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Spatial Variation of Soil Organic Carbon and Soil Carbon Sequestration Potential using Geostatistical Method in the Domain District of Biswanath Chariali, Assam

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Abstract

The present research was aimed to estimate the spatial variability of soil organic carbon and their sequestration potential in the part of Bishwanaath, Chariali district of Assam. The sample was collected from marked sample points representing variability of soil type and crops grown. The collected samples were analysed for Soil Organic Carbon (SOC) and further SOC sequestration potential was derived based on this analysed SOC and CSP interpolation method deriving data in unsampled point. Geostatistical method *viz.,* ordinary Kriging was employed for the detailed spatial distribution of SOC, CSP and interpolation map of SOC and CSP were generated. From the generated map it was revealed that SOC was lowest at the western part of study sites whereas the CSP is lowest at two spot where intensive cultivation of rice were practised since long time resulting comparatively less SOC build-up in the soil system. The remaining part of domain district were of medium to higher CSP potential. This difference in spatial variability in SOC and CSP might be due to the variation in soil physical properties specially bulk density of the respective soil sites. The Nugget to Sill ratio was quite high in CSP that indicating the management factor plays a very important role in soil carbon sequestration potential.

1. Introduction

Environmental conditions play a crucial role in determines ecosystem productivity as well as organic matter decomposition. Weather, soil type and past land management have a direct effect on the carbon sequestering potential. The agricultural soils are whethera sink or source of carbon depends on the actual organic matter content in the soil Vleeshouwers and Verhagen (2002). By changing agricultural management or land-use, soil carbon is lost more rapidly than it accumulates. The factors responsible for its variability and to quantify the spatial distribution patterns of SOC, statistics and geostatistics have been applied widely (Frogbrook and Oliver, 2001) emphasized that the study of spatial variability achieved through the analysis of the function of spatial covariance or semi-variogram. Many workers for spatial variability of soil properties like for phosphorus (Grewal*et al.,* 2001), salinity (Nayak *et al.,* 2002), boron (Chinchmalatpure *et al.,* 2005), micronutrients (Nayak *et al.,* 2006) and soil properties and hydraulic parameters (Santra *et al.,* 2008). Geostatistics is a technology for estimating the soil parameters values in nonsampled areas or areas with sparse samplings (Yao *et al.,* 2004). These nonsampled areas can vary in space (in one, two or three dimensions) from the sampled data (Zhu *et al.,* 2005). Geostatistics provides a set of statistical tools for a description of spatial patterns, quantitative modelling of spatial continuity, spatial prediction, and uncertainty assessment (Goovaerts, 1999). Geostatistical techniques incorporating spatial

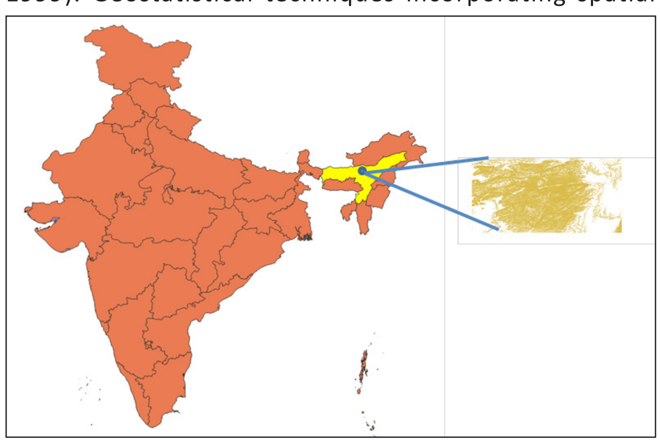

Figure 1: Study site

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information into predictions can improve estimation and enhance map quality (Mueller and Pierce, 2003).

2. Material and Methods

2.1. Study Area

Biswanathchariali (Figure 1) is situated between 26°30′ - 27°01′ N and 92.16′ - 93°43′ E with altitude ranging from 48-849 m above means sea level. The soil of the district can broadly be classified into three belts *viz.* Foothills of the Himalayas, Central belt of old alluvium and Low lying Riverine Belt. The foothill soil are alluvial laterite red soils washed down from hilly slope that are suitable for growing horticultural crops especially fruits. Soils of the central belt of old alluvium are sandy loam and silty clay in texture and acidic in reaction and aresuitable for paddy cultivation. The low lying reverine belt by the side of the river Brahmaputra is formed by the deposit carried on by the river and its tributaries during the flood to form alluvial fertile soil. The texture of the soil in this belt is sandy or loamy sand in nature with the reaction of neutral to slightly acidic. Different Rabi crops like pulses oilseeds, vegetable and spices like garlic are grown in this belt. Out of the total cultivable area of the district alluvial and sandy loam soils constitute 48.5% and 41.1% respectively. Sandy soil constitutes 8.6% of in the cultivable area.

2.2. Soil Sampling and Analysis

The soil was sampled from 26 sampling plots in January 2017 in agricultural land in the boundary of Bishwanath Chariali (Figure 1). A navigation system (GPS) installed in mobile app was used to collect each sample site information (Latitude and Longitude). In each plot, a soil pit was excavated and soil was sampled from two soil layers: surface soil (0-15 cm) and subsoil (15-30 cm). For each soil depth, approximately 1 kg of weight was collected for soil chemical analysis. In the laboratory, plant residues (*e.g.*, visible root and leaf litter) and rocks were removed, and then all soil samples were air-dried and passed through a sieve (0.15 mm) before measuring the SOC and Other Soil Parameters. SOC was determined using the Walkley Black 1934 Method. And converted into Soil carbon sequestration potential using equation (Yang *et al.,* 2007), CSP = SOC × BD × h × 10^{-1}.

SOC concentration (g kg^{-1}) for sampling layer, respectively; BD is the bulk density (g cm^{-3}), and his the thickness of the soil layer (cm). Interpolation method employed for deriving data in unsampled point. Kriging maps represent the detailed spatial distribution of SOC and CSP further, interpolation map of these parameters was done.

2.3. Geostatistical Methods

A geostatistical method is a spatial distribution and variability analysis method that was developed from classical statistics. The ordinary kriging (OK) interpolation method was used for prediction of the values of the unmeasured sites (un-samples locations) X_0 by assuming the z * (x_0) equals the line sum of the known measured value (field measured value). Kriging process is calculated by the following equation (Wang, 1999):

$$z^*(x_0)=\sum_{i-1}^{n}\gamma_i z(x_i)$$

Where, $z^*(x_0)$ is the predicted value at position, xo, $z(x_i)$ the known value at sampling site x_i, γ_i the weighting coefficient of the measured site and n is the number of sites within the neighbourhood searched for the interpolation.

Semivariograms were used as the basic tool to examine the spatial distribution structure of the soil properties. Based on the regionalized variable theory and intrinsic hypotheses Nielsen and Wendroth (2003), a semivariogram is expressed as:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{(i,j):h_{ij}=h} (x_i - x_j)^2$$

Where (h) is the semivariance, h the lag distance, Z the parameter of the soil property, N(h) the number of pairs of locations separated by a lag distance h, $Z(x_i)$, and $Z(x_i)$ are values of Z at positions x_i and x_{ih} (Wang and Shao, 2013). The empirical semivariograms obtained from the data were fitted by theoretical semivariogram models to produce geostatistical parameters, including nugget variance (C_0), structured variance (C_1), sill variance ($C_0 + C_1$), and distance parameter (k). The nugget/sill ratio, $C_0/(C_0 + C_1)$, was calculated to characterize the spatial dependency of the values. In general, a nugget/sill ratio of 25% indicates strong spatial dependency and 75% indicates weak spatial dependency; otherwise, the spatial dependency is moderate Cambardella *et al.* (1994). Low ratio indicating the spatial variability due to structural factor such as parent material, climate, weather, topography, whereas a higher ratio indicates the spatial variability due to the management factor.

2.4 Cross-Validation

Cross-validation technique was adopted for evaluating and comparing the performance of OK interpolation method. The sample points were arbitrarily divided into two datasets, with one estimate mean value against measured mean were used to validate the model. The root means square error (RMSE) is error based measures to evaluate the accuracy of interpolation methods. Estimating spatial variation of Soil carbon sequestration,

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i}-X_{o\,del,i})^2}{n}}$$

Where X_{obs} is observed values and X_{model} has modelled values at time/place.

3. Results and Discussion

3.1. Descriptive Statistic

The summary of the statistics for soil properties is shown in Table 1. The median of each soil properties was lower than the mean, which indicates that the effects of abnormal soil data on sampling value were nonsignificant. There was a difference in the Standard Deviation (SD) of the soil properties. The standard deviation 42% recorded in SOC whereas 48% in the CSP this show the medium variation in (15-50 %) according to guidelines provided by Warrick (1998). Skewness is the most common form of departure from normality. Both soil parameters show positive skewness but values were less than one, therefore, a logarithmic transformation was not performed. (Webster and Oliver, 2001).

Table 1: Descriptive statics of Soil organic carbon density and Soil carbon Sequestration potential

	Sill	Nugget	Range	Nugget/ Sill	Mean	Median	Kurtosis	Skewness	Standard Deviation	RMSE
Bishwanath Chariali (Study Area)										
Soil Carbon Sequestration (t C ha^{-1} Yr^{-1})	0.038	0.0291	0.03	0.13	1.51	1.39	2.93	0.52	48%	0.36
Soil Organic Carbon density (t C ha^{-1})	0.024	0.008	0.02	0.33	0.91	0.78	2.89	0.88	42%	0.58

3.2. Spatial Dependence of SOC and CSP

To identify the possible spatial structure of different soil organic carbon and Carbon sequestration potential, semivariograms were calculated and the best model that describes the spatial structure was identified based on minimum RMSE (Table 1). The range is expressed as a diameter of the zone of the influence this can be interpreted as distance over which a measured soil property of two samples was related and become similar (Figure 3) with decreasing the distance. Hence the range gives information aboutthe area of spatial dependence. The positive nugget value can be explained by sampling error, short-range variability, random and inherent variability. To define different classes of spatial dependence for the soil variables, the ratio, the nugget and sill was used (Cambardella *et al.*, 1994). In Bishwanth Chariali variable characteristics of soil organic carbon density and soil carbon sequestration potential (CSP) of soil which was generated from the semivariogram model. The mean SOC density 0.91 t C ha^{-1} and CSP was 1.51 t C ha^{-1} yr^{-1} recorded. The nugget variance represent is the structural variance, and (sill - nugget) represents the degree of spatial variability, which affected by both structural and management factors. The ratio between Nugget/sill the higher ratio indicates that the spatial variability is primarily caused by management factor, such as fertilization, farming measures, cropping systems and other human activities. The lower ratio suggests that the spatial variation mainly due to the structural factors, such as climate, topography, parent material, soil properties and other natural factors, play a significant role in spatial variability.

The value of 0.25, 0.25–0.75, and 0.75 can show strong, moderate and weak spatial autocorrelation in soil properties, respectively. As shown in Table 1, the Nugget/Sill C ratio values for SOC and soil carbon sequestration were 0.13 & 0.33, respectively. The very low nugget/sill ratio indicating weak spatial correlation therefore the variation was mainly due to structural factors. A similar result was also reported by Reza *et al.* (2012). The semivariance function model fits the exponential curve for soil carbon sequestration. The exponential curve gradually increased (Figure 2) with increasing spatial distance before stabilizing. The RMSE provides a measure of interpolation precision, with lower values indicating more precise methods the small value of RMSE (0.36 and 0.58 respectively for SOC and soil sequestration) indicating the model is a good fit for both soil parameters.

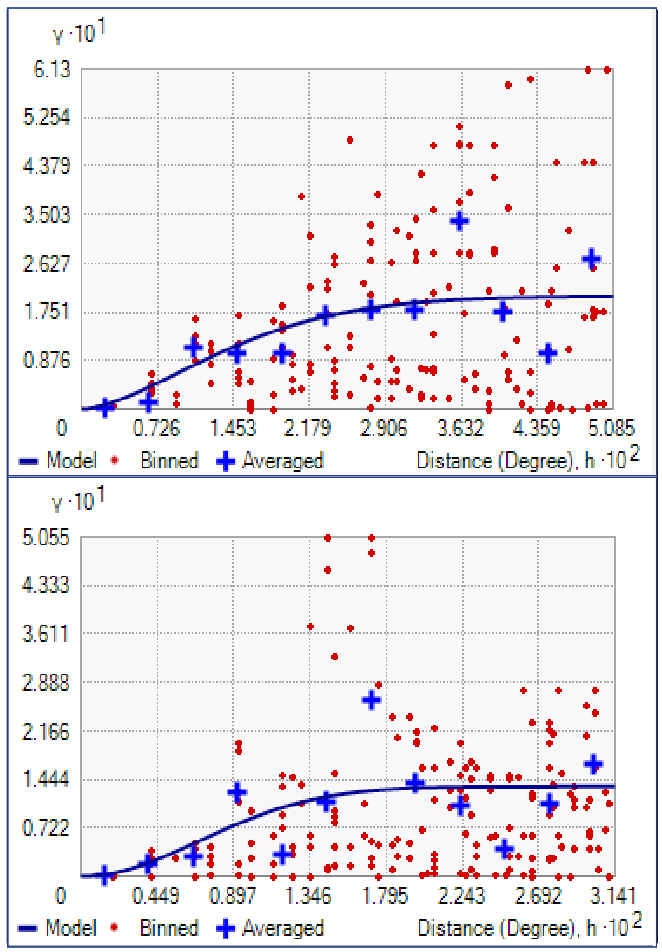

Figure 2: Semivariogram parameters of the best-fitted theoretical model to predict soil properties, (A) SOC (B) Soil Carbon Sequestration Potential of the study area

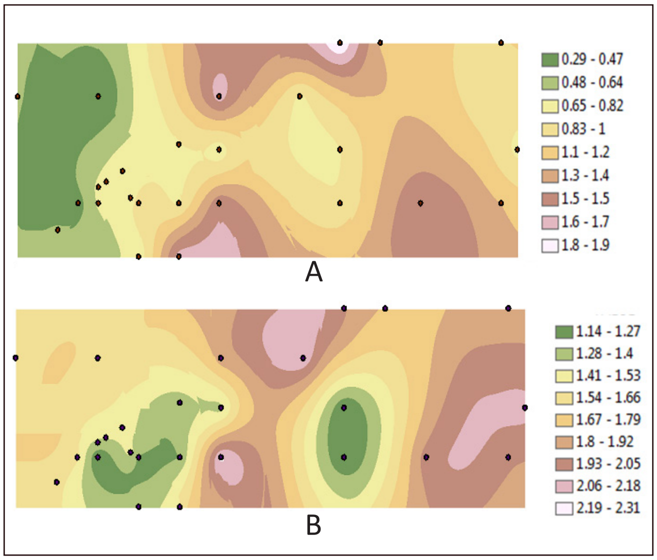

Figure 3: Spatial Variation of (A) SOC, (B) Soil Carbon Sequestration Potential of the study area by Ordinary Kriging

4. Conclusion

SOC varies spatially at various scales in all landscapes. The GIS approach is used to explore the extent of variation. The geostatistical analysis (Ordinary Kriging) showed that the eastern and central part had more SOC and soil sequestration potential compared to other parts of the study area. Both these soil properties decreased in the western part of the study area however it is increased in central, southwest and southeast quadrant. This interpolation map can be used to assess soil fertility status by correlating with other soil parameters. Kriging estimates are enhanced as sample size increases given an expected SD level. Moreover, the Kriging method required fewer samples than the classical method. In general, the geostatistical method on a large scale could be accurate and can be used to evaluate the spatial variability of soil properties for regional Scale in the Assam.

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