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Original article

Spatial Distribution of Some Soil Properties, Using Geostatistical Methods in Khezrabad Region (Yazd) of Iran

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Abstract

Soil is an important compartment of the environment that is particularly easy to compromise, sensitive to short and long-term pollution and directly affects sustainability of ecosystems and human health. A prerequisite of ecosystem management decisions is monitoring of the spatial distribution of soil characteristics that geostatistics methods are one of the most advanced techniques. In the present study, kriging, cokriging and IDW methods were used for prediction of spatial distribution of salinity, water at saturation percentage, sodium adsorption ratio and percentage of sand, silt and clay in soils of Khezrabad region in Yazd province of Iran. After data normalization, the variograme was developed. For selecting the best model for competing on experimental variograme, the lower RSS value was used. The best model for interpretative was selected by means of cross validation and error evaluation methods, such as RMSE method. The results showed that kriging and cokriging methods were better than IDW method for prediction of soil properties. Moreover, soil texture and saturation percentage were better predicted by kriging method, where on, soil salinity and sodium adsorption ratio were better determined by cokriging method. The sum of Ca^{2+}+Mg^{2+} and Na^{+} concentration which were highly correlated with soil salinity and sodium adsorption ratio, respectively, are used as auxiliary parameters in this study. Finally, the soil characteristics maps were prepared, using the best interpolation method in GIS environment.

Keywords: geostatistic, interpolation, soil properties, spatial distribution

1. Introduction

Variability is one of the intrinsic characteristics of the soil quality. Within an ecosystem, soil properties may show vast spatial variations.

These variations are mainly arising from factors and processes of pedogenesis and land use [16]. Many studies showed that there were strong spatial variations in soil properties [14].

Hence, geostatistical methods can be used for better understanding of spatial variations of the soil characteristics.

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Today different geostatistical techniques being widely used for prediction of spatial variations of the soil properties. Hosseini et al. [8] showed that the kriging and cokriging methods were suitable for estimating of soil salinity (EC) level and sodium adsorption ratio (SAR) in Alberta region, respectively.

Mohammadi [12] determined some of the topsoil properties including salinity, water at saturation percentage, sodium adsorption ratio and percentage of lime using geostatistical predictors and TM sensing-numerical information as a secondary variable. Results showed that geostatistical predictors had relative superiority to the equations having linear correlations. Also, kriging method was as a superior technique for estimating of spatial variations of the soil characteristics. Sokooti-Oscooei et al. [18] found that the kriging method with the gaussian model had higher accuracy for estimating of salinity levels in areas without any information. McBratney et al. [10] provided the comprehensive maps for physical, chemical, and biological soil properties by means of geostatistic methods, GIS and remote sensing techniques for vast areas of Australia. Meul and Van Meirvenne [11] used four techniques including the ordinary kriging, comprehensive kriging, simple kriging and cokriging methods for estimating of the silt content in Belgium. They also used digital elevation model (DEM) as a secondary variable. Results showed that the comprehensive kriging method had the lowest estimating error. Ersahin [5] used soil bulk density as an auxiliary variable in cokriging method to investigate the spatial variations of infiltration rate in North West of Tookat of Turkey. Results illustrated that the cokriging method was a suitable technique for estimating of infiltration rate. Robinson and Metternicht [14] used three different geostatistical techniques including IDW, cokriging and spilain methods for predicting of the levels of soil salinity, acidity and organic matter south west of Australia. Results showed that the cokriging, and spilain methods were the best techniques for estimating of soil salinity level and organic matter contents. Also, IDW method was suitable for predicting of soil acidity level. The present study was therefore, carried out with objectives to evaluate accuracy of different techniques including kriging, cokriging and IDW methods for prediction of spatial distribution of soil salinity, water at saturation percentage, sodium adsorption ratio and percentage of sand, silt and clay in soils of Khezrabad region in Yazd province of Iran.

2. Material and Method

Study area. The study area is located in the western south part of Yazd-Ardakan plain between 31°, 52′ to 32°, 12′ in northern latitude and 53°, 48′ to 54°, 08′ in eastern longitude as a rectangular shape. This area reaches to Shirkooh mountain range from western south direction and Yazd-Ardakan road from eastern north direction and is located in the Yazd providence of Iran (fig. 1). The dominant landforms of the study area consist of two main types: plains and mountains. The maximum elevation of the region is 2783 m a. s. l. and the minimum elevation is 1131 m a. s. l. The area is characterized by arid cold conditions. The annual total rainfall varies between 100 and 134 mm. The mean monthly temperature of the region is 13.2°C. The study area is located in the EW Slope with mean slope value of 6%. Soils moisture and temperature regimes are Aridic and Thermic, respectively. Based on American taxonomy comprehensive system (USDA 2003), these soils were classified as Haplogypsids Typic and Typic Torriorthents.

Sampling. For sampling, the classified randomized sampling method was used. In this method one of the plant types were considered as a separate plant communication and hence, in each of the plant communications randomized sampling carried out [7]. After identification of existing plant communications in the region, in each of the plant types some soil samples were taken from depths of 0 - 20 cm. due to scarce diversity of plant cover in the region just 24 samples were taken form the region. After transportation of disturbed soil samples to laboratory the samples were air-dried at room temperature and then, squashed. The dry samples were ground to pass through a 2 mm sieve. Although, in some of the experiments such as the determination of percentage of organic matter the soil samples passed through a 70 mesh sieve (having diameter less than 0.5 mm) were used. The majority of laboratory studies were performed according to Methods of Soil Analysis presented by Sparks et al. [20].

Spatial prediction methods. Geostatistical prediction includes two stages which is first identification and modeling of spatial structure. At this stage continuity, homogeneity and spatial structure of a given variable is studied using variogram. Second stage is geostatistical estimation using kriging technique which depends on the properties of the fitted variogram which affects all stages of the process. The geostatistical methods used in the present study were: (1) kriging, (2) cokriging and (3) IDW.

1.Kriging: 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 [6, 14]. The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value [3], and thus can depict autocorrelation at various distances. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at $Z(xi)$ and the value at $Z(xi + h)$ [9, 14] (Equation 1):

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [Z(xi) - Z(xi + h)]^2 \quad (1)$$

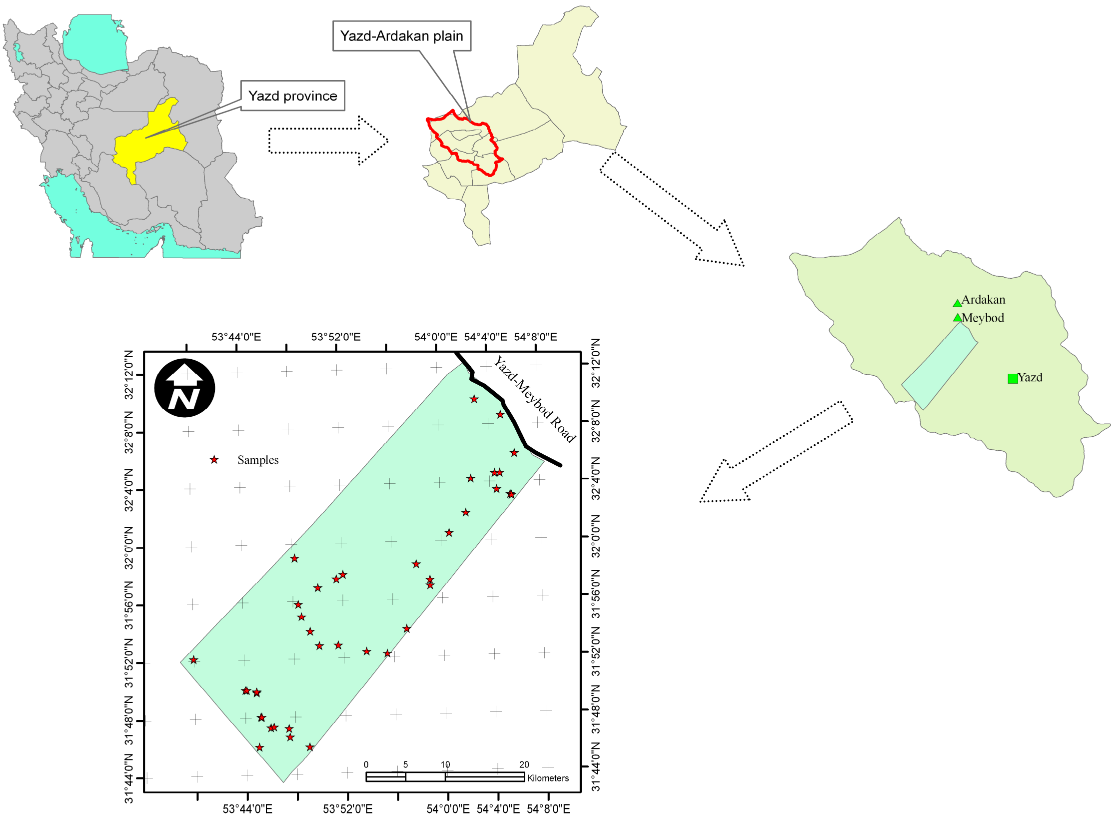


Figure 1. Study area and sampling locations

Where *n(h)* is the number of data pairs within a given class of distance and direction. If the values at *Z(xi)* and *Z(xi + h)* are auto correlated the result of Eq. (1) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model (e.g. spherical, exponential) is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure.

2. Inverse distance weighting (IDW): In interpolation with IDW method, a weight is attributed to the point to be measured. The amount of this weight is depended to the distance of the point to another unknown point. These weights are controlled on the bases of power of ten. With increase of power of ten, the effect of the points that are farther diminishes. Lesser power distributes the weights more uniformly between neighboring points. We should keep in mind that in this method the distance between the points count, so the points of equal distance have equal weights [1]. In this method the weight factor was calculated with (Equation 2):

$$\lambda_i = \frac{D_i^{-\alpha}}{\sum_{i=1}^{n} D_i^{-\alpha}} \qquad (2)$$

Where: λ_i is the weight of point, D_i denotes the distance between point i and the unknown point and α is the power ten of weight.

3. Cokriging: The "co-regionalization" (expressed as correlation) between two variables, i.e. the variable of interest, groundwater quality in this case, and another easily obtained and inexpensive variable, can be exploited to advantage for estimation purposes by the co-kriging technique. In this sense, the advantages of co-kriging were realized through reductions in costs or sampling effort. The crosssemivariogram was used to quantify cross-spatial auto-covariance between the original variable and the covariate [21, 22]. The cross-semivariance was computed by (Equation 3):

$$\lambda_{uv} h = \frac{1}{2} E[\{z_u(x) - z_u(x+h)\}\{z_v(x) - z_v(x+h)\}] \qquad (3)$$

Where: $\lambda_{uv}(h)$ is cross-semivariance between u and v variable, $Z_u(x)$ is primary variable and $Z_v(x)$ is secondary variable.

Comparison between the different methods. Finally, the criterion of root mean square error (RSME) was applied to evaluate model performances in cross-validation mode. The smallest RMSE indicate the most accurate predictions. The RMSE was derived according to (Equation 4):

$$R.M.S.E = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z(x_i) - Z^*(x_i))^2} \qquad (4)$$

3. Results and Discussions

Statistical data which were related to studied parameters were calculated (table 1). Then, the normality condition of data was investigated. The levels of skewness for percentages of sand and silt were lower than 0.5 therefore, the data related to these two soil characteristics did not normalize. Whereas, data related to water at saturation percentage (SP) and clay content were normalized using square root method due to the levels of skewness for these two soil parameter were between 0.5 - 1. Other soil properties such as EC and SAR had the levels of skewness more than 1 and hence, were normalized using logarithm method.

Table 1. Statistical analysis of soil properties

Soil properties	Min	Max	Mean	Standard deviation	Kurtosis	Skewness
SP (%)	14.73	39.81	25.51	7.03	- 0.41	0.72
SP (%)*	3.84	6.31	5	0.67	- 0.57	0.5
SAR	0.72	101.72	12.79	25.12	6.79	2.84
SAR**	- 0.33	4.62	1.46	1.39	- 0.27	0.7
EC (dS/m)	0.5	63.14	9.17	16.18	4.8	2.39
EC (dS/m)**	- 0.69	4.15	1.11	1.42	- 0.58	0.79
Silt (%)	16	46	28.6	8.25	- 0.83	0.4
Sand (%)	14.16	80.4	50.11	19.79	- 1.11	- 0.1
Clay (%)	7.6	50.84	22.08	12.38	- 0.72	0.56
Clay (%)**	2.76	7.13	4.51	1.32	- 1.17	0.21

*Using square root to normalized data; **Using logarithm to normalized data

The first step for making use of kriging and cokriging methods in the present study was to investigate the presence of spatial structure among available data by means of variogram analysis. For achieving to this issue, the needed variograms were computed using those data which were normalized before. Subsequently, variograms for kriging method were calculated (fig. 2).

After that, the best model for fitting on experimental variogram was selected based on less residual sums of squares (RSS) values [15] (table 2). Therefore, the spherical model was selected as the best suitable model for estimating of soil texture variables and water at saturation percentage. In addition, gaussian model was the best model for evaluating of soil EC and SAR.

Table 2. Selecting of most suitable model on experimental variogram according to RSS values

Soil properties	Models		
	Spherical	Exponential	Gaussian
EC	0.36	0.52	0.13
SP	0.104	0.116	0.106
SAR	0.6	1.11	0.3
Sand	52311	78452	55649
Silt	593	635	601
Clay	0.76	1.21	0.89

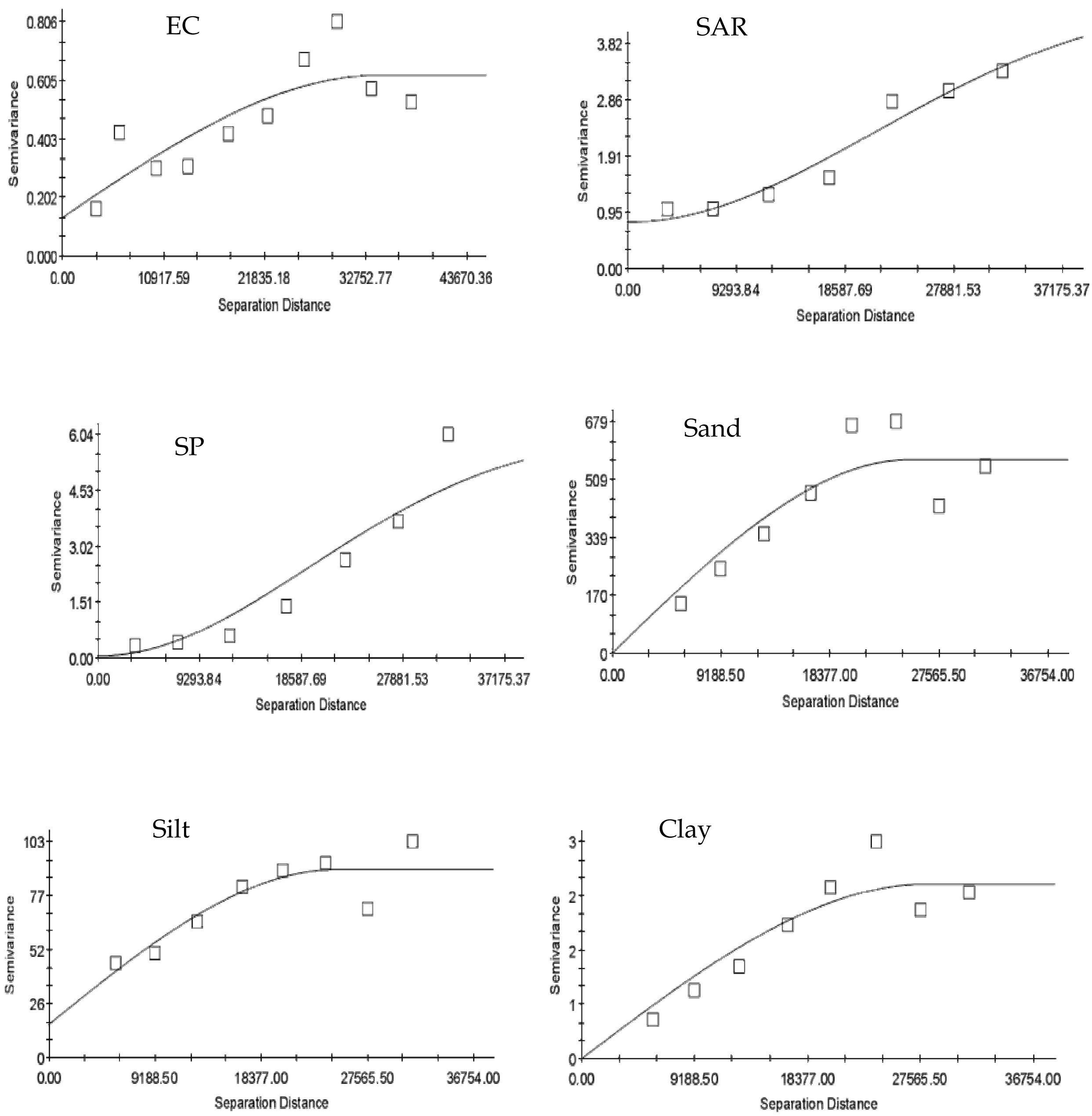


Figure 2. Variograms related to different soil properties of kriging method

The ratio of nugget variance to sill expressed in percentages (C_O/C_O+C) was regarded as a criterion for classifying the spatial dependence of soil parameters. Since this ratio for all of the soil properties were less than 25%, so these parameters showed strong spatial dependence. The range effect for soil texture was close to each other (24 - 28 km). Furthermore, the range effect for percentage of SP and the level of EC and SAR were approximately 34, 67 and 51 km, respectively (table 3). The first step in cokriging method was to compute of crossvariograms. The cross-variogrames were modeled as same as variograms. So that, the same restricted set of functions were available for them. Cross-variogrames were modeled to predict the spatial relations between two variables in cokriging method. Typically the major aim was estimating of just one variable in this technique. However, more variables which were regarded as auxiliary variable were stimated in the present study. In general, cokriging reduces the estimations of variance. But, this reduction strongly depends on the number of sampling. Moreover, in cokriging method, after creating a correlation matrix, a parameter which had the highest correlation coefficient with primary variable was selected as an auxiliary variable (table 4). Hence, for estimating of percentages of sand, silt and SP (r = - 0.935**, r = 0.517** and r = 0.606**, respectively), the clay percentage was used as an auxiliary variable. Also, the concentrations of Ca^{+2} + Mg^{+2} (r = 0.9*) and clay percentage (r = 0.68**) we used as an auxiliary variable for predicting of EC and SAR, respectively. Then, the cross variograms for the mentioned parameters were developed (fig. 3).

Table 3. Best-fitted variogram models of different soil properties and their parameters

Soil properties	Models	Nugget (C_O)	Sill (C_O+C)	Range effect (km)	C_O/C_O+C)(%
SP	Spherical	0.13	0.62	34.13	0.21
SAR	Gaussian	0.8	4.61	51.337	0.17
EC	Gaussian	0.07	6.14	67.284	0.01
Silt	Spherical	16	89.5	24.79	0.17
Sand	Spherical	1	56.67	25.17	0.01
Clay	Spherical	0.1	2.6	28.01	0.04

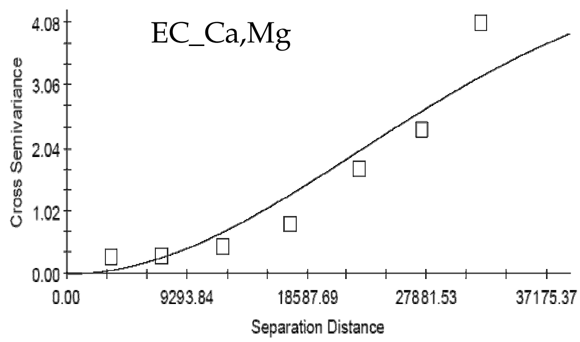
Table 4. Correlation matrix of soil properties

	EC	SP	Sand	Silt	Clay
EC	1				
SP	0.377	1			
Sand	- 0.608**	- 0.471*	1		
Silt	0.505*	0.325	- 0.822**	1	
Clay	0.604**	0.517**	- 0.935**	0.606**	1
Ca^{+2}+Mg^{+2}	0.9**	0.373	- 0.473**	0.338	0.558**
Na^+	0.767**	0.297	- 0.542**	0.336	0.614**
HCO_3^-	0.733**	0.391	- 0.408*	- 0.309	- 0.483*
Cl^-	0.711**	0.49*	- 0.454*	0.175	0.573**
SAR	0.699**	0.21	- 0.582**	0.323	0.68**

Table 4 - continued

	Ca^{+2} + Mg^{+2}	Na^+	HCO_3^-	Cl^-	SAR
EC					
SP					
Sand					
Silt					
Clay					
Ca^{+2}+Mg^{+2}	1				
Na^+	0.683**	1			
HCO_3^-	- 0.781**	- 0.552**	1		
Cl^-	0.765**	0.797**	- 0.488*	1	
SAR	0.623**	0.972**	- 0.502*	0.722**	1

** $p < 0.01$ *; $p < 0.05$; $p > 0.05$ ns



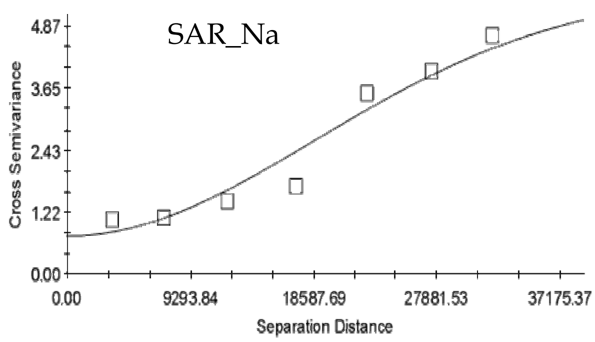


Figure 3. Cross variogram of three different soil properties by using of cokriging method

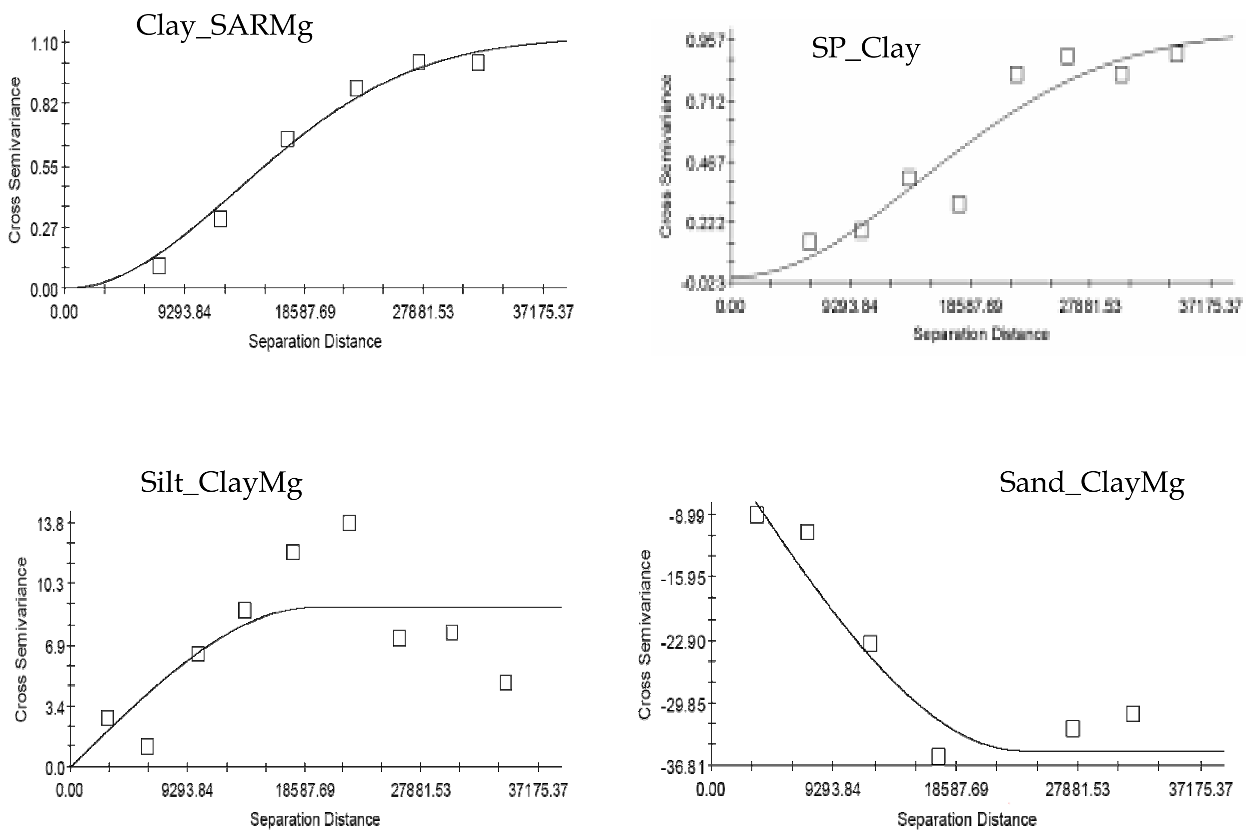


Figure 3 - continued. Cross variogram of three different soil properties by using of cokriging method

After modeling of variogram, three different techniques including kriging, cokriging and IDW methods were used to predict the spatial distribution of soil characteristics. The RMSE was developed to evaluate the three geostatistical techniques. Results showed that kriging and cokriging methods were expected to be superior to IDW method for estimating of soil properties (table 5). Results also indicated that for prediction of foil texture and percentage of SP, kriging predictor had the lowest error. Furthermore, cokriging predictor was the most suitable method for estimation of soil salinity by means of auxiliary variable of Ca^{+2}+Mg^{+2} and based on RMSE criterion. Moreover, cokriging method had the most accuracy for prediction of the SAR by means of the auxiliary variable of Na^{+} and based on RMSE criterion. Finally, the maps of spatial distribution of soil properties were prepared using the best interpolation method in GIS environment (fig. 4). Results showed that most of the soil characteristics had the high levels of skewness.

This phenomenon was probably because of small number of samples and their low suitable distribution. However, using square root and logarithm models were able to normalize data in large quantities. Having of stability and firmness in spatial structure for all the studied soil properties showed a strong spatial connection and high accuracy among the models extracted from these fittings. These properties had a large and prominent role for increasing of the estimation accuracy.

These results were similar to the findings of Mohammadi [12] and Sokooti-Oscooei et al. [18]. They reported that geostatistic methods had more considerable accuracy than IDW method for all studied parameters.

Furthermore, the results obtained from evaluation of different methods showed that the cokriging method increased prediction accuracy for estimation of soil silt content compared with the other methods which is in line with the work done by Meul and Van Meirvenne [11]. They similarly recognized that the cokriging method had most superiority to other methods to prediction of the silt content as well. Similarly, Sokooti-Oscooei et al. [19] reported that cokriging method was a suitable method for estimating of percentages of sand, clay and SP. Moreover, the great efficiency of the geostatistical methods is supported by other researchers.

Wei et al. [23] found that the kriging method could predict organic matter distribution with a high accuracy in north east of China. Xiaopeng and Lingqing [24] confirmed the high accuracy of the kriging method for estimating mercury pollution in the city of Baoji in Chaine. Shi et al. [2005] reported that the cokriging method with auxiliary parameters of Na^{+} and Ca^{+2}+Mg^{+2} was the most suitable method for prediction of SAR and EC in a coastal saline field in China [17]. Similarly, Hosseini et al. [8] found that the cokriging method had the most accuracy for estimation of SAR level.

Table 5. Results of the interpolation error for estimation of soil properties

Soil properties	Cokriging	Kriging	IDW			
			Exp 1	Exp 2	Exp 3	Exp 4
EC	8.22	10.92	12.25	12.44	13.27	13.94
SP	6.34	6.07	6.16	6.14	6.28	6.53
SAR	12.85	24.03	23.64	26.15	28.85	30.78
Sand	8.25	8.14	13.34	13.45	14.43	15.61
Silt	7.354	6.84	7.37	7.47	7.91	8.36
Clay	7.42	7.09	7.35	7.38	7.83	8.4

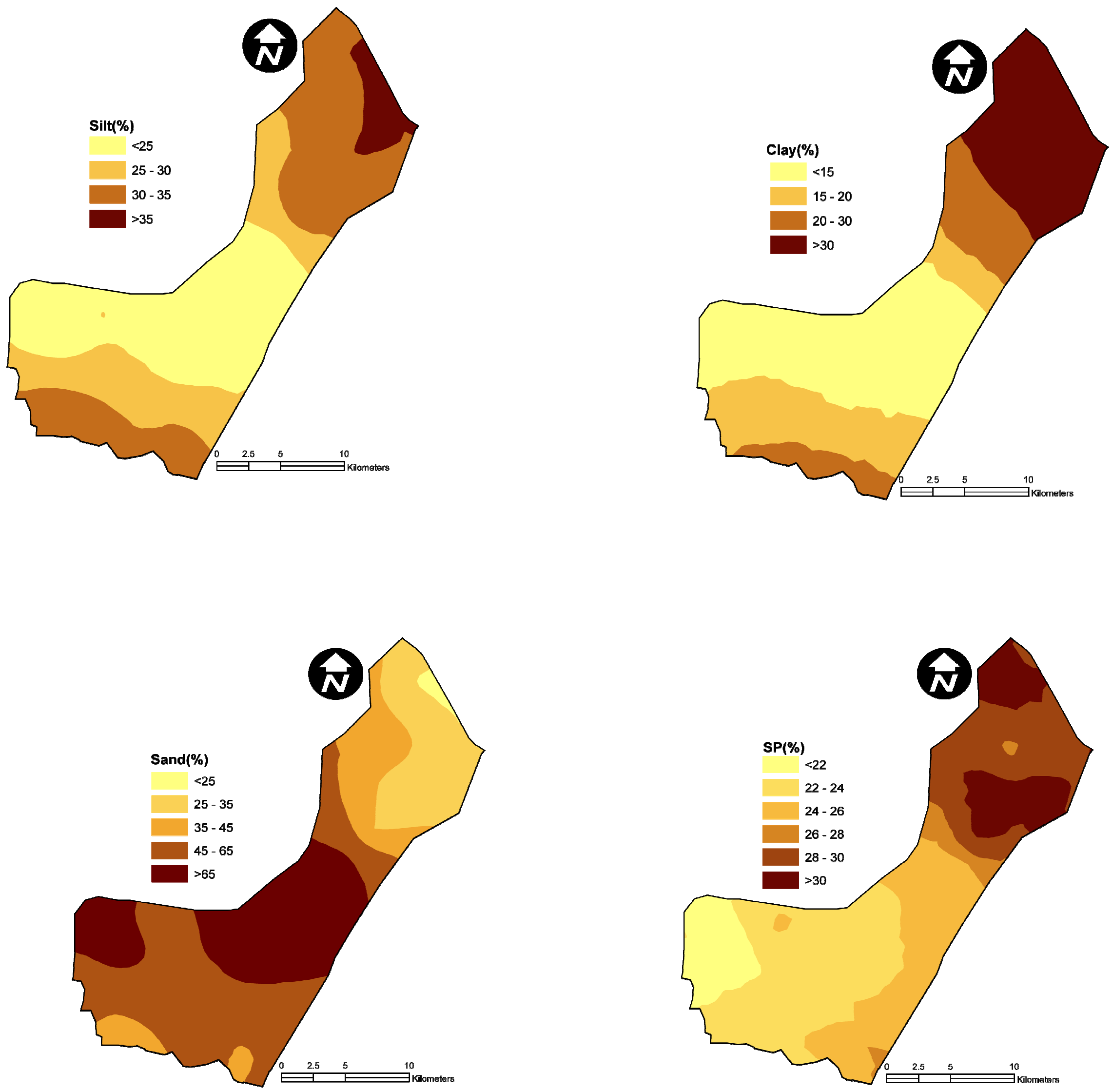
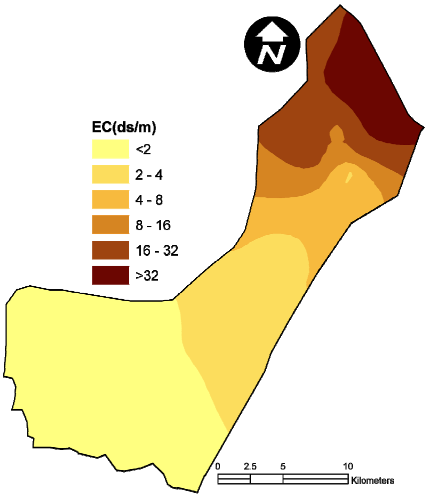


Figure 4. The maps of spatial distribution of soil properties of cokriging method



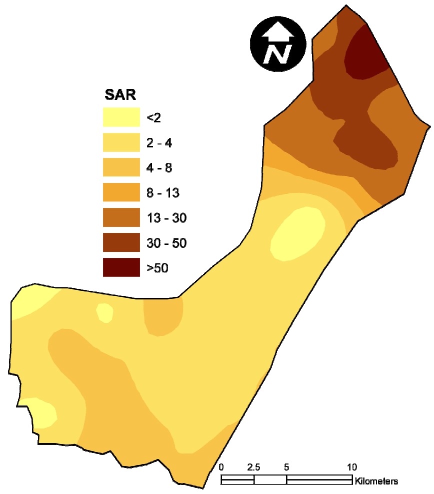


Figure 4 - continued. The maps of spatial distribution of soil properties of cokriging method

5. Conclusions

As a general principle, soils located in the plains have heavier texture compared with the soils of areas on high elevations. But according to the results of this study the procedure of variations was different from this general principle and a different behavior was observed. The main reason for this behavior was probably because of the large number of flood-channels in the middle section of the study area. These flood-channels are responsible for the various types of soil erosion in these sections. Due to silt particles are more sensible to erosion than the other soil particles; the percentage of silt in this area was in low levels. Moreover, the percentage of sand particles increased because of decreasing the soil silt content by erosion in these areas (fig. 4).

The high level of clay particles in the soil causes an increase in soil porosity and hence, will enhance the percentage of soil water saturation. Therefore, percentages of clay and SP had similar variations (fig. 4). In addition, the soil EC and SAR levels in the study area had large variations. The most levels of EC and SAR observed in the sections of the study area having low elevations (fig. 4). The main reason of soil salinity and sodocity in this area was probably due to the great content of clay particles in the soil surface and consequently gathering of specific salts in the surface sections of the topsoil. On the other hand agricultural activities without consideration to cultivation potential of this area and irregular extraction of groundwater with exceeding use of groundwater can enhance these processes. With respecting to spatial distribution maps of soil properties it seems that in the south west of study area the soil texture is coarser than other sections. So these sections had higher infiltration rate compared with the other areas. Therefore, these areas are suitable for infiltration of water into the soil for nutrition of groundwater tables. Furthermore, in the north east of study area the soil clay content was very high and the poor drainage condition of this section was because of these very levels of clay. Moreover, soils in these regions had high salinity and sodicity and hence, land proportion was in poor condition for various usages such as crop production.

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