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Spatial variation of soil organic carbon in Sefid-Rood river delta, Gilan Province

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Abstract

Soil organic carbon (SOC) plays an important role in soil physico-chemical processes as well as in soil fertility and soil quality. Management of SOC can reduce soil erosion and improve crop productivity. Accurate estimation of SOC variability could provide reliable information for understanding nutrients cycling and sediment. Therefore, the present research was aimed to investigate the spatial variation of soil organic carbon in Sefid-Rood river delta. In this regard, soil sampling was performed from 0-30 cm soil depth with their GPS-based coordinates. SOC values for 200 soil samples were measured using standard methods. For geostatistical analyses, semivariogram were developed and then the suitable theory model fitted to the experimental semivariogram. The information generated from the fitted model was applied to make use of ordinary kriging to estimate the value of organic carbon in the unknown locations. Cross validation technique and statistical parameters of root mean square error (RMSE), mean absolute error (MAE) and mean bias error (MBE) were also used. According to the results, the Gaussian model was selected as the best-fit model for the semivariogram with an effective radius of 3.64 km, a nugget effect of 0.17% and a sill of 0.48 was selected. The obtained results showed that the less SOC mostly in the south and northwest of the study area. In these parts, manure can be used to increase soil organic carbon.

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Introduction

Soil organic carbon is one of the most important indicators of soil fertility, productivity and quality. Decline in SOC creates an array of negative effects on land productivity (Black, 1982). Hence maintaining and improving its level is a pre-requisite to ensure soil quality, crop productivity and sustainability of agricultural ecosystems (Boken *et al.,* 2004).

Sustainable management of lands requires the understanding and evaluation of spatial and temporal variations of resources. For this purpose, understanding the spatial distribution of soil properties is of utmost importance (Sarmadian and Taghizadeh, 2010). Nutrients zoning maps are the right tools that can provide necessary facilities for the sustainable land management. To investigate the spatial variations of carbon sequestration, geostatistics can be used. Interpolation is the procedure of predicting the value of attributes at unsampled sites from measurements made at point locations within the same area. Interpolation used to convert data from point observations to continuous fields so that the spatial patterns sampled by these measurements can be compared with spatial patterns of other spatial entities. The rationale behind spatial interpolation is the very common observation that, on average, values at points close together in space are more likely to be similar than points further apart. Optimizing spatial sampling scheme to reduce sampling density and estimation of unsampling values can save time and costs (Sarmadian *et al.,* 2014).

From a geostatistical standpoint, each sample can have spatial relationship with its surrounding samples to a maximum distance. This maximum distance, called range, is of great importance. Actually, it indicates the distance in which geostatistical estimators could be used and the factors affecting effective radius should be determined (Hasanipak, 2008).

Meul and Van Meirvenne, 2003 used ordinary kriging, comprehensive kriging, simple kriging and cokriging methods for estimation of silt content in Belgium. The results showed that the kriging method is estimated have the lowest error.

Zhang *et al.*, 2004 reported that geostatistics could be accurately used to temporal-spatial variability of soil organic carbon stocks. In this study, the temporal-spatial variability of SOC stocks was determined in a basin in subtropical China from 1981 to 2002. ArcGIS software was utilized for spatial analysis of semivariance, ordinary kriging, and probability kriging. Geostatistical results showed a moderate spatial dependence for SOC in both years. The range of SOC changed from 2.04 km in 1981 to 7.15 km in 2002. The mean topsoil SOC increased by 4.6% from 1981 to 2002.

In a research conducted by Amirnejad *et al.*, 2011 soil properties including bulk density, saturated hydraulic capacity, available water holding capacity and organic carbon percentage were measured in rice and wheat cultivated lands. The obtained results were different between the two cultures and ordinary Kriging was used to estimate the soil properties due to lower error. Meanwhile, Gaussian was determined as the best model for estimating organic carbon.

Chual *et al.*, 2012 investigated and analyzed the spatial variation of soil organic carbon in Jiangsu province of china. The Kriging method was use for Interpolating values of SOC density in the surface layer based on a spherical model. Results showed that high SOC densities were usually found in limestone and paddy soils and low densities in coastal saline soils and alluvial soils.

In a study, cambule *et al.*, 2014 investigated the distribution of soil organic carbon in the Limpopo National Park in Mozambique by ordinary Kriging and universal kriging. Results showed that the validation root mean square error of prediction (RMSEP) was about 30% of the mean predictions for both OK and UK. The range of total SOC stock of the

10,410-km^2 study area was estimated at 15,579–17,908 Gg. The spatial distribution is rather homogenous, suggesting levels are mainly determined by regional climate.

Farajnia and Kalantari, 2015 studied the spatial distribution of soil microelements Fe, Zn, Mn and Cu at Malekan, Iran, using geostatistics technique. The semivariograms were developed and then the most suitable theory models fitted to the experimental semivariograms and its parameters were used to do ordinary kriging. Results showed that Fe element had moderate and Cu, Mn, and Zn had stronger spatial structures in the study region. Generated maps showed that study region suffers from Fe and Zn deficiency so that more than 80 percent of the agricultural areas need for Fe and Zn fertilizers. Moreover there was no deficiency for Mn and Zn elements in more than 85% of the region.

This study aimed to characterize SOC in wet ecosystem of Sefid-Rood river delta in Gilan province, Iran, and particularly to investigate the amount of soil organic carbon in the region and produce distribution map.

Materials and methods

Study Area Characteristics

The study area is located in northern Iran bordering to Caspian Sea in Gilan province of Iran. It lies between longitudes 49° 31' 0''E and 49° 45' 0''E and latitudes 37° 7' 30''N and 37° 27' 8''N. The climate of the region is humid with the mean annual precipitation of 1330 mm. The mean annual temperature of the region is 15.8 °C. The mean humidity is 75% and the annual real evapotranspiration is 900 mm. The highest point of this area is 47 m higher than sea level in the South of study area and its minimum height is -28 m under sea level in the north of study area. The soil moisture and temperature regimes of the region by means of Newhall software are Udic or Aquic and Thermic, respectively. The major geological formations are composed of deltaic deposits, young deposits, langonal, organo-detritic deposits and Beach deposits and blown sand of Quaternary period. The physiographical units of the region from south to north direction are river alluvial plains and low lands. According to soil taxonomy system the soil of the region classified in three orders of Alfisols, Inceptisols and Entisols. Rice planting is the dominant land use. In this area for determining SOC 200 samples were collected randomly from 0-30 cm soil depth with their GPS-based coordinates. Fig. 1 shows the study area and distribution of sampling points.

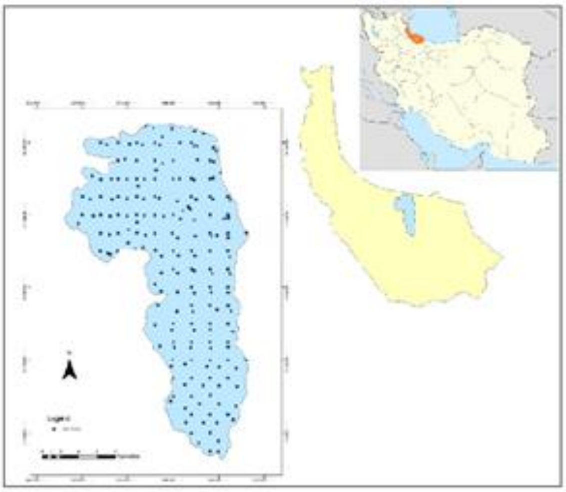

Fig. 1. Geography position of studied area together with distribution of sampling points.

Soil sample analysis

After drying the samples in air, they were ground and passed through a two-millimeter sieve. Soil organic matter was measured by the Walkley and Black method(Ali Ehyaei and Behbehani Zade, 1993).

Normalizing of data

The first step for using the ordinary kriging method is to study the existence of spatial structure between data by analysis semivariogram. The condition of this analysis is that data must be normal. One of the evaluation methods for nominate normality of data is usage of Kolmogrof- Smirnov (K-S) test. In order to know the SOC data were normal, Kolmogrof- Smirnov test was used.

Analysis of variogram

In order to define the spatial continuation of a parameter it is necessary to draw its semivariogram.

Calculation of a semivariogram diagram is the most important activities of geostatistic that is ejaculated by equation (1).

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

In this equation γ(h) is the semivariogram value for the double points, which their distance is (h). N is the number of double points, which their distance is (h). Z(x) is the value of parameter (x) and Z(x+h) is the observed value of the parameter that its distance with (x) is (h). For drawing semivariogram first it is needed to calculate the value of y(h) in lieu of various values of (h) and then dram the obtained values in lieu of different distances of (h) in a diagram. The variogram, which obtained with samples measured is called experimental semivariogram.

Semivariogram has characteristics such as sill, range effect and nugget effect (Utset *et al.*, 2000) the value of sill is the greatest value of semivariogram which indeed is the spatial variance of the concerned parameter. The least point of semivariogram is nugget effect, which presents error of measuring and range effect presents the distance, which at that semivariogram reaches to the greatest value (Mohammadi, 2006). The ratio of nugget effect to sill can consider for valuation of spatial structure of data. When this ratio is smaller than 0.25 the concerned parameter has a strong spatial steal structure, between 0.25-0.75 spatial structure is middle, and when it is greater than 0.75 spatial structures is weak (Shi *et al.*, 2007).

To select the most appropriate fitted model to the experimental semivariogram and other features of semivariogram, different models were evaluated using cross validation. Different models with varying parameters were selected and after the implementation of kriging, the models with lower estimated error were selected. To investigate the spatial structure, semivariogram, representing the average spatial variation of soil organic carbon, was used.

Ordinary 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. The experimental semivariogram measures the average degree of dissimilarity between unsampled values and a nearby data value, and thus can depict autocorrelation at various distances. The value of the experimental semivariogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at Z(x) and the value at Z(x + h) (Equation 1).

From analysis of the experimental semivariogram, a suitable model (e.g. spherical, exponential, Gaussian) is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure (Ayoubi *et al.*, 2007).

Evaluation procedure

In this study, the performance of the interpolation method, was assessed by comparing the deviation of estimates from the measured data by performing a cross-validation technique and statistical parameters, MAE, MBE and RMSE were calculated. Equations (2) and (3), respectively calculated MAE and MBE.

$$\mathbf{MAE} = \frac{1}{n}\sum |Z^* - Z| \quad \textbf{(2)}$$

$$\mathbf{MBE} = \frac{1}{n}\sum (Z^* - Z) \quad \textbf{(3)}$$

Equation (4) also calculated root mean square error (RMSE).

$$\mathbf{RMSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n} (z - z^*)^2} \quad \textbf{(4)}$$

in these equations, n: Number of observation points, Z*: Estimate the amount of i points, Z: Average values of observation.

In a cross-validation procedure each data point is removed from the data set, one at a time, and predicted value is return by performing interpolation algorithm on the rest of dataset. This yield a list of estimated values of variable data paired to the test data. Finally, the spatial distribution map of SOC was plotted using ArcGIS (10.1) software.

Results

Exploratory analysis including descriptive statistics was implemented. Values of minimum, maximum, mean, variance, standard deviation, coefficient of variation, SD, skewness and kurtosis for the entire basin are presented in Table (1).

Table 1. Descriptive analysis of soil organic carbon.

Coefficient Variation	Std.Deviation	Max	Min	Kurtosis	Skewness	Mean
0.54	1.2	7.96	0.57	3.21	1.80	2.21

In this study, the normal distribution of the data was tested via Kolmogorov-Smirnov test. The data distribution is regarded normal if it has a ration larger than 0.05. Results show that the SOC does not follow the normal distribution. Therefore, it is necessary to close the data distribution to normal distribution by using one of the existing methods. In this study, normalizing the data was done through the logarithm making method.

The first step for making use of the kriging method in the present study was to investigate the presence of spatial structure among the available data by means of semivariogram analysis. This was achieved using those data, which were normalized. Subsequently, semivariogram for the kriging method were calculated (Fig. 2).

The Gaussian model was selected as the most suitable model for estimation of SOC. Effective radius, nugget effect and sill were calculated to be 3.64 Km, 0.17 and 0.48 respectively. The ratio of nugget variance to sill expressed in percentages (C_0/C_0+C) was regarded as a criterion for classifying the spatial dependence of soil parameters. Since this ratio SOC was between 25 and 75, this parameter showed moderate spatial dependence (Table 2).

Table 2. Best-fitted semivariogram model of SOC and it's parameters.

Model	Sill	Nugget	Range (km)	$\left({}^{c_0}/_{c_0+c}\right)$	RMSE	MAE	MBE
Gaussian	0.48	0.17	3.64	41.4	1.21	0.85	0.01

Finally, the Zoning map of SOC developed using ordinary kriging method seen in fig. 3. The SOC value increased from the southern to northern part in the study area and elevation decreased in this direction.

According to table (1), the amount of organic carbon the study area is in a range of 0.57 to 7.96 percent and the average is 2.21 percent. Optimal level of Soil organic carbon for rice estimated between 2-3%. According to the map (fig. 3.), less organic carbon, mostly in the south and northwest areas of study. In these parts can be used manure to increase soil organic carbon (shahdi *et al.*, 2012).

Discussion

The presented SOC stocks indicate a large spatial variability along an elevation gradient. The results of this research are in line with the results of Wang *et al.*, 2010, that determined the distribution of soil organic carbon in the lands of North East China using ordinary kriging. Their results showed that maximum carbon accumulation was recorded for the regions having lower altitude. These findings were in consistence with the distribution of organic carbon in Sefid-rood river delta. Areas with higher organic carbon located in low lands of study area with poor drainage that waterlogging in Most of the year. These leading to increased accumulation of organic carbon in the soil.

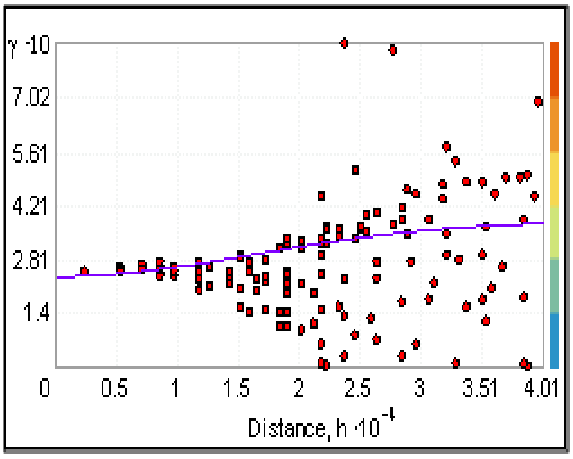

Fig. 2. Soil organic carbon semivariogram.

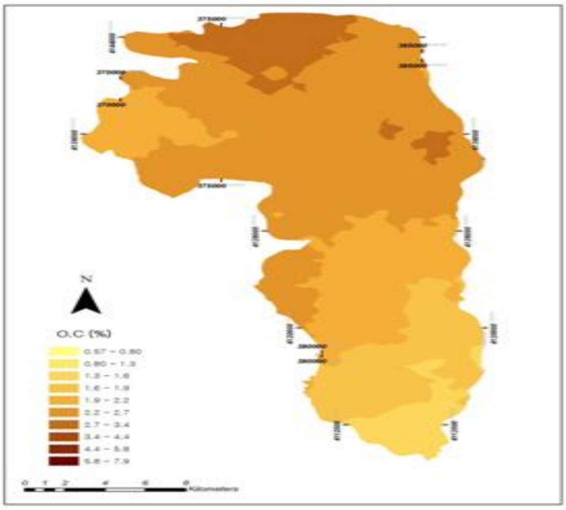

Fig. 3. Organic carbon zoning map by kriging method in study area.

Law *et al.*, 2009 introduced ordinary kriging as the best interpolation method. Parvizi, 2010 also used interpolation method for estimating soil organic carbon in the entire Karkheh watershed. Results showed that ordinary kriging, cokriging with covariable of lime percentage, and interpolation using RBF had the highest accuracy. Kabindra *et al.,* 2014 used ordinary kriging method for digital mapping of soil organic carbon contets and stocks in Denmark. They suggested that in areas with low organic matter, manure should be used to increase soil organic matter.

Conclusion

This study has used kriging, a spatial interpolation technology, to determine the SOC storage in the Sefid-Rood river delta, Gilan Province, Iran. Geostatistical methods could be used in the estimation of soil organic carbon. Kriging is an accepted way of interpolation of soil properties, but geostatistical methods can be evaluated by cross validation technique, however, it is recommended to evaluate other geostatistics methods including fuzzy kriging. In addition, the use of auxiliary data such as geology and land use or soil type as well as sub-division of study area may improve the prediction by reducing the overall variability and better to highlight the SOC relationship with environmental predictors. In the study area, where there is a lack of organic matter recommended to use manure to enhance soil organic matter level.

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