Chemical Science Review and Letters ISSN 2278-6783

Research Article

Geostatistical Analysis for Spatial Variability Mapping of Soil Organic Carbon of Research Farm of SKUAST-K

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Abstract

Soil organic carbon (SOC) is an important component for assessing the quality of the soil and has a significant role in soil protection, nutrient cycling and global climate changes. To explore and recognize the spatial distribution and variability of soil properties, geostatistics has become an important tool. This study involved grid sampling at a fixed distance of 70×70 m^2 of the Research Farm of Wadoora, SKUAST-K, where the actual field sampling data was combined with geostatistics to study the characteristic and spatial variability of soil organic carbon content A total of 90 soil samples were collected. The mean SOC content was found to be 13.48 g/kg. The variogram model of semi-variance function graph showed that the Gaussian model was the best fit. The range for the Gaussian model of soil organic carbon in the surface soil of research farm was found to be 166.69 m. As the average sampling grid interval was 70 m smaller than the minimal range, indicated that the sampling interval met the requirement for spatial variability analysis. The ratio of nugget to sill showed moderate spatial dependence. Ordinary Kriging interpolation was used to directly visualize the spatial distribution of SOC in the area. The results suggest that the ordinary Kriging interpolation directly reveal the spatial distribution of SOC and the sample distance about this study is sufficient for interpolation or plotting.

Keywords: Kriging, Nugget, Range, Soil organic carbon, Spatial variability, Sill

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Introduction

The global organic carbon pool approximates 1500 Pg [1]. The amount of carbon in the atmosphere is double this amount and in terrestrial vegetation the amount is 2-3 times [2].To mediate the process of carbon circulation, soil organic carbon plays a very important role. Soil organic matter forms an essential component of soil, which affects all the processes including physical, chemical and biological ones. Furthermore, soil organic matters significantly affect plant growth and fertility of soil thus acting as one of the important indicators of soil health. It not only releases the nutrients for plant growth but is a buffer against harmful substances. Organic carbon present in the soil is affected by climate change and the content of atmospheric CO_2 [3, 4]. Recently, the concern related to the organic C storage of soils has gained impetus because of its role in the increase in atmospheric CO_2 level and global warming as the CO_2 accumulation in the atmosphere can be reduced by conserving and sequestering C into the soil through different management practices [5]. Keeping in view, the importance of organic carbon in the soil, we should clearly understand the contents of soil organic carbon as well as soil organic matter and their spatial variability.

Spatial variability is a term indicating changes in the value of a given property over space [6]. Knowledge of the spatial variability of soil properties is essential for site specific soil management [7] and evaluation of various agricultural land management practices that can help to explain the significant effects on the spatial distribution of crop yield and quality. The study of spatial variability achieved through the analysis of the function of spatial covariance or semivariogram is not the final goal of spatial analysis but to estimate the values for unsampled locations [8]. So the present study was carried out to know the spatial variability of the soil organic carbon of the research farm of Wadoora campus of SKUAST -K.

Materials and Methods

Study Area, Soil sampling and analysis

The study area is the Research farm of SKUAST-K, Wadoora **Figure 1**. The geographical coordinates of the study area are between 34°20'37.88" and 34°21'17.08"latitudes and 74°23'23.25" and 74°24'27.67"longitude. The climate is temperate and characterized by mild summers and chilling winters**.** Soil samples (0-15 cm) were collected in a systematic grid specified at 70 × 70 m^2. The soil samples were air dried in shade, ground and passed through a 0.2 mm sieve. The organic carbon was determined using Walkley–Black method [9]. Data collected was transferred into Arc GIS software, where a map of the perimeter points was generated.

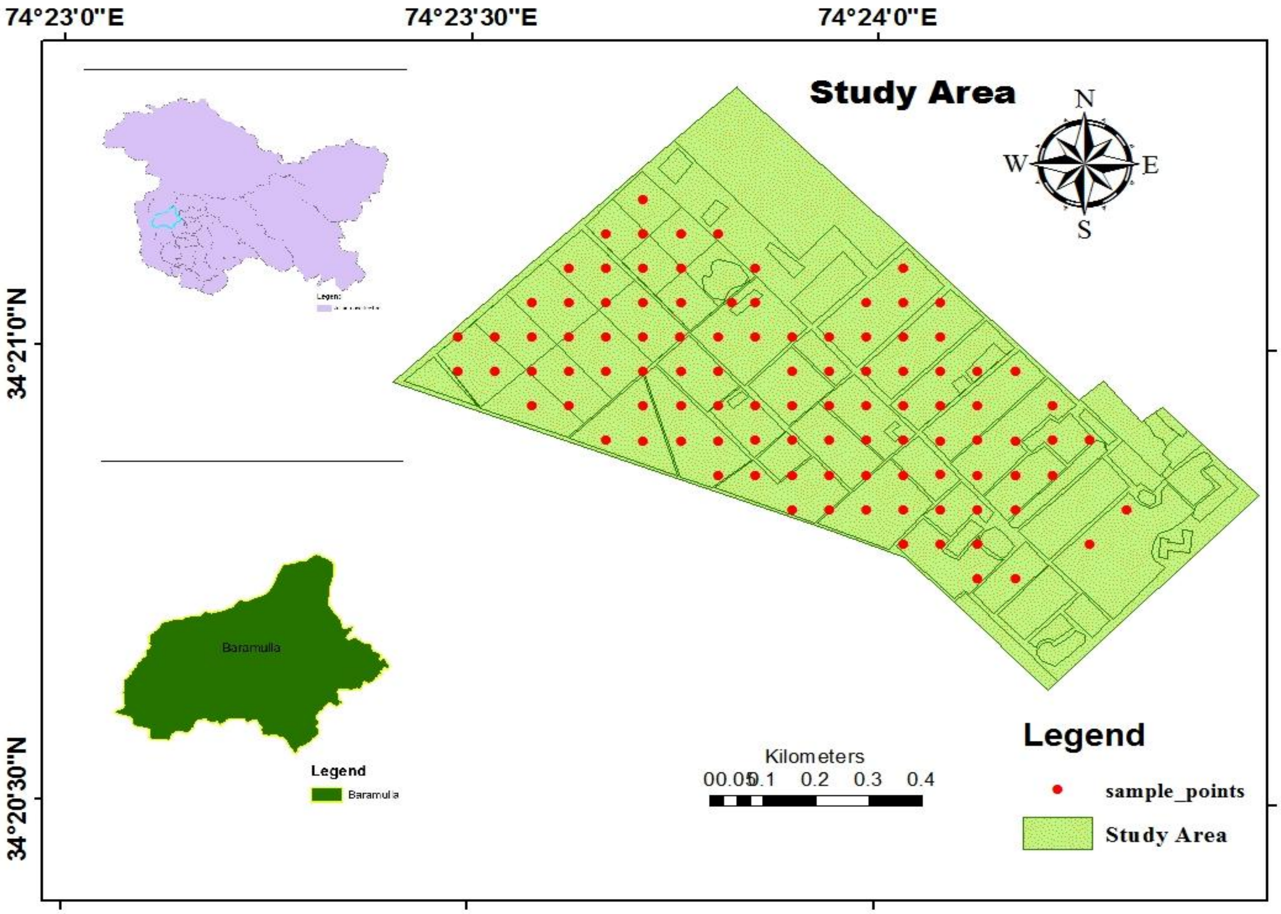

Figure 1 Georeferenced sampling sites of research farm of SKUAST-K,Wadoora

Statistical and geostatistical analysis

Descriptive statistical methods which include the description of mean, minimum and maximum values, standard deviation and coefficient of variation.were carried out by using SPSS. Exploratory data analysis was performed to describe the shape and flatness of data distribution respectively or normality of data or presence of any possible outliers [10] by plotting the histograms and normal Q-Q plots, Data that is not normally distributed is subjected to transformation. As the data was normally distributed semivariograms were developed for each parameter to evaluate their degree of spatial continuity and to determine these continuity changes as a function of distance and direction. Variogram involves plotting the relationship between the semivariance ***(γ(h))*** and the lag distance ***(h)*** [11]. The essentiality of this step lies in the determination of optimal weights for interpolation [12]. The formula applied to the variogram is:

$$\gamma(h) = \frac{1}{2N\,(h)} \sum_{i=1}^{N(h)} \left(Z(xi) - Z(xi+h)\right)^2$$

where, γ(h) is experimental semivariance, N(h) is the number of pairs of measured values $Z(x_i)$, $Z(x_i + h)$ separated by a vector (h). In geostatistics, Z (x_i) is described as regionalized variable [13].

Semivariogram has three important characteristic parameters which are distinguished as the effect of nugget, sill and range. When the function of semivariogram increases not from zero but from a certain value instead, it is called the effect of nugget (C_0) and shows that the physical variable is studied with the scale lower than the sampling range. The other reason might be the low measurement accuracy [10].The value at which the semivariogram function does not increase any further and this value is found to be approximately equal to the sample variance (s^2) is sill, whereas the distance from zero to the point at which 95% of the constant value has been reached by the semivariogram, is range [14]. The nugget/sill ratio, $C_0/(C_0 + C_1)$ is calculated to characterize the spatial dependency of the values, where <25 % indicates strong spatial dependency and >75 % indicates weak spatial dependency; otherwise, the spatial dependency is moderate [15].

The experimental variogram was fitted to a model which will best suit in order to display the spatial autocorrelation which exists. The most commonly used variogram models are linear, spherical, exponential, and Gaussian [16-18]. After the calculation of semivariogram, ordinary kriging analysis was carried out using GIS software. Kriging is a geostatistical exact interpolation technique based on a statistical model [19].The model used allows interpolation of unknown values based on values at neighbouring points [20]. It is an optimal method because the interpolation weights are chosen to provide for the value at a given point the Best Linear Unbiased Estimate (BLUE) [21]. The generally formula for kriging is:

$$Z\ (s_o) = \sum_{i=1}^{N}\ [\lambda_i z\ (s_i)]$$

where $Z\ (S_O)$ is the value to be estimated at the location of x_0, $Z\ (s_i)$ is the known value at the sampling site S_i.

The final step involves the cross validation of the method. It is done to evaluate and compare the performance of different interpolation methods through mean square error (MSE), average standard error (ASE), root-mean-square error (RMSE) and the standardized root mean square error (RMSSE)

Results and discussions

Spatial analysis conducted for the 0-15 cm soil layer, showed patchy structure for the soil organic carbon. Most of the area falls under high organic carbon content values, leaving few patches in lower to moderate category. The descriptive statistics of the parameter revealed mean to be 13.48g/kg, standard deviation 4.43 and variance 19.68 (**Table 1**). The skewness was found to be 0.51 and kurtosis 0.140 which conform to the limits of normality. Coefficient of variation was found to be 33 %, thus the parameter is moderately variable. Similar results have been found by [5, 22]. Q–Q plots and histograms were used for the evaluation of distribution of data and it was found that the parameter of soil organic carbon followed normal distribution. So, there was no need for the transformation of data as indicated by **Figure 2**.

Table 1 Descriptive Statistics of the soil organic carbon in the study area

O.C g/kg	N	Range	Min.	Max.	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
O.C	101	20.40	3.90	24.30	13.4861	4.43642	19.682	.506	.240	.140	.476

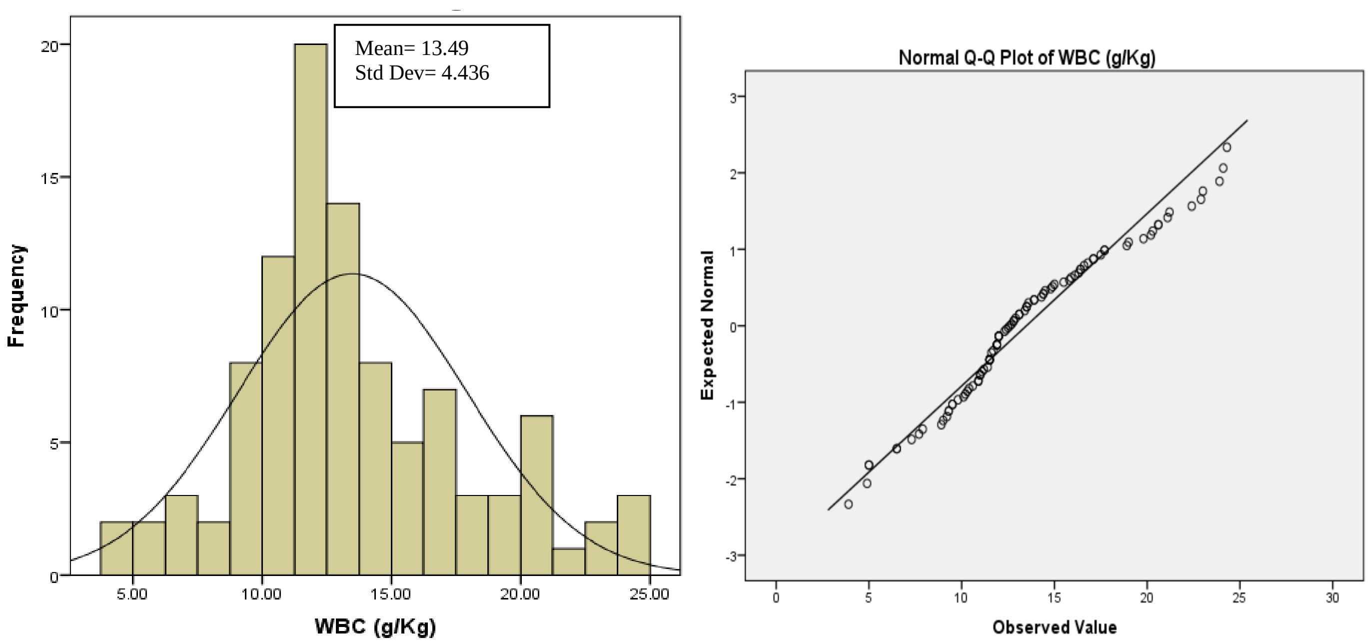

Figure 2 (a)Histogram and (b) Normal QQ plots for soil organic carbon

The best fitting model was selected based on the Root mean square error. Gaussian model with lowest RMSE was found most suitable **Figure 3**. The parameters of the model best fitted to soil organic carbon is given in **Table 2**. The range for the Gaussian model of soil organic carbon in the surface soil of research farm was found to be 166.69 m. A large range indicates that the measured soil parameter value is influenced by both natural and anthropogenic factors over greater distances. In general, the sampling distances that are outside of the range are invalid for interpolation or plotting. The average sampling grid interval was 70 m in this study. This sampling grid was smaller than the minimal range, which indicates that the sampling interval in the study area met the requirements for spatial variability analysis [5]. Thus it can be an effective criterion for the evaluation of sampling design and the mapping of soil properties [23]. Out of total variance, the nugget variance which is an indication of micro-variability was 9.43 while as the sill value which indicates the amount of variation was found to be 20.91. The high value of nugget was probably because of high soil heterogeneity resulting in large spatial variability of the soil organic carbon [24]. Based on the ratio of nugget and sill value which was found to be 0.45, the spatial dependency of the data was found moderate. The moderate spatial dependence of the soil properties may be controlled by intrinsic variations in soil characteristics such as texture and mineralogy as well as the extrinsic variations such as fertilizer application, tillage, soil and water conservation and other management practices [15]. To visualize directly the spatial distribution of SOC content in the study area according to the obtained semi-variogram model, the ordinary kriging interpolation method was adopted to interpolate the study area and to generate a spatial distribution diagram of SOC content **Figure 4**. The spatial distribution of SOC was observed to be in the form of patches or speckles. The figure depicts comparatively low carbon status in north, north- east, mid south and some patches in west. Some of these zones are under construction and others under intensive crop cultivation. The eastern, south east and south west areas show higher carbon content which might be due to fact that some areas are undisturbed fields while others are under orchards or woodlands. The distributions of SOC contents in soils results from the combined effects of soil parent material, climate, topography, landscape, and human intervention [25]. As the study area was small with a uniform climate, soil parent material, and soil type, the variation in the SOC content could be mainly due to human activities.

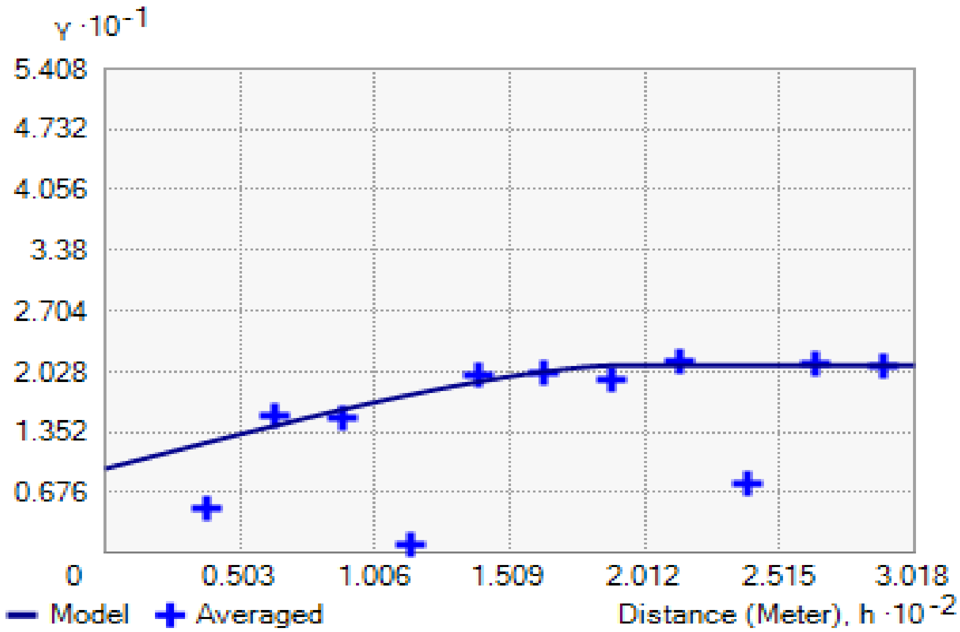

Figure 3 Semivariogram obtained for soil organic carbon from Arc GIS

Table 2 Values of model parameters used to find the best semivariogram

Soil parameter	Model	Nugget	Sill	Partial Sill	Range	Nugget/Sill	SD
Soil organic Carbon	Gaussian	9.43	20.98	11.55	166.69	0.45	Moderate

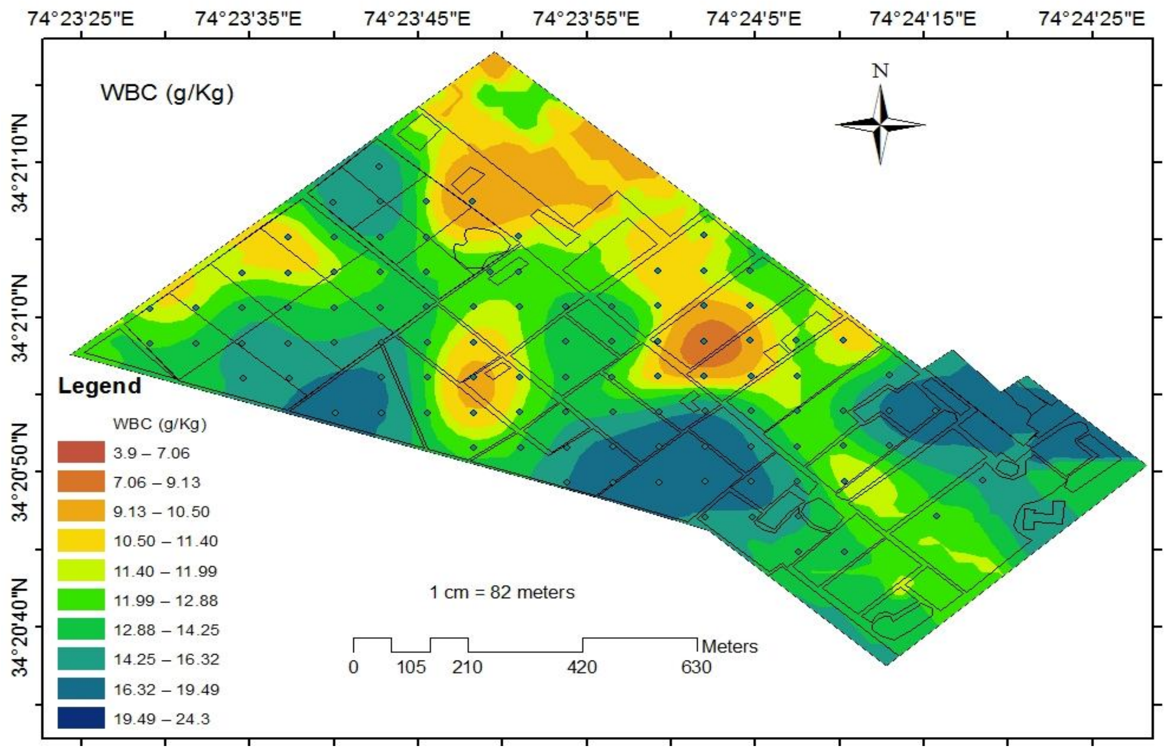

Figure 4 Spatial dependence of soil organic carbon of Research Farm, Wadoora

Conclusion

Understanding the spatial distribution and accurate mapping of soil properties is essential for precision farming, environmental monitoring and modelling. The map for organic carbon can be used to assess the soil fertility and to estimate the C storage. Spatial dependence of soil organic carbon was found to be moderate in the study area. Previous studies have shown that the distributions of SOC contents in soils result from the combined effects of soil parent material, climate, topography, landscape, and human intervention. In the present study, as the study area was small with a uniform climate, soil parent material, and soil type, the SOC content variations were mostly related to the landscape and human activities. The study also provides valuable information regarding sampling strategy. It provides an insight into the potential of adjustments in agronomic measures, such as in fertilization application of organic manure.

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Publication History
Received 02nd Mar 2018
Revised 16th Apr 2018
Accepted 04th May 2018
Online 30th May 2018