International Journal of Ecology and Environmental Sciences 40 (2-3): 189-197, 2014
ISSN: 0377-015X (Print); 2320-5199 (Online)

Effect of Land Use and Topography on Spatial Distribution of Soil Organic Carbon in Semi-arid Subtropical Ecosystems in Uttar Pradesh, India

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ABSTRACT

The increasing atmospheric CO_2 concentration could be mitigated with adoption of appropriate carbon sequestration strategies. For this purpose, it is essential the understanding the relationship between soil organic carbon (SOC) content and land uses and land forms, and precise and accurate estimation. In this study, SOC stock is estimated for different physiographical units and land uses in Uttar Pradesh, Indo-Gangetic plains and also its spatial variation. The nugget to sill ratio of SOC was 0.44 and 0.09 at 0-30 and 0-100 cm, and 0.78 and 0.76 for SIC at 0-30 and 0-100 cm. SOC stock at 0-30cm depth had a moderate spatial dependence, and a strong spatial dependence at 0-100cm, but soil inorganic carbon (SIC) stock had a weak spatial dependence at 0-30cm and moderate spatial dependence at 0-100cm depth. The SOC was varied 2.3-99.92 (x 10^6g ha^{-1}) at 0-30 cm and 17.34-310.2 (x 10^6 g ha^{-1}) at 0-100 cm. The forests in northern and south-eastern part of the study site were accumulated higher SOC and also high SOC storage was noted in those part of following rice–wheat, and sugarcane–wheat system. Less SOC stock at 0-100cm was found in eastern most and north western part and also scattering patches of central part confined to recent alluvium. High SIC was confined to south-west part of the study area where lands are salt affected. Forest area had a minimum SIC stock. This spatial variability of SOC could be very important for site-specific carbon management programme.

Key Words: Soil Organic Carbon, Indo-Gangetic Plain, Spatial Variation and Ordinary Kriging

INTRODUCTION

Soil carbon (C) in the same field is fairly static over time and spacewith geology, topography, climate and soil and crop management (Quine and Zhang 2002, Wang et al. 2009). A better understanding of spatial variability of soil C is essential for planning future management of sustainable soil management and also identifies effective strategies of soil C sequestration. Efficient and accurate data collection and assessment could help in better soil and crop management of maximizing productivity, and mitigation of climate change (Chung et al. 2008, Luo et al. 2010, Mendonça-Santos et al. 2009) but lack of detailed soil surveys is a major difficulty of soil mapping. Geostatistical techniques, such as Kriging, have been used to describe and predict the spatial variability of the soil property including soil organic carbon (SOC) in non-sampled areas from the soil properties value of sample, minimize estimation error and integrate this information into mapping through spatial interpolation (Webster and Oliver 2001, Yao et al. 2004, Gilbert and Wayne 2008, Santra et al. 2008). This spatial correlation analysis between SOC and environmental factors enable to have a deeper understanding of the biogeochemical and physico-chemical processes and the major controls on these processes within ecosystems (Chevallier et al. 2000). SOC stock is estimated into two ways: (i) point measurements of SOC content for different strata is multiplied by bulk density, depth and aerial extent of that stratum, and (ii) geo-statistical approaches for estimation of spatial variable SOC stock (Thompson and Kolka 2005). The major limitations of first approach are the errors associated in upscaling the area. The geostatistical approach is the most prudent for SOC stock calculation because of use actual SOC data, delineating boundary line of homogeneous SOC stocks within the area, and easily assesses different cropping systems in terms of its carbon-capturing potential using spatial variation of SOC content (Santra et al. 2012). In India, the studies on SOC stock estimation were concentrated mostly on a regional scale and based on the first approach (Bhattacharya et al. 2000, 2007, Singh et al. 2007). Geostatistical approach of SOC stock calculation by considering its spatial variation is limited in Indo-Gangetic alluvial plain (IGP) of India. IGP covers 13% of total geographical area of the country, and major contributor of agricultural productions in India. The reliable estimates of SOC stock and their spatial variability could be essential for soil C sequestration programs in such similar plains. Such study could provide the base line information of understanding the biophysical processes impact on the net flux of soil C in plains of India. Keeping in view, the present study attempts to estimate the soil carbon stock for semi-arid subtropical Uttar Pradesh (IGP), India using geostatistical approach.

MATERIAL AND METHODS

Site Description

Uttar Pradesh lies between 23º 52' and 30º 24' N and 77º 05' and 84º 38' E with a geographical area of 24093 km^2 (about 7.3% of country's geographical area). It is a landlocked state bounded by Tibet and Nepal in the north, Himachal Pradesh in the north-west, Haryana and Delhi in the west, Rajasthan in the south-west, Madhya Pradesh and Chhattisgarh in the south, Jharkhand in the south-east and Bihar in the east. The state is divided into three physiographical regions viz. the northern mountains of Siwaliks, the southern hills and plateau and the vast alluvial Gangetic plains between the two. The state is fed by five major rivers namely the Ganga, the Yamuna, the Ramganga, the Gomati and the Ghaghra which drain into the Bay of Bengal. The state has a semi arid-subtropical climate with 1,000-1,200 mm annual rainfall and 5º-45ºC temperature (Anonymous 2006). The net cropped and non-agricultural area were as 20,282,159.46 ha and 3,437,376.00 ha (84.18 and 14.26% of the total geographical area) respectively. The cropping pattern was found in the following order in terms of area in hectares was: rice-wheat > sugarcane > rice-pulses > sugarcane-wheat > maize⁄jowar-wheat > rice-fallow > maize-pulses > fallow-wheat > fallow-pulses > maize-fallow > current fallow (Singh et al. 2011; Figure 1). Soil texture is varied from alluvium with coarse loamy to fine loamy, and dominant soil orders are Inceptisols > alfisols > vertisols and entisols (Singh et al. 2004).

Soil Sampling and Process

To achieve the aforesaid objectives, soil samples from 239 soil pedons were collected at five depths (0-15cm, 15-30cm, 30-50cm, 50-100cm and 100-150cm) during post harvest period (October to November and April to June). It was considered the variations topography/ physiography from topographical maps of 1:250000 scale, crop-ping pattern, and soil map (Singh et al. 2011, Singh et al. 2004). The spatial coordinates of each sampling point were recorded using global positioning system (Figure 2). Soil samples were air-dried, ground and passed through 0.5 mm sieve. Total organic carbon (TOC) of each soil sampling depth was determined using CHN-O-RAPID analyzer (Anonymous 2006). Calcium carbonate equivalent was determined by the standard titration method and then SIC is calculated (Black 1965, Jackson 1973). A factor of 0.12, the mole fraction of carbon in $CaCO_3$, was used to convert calcium carbonate to Soil inorganic C (SIC) Content (Mi et al. 2008). Bulk density was determined by clod method (Black 1965).

Geostatistical Analysis

Geostatistical analysis consisting of semivariogram calculation, cross-validation and mapping was performed using the geostatistical analyst extension of ArcGIS 9.3.1 version (ESRI 2009). Variable z of unsampled location is estimated based on the weighted average of neighbor measured locations and also assuming of having similarity and correlated of more closed points (Yaserebi 2009). Semivariogram is described the spatial variability, it is half of squared difference between paired data values $z(x_i)$ and $z(x_i+h)$. Graphically, it is represented by the average difference in attribute values between observations (i.e. semivariance $\gamma(h)$) versus distances apart (i.e. *lag* (h)); Figure 3).

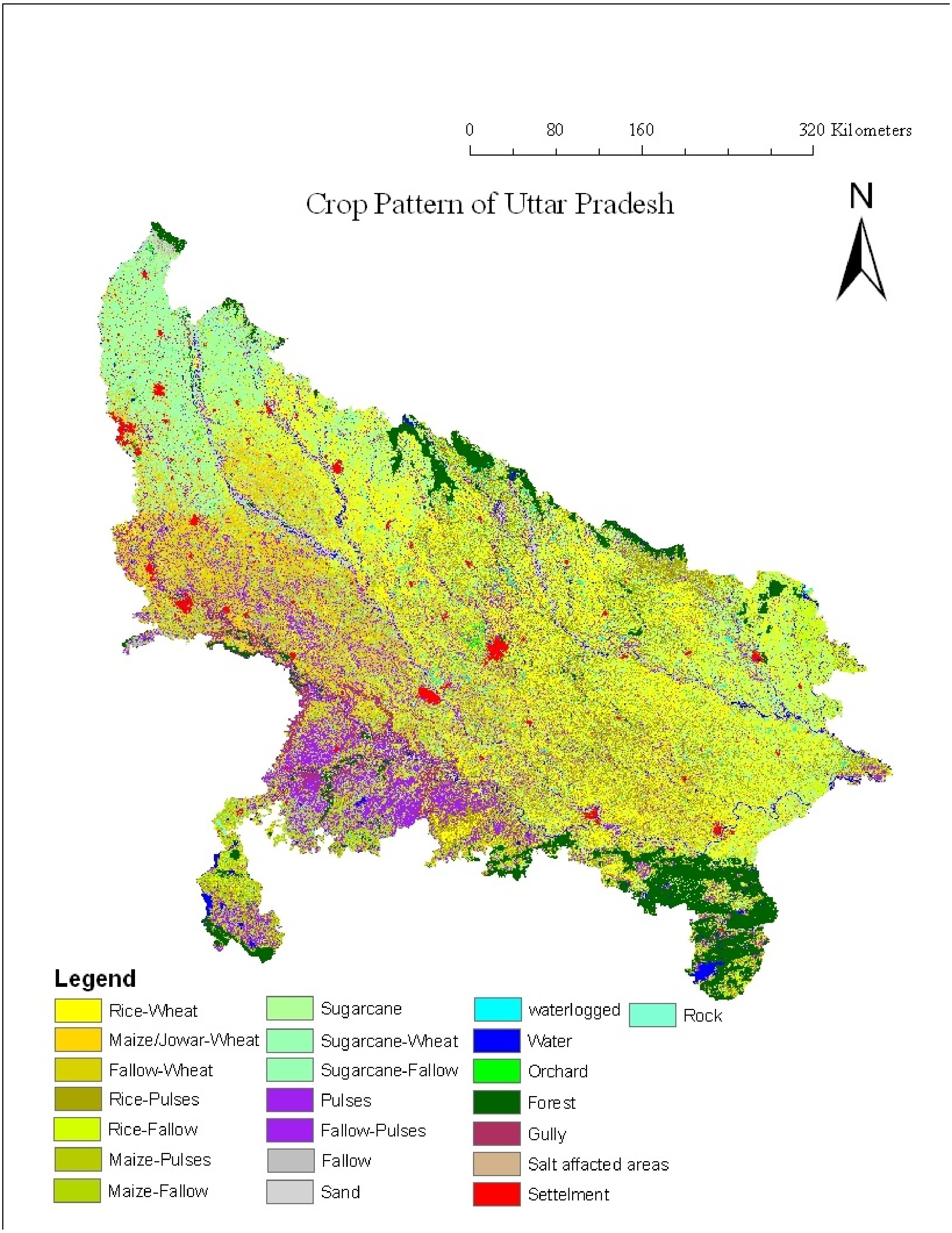

Figure 1. Cropping pattern of Uttar Pradesh (Singh et al. 2011)

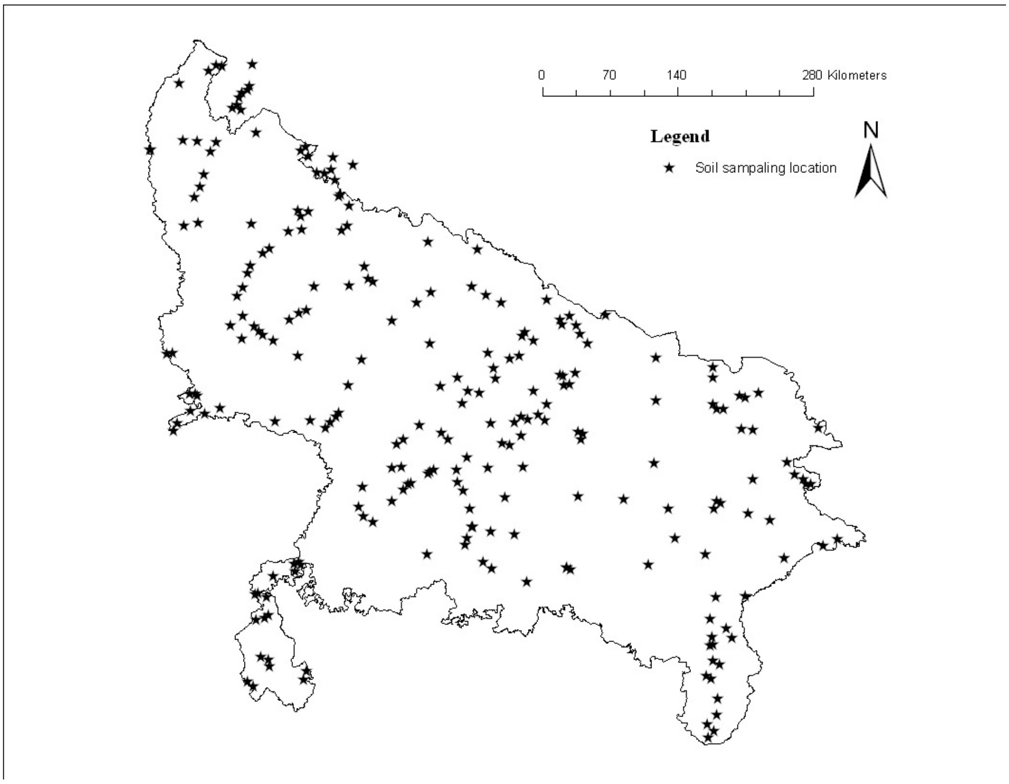

Figure 2. Study site and global positioning system (GPS) locations of soil sampling site.

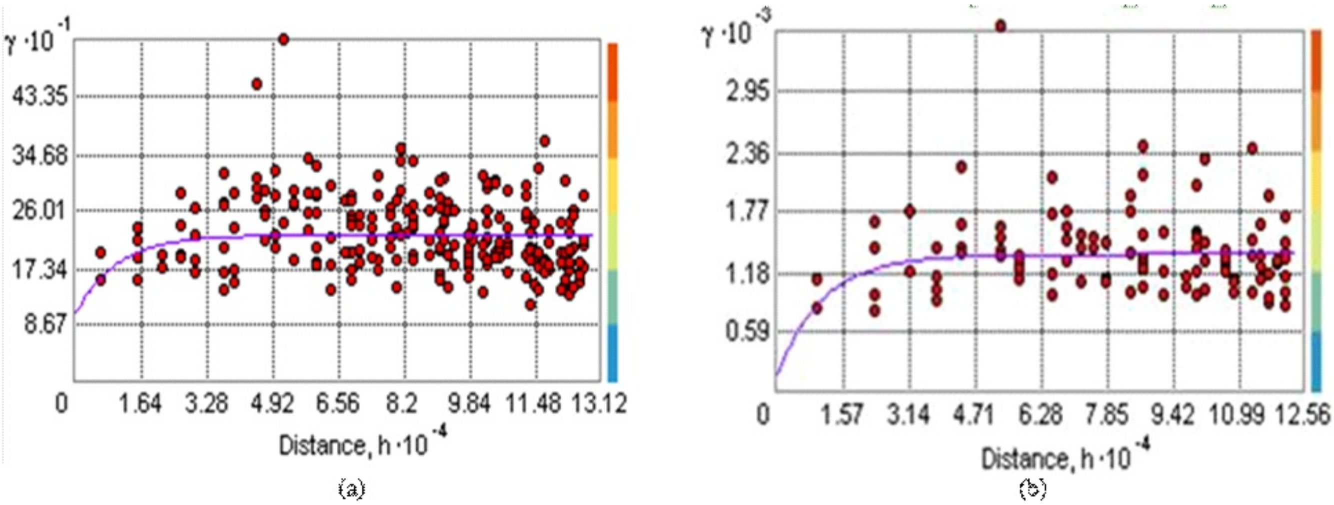

Figure 3.: Semivariogram of (a) simple kriging with exponential model at 0-30 and (b) ordinary kriging with exponential model at 0-100cm depth for soil organic carbon mapping.

The semivariance, γ, at a given lag, *h,* is estimated by

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

where $z(xi)$ is the value of the variable z at location of xi, h the lag and $N(h)$ is the number of pairs of sample points (x_i, x_i+h) for property z separated by distance *h.*

Semivariogram can be computed in different directions for determining any anisotropic variation. The lag at which the semivariance becomes constant is called the *sill* (i.e. one value for a variable does not influence neighboring values). The distance at which the semivariance reaches the sill is called the *range* (Lopez-Granados et al. 2002). The semivariogram intercept on the y-axis is known as the *nugget* (describes the variation occurring at shorter distance than the minimum sampling interval). Best-fit model were selected with smallest nugget values with minimum root mean square error (RMSE). The expression of RMSE is given below.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2}$$

RESULTS AND DISCUSSION

Summary Statistics

The statistical summary of soil carbon stock at 0-30 and 0-100cm depth are shown in Table 1. The coefficients of skewness and kurtosis will decide how far the data is nearer to the normal distribution. A logarithmic transformation is considered where the skewness is greater than one (Webster and Oliver 2001). The skewness of SOC were 0.25at 0-30 cm and 1.07 at 0-100 cm depth and skewness of SIC were 3.17 at 0-30cm and 2.29 at 0-100cm depth before transformation. The skewness of SIC after log transformation was 0.03 and 0.64 at 0-30 and 0-100 cm depth (Table 1). A number of semivariogram were tested and selected the semivariogram with the best fit model based on minimum root mean square error (RMSE) (Tables 2 and 3). The variance is a strong spatial dependence if the nugget-to-sill ratio < 0.25, a moderate spatial dependence of the ratio between 0.25-0.75, and a weak spatial dependence of ratio > 0.75 (Liu et al. 2006). The partial sill is the sill minus nugget. The nugget to sill ratio of the study site were 0.44 and 0.09 for SOC at 0-30 and 0-100 cm, and 0.78 and 0.76 for SIC at 0-30 and 0-100 cm (Table 3, Figures 3 and 5).

Spatial variation of soil organic carbon

The SOC was varied 2.3-99.92 (x 10^6 g ha^{-1}) with an average of 39.49 (x 10^6 g ha^{-1}) at 0-30 cm. The forest soil was showed the maximum SOC and minimum SIC stock. The possible reason was that the forest soil was not disturbed and high addition of organic matter through the liter fall of trees. SOC stock at 0-30cm depth had a moderate spatial dependence that mean SOC stock at 0-30cm depth was more or less uniform except the higher SOC stock at forest areas especially at north-east and south-east part of the study site. The SOC stock at 0-100 cm was varied 17.34-310.2 (x 10^6 g ha^{-1}) with a mean value of 93.638 (x 10^6 g ha^{-1}). The SOC at 0-100cm had a strong spatial dependence. The spatial variability of SOC at this depth (i.e. 0-100cm) was much cleared, and forests in northern and south-eastern part reflect the higher SOC stock following rice–wheat, and sugarcane-wheat system. The long duration of sugarcane might reduce tillage practices and slows down decompositions of organic matter (FAO 2001, Six et al. 2002, West and Post 2002). Consequently it was increased the SOC content in sugarcane cultivation. More soil carbon was stored under anaerobic part of rice-wheat system. It was also reported that soil carbon content was also increased

Table 1. Statistical summary of soil carbon stock (10^6 g ha^{-1}).

Soil Carbon	Transformation	Minimum	Maximum	Mean	Std. Dev.	Skewness	kurtosis	1st Quartile	Median	3rd Quartile
Soil carbon stock at 0-30cm soil depth										
SOC	None	2.73	99.92	39.50	15.29	0.25	3.84	29.69	40.19	48.47
SIC	None	0.16	84.41	12.01	12.77	3.18	15.16	5.17	7.98	12.65
	Log	-1.83	4.44	2.16	0.78	0.03	5.84	1.64	2.08	2.54
Soil carbon stock at 0-100cm soil depth										
SOC	None	17.34	310.2	93.64	37.52	1.07	7.98	71.13	93.49	114.81
SIC	None	4.28	276.36	50.35	51.18	2.29	7.98	21.48	31.14	54.02
	Log	1.45	5.62	3.58	0.77	0.64	3.17	3.07	3.44	3.99

SOC-Soil organic carbon, SIC-Soil inorganic carbon by changing monoculture to continuous rotation cropping and changing fallow system to continuous monoculture to continuous rotation cropping system (West and Post 2002). Less SOC stock at 0-100cm was found in eastern most and north western part and also scattering patches of central part confined to recent alluvium. The abundance of gravel and stone and severe erosion in the Siwalik hill might lead to lowering SOC in western part (Figure 4). The soil inorganic carbon (SIC) stock had a weak spatial dependence at 0-30cm and moderate spatial dependence at 0-100cm depth (Figure 6). This may be due to intrinsic and extrinsic factors (i.e. soil forming processes and management practices) (Zhang and McGrath 2004, Chai 2008). High SIC was confined to south-west part of the study area where lands are salt affected. Forest area had a minimum SIC stock.

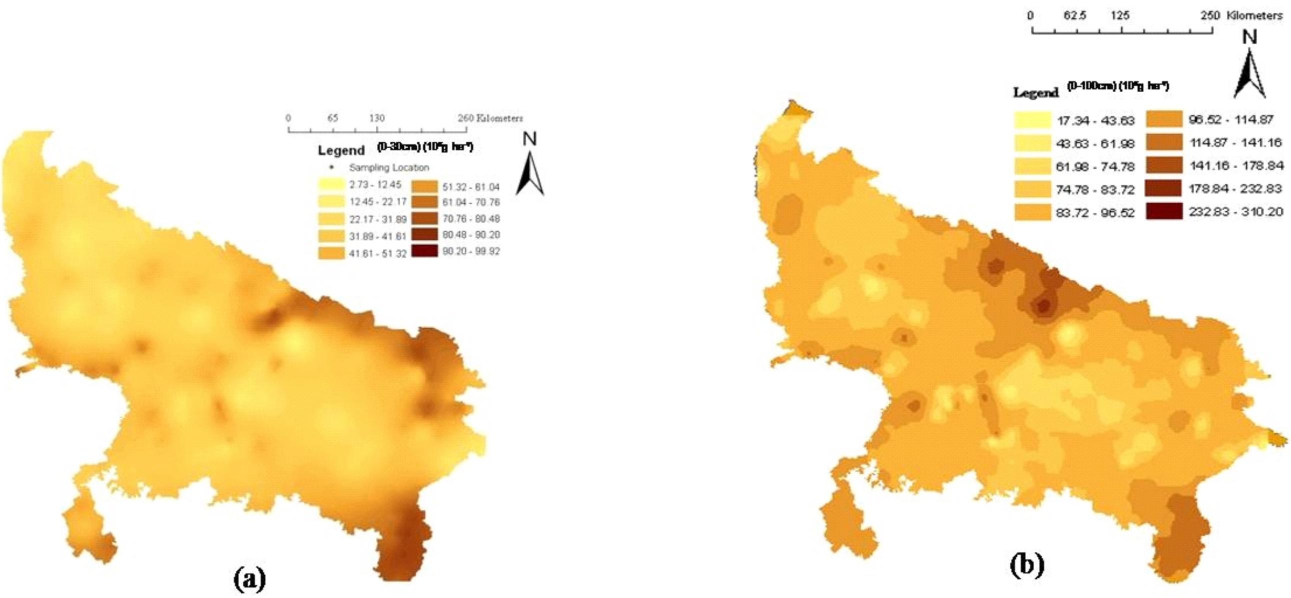

Figure 4. Soil organic carbon mapping using (a) simple kriging with exponential model at 0-30 and (b) ordinary kriging with exponential model at 0-100cm depth.

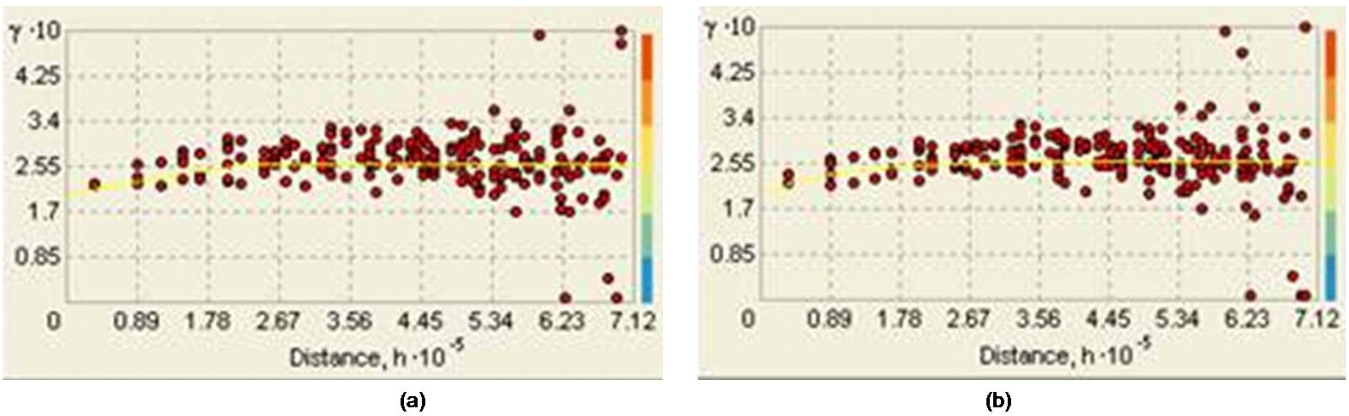

Figure 5. Semivariogram of indicator kriging with (a) spherical model at 0-30 and (b) exponential model at 0-100cm depth soil inorganic carbon mapping using.

Table 2. Comparative evaluation of different semivariogram of soil carbon stock (10^6 g ha^{-1}).

Semivariograms	Model	Mean	Root Mean Square	Average S.E.	Mean Standardized	Standardized Root M.S.	Regression Equation
Soil organic carbon at 0-30 cm depth							
Ordinary kriging	Exponential	-0.23	14.65	14.63	-0.015	1.00	0.116*X+33.679
Simple kriging	Exponential	-0.02	14.5	14.33	-0.001	1.01	0.069*X+37.033
IDW	Optimized Power	1.32	0.15	15.81			0.102*X+12.012
RBF	Spline with Tension	0.14	15.77				0.095*X+12.092
Soil inorganic carbon at 0-30 cm depth							
IDW SIC	Optimized Power	1.0	0.36	12.41			0.157*X+9.487
Global Polynomial Interpolation		Power 3	0.003	12.03			0.149*X+9.335
Local Polynomial Interpolation		Power 2	0.01	11.92			0.133*X+9.712
RBF SIC	Spline with Tension	0.19	12.34				0.137*X+9.461
Ordinary kriging	Exponential	0.06	12.05	12.21	-0.006	0.93	0.118*X+9.950
Simple kriging	Exponential	-0.08	12	10.73	0.007	1.03	0.118*X+9.950
Indicator kriging	Spherical	0.004	0.48	0.47	0.008	1.01	
Soil organic carbon at 0-100 cm depth							
Ordinary kriging	Exponential	-0.87	35.51	33.17	-0.02	1.05	0.125*X+80.485
Simple Kriging	Exponential	-0.22	35.03	34.65	-0.004	1.01	0.098*X+83.893
Simple Kriging	Tetraspherical	0.10	34.25	32.88	0.004	1.04	0.199*X+73.019
Simple Kriging	Gaussian	0.18	33.92	32.46	0.006	1.04	0.214*X+71.966
Simple Kriging	Pentaspherical	0.07	34.25	32.97	0.004	1.035	0.197*X+73.046
Simple Kriging	Circular	0.16	33.95	32.44	0.008	1.041	0.207*X+72.190
Simple Kriging	Spherical	0.12	34.09	32.69	0.005	1.037	0.221*X+71.611
IDW SIC	Optimized Power	1.0887	1.39	58.08			0.113*X+46.912
RBF SIC	Spline with Tension	0.79	58.01				0.132*X+45.445
Soil inorganic carbon at 0-100 cm depth							
Global polynomial Interpolation		Power 3	0.019	48.47			0.156*X+38.66
Local polynomial Interpolation		Power 3	0.358	48.08			0.168*X+38.056
Ordinary kriging	Exponential	-0.96	48.29	48.32	-0.037	0.994	0.123*X+40.442
Simple kriging	Exponential	-1.14	48.19	43.18	-0.015	1.082	0.111*X+40.648
Universal Kriging	Exponential	-1.33	48.33	49.64	-0.040	0.969	0.133*X+38.848
Indicator kriging	Exponential	0.008	0.48	0.48	0.017	0.998	
IDW	Optimized Power	1.000	1.68	49.23			0.161*X+39.865
RBF	Spline with Tension	0.73	49.08				0.152*X+39.757

CONCLUSION

Accurate mapping of widely variable SOC is very difficult in a large-scale. Such a spatial variability map might increase the efficiency of input, improving the economic margins of crop production and reducing environmental risks. A comprehensive understanding of spatial variability of SOC would be essential in agriculture.

Table 3. The selected semivariogram with best fit models of soil carbon stock.

Variable	Model	Property unit Nugget	Partial Sill	Range (Ao)	No. of lags	Lag size	Regression equation
Soil organic carbon at 0-30 cm depth							
Simple kriging	Exponential	96.96	125.55	30880.40	12	10807.00	125.55*Exponential(30880)+96.959* Nugget
Soil inorganic carbon at 0-30 cm depth							
Indicator kringing	Spherical	0.20	0.06	273580.00	12	59070.00	0.06*Spherical(273580) + 0.20* Nugget
Soil organic carbon at 0-100 cm depth							
Ordinary kriging	Exponential	125.52	1221.9	33304.10	8	15466.00	1221.9*Exponential(33304)+125.52* Nugget
Soil inorganic carbon at 0-100 cm depth							
Indicator Kriging	Exponential	0.20	0.06	290340.00	12	59070.00	0.06*Exponential(290340)+0.20*Nugget

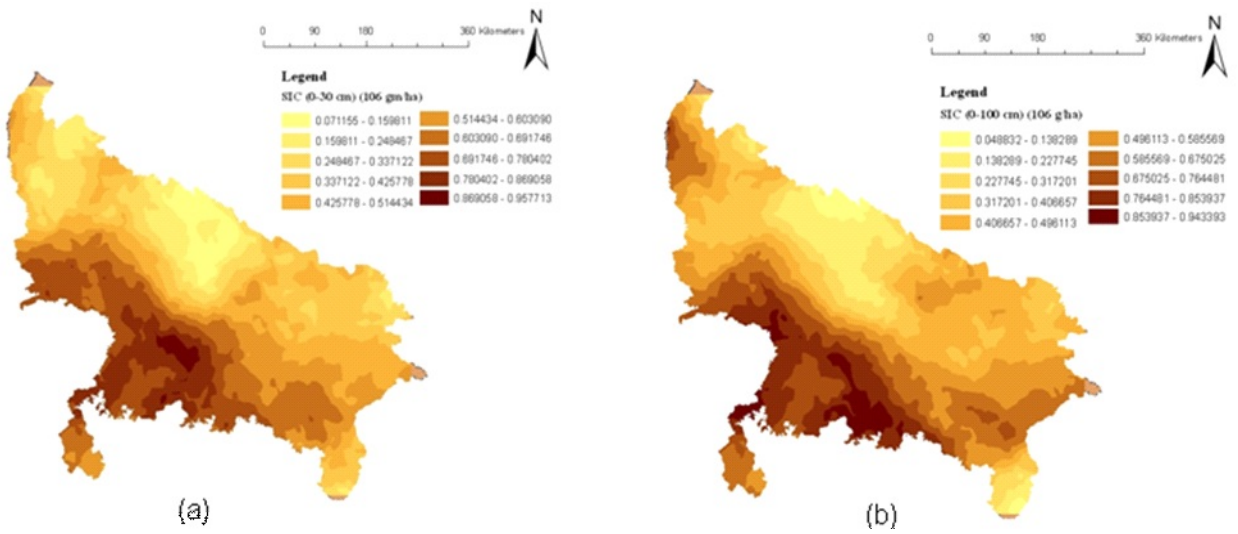

Figure 6: Soil inorganic carbon mapping using indicator kriging with (a) spherical model at 0-30 and (b) exponential model at 0-100cm depth.

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Received 21 May 2014;
Accepted after revision 18 August 2014

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