Intelligent Environments 2020
C.A. Iglesias et al. (Eds.)

doi:10.3233/AISE200034

Geospatial Technologies in Precision Farming: A Case Study

Md. Jashim UDDIN[1,2], Peter S. HOODA[2], Abdus Salam Mohammad MOHIUDDIN[1], Mike SMITH[2]

[1]*Department of Soil, Water and Environment, University of Dhaka, Dhaka 1000, Bangladesh*
[2]*School of Natural and Built Environments, Kingston University London, Kingston upon Thames, KT1 2EE, United Kingdom.*

Abstract. The knowledge of spatial variability in soil organic carbon (SOC) is an important consideration in precision agriculture as well as site specific nutrient management. Geostatistical analyses coupled with GIS and GPS are effective tools in assessing the spatial variability and mapping of SOC. A total of 268 soil samples were collected in a systematic grid design (1-minute interval) using GPS covering four sub-districts: Delduar, Melandah, Mirpur and Fultala under two major alluviums - the Ganges and the Brahmaputra. The classical statistics showed that SOC values are normally distributed in the Fultala sub-site whereas in the other sub-sites, the SOC contents were not normally distributed. The semivariogram model also shows that the Fultala sub-site appears to have a strong structure and a gradual approach to the Gausian model providing the best fit where as the other sites show a weak spatial dependency. Due to salinity and other constrains, Fultala sub-site bears a relatively low cropping intensity and hence tillage and crop management are much lower than the other sites. GIS based interpolated values of SOC ranged from 0.39 to 2.02 % in the Fultala sub-site. Interpolated values of SOC ranged from 0.40 to 2.60% in the Delduar sub-site, 0.40 to 1.35% in the Melandah sub-site and 0.38 to 1.39% in the Mirpur sub-site respectively. Clearly, the sites where SOC is low, a pragmatic and location-based policy should be adopted to maximize SOC sequestration. Therefore, the geospatial technologies can help better management of agricultural land by targeting management practices appropriate to the SOC levels.

Keywords: Geostatistics; GIS-GPS; Kriging; spatial variability; precision farming.

1. Introduction

Soil organic carbon (SOC) has an important influence on the physical, chemical and biological properties of soil and is critical for improving soil fertility and quality, increasing the water holding capacity of soil, reducing soil erosion, and enhancing crop productivity [1-2].

---

[1]Corresponding author, Md. Jashim Uddin, Department of Soil, Water & Environment, University of Dhaka, Dhaka 1000. Bangladesh; E-mail: juswe@du.ac.bd

With climate change and environmental issues dominating global concerns, SOC has received increasing attention worldwide because of its important role in the global carbon cycle and its potential feedback on the global warming [3-4]. Soil organic carbon and its relation to site characteristics is important in evaluating regional, continental, and global soil C stores and projecting future changes [5].

However, due to high soil heterogeneity, it is difficult to obtain an accurate assessment of SOC stock [6]. As a result, there is a considerable interest in understanding the spatial variability of SOC in different terrestrial ecosystems [7-8]. Geostatistics has been widely used to assess the spatial characteristics of SOC [9]. SOC is a determinant of SOC stock [6], and its spatial distribution is intimately related to the changes in environmental factors [10-11]. However, the relative importance of the edaphic factors as drivers or constraints of spatial heterogeneity of SOC content in the alluvial soils of Bangladesh is not well understood.

GIS is useful to produce interpolated maps for visualization, and for raster GIS maps; algebraic functions can calculate and visualize the spatial differences between the maps [12]. For studies on the spatial distribution patters of SOC, geostatistics has been widely applied [13-15] and based on the theory of regionalized variables [16], geostatistics provides tools to quantify the spatial features of soil parameters and allows for spatial interpolation. The krigged maps of soil parameters can help to become familiar with the characteristics related to the analysed soil properties and accordingly can plan prcision agricultural planning [17]

The vast majority of farmers in developing countries like Bangladesh are smallholder farmers, meaning that they grow food on a small piece of land largely to feed their families. They often make field decisions on the basis of generic recommendations or historical information rather than factual recommendations. Farming practices based on historical information often do not achieve maximum production benefits; thus, it is important that small holding farmers should follow factual/science-based recommendation. In recent years, climate change has also become a burning issue in developing countries like Bangladesh. Considering the above issues, the concept of precision can help increase crop productivity and mitigate CO_2 emissions by sequestering SOC.

This study makes use of GIS and GPS in combination with classical statistics and geostatistics to assess the spatial variation characteristics of SOC in the Brahmaputra and the Ganges alluviums of Bangladesh. The specific objectives of this research were to measure the SOC and to make an outline on precision farming depending on the SOC status.

2. Materials and Methods

2.1. Soil sampling, processing and SOC analysis

Soil samples were collected in one-minute latitude and longitude interval (1 minute = 1600 m and 1 second = 26.5 m), equating to a grid size of 1600 m. Whilst a smaller size grid would have better captured the spatial variability, resource and time contraints prevented the use of a more intensive sampling strategy. GPS Magellan (Model: 320) was used to identify the geographic coordinates as well as sampling locations. Land and soil resource utilization guides (LSRUG) of the Soil Resource Development Institute (SRDI) were used as a base material during field visits and soil samplings. Four Upazilas or sub-sites (Delduar, Melandah, Fultala, and Mirpur) were selected across the two major alluviums of Bangladesh where they fall under the diverse agro-ecological regions. Delduar and Melandah Upazilas under the Brahmaputra alluvium covered 66 and 80 grid points respectively. Mirpur and Fultala sub-sites under the Ganges alluvium covered 96 and 26 grid points respectively. Thus, 268 soil samples were collected from the 0-30 cm depth on a grid basis across the four sub-sites. Soil samples from each sampling were collected in polythene sample bags. The bags were sealed properly precluding moisture loss from the samples and transferred as quickly as possible to the laboratory for relevant analyses. Prior to analysis, the soil samples were spread on a polythene sheet and big lumps were broken and air dried under shade. The soil samples were then gently ground by rolling a wooden rod and also with a wooden hammer, passed through a 2-mm (10 mesh) sieve, and mixed thoroughly. The samples were then preserved in plastic bags for laboratory analysis. Organic carbon in soil was determined by the wet oxidation method of [18] as described by [19].

2.2. Classical statistics and Spatial Analysis

SOC variability was tested within the sub-sites where a classical statistical analysis was used. This illustrates the trends and the overall variation of the SOC variables. This test includes descriptions of the minimum, maximum, mean, skewness, kurtosis, standard deviation (SD), coefficient of variations (CVs), histogram and Q-Q plots. All the above analyses were done using the statistical package SPSS version 20.0 (SPSS Ins., Chicago, IL, USA). Geostatistical analysis, construction of semivariogram, and spatial structure of SOC variability were performed with GS^+ version 10.0 using Gamma Design Software, Plainwell, Michigan, USA [20]. Spatial interpolation through kriging and IDW were done with the GIS software ArcGIS version 9.3 (ESRI Inc., Redlands, California, USA). Data interpolation through kriging and Inverse Distance Weighting (IDW) were performed in ARCGIS 9.3 [21]. When the spatial structure is strong, krig interpolation was done and on the other hand, when the spatial structure is weak, then IDW interpolation was used.

3. Results and Discussion

3.1. Classical statistics and Geostatistics

Classical statistics of the SOC dataset of the four sub-sites are summarized in Table 1. Mean contents of SOC across the four sub-sites of the two alluviums were different and ranged from 0.69 to 1.14%. From Table 1, it may be noted that Delduar and Fultala sub-sites have very similar mean SOC values and Melandah and Mirpur sub-sites have similar mean SOC. SOC variation is higher in the Delduar and Fultala sub-sites than the other two sub-sites. Co-efficient of variation (CV) across the four sub-sites varies from 30.9 to 47.8% indicating a moderate variability in SOC. CV values also indicate the trends in mean SOC across the four sub-sites i.e., Delduar and Fultala sub-sites have similar CV whereas Melandah and Mirpur sub-sites have similar CV. Overall, the extent of SOC variability across the sub-sites of the Brahmaputra and the Ganges alluvium soils can be considered as moderate. The moderate CV of SOC across the study sites may be due to the heterogeneity of topographic units and soil types [8].

Table 1: Summary statistics of SOC contents in the four subsites of the Brahmaputra and the Ganges Alluviums

Variables	SOC (%)			
	Delduar	Melandah	Fultala	Mirpur
Mean	1.14	0.75	1.13	0.69
Minimum	0.40	0.40	0.30	0.38
Maximum	2.60	1.35	2.30	1.39
SD	0.553	0.246	0.511	0.214
CV(%)	47.8	32.8	45.1	30.9
Skewness	0.30	0.27	0.44	0.25
Kurtosis	0.59	0.53	0.858	0.49

SD= Standard Deviation, CV= Coefficient of Variation,

It is important to test whether the SOC contents followed a normal distribution or not. To test this, two methods were used. First, the histograms of SOC were plotted with a normal distribution curve. This shows that SOC is positively skewed across the three sub-sites except at Fultala. Second, a Quantile-Quantile (Q-Q) plot was used, which also shows that the SOC is normally distributed only in the Fultala sub-site with a straight line. From these tests, it is important to note that SOC datasets do not fall on a straight line in the sub-sites of Delduar, Melandah, and Mirpur; thus Fultala is the only sub-site where SOC is normally distributed. In recent years, spatial dependence models of geostatistics have gained popularity as they allow the quantification of landscape spatial structure from point-sampled data. The understanding of the spatial variability of SOC levels between and within farms is very important for refining the farm management practices and implementing precision farming.The spatial dependence of SOC was determined by the semivariogram analysis. In the current study, the tested SOC in each sub-sites was modeled with linear, spherical, Gaussian or exponential semivariograms with a nugget effect.The values of the different semivariogram parameters i.e., nugget (Co), sill (C+Co), range (Ao), and nugget/sill ratio are given in Table 2. Generally, the nugget effect can be defined as an indicator of continuity at close distances.

Table 2: Parameters of the semivariogram models estimated for the SOC contents across the study sites

Sub sites	Model	Nugget (Co)	Sill (C+Co)	Co/C+Co	Range (Ao)	RSS*	R^2
Delduar	Spherical	0.037	0.330	0.113	0.02	0.006	0.233
Melandah	Linear	0.067	0.067	1.00	0.10	0.005	0.138
Fultala	Gaussian	0.064	0.296	0.216	0.03	0.001	0.946
Mirpur	Exponential	0.029	0.058	0.499	0.07	0.002	0.055

*RSS= Residual Sum of Squares

The semivariogram for SOC across the four sub-sites are shown in Figures 1-4. The semivariogram of the Fultala sub-site appears to have strong structure and a gradual approach to the range, with the Gaussian model providing the best fit. It shows a nugget (Co) of 0.064; a sill (C+Co) equal to 0.296; range (Ao) equal to 0.03; coefficient of determination (R^2) of 0.946; and a residual sum of squares (RSS) equal to 0.001. This semivariogram appears to exhibit a pure nugget effect, possibly because of a too sparse sampling to adequately capture autocorrelation. On the other hand, the other three sub-sites (Delduar, Melandah and Mirpur) show similarity to the Fultala sub site regarding the nugget effect, sill, range and RSS. However, the coefficient of determination (R^2) clearly shows that SOC datasets at these three sub-sites do not adequately fit to any of the semivariogram models. The lowest RSS value is one of the criteria of selecting the best fitted models [22]. In the case of Fultala, R^2, RSS and nugget-to-sill ratio reveal that at this sub site SOC is strongly spatially dependent (Table 2). The other sub sites i.e., Delduar, Melandah, and Mirpur, show a weak spatial dependency as they have $R^2<0.5$.

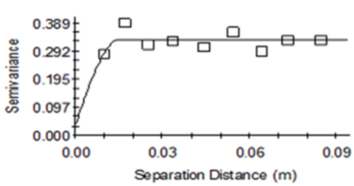

Figure 1: The semivariogram model of SOC at the Delduar sub-site of the Brahmaputra alluvium

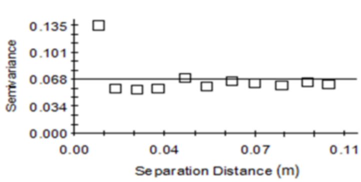

Figure 2: The semivariogram model of SOC at the Melandah sub-site of the Brahmaputra alluvium

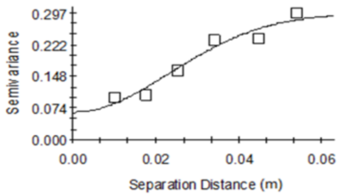

Figure 3: The semivariogram model of SOC at the Fultala sub-site of the Ganges alluvium

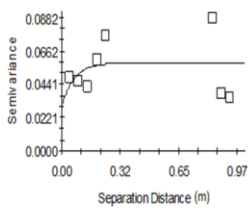

Figure 4: The semivariogram model of SOC at the Mirpur sub-site of the Ganges alluvium

Spatial variability of soil properties may be affected by both intrinsic i.e., soil forming factors such as parent materials and extrinsic factors i.e., soil management practices such as fertilization, tillage and general soil management practices [23]. They also added that strong spatial dependency of SOC can be attributed to intrinsic factors whereas weak spatial dependency can be attributed to extrinsic factors.Thus, the strong spatial dependence of SOC across the Fultala sub-site may be attributed by the structural or intrinsic factors which is governed by the larger resolution sampling design.The structural or intrinsic factors are the topographic units, SOC contents, mineral composition and soil type, etc. The possible causes of spatial variability in SOC may be the topographic land units and soil types, though other factors such as land use and management are also associated. The spatial variation in SOC may be partly attributed to the complex topography in the landscape [8]. The Fultala sub-site occupies three diverse physiographic units, Ganges tidal floodplain i.e., saline soils, peat soils with high SOC contents and non-saline soils. Due to its inherent low fertility nature [24], this sub-site bears a relatively low cropping intensity. Hence, tillage and crop management activities are much lower than any other sites.

As a result, the spatial structure of SOC in the Fultala sub-site is not influenced by the soil fertilization and cultivation practices. As such, the spatial dependence remains strong in this sub-site. On the other hand, agricultural activities (such as tillage, irrigation practices; and land use intensification by higher cropping intensity), are the random factors which prevail across the other three sub-sites. Thus, it would appear that the SOC in the three sub-sites lacks spatial dependence. This is possibly attributed due to extrinsic factors of soil fertilization, which weakened their spatial correlation after a long history of cultivation. The weak spatial dependence of SOC across the Delduar, Melandah and Mirpur sub-sites is likely attributed by the human activities such as tillage, cropping system management, irrigation practices, land use cover, manure and fertilizer, crop residue management and cropping intensity etc. [25].

3.2. Spatial Interpolation of SOC

In order to apply agricultural practices precisely and appropriately, it is important to investigate the spatial distribution of SOC across the four sub-sites. The parameters derived from the geostatistical models were used for kriging and inverse distance weighted (IDW) i.e., spatial interpolation by which spatial distribution maps of SOC across the study sites were produced (Figures 5-8). The maps of SOC distribution clearly show how the predicted values are spatially distributed. The interpolated krig map for Fultala (Figure 5) shows a strong spatial dependence. SOC concentration in this sub-site decreased from south to north, which was apparently related to the nature of soil and topographic conditions. On the other hand, weighted interpolation SOC maps were prepared for the other three sub-sites (Figures 6-8) which showed weak spatial dependence. It may be noted that weighted interpolation is used where data have weak spatial dependence or no spatial dependence. IDW is based on values at nearby locations weighted only by distance from the interpolation location, Bulls eye effect was found in this IDW datasets. Thus, IDW helps to compensate for the effects of data clustering, assigning individual points within a cluster less weight than isolated data points or treating clusters more like single points. IDW-interpolated maps for the other three sub-sites indicate that the spatial structure is dispersed due to the continuous management of the soil resources i.e., a weak SOC spatial dependency. Besides, it should be mentioned that the SOC were concentrated in some particular areas or land types of the Delduar, Melandah and Mirpur sub-sites which may be due to their local variability of land types and differences in land management practices and intensities.

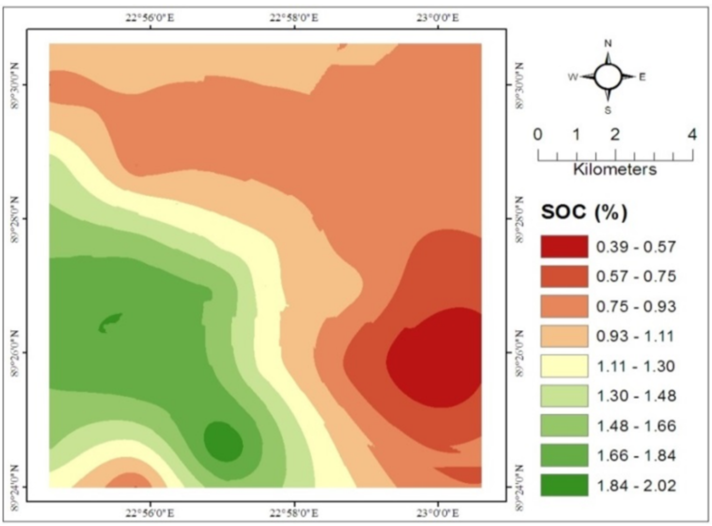

Figure 5: Distribution of SOC contents (%) in the Fultala sub-site using Kriging

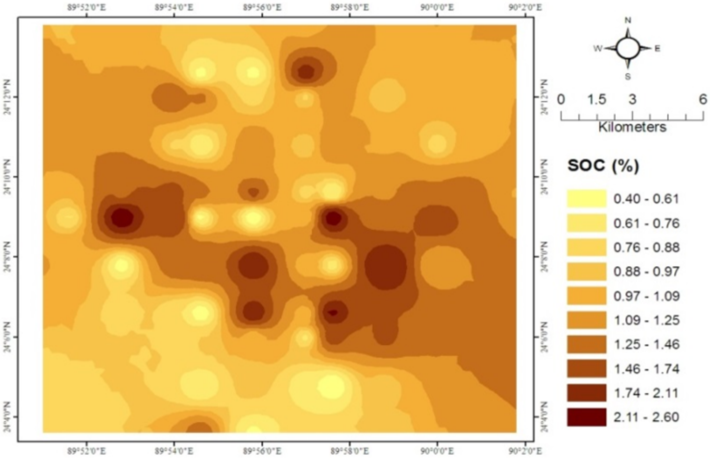

Figure 6: Distribution of SOC contents (%) in the Delduar sub-site using IDW

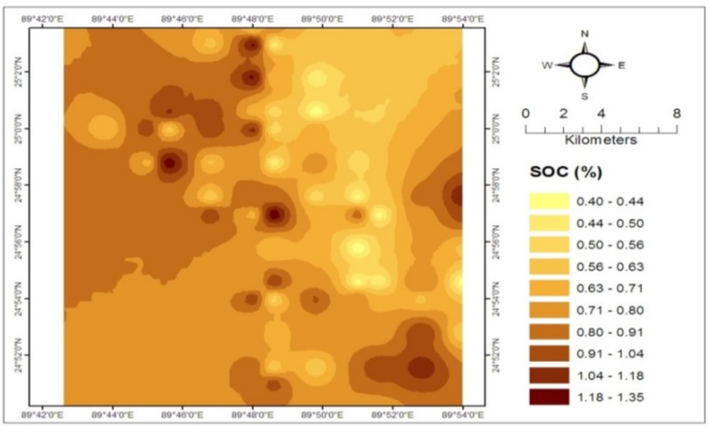

Figure 7: Distribution of SOC contents (%) in the Melandah sub-site using IDW

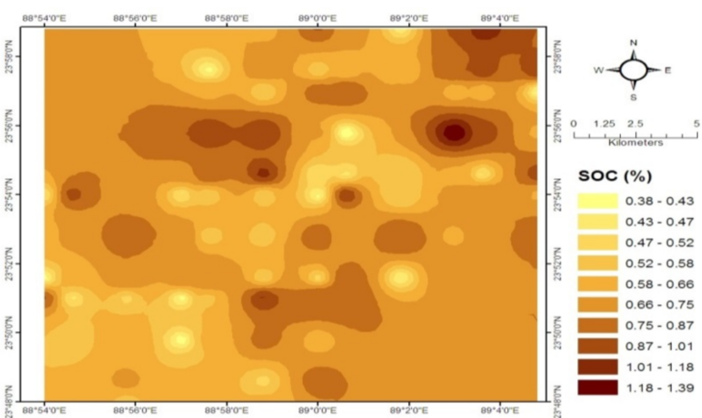

Figure 8: Distribution of SOC contents (%) in the Mirpur sub-site using IDW

In this study, the weak spatial dependent sites possess a relatively flat topography (only 2 m elevation variation), the SOC distribution should not only be linked to water erosion processes, but also to tillage erosion. Indeed, widespread adoption of mechanized agriculture that promotes more intensive continuous tillage accelerates SOC oxidation [26] and predisposes soils to increased erosion [27]. Tillage, especially the conventional 30-cm deep tillage, is one of the major practices that affects SOC. Tillage thus accelerates runoff during the rainy season and destroys natural soil aggregates. This traditional tillage does not leave any residues on the soil surface to reduce rainfall erosivity. Thus, conventional tillage reduces SOC, weakens soil structure, ultimately causing soil compaction and sealing -affecting soil porosity, aeration and decomposition of organic matter that exacerbates the soil pulverization during the dry periods which are also reported in case of conventional tillage [28]. Interpolated values of SOC in the surface layer (0-30 cm), obtained by kriging ranged from 0.39 to 2.02% in the Fultala sub-site (Figure 5). The highest SOC tended to occur in the Fultala sub-site, where the landscape is diverse with low cropping intensity. This sub-site belongs to the south-western coastal plain of Bangladesh where the major land use is the rice-shrimp integrated farming. This topographic diversity mainly causes high variability in SOC. SOC levels are generally reflecting the intensity of agriculture and land management practices [29]. On the other hand, SOC interpolated by IDW ranged from 0.40 to 2.60% in the Delduar sub-site, 0.40 to 1.35% in the Melandah sub-site and 0.38 to 1.39% in the Mirpur sub-site respectively (Figures 6-8). The lower SOC levels in these sub-sites may be attributed to more intensive cropping with high yielding varities (HYV) of rice.

4. Conclusion

Understanding the spatial variability of SOC is important for best soil management and targeted precision farming practices. The findings revealed that the SOC is low in all stdudy sites. Agricultural activities such as excessive tillage, improper cropping system management, land use intensification by high inputs, etc. are the random factors that prevail which may be responsible for the weak spatial dependence after a long history of agricultural use. While reducing cropping intensity is difficult given the need to increase food production better crop residue management and reduced tillage should be considered to increase SOC levels. It is important to initiate location-based policy to maximize SOC sequestration as well as precision farming in Bangladesh and other similar climatic and framing situations to restore soil health and agricultural productivity at farm level.

References

[1] Rossi J, Govaerts A, De Vos B, Verbist B, Vervoort A. Spatial structure of soil organic carbon in tropical forest-A case study of Southeastern Tanzania. Catena. 2009;77:19-27.

[2] Wang DD, Shi XZ, Wang HJ, Weindorf DC, Yu DS, Sun WX, Ren HY, Zhao YC. Scale effect of climate and soil texture on soil organic carbon in the uplands of northeast China. Pedosphere. 2010;20:525-535.

[3] Davidson EA, Janssen IA.Temperature sensitivity of soil carbon decomposition and feed backs to climate change. Nature.2006;41:12-15.
[4] Su ZY, Xiong YM, Zhu JY, Ye YC, Ye M. Soil organic carbon content and distribution in a small landscape of Dongguan, South China. Pedosphere. 2006;16:10-17.
[5] Feng Q, Endo KN, Cheng GD. Soil carbon in desertified land in relation to site Characteristics. Geoderma. 2002;106:21-43.
[6] Don A, Schumacher J, Scherer-Lorenzen M, Scholten T, Schulge ED. Spatial and vertical variation of soil carbon at two grassland sites- implications for measuring soil carbon stocks. Geoderma. 2007;141:272-282.
[7] Arrouays D, Deslais W, Badeau V. The carbon content of topsoil and its geographical distribution in France. Soil Use and Management. 2001;17:7-11.
[8] Liu DW, Wang ZM, Zhang B. Spatial distribution of soil organic carbon and analysis of related factors in croplands of the black soil region, Northeast China. Agriculture, Ecosystems and Environment. 2006;113:73-81.
[9] Evrendilek F, Celik I, Kilic S. Changes in soil organic carbon and other physical soil properties along adjacent Mediterranean forest,grassland, and crop land ecosystems. Journal of Arid Environments. 2004; 59:743-752.
[10] Wheeler CW, Archer SR, Asner GP. Climatic/edaphic controls on soil carbon/nitrogen response to shrub encroachment in desert grassland. Ecological Applications. 2007;17:1911-1928.
[11] Throop HL, Archer SR. Shrub (Prosopis velutina) encroachment in a semi-desert grassland: Spatial-temporal changes in soil organic carbon and nitrogen pools. Global Change Biology. 2008;14:2420-2431.
[12] Wang ZM, Zhang B, Song KS, Liu DW, Li F, Guo ZX, Zhang SM. Soil organic carbon under different landscape attributes in croplands of Northeast China. Plant,Soil and Environment. 2008;54:420-427.
[13] Saldana A, Stein A, Zinck JA.Spatial variability of soil properties at different scales within three terraces of the Henare River (Spain). Catena. 1998;33:139-153.
[14] McGrath D, Zhang CS. Spatial distribution of soil organic carbon concentrations in grassland of Ireland. Applied Geochemistry. 2003;18:1629-1639.
[15] Sepaskhah AR, Ahmadi SH, Nikbakht Shahbazi AR. Geostatistical analysis of sorptivity for a soil under tilled and no-tilled conditions. Soil and Tillage Research. 2005;83:237-245.
[16] Webster R, Oliver MA. Geostatistics for Environmental Scientists. 2nd edition; John Wiley and Sons Ltd, UK. 2007. 299 p.
[17] Ramzan S, Wani MA, Bhat MA. Assessment of spatial variability of soil fertility parameters using spatial techniques in temperate Himalayas. International Journal of Geosciences. 2017;8:1251-1263.
[18] Walkley A, Black IA. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Science.1934;37:29-38.
[19] Nelson DW, Sommers LW. Total carbon, organic carbon and organic matter. In: Page AL, Miller RH, Keeney DR, eds. Methods of Soil Analysis. Part 2. Agronomy monograph, 2nd edition, ASA and SSSA. Inc. Madison, Wisconsin, USA; 1982. p. 539- 577.
[20] Robertson GP. GS+: Geostatistics for the environment sciences. GS+ user's guide version 10.0. Plainwell, Gamma design software; 2008. 200 p.
[21] ESRI, Environmental Systems Research Institute, ARCGIS ver. 9.3. Redlands, USA; 2000. 198 p.
[22] Robinson TP and Metternicht G.Testing the performance of spatial interpolation techniques for mapping soil properties. Computers and Electronics in Agriculture. 2006;50(2):97-108.
[23] Cambardella CA, Moorman TB, Novok JM, Parkin TB, Karlen DL, Turco RF, Konopka AE. Field-scale variability of soil properties in Central Iowa soils. Soil Science Society of America Journal. 1994;58:1501-1511.
[24] FRG. Fertilizer Recommendation Guide. Bangladesh Agricultural Research Council (BARC). 2018. 274 p.
[25] Kilic K, Ozgoz E, Akbas F. Assessment of spatial variability in penetration resistance as related to some soil physical properties of two fluvents in Turkey. Soil and Tillage Research.2004;76:1-11.
[26] Polyakov VO, Lal R. Soil organic matter and carbon di oxide emission as affected by water erosion on field runoff plots. Geoderma. 2008;143:216-222.
[27] Rasmussen PE, Albrecht SL, Smiley RW. Soil carbon and nitrogen changes under tillage and cropping systems in the Semi-arid Pacific North-west agriculture. Soil and Tillage Research. 1998;47:197-205.
[28] Bot A, Benites J. The importance of soil organic matter: key to drought-resistance soil and sustained food production. Food and Agriculture Organization of the United Nations, FAO. Rome. 2005; FAO Soil Bulletin 80.
[29] Uddin MJ, Hooda PS, Mohiuddin ASM, Smith M, Waller M. Land inundation and cropping intensity influences on organic carbon in the agricultural soils of Bangladesh. Catena. 2019;178:11-19.