1997, Nalder and Wein, 1998; Johnston et al., 2001). IDW predicts the values for unmeasured locations using the observed values around the prediction site. In the inverse distance weighted interpolation method, as in kriging, the weighted average of observed data points within a site near the unmeasured site is the base for predictions of values in unmeasured locations. The interpolation equation is (Burrough et al., 1998):

$$\hat{Z}(x_0) = \frac{\sum_{i=1}^{n} Z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}}$$

(1)

where x_0 is the calculation site and x_i are the nearby sampled sites. The weights (r) concern distance by d_{ij} which is the distance between the calculation site and the measured sites. The equation included the influence of giving relatively large weights to the sampled sites near the interpolation site compared with those sites that are far away and have little effect. The larger the weight applied is, the more effective locations close to x_0 will be given.

- Global polynomial interpolation (GPI)

Global polynomial interpolation (GPI) fits a smooth surface defined by a mathematical function to the input measured sites. In this technique, a slowly changing surface is created and coarse-scale patterns in the data are identified. GPI produces a gradually differing map by applying low-order polynomials which probably explains some of the physical process. Also, the estimated surfaces are completely susceptible to outliers, particularly at the edges (Johnston et al., 2001). First-, second-, and third-order global polynomials (GPs) fit a single plane through data points, a surface with one and two bends in it, respectively. Although, since surfaces have different shapes (slopes and levels), a single GP is not able to fit very well (Johnston et al., 2001).

- Local polynomial interpolation (LPI)

Compared with GPI that fits only a polynomial to the total surface, Local Polynomial Interpolation (LPI) is able to fit several polynomials, everyone within determined overlapping nearby locations. The finding of nearby sites may be defined through the search neighborhood dialog. LPI allows the determination of the maximum and minimum number of sites, the shape, and the sector configuration. It also provides a slider which helps to determine the width of the nearby locations in conjunction with a power parameter that, based on distance, decreases the weights of the sample points within the nearby location (Rajagopalan and Lall, 1998; Johnston et al., 2001). Thus, LPI produces surfaces that account for more local variation (Rajagopalan and Lall, 1998; Johnston et al., 2001).

- Radial Basic Function (RBF)

Radial Basic Function is an interpolation method and a type of artificial neuron network. This method is able to estimate levels past the measured values (Alijani and Yousefi Ramandi, 2015).

- Kriging

Over the last few decades, kriging has become known as the main, basic method of geostatistics (Caruso and Quarta, 1998). This method estimates weights using observed values to predict values at unsampled sites. Unlike IDW interpolation in which the closest sampled values have the most effect, kriging weights are more complicated. In IDW a simple algorithm from distance is the base of the estimation, but kriging applies a semivariogram developed from the spatial structure to calculate the weights. To produce a map of the phenomenon using the kriging method, the semivariogram and the spatial arrangement of sampled values of neighboring sites form the base for predictions of values at the unmeasured location (Collins 1996, Johnston et al. 2001). The current study applied four different kriging methods.

- Ordinary Kriging (KO)

Ordinary kriging is the most general and most widely applied among the kriging methods. It calculates values for unmeasured sites using the observations at nearby locations and a variogram model (Nalder and Wein, 1998; Johnston et al., 2001; Apaydin et al., 2004). Geostatistic must be applied in the presence of a spatial structure where records close to each other are more similar than records that are far apart (Goovaerts, 1999). The experimental variogram estimates the mean rate of dissimilarity between unobserved values and a close observation value (Deutsch and Journel, 1998) and therefore may depict autocorrelation at different distances.

- Simple Kriging (KS)

The simple kriging method applies the average of total values. Compared with ordinary kriging, this method may be less accurate, but it generally creates a smoother map (Apaydin et al., 2004).

- Universal Kriging (KU)

The universal kriging method model trend of data uses a deterministic function like a polynomial. This polynomial result from subtracting the original sampled sites and the random errors applied for the model of the autocorrelation. After fitting the model to the random errors and before the prediction, the polynomial is added back to the predictions so as to get meaningful outcomes (Nalder and Wein, 1998; Johnston et al., 2001).

- Disjunctive Kriging (KD)

Bivariate normality is the fundamental assumption of disjunctive kriging. It is hard to verify and also includes mathematically and computationally complicated solutions. This method can apply either semivariograms or covariances, and it may apply transformations, but it is not able to provide error measurement (Johnston et al., 2001).

Evaluation and Comparison

Cross validation applied is a tool for comparing sampled values with interpolated values. It can provide a selection between various weighting methods, search strategies, or calculation techniques. The measured value at a particular site is removed temporarily from the estimation; then, the remaining samples are applied to calculate the value at the same site. After calculation, the estimated value may be compared with the sampled value that was previously discarded from the measured data. In the current study, all parameters of methods were optimized to ensure minimum cross validation error.

Comparisons between various methods were made using several indices. Four different ways of estimating the mean of errors were applied for the comparisons. These four ways were included mean absolute error (MAE), estimating a value of how far the calculation may be in error, without considering its sign; mean bias error (MBE), a calculation of overall bias error or systematic error; and root mean square error (RMSE), estimating a value which is sensitive to outliers.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \tag{2}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{4}$$

Where P_i is the estimated value, O_i is the sampled value and n is the number of cases.

Results and Discussion

The Standardized Precipitation Index was applied as a tool for monitoring drought phenomena in the study area. Variograms for various months were used to determine whether or not SPI is a spatial variable. To generate the variogram, first a theoretical model of the index was prepared; then, a suitable model was identified from among Circular, Exponential, Gaussian, and Linear models. After that, interpolation techniques were applied for spatial analysis. Finally, the best model was chosen through a comparison of error. In the current study, MAE, MBE, and RMSE were applied to identify the best method. The results indicated that as distance increases, the variance is also increased.

Results also showed that, based on MAE and MBE indices among deterministic methods, RBF and LPI techniques were the best (Table 1). Based on both MAE and MBE indices, the DK technique was identified as the best among kriging methods (Table 2). Comparisons between geostatistical and deterministic methods showed that the kriging method was better than the others (Table 3). Based on the results, the SPI drought index ranking of all kriging methods determined for the years 1987, 1991, 1994, 1996, 1998, and 2007 are shown in Table 4. Results indicated that during most of these years, the DK and OK techniques with Gaussian semivariograms were the best. Annual prediction maps of drought severity were created for 3- and 12-month periods of SPI using 8 interpolation techniques (Figure 2).

Table 1. Assessment of deterministic methods for spatial analysis of SPI drought index

SPI								
	MAE				MBE			
Method	IDW	GPI	LPI	RBF	IDW	GPI	LPI	RBF
1987	0.4797	0.4346	0.4388	0.4445	0.0459	-0.0028	-0.0421	0.0159
1991	0.3580	0.4130	0.4781	0.3536	-0.0097	0.0059	-0.0240	0.0029
1994	0.2867	0.3090	0.3206	0.2809	0.0129	0.0015	-0.0131	0.0176

1996	0.0605	0.0650	0.0695	0.0604	-0.0026	-0.0015	0.0049	-0.0011
1998	0.1028	0.1026	0.1125	0.1030	-0.0136	0.0023	-0.0148	-0.0080
2007	0.1475	0.1479	0.1707	0.1505	0.0051	0.0041	0.0105	0.0056

Table 2. Assessment of geostatistic methods for spatial analysis of SPI drought index

SPI								
	MAE				MBE			
Method	OK	SK	UK	DK	OK	SK	UK	DK
1987	0.4213	0.4166	0.4213	0.8112	0.8091	0.4180	-0.0183	0.0376
1991	0.3602	0.3502	0.3602	0.8800	0.8821	0.3472	0.0166	-0.0185
1994	0.2924	0.3232	0.2924	0.9264	0.9279	0.3037	0.0058	0.0188
1996	0.0633	0.0603	0.0633	0.2946	0.2961	0.0593	-0.0041	0.0003
1998	0.1032	0.1005	0.1032	0.3120	0.3199	0.1019	-0.0031	-0.0073
2007	0.1511	0.1322	0.1511	0.3075	0.2819	0.1298	0.0083	-2.70E-13

Table 3. Assessment of geostatistic and deterministic methods for spatial analysis of SPI

SPI										
	MAE					MBE				
Method	IDW	GPI	LPI	RBF	kriging	IDW	GPI	LPI	RBF	kriging
1987	0.4797	0.4346	0.4388	0.4445	0.4180	0.0459	-0.0028	-0.0421	0.0159	-0.7690
1991	0.3580	0.4130	0.4781	0.3536	0.3472	-0.0097	0.0059	-0.0240	0.0029	-0.8708
1994	0.2867	0.3090	0.3206	0.2809	0.3037	0.0129	0.0015	-0.0131	0.0176	-0.9181
1996	0.0605	0.0650	0.0695	0.0604	0.0593	-0.0026	-0.0015	0.0049	-0.0011	0.2893
1998	0.1028	0.1026	0.1125	0.1030	0.1019	-0.0136	0.0023	-0.0148	-0.0080	0.3151
2007	0.1475	0.1479	0.1707	0.1505	0.1298	0.0051	0.0041	0.0105	0.0056	0.2345

Table 4. The Assessment of geostatistic methods for spatial analysis of SPI drought index during 1987, 1991, 1994, 1996, 1998 and 2007

SPI	Year	Model	Semivariogram	RMSE
	1996	SK	Circular	0.0974
3 months	1998	DK	Gaussian	0.1325
	2007	SK	Gaussian	0.2332
	1996	DK	Circular	0.0974
12 months	1998	DK	Gaussian	0.1623
	2007	OK	Spherical	0.2252
	1987	OK	Gaussian	0.3593
3 months	1991	DK	Circular	0.2268
	1994	OK	Gaussian	0.3402
	1987	OK	Gaussian	0.4663
12 months	1991	DK	Spherical	0.5038
	1994	OK	Spherical	0.4703

Inverse distance weighted

Results showed that IDW did not have the lowest RMSE, MAE, and MBE values (Tables 3 and 5). Depending upon the sampled data, the pattern of IDW was very changeable (Fig. 2a). When the data were sparse, IDW showed improbable results. As noticed before by Johnston et al. (2001), adhering to the observed range of data was an advantage of IDW. The results of other studies have indicated that IDW was only suggested by Dirks et al. (1998).

Global polynomial interpolation

Results of the current study indicated that GPI had the poorest outcome. It had the lowest MBE values during the years 1987, 1996, and 2007 (Tables 3 and 5). The GPI pattern included almost straight lines, and its variability was small (Fig. 2b). This technique may produce suitable results for slowly varying surfaces, but in the current study area, significant changes were observed from site to site.

Local polynomial interpolation

The LPI method showed different results. Based on MAE and MBE values, this method had the poorest and best results, respectively (Tables 3 and 5). The pattern generated by the LPI method was similar to that of GPI, but it had greater variability (Fig. 2c). Because it determined smaller areas with many polynomials rather than total area, the LPI method generated equal or smaller error rates than those of GPI. Therefore, this method was determined not to be a suitable method for the study area, and it cannot be recommended.

Kriging

The results indicated that most of the four kriging methods had minimum values of MAE and MBE; however, the UK and SK techniques showed more low values of MAE and MBE than the others (Table 2). The study results of Tabios and Salas (1985) for precipitation interpolation in the central USA indicated that the UK method produced lower MAE than the KO technique, but in a study by Apaydin et al. (2004) and the current research, similar MAE values were generated. The results of Goovaerts (2000) indicated that KO generated the most accurate rainfall values. In the study area, the SK method produced the lowest MAE values. The patterns produced by KO and KU were similar to those of the IDW and RBF techniques (Figs. 2e and 2g). Apaydin et al. (2004) compared various interpolation techniques for different regions and found that the KO and KU methods were similar to the LPI method.

Radial Basic Function

The RBF method also showed different results. Based on MAE and MBE values, it showed the best and poorest results, respectively (Table 3). The pattern generated by the RBF method was similar to that of IDW, but its variability was lower (Fig. 2d). Based on the results of the geostatistical method assessment for spatial analysis of SPI, MAE, and RMSE values in the study area for 1994, the RBF method was determined to be the best technique (Table 5).

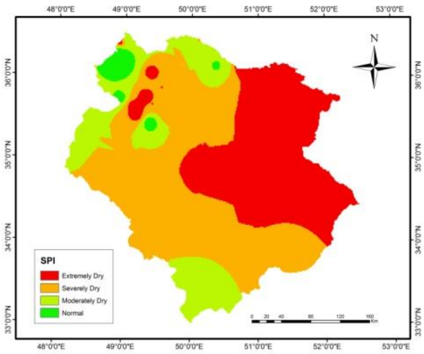
Table 5. Assessment of geostatistic and deterministic methods based on RMSE, MBE and MAE for spatial analysis of SPI drought index in 1994

Indices Method	RMSE	MBE	MAE
IDW	0.4523	0.0129	0.2867
GPI	0.4929	0.0015	0.3090
LPI	0.5155	-0.0131	0.3206
RBF	0.441	0.0176	0.2809
OK	0.4703	0.0060	0.2917
SK	0.5163	0.0185	0.3229
UK	0.4703	0.0060	0.2917
DK	0.4961	-0.0114	0.3099

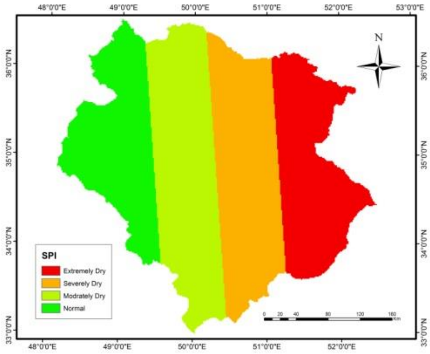
Conclusion

This study aimed to identify the best method (lowest cross validation error) for spatial interpolation of SPI using kriging, Inverse Distance Weighted (IDW), Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI), and Radial Basic Function (RBF) methods in the Salt Lake Basin of Iran for the years 1969 to 2009. Based on the results of this research, the following conclusions have been made:

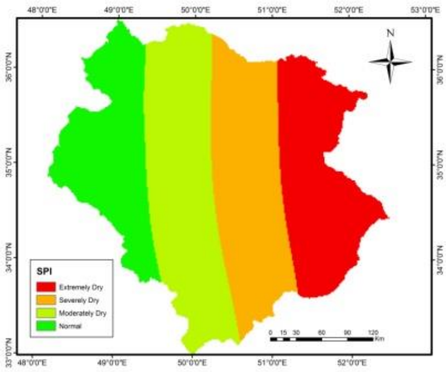
The best method for spatial analysis of drought was determined using the results of error criteria. The results indicated that based on MAE and MBE values, that UK among kriging methods and RBF and GPI among deterministic techniques are the most suitable for spatial analysis and interpolation of SPI. The results showed that nearby locations had an important effect on MAE and MBE values in IDW methods. Therefore, the results will change when different nearby locations are used. The results illustrated that better outcomes will be achieved when more nearby locations are used. A suitable spatial analysis and phenomena assessment were completely dependent upon the number and distribution of sampled locations.



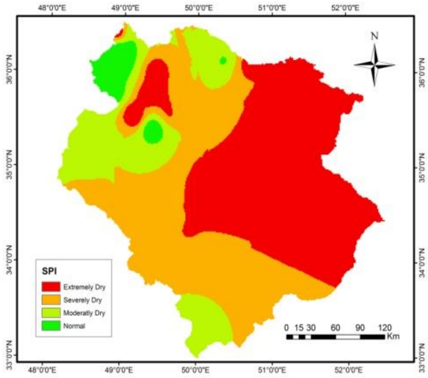
IDW (a)



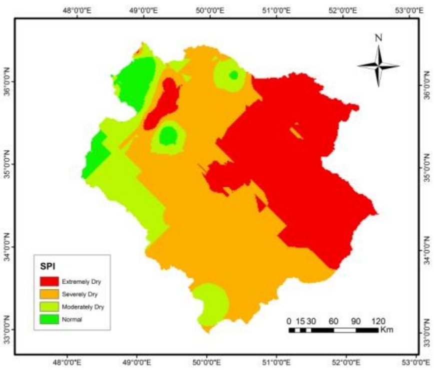
GPI (b)



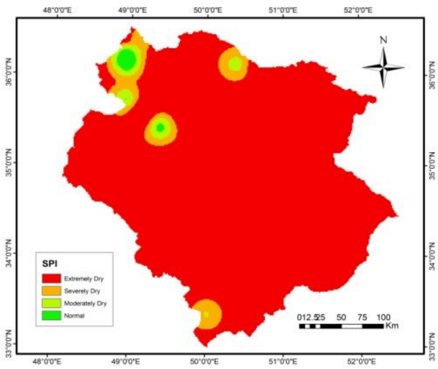
LPI (c)



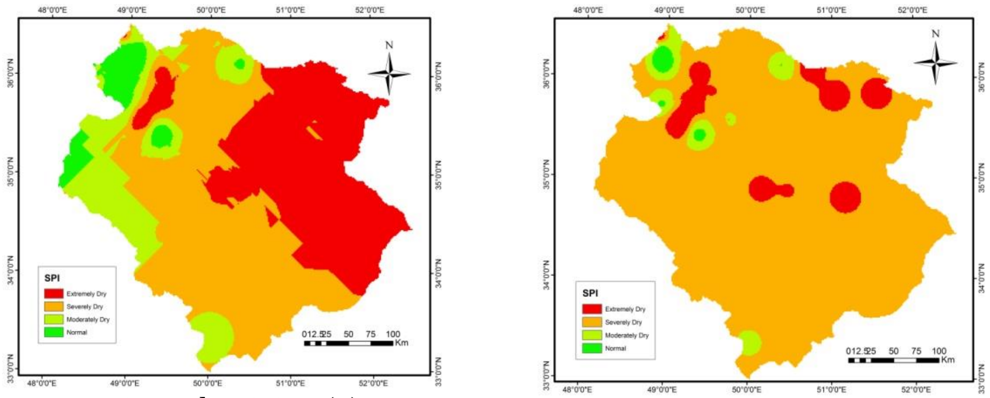
RBF (d)



Ordinary Kriging (e)



Simple Kriging (f)



Universal Kriging (g) Disjunctive Kriging (h)

Figure 2. The SPI interpolation maps for 1996 year based on various Methods

The ecological and environmental importance of the Salt Lake Basin of Iran will increase with the implementation of regional development projects. Spatial analysis and interpolation techniques provide for the prediction of climate-dependent variables for catchment assessment and management, soil–plant–water interaction studies, and crop growth modeling; however, temporal and spatial measurements of meteorological variables are not yet completely suitable in some parts of the study area.

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