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Spatio-Temporal Analysis of Drought Severity Using Drought Indices and Deterministic and Geostatistical Methods (Case Study: Zayandehroud River Basin)

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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 interpolation 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) techniques were assessed for the derivation of maps of drought indices at 19 climatic stations in Zayandehroud River Basin of Iran. Monthly rainfall data of period 1989 to 2013 were taken from 19 meteorological stations. The results showed that based on the used error criteria, kriging methods were chosen as the best method for spatial analysis of the drought indices and also, the lowest error (RMSE) and R^2 is related to the kriging method. The results showed that SK and OK were more suitable for the spatial analysis of the Z-Score Index (ZSI) and the Standard Precipitation Index (SPI) index. The mean errors (RMSE) of kriging methods for ZSI and SPI indices were 0.40 and 0.19 respectively.

Keywords: Drought; Spatial analysis; ZSI; SPI; Zayandehroud

1. Introduction

Drought as a creeping hazard and complex natural phenomenon has significant effects on water resource management (Bazrafshan and Khalili, 2013). Generally, 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 (Jeyaseelan, 1999; Bhuiyan, 2004; Azarakhshi, *et al.*, 2011; Dastorani and Afkhami, 2011; Morid *et al.*, 2006; Nohegar *et al.*, 2013; Zarei *et al.*, 2013; Asefjah *et al.*, 2014). Wilhite and Glantz (1985) classification suggested four categories of droughts that could be determined as meteorological, hydrological, agricultural, and socio-economic drought which, respectively, are the negative departure of precipitation from the normal precipitation, the shortage in surface and subsurface water supplies, lack of soil moisture needed for the development of a special crop, and the failure of water resources to get the water demands over a period of time.

Beran and Rodier (1985) and Panu and Sharma (2002) suggested that it is possible to estimate well the probable timing of drought inception and termination reasonably during a short period. The consequences of drought depend on social vulnerability at the time the drought occurs.

Many different drought indices have been introduced and used as drought monitoring tools

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at different parts of the world (Asefjah *et al.*, 2014); the estimation of most of these indices are done based on climate data (rainfall, or temperature). These indices make it possible to track and evaluate drought events beginning and severity; therefore, it is important to determine and compare the spatial and temporal characteristics between different areas (Alley, 1984). The aim of regionalizing the displayed data is to provide a map to demarcate growth areas (Jansen *et al.*, 2002). Among a large number of interpolation algorithms, geostatistic and deterministic methods are widely applied. Geostatistical theory is based on a stochastic model which allows optimal estimations at arbitrary locations in the selected area (Wamling, 2003). There are a group of techniques such as kriging, cokriging, and kriging with an external drift, Thin Plate Smoothing Spline (TPSS), Radial Basis Functions (RBF) etc. (Zheng and Basher, 1995), which belong to the geostatistics approaches family. Many related studies have been done on applying geostatistics techniques for interpolation such as Price *et al*. (2000), Apaydin *et al*. (2004), Russo *et al*. (2005), Banejad *et al*. (2006), Eivazi and Mosaedi (2011), and Alijani and Yousefi Ramandi (2015). In most of these researches, the main objective was comparing these spatial interpolations.

For spatial drought monitoring, some researchers applied the WMA method (Smakhtin *et al.*, 2007; Svoboda, 2004), and some authors suggested simple multiple linear regression-based models (Loukas *et al.*, 2004; Livada and Assimakopoulos, 2007).

The precipitation spatio-temporal variability is significant in arid and semi-arid regions of the world, such as Iran, (Naserzadeh and Ahmadi, 2012; Shahabfar and Eitzinger, 2013; Zarei *et al*., 2013; Asefjah *et al*., 2014). Thus, the current study assessed kriging (K) techniques and inverse distance weighted (IDW) method to identify the optimum method for SPI and ZSI indices. The main objective was to identify drought occurrence periods and intensities across Zayandehroud River Basin, Iran, by various drought indices, comparing various drought indices and developing a drought zone scheme of the study area via IDW and kriging methods.

2. Materials and Methods

2.1. Study Area

The Zayandehroud River Basin is located in the central part of Iran with geographical coordinates of longitude 52º1'-52º7' E and a latitude 32º36'-32º40' N (fig.1). The maximum precipitation of the basin occurs during winter in January and February and the minimum in summer in July and August. The average annual precipitation is 105.84 mm and the average annual temperature is over 14.9°C. The average evaporation is 2219.3 mm and it includes an arid and semi-arid climate. In current research the precipitation records from 19 rain gauged stations in the basin have been applied (Table 1). The record length at these stations is from 1989 to 2013. The regression equations with the nearest suitable station were applied for the estimation missing data.

2.2. Drought Indices

The Standardized Precipitation Index (SPI), one of the most widely applied drought indices, was developed by McKee *et al.* (1993). Quantities and descriptive features of this index are indicated in Table 1. SPI was calculated by GIS software's (Rossi *et al.*, 2007). Many researchers have carried out drought severity evaluation such as Edossa *et al.* (2010), Pandey *et al.* (2010), Vasiliades *et al.* (2010), and Vangelis *et al.* (2010). In this study, the Z-score index as an alternative meteorological drought index was applied using the following equation:

$$SPI = \frac{Pi - \bar{P}}{S} \quad (1)$$

Where S is the standard deviation; P is the mean monthly precipitation, and P_i is precipitation in a specific month. Higher value of this index shows more severe drought. Since the standardized ZSI and SPI are performed in similar manners (McKee *et al.*, 1993), they have similar interpretations of results. Thus, the ZSI values could be compared with the same thresholds as that of the SPI method (Table 2).

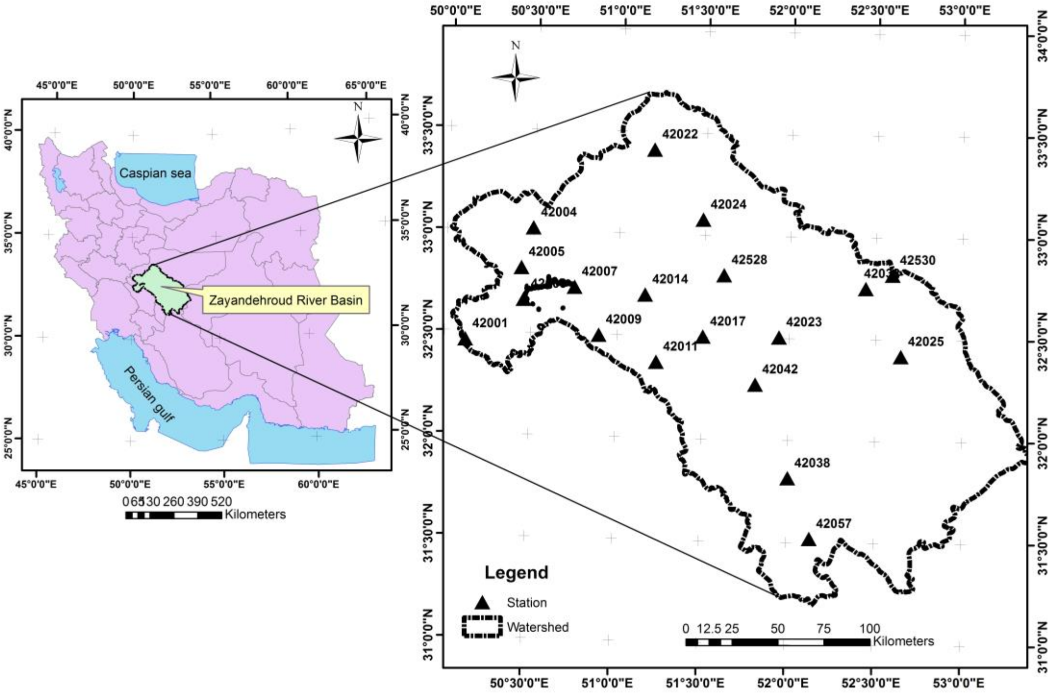

Fig. 1. Geographic location of the Zayandehroud River Basin in Iran

Table 1. General characteristics of the studied rain gauged stations

Station	X coordinate	Y coordinate	Altitude (m)	P (mm)	Climatic classification
Chelgerd	50.1	32.5	2372	1399.5	Very humid
Ghale Shahrokh	50.5	32.7	2109	397.4	Mediterranean
Damaneh Faridan	50.5	33.0	2388	358.6	Semi-Arid
Eskandari	50.4	32.8	2172	390.5	Mediterranean
Zayandehroud Dam	50.7	32.7	2173	229.4	Semi-Arid
Zamankhan Bridge	50.9	32.5	1880	347.6	Semi-Arid
Kaleh Bridge	51.2	32.4	1771	185.7	Semi-Arid
Tiran	51.2	32.7	1890	169.7	Arid
Zafreh	51.5	32.5	1648	147.0	Arid
Vazvan	51.2	33.4	2013	157.6	Arid
Ziar Brovan	51.9	32.5	1559	106.9	Arid
Morcheh Khort	51.5	33.1	1694	110.2	Arid
Varzaneh	52.6	32.4	1495	90.1	Hyper Arid
Koohpayeh	52.4	32.8	1910	118.8	Hyper Arid
Maghsoodbeyk	52.0	31.8	1991	114.5	Hyper Arid
Mahyar	51.8	32.3	1686	140.8	Arid
Izadkhast	52.1	31.5	2217	155.6	Arid
Jafar abad	51.6	32.8	1582	154.9	Semi-Arid
Harizeh	52.6	32.8	2162	157.5	Semi-Arid

Table 2. Classification of drought according to the SPI and ZSI_{st} values

State	Range	SPI and ZSI_{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

2.3. Spatial Interpolation Techniques

Deterministic and geostatistical procedures are the two main interpolation techniques. Geostatistics was initially used in mineral mining and is recently applied in many disciplines such as hydrogeology, hydrology, meteorology, and epidemiology. The prefix geo is generally associated with geology, owing to its origination from mining (Majani, 2007). Two methods for drought index mapping at different spatial units are outlined in the next section.

A spatial distribution map was created by geostatistics and deterministic methods in Arc GIS. Kriging and IDW techniques were applied to analyze the spatial variation of drought index and to generate the drought severity zoning in the study area.

The IDW method estimates the values of non-observed data sites by weighting observations based on their distance from non-observed data sites (Shepard, 1968). In order to predict a value for any unsampled location, the IDW method applies the observed data around the estimation site. The IDW formula gives data sites close to the interpolation point relatively large weights, but those far away exert little influence.

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

$$Z(s_i) = m + e(si) \tag{2}$$

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, 1993). In particular, in the UK (Ver Hoef, 1993), such a trend can be modeled as a linear function in p explanatory variables (climatic, geographical, and topographical covariates) and p unknown constants βj, which yield for the observation at Si:

$$Z(s_i) = \sum_{j=1}^{p} xi(si)\beta j + s(si) \tag{3}$$

Here, Xj (si), *j* = 1. .. *P* represents covariates values sampled 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 one (sj), i ≠ j =1, . . , n.

While kriging is the most popular as the best linear unbiased (spatial) predictor (BLUP), there are issues of non-stationarity in real-world data-sets which may limit its applications. Rather than using the UK with a trend function modeled via a set of covariates, some researchers (such as Agnew and Palutikof, 2000; Ninyerola *et al*., 2000; Antonic *et al*., 2001) have suggested a simpler method based on RK, i.e. 'kriging after de-trending' where the trend function and evaluated residuals are modeled separately.

Indicator variograms were calculated and indicator kriging performed applying the Auto-IK approach of Goovaerts (2009).

2.4. Evaluation and comparison Criteria

Various methods of interpolation based on cross-validation were investigated and evaluated. In these techniques, one point was temporarily removed, and by applying the desired interpolation, the value for that point was calculated, so the deleted amount return instead of itself and for the rest of points is done this calculated. Considering survey amounts and drought intensity estimated through ZSI and SPI, the best zoning and spread drought by assist ones of interpolation methods with minor errors was accomplished for the three driest years, 1999, 2004, and 2009. The most appropriate technique for drought severity interpolation was determined based on the estimated values of the correlation coefficient (R^2) and Root Mean Squared Error (RMSE) indices.

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

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

3. Results and Discussion

3.1. Comparison of interpolation techniques

The estimation values of correlation coefficients of SPI and ZSI for each station and each time scale are provided in Table 3. All the interpolators applied for SPI were compared on the basis of correlation coefficient (R^2) and 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) techniques, were estimated applying optimal power function. The ranking of all interpolation techniques during the three driest years of 1999, 2004, and 2009 are shown in Tables 4 and 5. Among the various criteria of spatial interpolation, the extent of the study area also played a key role. Similar results were obtained by Collins (2000) who compared various interpolation techniques for different regions (region 1 had large spatial extent, and region 2 was small). Kriging, using optimal power consistently, gave better results compared with other techniques.

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

	Station	Time scales	
		3 month	12 month
1	Chelgerd	0.41	0.49
2	Ghale Shahrokh	0.55	0.53
3	Damaneh Faridan	0.25	0.29
4	Eskandari	0.64	0.61
5	Zayandehroud Dam	0.42	0.50
6	Zamankhan Bridge	0.54	0.53
7	Kaleh Bridge	0.25	0.29
8	Tiran	0.63	0.61
9	Zafreh	0.45	0.52
10	Vazvan	0.55	0.53
11	Ziar Brovan	0.25	0.29
12	Morcheh Khort	0.60	0.58
13	Varzaneh	0.39	0.47
14	Koohpayeh	0.56	0.52
15	Maghsoodbeyk	0.26	0.31
16	Mahyar	0.66	0.63
17	Izadkhast	0.44	0.46
18	Jafarabad	0.46	0.46
19	Harizeh	0.47	0.49

The best zoning was identified for years with drought intensity in which of periods (Tables 4 and 5). The results showed that IK technique with tree frequencies is more suitable for spatial analysis of the ZSI index, and PK and SK methods are more suitable for spatial analysis of the SPI index. Kriging method mean errors (RMSE) for the selected years for ZSI and SPI indices were 0.85 and 0.84, respectively. These results are consistent with the findings of Khalili *et al*., (2011) in Iran, Diodato (2005) in southern Italy, and Rusoo *et al*. (2005) in central Italy.

Table 4. The Assessment of interpolation techniques for spatial analysis of ZSI drought indices during 1999, 2004 and 2009

ZSI	Year	Model	MODEL	R^2	RMSE
3 Month	1999	OK	Gaussian	0.459	0.553
	2004	OK	Gaussian	0.446	0.563
	2009	OK	Circular	0.455	0.553
12 Month	1999	SK	Gaussian	0.487	0.405
	2004	SK	Circular	0.483	0.422
	2009	SK	Gaussian	0.478	0.409

Table 5. Assessment of interpolation techniques for spatial analysis of SPI drought indices during 1999, 2004 and 2009

SPI	Year	Model	MODEL	R^2	RMSE
3 Month	1999	SK	Circular	0.32	0.1951
	2004	SK	Exponential	0.62	0.245
	2009	OK	Gaussian	0.61	0.3131
12 Month	1999	OK	Gaussian	0.56	0.3048
	2004	SK	Gaussian	0.61	0.2653
	2009	SK	Circular	0.54	0.3031

Table 6 shows the drought years with the best zoning and less errors. Classifications for each driest year's values for the 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.

Table 6. The best zoning during the driest years based on ZSI and SPI indices

ZSI		Range Drought	Drought classes	SPI		Range Drought	Drought classes
3 Months	2009	-0.232	Near normal	3 Months	2009	-0.465	Near normal
12 Months	2009	-0.983	Near normal	12 Months	2004	-1.205	Moderately dry

After spatial analysis of the interpolation techniques, these techniques were evaluated in two ways. The evaluation criteria in the first method are the error criteria (RMSE) and R2. Table 6 shows the estimated amount of error and deviation values of these techniques versus the real values. For SPI and ZSI indices, the lowest error (RMSE) was related to the kriging method. In all periods, this method had more accurate calculations for other years. The highest volatility of RMSE was related to the IDW method. Therefore, if R2 is considered a major factor for selecting methods, the kriging method can be introduced as a better method. Even if the same time to be consider the both error criteria for optimization method, kriging method is known as the best method. For methods analysis of ZSI index was determined that Kriging method can be a good estimation of this index in unknown points with least error (RMSE).

The spatial distribution pattern of annual analysis has been showed in fig. 26 (a-d). In Fig. 2, part a for SPI 3 months and part b for SPI 12 month, part c and d for ZSI 3 and 12 months show spread severity of drought located in north and western north of study region.

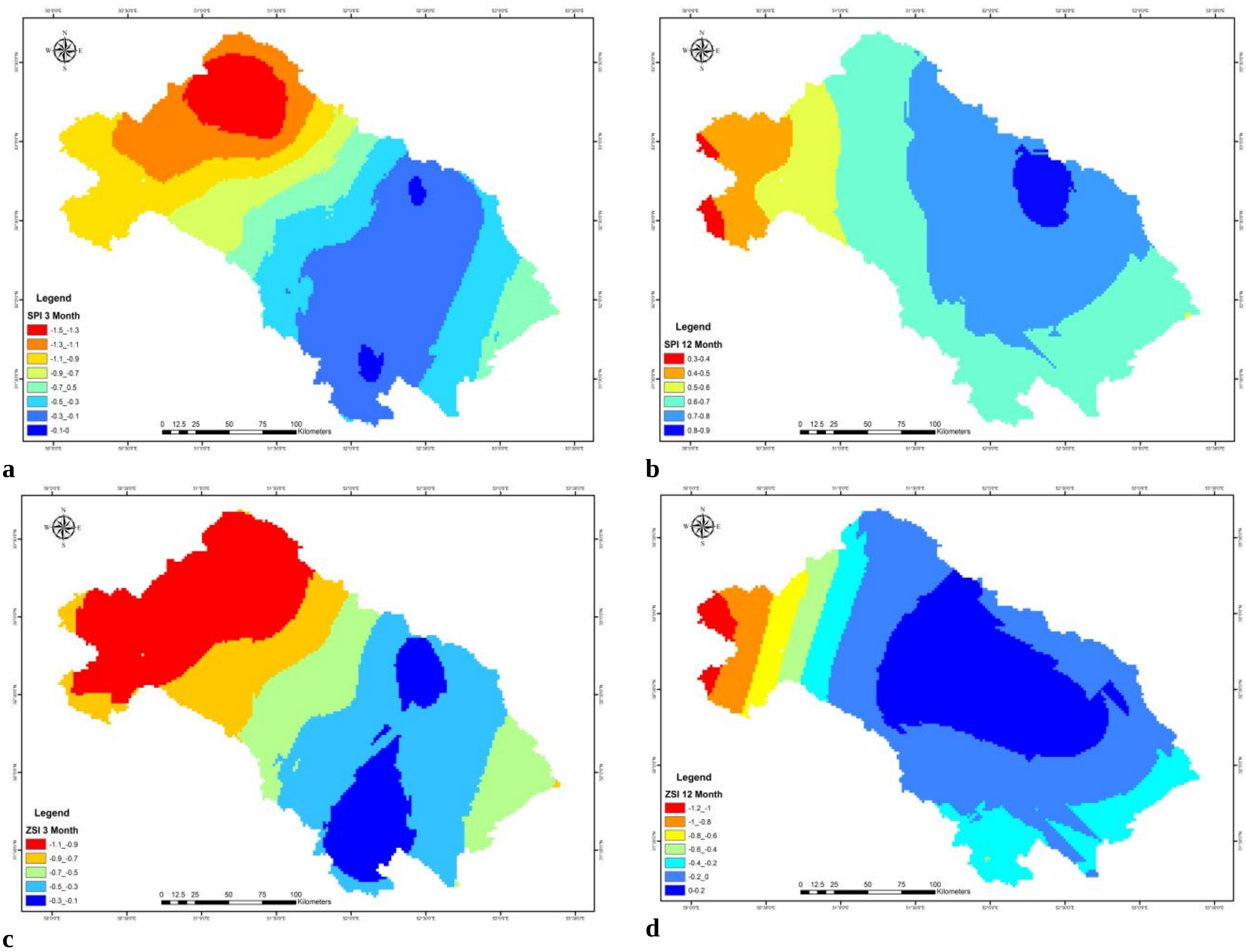

Fig. 2. The best zoning based on SPI and ZSI indices in the study area
a= SPI 3 Month (2009), b= SPI 12 Month (for 2009), C= ZSI 3 Month (2009), d= ZSI 12 Month (2009)

4. Conclusion

Current research was carried out to determine the best technique (lowest cross validation error) for spatial interpolation of SPI and ZSI drought indices using of kriging and Inverse Distance Weighted (IDW methods in the Zayandehroud River Basin of Iran for 1989 to

2013. Based on the results of this study followed conclusions have found.

The best method for spatial analysis of the drought was identified applying the results of error criteria. The results showed that based on R^2 and RMSE values, among kriging methods, SK identified as the appropriate technique for spatial analysis and interpolation of SPI index. The results showed that close locations had important effect on values of R^2 and RMSE in IDW technique. Thus, results will change using different close sites. Obtained results showed that better outcomes will receive using more close sites. An appropriate spatial analysis and phenomena assessment were completely depended on number and distribution of sampled locations.

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

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