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Prediction of Spatial Distribution of Organic Carbon in Lower Brahmaputra Active Floodplain Soils of Bangladesh

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ABSTRACT: Soil acts as a large reservoir of Organic Carbon (OC) but the amount varies significantly with space and time. Thus, soil analysis and interpretation of spatial variability of Soil Organic Carbon (SOC) are keys to site-specific management. The study aimed to characterize the spatial variability of SOC in an active floodplain. Soil samples were collected in three major landform categories (natural levee, back slope, marsh land) from the lower Brahmaputra River floodplain and then analyzed for SOC measurement in the laboratory. The measured data were then analyzed for spatial variability interpretation using descriptive statistics and geo-statistical analysis. The study found that the amount of SOC varies with landform variation, soil texture and distance between sample points. The topsoil of marsh land has the highest (1.41%), back slope holds a moderate amount (1.15%) and the natural levee has the lowest (0.75%) amount of SOC. The amount of clay particles at the top layer was found to be positively correlated to the SOC whereas in the same layer of sand and silt showed a negative correlation. The geo-statistical analysis illustrated the nugget effect. Low (<1%) SOC is commonly found in the agricultural soils of Bangladesh which was corroborated in this study; moderate (1.1%) SOC was found in the floodplain. This study aimed to provide an insight into spatial variability to assist in predicting SOC in the active floodplain; consequently, the interpretation of spatial variability analysis can be implemented for site specific management strategies and to calculate carbon stock in floodplain soils.

Keywords: Soil Organic Carbon (SOC), Spatial variability, Geo-statistical analysis, Interpolated map, Site specific management

INTRODUCTION

Soil is a dynamic natural body which develops because of pedogenic natural processes during and after the weathering of rocks (Breemen and Buurman, 2002; Jenny, 1994; Nortcliff et al., 2011). It consists of mineral and organic constituents, possessing definite chemical, physical, mineralogical and biological properties which vary according to depth over the surface of the earth, and it provides a medium for plant growth (Biswas and Mukherjee, 1994; Mzuku et al., 2005). Soils are characterized by a high degree of spatial variability due to the combined effect of physical, chemical, and biological processes that operate with different intensities and at different scales (Goovaerts, 1998; Pennock and Kessel, 1997; Sağlam et al., 2011; Tan et al., 2003; Trangmar et al., 1987). Soils, in particular, are a large organic carbon (OC) reservoir with significant spatial variability (Batjes, 1996; Lal, 2004). Organic carbon in soils and sediments is widely distributed over the earth's surface occurring in almost all terrestrial and aquatic environments (Jobbágy and Jackson, 2000; Schnitzer and Khan, 1978). The floodplain surface and its shallow subsurface host a large reservoir for OC, including surface organic layers and soil organic carbon (Lininger et al., 20118; Perry et al., 2008).

Carbon (C) moves from the atmosphere to plants and soils and then, back in a grand cycle (Donovan, 2013) and in the context of the carbon cycle, floodplains can act as a major component of the biospheric carbon pool (Aufdenkampe et al., 1996; Battin et al., 1994). Like other soil properties, SOC levels exhibit variability because of dynamic interactions between parent material, climate, and geological history, on a regional and continental scale (Wang et al., 2001). Sanchez et al. (1997) stated that the nature and quantity of soil organic carbon affect many of the physical, chemical, and biological properties of soils. Soil pH, buffering capacity, nutrient supplies, and the activity of soil biota are all intimately related to soil organic carbon. Due to the importance of these relationships, soil organic carbon is considered a critical component when assessing soil quality (Karlen et al. 2008).

Studies on SOC showed the highest levels of C at the surface horizons, decreasing quickly with

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increasing soil depths and then sometimes changing slightly after a certain depth (Wang et al. 2010). The relative distributions of SOC with soil depth have been reported globally and are known to have a strong association with topography, soil types, vegetation types, soil properties, landuse and climate (Xiao-Wei et al. 2012; Yao et al., 2010; Zhang et al. 2013). Slope and surface characteristics are major topographical parameters that control the movement of water, sediments, and nutrients, and hence, modify soil formation, soil depth, moisture status, biomass production, and C inputs (Egli et al. 2009**)**. Yao et al. (2010) illustrated that clay provides both chemical and physical mechanisms to protect SOC from microbial decomposition.

Low SOC is a general problem in most agricultural soils of Bangladesh. More specifically, it was reported that almost 50% of the land area in Bangladesh has <1% SOC (Karim and Iqbal, 2001) which was later supported by (Rijpma and Jahiruddin, 2004; Uddin and Rahman, 2020) who also noted that about 60% of arable land has 0.87% OC. A similar trend was observed in the case of organic matter (OM) which was reported to vary between 10 g/kg and 17 g/kg (Hossain, 2001) and for basin soil, organic carbon was 0.095 g/kg (Uddin et al., 2020). The depletion of soil organic matter is reflected in low productivity which, unless addressed as a priority, may lead to a serious threat to the future sustainability of agriculture in Bangladesh. Huq and Shoaib (2013) and later Uddin et al. (2019) reported that several factors are responsible for low OM availability and includes intensive cropping, rapid decomposition of organic matter, deforestation, soil erosion, removal of crop residues, inundation etc. A better understanding of spatial variability of SOC is also important for refining agricultural management practices and for improving sustainable landuse. It provides a valuable base against which subsequent and future measurements can be evaluated (Liu et al., 2006).

Place-to-place variations within soil units influence floodplains study and use of soil, but this is seldom formally acknowledged in soil maps and descriptions (Campbell, 1979). This spatial information based on descriptive statistics and geo-statistics allow accurate description of the floodplain soil variation (Oliver and Webster, 2015; Webster and Oliver, 1990). Kriging is commonly used as a method in spatial interpolation, after estimating semi-variogram parameters of soil properties using geostatistical tools (Goovaerts, 1998; Zhao et al. 2015; Zhao et al. 2009). Presence of accurate information about the variability of soil properties is important to apply this information in environmental predictions, appropriate farming practices, and natural resource management (Minasny et al., 2013; Mousavi et al. 2017). Given this background in the context of a floodplain, knowledge of spatial variation of soil properties is important in precision farming and environmental modelling (Breemen and Buurman, 2002).

Studies at a national scale provide generalized insights of SOC but at a local scale, uncertainty remains about the OC concentration in floodplain soils. It remains to be determined if it follows a predictable longitudinal variation or is controlled by local factors (Scott and Wohl, 2018). A floodplain has a landmass of different height, and the altitude controls the inundation level, vegetation type, agricultural practice, biogenic activity, and so on; all these factors are linked to the availability of SOC. Thus, it is expected that in the study area the amount/ percentage of SOC availability should reflect the heterogeneity within the floodplain with varying landform/ elevation, soil layer, soil texture and distance from the bank line. Considering these floodplain heterogeneities, this study seeks to explore the availability of SOC across the floodplain and to examine if there is any pattern to these occurrences which could be used for further predictions.

MATERIALS AND METHODS

Study Site

This study was carried out on an active floodplain (regularly flooded on a periodic basis); a portion of the lower Brahmaputra River system located in Bangladesh. The lower Brahmaputra River is braided in nature and the study floodplain belongs to the young Brahmaputra. According to Banglapedia, (2020), this young Brahmaputra floodplain comprises 5924 km^2; the soil is of Gheor series (SRDI, 2003) and types are generally non-calcareous alluvium and grey in colour. They are mostly raw silty alluvium, which restricts the penetration of vegetation roots because of poor air causes aeration deficit. It has low fertility and poor moisture holding capacity (Huq and Shoaib, 2013). Figure 1 shows the location of the study area, which covers 39.21 km^2 area of the study floodplain. The study site is characterized by a tropical monsoon climate and average annual temperature and rainfall are 25.7^o C and 186 cm, respectively (SRDI, 2003). The study identifies three major landforms (Figure 1) are: a) Natural levee (8 km^2), b) Back slope (27.23 km^2), and c) Marsh land (3.97 km^2.

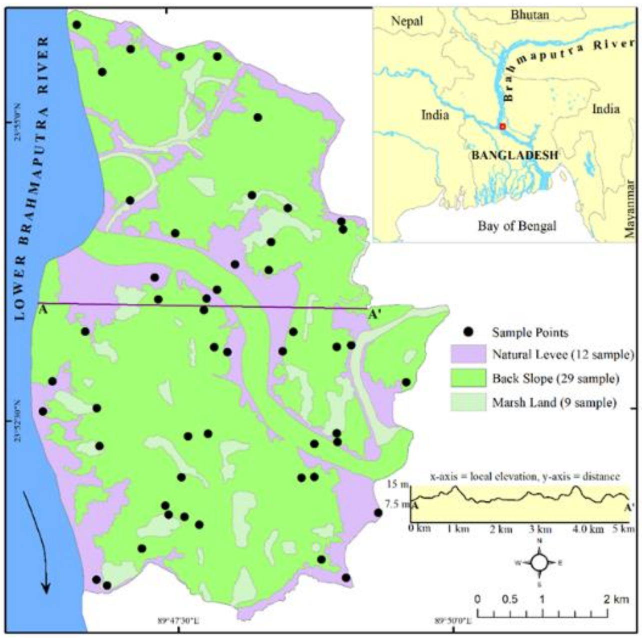

Figure 1: Study Site and Soil Sampling Location of the Lower Brahmaputra River Floodplain Along with Major Landform Types

Soil Sampling and Lab Analysis

Soil samples were collected during mid-May to early June 2019 from the study site. A systematic unaligned random sampling method was used for soil sample collection and the collected soil was mostly from agricultural land under different landform types (Figure 1). Considering the time, resources, and minimal requirements of samples for spatial prediction, it was (Figure 1) decided to collect soil samples from 50 sample points under three major landform types. For even distribution of sample numbers under each landform type, the samples were divided proportionately to the landform area. So, a total of 50 samples were collected from topsoil layer (depth 0-10 cm). A soil auger was used to collect the sample from the site and the position (latitude and longitude) values of each sampling point were recorded using a Global Positioning System (GPS, accuracy 3 m). The collected samples were then prepared for laboratory analysis and the amount of SOC was measured using the Walkley and Blacks' (1934) wet oxidation method. The textural properties of soil was measured using the Hydrometer method.

Data Analysis Method

To study the relationship between SOC and the factors affecting it and to quantify the spatial distribution patterns of SOC, statistics and geo-statistics have been widely applied. The data analysis conducted in two stages:

Descriptive Statistics

Distribution was analyzed by descriptive statistics (minimum, maximum, mean, median, standard deviation/ SD), and the coefficient of variation/ CV. In statistical analysis CV <15% signifies low variability, CV <35% signifies moderate variability, CV >35% signifies high variability (Daniel et al., 2017). The relation between SOC and soil texture was explored using correlation analysis and then the significance of the relation was tested by Regression analysis. All the descriptive statistical analyses were conducted using Microsoft Excel 2013 software.

Geostatistical Analysis

Geostatistical parameters were calculated for each variable as a result of the corresponding semi-variogram. Geostatistical analysis, including fitting the semi-variogram model and the ordinary kriging procedure, was carried out using ArcGIS (v.10.6) to assess the degree of spatial variability of each soil property used in this study. Based on the theory of a "regionalized variable" (Matheron, 1963), geo-statistics provides advanced tools to quantify the spatial features of soil parameters and to carry out spatial interpolation. Spatial structure referring to the spatial autocorrelation of field data was investigated through variogram analysis; the experimental semi-variance $\hat{\gamma}(h)$ is the average of the squared variance between the pairs of field observations and is calculated using:

$$\hat{\gamma}(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}[\,z\,(s_i\,+h)\,-z(s_i)\,] \qquad (1)$$

Where, $\hat{\gamma}(h)$ is the predictor of experimental semi-variance at distance lag h, $N(h)$ is the number of data pairs separated by distance h, $z(s_i)$ and $z(s_i\,+h)$ are actual measurements of two locations separated by h (Cressie, 1990).

A variogram is usually characterized by three measures- nugget, sill, and range. A variogram function is fitted to the experimental variogram to obtain geo-statistics, including nugget variance (C0), structured variance (C1), sill (C0 + C1), and range (A0) (Huang et al., 2015). Kriging depends on first computing an accurate variogram (Figure 4), which measures the nature of spatial dependence for the soil property (Burgess and Webster, 2019).

$$Degree\ of\ spatial\ dependence = \frac{C0}{C0+C1} \times 100\% \qquad (2)$$

Where, nugget variance (C0), structured variance (C1), sill (C0 + C1), and range (A0).

To explore the degree of spatial dependency, the ratio of the nugget to the sill (i.e., the nugget ratio) was calculated. According to (Huang et al., 2015) a nugget ratio <25% indicates a strong spatial dependency; a nugget ratio >75% indicates no spatial dependency; otherwise, the spatial dependency is moderate.

RESULTS

Descriptive Statistics of SOC and Soil Texture

Table 1 shows the descriptive statistical analysis value of SOC and soil textural properties (i.e. Sand, Silt, and Clay) of the Lower Brahmaputra River Floodplain. The minimum and maximum values of topsoil SOC were 0.19% and 1.95%, respectively. CV values of all selected properties, except silt (16.98%), showed strong variability, ranging from 40.7% for clay particle up to 150.92% for sand. The study found that the average amount of SOC for the topsoil layer is 1.1%.

Table 1. Descriptive Statistical Summary (Minimum, Maximum, Median, Mean, Standard Deviation) and Coefficient of Variation of SOC and Textural Properties across the Lower Brahmaputra Active Floodplain

Soil Properties %	Min	Max	Median	Mean	SD	CV%
SOC	0.19	1.95	1.12	1.1	0.46	41.58
Sand	0.01	44.54	2.42	6.41	9.68	150.92
Silt	38.49	85.41	64.61	63.1	10.71	16.98
Clay	7.12	58.98	30.37	30.52	12.42	40.70

Variability of SOC and Textural Properties in Different Landforms

The spatial variability of the mean amount of SOC and soil textural properties within the identified landform types across the selected floodplain topography is presented in Table 2. The study found that the amount of SOC and clay increase with decreasing land elevation while the sand and silt particles showed the opposite trend; the relationship is illustrated in Figure 2. For example, SOC of topsoil increased with decreasing elevation as it resulted in the lowest (0.75%) mean amount in the natural levee, followed by medium (1.15%) in the back slope and the highest (1.41%) in the marsh-land (note that the natural levee has the highest elevation, the back slope is moderately elevated and the marsh-land lies at the lowest level). The reverse scenario is seen for sand particles as the mean amount decreased (8.47%, 6.2%, and 4.37%) with waning elevation (natural levee, back slope, marsh land).

Table 2. Variability of Mean Values of Selected Soil Properties within the Identified Landform Types (Natural Levee /NL, Back Slope/BS and Marsh land/BS)

Landform Types	Number of samples	SOC%	Sand%	Silt%	Clay%
NL	12	0.75	8.47	67.00	24.51
BS	29	1.15	6.2	63.17	30.64
ML	9	1.41	4.37	57.46	38.17

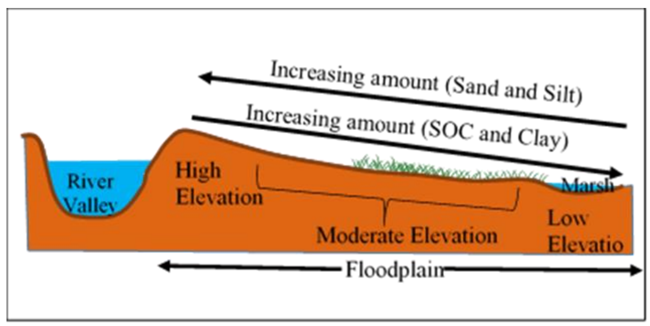

Figure 2: Land Elevation Controls the Variation of SOC in Floodplain. High Elevated Area Possess Low SOC due to Low Clay and High Sand While Low Lying Area Does the Opposite

Spatial Relation between SOC and Soil Textural Properties

Following is the correlation (r) matrix table (Table 3) of SOC, Pearson correlation coefficient. The topsoil and subsoil SOC showed high strong positive correlation (r = 0.69). Among textural properties, only the clay particle resulted in a positive correlation with both topsoil (r = 0.63) and subsoil (r = 0.28) SOC while all other (i.e. sand, silt) properties are negatively correlated with each other. There is a strong negative correlation between the silt and clay particles (r = -0.66) and moderate for topsoil SOC and clay (r = -0.47) and Clay and sand particles (r = -0.55). There is a weak to extremely weak/ no relation between topsoil textural properties and subsoil SOC.

Table 3. The Correlation Matrix Calculated through Pearson's Correlation r of Selected Soil Properties

Soil Properties	SOC %	Sand %	Silt %	Clay %
SOC%	1			
Sand%	-0.47**	1		
Silt%	-0.31*	-0.26	1	
Clay%	0.63**	-0.55**	-0.66**	1

* presenting p <0.05 and ** presents p <0.01. The value of p is obtained by regression analysis.

Spatial Variability of SOC

Maps derived from the geo-statistical kriging method are presented in Figure 4 showing predicted spatial variation of topsoil SOC. A spherical model was used to calculate the variogram for SOC, as it fitted for both topsoil SOC. Figure 3 presents the fitted variogram graph of SOC.

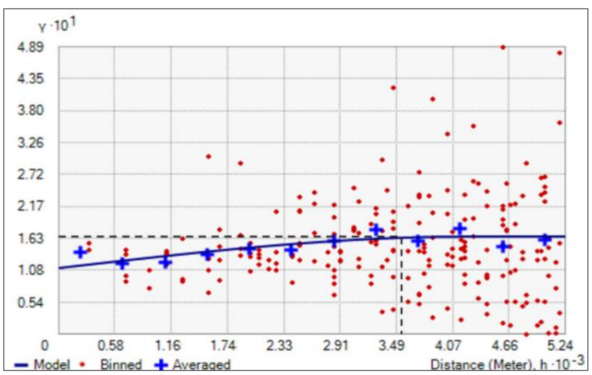

Fig. 3. Fitted Variogram Graph of SOC (0-10 cm) in Which the x- axis is Lag Distance (h) and on the y-Axis is Semi-Variance $\hat{\gamma}$.

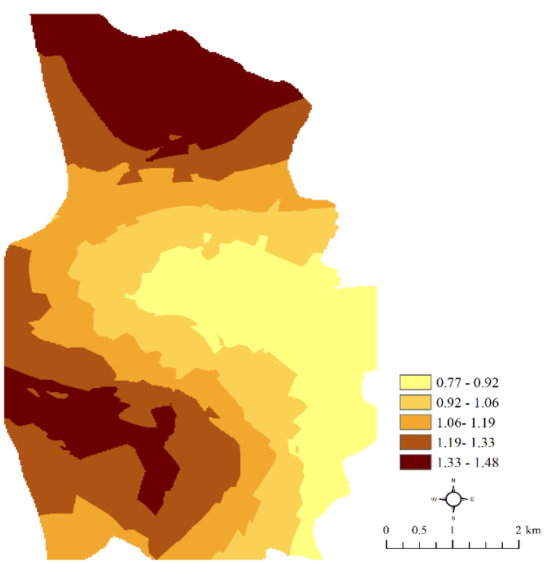

Figure 4: Krigged Maps of SOC (0-10 cm) of Lower Brahmaputra Active Floodplain. Predicted Map Presents More Diversity and Area with High to Moderate SOC.

Variogram of topsoil SOC show the nugget effect (0.13) and moderate spatial dependence (59.09) where spatial dependence is calculated from nugget (0.13) and sill (0.09). The lag distance for measured variogram was 670.46 m. The Root Mean Square Error (RMSE) was found low (0.43) from predictions variogram. The results indicate that topsoil SOC covered a high range 4224.09 m. The prediction map reflected the effect of landform variation as the high predicted SOC cluster around low elevated area and low SOC near high elevated land area.

DISCUSSION

The primary finding of the study is that there exists heterogeneity in the distribution of SOC throughout the floodplain with varying conditions, thus, the hypothesis is accepted. The results showed that there exist strong variability (CV) for most of the properties, considering topographic variations or variations in soil depth or among the selected soil properties. The average amount of SOC in the study floodplain found moderate (1.1%) which is a common phenomenon for the soils of Bangladesh as described in the introduction. Results showed that there is an inverse relationship between land level and SOC, with decreasing land level (Natural levee to marsh land) the amount of SOC increases. Shelukindo et al. (2014) determined that topography modifies overall climatic conditions and sediment deposition which affect the decomposition, accumulation, and formation of SOC in the floodplain.

The textural properties were included in the study as they are a direct controlling factor of SOC concentration in a floodplain. In this study area, it was found that soils fall under 6 different textural classes and the amount of sand, silt, clay varies at the intense range (very low to very high). Huq and Shoaib (2013) described tidal and estuarine floodplains containing low sand (<5%) compared to meandering floodplains, while this study had a braided river floodplain containing very low (<1%) amounts of sand, especially in agricultural soils. The results also presented a strong positive correlation (r = 0.63) between SOC and clay, which is statistically significant (p <.05); the reason behind this might be due to the formation of clay-organic complex.

Spatial dependency that predicted the spatial variation of SOC was the main focus of the study. The geo-statistical analysis resulted in a long-range dependency for SOC (variogram range A0 > 400 m) which reflects the topographic variation as confirmed earlier by Liu et al. (2013). The prediction map of topsoil SOC (Figure 4) indicates a high concentration of SOC on the southwestern and midwestern part of the floodplain which is acceptable because the area is mostly low lying facilitating the accumulation of SOC. The study considered the local variation of land level/altitude which was considered during soil sampling as it is the most important factor influencing SOC concentration. The relation between SOC and land level is reflected in the predicted maps.

CONCLUSIONS

The active floodplain has a distinct environmental setting and provides a suitable condition for OC generation. In the study area, the available volume of SOC is slightly higher (1.1%) than the national average (<1%) but the difference is not an outlier. The available amount of SOC in the floodplain is moderate and the spatial dependence is also moderate. Local factors, land level variations and textural variations are appeared to be very closely related to SOC concentration in the studied floodplain soils. The study tried to provide a comprehensive characterization of the distribution of SOC and its spatial prediction in an active floodplain at the local scale. This prediction approach can be used in farm-level/site-specific agricultural practices such as a better understanding of the concentration of SOC, agricultural zoning, or grading the use of fertilizer or calculation of the carbon stocks.

In this study, it was not possible to incorporate the relationship between subsoil SOC and textural properties. Furthermore, with other influential factors (e.g., organisms, time, vegetation type, soil chemical properties etc.) affecting SOC concentrations were not determined. Thus, there remains scope for further study on floodplain SOC and its distribution in space. Besides, there are limited studies on the spatial variability of SOC within and among different floodplain soils of Bangladesh at a local scale. This research makes an important contribution to studies related to the prediction of floodplain soils and agricultural management strategies.

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