Pedometric mapping of soil organic carbon loss using soil erosion maps of Tripura

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Importance of soil organic carbon (SOC) in maintaining soil productivity and natural ecosystem has been a major concern throughout the globe. SOC in the humid tropical climate becomes more important in view of undulating hilly terrain in the northeastern region of India. The major concern in such landscape is soil erosion and the necessary conservation practices. In the present study, we discuss the technique of pedometric mapping to link SOC and soil loss. The best-fit semi-variogram model for SOC was found to be exponential model ($R^2 = 0.90$). The best fit semi-variogram models for soil and SOC losses are spherical ($R^2 = 0.95$) and exponential ($R^2 = 0.77$) respectively. The spatial distribution of SOC, soil and SOC loss was found to be related with topography and different land-use types and showed moderate spatial dependence. With the help of 196 grid observations, the present study shows a threshold limit of 150 kg ha^{-1} year^{-1} SOC loss above which the areas are to be considered as susceptible demanding immediate conservation measures. Pedometric mapping using SOC and soil loss can, thus, be a tool to prioritize areas in humid tropical climate for conservation agriculture.

Keywords: Conservation agriculture, pedometric mapping, soil erosion, soil organic carbon.

TRADITIONALLY, soil management and land-use planning have been the main broad aims of soil survey at all scales. However, with increasing concern on environmental issues, it has moved from its traditional subjective conjecture to more quantitative modelling with accompanying accuracy and uncertainty issues[1]. Effective soil management requires an understanding of soil distribution patterns within the landscape. Spatial and temporal variability of the soil environment is its inherent and unavoidable feature. In recent years, special attention has been given to variability in various soil parameters, viz. soil organic carbon (SOC) and its relation to soil health and environment. This variability is related to the spatial and temporal variation of soil-forming factors, and human activity[2]. The intensity of erosion and deposition of eroded materials may also affect the temporal and spatial variation of soil properties[3]. The fact of the matter is that the natural and anthropogenic components of the soil are not sufficiently identified and, so far, are the least known[2].

For the last few decades, several quantitative methods are being used to describe, classify and study the spatial distribution patterns of soil in a more objective way. The methods are collectively categorized in the emerging field of soil science as pedometrics[1]. Geostatistics is one of the most popular tools of pedometrics as well as of digital soil mapping. Pedometrics addresses the issues related to the application of mathematical and statistical methods for the study of the distribution and genesis of soils. Geostatistics is defined as the creation and the population of geographically referenced soil database generated at a given spatial resolution using field and laboratory observations coupled with environmental data through quantitative relationship. Several studies have shown that combining soil maps and soil information from point observations can improve spatial prediction than using soil maps alone[4–9]. The true soil type, typically unknown, thus can be represented with a probability model. When a probability model is available, this may be used for spatial prediction of the soil property. Probability distribution of soil type can be obtained from soil maps using pedometric methods such as indicator krigging[6,9]. Soil survey reports accompanying traditional soil maps often provide areal estimates of soil type occurring within the map units[10]. Such information may be used to define a frequency distribution for each map unit, which can again serve as a probability distribution of any map unit.

In recent years, statistics and geostatistics have been used widely to quantify the spatial distribution patterns of SOC[11–13] and also its distribution in different bio-climatic and ecological regions[14]. Soil organic carbon refers to the carbon associated with organic matter (OM) present in the soils. It is the organic fraction of the soil with decomposed plant and animal materials as well as microbial organisms[15]. Soil organic carbon is important for all aspects of soil fertility, namely chemical, physical and biological fertility (Table 1) and thus, it is an most important indicator for soil health and agricultural sustainability[15]. The amount of SOC, at any time, is dependent on a complex

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Table 1. Effects of soil organic carbon (SOC) on soil fertility

Soil fertility	Effects of SOC
Chemical fertility	
Provides nutrients available to plants	Microbial decomposition of SOC releases nitrogen, phosphorus and a range of other nutrients for use by plant roots.
Physical fertility	
Improves soil structure and water-holding capacity	In the process of decomposition, microbes produce resins and gums that help bind soil particles together into stable aggregates. The improved soil structure holds more water available to plants, allows water, air and plant roots to move easily through the soil, and makes them easier to cultivate.
Biological fertility	
Provides food for soil organisms	Organic carbon is a food source for soil organisms and microorganisms. Its availability controls the number and type of soil inhabitants and their activities, which include recycling nutrients, improving soil structure and suppressing crop diseases.
Buffers toxic and harmful substances	SOC can reduce the effect of harmful substances such as toxins and heavy metals by sorption, and assist degradation of harmful pesticides

Source: Chan[15].

set of interactions among physical, chemical and biological processes. The role of SOC has recently received increased attention because of its potential to improve soil quality through carbon sequestration[14] and its strong influence on the persistence and degradation of pesticides and organic wastes in soils[16,17]. Excluding carbonate rocks, soils represent the largest terrestrial stock of C, holding between 1400 Pg and 1500 Pg C (1 Pg = 10^{15} g)[18]. Thus changes in terrestrial SOC stocks can be of global significance and may either mitigate or worsen climate change. However, due to various forms of soil degradation SOC loss has been reported from various parts of the world[19–22]. Soil erosion is the most widespread form of soil degradation and significant amounts of carbon are either relocated in soils at lower elevations, water bodies and sediments or degraded to CO_2 during soil erosion[23]. Soil erosion has long been recognized as an important factor in reducing the productivity of many soils. Decline in SOC with degree of erosion is reported for all soils, except Vertisols in Alabama[19], piedmont soils in Georgia[20], loess soils (Mollisols and Alfisols) in Illinois[21], and Alfisols in Ohio[22]. Decline in SOC was also observed in the Ap horizon of two moderately eroded Kentucky soils[24]. The range of SOC lost by erosion in the top 25 cm of moderately and severely eroded soils can be as much as 19–51% for Mollisols and 15–65% for Alfisols[25]. Estimation of the spatial distribution of the loss of soil organic carbon is also essential in view of its impact upon the bulk density, aggregate stability, compaction and fertility of the soil. The production of digital soil maps, as opposed to digitized (existing) soil maps, is moving inexorably from research phase to production of maps at the sub-country and country level. Since 1960s, there has been an emphasis on what might be called geographic or purely spatial approaches, to enable prediction of soil attributes from spatial position largely by interpolating soil and observation locations.

To study loss of soil and SOC by erosion, ideal study areas could be tropical hills with agriculture, degraded forests and other marginal lands. Tripura, in northeast India, would be a model area for such study in Southeast Asia. In view of this, an attempt has been made to predict spatial distribution of SOC vis-à-vis soil erosion in Tripura as a case study using geostatistics technique. This will not only help in better understanding of the spatial variability of SOC and sustainable land-use, but may also serve as a model for understanding similar areas in other parts of the world.

Materials and methods

Study area

Tripura is situated between 22°57′ and 24°32′ N and 91°09′ and 92°20′E. It covers an area of 10,49,100 ha. The state is bounded by Bangladesh in the south, north, west and southeast, Mizoram in the east and Assam in the northeastern part of India (Figure 1). The climate of the state is humid subtropical characterized by high rainfall with annual rainfall of 2000–3000 mm.

Out of the total geographical area of about 1 m ha of the state, 58% is occupied by forest followed by net area sown (NAS) with 26%. The area sown more than once is 65% of NAS[26]. The valley land (*lungas*) is well suited for common agricultural crops, whereas the high lands (*tillas*) are fit for plantation crops but often used for shifting cultivation called *jhum* by the tribals. Rice occupies 58% of the total cropped area, leaving 2% for cash crops like rubber (21,000 ha) and tea (5,780 ha). Sugarcane,

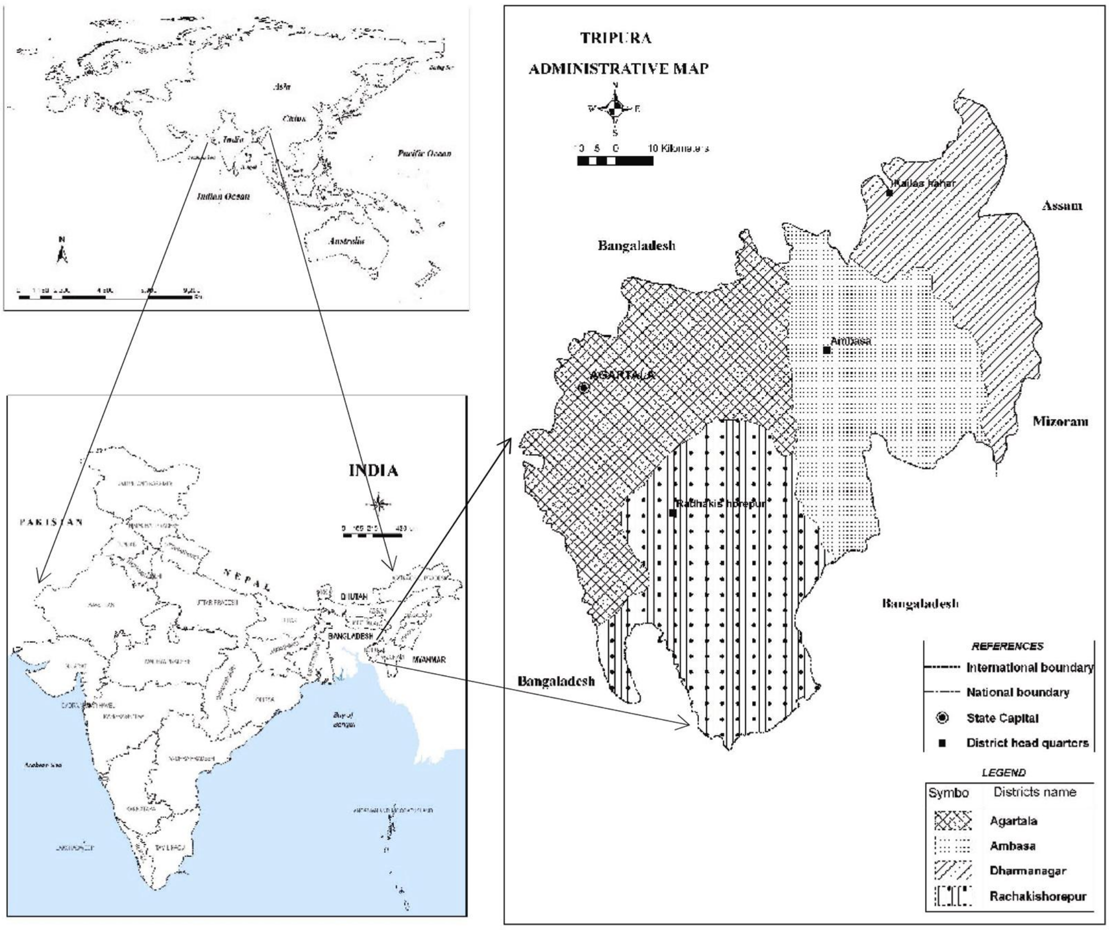

Figure 1. Location of the study area.

potato, groundnut, ginger and turmeric are also cultivated on the *tilla* and *lunga* lands. Double cropping is practised in areas where irrigation is available. Tropical and subtropical fruits like pineapple, jack fruit, orange, litchi, and banana are successfully grown on *tillas*.

Tripura was surveyed for the expansion of rubber cultivation with financial assistance from World Bank through Rubber Board of India, Kottayam, Kerala and with the assistance of the Departments of Agriculture and Horticulture, Tripura[26–31]. The entire state was surveyed at 1 : 50,000 scale at soil series association level (Figure 2). This is contrary to the approach adopted for the bigger states, where the soil survey was carried out at 1 : 250,000 scale. For the larger states, the grid point observations were taken as mini-pits (soil profile of 0–50 cm depth followed by the auger holes up to 150 cm depth or depth of the rock strata, whichever is less). Tripura being a small state, we took the grid point observations at 5 km intervals to increase the frequency of the observations for better representation of soils in different physiographic units. During that study the soil organic values were generated for different grid points as well as benchmark spots.

The soils of Tripura have been developed on many rock formations. These soils are classified into two broad groups, viz. alluvial and red soils, of which the former occupies about 77% area of the state. The soils belong to 4 orders, 7 suborders, 9 great-groups and 19 subgroups according to the US soil taxonomy[32]. Paddy soils are, by and large, grouped into Inceptisols with aquic moisture regime and are taxonomically grouped as Aquepts. About 62% of the state is subject to moderate soil erosion[26].

Estimation of soil and organic carbon loss

The spatial distribution of soil erosion in Tripura was studied and mapped by the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) of the Indian Council of Agricultural Research (ICAR) based on universal soil loss equation (USLE)[33]. NBSS&LUP has been engaged in estimating soil loss at various scales of mapping[34,35]. It may be mentioned that loss of crop productivity due to loss of topsoil may be compensated by the use of manures and fertilizers. At the same time, the loss of top soil by soil erosion is also compensated by the formation of fresh soil through pedogenesis[34,36]. The FAO model used for this study confirmed the concurrence of the reverse phenomenon of soil formation and erosion to actuate soil loss estimation. Soil erosion in Tripura was estimated from data collected from fixed location in modes of a grid and mapped (200 grid observations of 5 × 5 km size, except the inaccessible areas)[34,37]. From a comparative study of the two contrary processes, viz. soil loss and its formation, it was estimated that Tripura could tolerate a loss of 29 Mg ha^{-1} $year^{-1}$ of soils[27]. USLE is a widely accepted model equation for prediction of long-term average annual soil loss from a specified field area in specified cover under a known set of management practices. The equation predicts soil loss due to sheet or rill erosion. It computes soil loss for a site as a product of five erosion factors as expressed

$$A = R \times K \times LS \times C \times P, \quad (1)$$

Where A is the annual soil loss (t ha^{-1}), R the rainfall erosivity factor to account for the erosive power of rain and related to the amount and intensity of rainfall over the year; K the soil erodibility factor, which depends on the soil particle distribution, organic matter and permeability; LS a combined factor to account for the length and steepness of the slope; C a combined factor to account for the effects of vegetation cover and management techniques influencing the rate of the soil loss, and P is the physical protection factor related to soil conservation measures such as terracing and strip cropping.

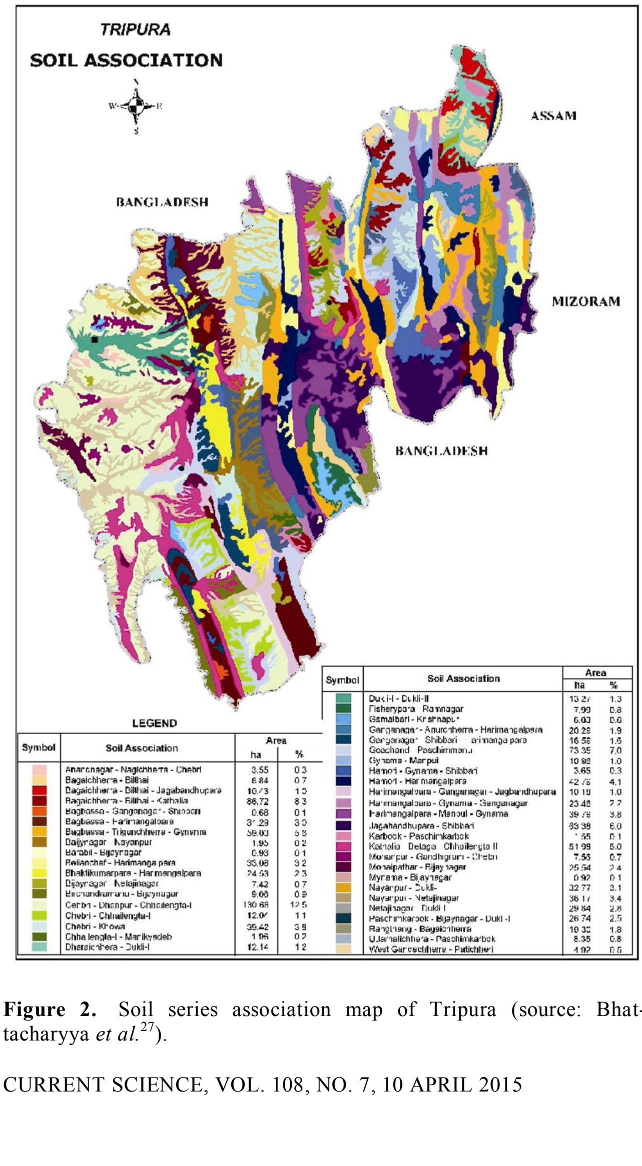

Figure 2. Soil series association map of Tripura (source: Bhattacharyya *et al.*[27]).

Estimation of USLE parameters

Rainfall erosivity factor: The rainfall erosivity factor (R) is determined from the annual total of erosion index (EI) (product of kinetic energy and the 30 min rainfall intensity) value, which is also referred as the rainfall erosion index. For the present study, the rainfall intensity for 30 min was not available; the R factor was computed for all grid points in Tripura using the following linear equation[38]

$$EI \text{ (or } R) = 79 + 0.363X, \quad (2)$$

where X is the annual rainfall (mm).

Soil erodibilty factor (K): The soil erodibility factor relates to the rate at which the soil particles get detached and transported by the raindrops. This factor depends on the topographic position, slope steepness and the amount of disturbance created by man; however, the soil properties are the most important influencing factors. K factor varies with soil texture, aggregate stability, soil permeability and infiltration, organic matter and soil mineralogy[38].

For the present study, the K factors for each grid point in Tripura have been determined using the empirical equation

$$100K = 2.1M^{1.4}\,(10^{-4})\,(12 - a) + 3.25\,(b - 2) + 2.5\,(c - 3), \quad (3)$$

where M = % silt × (100 – % clay), a is the organic matter (%), b the soil structure code used in soil classification that varies from 1 to 2 in all the soils of Tripura, and c is the profile permeability code, which varies from 1 to 5 in all the soils of Tripura.

Topographic factor (LS): This accounts both the length (L) and steepness (gradient) of slope (S) that affect soil erosion by water in a landscape. This is one of the main factors for soil loss predictions in the USLE. It is generally accepted that erosion increases with increasing slope length, as the greater accumulation of run-off on longer slopes increases its detachment and transport capacities[38]. LS can be obtained from the equation

$$LS = (\lambda/22.13)^m(65.41 \sin^2 A + 4.56 \sin A + 0.065), \quad (4)$$

where λ is the slope length (m), A the slope steepness (degrees), and m is a factor ranging from 0.2 to 0.9. In the present study, m values of 0.2, 0.3, 0.4 and 0.5 were used for slope gradients less than 1%, 1–3%, 3.5–4.5% and 5% or greater respectively[33].

Equation (4) has been used to estimate LS factor for all the grid points in Tripura.

Land cover and management factor: The land cover and management factor (C) reflects the combined effect of cover, crop sequence, productivity level and length of growing period, tillage practices, residue management and the expected time distribution of erosive rainstorm with respect to seeding and harvesting date in the locality. Several authors have studied soils with various types of covers to find the C factor[38]. For Tripura, however, the C factor for each grid point was selected on the basis of the main crop grown in that grid point (Table 2).

Conservation practice factor: The conservation practice factor (P) in the USLE takes into account the impact of conservation practices on soil loss. The most important of these conservation practices are contour cultivation, strip cropping, terrace system and field bunding used for effectively minimizing the soil loss. It has been found that the P factor varies with the type of conservation practices adopted (Table 3).

The major in-built limitation of the USLE model is that it neglects certain interactions between factors in order to distinguish more easily the individual effect of each factor[39]. In the present study, we used the soil information generated for the grid points at an interval of 5 km × 5 km. Therefore, we could estimate the parameters of the USLE for each grid point at this grid interval and thus obtained only one set of values of the USLE parameters for an area of 2500 ha. This results into the average estimates of the soil and SOC losses for an area of 2500 ha.

Table 2. C factor values used in assessing soil erosion of Tripura

Cover and management (C)	C-factor value
Forest and grasslands	0.01
Degraded forest/wasteland	0.14
Croplands	0.20–0.43
Degraded (waste) lands	0.50
Fallow lands	1.00

Source: Singh *et al.*[38].

Table 3. P factor values used in assessing soil erosion of Tripura

Conservation practice (P)	P-factor value
Terracing	0.10
Contour bunding	0.20
Contour cultivation	0.28
Field bunding	0.30
Cultivated fallow	1.00

Source: Singh *et al.*[38].

Five-kilometre grid point observations showing different attributes like rainfall erosivity (R), soil erodibility (K), length and steepness (LS), crop (C), conservation (P) and soil loss factors were utilized for all the grid points (Figure 3).

For estimating soil organic carbon loss for Tripura, the data of grid point observation with respect to soil organic carbon (%) and soil loss (t ha^{-1} year^{-1}) were tabulated. Grid-wise datasets have the advantage of being spatially explicit. From the values of organic carbon and soil loss (t ha^{-1} year^{-1}), soil organic carbon loss (t ha^{-1} year^{-1}) for the grid points was estimated. Figure 4 shows the schematic diagram for estimating soil carbon loss from land resource inventory (LRI) of Tripura[40,41].

Statistical and geostatistical analysis

The statistical analyses were carried out for some important parameters indicating the central tendency and spread of the estimated SOC, soil loss and SOC loss in Microsoft Excel 2007 and SPSS (version 18.0). These include mean, standard deviation, coefficient of variation (CV) and extreme maximum and minimum values. The coefficient of skewness and kurtosis were also determined to test the normality of the datasets. Geostatistics

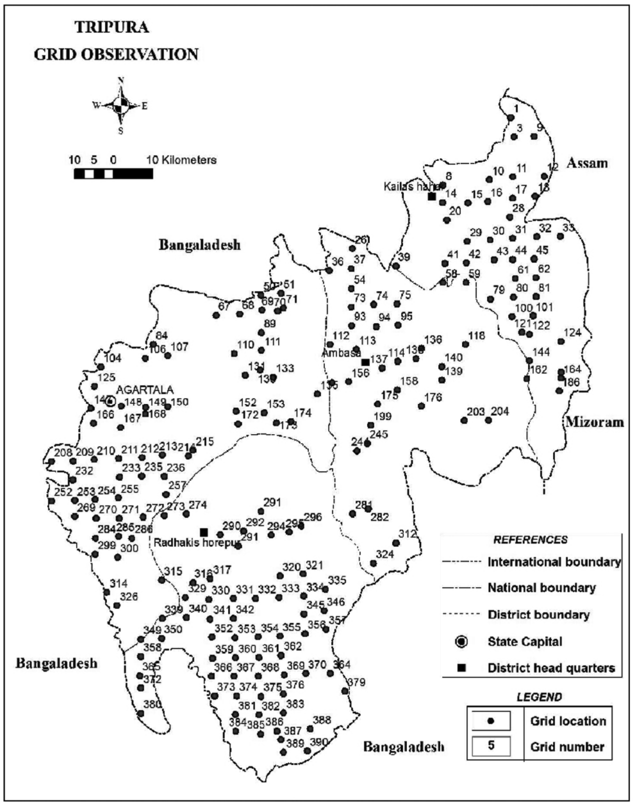

Figure 3. Study area showing grid point observations (5 km interval; Source: Bhattacharyya *et al.*[27]).

uses the semivariance analysis to measure the spatial variability of a regionalized variable, and provides the input parameters for the spatial interpolation of kriging. Semivariance, $\gamma(h)$, is defined as the half average squared difference of values separated by a distance h between the components of data pairs. Semivariance is calculated as follows

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2, \quad (5)$$

where $N(h)$ is the number of data pairs, $Z(x_i)$ and $Z(x_i + h)$ are the values at positions x_i and $x_i + h$ respectively. In the present study, a geostatistical tool GS+ (version 5.1) was used to evaluate several semi-variogram functions for SOC and soil loss in Tripura. Semivariograms were calculated both isotropically and anisotropically. The anisotropic calculations were performed in four directions (0°, 45°, 90° and 135°) with a tolerance of 22.5° to determine whether semi-variogram functions depended on sampling orientation and direction (i.e. they were anisotropic) or not (i.e. they were isotropic). Also, 0° corresponds to E–W and 90° to the N–S direction. Spherical, exponential, linear, Gaussian and pure nugget models were fitted to the experimental semi-variograms. The model parameters, viz. nugget semivariance, range, and sill or total semivariance were determined. Ratio of nugget semivariance to the total semivariance (sill semivariance) was used to define different classes of spatial dependency[42]. If the ratio was less than 25%, the variable was considered to be strongly spatially dependent, or strongly distributed in patches. If the ratio was between 25% and 75%, the variable was of moderate spatial dependency; if the ratio was greater than 75%, the variable had weak spatial dependency[43]. However, if the ratio was 100%, or the slope of the semi-variogram was close to zero, the variable was considered to be non-spatially correlated (pure nugget). Semi-variogram models were cross-validated to check their validity and compare values estimated from them with the actual values[44–46]. Differences between estimated and experimental values are summarized using the crossvalidation statistics: mean error (ME, eq. (6)), root mean squared error (RMSE, eq. (7)), average standard error (ASE, eq. (8)), mean standardized prediction error (MSPE, eq. (9)) and root mean square standardized prediction error (RMSPE, eq. (10)).

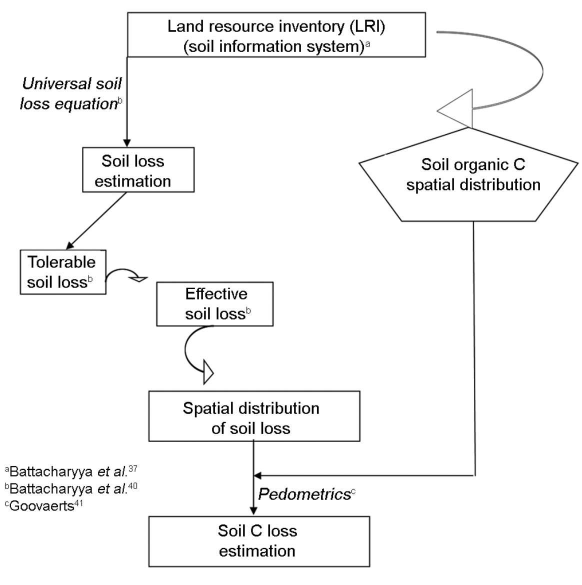

Figure 4. Schematic diagram for estimating soil C loss from the land resource inventory.

$$\mathrm{ME} = \frac{1}{N} \sum_{i=1}^{N} \{z(x_i) - \hat{z}(x_i)\}, \quad (6)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \{z(x_i) - \hat{z}(x_i)\}^2}, \quad (7)$$

$$\mathrm{ASE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \sigma^2(x_i)}, \quad (8)$$

$$\mathrm{MSPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{\mathrm{ME}}{\sigma^2(x_i)}, \quad (9)$$

$$\mathrm{RMSPE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\frac{\mathrm{ME}}{\sigma^2(x_i)}\right)^2}, \quad (10)$$

where $\hat{z}(x_i)$ is the predicted value, $z(x_i)$ the observed (known) value, N the number of values in the dataset and σ^2 is the kriging variance for location x_i (refs 4, 47–49).

For an unbiased semi-variogram model, the mean error should be zero. The calculated ME, however, is a weak diagnostic for kriging as it is insensitive to inaccuracies in the semi-variogram model. The value of ME also depends on the scale of the data, and is standardized from its division by the krigging variance to obtain the MSPE. An accurate semi-variogram model should have a MSPE close to zero. For a semi-variogram model that provides accurate prediction of variability, the values of RMSE and ASE should be as small as possible. The value of RMSPE should be equal to 1 (in this case RMSPE equals the krigging variance) for an accurate variogram model. However, if RMSPE is greater than 1, then the model will under-predict the variability and if it is less than 1, the model will over-predict the variability. Similarly, if the average kriging standard errors are greater than the root mean square errors, the variability is overestimated, if the average kriging standard errors are less than the root mean square errors, then the variability is underestimated[47,48].

Results and discussion

Soil loss and its evaluation

It has been reported that the loss of topsoil by erosion is compensated by the formation of fresh soil through pedogenesis[34,36]. It is, therefore, interesting to observe that the processes of soil formation and soil erosion occur simultaneously in nature. To estimate effective loss of topsoil, it is, therefore, necessary to consider and quantify the formation of regenerated soil. Since soil formation is governed by climate as one of the parameters[50], its formation varies from less than 0.25 mm $year^{-1}$ in dry and cold environments to greater than 1.5 mm $year^{-1}$ in humid and warm environments[36]. Topsoil formation at the rate of 1 mm $year^{-1}$ is equivalent to annual addition of 13.3 t ha^{-1} $year^{-1}$, taking an account of the weight of a hectare furrow slice (15 cm depth) soil as 2.2×10^6 kg. Since Tripura represents a humid climate, the limit of 2.0 mm $year^{-1}$ soil formation should be around 29 t ha^{-1} $year^{-1}$ $(2.2 \times 10^3/150) \times 2.0 = 29$ t ha^{-1} $year^{-1}$ soil). The rate of topsoil formation was given due consideration in assessing soils at various grid points. In terms of susceptibility, in an earlier study, the soil loss assessed[27] was used to determine the spatial variability as shown in the revised soil loss map of Tripura. Assuming soil loss of 29 t ha^{-1} $year^{-1}$ as the tolerable limit, we find nearly 61% and 39% areas under tolerable and susceptible to soil erosion respectively.

Statistics and semi-variogram models

Statistics: A summary of descriptive statistics of SOC, soil loss and SOC loss of 196 grid points, analysed for Tripura is presented in Table 1. SOC varies more or less uniformly in the entire state with a mean value of 0.95% and CV of 41%, which is also supported by the trend analysis (Figure 5 *a*) and histogram plotting of SOC (Figure 6 *a*). The spatial distribution of SOC followed a second-order global trend, with higher values in the northeast and eastern parts of the state. The histogram of SOC indicates that its spatial distribution followed approximately a normal probability distribution (skewness of 0.684; Table 4), suggesting no need for any transformation. There were wide spatial variations in the soil loss and SOC loss across the state with 199% and 223% respectively (Table 4). The soil loss followed a second-order global trend (Figure 5 *b*) in the spatial distribution with higher values in northeast and eastern parts of the state dominated by the hilly terrain[25]. Similar trend was also observed in the spatial distribution of SOC loss (Figure 5 *c*). The histogram plots of soil loss and SOC loss (Figure 6 *b* and *c*) indicate that the spatial distribution of these parameters did not follow the normality with skewness values of more than 1 (Table 4), which necessitated the log transformation of soil and SOC losses (Figure 6 *b* and *c*).

Semi-variogram models: The semi-variogram models and best-fit model parameters for the SOC, soil loss and SOC loss are presented in Table 5 and Figure 7. All the semi-variogram models show positive nugget, which can be due to sampling error, short-range variability, and random and inherent variability. The best-fit semi-variogram model for SOC was found to be exponential model with a R^2 value of 0.90 (Table 5). For soil and SOC losses (after log transformation), the best-fit semi-variogram models are spherical and exponential models with R^2 values of 0.95 and 0.77 respectively. The nugget-to-sill ratio of SOC, soil loss (log transformed) and SOC

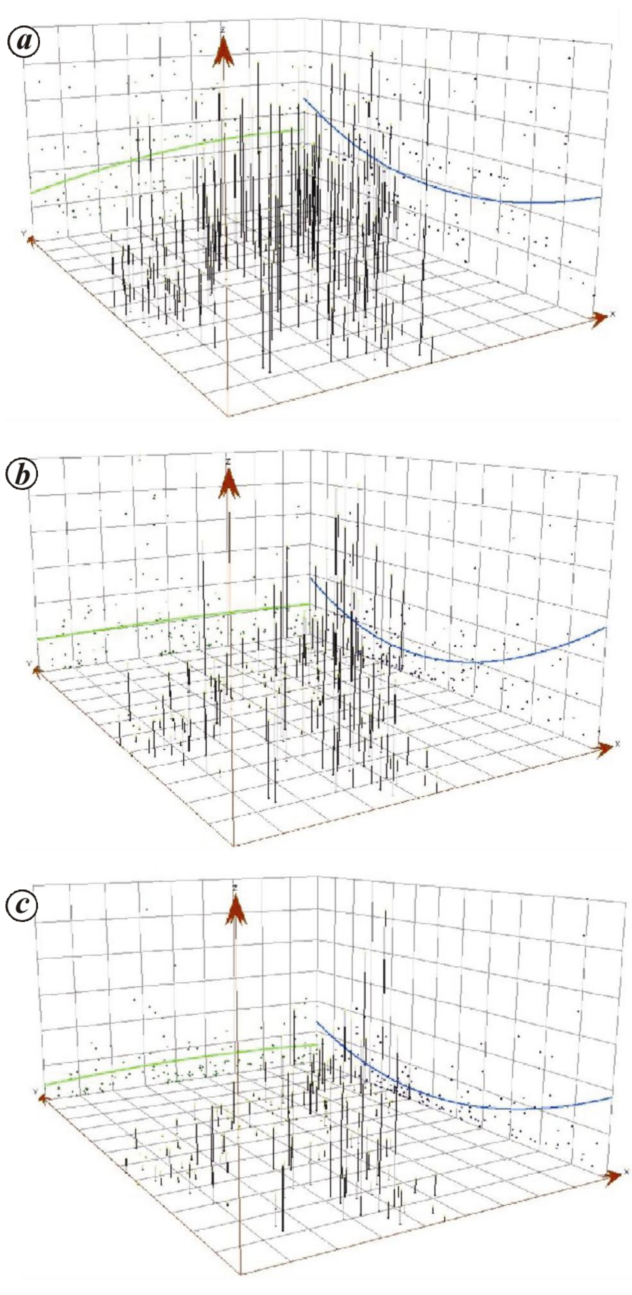

Figure 5. Trend analysis: (***a***) soil organic carbon, (***b***) soil loss and (***c***) soil organic carbon loss in Tripura.

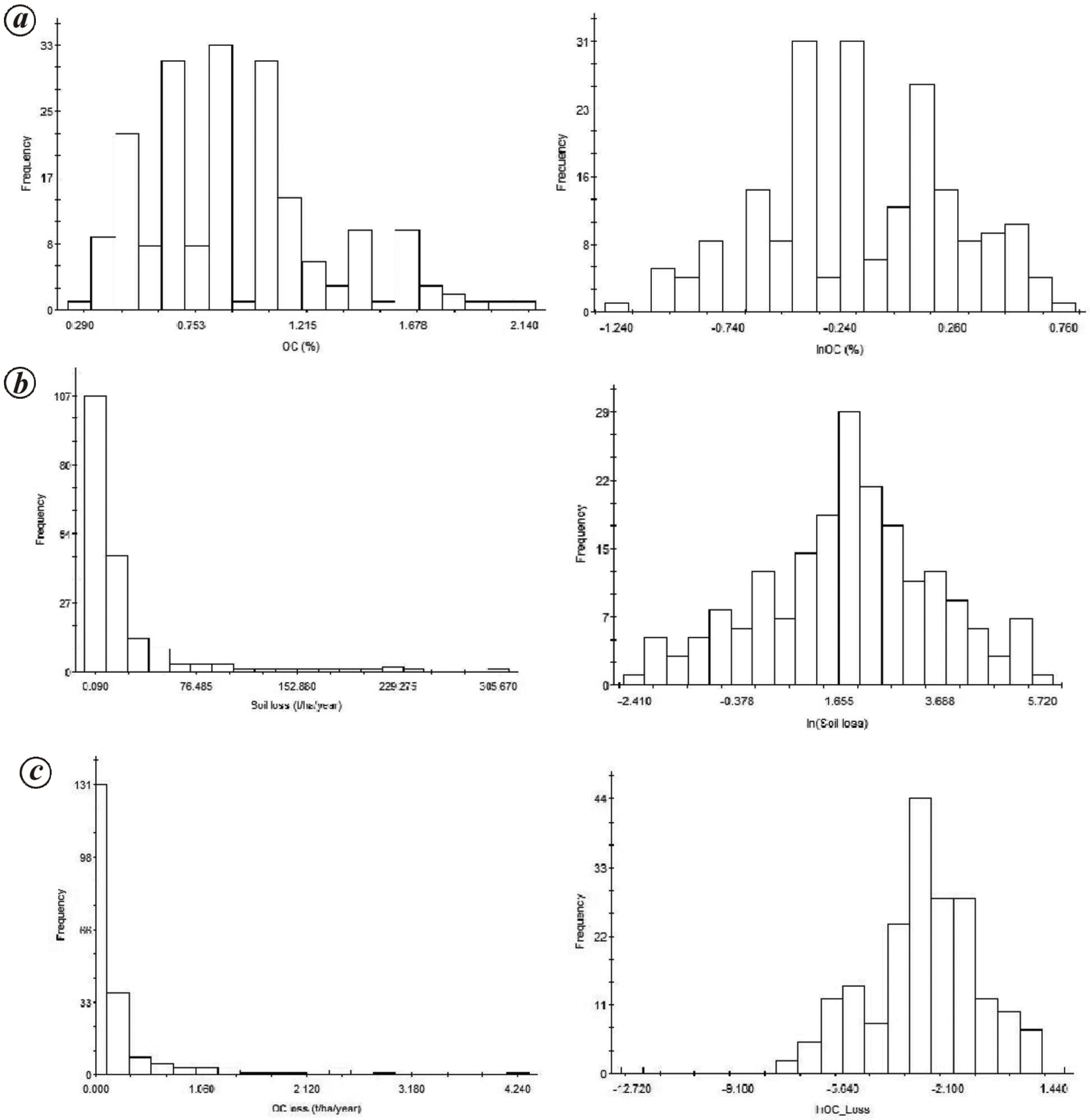

Figure 6. Histogram of non-transformed and transformed (natural log): (***a***) SOC, (***b***) soil loss and (***c***) SOC loss.

Table 4. Descriptive statistics of SOC, soil loss and SOC loss in the study area

Soil parameter	Mean	SD	CV (%)	Skewness	Kurtosis	Minimum	Maximum
SOC (%)	0.95	0.391	41.2	0.684	–0.047	0.29	2.14
ln SOC (%)	–0.14	0.423	314.3	–0.182	–0.553	–1.24	0.76
Soil loss (t ha^{-1} $year^{-1}$)	23.60	46.936	198.9	3.496	13.289	0.09	305.67
ln Soil loss (t ha^{-1} $year^{-1}$)	1.86	1.728	92.9	–0.133	–0.223	–2.41	5.72
SOC loss (t ha^{-1} $year^{-1}$)	0.23	0.514	223.5	4.515	25.069	0.00	4.24
ln SOC loss (t ha^{-1} $year^{-1}$)	–2.94	1.937	65.9	–0.757	2.571	–12.72	1.44

loss (log-transformed) showed moderate spatial dependence with values of 32.0, 45.1 and 31.0 respectively (Table 5).

The cross-validation results (Table 6) indicate that the mean error and mean standardized prediction error are close to zero for the best-fit (exponential) semivariogram model of SOC (exponential), suggesting unbiased predictions. However, the average standard errors are less than the root mean square errors indicating that the model under-predicts the variability. The root mean square standardized prediction errors also suggests the same, since it is greater than 1.

Table 5. Parameters of semi-variogram models for SOC, soil loss and SOC loss in the study area

Soil parameter	Model	Nugget	Sill	Range (m)	R^2	Spatial dependency (%)
SOC (%)	Exponential	0.0517	0.1634	37,500	0.90	32.0
ln SOC (%)	Exponential	0.0722	0.2064	59,100	0.93	35.0
Soil loss (t ha^{-1} $year^{-1}$)	Spherical	1506.0	3013.0	211,000	0.53	50.0
ln Soil loss (t ha^{-1} $year^{-1}$)	Spherical	1.354	3.004	44,500	0.95	45.1
SOC loss (t ha^{-1} $year^{-1}$)	Linear	0.2204	0.2204	57,761	0.20	100.0*
ln SOC loss (t ha^{-1} $year^{-1}$)	Exponential	1.171	3.771	35,100	0.77	31

*Pure nugget.

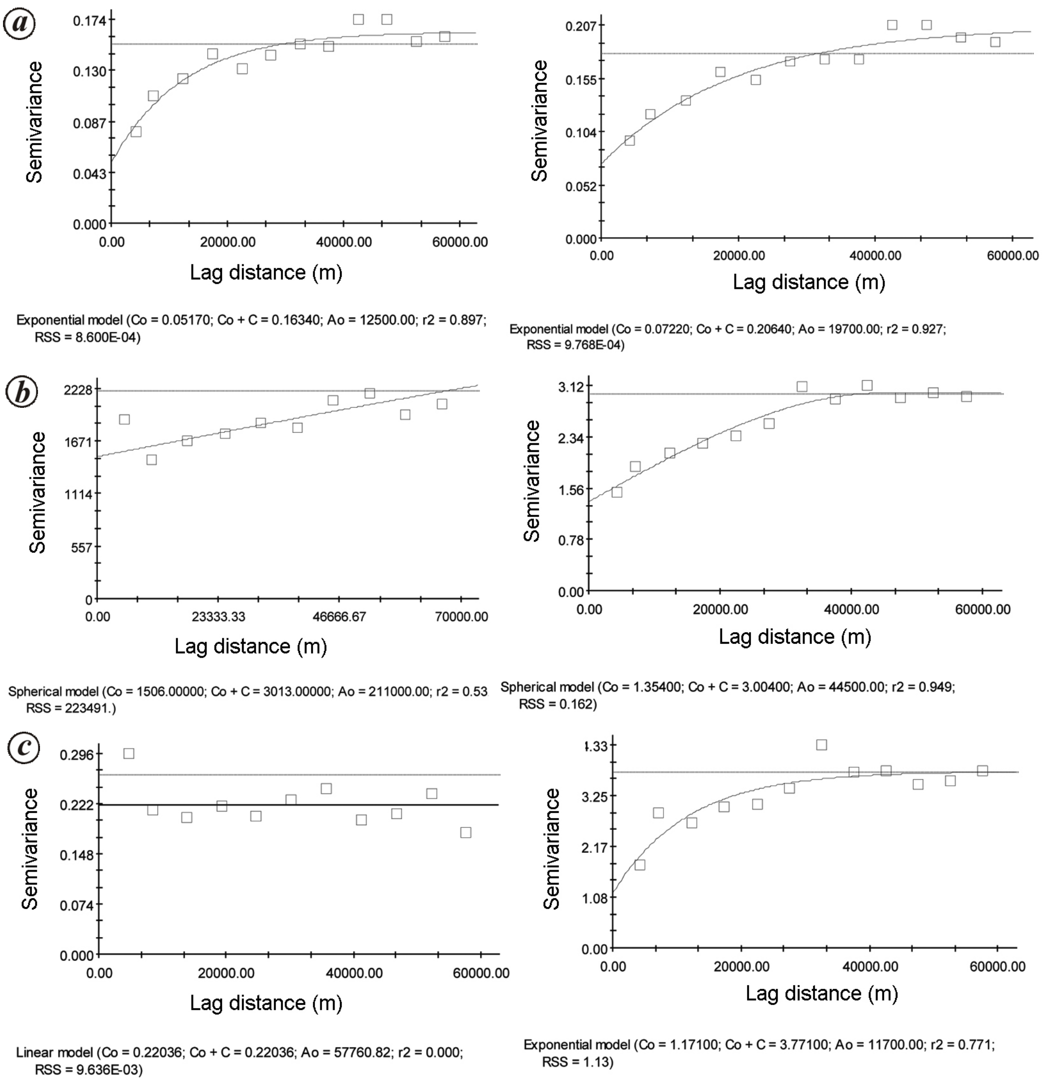

Figure 7. Semi-variogram models of non-transformed and transformed (natural log): (***a***) SOC, (***b***) soil loss and (***c***) SOC loss.

The best-fit spherical model for soil loss (log-transformed) had ME more than zero (1.9814) and MSPE close to zero. The ASE is more than RMSE and RMSPE is less than 1, suggesting that the semi-variogram model over-predicts the variability with some bias.

For SOC loss (log-transformed), the best-fit semi-variogram model (exponential) is relatively unbiased with the values of ME and MSPE close to zero. However, ASE is more than RMSE, suggesting over-prediction of the variability, which is also substantiate by the RMSPE with a value less than 1.

The spatial distribution of SOC, soil loss and SOC loss (Figures 8 *a–c*), was in agreement with the topography and the different land-use types. In the western parts, the

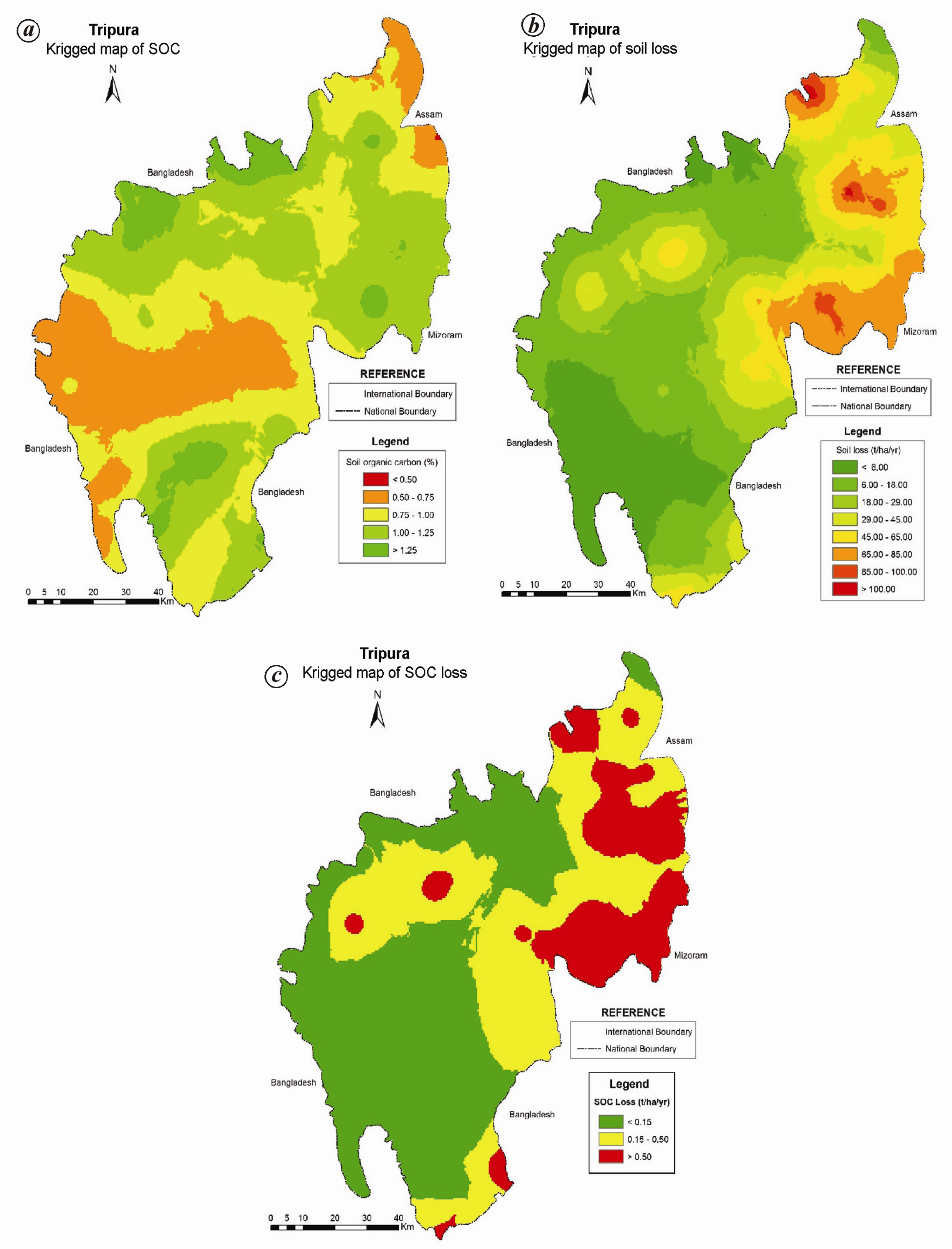

Figure 8. Spatial distribution of (***a***) soil organic carbon; (***b***) soil loss and (***c***) soil organic carbon loss in Tripura.

Table 6. Cross-validation of the results obtained using various models

		Prediction errors				
Soil parameter	Model	ME	RMSE	ASE	MSPE	RMSPE
SOC (%)	Exponential	–0.0026	0.3623	0.3229	–0.0041	1.1108
Ln SOC (%)	Exponential	–0.0028	0.3583	0.3446	–0.0424	1.1544
Soil loss (t ha^{-1} $year^{-1}$)	Spherical	–0.1001	45.1767	40.9205	–0.0022	1.1007
ln Soil loss (t ha^{-1} $year^{-1}$)	Spherical	1.9814	46.7751	89.0944	–0.0463	0.7785
SOC loss (t ha^{-1} $year^{-1}$)	Linear	–0.0081	0.4917	0.4744	–0.0170	1.0357
ln SOC loss (t ha^{-1} $year^{-1}$)	Exponential	0.0839	0.5491	1.6603	0.0194	0.4691

Table 7. Soil orders in Tripura and their susceptibility to SOC loss*

Ranking	Susceptibility to SOC loss		
Soil	Most susceptible (>0.5 t ha^{-1} $year^{-1}$)	Intermediate susceptible (0.15–0.5 t ha^{-1} $year^{-1}$)	Least susceptible (<0.15 t ha^{-1} $year^{-1}$)
Entisols	Typic Udorthents (G11, G14, G43) Lithic Udorthents (G15)	Typic Udorthents (G36, G44, G58, G111, G245, G332) Typic Udipsamments (G59) Aquic Udorthents (G324, G335)	Typic Udorthents (12, 33, 121, 152, 292, 317, G354, G356, G360, G362) Aquic Udorthents (G54, G73, G346) Typic Fluvaquents (G158, G299) Typic Udifluvents (G254)
Inceptisols	Typic Haplustepts (G8, G29, G30, G31, G101, G131, G164, G166) Humic Haplustepts (G186) Aquic Haplustepts (G32, G79, G125, G168, G281)	Typic Haplustepts (G3, G45,G61, G74, G100, G124, G368, G211, G282, G334) Humic Haplustepts (G80, G81, G156) Aquic Haplustepts (G107, G112, G139) Fluventic Haplustepts (G140) Typic Epiaquepts (G149, G67, G252) Aeric Epiaquepts (G236)	Typic Haplustepts (G1, G9, G10, G16, G17, G18, G28, G51, G68, G75, G93, G106, G110, G135, G162, G167, G172, G173, G208, G210, G233, G235, G244, G253, G255, G273, G286, G290, G315, G321, G333, G339, G342, G345, G349, G350, G352, G353, G355, G357, G359, G361, G364, G365, G366, G367, G370, G372, G373, G374, G380, G381, G385, G388) Humic Haplustepts (G26, G37, G39, G42, G94, G95, G104, G118, G232, G296, G329, G330, G331) Aquic Haplustepts (G20, G133, G144, G155, G214, G215, G269, G270, G271, G272, G274, G284, G285, G294, G295, G314, G320, G326, G340, G341, G369, G376) Fluventic Haplustepts (G113, G176) Typic Epiaquepts (G41, G50, G52, G69, G70, G71, G84, G89, G136, G137, G147, G148, G150, G153, G212, G213, G257, G291, G300) Lithic Haplustepts (G145) Typic Endoaquepts (G122, G375, G382, G383, G384, G386, G387, G390)
Alfisols	Typic Hapludalfs (G199)	Typic Hapludalfs (G204)	Typic Hapludalfs (G175, G209,G358)
Ultisols	Typic Hapludults (G203)	Typic Hapludults (G138)	Typic Hapludults (G114, G174, G316)

*Source: Bhattacharyya *et al.*[27].

slope gradient is very small compared to the eastern parts. Hence SOC and soil loss show an increasing trend towards the northeastern part of the state (Figures 5 *a* and *b*; 8 *a* and *b*).

Pedometrically modelled soil organic carbon

The spatial variability of SOC generated from the grid points was classified into five different ranges (Figure 4). Most of the areas in north–south (adjoining state of Mizoram), central and parts of western, central highlands and southern hills contain >1% SOC. According to the US soil taxonomy, Mollisols with the mollic epipedon, referred as brown forest soils, containing greater or to 1% SOC on the surface[32] are considered to be the best quality soils in the world[51] and have the capacity to sequester more organic carbon[52]. By this standard, nearly 48% area in Tripura has more than 1% SOC on the surface (Figure 8 *a*). Subsequent studies on carbon in Tripura soils

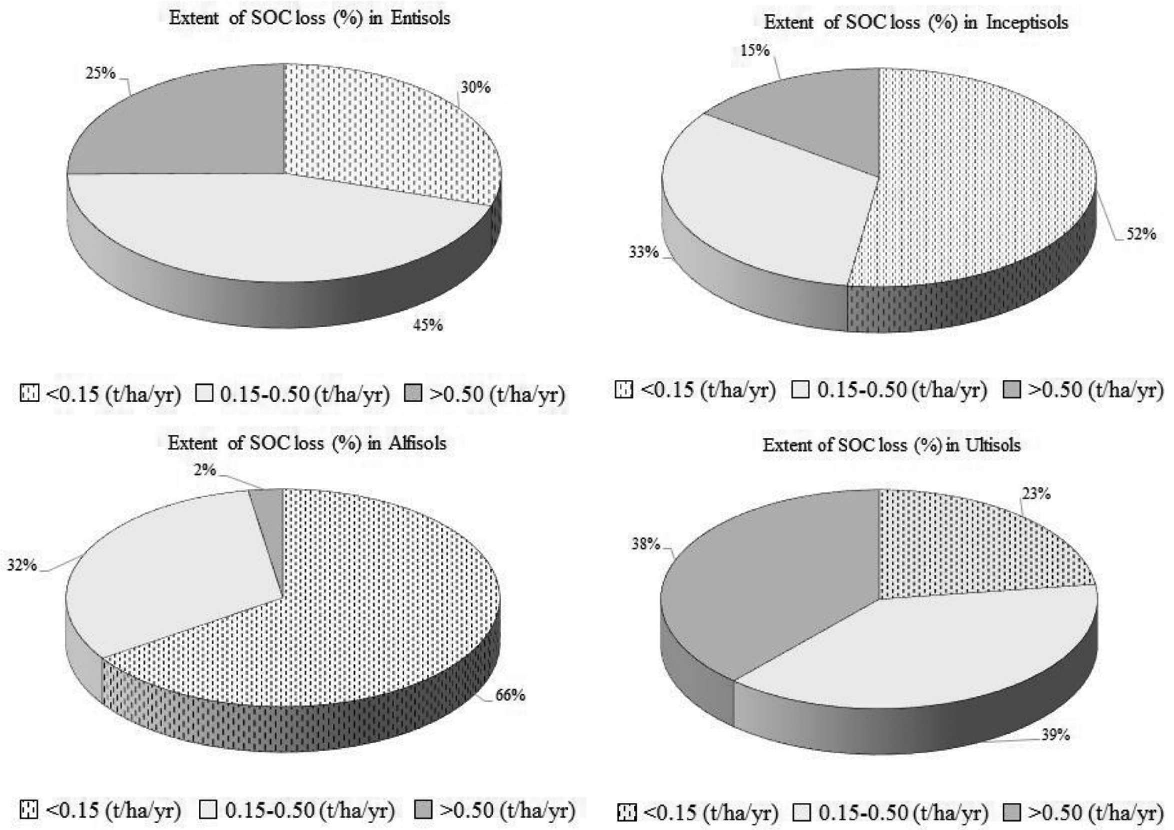

Figure 9. Extent of SOC loss in different soil orders of Tripura.

indicated that the total SOC stock is maintained at 0.046 Pg m ha^{-1} (ref. 37), which is nearly double the all-India average of 0.029 Pg m ha^{-1} SOC[53]. Using the 14 agro-climatic zones (ACZs) concept of the Planning Commission, India, ACZ2 representing the entire north-eastern region stored SOC at the rate of 0.064 Pg m ha^{-1} (ref. 14). Such threshold values of SOC stock ranging from 0.05 to 0.06 Pg m ha^{-1} should, therefore, be maintained in the green belt area to protect natural ecosystem[37]. In view of maintaining the natural ecosystem, we thought it prudent to bridge two sets of information on soil loss and soil organic carbon status to assess SOC loss in the state as detailed in the following paragraphs.

Soil organic carbon loss

As mentioned earlier, considering 29 t ha^{-1} $year^{-1}$ soil loss as the tolerable limit and 0.5% SOC on the surface as the minimum value to maintain a threshold SOC stock of 0.05–0.06 Pg m ha^{-1}, we found 0.15 tonnes (~150 kg) SOC/ha/year ($29 \times 0.5/100 = 0.145$ t ha^{-1} $year^{-1}$) as the tolerable limit of SOC loss in Tripura. The spatial variability of SOC loss in the state indicates that most of the areas in the north, north–south extending further in the southern part are under threat for SOC loss beyond the tolerable limit (Figure 8 *b*). It may be mentioned that Tripura has an area of 20% under valleys and inter-hill basins. Most of these areas are used for agriculture (submerged paddy). These soils are subjected to erosion within the tolerable SOC loss limit and are also characterized by high SOC build-up due to reduced moisture regime in the soil profile[54] and thus fall under tolerable SOC loss. On the contrary, in the hills and the *tilla* lands, the situation is different. Hilly areas of Tripura in the north, central and southern parts have different elevations, mean annual rainfall and different types of vegetation. In the *tilla* lands, agriculture and horticulture are gradually dominating the land-use. Many such areas still remain under the category of degraded forest[26], which are vulnerable to SOC loss. We find more number of grid points in the less susceptible class of SOC loss after grouping the soil mapping units (Table 7 and Figures 8 *c* and 9). Field information indicates that many such areas have flat slope and are under cultivation. These soils used for bunded paddy arrest SOC loss. Earlier, while explaining carbon transfer model vis-à-vis management interventions for chemically degraded lands, it was reported how conservation agriculture should form a part of management technique in semiarid and arid bioclimates[40]. With the help of a threshold value of SOC stock of 0.03 Pg m ha^{-1}, nearly 156 m ha was reportedly prioritized for conservation agriculture. Like SAT, humid tropic climate requires conservation not only to protect soil erosion but also to prevent SOC loss for preserving soil fertility, as shown in this study.

Conclusion

A better understanding of the spatial variability of soil and SOC loss is useful for monitoring the soil quality and health. It helps in suggesting management options for sustainable agriculture, particularly for Tripura, as well as other parts of the northeastern region of India. Pedometric mapping of SOC loss can be used as a tool to prioritize areas for conservation agriculture in the northeastern region of India. Since the landscape of the study area resembles most of the Southeast Asian countries, such information could serve as a model for estimating tolerable SOC loss in similar landscape elsewhere in the humid tropical climate for conservation agriculture.

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ACKNOWLEDGEMENT. We thank the Director, ICAR-NBSS&LUP, Nagpur for providing the necessary facilities during this study.

Received 6 June 2014; revised accepted 20 January 2015