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RESEARCH PAPER

Estimation of accumulated soil organic carbon stock in tropical forest using geospatial strategy

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Digital soil carbon map;
Regression analysis

Abstract Soil organic carbon (SOC) is a dynamic soil property that represents the key component of the forest ecosystems. The main objective of the present study is to evaluate SOC using the remote sensing images as well as field methods at Ranthambhore Tiger Reserve Forest area. The soil samples were collected randomly from the region at several field locations, to estimate the surface soil carbon concentrations in the laboratory. The study derived results for bare soil index, NDVI, SOC and relationship of SOC with NDVI using regression analysis, while comparing reference SOC (field measured SOC) and predicted SOC (estimated from satellite image). The remote sensing images were used to predict the precise carbon content associated with organic matter in the soil using NDVI and related equations, to prepare digital soil organic carbon map. The relationship between the NDVI and both reference/predicted SOC is established using the equation to derive the digital SOC for the study area using remote sensing data. The statistical relationship between reference SOC, pH concentrations, and NDVI values were presented against the predicted SOC to provide the variation between each variable.

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1. Introduction

Forest ecosystem has a high carbon density and is considered to have a considerable potential as carbon sinks (Halliday et al., 2003; Perruchoud et al., 1999) containing about 80% of terrestrial above ground carbon on one hand and more than 70% of all soil organic carbon on the other (Batjes, 1996; Jobbágy and Jackson, 2000). The soil carbon is almost three times that in the aboveground biomass and about double that in the atmosphere. Reliable estimates have been difficult to obtain due to a lack of global information on varieties of soils and the amount of soil carbon in each territory (Eswaran et al., 1993). Soil carbon adds up to the principal terrestrial pool of carbon playing considerable function in the universal carbon cycle. Forest is a natal unit having a gargantuan social organisation of living communities at work. The quantity of carbon exchanged between the forest and the atmosphere in the form of CO_2 via photosynthesis and respiration was found to be seven times the anthropogenic carbon emission. An increase in soil respiration increases the CO_2 emission from forest ecosystems. The soil organic matter on the surface is directly related to the carbon input. Forests present considerable resources and carbon storage put to one side of the earth's surface, where soil store carbon double and triple the amount of carbon in above ground biomass and available in the atmosphere (Kumar et al., 2013).

In the forest, the different tree species have a different outcome along the carbon storage of ecosystem, for example superficial rooting coniferous species tend to accumulate Soil Organic Matter (SOM) in the forest floor, but are low in the mineral soil, compared with deciduous trees (Jandl et al., 2007). At identical biomass volumes, trees with a high wood density such as deciduous tree species, accumulate more carbon than trees with light wood like Coniferous tree species i.e. pines (de Vries et al., 2002; Fissore et al., 2008; Jandl et al., 2007). Moreover, the boreal forests accumulate carbon in woody biomass as well as in litter, coarse woody debris, and peat (Kurbanov, 2000). Fissore et al., 2008 demonstrated that the SOC rate in quality and in terms of quantity may have decreasing trends in response to global heating, instead of soil decomposing favouring conditions of soil chemistry.

The balance between the carbon input by the forest and microorganism determines the soil carbon pool. Soil organic carbon is the amount of carbon present in the organic matter of the soil. Soil organic matter includes all the material of biological origin found in soil like plant residues, living roots, biological organism, and decomposing, decomposed or burnt material of varying sizes. The amount of soil organic carbon has direct relation with the crop productivity, fertility, soil type, physical characteristics and health of vegetation as well to list. Soil organic carbon is the largest terrestrial carbon pool playing as a key variable in the estimation of the terrestrial carbon dynamics. Whenever the organic matter is decomposed it releases some amount of carbon dioxide (CO_2) in the atmosphere. There is always a cycle of entry and exit of the amount of carbon between the terrestrial ecosystem and the atmosphere, making variable amount or level of carbon content in the soil (Fung et al., 2007; Hese et al., 2005; Houghton, 2005; IPCC, 2014; Penman et al., 2003; Ramankutty et al., 2007). Hence, soil carbon acts as a major determinant of the amount of CO_2 released into the atmosphere.

Soil acts as a source or sink of greenhouse gases like CO_2, CH_4, N_2O etc., depending on the management and land use (Lal, 1999). Further, CO_2 that forms a part of chemical processes, also controls the pH value of the soil as well as Soil Inorganic Carbon (SIC). The spatial pattern of the SIC is basically controlled by chemical and physical processes of the soil formation while biotic processes drive the spatial pattern of the SOC (Shi et al., 2012). Previous studies have shown the relationship of temperature and precipitation with inorganic carbon of the soil (Li et al., 2007; Mi et al., 2008; Yang et al., 2010). The negative correlation between the pH and SOC is also confirmed in the studies (McIntosh and Allen, 1993; Shi et al., 2012), concluding that acidified soil inhibits the decomposition of SOC, thus avoids loss of carbon from the soil to the atmosphere (Shi et al., 2012). This is further confirmed that soil pH declines when soil organic carbon increases under Hieracium species (also known as the *hawkweed*) in New Zealand (McIntosh and Allen, 1993). There is also a reporting of positive correlation of SOC quality to pH, but negatively related to cation exchange capacity CEC (Fissore et al., 2008). They also provided that the SOC quality varies according to mean annual temperature and forest types, and is well studied along the forest in North America. As discussed above, SOC is related to soil chemistry (chemical or physical), its concentration varies with silt, clay (not sand), and pH. SOC is also correlated with temperature, rainfall, and forest types and SOC concentration decreases exponentially with the time period (1987–2001) in the extensive cultivation conditions in agricultural regions, while the modeled SOC remains stable in that time period (1987–2001) as demonstrated by Brye et al. (2004).

Previously, SOC was determined using the visible and infrared channels of hyperspectral images with a field spectrometer to match the spectra of field and satellite images (Gomez, 2008). The Indian terrestrial ecosystem has variant carbon source and sink due to varied land use, land cover management, monsoon based climate and so on due to which the ecosystem is spatially and temporarily variable. The soil carbon is estimated for the Amazon forests, Boreal forests, tropical forest, coniferous forest, etc. using either field investigations or remote sensing applications (Davidson et al., 2008: Frolking et al., 1999; Cochrane et al., 1999; Gupta et al., 2014). Land use, land cover, climate, soil texture, topography, hydrology and other primary variables influence the production as well as decomposition process of soil carbon stocks (Houghton and Hackler, 1999; IPCC, 2014; Rani et al., 2011; Righelato and Spracklen, 2007). The recent advances in remote sensing and mapping have helped in detailed mapping of soil organic carbon, in analyzing soil properties its characteristics and heterogeneity of soil.

There are studies related to digital soil mapping (Abdel-Kader, 2011; Ismail and Yacoub, 2012) to predict the soil distribution in reference to soil maps and field data. These types of studies can be used to evaluate the variation in soil properties (Ali and Moghanm, 2013) using the remote sensing techniques. These digital soil mappings were also used to assess the soil degradation (El Baroudy and Moghanm, 2014) which may affect the soil productivity (Abdel Kawy and Ali, 2012). The assessment and digital soil mapping along with soil organic carbon is not only important for soil protection, assessing forest canopy density, but also for strategies to mitigate global warming, (Cochrane et al., 1999; Davidson et al., 2008; Houghton et al., 2000; Hirsch et al., 2004;

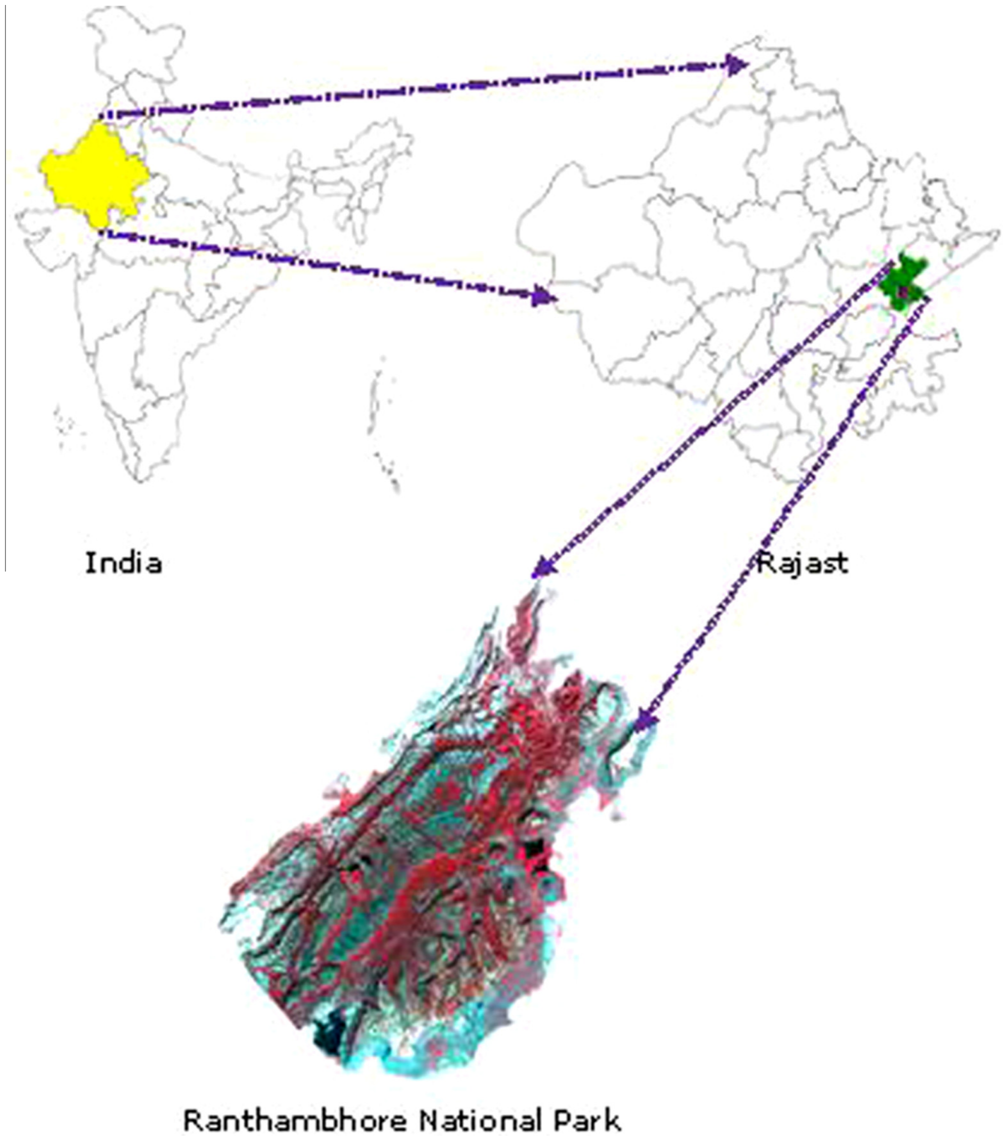

Figure 1 Location map of the Ranthambhore national park, and for the band combination of satellite image see Table 1.

Meyfroidt and Lambin, 2008; Rikimaru et al., 2002; Vargas et al., 2008).

This main objective of the study is to estimate the SOC using remote sensing that is dependent upon the NDVI, thus, this study mainly aims to assess the SOC (soil organic carbon) in relation to the bare soil index and soil organic carbon. The field methods included the several sampling units and bare soil index, while the remote sensing methods included the use of different bands like red band, blue band, green band and NIR bands of the satellite images for the estimation of bare soil index map of the study site. This, further, involved the generation of NDVI of the study site that is used to predict the SOC using regression modeling.

2. Materials and methods

2.1. Study area

The Ranthambhore Tiger Reserve Forest is situated in Sawai Madhopur and Karauli district of Rajasthan. The geographic extent of this study area is found to be 25° 12 N–26° 54 N latitude and 76° 22 E–76° 39 E longitudes. It is right now the only forest reserve in Rajasthan state and in the entire Aravali hill ranges where tigers exist. Ranthambhore Tiger Reserve Forest (RTR) spans over 1334 km^2 of area, of which 282 km^2 is the Ranthambhore Tiger Reserve (RTR) Forest (refer to Fig. 1 for the location of study area). The topographic or terrain feature of Ranthambhore national park is flat and rocky with some hilly areas having gentle slopes. The altitude of hills varies from 244 m to 507 m above mean sea level. The temperature of this area ranges from 12 °C to 47 °C with an average annual rainfall of 600 mm. The forests are mainly of edaphic climax and belong to the subgroup 5B-Northern Tropical Dry Deciduous forests and subgroup 6B-DS1-*Zizyphus* scrub. The degradation stages found here are DS1-Dry deciduous scrub and SS4-Dry Grasslands (Champion and Seth, 1968) according to the vegetation map prepared by French Institute, Pondicherry. The area is representative of dry deciduous *Anogeissus pendula* forest sub type in association with *Acacia*, *Capparis*, *Zizyphus* and *Prosopis* species.

2.2. Data used

The data used to carry out the research includes the satellite data, field data and other spatial data sets. Primary data were obtained during the field observation via field surveys and measurements of samples collected (see Table 2) from the study area while the satellite data used for soil carbon estimation is IRS P-6 Linear Imaging Self Scanning Sensor III (LISS III) satellite images. The specifications of LISS-III Sensor are illustrated in Table 1.

2.3. Image interpretation

The present study utilises satellite imagery and toposheet acquired from the survey of India. This toposheet helps in the refinement or rectification and georeferencing of the satellite imagery using ERDAS IMAGINE 2011© software. Various digital preprocessing techniques like geometric distortion removals, atmospheric correction algorithms, image registration, enhancement and data transformations were used, that helped in identification and image interpretation of the different features in the imagery. The digital pre-processing technique was used for identifying different features and classes in the imagery (Pandey et al., 2012; Sharma et al., 2012). For verification and accuracy of the land use/land cover map proper ground survey with GPS points led to easy identification of the features. The four bands corresponding to Near Infra-Red, Red, Green and Blue of Linear Imaging Self Scanning Sensor III imagery helped in identifying image characteristics and ground features after image pre-processing technique. Ground truthing of the study area helped out in identifying the different features and land use/land cover correctly (Kumar et al., 2012).

Table 1 Satellite data and their specification.

Specification particulars	
Satellite	IRS P-6
Sensor	LISS III-solid state push broom cameras
Band combination	3, 2, 1 (RGB combination of the image for study area)
Temporal resolution	5 days
Spatial resolution	PAN < 6 m, MSS 23.6 m

2.4. Determination of sample size

Reconnaissance survey has been carried out at the beginning of the field in order to be familiar with the study area and for ground truth observations needed for preparing the interpretation keys which are essential in bare soil index classification. The precision of the sample estimate of the population depends not only upon the size of sample, but also on the variability in the population which is very high. Sampling variance can be reduced by dividing the population into the number of homogeneous groups and then selecting a random sampling from these groups of population independently. The homogenous group in which the population is divided are called strata and the procedure of sample selection is called stratified random sampling. The use of stratification is possible only when the complete frame for all strata and size are variable. Effectiveness of stratification can be investigated by the analysis

Table 2 Estimated soil organic carbon, and pH of the soil samples.

Plot no.	Sampler radius (cm)	Sampler volume (cm^3)	Soil weight (gm)	Bulk density (g/m^3)	NDVI	pH	Reference SOC (t/ha)
1	3.8	453.64	360	0.793	0.112	6.1	6.18
2	3.8	453.64	320	0.705	0.114	6.4	6.13
3	3.8	453.64	342	0.753	0.123	6.3	7.46
4	3.8	453.64	348	0.767	0.129	6.2	8.28
5	3.8	453.64	347	0.764	0.134	7.1	8.94
6	3.8	453.64	362	0.797	0.141	7.2	9.81
7	3.8	453.64	322	0.709	0.145	7.1	9.51
8	3.8	453.64	330	0.727	0.153	7.1	11.20
9	3.8	453.64	306	0.674	0.189	7.2	11.19
10	3.8	453.64	315	0.694	0.141	7.2	9.16
11	3.8	453.64	300	0.661	0.152	7.1	11.24
12	3.8	453.64	344	0.758	0.162	7.2	11.98
13	3.8	453.64	325	0.716	0.185	7.3	12.82
14	3.8	453.64	356	0.784	0.192	7.3	14.67
15	3.8	453.64	345	0.760	0.313	7.4	14.14
16	3.8	453.64	349	0.769	0.236	7.2	15.30
17	3.8	453.64	351	0.773	0.242	7.1	15.31
18	3.8	453.64	349	0.769	0.249	7.4	16.23
19	3.8	453.64	342	0.753	0.258	7.2	16.58
20	3.8	453.64	352	0.775	0.391	7.5	17.84
21	3.8	453.64	312	0.687	0.298	8.2	16.85
22	3.8	453.64	326	0.718	0.316	8.1	18.82
23	3.8	453.64	356	0.784	0.346	8.2	21.65
24	3.8	453.64	321	0.707	0.352	8.3	21.08

of variance. The variance of the total population is made up of the variance within individual strata and of variance within the strata.

In the present study, stratified random sampling was carried out. The number of sampling units was calculated by the following formula (Walkley, 1947).

$$N = \frac{t^2(CV)^2}{E^2} \tag{1}$$

where, N = number of samples required for allowable error (E%), t = value of t-statics at 95% level significance: 1.96, and CV = co-efficient of variation ± 33.5.

Assuming E% is equal to 10% the required number of sample unit comes out to be 26. These sample plots were allotted to different strata of homogeneous vegetation according to stratified random sampling method. In this study, the sizes of the samples were taken as 24 due to inaccessibility and severe cold.

2.5. Data collection

The estimation of soil organic carbon requires a proper management plan for plot layout and a lot of precautions for collecting samples. These major precautions to be taken in the field during plot layout can be listed as follows: First, any aspect chosen on the hills should have all the plots within the same aspect; Second, major stream should be avoided inside the plot, i.e., the plot should be laid on the one side of the stream within the frame of 31.62 * 31.62 m; Third, the direction/side of the plot should be fixed which is followed uniformly thereafter; Fourth, all the baggage should be kept

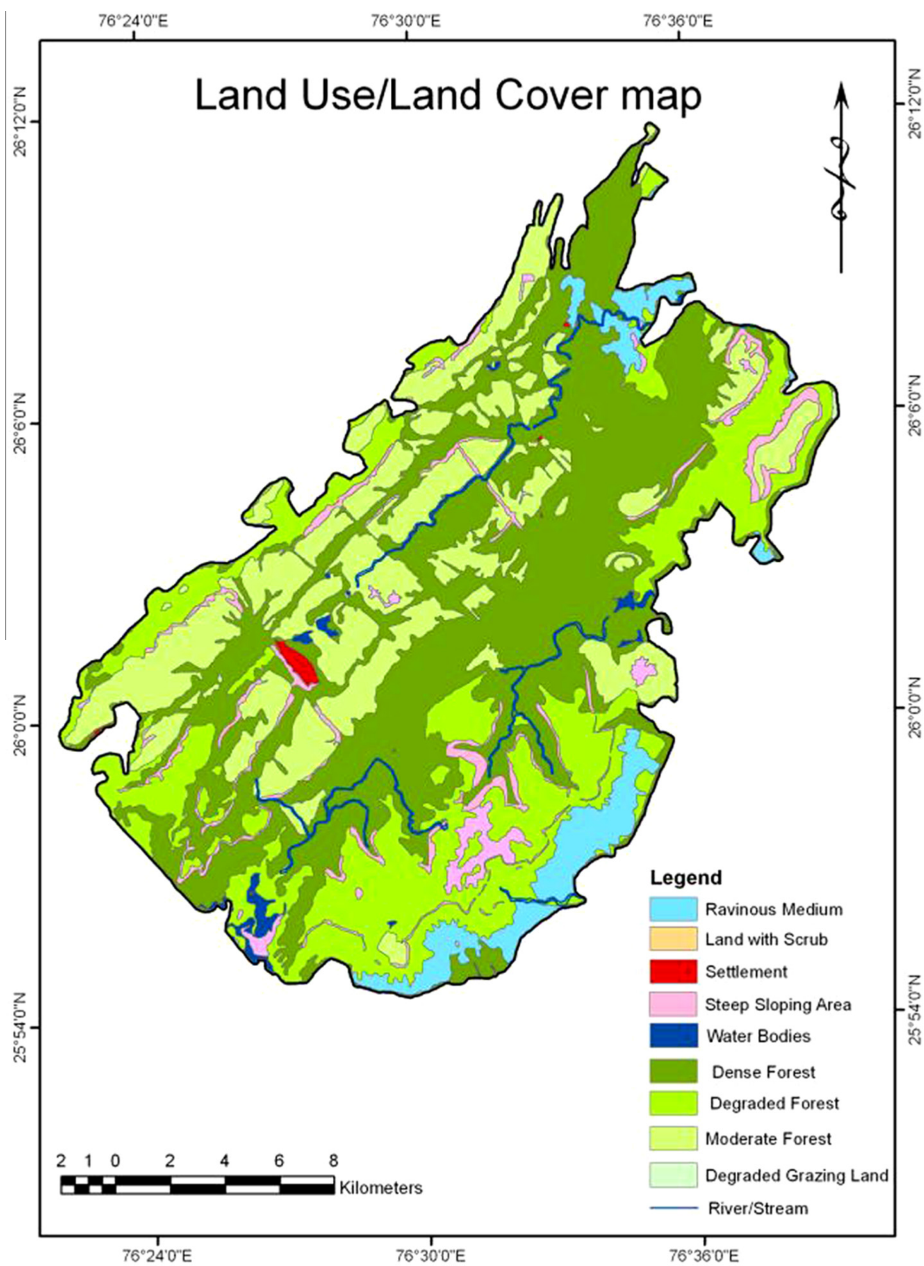

Figure 2 LU/LC map of the study area.

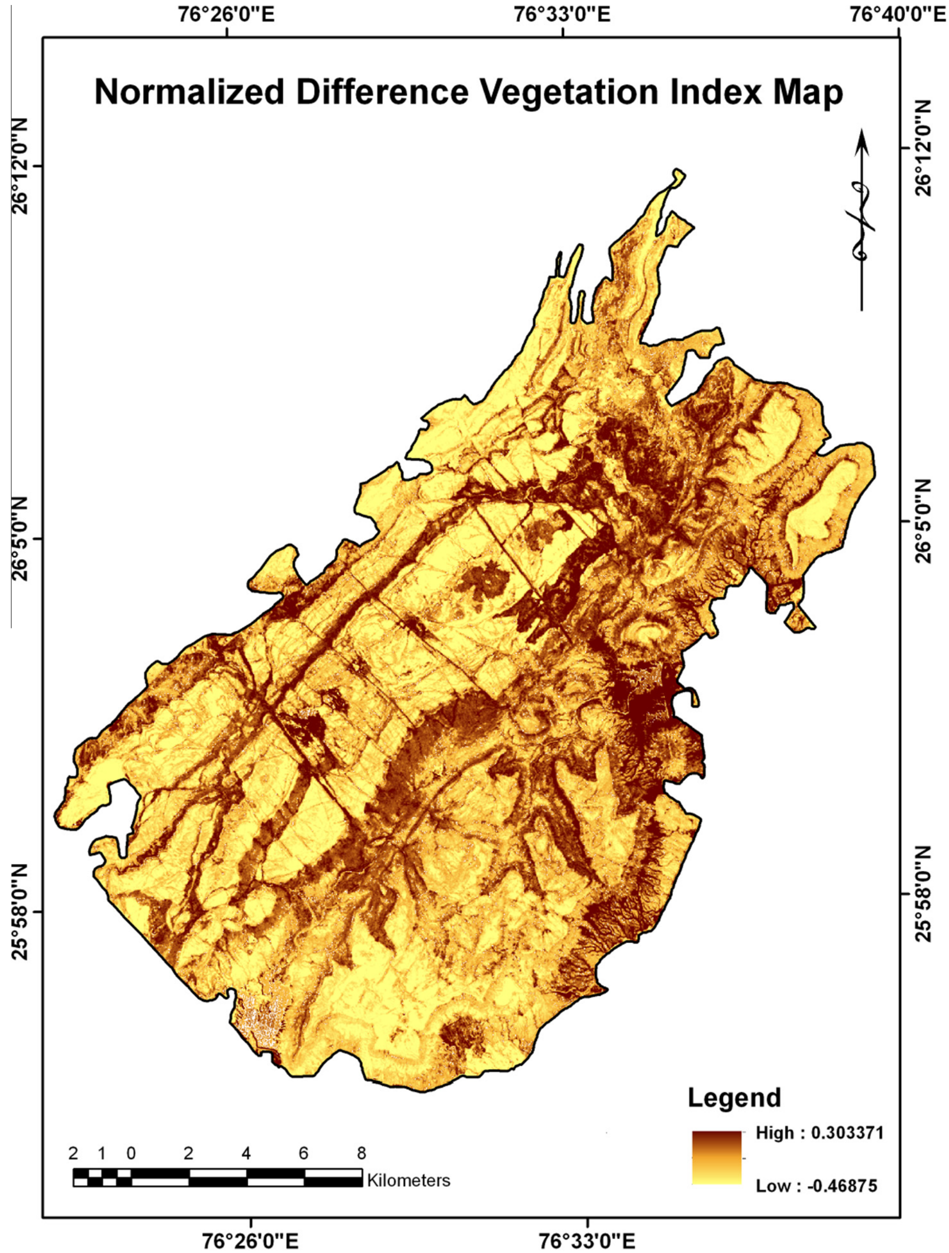

Figure 3 NVDI image of the study area.

outside the proposed plot which is important to avoid trampling of the herbaceous flora of that corner. A total of 24 soil samples was collected from the study area of Ranthambhore national park with the sampler having a radius of 3.8 cm with soil depth of 5 cm (refer to Table 2). Each soil sample varies with their properties (bulk density (g/m^3), SOC, pH, etc.) with the change of the sampling locations due to different environmental conditions like exposed soil, forest covered soil, etc. Estimation of soil organic carbon in each soil sample (humus 0–15 cm and mineral 15–30 cm) was determined using the procedure given by Walkley–Black method or modified Mebius procedure (Yeomans and Bremner, 1988). It involves digestion of the soil sample which is digested with an acidified dichromate ($K_2Cr_2O_7$–H_2SO_4) solution for 30 min that was preheated to 170 °C. The excess unreacted dichromate was digested with an acidified solution of ferrous ammonium sulphate during titration, with the use of N-phenylanthranilic acid as an indicator. This procedure is quick and precise that is commonly used for routine analysis of soils for organic carbon (this chemical is generally used in routine Kjeldahl analysis of soils for total nitrogen). In short, carbon is oxidised by the dichromate ion and the excess dichromate ion is then back titrated with ferrous ion (Walkley and Black, 1934).

2.6. Bare soil index and NDVI

Bare soil is the soil that remains uncovered by any grass, wood chips, any live ground covers, artificial turfs and similar covering. It is the soil or sand on the earth's surface. The following formulae are used to calculate the bare soil index of a region

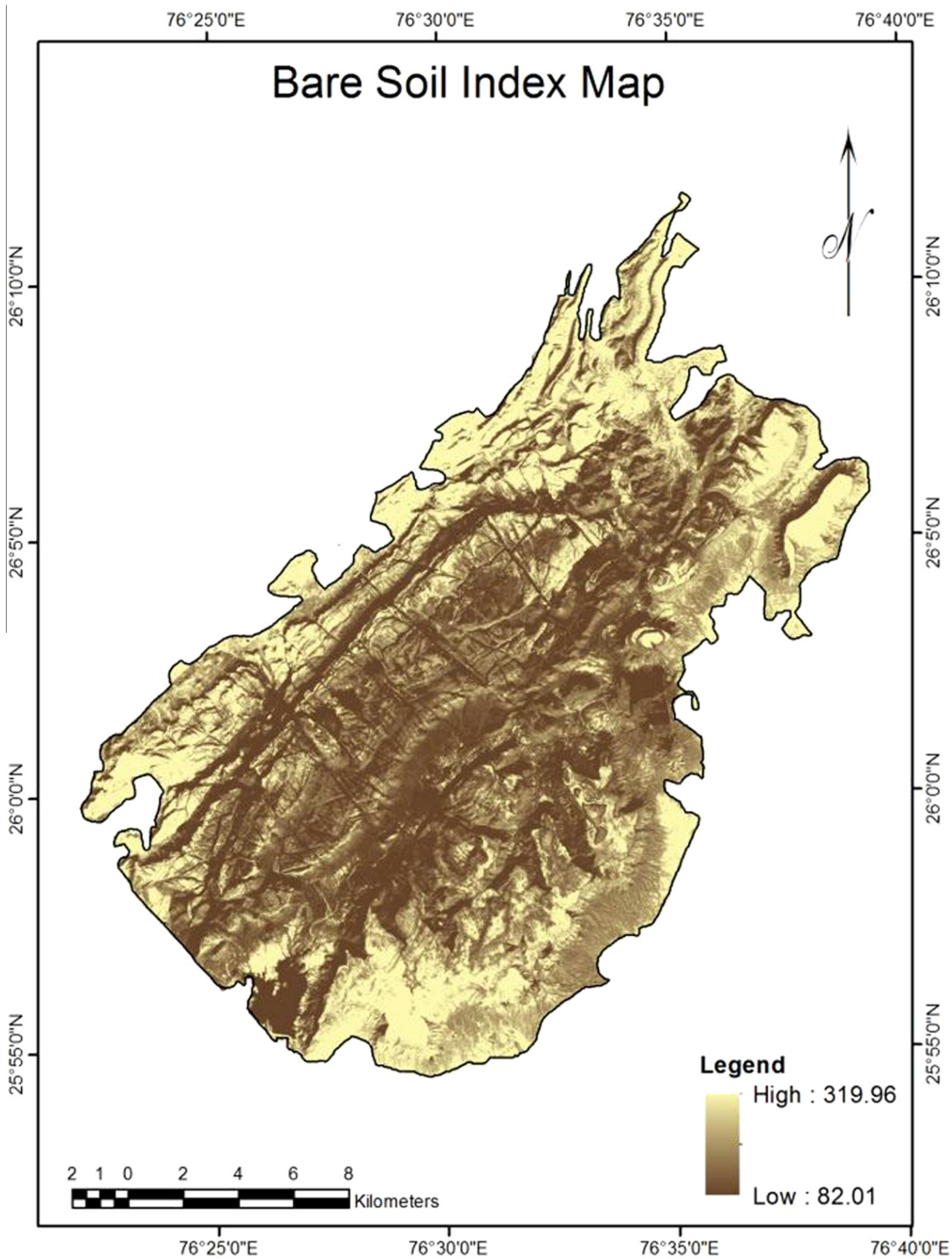

Figure 4 Bare soil index map of the study area.

(refer to the Fig. 4). The BSI is a normalised index of the difference sums of two separating bands of the satellite image (for the vegetation). The formulae used for calculating the bare soil index is given below (Jamalabad and Abkar, 2004) as:

$$BSI = \frac{[(B5 + B3) - (B4 + B1)]}{[(B5 + B3) + (B4 + B1)]} * 100 + 100 \quad (2)$$

where, BSI = bare soil index, B1 = Blue Band, B3 = Green Band, B4 = Red Band, and B5 = Near Infra-Red Band.

NDVI values estimate the vegetated and non vegetated regions. The equation to calculate the NDVI using the satellite image is given below:

$$NDVI = \frac{[(NIR) - (Red)]}{[(NIR) + (Red)]} \quad (3)$$

where, NIR and Red belong to Near-Infra Red and Red band of the satellite image respectively.

2.7. Estimation of soil organic carbon

In the process of estimation of soil organic carbon firstly soil samples were collected by a proper field investigation which needs some precautionary measures. Keeping these measures in mind plot layout was prepared. Several precautions are taken to avoid any trampling, avoiding streams in the

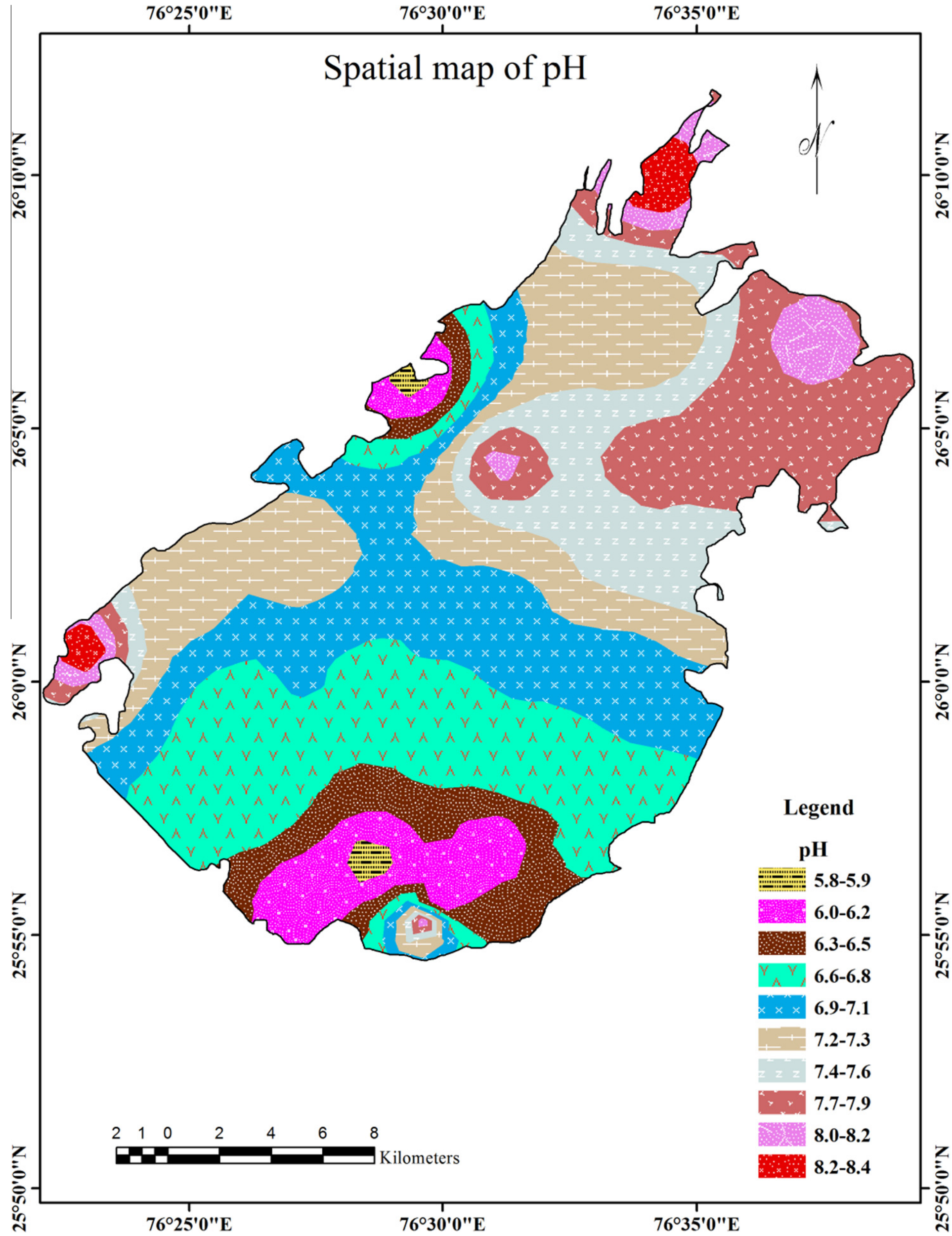

Figure 5 Spatial map of the pH of the soil in the study area.

sampling plots, etc. as listed previously. The procedure given by (Walkley and Black, 1934; Yeomans and Bremner, 1988) is then used in each soil sample for determining the organic soil carbon (Walkley, 1947). The 24 soil samples (from several locations of the Ranthambhore Tiger Reserve Forest) were collected with the sampler of radius 3.8 cm with the soil depth of 10 cm. The sampler volume was found to be 453.645 cm and the soil is collected having the bulk density of 0.75 g/m^3. The pH of soil is estimated using the laboratory methods and pH ranges from 5.8 to 8.4 in the soil samples of the study area (see Table 2).

For the laboratory analysis for finding the field measured value of soil organic carbon, 1 g soil was taken in a 500 ml. *Erlenmeyer* flask. It was then mixed with 10 ml of 1 N potassium dichromate solution followed by 20 ml of sulphuric acid and was mixed by gentle rotation for 1minute so that homogenous mixture is formed. The flask is then allowed to stand for 30 min. The solution was then diluted to 200 ml by deionised water. Again, 10 ml. phosphoric acid, 0.2 g ammonium fluoride, and 10 drops diphenylamine indicator were added to the solution for additional test. The solution was titrated with 0.5 N ferrous ammonium sulphate solution until the colour changes from dull green to turbid blue. The titrating solution was added drop by drop until the end point is reached when the colour shifts to a brilliant green. Similarly, the blank control sample was prepared in the same manner. One duplicate sample and one quality control sample were prepared with each set of samples analysed. The estimated percentage soil organic carbon was shown in Table 2. The formulae used for calculating the bare soil index is given as:

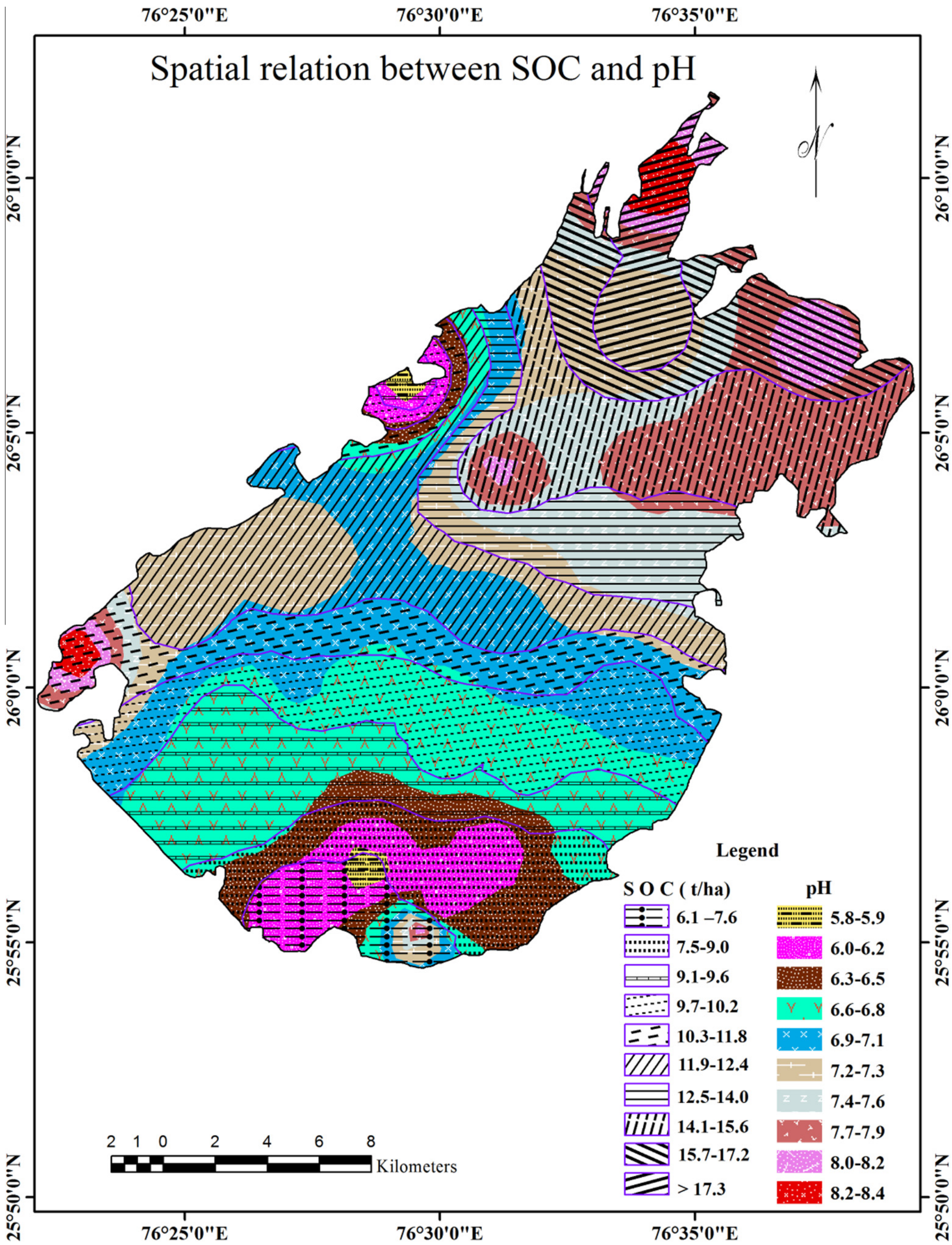

Figure 6 Spatial relationship between the pH and SOC of the soil in the study area.

$$\%\,\text{Estimated Soil organic carbon} = 10[1(S \div B)] * 0.67 \qquad (4)$$

where; S = Sample titration, and B = Blank titration.

3. Results and discussion

This section provides the soil estimation from the field as well as from the satellite images. Land Use Land Cover (LULC) result assesses the utilisation of the study area for different purposes. Whereas, NDVI map is used in conjunction with the band math equations to generate the digital SOC map. This SOC generated map provides digital values of the same spatial locations as that of the field collected sample places, are compared with each other using the regression analysis. The results of soil carbon measured from the field data and predicted from the satellite image provide a reliable outcome with the best fit with regression analysis.

3.1. Land use/land covers classification

LULC map provides the information about the current state of the landscape measuring current condition and how they are undergoing changes. This process quantifies the current land resources into various thematic categories like water, forest and paved land surfaces. In the present study LULC was prepared which was validated with the accurate GPS points taken during field visits, where half of them were used as training set while rest half ware used to validate the features in the

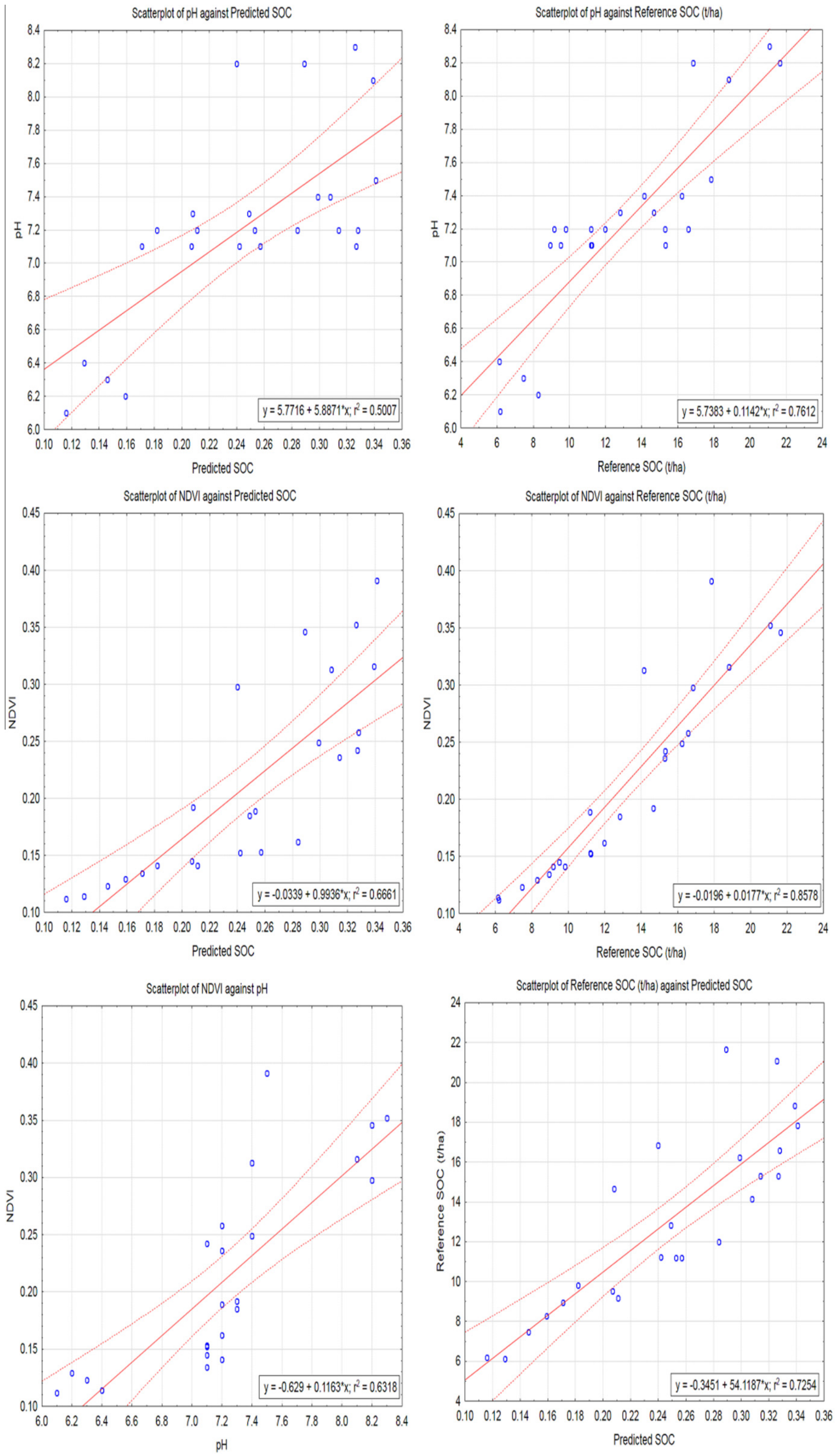

Figure 7 Regression analysis plots between different variables for reference SOC and predicted SOC (a) pH against Predicted SOC, (b) pH against reference SOC, (c) NDVI against Predicted SOC, (d) NDVI against reference SOC (e) between pH and NDVI (f) reference and predicted SOC.

field for accuracy. LULC map provides the information about the current state of the landscape measuring current condition and how they are undergoing changes (Pandey et al., 2012; Sharma et al., 2012; Kumar et al., 2010; Banerjee and Srivastava, 2013). This process quantifies the current land resources into various thematic categories like water, forest and paved land surfaces. The land use/land cover map of the present study classifies the land into the following classes as dense forest, degraded forest, moderate forest, water body, settlement, scrub land, and river/stream (Kumar et al., 2012). The land use/land cover map generated is shown in the Fig. 2.

3.2. Bare soil index and NDVI maps

NDVI map generated using the Red and NIR bands of the satellite image is shown in Fig. 3, that will be used in the band math equation to find the SOC. Similarly, BSI map of the study area is generated using Eq. (2). It has been assessed that when the BSI value is lower that means it has vegetation, if BSI value is higher that means there is more bare soil. Thus, the low BSI value is associated with soil covered with vegetation or water, etc. (high NDVI values or negative NDVI), whereas high BSI values mean it has more open and bare soil (low NDVI values but greater than zero). Thus, the low BSI value is associated with soil covered with vegetation or water, whereas high BSI values mean it has more open and bare soil.

3.3. Soil pH and soil organic carbon

pH of the soil contributes an important factor in the analysis of the Soil, Inorganic carbon (SIC), but its contribution towards organic carbon cannot be overruled. The pH of the soil samples was analyzed with the standard method of pH estimation. Spatial map of the pH is generated from the measured pH values from the collected samples in the study site (see Fig. 5). The spatial correlation map of pH and measured SOC (see Fig. 5) is produced, compared and analyzed for the results. Spatial variability map between pH and predicted SOC is prepared using the arcGIS to represent the dependence of SOC upon pH in the study area (see Fig. 6). Thereafter, Regression analysis is performed between the spatial variability maps of SOC (field measured values) with the spatial map of pH (See the Fig. 7(a)). The statistical regression between pH and predicted SOC (digital) is reported in the study, and it has an R^2 value of 0.50.

3.4. Soil organic carbon and regression analysis

Regression analysis is widely used for estimating the relationships among variables as well as for prediction. The statistical regression between estimated soil organic carbon and predicted soil organic carbon in the present study is used to determine the best correlation value given by the coefficient of determination R^2. Different models were compared to determine which one has better fit compared to the others. R^2 (coefficient of determination) has long been used to compare models. The regression analysis can be done by knowing the value of the coefficient of determination R^2. There are three types of models which are used to compare the best suited model fitting the concerned soil estimation viz., logarithm model ($y = a + b * \ln(x)$), power exponential model ($y = a * e^{bx}$) and linear model ($y = a + b * x$).

The relationship between the pH and SOC of the study area has been shown in the graph (see the Fig. 7(f)) that has a correlation of coefficient as 0.72. R^2 value has long been used to compare all these models and linear equation was found to give the best results. Total carbon is determined using band data and NDVI (refer to the Fig. 10 and Eq. (3)) generated using RED and NIR bands of the satellite data (refer to Table 3). Thereafter, this correlation, regression equation was used to calculate the SOC using the NDVI values. The use of NDVI to calculate the SOC using remote sensing images is given below:

$$\mathrm{SOC} = 0.163 + 0.019 * \mathrm{NDVI} \quad (5)$$

where, SOC = Soil organic carbon, and NDVI = Normalised Difference Vegetation Index. Thus, the relationship between predicted SOC and NDVI is established using remote sensing techniques using above Eq. (5). Therefore, the predicted SOC digital map helps in the assessment of the SOC for each pixel of the image, thus corresponding to the points of the field or study area.

The relationship between the NDVI and predicted SOC is estimated using Eq. (5), and the digital map of SOC was generated using the remote sensing data, and spatial data of the field investigations. The statistical correlation between predicted and reference SOC values gives the regression curve which helps in the determination of the coefficients of correlation (R^2). Hence, by using the linear model positive correlation between reference SOC values (field measured) and predicted SOC (estimated digital SOC values) was observed. The determination of the coefficient (r^2) between the predicted and reference soil carbon value of the study area is found to be 0.7254 (refer to the Fig. 7(f)). The residual plot between the reference and predicted SOC were plotted and the result shows that all samples were randomly distributed between both of them (refer to Fig. 8). SOC map was generated through band math equations in the remote sensing software. Different analysis were performed and relation between NDVI, pH, refrence SOC and predicted SOC were drawn (refer to Fig. 7(a)–(f)).

Table 3 Correlation between estimated and predicted SOC.

Plot no.	Soil weight (gm)	Predicted SOC	Reference SOC
1	360	0.116	6.18
2	320	0.129	6.13
3	342	0.146	7.46
4	348	0.159	8.28
5	347	0.171	8.94
6	362	0.182	9.81
7	322	0.207	9.51
8	330	0.257	11.20
9	306	0.253	11.19
10	315	0.211	9.16
11	300	0.242	11.24
12	344	0.284	11.98
13	325	0.249	12.82
14	356	0.208	14.67
15	345	0.308	14.14
16	349	0.314	15.30
17	351	0.327	15.31
18	349	0.299	16.23
19	342	0.328	16.58
20	352	0.341	17.84
21	312	0.24	16.85
22	326	0.339	18.82
23	356	0.289	21.65
24	321	0.326	21.08

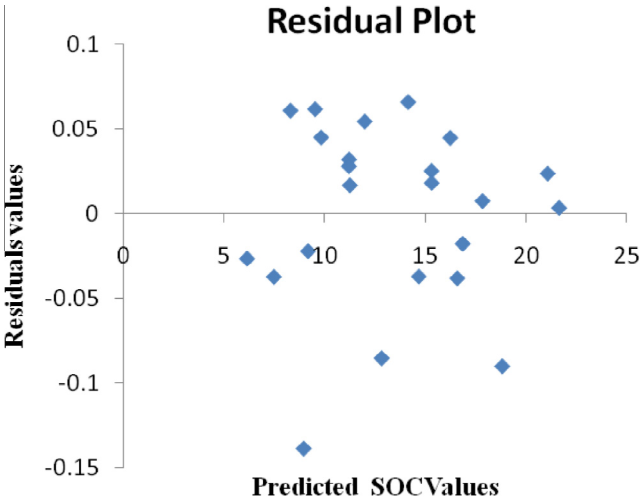

Figure 8 Residual plot based on the reference and predicted SOC, the difference between the two values.

Fig. 7(a)–(f) shows a graphical representation of the manner in which correlation merely studies the degree of relationship in order to predict the quantified change in one dependent variable as a result of change in other independent variables. Coefficient of determination equals the square of the Pearson correlation coefficient between the reference and predicted data values of the dependent variable. Scatter plot may be of any shape including straight line but must be drawn without bias as shown in the Fig. 7(a)–(f). Linear or straight line relationship was obtained by some transformation of predicted and reference SOC. In other plots the independent variables used are pH and NDVI. The residual plot represents the difference in values of predicted and reference SOC, which are scattered randomly along the x-axis (as shown in Fig. 8).

Fig. 9 represents the 3D surface plot of SOC against pH and NDVI. The colour variance shows the level of signification among SOC, pH and NDVI. When the Soil organic carbon concentration is increase in soil then pH and NDVI is also high. We have also provided a 3D graph to represent the relationship of predicted SOC in conjunction with two independent variables. This graph demonstrates how the predicted SOC varies with pH and NDVI values at different ranges.

Thus, the relationship between predicted SOC, pH and NDVI is plotted in 3D-graph demonstrating the SOC depends upon the pH and NDVI, establishing a dependant variable and independent variables (refer to Fig. 9). Thus, digital carbon maps (refer to the Fig. 10) are generated from the independent

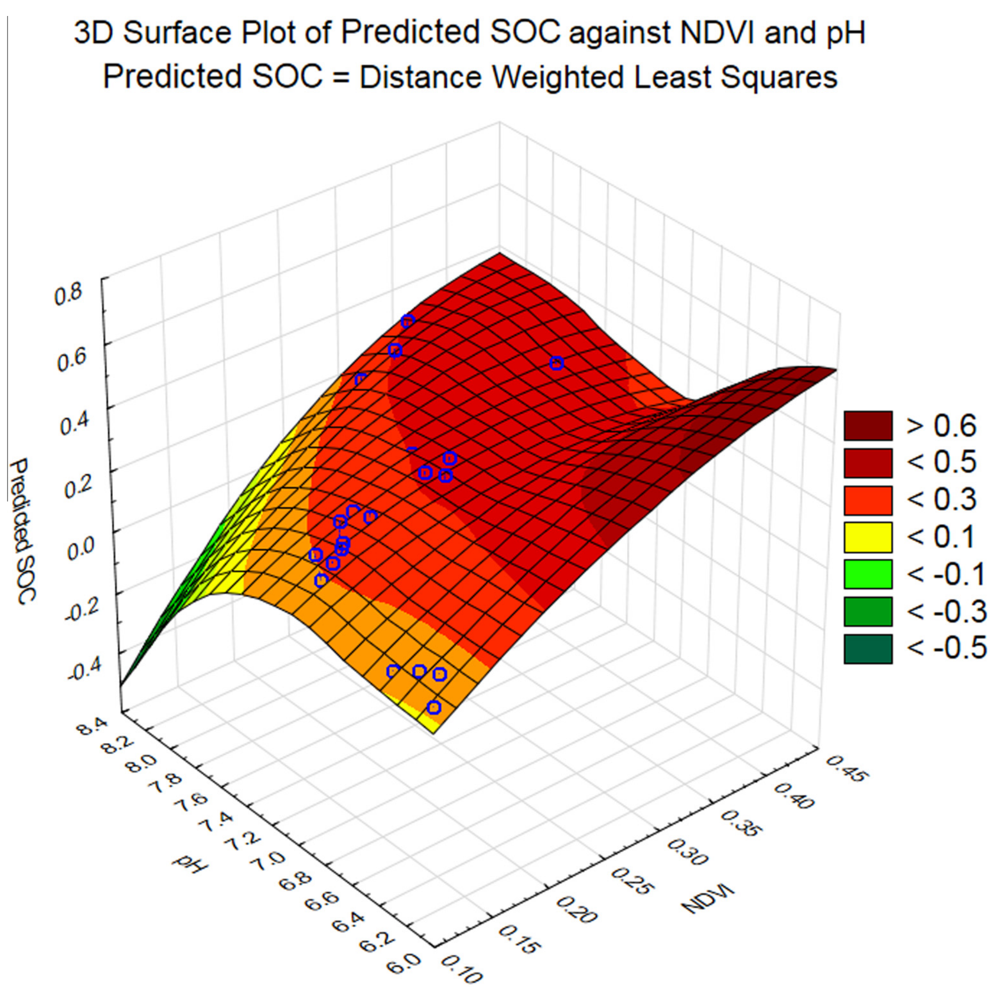

Figure 9 3D-graph between the predicted SOC, pH and NDVI calculated using the digital satellite imagery.

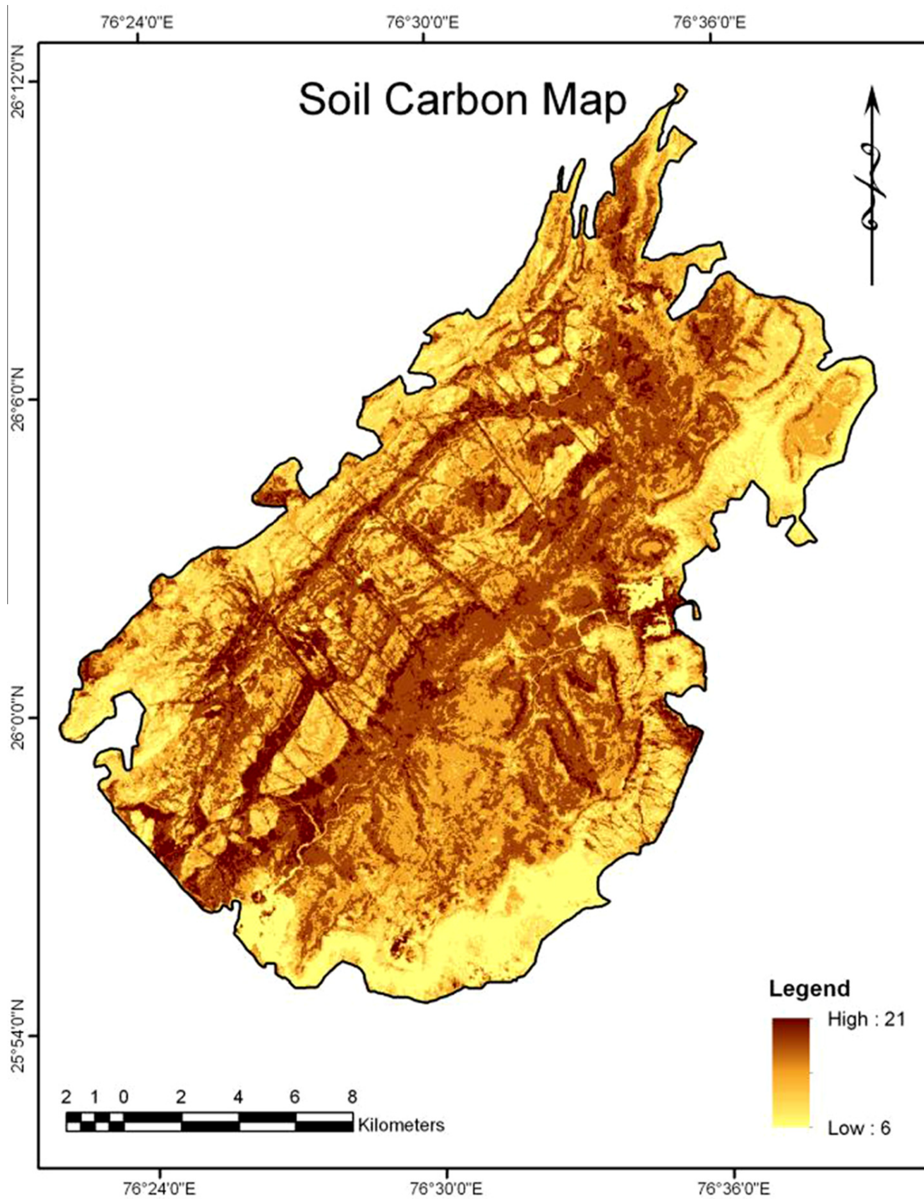

Figure 10 Digital soil carbon map of the study area.

variables using linear equations and compared with the reference SOC, as indicated by the R^2 value (refer to Fig. 7).

The outcomes of the present study can be used to predict the nitrogen content of the soil and above ground biomass of the forest ecosystem related to carbon sequestration (total carbon of the forest). This can be predominant in the forest ecosystem, will respond to the further investigation and analysis with all components, and help with management practices towards sustainable use of carbon and forest resources.

4. Conclusion

This study estimates the amount of soil organic carbon present in the study area using the geospatial methods with linear regression model as well as relationship between reference soil carbon against NDVI, pH of the soil. The relationship between different variable and soil Carbon can be described by a linear model. This helps in determining and predicting the soil condition of the region. R^2 (coefficient of determination) has long been used to compare models for forest parameters like tree volume, above ground biomass, leaf area index and heights.

The BSI map indicates the middle part of the study area is having the lowest BSI values, which confirm that soil is not bare, and it corresponds to the vegetated and the forest region. The outer part of the study area has highest BSI values, that corresponds to the non-vegetated region (refer to the Fig. 4). Similarly, the region of low BSI values corresponds to the low NDVI values of the study area (refer to the Fig. 3).

The linear model was found to be the best model on the basis of which the biomass and digital carbon maps are generated. Using statistical software the correlation between estimated and reference values was generated. Linear regression was the first type of regression analysis to be studied rigorously, and to be used extensively in practical applications. This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine. These collected data containing the information on location, soil type, texture, and measured/estimated bulk density help in estimating the soil organic carbon present in the soil of Ranthambhore national park for a depth of 5 cm. The reference SOC densities were combined with the remote sensing predicted SOC results and compared. The study exposes the approaching of LISS III image in evaluating the SOC for the heterogeneous tropical forest. The extraordinary positive correlation between the predicted SOC directly from field parameters and reference SOC from spectral band information demonstrates the fact that NDVI can be considered to be an effective spectral vegetation index to estimate SOC.

Finally, the digital SOC map estimated using the remote sensing image (IRS-LISS III) shows resemblance with reference SOC observations (field measured). Thus, there is potential for the use of remote sensing for predictions of soil organic carbon that matches the field observations. Thus, this proficiency will allow getting the digital soil maps in terms of carbon, and farther it will aid the execution of strategic management for soil conservations or utilising the ground conditions for farming in agricultural areas. Thus, it can be addressed that remote sensing in conjunction with GIS and field investigations are now providing the new tools for soil measurements in terms of carbon, moisture, etc. Prediction of SOC plays a very important role in the forest ecosystem, as it often changes and relies on the correlation between SOC and other soil parameters (either chemical or physical properties of soil which are considered to be stable over time and space).

Future studies need the incorporation of long term, multi-factor experimental design for other environmental variables (temporal and seasonal variability like autumn time SOC, Spring time SOC, etc.) and Shadow Index (SI), Salinity Index (SSI), EC to validate the robustness of the SOC estimation using remote sensing. These might prove useful and beneficial to test the relationship for generating more accurate and precise digital soil organic carbon map. The future studies will include the other soil parameters, like estimation of soil nitrogen and assessing nitrogen content through the remote sensing approaches, generating the digital nitrogen maps and comparing both the outcomes. This will be performed with the incorporation of field based results and generating the nitrogen maps including these soil parameters. This will enhance the advantage of measuring the other forest parameters like tree volume, above ground biomass, leaf area index and heights and comparing them with the remote sensing measurements.

Conflict of interest

The authors declare no conflict of interest.

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