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Spatial variation of soil organic carbon in damavand rangelands

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Abstract

Sustainable management of ecosystems requires the understanding and evaluation of spatial and temporal variations of its characteristics for the optimal and sustainable utilization of resources. For this purpose, understanding the spatial distribution of soil properties is of utmost importance. Therefore, the present research was aimed to investigate the spatial variation of soil organic carbon in a part of Damavand Rangelands. In this regard, soil sampling was performed from 0-30 cm soil depth and the amount of soil organic carbon, total nitrogen content, the percentage of clay, sand and silt, pH, and bulk density was measured. To investigate the spatial variations, geostatistical methods including Ordinary Kriging (OK), Cokriging, and Inverse Distance Weighting (IDW) were evaluated. Cross Validation technique and statistical parameters of RMSE, MAE and MBE were also used. According to the results, spherical model was selected as the best-fit model for the semi-variogram of organic carbon with an effective radius of 1500 meters, a nugget effect of 0.02% and a sill of 0.025%. In the cokriging method, clay content was used as a covariable for predicting SOC ($P< 0.01$, r= 0.838**) . According to the variogram analysis, a spherical model with an effective radius of 1000 meters, a nugget effect of 0.085% and a sill of 0.165 was selected. The correlation coefficient of the model was calculated to be 0.084. The obtained results showed that the cokriging method had smaller errors (RMSE=0.1020) as compared to the other two methods. Therefore, this method was used for mapping soil organic carbon.

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Introduction

Rangelands are considered as one of the most important land ecosystems for carbon sequestration.

Although the amount of carbon sequestration per unit area is negligible, rangelands have high potential for carbon sequestration due to their large area (Schuman *et al.*,2002).

Sustainable management of ecosystems requires the understanding and evaluation of spatial and temporal variations of its characteristics for the optimal and sustainable utilization of resources. Maintaining soil quality is among the most important factors contributing to the sustainable management of ecosystems. For this purpose, understanding the spatial distribution of soil properties is of utmost importance (Sarmadian and Taghizadeh, 2010).

To investigate the spatial variations of carbon sequestration, geostatistics can be used. From a geostatistical standpoint, each sample can have spatial relationship with its surrounding samples to a maximum distance (span). This maximum distance, called effective radius, is of great importance.

Actually, it indicates the distance in which geostatistical estimators could be used (Hasanipak, 2008) and the factors affecting effective radius should be determined. Zhang and McGrath, 2004 investigated and analyzed the spatial variation of soil organic carbon in a rangeland region at South-East Ireland using geostatistical methods including Kriging, classical statistics and GIS.

Sampling was performed on a grid of 10 × 10 km and the outliers were detected and removed with Moran I index. Results showed that geostatistics had a good ability to interpret spatial and temporal changes in soil organic carbon and the effect of geology and topography was more than any other factors explaining the distribution of soil organic carbon.

Simbahan *et al.*, 2006 prepared the carbon distribution map using multivariate sources and secondary data. In this regard, Ordinary Kriging (OK), Cokriging (COK), and Regression Kriging (RK) were used. The electrical conductivity of each soil series and elevation maps were used in preparation of spatial distribution pattern of carbon. In addition, electrical conductivity was detected as a very helpful factor for carbon mapping. To reduce the uncertainty, it was suggested to perform independent measurements and multivariate secondary data in the regression kriging (RK) be used for soil organic carbon mapping.

In a study, Liu *et al.*, 2006 investigated the distribution of soil organic carbon and the effect of land use, soil and topography on farmlands using GIS and classical geostatistics. Data were fitted with lognormal distribution and the exponential variogram model was used. Classification method was used to investigate the effect of land use, soil type, elevation and slope. In addition, ANOVA and mean comparison were performed to compare the means of different classes.

Lufafa *et al.*, 2008 reported that geostatistics could be accurately used to estimate the amount of carbon storage. In this study, samples were taken from a depth of 20 cm and geostatistics was used to quantify the scale and degree of spatial dependence of soil carbon. Soil carbon variogram, representing a moderate spatial dependence, had a correlation of less than 0.56-1.34 in tree planting areas and showed a closer relationship with soil carbon levels as compared to shrub planting areas.

In another study, Vasques *et al.*, 2010 measured the total carbon content of four depths including 0-30, 30-60, 60-120 and 120-180 cm and presented a model of spatial distribution of carbon. In this research, ANOVA was used and regression block Kriging was compared with lognormal block Kriging. Soil depth, land use, soil type, soil drainage class and geological unit affect the total carbon content of soil.

The majority of environmental factors have spatial correlation with the spatial distribution of total carbon. In three soil surface depths, regression Kriging performed better than block Kriging, indicating that in most cases, environmental factors were determinants for spatial distribution of carbon. As a result, a spatial distribution pattern was generated in the study area (Florida), which provided information for soil conservation in Florida and similar conditions in Southeast America and other regions.

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.

The use of appropriate techniques for spatial evaluation and determining the role of physical and management factors in spatial distribution of soil quality properties and in particular soil organic matter as well as its destruction or sequestration is necessary.

However, very little research has been done on spatial modeling as a basic tool, required for soil management. Therefore, this research was aimed to investigate the amount of soil organic carbon accumulation in the region and produce distribution map.

Materials and methods

Study Area Characteristics

The study area is located in northeast of Tehran. It lies between longitudes 51° 59' 11''E and 52° 2' 37''E and latitudes 35° 38' 1''N and 35° 40' 33''N. The altitude of the study area varies between 1800 to 2200 m a.s.l. The total area is 410 hectares. At this stage, initially maps and other information of the study area were prepared by library studies and or referring to relevant institutions. In this regard, all existing maps including topography, soil, climate, geology, land use, together with aerial photos and satellite images of ETM+ 2002, IRS 2007, and MODIS 2010 were collected, Some of copied information was digitized. Some maps or secondary data including DEM map, slope, aspect, and land use were also prepared from the mentioned maps on a scale of 1:25000.

Sampling point selection

Then, according to the information, land unit map was produced for sampling and field studies. After determining the points and conveying the transferring to GPS, surface sampling was performed from a depth of 0-30 cm (plowing depth). After drying the samples in air, they were ground and passed through a two-millimeter sieve.

Laboratory analysis

Soil physical and chemical characteristics were measured including soil texture by hydrometer method as well as by soil texture triangle (the percentage of sand, silt and clay), organic matter by the Walkley and Black method, soil acidity using a pH meter, lime with neutralization method using hydrochloric acid and titration method, and bulk density by the clod method (liquid paraffin).(Ali Ehyaei and Behbehani Zade, 1993).

Statistical and geostatistic analysis

To estimate the spatial variation of soil organic carbon at not sampling points, geostatistical interpolation techniques, including Kriging, weighted moving average, and cokriging were used using ARCGIS software and the layer was prepared after geostatistical calculations.

To evaluate the interpolation methods, cross validation technique and statistical parameters, MBE and MAE were calculated. When MAE and MBE are equal or close to zero, this indicates that, the used method simulates the fact well while taking distance from zero shows the low accuracy or large deviations. MAE and MBE were calculated by Equations 1 and 2, respectively:

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

$$MBE = \frac{1}{n}\sum(Z^* - Z) \quad (2)$$

Root mean square error (RMSE) was also calculated by Equation 3.

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(Z - Z^*)^2} \quad (3)$$

Methods used in estimating the amount of soil organic carbon included ordinary kriging, Inverse distance weighting and cokriging. For geostatistical interpolation (kriging and cokriging), data were normalized by logarithmic transformation and then interpolation was performed on them.

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

Results and discussion

The characteristics of descriptive statistics for the collected samples are discussed here.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	Median	Mean
0.50	0.22	0.92	0.18	2.4	0.017	0.40	0.44

Normal distribution of data is essential for the interpolation of some geostatistics methods. In this study, normality was considered in order to map the spatial variability of data and in particular, determining the spatial distribution of soil organic carbon. If the values of skewness and kurtosis are closer to zero, the data distribution will be closer to normal.

According to the variography analysis, effective radius, nugget effect and sill were calculated to be 1500 meters, 0.02% and 0.025%, respectively (Fig. 1).

A correlation coefficient of 0.94 was calculated for the fitted exponential model.

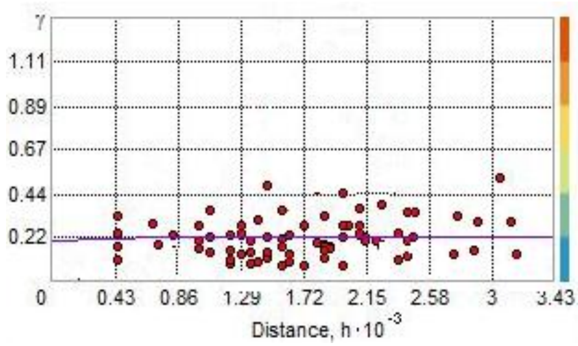

Fig. 1. Soil organic carbon variogram.

Several factors may affect the distribution of soil organic carbon, among which the percentage of nitrogen and clay could be mentioned. According to the results, the highest significant correlation was found between soil carbon and clay ($P<0.01$, $r=0.838^{**}$). The exponential model was fitted to the semivarogram of clay with an effective radius of 1000 m, a nugget effect of 0.085% and a sill of 0.165% (Fig.

2). The scatter plot of estimated and observed values is presented in Fig. 3.

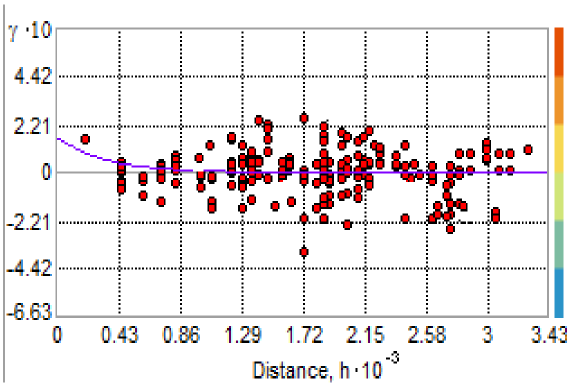

Fig. 2. Soil organic carbon and clay covariogram.

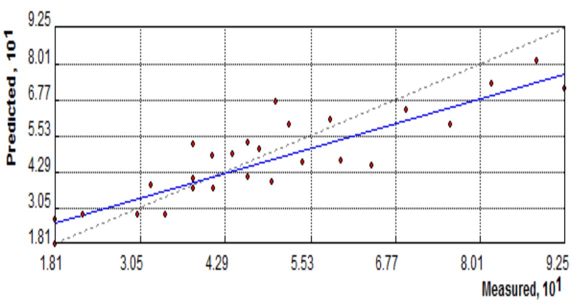

Fig. 3. Scatter plot of estimated and measure values in cokriging interpolation method for soil organic carbon data.

To select the proper geostatistical methods to estimate the amount of soil organic carbon, the deviation and accuracy of these methods were evaluated and results are presented in Table 2.

According to Table 2, cokriging method has less error and deviation as compared to kriging and weighted moving average methods. Therefore, cokriging method was selected as appropriate model for estimating of soil organic carbon and soil organic carbon map was drawn (Fig. 4).

Table 2. Evaluation of used methods for estimating soil organic carbon.

Methods	MBE	MAE	RMSE
IDW	-0.0283	0.1948	0.2192
Kriging	-0.0112	0.1889	0.2057
Cokriging	-0.0110	0.1754	0.1020

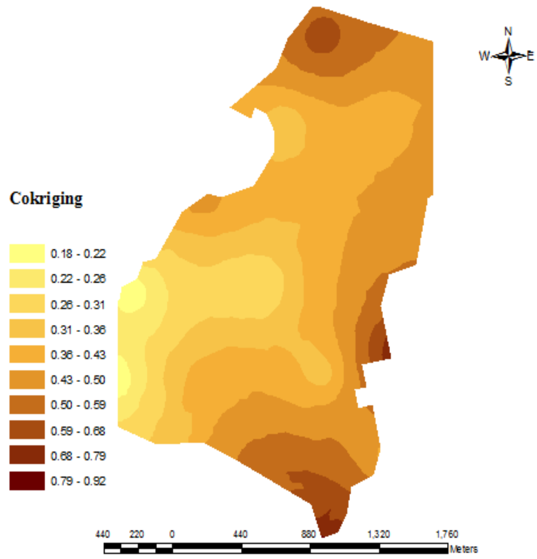

Fig. 4. Organic carbon zoning map by Cokriging method in the study area.

According to the map prepared based on average organic carbon, in general, the region faces a shortage of soil organic carbon so that in most of the study area the percentage of organic carbon accumulation is less than 0.6% and the amount of vegetation in these areas is less.

Wang *et al.*, 2009 determined the distribution of soil organic carbon in the lands of North East China using ordinary kriging. Sampling was systematic and spherical was identified as appropriate variogram model. Results showed that maximum carbon accumulation was recorded for the regions having lower altitude and more vegetation. These findings were in consistence with the distribution of organic carbon in Damavand.

Law *et al.,* 2009 introduced ordinary kriging as the best interpolation method. Exponential and or spherical were identified as appropriate variogram model. 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.

Geostatistical methods, having a high correlation coefficient and low error, could be used in the estimation of soil organic carbon. Cokriging, with an effective radius of 1000 m, and exponential variogram model showed the highest accuracy in the zonation of soil organic carbon. Geostatistical methods are evaluated by cross validation technique. However, it is recommended to evaluate other geostatistics methods including fuzzy kriging.

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