RESEARCH PAPER

Spatial soil organic carbon (SOC) prediction by regression kriging using remote sensing data

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SOC; Hybrid interpolation; Regression kriging; Predictor variables

Abstract  The present study has illustrated the estimation of the soil organic carbon (SOC) distribution from point survey data (prepared after laboratory test) by a hybrid interpolation method, viz. regression kriging (RK) in a part of the Narmada river basin in the central India. In this study, eight selected predictor variables are used such as, brightness index (BI), greenness index (GI), wetness index (WI), normalized difference vegetation index (NDVI), vegetation temperature condition index (VTCI), digital elevation model (DEM), and slope and compound topographic index (CTI). The RK method has given satisfactory results as observed from the level of accuracy. Finally, the amount of SOC content in varied slope, soil and landuse categories has been analysed. Concentration of SOC has been observed to be more in low elevated areas in clay soil with mainly agricultural and vegetated lands.

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1. Introduction

Soil is considered to have the largest stock of organic carbon store in the world. It occupies approximately 75% of TC (Total Carbon) pool of terrestrial ecosystem. Soil stores 1500–1600 pg C where vegetation and atmosphere reserve 620 pg and 780 pg C (Jobbagy and Jackson, 2000; Chung et al., 2008; Greve et al., 2009; Luo et al., 2010; Elbasiouny et al., 2014). Soil organic carbon (SOC) is one of the most important components of soil quality and soil health (Gregorich et al., 1994) that has an important role in the agricultural productivity (Stevenson and Cole, 1999). Soil structure, water holding capacity, cation-exchange capacities Carbon/Nitrogen ratio (C/N) etc. are important determinants of soil fertility, which are controlled by SOC. It also plays an important role in the soil organic matter (SOM) humification
process (USDA-NRCS, 1995). It is difficult to assess SOC stock from the point location data. Location points of SOC are used to estimate the SOC stock by spatial interpolation techniques considering various factors affecting SOC. SOC distribution is influenced by number of factors such as soil type, climate, terrain, hydrology, landuse, geology etc. (Fang et al., 2012). Spatial representation of the SOC is considered very essential for regional planning and management, and remote sensing and GIS play vital roles in the preparation of spatial illustration (Piccini et al., 2014).

SOC is sampled from some finite location points which are distributed according to systematic or non-systematic patterns. Spatial distribution of soil mapping using location samples has been prepared by different geostatistics methods (Burgess and Webster, 1980; Oliver and Webster, 1991; Kanevski and Maignan, 2004; Duffera et al., 2007; Marchetti et al., 2012). Geostatistics has an ability of distinguishing the continuous nature of SOC and is able to detect random variations during modeling, which depends on the spatial correlation of soil properties within the landscape. Prediction using sample points is carried out by the spatial behaviour and spatial distribution of parameters to minimize the error (Webster and Oliver, 2001).

There is no particular method which predicts the SOC with best accuracy. Inverse Distance Weighting, Splines, etc. are the deterministic interpolation methods where results tend to oversimplify the reality as the spatial autocorrelation of the data is not considered (Robinson and Metternicht, 2006). Researchers usually prefer the geostatistical methods where spatial autocorrelation is considered to interpolate into a continuous surface from sample points (McBratney et al., 2003). Kriging interpolation method is a geostatistical method and it is very popular nowadays (Huang and Chen, 2007; Mishra et al., 2009). It has an important role in understanding the advantages and disadvantages of SOC distribution. Soil scientists have examined the accuracy of SOC prediction by comparing different methods such as linear regression, ordinary kriging, cokriging, regression kriging, inverse distance weighted, splines etc. (Muel and Van Meirvenne, 2003; Liu et al., 2006; Chai et al., 2008; Sunfleth and Duttmann, 2008). Kriging and its derivative methods are considered to be more accurate and stable for prediction of SOC (Hengl et al., 2007; Kerry and Oliver, 2007).

Majority of the studies on distribution of SOC are based on various methods, accuracy of the results, obtaining samples, etc. Some studies are also based on interpolation such as linear regression (Zhang et al., 2012), cokriging (Eldeiry and Garcia, 2010) and ordinary kriging (Minsasny and McBratney, 2007; Maynard et al., 2011). The regression kriging (RK) method is also easy to use and has better accuracy. As observed from different studies, selection of the suitable parameters and methods to derive the independent variables are limited.

SOC is spatially extremely variable in the complex terrain. The present study area has a diversified pattern of landuse/landcover. Mainly agriculture based economy is prominent that depends on the local agricultural production. Therefore, SOC is a valuable parameter of soil, which has a great impact on the agricultural productivity. The main objective is the assessment of SOC distribution with the RK method in a varied soil, slope and landuse/landcover type. Collection of samples, testing of the samples and selection of independent parameters are explained in the present research. Finally, the relationships are illustrated obtained from the variation of SOC due to different independent parameters.

2. Study area

A part of the Narmada River basin is taken as the study area, which is situated in the districts of Harda, Dewas, East Nimar (Khandwa) and West Nimar (Khargone) in Madhya Pradesh of the central India. The area is geographically located between 21°23′7.7″N and 22°55′08″N and 75°21′07″E and 77°21′17″E with a coverage of 20,558 km² (Fig. 1). Hot, dry summer season (April–June), monsoon rainy season (July–September) and cool, dry winter season characterized the area that indicates a subtropical type of climate. Mean annual rainfall is about 1370 mm which is spatially decreasing from east to west (Mondal et al., 2014b) and the temperature range varies from 40 °C in summer to 10 °C in winter. Main river is located in the middle part of the study area that is flowing from east to west. The higher elevated area is situated in the northern and southern boundaries. Range of elevation is from 108 m to 982 m.

3. Materials and methodology

3.1. Materials

Table 1 summarizes the input data for estimation of the SOC stock distribution in different landuse/landcover categories, soil types and elevation. To estimate the SOC stock of the study area, a detailed field survey is carried out and 210 soil samples are collected from the entire study area (Fig. 1). The sample points are collected on the basis of the purposive stratified random sampling method in which landuse, slope, soil types are mainly considered while collecting the samples from the field (sampling was carried out along the accessible roads). Then, these soil samples are tested in the laboratory to obtain SOC content.

3.2. Methodology

Predictand is a variable that may be inferred through knowledge of the behaviour of one or more predictor variables. It is a dependent variable. Predictor variables are the independent variables used in the regression analysis for the prediction of the target variable. The procedures followed in the estimation of SOC distribution is given in the flowchart in Fig. 2. Different predictor variables are extracted and are further used along with the sample points in the estimation of the SOC distribution. The RK method is applied for interpolation. The model is validated with the collected soil sample points. Finally, the SOC distribution of the study area has been mapped.

3.2.1. Predictand variable

The tasseled cap (brightness index, greenness index and wetness index) and NDVI expresses the biophysical characteristics of land surface. This method can be used in the change of forest, vegetation, agriculture related studies in national, regional, and global levels. Similarly, VTCI provides the information on vegetation and moisture status simultaneously and take crucial
role in drought monitoring studies. Three predictors (tasseled cap, NDVI, VTCI) are highly correlated with SOC distribution. On the other hand, topographic predictors such as elevation (DEM), slope and CTI are important for SOC distribution. Generally, DEM and slope have positive relation with SOC while CTI shows negative correlation.

3.2.1.1. Testing (SOC). Soil organic matter or SOM is considered as the seat of nitrogen in soil and its determination is an index of the nitrogen availability in the soil. Two methods are generally used in the determination of SOM, (a) titration method (Walkley and Black, 1934) and the (b) colorimetric method (Datta et al., 1962). Organic matter is oxidized with the chromic acid in both the methods. In case of titration, there is a back titration of the unconsumed potassium dichromate against the ferrous sulphate or ferrous ammonium sulphate (redox titration). The sample carbon is oxidized as:

$$2H_2Cr_2O_7 + 3C + 6H_2SO_4 = 3Cr_2(SO_4)_3 + 3CO_2 + 8H_2O$$  \(\text{(1)}\)

Therefore, \(2H_2Cr_2O_7\) or \(2K_2Cr_2O_7 \equiv 3C\) \(\text{(2)}\)

Or, 588 g of \(2K_2Cr_2O_7\) \(\equiv 36\) g of C \(\text{(3)}\)

Or, 12 litres of \(1NK_2Cr_2O_7\) \(\equiv 36\) g of C \(\text{(4)}\)

Or, 1 ml of \(1NK_2Cr_2O_7\) \(\equiv 0.003\) g of C \(\text{(5)}\)

---

![Study area](image)

**Figure 1** Study area.
In this study, the titration method has been used for obtaining carbon content of the soil.

3.2.2. Predictor variable

3.2.2.1. Tasseled cap indices. The tasseled cap transformation is given by Kauth and Thomas (1976) and is also known as the Kauth–Thomas transformation. It gives a measure of the brightness index, greenness index and wetness index of a pixel and uses a linear combination of six frequency bands of the Landsat. The brightness, greenness and wetness indices can be computed as:

\[ \text{tas.cap}_i = \left( \frac{\text{coeff}_1}{C^2_{\text{band}_1}} \right) + \left( \frac{\text{coeff}_2}{C^2_{\text{band}_2}} \right) + \left( \frac{\text{coeff}_3}{C^2_{\text{band}_3}} \right) + \left( \frac{\text{coeff}_4}{C^2_{\text{band}_4}} \right) + \left( \frac{\text{coeff}_5}{C^2_{\text{band}_5}} \right) + \left( \frac{\text{coeff}_7}{C^2_{\text{band}_7}} \right) \]

where, \( \text{tas.cap}_i \) stands for the computed tasseled cap index for the brightness, greenness or wetness on the basis of the coefficients used, bands represent the TOA (top of atmosphere) reflectance, and the coefficients are constants given by Huang et al. (2002). The band coefficients of Landsat are given in the Table 2.

The tasseled cap transformation is a mechanism to reduce the volume of band data with the minimum loss of information. It is frequently used in the monitoring of landuse/land cover change and also in the vegetation mapping (Franklin et al., 2002; Dymond et al., 2002). The tasseled cap indices have been derived in the following steps of converting DN to radiance and then radiance to reflectance in the Landsat TM images. The Digital Number (DN) of the Landsat TM images is converted to radiance at the beginning. And then it is converted into spectral reflectance enabling the identification of
the spectral properties of the pixels of the images. At the first stage, DN value has been converted into spectral radiance ($L_{TOA}$) after checking the gain value using the official NASA approved ranges of $L_{max}$ and $L_{min}$ with the following formula (Chander and Markham, 2003; Melesse, 2004).

$$L_{TOA} = \frac{L_{max} - L_{min}}{QCAL_{\text{max}} - QCAL_{\text{min}}} \times (DN - QCAL_{\text{min}}) + L_{min}$$

where, $L_{max}$ is the maximum radiance (in W/m$^2$sr-1μm$^{-1}$), $L_{min}$ is the minimum radiance (in W/m2sr-μm), QCAL max is the maximum DN value possible (255), and QCAL min is the minimum DN value possible (0 or 1).

Radiance value is then converted into reflectance using the following equation (Akumu et al., 2010).

$$\rho = \frac{L_{TOA} \pi d^2}{ESUN_c \cos \theta_z}$$

where, $\rho$ is the reflectance, $d$ is the earth sun distance (AU), ESUN$_c$ is the Band dependent exoatmospheric irradiance (W m$^{-2}$μm$^{-1}$) and $\theta_z$ is the solar zenith angle (degree)

$$d = 1.001672 \times \sin \left( \frac{2\pi (J - 93.5)}{356} \right)$$

where, $J = $ Julian day

Radiance is calculated from bands 3, 4 and band 6 of Landsat TM5 data. Reflectance and brightness temperature are calculated from the radiance of the sensor where the reflectance is calculated with respect to bands 3 and 4.

Finally, tasseled cap is computed using the equation 6 and with the coefficients illustrated in the Table 2.

3.2.2.2. Normalized difference vegetation index (NDVI). The NDVI gives the estimation of the health of vegetation and is a measure of monitoring changes in vegetation. The possible range of NDVI varies from $-1$ to $+1$ (NOAA Coastal Service Centre, 2007). The NDVI method is given as (Sinha et al., 2015)

$$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}}$$

where $\rho_{\text{NIR}}$ and $\rho_{\text{RED}}$ are the spectral reflectance of the band near-infrared and red, respectively in the LANDSAT TM5 satellite data (Yongnian et al., 2010). The NDVI derived from the Landsat TM data along with the terrain attributes are utilized in the prediction of the soil organic carbon and NDVI has been observed to have a good correlation of more than 0.5 with the SOC. Therefore, it is proved to be a good estimator (McKenzie and Ryan, 1999).

3.2.2.3. Vegetation temperature condition index (VTCI). To calculate VTCI, emissivity is first calculated from the NDVI and then LST is computed from the emissivity.

3.2.2.4. Emissivity. In case the NDVI $< 0.2$: Here, the pixel is considered as bare soil and the emissivity is obtained from the reflectivity values in the red region.

In case the NDVI $> 0.5$: Pixels having NDVI values higher than 0.5 have been considered as fully vegetated, and a constant value for the emissivity is taken which is 0.99.

In case $0.2 \leq \text{NDVI} \leq 0.5$: In this condition, pixel is composed with a mixture of bare soil and vegetation, and the emissivity is calculated by the following formula,

$$\varepsilon = \varepsilon_v P_v + \varepsilon_s (1 - P_v) + \Delta \varepsilon$$

$$P_v = \left[ \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right]^2$$

where, $\varepsilon_v$ represents the emissivity of the vegetation; $P_v$ signifies the proportion of the vegetation; $\varepsilon_s$ is the soil emissivity and $\Delta \varepsilon$ stands for emissivity difference, which remains negligible when affected by the geometrical distribution of the natural surfaces and internal reflections. Calculation of $\Delta \varepsilon$ can be done by the following equation.

$$\Delta \varepsilon = \frac{(1 - \varepsilon_v)(1 - P_v)}{F_v}$$

where, $F$ stands for the shape factor (Sobrino et al., 1990) whose mean value is 0.55 by assuming different geometrical distribution. The calculation for $\varepsilon$ at that particular range (0.2 $\leq$ NDVI $\leq$ 0.5), $m$ and $n$ is done using the following formula.

$$\varepsilon = m P_v + n$$

$$m = \varepsilon_v - \varepsilon_s - (1 - \varepsilon_v) F_v$$

$$n = \varepsilon_v + (1 - \varepsilon_s) F_v$$

3.2.2.5. Land surface temperature. Removal of atmospheric effects in the thermal region is the essential step needed to use the thermal band imagery for absolute temperature studies.

$$L_{\text{TOA}} = \tau \varepsilon L_T + L_u + \tau (1 - \varepsilon) L_d$$

where, $L_{\text{TOA}} =$ Space reaching or TOA radiance measured by the instruments $L_u =$ upwelling or atmospheric path radiance, $L_d =$ downwelling or sky radiance, $\varepsilon =$ emissivity, $\tau =$ atmospheric transmissivity, where, $T =$ the temperature in Kelvin; $L_d =$ spectral radiance in W/m$^2$sr-1μm$^{-1}$, and $k_1$ and $k_2$ are the calibration constants

$$T = \frac{K_2}{\ln \left( \frac{k_2}{k_1} + 1 \right)}$$
\[ L_T = \text{radiance} \text{ band} \ 6 \ (\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{µm}^{-1}), \quad T = \text{brightness temperature (Kelvin)}, \quad K_1 = \text{Constant} \ 1 \ (\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{µm}^{-1}), \quad K_2 = \text{constant} \ 2 \ (\text{Kelvin}). \]

The VTCI gives information about the moisture status and vegetation simultaneously and also plays a key role in the drought monitoring and assessment (Parida, 2006). The VTCI is a combination of land surface temperature (LST) and NDVI that furnishes information about both moisture status and vegetation (Wan et al., 2004). The VTCI is given as,

\[
\text{VTCI} = \frac{(\text{LST}_{NDVI_{\text{max}}} - \text{LST}_{NDVI_{\text{min}}})}{(\text{LST}_{NDVI_{\text{max}}} - \text{LST}_{NDVI_{\text{min}}})} \tag{19}
\]

where, \( \text{LST}_{NDVI_{\text{max}}} = a + b \cdot \text{NDVI} \) and \( \text{LST}_{NDVI_{\text{min}}} = d + b' \cdot \text{NDVI} \).

3.2.2.6. Digital elevation model (DEM). The digital topographic attributes and the hydrological parameters are considered to have been extensively used for the mapping of spatial distribution of the SOC concentration (Moore et al., 1993; Florinsky et al., 2002). There is a negative relationship between the DEM and slope with the SOC as reported by Zhong and Xu (2009).

3.2.2.7. Slope in percentage and compound topographic index (CTI). The slope is also negatively related to the SOC as mentioned in the previous paragraph. Slope map (%) is derived from the DEM. The CTI is an important topographic variable that shows the sediment and water movement in a landscape. It is a function of the slope and the area contributed by upstream per unit width orthogonal to the direction of the flow and is useful in the prediction of soil properties (Gessler et al., 1995). CTI is given as (Beven and Kirkby, 1979)

\[
\text{CTI} = \ln(A_s / \tan \beta) \tag{20}
\]

where \( A_s \) represents the specific contributing area in \( \text{m}^2 \) per unit width orthogonal to the direction of the flow and \( \beta \) denotes the angle of slope.

3.2.3. RK methodology

Location points of SOC samples are interpolated in spatial domain by the RK method. This method can consider the auxiliary variables at those location points for interpolation of the outputs, which is restricted in the simple kriging method (Hengl et al., 2007). Remote sensing images, geology, soil, landuse, elevation are considered as common auxiliary predictors (McKenzie and Ryan, 1999). Topographic parameters (DEM, slope, compound topographic index (CTI), seasonal mean NDVI, vegetation temperature condition index (VTCI) and tasseled cap indices (greenness index, brightness index and wetness index) have been used as the predictor variables here. RK combines the two approaches of regression and kriging where regression is applied to fit the explanatory variation and the simple kriging with an expected value of 0 is applied to fit the residuals, i.e. unexplained variation (Hengl et al., 2004; Mukherjee et al., 2015):

\[
\hat{z}(s_0) = \hat{m}(s_0) + \hat{\epsilon}(s_0) \tag{21}
\]

\[
= \sum_{k=0}^{p} \hat{\beta}_k q_k(s_0) + \sum_{i=1}^{n} \hat{\zeta}_i e(s_i) \tag{22}
\]

where, \( \hat{z}(s_0) \) denotes the interpolated value of the location, \( s_0 \), \( \hat{m}(s_0) \) gives the fitted drift, \( \hat{\epsilon}(s_0) \) denotes the interpolated residual, \( \hat{\beta}_k \) stands for the estimated drift model coefficients (\( \hat{\beta}_0 \) is the estimated intercept), \( \hat{\zeta}_i \) denotes the kriging weights that is determined by the spatial dependence structure of the residual and \( e(s_i) \) gives the residual at location \( s_i \).

3.2.4. Validation methods of the model

The RK model efficiency for SOC interpolation is estimated by the Root Mean Square Error (RMSE) and Mean error (ME). During calibration and validation, 70% and 30% of total SOC location data (210 samples) have been used in the model (RK).

RMSE shows the difference between the observed and the computed or predicted values and the difference is the residual.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{23}
\]

where, \( n \) is the number of validation points, \( y_i \) is the predicted value and the \( \hat{y}_i \) is the actual or observed value.

ME is taken as the mean of residuals and it calculates the deviation of the predicted value. The ME will be 0, if the predicted results are unbiased (Robinson and Metternicht, 2006). ME is given as,

\[
\text{ME} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i) \tag{24}
\]
where, \( n \) is the number of validation points, \( y_i \) is the predicted/observed value and the \( \hat{y}_i \) is the actual or observed value.

4. Results and discussion

4.1. Predictor variables

Brightness index is the weighted sum of all the six bands and gives the measurement of the overall reflectance (such as differentiating between the dark and light soils). The brightness index map of the study area is given in Fig. 3. The greenness index is a measure of the presence of green vegetation and its density. Wetness index gives a measurement of the vegetation density, soil moisture content and the other scene class characteristics (Crist and Cicone, 1984; Cohen et al., 1995). The greenness index and wetness index maps of the study area are given in Fig. 3. The NDVI map of the study area is illustrated in Fig. 4, indicating that the health of vegetation is best around the dam area in the eastern part of the region showing higher NDVI values. The surface emissivity map of the study area is shown in Fig. 4. The land surface temperature or LST of the study area is shown in the Fig. 4 indicating lower temperature in the southeastern part of the area where NDVI is also high. The generated VTCI map is illustrated in Fig. 4. The slope map of the study area is indicating higher slopes in the north, southwest and southeast edges in the higher elevated areas, while the lower slopes are observed in the plains or in areas with lower elevation (Fig. 5). The compound topographic index of the study area is shown in the Fig. 5. Descriptive statistics of all variables (predictand and predictor) are shown in the Table 3.

4.2. SOC prediction

The carbon stock is measured from the field collected samples given in Table 4. It can be observed that the stock decreases with the increasing slope. In the soil categories, clay has the highest content of carbon, followed by clay loam, sandy clay loam and sandy loam. More carbon is found with the greater amount of clay content. In the landuse types, vegetations have the highest content of carbon, followed by the agricultural and fallow lands. Settlement has the lowest carbon stock. The spatial distribution of the SOC stock is given in Fig. 6.

Figure 4   NDVI, surface emissivity, LST and VTCI.
The range of SOC stock varies from 0.28 to 31.95 g kg\(^{-1}\) in the entire area. Lowest carbon stock is observed mostly in the extreme southwest of the study area while very high stock of SOC is observed on both sides of the river and in the areas surrounding the Indira Sagar dam. Low areas in the east and the entire central part have higher SOC stock. The model performance is 0.23 and 0.28 m in RMSE, and 0.67 and 0.72 in ME in calibration and validation respectively.

Table 3  Descriptive statistics of all variables.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOC</td>
<td>0.28</td>
<td>31.95</td>
<td>11.51</td>
<td>5.96</td>
</tr>
<tr>
<td>BI</td>
<td>−0.63</td>
<td>0.75</td>
<td>0.30</td>
<td>0.06</td>
</tr>
<tr>
<td>GI</td>
<td>−0.41</td>
<td>0.27</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>WI</td>
<td>−0.33</td>
<td>0.14</td>
<td>−0.12</td>
<td>0.06</td>
</tr>
<tr>
<td>NDVI</td>
<td>−0.43</td>
<td>0.96</td>
<td>0.38</td>
<td>0.20</td>
</tr>
<tr>
<td>VTCI</td>
<td>0.00</td>
<td>1.00</td>
<td>0.53</td>
<td>0.11</td>
</tr>
<tr>
<td>DEM</td>
<td>108.00</td>
<td>982.00</td>
<td>328.66</td>
<td>113.71</td>
</tr>
<tr>
<td>Slope</td>
<td>0.00</td>
<td>176.51</td>
<td>5.59</td>
<td>6.55</td>
</tr>
<tr>
<td>CTI</td>
<td>5.07</td>
<td>21.25</td>
<td>12.08</td>
<td>1.53</td>
</tr>
</tbody>
</table>

Table 4  Measured carbon stock.

<table>
<thead>
<tr>
<th>Different categories</th>
<th>Area (km(^2))</th>
<th>Area (%)</th>
<th>Carbon stock (g kg(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (in degrees)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 2</td>
<td>9948.77</td>
<td>48.39</td>
<td>12.77</td>
</tr>
<tr>
<td>2 to 5</td>
<td>7414.87</td>
<td>36.06</td>
<td>12.02</td>
</tr>
<tr>
<td>6 to 10</td>
<td>2133.27</td>
<td>10.38</td>
<td>9.63</td>
</tr>
<tr>
<td>11 to 20</td>
<td>885.53</td>
<td>4.31</td>
<td>7.2</td>
</tr>
<tr>
<td>&gt; 20</td>
<td>178.43</td>
<td>0.87</td>
<td>5.77</td>
</tr>
<tr>
<td>Soil types</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clay</td>
<td>14952.58</td>
<td>72.72</td>
<td>12.68</td>
</tr>
<tr>
<td>Clay loam</td>
<td>2895.74</td>
<td>14.08</td>
<td>11.5</td>
</tr>
<tr>
<td>Sandy clay loam</td>
<td>827.78</td>
<td>4.03</td>
<td>9.39</td>
</tr>
<tr>
<td>Sandy loam</td>
<td>1884.75</td>
<td>9.17</td>
<td>8.5</td>
</tr>
<tr>
<td>Landuse</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>937.35</td>
<td>4.56</td>
<td>0</td>
</tr>
<tr>
<td>Settlement</td>
<td>2164.64</td>
<td>10.53</td>
<td>8.74</td>
</tr>
<tr>
<td>Vegetation</td>
<td>4695.65</td>
<td>22.84</td>
<td>15.6</td>
</tr>
<tr>
<td>Agriculture</td>
<td>8275.71</td>
<td>40.26</td>
<td>12.24</td>
</tr>
<tr>
<td>Fallow land</td>
<td>4484.66</td>
<td>21.81</td>
<td>9.65</td>
</tr>
</tbody>
</table>

Figure 6 Distribution of SOC across the study area.

4.3. Discussion

RK method has given satisfactory results in this study due to the selection of more number of predictors for this model. The RK method can perform better in respect to ordinary kriging (OK) due to additional capacity of more number of auxiliary information (Piccini et al., 2014). The higher degree of slope results in higher rates of erosion, which increases with the increasing rainfall. Therefore, the high slopes have a greater loss of SOC due to the less developed soil profile and comparatively thin soil layer leading to lowest content and maximum removal of SOC (Booikhagen et al., 2005). Less than 2° slopes has the lowest rate of erosion, while more than 20° slopes have the highest rate of erosion resulting in highest SOC loss. Hence, high erosion rate in steep slopes along with low carbon stock causes further depletion of SOC, whereas low areas have better retention of the SOC stock. The SOC content of the soil is dependent largely on the quality of organic restitution to the soil and soil management practices (Chan, 2008). SOC is positively correlated with the silt-plus-clay, negatively correlated with sand and insignificantly correlated with pH (McGrath and Zhang, 2003). The clay soils have more stock of SOC than the sandy soils. Clay soil is rich in
organic matter and has high SOC stock. This gradually decreases with clay loam, sandy clay loam and sandy loam. Therefore, areas with sandy soils experience lower stock of SOC. Land use types also influence the SOC stock. Forest area is shown under vegetation type of land. Forest area has shown more SOC concentration in this study, which is similar to the study of higher SOC stock as observed in Indian forests (Chhabra et al., 2003), while the amount of SOC is very limited in arid and semiarid region (Singh et al., 2007). Vegetation has the highest SOC stock followed by agriculture, fallow land and settlement. Lowest SOC stock in settlement is observed due to the existence of concrete cover over the soil. Vegetation has a higher stock of SOC due to healthy plants that give a regular supply of organic matter to the stock after decomposition. Fallow lands are open lands with little vegetation, so they have higher stock than settlements.

5. Conclusion

The spatial distribution of SOC stock across the study area is shown by RK interpolation technique. Distribution of soil organic carbon stock is highest in the vegetation area (mainly forest) followed by the agricultural lands. Lowest SOC is observed in settlements. SOC concentration is less in high slope areas and high in low slope areas. Clay type of soils store high amounts of SOC and sandy soil has lowest SOC stock. More vegetation, low degree of slope and clay soil will have high SOC content, while less vegetation, higher degree of slope and more sandy soil (or less clay soil) will lead to low content of SOC. To get a better result of SOC distribution, various types of spatial predictors are considered which have more control on the SOC intensity of soil. Complex methodology of remote sensing and GIS technology has been used to extract different predictors. The maps may not be more accurate in comparison to the traditional ones, but in addition it gives a quantitative estimation of the error. Besides, these are obtained at comparatively low costs, and can be considered as useful tool for the agri-environmental evaluation.

In the present study area, distribution scenario of SOC can help in crop selection for better management of agricultural production. This study has also explained in details the SOC distribution using RK method that can be applied in different study areas with other soil components. RK model has only been selected for the study where other models can be compared in future.

Conflict of interest

There is no conflict of interest.

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