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USE OF HYPERSPECTRAL REMOTE SENSING FOR QUANTITATIVE ESTIMATION OF SOIL ORGANIC CARBON

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ABSTRACT

Soil organic carbon (SOC) appears as a promising indicator to know the overall fertility status of soil. In the present investigation, a remote sensing based approach for estimation and mapping of soil organic carbon using hyperspectral remote sensing imagery was used. Soil samples (Mollisols) were collected from the agricultural farm of GBPUA&T, Pantnagar, Uttarakhand, India. VIS-NIR spectra were collected over the sampling points. Using hyperion sensor VIS NIR spectra was transformed into different spectral indices like Brightness Index (BI), Hue Index (HI), Saturation Index (SI), Coloration Index (CI), Redness index (RI) Normalized Difference Vegetative Index (NDVI) and Ratio Vegetation Index (RVI). Results indicated that soil organic carbon was significantly correlated with spectral indices *viz* blue (487.86nm), green (569.27nm), SWIR (2345.1nm) bands and brightness index. Multiple regression models were also developed to estimate soil organic carbon based on spectral indices. The comparison between observed and estimated SOC showed quite good agreement with R^2 of 0.83 in multivariate model-10 and RMSE of 0.15. Later, multivariate model was used to generate the layer of SOC representing spatial distribution. This showed the capability of hyperspectral remote sensing for estimation of SOC which can act as a base map to predict management practices in precision agriculture.

KEY WORDS
Hyperion
Hyperspectral remote sensing
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INTRODUCTION

During last decades there has been a rapid extension in technologies for agriculture advancement including Global Positioning System (GPS), Geographic Information Systems (GIS), remote sensing and crop simulation models (Garofalo *et al.,* 2009; Hbirkou *et al*., 2012 and Puranik *et al.,* 2014). Organic carbon (OC) plays a major role in keeping fertility of soil and thereby flourish the biological activity (Gebbers *et al.,* 2010 and Rajan 2011). Conventional techniques for identifying soil organic carbon (SOC) require very dense sampling and need more time for characterization of spatial variability within an area. However imaging spectroscopy technology in the visible (VIS) and near-infrared (NIR) region is a more efficient, faster and less expensive that provides data with high temporal and spatial resolution (Simbahan *et al.,* 2006, Stevens *et al.,* 2010). Hyper spectral images due to high number of spectral bands and improved spatial and radiometric resolution provides more information than traditional multispectral images. Several studies have used hyperspectral remote sensing imageries to estimate soil properties (Ray *et al.,* 2004; Gomez *et al*., 2008; and Nowkandeh *et al.* 2013). The present hyperspectral sensors can be used to map the characteristic of soil properties with great accuracy. Therefore in the present study, an attempt has been made for mapping of soil organic carbon using hyperspectral remote sensing in Mollisols of Uttarakhand.

MATERIALS AND METHODS

Study area

The study was carried at Agricultural farm GBPUA&T, Pantnagar, U.S. Nagar (Uttarakhand) which is located at 29°N latitude, 79.29°E longitude and with an altitude of 243.80m from the mean sea level in the *Tarai* belt, about 30 km southward of foot hills of the Shivalik range of Himalayas. Hyperion image covering whole University Farm including Nagla farm, Vegetable Research Centre, Crop Research Centre and Horticulture Research Centre etc has been shown in figure1. The study area falls under sub-humid to sub-tropical climate with hot dry summers and cool winters.

Data Acquisition

Remote sensing data acquisition

The Cloud free Hyperion imagery of May 2nd, 2013 was acquired from the United States Geological Survey (USGS) archive (http://earthexplorer.usgs.gov/). Hyperion, the first spaceborne Hyperspectral sensor was launched on 21st November 2000 as part of NASA's New Millennium Program. Hyperion has 242 spectral bands spanning a spectral range from 0.4 to 2.5 micro-meter, with a sampling interval of 10nm. The imagery was received as a full long scene (185-km strip) and at level

1 (L1GST) processing level in GeoTIFF format, written as band-interleaved-by-line (BIL) files stored in 16-bit signed integer radiance values. The L1GST product is radiometrically corrected, geometrically resampled, and registered to a geographic map projection with elevation correction applied.

Soil data

Soil samples were collected from 25 locations of university farm using hand held khurpi. To get good representation of site, four soil samples were collected from a field at 0-15cm depth. Thereafter, all four soil samples were properly mixed and half a kilo soil samples has been taken for further processing. The field work was undertaken during the month of May on a clear sunny day. The soil organic carbon content was determined by Walkley and Black (1934) method.

Pre-processing and atmospheric correction of hyperion image

The Hyperion EO-1 sensor records radiance of 242 spectral bands with band width of 10nm. In order to standardize L1GST hyperion image into ENVI format band, the original image was imported using Hyperion Tools 2.0 (White 2013) that contains wavelength, full width half maximum and bad band information.. Although Hyperion Tools 2.0 also flags bad bands, visual inspection revealed additional bands dominated by noise. In this study, 147 bands were used finally used which are: bands 9 – 55, 86 – 119, 133 – 164, 183 – 184, 188 – 200, and 202 – 220. The image was atmospherically corrected into the surface reflectance using QUAC (Quick atmospheric correction technique).

Computation of Spectral Indices

Various soil-related spectral indices were computed from Hyperion data, after converting the digital numbers into radiance values. Those indices included soil related indices such as, Brightness Index (BI), Hue Index (HI), Saturation Index (SI), Coloration Index (CI), Redness index (RI) Normalized Difference Vegetative Index (NDVI) and Ratio Vegetation Index (RVI). The statistical models for estimating these indices are presented in Table 1.

Where R = 681.19nm, G = 569.27nm, B = 487.87nm, NIR = 894.88nm.

Development of multivariate model

In the present study, stepwise multivariate statistical regression was carried out using SPSS package to model the relationship between spectral indices and soil organic carbon. The representative expression of multivariate model has been mentioned below:

$$Y = b0 + b1X1 + b2X2 + ... + bnXn$$

Where, Y = dependent variables, b0 = estimated constant, bn = estimate coefficients, Xn = independent variables

Spectral indices mentioned in Table 1 together with different individual's bands were used as independent variables, while SOC has taken as dependent variable.

Statistical analysis

Correlation coefficient

A relationship was established between observed and estimated SOC to analyze the accuracy of multivariate model.

$$R = \frac{\sum_{n}^{N} = 1(Rn - R')(Cn - C^1)}{\sqrt{\sum_{n}^{N} = 1(Rn - R^1)^2 * (Cn - C^1)^2}}$$

Where, r is the correlation coefficient, R is the selected variables (spectral band values and indices, N is the number of soil samples, here N is 25, Cn is soil organic carbon content of sample n and R' as well as C' are the mean values.

Root Mean Square Error (RMSE)

The RMSE has been used as a criterion for model evaluations and has been computed as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X\,mod\,el,i)^2}{n}}$$

where Xobs is observed values and Xmodel is modelled values

Estimation of soil organic carbon

Model was developed by analyzing the relationship between SOC and spectral indices derived using Hyperion hyperspectral reflectance image and was finally used for mapping the distribution of SOC. The complete approach of estimating spatial distribution of SOC has been presented in figure 2.

RESULTS AND DISCUSSION

Laboratory analysis results

Results of chemical analysis of 25 soil samples showed high spatial variability in SOC content among the different soil sampling sites. This may be due to natural or by human activity (Olorunlana, 2015). The soils of Pantnagar belong to Mollisols order according to U.S.D.A. Taxonomic System (Soil Servey Staff, 1978) and have six soil series *viz*. Patharchatta sandy loam, Nagla loam, Haldi loam, Phoolbagh clay loam, Khamia sandy loam and Beni silty clay loam (Deshpandey *et al*., 1971). The statistical summary (Table 2) of above soil samples of different locations showed the minimum, maximum, mean,

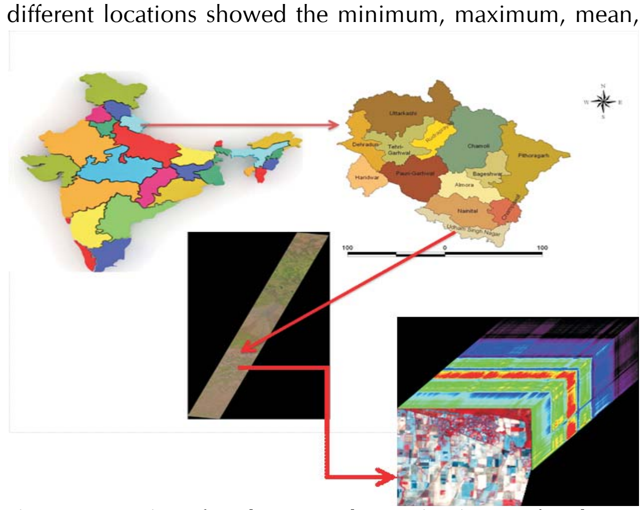

Figure 1: Location of study area and Hyperion image of 2nd May, 2013 showing agriculture farm of the GBPUA&T, Pantnagar

Table1: Spectral indices calculated using hyperion image for soil organic carbon study

Index	Formula Index	References
BI	$\{(B^2+G^2+R^2)/3\}^{1/2}$	(Mathieu and Pouget, 1998)
RI	$R_2/(B^*G_3)$	(Mathieu and Pouget, 1998)
SI	(R-B)/(R+B)	(Mathieu and Pouget, 1998)
CI	(R-G)/(R+G)	(Mathieu and Pouget, 1998)
HI	(2*R-G-B)/(G-B)	(Mathieu and Pouget, 1998)
RVI	NIR/R	(Jordan, 1969)
NDVI	(NIR-R)/(NIR+R)	(Rouse *et al.*, 1974)
CDI (Carbon difference index) was developed by taking the difference between band199 and band184		
Where, R, G, B and NIR are red, green, blue and near infrared bands respectively		

Table 2: Laboratory analysis of soil properties

Parameters	Minimum	Maximum	Mean	Median	Std. Dev.	C.V. (%)
SOC (%)	0.37	1.77	.79	.63	0.37	47

Table 3: Correlation study of spectral parameters derived from Hyperion image and SOC

S. No.	Spectral Parameters	Coorelation with SOC
1	Blue (487.86nm)	-0.375
2	Green (569.27nm)	-0.346
3	Red (681.19nm)	-0.287
4	Band 97 (1114.2nm)	-0.08
5	Band 114 (1578.3nm)	-0.382
6	Band 201(2163.4nm)	-0.382
7	Band215 (2304.7nm)	-0.384
8	Band 219 (2345.1nm)	-0.503
9	RVI	-0.1
10	NDVI	-0.033
11	CDI	0.05
12	HI	0.037
13	BI	-0.420
14	CI	0.045
15	RI	-0.043
16	SI	-0.041

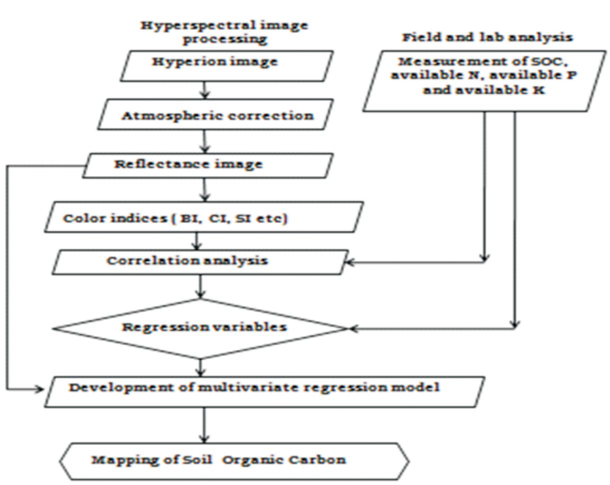

Figure 2: A flow chart summarizing the analytical and technical stages

median, standard deviation and coefficient of variation (CV). SOC content of samples ranged between 0.37% to 1.77% with mean value of 0.98%. Variability of soil was analyzed by estimating coefficient of variation (CV) and it was found 47 % with the standard deviation (Std. Dev.) of 0.37.

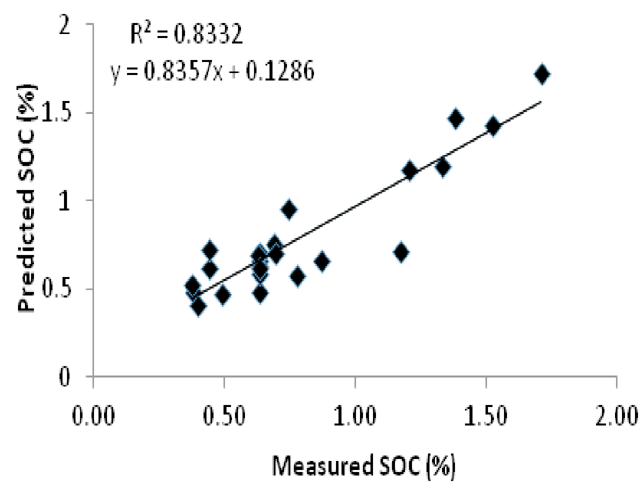

Figure 3: A scatter plot presenting the correlation against predicted SOC and measured SOC (n=25)

Pearson correlation and Multiple regression test results

The statistical analysis was performed using SPSS package between soil organic carbon and different spectral indices (Table 3). As SOC increases, the soil appears darker and consequently, the reflectance from soil surface will decrease and hence in general there is a negative correlation between SOC and reflectance of Hyperion bands. Furthermore, as wavelength increases from visible to Short wave infrared (SWIR) the correlation shows an ascending (-0.08 in band 97) and then a descending (-0.38 in band 114, -0.38 in band 215, -0.50 in band 219) pattern. Similar findings were reported by Ladoni, *et al*. (2010) and Nowkandeh *et al.* (2013). The highly significant correlations with blue band (-0.37), green bands (-0.35), brightness index (-0.42) and SWIR in SOC showed conformity with study conducted by Chen *et al.* (2000) and Ray *et al*. (2004).

Multivariate statistical regression models for organic carbon SOC

The multivariate models were developed between SOC and spectral parameters using stepwise regression technique. Ten models were developed for SOC and providing R2 value from 0.25 for model-1 to 0.83 for model-10. The reasonably good multiple regression model were noticed from model-6 (R2=0.65) to model-10 (R^2=0.83). Model-1 (R^2=0.25),

Table 4: Empirical equations between organic carbon and spectral parameters derived using stepwise regression technique

S. No.	Model	R^2
1	O.C. (%) = 1.18-1.46* Band 219	0.25
2	O.C. (%) = 1.79-1.695*Band219-1.593*Band97	0.31
3	O.C. (%) = 2.03-2.35*Band219-3.53*Band97+2.32*Band33	0.35
4	OC (%) = 2.302-2.17*Band219-3.48*Band97-3.82*Band33-3.10*BI	0.39
5	O.C. (%) = 3.36-1.34*Band219-3.34*Band97+2.94*Band33-9.15*BI+61.59*RI	0.53
6	O.C. (%) = 4.53-1.34*Band219-6.11*Band97+2.72*Band33-12.66*BI+119.26*RI+0.27*RVI	0.65
7	O.C. (%) = 4.65-2.06*Band219-5.68*Band97+1.64*Band33-15.73*BI+141.54*RI+0.39*RVI+2.14*Band215	0.71
8	O.C. (%) = 4.69-1.69*Band219-4.78*Band97+1.64*Band33-17.32*BI+150.82*RI+0.32*RVI+2.07*Band215+0.13*CDI	0.73
9	O.C. (%) =5.0-1.52*Band219-5.22*Band97+2.15*Band33-17.63*BI+150.43*RI+0.27*RVI+1.64*Band215+0.18*CDI+.001*HI	0.77
10	O.C. (%) = 4.55-1.36*Band219-2.20*Band97+0.29*Band33-20.07*BI+162.46*RI+0.68*RVI+1.86*Band215+0.24*CDI+.002*HI-2.35*NDVI	0.83

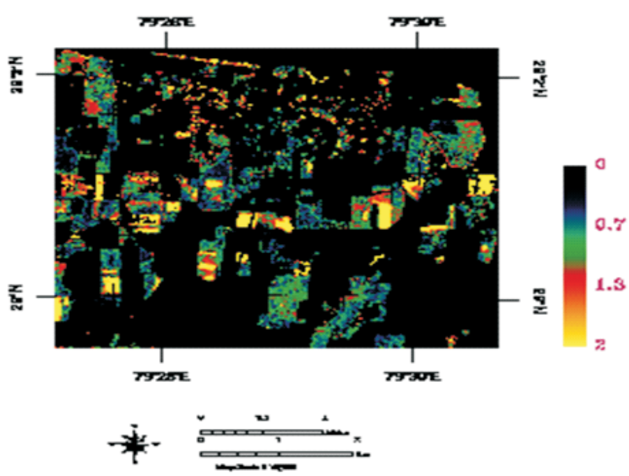

Figure 4: Spatial distribution of SOC

model-2 (R2=0.31), model-3 (R^2=0.35) model-4 (R^2= 0.39) and model-5 (R^2= .53) did not exhibit significant results. The most appropriate multivariate model for SOC estimation was model-10 having coefficient of determination (R^2) as 0.83 and RMSE has been observed as .15. Srivastava, *et al.*, 2004; Kadupitiya *et al.*, 2010; Sahoo, et al., 2012; Ghosh *et al.*, 2012 obtained good calibration for SOC based on spectral reflectance.

A scatter plot exhibiting one to one relationship between observed and predicted SOC (from model-10) values has been shown figure 3. Results showed a good agreement between the predicted values and the measured values. Ray *et al.*, 2004 and Luo *et al.*, 2008 calculated several soil color indices namely brightness index, coloration index, hue index, redness index and saturation index using Hyperion Hyperspectral data for statistical modeling of SOC. An overall accuracy of 83% was achieved showing the significance of the technique.

Variability map generation

Based on the statistical analysis, multivariate model was used to map the spatial distribution of SOC. SOC variability map was generated using hyperion hyperspectral image with the help of the model-10 having R^2 value of 0.83. The band math function embedded in ENVI 4.8 software has been used to generate SOC layer (Fig.4). The values of SOC content vary from 0.37 to 1.77% (Table 2) over the agriculture farm region of Pantnagar. Most of the regions come under the range of high organic carbon content (*i.e.* 0.7-1.3%, Deshpande *et al.*, 1971). The spatial distribution of SOC can be used for site specific soil management. In the past also (Zheng, 2008, Wang *et al.*, 2010) remote sensing techniques have been used to generate soil fertility map, which also exhibited similar kind of SOC distribution. In order to achieve higher accuracy it would be appropriate to collect soil samples at the time of satellite pass. Further, research is recommended for different locations, climate, vegetation soil types and surface conditions.

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