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Using geostatistical method for prediction the spatial variability of soil texture and its effect on environment (case study: Farahan Plain of Markazi Province, Iran)

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Abstract

Soil texture is one of the most important soil properties governing most of the physical, chemical and hydrological properties of soils. Variability in soil texture may contribute to the variation in nutrient storage and availability, water retention and transport and binding and stability of soil aggregates. It can directly or indirectly influence many other soil functions and soil threats such as soil erosion. Geostatistics has been extensively used for quantifying the spatial pattern of soil properties and Kriging techniques are proving sufficiently robust for estimating values at unsampled locations in most of the cases. For this purpose, 50 soil samples were provided from fields of Farahan plain during May 2014. Soil texture was measured for each sample. The Kriging method with Circular, Spherical, Tetra spherical, Pent spherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, k-Bassel, J-Bassel and Stable semivariograms for Prediction the Spatial Variability of Soil Texture in Farahan plain. The performance of methods was evaluated using by Root Mean Square Error (RMSE). The results showed that The Exponential has higher accuracy with RMSE=0.19221 for representing the spatial variability of semivariograms. Spatial variability of map showed loamy-sandy texture is higher in the central of Farahan plain than in the northern and southern area.

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Introduction

Soil texture, the relative percentage of sand, silt, and clay, is one of the most important physical soil properties that governing nearly all of the other attributes of soils (Zhai *et al.* 2006; Adhikari *et al.* 2009). Considering the effects of the soil texture on soil-water retention, its availability and transform (Katerji and Mastrorilli 2009), leaching and erosion potential (Adhikari *et al.* 2009), plant nutrient storage (Kettler *et al.,* 2001), distribution of plant and animal species in arid and semi-arid regions (Scull *et al.* 2004), and organic-matter dynamics (Kong *et al.* 2009), it plays a key role in total behavior of soil. As other environmental variables, soil texture changes in space and time. These temporal and spatial soil texture variabilities may lead to structural differences in soil quality (Kettler *et al.* 2001). Detailed information about the soil quality factors and their distribution patterns in field scale is essential requirement for site-specific management (Emadi *et al.* 2008). The characterization of the soil texture spatial variability pattern, therefore, may be helpful in schematization permanent land management practices and also precision agriculture (Yemefack *et al.* 2005; Emadi *et al.* 2008).

To achieve such an important purpose, geostatistics (e.g., Goovaerts 1997; Webster and Oliver 2001; Nielsen and Wendroth 2003) as a powerful pedometrical instrument, can be used to produce a thematic map of the soil texture. In recent years, some researchers focused on using geostatistics and different kriging methods to better understand soil properties spatial variability pattern, such as soil particles, over small to large spatial scale (Lark 2002; Emadi *et al.* 2008; Yasrebi *et al.* 2008).

Istock and Cooper (1998) used kriging method to estimate heavy metals and found that the used method is the best estimator for spatial prediction of metals. In another research, spatial distribution maps were constructed for EC and pH of soil extracts using ordinary kriging interpolation in the agricultural lands of Rhodope District, northeastern Greece. Nemes *et al.* (1999) studied distribution patterns of the soil particles using four different interpolation procedures, i.e., loglinear interpolation method, Gompertz curve, nonparametric spline function and similarity indices, and stated that among them, the last one which uses an external source of soil information was capable of giving the most accurate interpolations Scull *et al.* (2004) compared several statistical and geostatistical techniques to reach more precise soil particle maps. Their results showed that predictive soil mapping techniques, such as linear regression and Kriging could be used to produce thematic maps of the particles that quantitatively express soil variability with high levels of accuracy. In order to supply the predictive surface map of hydraulic parameters in an agricultural farm, Santra *et al.* (2008) studied the spatial variability of the soil particles by kriging method. The results showed that spatial prediction of basic soil particles using geostatistics is better than assuming mean of the observed value for any unsampled location.

Yu *et al.,* (2008) analyzed the distribution of surface soil pH by combining classical statistics method with geostatistic method under three irrigation methods (furrow, drip and subsurface irrigation) in greenhouse. The results indicated that supplying method and quantity of water by irrigation can affect the spatial variability of soil pH. Adhikari *et al.* (2009) created the continuous maps of soil texture components and to better understand of their variability pattern suggested supplying information layers such as topographical parameters, land use, parent material and soil erosion, for factors which might influence the spatial distribution of the soil texture. The aim of this study provide the continuous maps of soil texture by Kriging method and Determine the error and access to accuracy maps by Kriging method in Farahan plain.

Method and material

Study Area

The study area refers the Farahan plain located in the province of Markazi, Iran with the geographic coordinates from 49˚ to 50˚E longitude and 33˚ to 34˚N latitude (Fig. 1). The entire area of Farahan plain is 35298/27 hectares with minimum elevation of 1658 m and maximum elevation of 1705 m above sea level. Climatic conditions can be characterized by an annual mean temperature of 13.7 ᶜ and with the annual precipitation of 325 mm. According to De-Martine advanced climatic classification system, this area has Mediterranean climatic class.

Data Sampling and Analysis

Soil samples were randomly taken from 50 locations in May 2014. Sampling points are showed in Fig. 1. Samples were taken at depths of 0–30 cm and air-dried to remove stones and coarse crop residues. Soil texture was analytically measured in sampled soils.

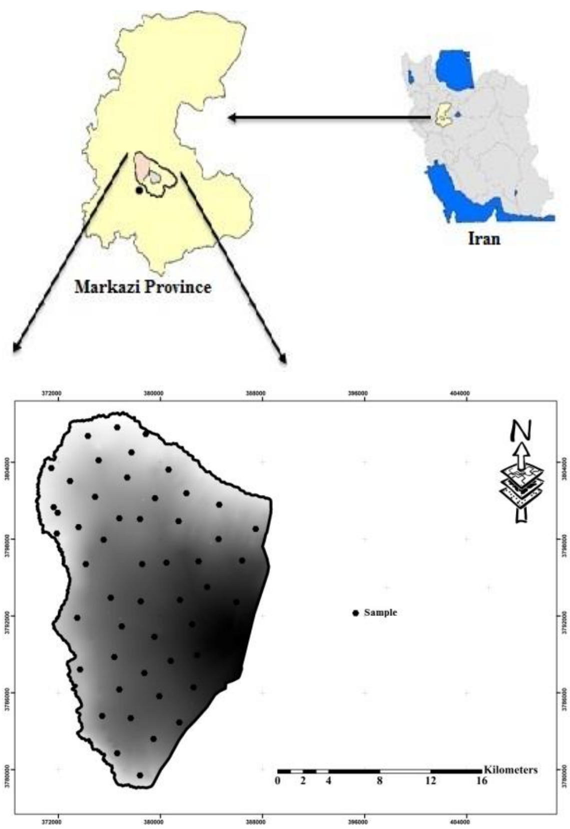

Fig. 1. The map of Farahan plain in Iran.

Geostatistical analysis

In general, geostatistical methods were used to estimate and map in this agricultural areas. It is based on the theory of a regionalized variable which is distributed in space (with spatial coordinates) and shows spatial auto correlation such that samples close together in space are more alike than those that are further apart. Geostatistics uses the variogram technique (or semivariogram) to measure the spatial variability of a regionalized variable, and provides the input parameters for the spatial interpolation of kriging (Goovaerts, 1999; Webster and Oliver, 2001).

The semivariogram (variogram) was used in this study to analyze discrete soil samples. Semivariograms are a key tool in regionalized variables theory and are formed by three constituents: sill, range and nugget with increasing lag between samples; semivariance is increased to a maximal asymptotic value (sill). With this lag, semivariance is approached the observation variance. This lag is called range beyond which variables are independent with no correlations. Nugget occurs when semivariogram is not started exactly at intersection of coordinates generally due to laboratory test errors, a sharp variation of soil properties or when sampling distance is greater than range. Initial slope intensity in semivariogram exhibits variability as a function of distance and reduction of correlation between samples (Mashayekhi *et al.*, 2007).

Semivariogram is computed as half the average squared difference between the components of data pairs (Goovaerts, 1999, Webster and Oliver, 2001): The function is expressed as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i - Z(x_i + h)]^2 \qquad (1)$$

Where N (h) is the total number of data pairs separated by a distance; h; Z represents the measured value for soil property; and x is the position of soil samples.

Before the geostatistical estimation, a semivariogram is calculated for classes of distance between sample pairs. Several standard models are available to fit the experimental semivariogram, e.g., spherical, exponential, Gaussian, linear and power models (Shi *et al.*, 2007). In this study, the Circular, Spherical, Tetra spherical, Pent spherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, k-Bassel, J-Bassel and Stable models were selected.

Interpolation method

In this study, spatial patterns soil texture was determined using the geostatistical and interpolation methods such as, Kriging.

Kriging

Among the geostatistical techniques, kriging is an important tool in geostatistics. Kriging is a linear interpolation procedure that provides a best linear unbiased estimation for quantities which vary in space. Kriging estimates are calculated as weighted sums of the adjacent sampled concentrations. That is, if data appear to be highly continuous in space, the points closer to those estimated receive higher weights than those farther away (Cressie, 1990). Kriging (Krige, 1951) is regarded as an optimal method of spatial prediction. It is a theoretical weighted moving average:

$$\overset{\Delta}{z}(x_0)=\sum_{i=1}^{n}\lambda_i z(x_i) \qquad (2)$$

Where $\overset{\Delta}{z}$ is the value to be estimated at the location of x0, z(xi) is the known value at the sampling site xi and n is the number of sites within the search neighbourhood used for the estimation. The number n is based on the size of the moving window and is defined by the user. Kriging is different from other methods (such as IDW), because the weight is no longer arbitrary. The weights depend on the parameters of the semivariogram model and the sampling configuration and are decided under the conditions of unbiasedness and minimized estimation variance (Deutsch and Journel, 1998; Zhangand McGrath, 2004; Robinson and Metternicht, 2006).

Data sets were analyzed with different software packages. The geostatistical and interpolation analysis were carried out with GS^{+} and geostatistic extension of ArcGIS.

Performance evaluation

Coefficient of correlation (R) and root mean square error (RMSE) were used to evaluate the performances of models and select the best one. In brief, the models predictions are optimum if R and RMSE are found to be close to 1 and 0 respectively. The higher the R value (with 1 being the maximum value) and he lower the RMSE values (with 0 being the minimum value) the better is the performance of the model.

$$R=\sqrt{\frac{(\sum_{i=1}^{n}(Q_o-Q_{Ave})(Q_E-Q_{Ave-E}))^2}{\sum_{i=1}^{n}(Q_o-Q_{Ave})^2(\sum_{i=1}^{n}Q_E-Q_{Ave-E})^2}} \qquad (3)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_o-Q_E)^2} \qquad (4)$$

Where Q_o, Q_E, n, Q_{Ave} and Q_{Ave-E} are observed, estimated, number of data, mean observed and mean estimated soil texture respectively.

Results and discussion

Measured variables in the data set were analyzed using SPSS 20.0 software to obtain the minimum, maximum, mean, median, variance, coefficient of variation (CV), skewness and peakness (kurtosis) coefficient. .Table 1 lists the summary statistics of the raw data of soil texture including minimum, maximum, mean, median, variance, skewness and kurtosis. To evaluate the normality of data a formal kolmogorov-Smirnov statistic test was executed. For this data to be normally distributed the p value should be more than 0.05. The p-value for raw soil texture was 0.31, 0.13 and 0.21 so geostatistical analysis could be used for this data (table 1, fig. 2).

Table 1. The statistical values of soil texture properties.

Depth (cm)	Variable	Mean	Med	Var	Min	Max	Skw	Kurt	CV	P value[a]
0-30	Clay	23.9	24.0	19.16	13.0	37.0	0.37	0.84	18.31	0.31
	silt	34.8	60.0	50.32	12.0	52.0	−0.61	1.19	20.38	0.13
	sand	28.9	29.0	25.12	15.0	52.0	0.76	3.93	17.35	0.21

Med median, Var variance, Min minimum, Max maximum, Skw skewness, Kurt kurtosis, CV coefficient of variation.

[a]Shows confidence level of Kolmogorov–Smirnov test.

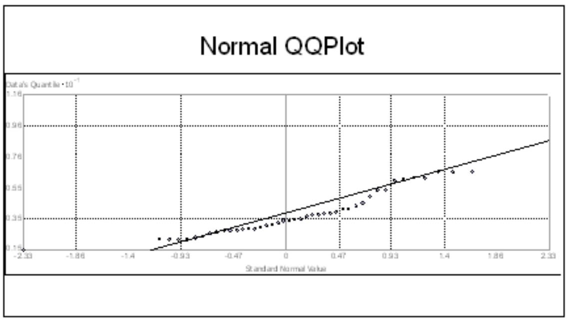

Fig. 2. qq-plot of raw of soil texture.

Kriging method executed with Circular, Spherical, Tetra spherical, Pent spherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, k-Bassel, J-Bassel and Stable semivariograms were performed on data.

The attributes of the semivariograms of soil particles for the data are summarized in Table 2. With attention to fig. 3, Semivariograms analysis indicated that best fitted to Exponential model with nugget, sill, and nugget/sill is equal to 0.153, 0.349 and 0.560, respectively. In this research, nugget/sill ratio (56%) indicated moderate spatial dependence at the large scale of the Farahan plain. The obtained results showed that Exponential outperformed all other models. These results are in accordance with Cambardella *et al.* 1994; Vieira and Paz Gonzalez 2003.

Table 2. The best-fitted semivariogram models and their parameters for soil texture.

	model	Nugget (Co)	Sill (Co+C)	Range ParameterAo	Effective Range (m)	C/(Co+C)	R^2
Soil texture	Exponential	0.153	0.349	800.70	271	0.560	0.982

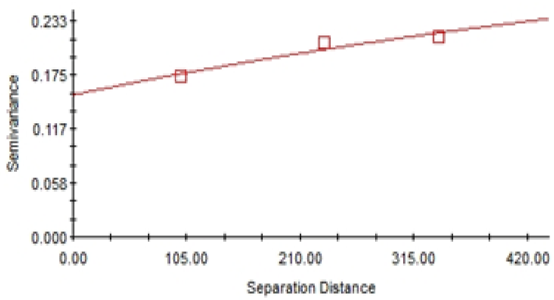

Fig. 3. Empirical and fitted Exponential semivariograms for the soil texture

The results of geostatistical analyses of soil texture have been presented in Table 3. The results showed that kriging (Exponential model) with RMSE = 0.19282 was the best method to estimate soil texture, because it had the highest precision and lowest error for estimation of these elements.

The cross-validation statistic given in Table 3 shows how well soil particles can be estimated by application of the ordinary kriging method. Hengl *et al.* (2004) argued that a value of RMSE% below 40% means a fairly satisfactory accuracy of prediction. Therefore, the kriging model performed best for both the soil particles in the studied area.

Table 3. Results of geostatistical analyses of soil texture in Farahan plain of Markazi province, center of Iran.

RMSE	Model type	Method type
0.19392	Circular	
0.19567	Spherical	
0.19412	Tetraspherical	
0.19532	Pentaspherical	
0.19282	Exponential	
0.19492	Gaussian	Kriging
0.19562	Rational Quadratic	
0.19472	Hole Effect	
0.19472	k-Bassel	
0.19504	J-Bassel	
0.19551	Stable	

In order to understand spatial variation of soil texture, a map was provided by kriging method for Farhan plain of Markazi province (Fig. 4). spatial variability of map showed loamy-sandy texture is higher in the central of Farahan plain than in the northern and southern area.

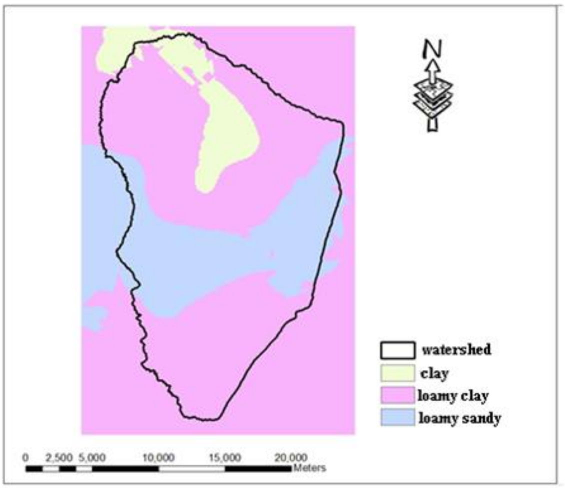

Fig. 4. Interpolation map of soil texture produced by Kriging.

Conclusion

Soil texture as an important soil property to support different agricultural and land use management practices was mapped in the Farahan plain using kriging estimator. Results of this research indicated that geostatistics are more suitable methods for estimation of soil properties. The Exponential model is found to be the best model representing the spatial variability of semivariograms. In this research, the nugget/sill ratio of soil texture belonged to the scope of moderate spatial dependence. spatial variability of map showed loamy-sandy texture is higher in the central of Farahan plain than in the northern and southern area. It is suggested that in the future studies, other interpolation methods such as co-kriging and soil properties such as Na and SAR be used in order to prepare precision maps.

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