Use of multispectral remote sensing data for site-specific soil fertility management

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ABSTRACT : This present study was conducted at agricultural farm of Govind Ballabh Pant University of Agriculture and Technology, Pantnagar, Uttarakhand. Thirty soil samples were collected from the different locations with the help of Global Positioning System (GPS). The samples were analyzed for soil organic carbon and available nitrogen. Various soil-related indices were calculated from LANDSAT-8 OLI/TIRS multispectral data, which included Saturation Index (SI), Hue Index (HI), Coloration Index (CI), Normalized Difference Vegetative Index (NDVI) and Ratio Vegetation Index (RVI). Variability of soil and spectral parameters were analyzed by estimating coefficient of variation (CV). The correlation analysis was carried out to study the relationship between soil and spectral parameters. Multiple regression models were generated, using stepwise regression technique, to estimate soil properties from LANDSAT-8 OLI/TIRS multispectral data. The results showed that, among soil parameters the variability was highest for organic carbon (CV=40.56%), followed by available N (CV=20.37%). Among the spectral parameters the CV was highest for CI (152.17%), followed NDVI (27.76%), SI (22.05%), HI (12.63%) and RVI (3.41%). The multiple regression equation between OC and spectral indices was significant with $R^2 = 0.65$. Available N though individually had significant correlation with spectral parameters but did not form a significant multiple regression equation. These empirical equations were used to generate soil fertility variability plans.

Key words: Available N, multiple linear regression model, organic carbon, remote sensing, precision farming, soil fertility mapping

Remote sensing has become an invaluable tool in agriculture research because of its ability to non-destructively analyze soil properties and characterize the heterogeneity of the soil. Remotely sensed estimations of soil surface properties can lead to improved representation of spatial heterogeneity (Garey *et al.*, 2004). Soil chemical properties are neither static nor homogeneous in space and time. Acquiring spatial soil variability analytically in the laboratory is time- and cost-intensive, which is especially true for large-scale applications with a necessarily high number of soil samples (Viscarra-Rossel and McBratney, 1998; Plant, 2001). Its high cost has hindered the introduction of precision agriculture in several parts of the world (Demattê, 2001). Precision farming needs the identification of even short- or medium-term changes in the nutrient status of the soils. Soil fertility variability management is one of the important areas in which Precision farming has been commercially applied. In this respect, remote sensing has been shown to be a valuable source of information in soil fertility variability management, especially after the establishment of precision agriculture. Hence, soil fertility variability map is one of the major inputs required for precision farming.

The study was carried in the farm of Govind Ballabh Pant University of Agriculture and Technology, Pantnagar, U.S. Nagar (Uttarakhand). Pantnagar is situated in the *Tarai* belt, about 30 km southward of foot hills of the Shivalik range of Himalayas at 29°N latitude, 79.29°E longitude and at an altitude of 243.80 m above the mean sea level. The study was carried out during April when the most of the fields in the farm were fallow. LANDSAT-8 OLI/TIRS multi-spectral data of 23rd April 2014 shows the layout of the farm fields (Fig. 1).

MATERIALS AND METHODS

Soil Parameters

Thirty soil samples (surface soil) were collected from the fallow fields of different locations of Pantnagar Farm during the month of April 2014. The locations of the soil samples were identified using a Global Positioning System (GPS). The samples were analyzed for soil organic matter (%) and available nitrogen (kg/ha). The methodology for determining soil chemical (fertility) parameters is given in Table.1

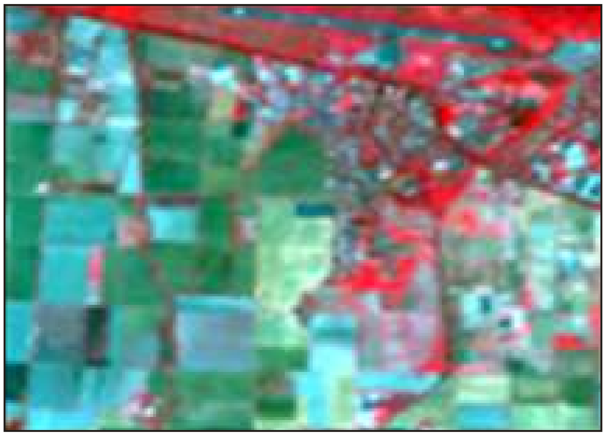

Fig. 1: LANDSAT-8 OLI/TIRS image of 23rd April, 2014 showing the Pantnagar farm

Satellite data

Cloud free LANDSAT-8 OLI/TIRS multispectral data of 23 April 2014 having path 145 and row 40 (Containing Pantnagar and adjoining region) was acquired and during the period when most of the fields were fallow. LANDSAT-8 OLI/TIRS image was used to look at bare soil reflectance. Bare soil was targeted to prevent any vegetation from interfering with the results. The general description of LANDSAT-8 OLI/TIRS image is shown in the Table 2.

Computation of Spectral Indices

Various spectral indices were calculated from LANDSAT-8 OLI/TIRS multispectral data, after converting the digital numbers into radiance values. Five indices were calculated from the following formula:

Index	**Formula**	**Reference**
Saturation Index (SI)	$SI=\frac{R - B}{R + B}$	Mathieu and Pouget,1998
Hue Index (HI)	$HI=\frac{(2 * R - G - B)}{(G - B)}$	Mathieu and Pouget,1998
Coloration Index (CI)	$CI=\frac{(R- G)}{R + G)}$	Mathieu and Pouget,1998
Normalized Difference Vegetative Index (NDVI)	$RVI=\frac{(NIR)}{R}$	Jordan,1969
Ratio Vegetation Index (RVI)	$NDVI=\frac{(NIR - R)}{(NIR + R)}$	Rouse *et al.*,1974

Table 1: Methodology for determining soil chemical parameters

Parameter	**Method**	**Reference**
Organic Matter	Chromic acid titration	Walkley and Black (1934)
Available N	Alkaline Permanganate Extractable Method	Subbiah and Asija (1956)

Table 2: Description of LANDSAT-8 OLI/TIRS spectral bands

Bands	**Description**	**Wavelength (µm)**	**Resolution (m)**
1	Coastal aerosol	0.43-0.45	30
2	Blue	0.45-0.51	30
3	Green	0.53-0.59	30
4	Red	0.64-0.67	30
5	Near-infrared (NIR)	0.85-0.88	30
6	Short-wave infrared (SWIR 1)	1.57-1.65	30
7	Short-wave infrared (SWIR 2)	2.11-2.29	30
8	Panchromatic	0.50-0.68	15
9	Cirrus	1.36-1.38	30
10	Thermal infrared (TIRS) 1	10.60-11.19	30
11	Thermal infrared (TIRS) 2	11.50-12.51	30

Where, R, G, B and NIR are red, green, blue and near infrared bands respectively of LANDSAT-8 OLI/TIRS multispectral image.

Correlation analysis

A correlation analysis was performed by computing the correlation coefficient between soil organic matter/available nitrogen data and selected variables (spectral bands & indices values), the formulation is:

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

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 30, Cn is soil organic carbon/available nitrogen content of sample n and as well as are the mean values.

Multivariate statistical regression

Multiple regression models were generated, using stepwise regression technique between soil spectral parameters the help of SPSS software. The empirical models were generated only for those parameters, where correlation was significant. These empirical equations were used to generate soil fertility variability maps from LANDSAT-8 OLI/TIRS data. To summarize the above technical steps, a flow chart is provided (Fig. 2) that describes in detail the procedures.

RESULTS AND DISCUSSION

The Variability Analysis

The mean, standard deviation and coefficient of variation of the soil and spectral parameters for 30 locations are presented in Table 3. The variability analysis, as reflected by the coefficient of variation, showed that, among soil parameters the variability was

Table 3: Variability of field and spectral parameters for the soil

Parameter	Mean	Std. Dev.	C.V. (%)
O.C. (%)	0.78	0.32	40.56
Available N (kg/ha)	103.29	21.04	20.37
B	84.2	3.39	4.03
G	74.83	4.93	6.59
R	67.87	4.60	6.79
NIR	60.00	4.47	7.45
NDVI	-0.06	0.02	-27.76
RVI	0.88	0.03	3.41
HI	2.34	0.30	12.63
CI	-0.07	0.10	-152.17
SI	-0.11	0.02	-22.05

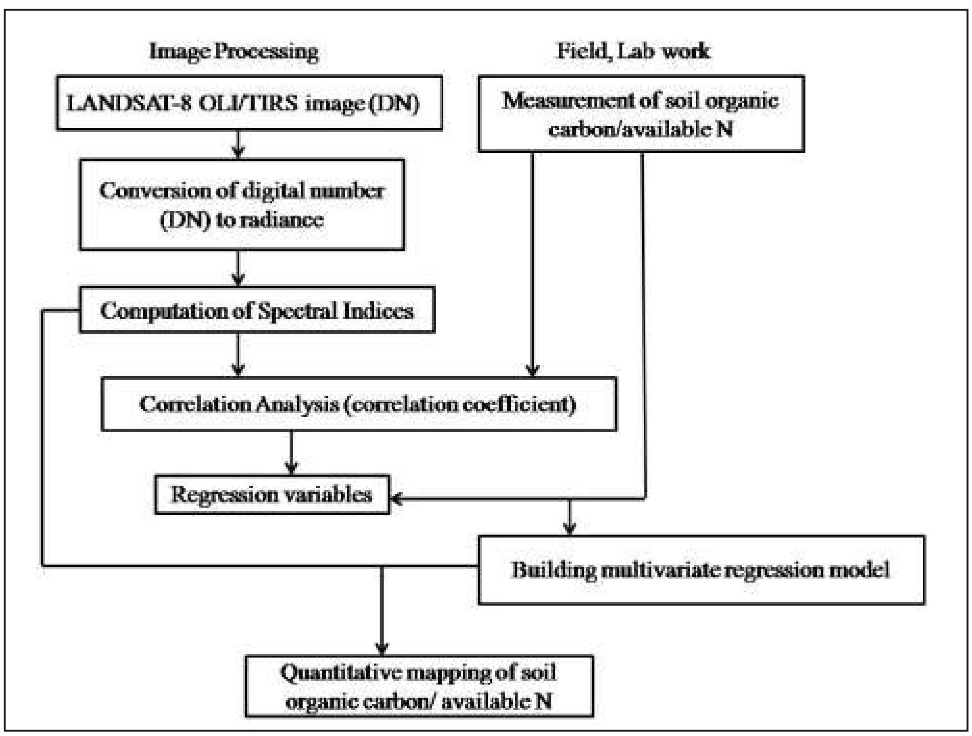

Fig. 2: Flow chart that summarizes the analytical and technical stages of soil fertility mapping

Table 4: Correlation study of spectral parameters derived from LANDSAT-8 OLI/TIRS data and soil parameters

S.No.	Spectral Parameters	Organic Carbon (%)	Available N (kg/ha)
1	B	0.077	-0.104
2	G	-0.134	-0.279
3	R	-0.370*	-0.407*
4	NIR	-0.529**	-0.487*
5	RVI	-0.444*	-0.262
6	NDVI	-0.27	-0.006
7	HI	0.329*	0.242
8	CI	0.42*	-0.437*
9	SI	-0.588**	-0.479*

highest for organic carbon (CV=40.56%), followed by available N (CV=20.37%). Among the spectral parameters the CV was highest for CI (152.17%), followed by NDVI (27.76%), SI (22.05%), HI (12.63%) and RVI (3.41%).

Analysis of Interrelationship of Variability

The soil organic carbon (OC) and available N were significantly correlated with spectral indices (Table 4). The number of data points was 30 for organic carbon (OC) available N content. For soil organic carbon (OC) highly significant correlations were found with the radiance of NIR (Near infrared) and SI (Saturation Index). The R (red) and RVI and HI also produced significant correlations. B, G, NDVI and CI did not have significant correlation with organic carbon (OC). Most of these correlations, except for B, HI and CI were negative for organic carbon. R, NIR, CI and SI had significant negative correlations with available nitrogen. All the bands and indices except HI had negative correlation with available nitrogen. The significant correlation was not observed with B, G, RVI, NDVI and HI.

Multivariate statistical regression models for organic carbon and available N

The multiple regression equations were generated between organic carbon and spectral parameters using stepwise regression technique. Empirical models were generated only for those parameters for which the correlations were significant (Table 5). However, Available N, though individually had significant correlation with spectral parameters, did not form a significant multiple regression equation.

Variability mapping

The soil fertility parameter variability maps were generated for organic carbon (OC) and available N using above mentioned regression equation with the help of ENVI-4.7. The continuous map of organic carbon and available N is presented in Fig. 3. The classes for organic

Table 5: Empirical equations between organic carbon and spectral parameters derived using stepwise regression technique.

S. No.	Model	R^2
1	O.C. (%) = 41.872-20.14*SI-52.103*RVI-0.417*HI+0.738*NIR-0.598*CI	0.65
2	Available N (kg/ha) = 85.1361 + 1.6340*R - 2.3025*NIR + 458.6093*CI - 613.3848*SI	0.27

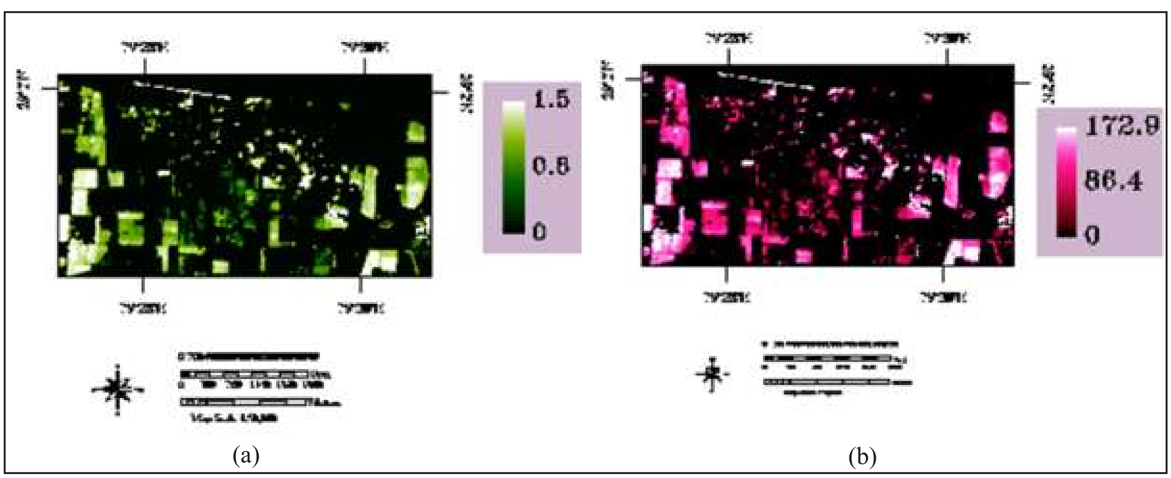

Fig. 3: Continuous map generated from LANDSAT-8 data a) Organic carbon content b) Available N

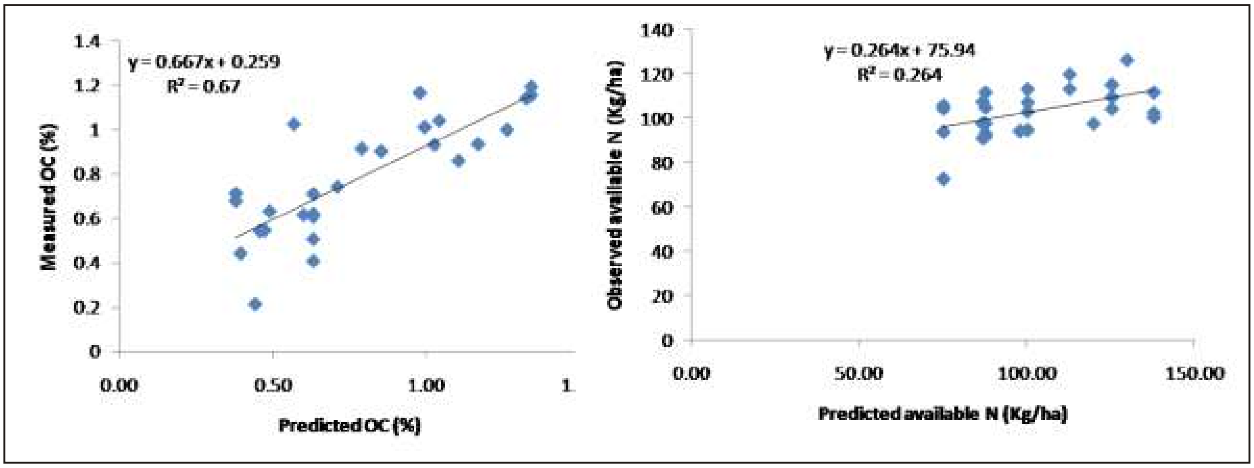

Fig. 4: A scatter plot presenting the correlation against predicted and measured a) Organic carbon b) Available N

carbon had average values from 0.8 % to 1.5%. Similarly the available N had average values of 86.4 and 172.9 Kg/ha over the Pantnagar farm.

The accuracy of quantitative mapping was evaluated by calculating the R^2 value of a linear regression relating the measured soil organic matter and available N (thirty samples) with the predicted ones. The relationship between measured and predicted values was plotted in Fig. 4. The result revealed a good relationship between the measured soil organic matter content and the predicted ones with the R^2 of 0.67 and a non-significant relationship between the measured available N and the predicted ones with the R^2 of 0.264.

CONCLUSION

The results of the study conveys that we can predict the soil organic matter concentration at 67% confidence while ±33% error and available N at only 26.4% confidence. The accuracy estimation illustrated that the quantitative map of soil organic matter content was reliable The remote sensing model of available N prediction had a relatively low coefficient of determination (R^2 = 0.27). This means that available N prediction by LANDSAT-8 OLI/TIRS based model had low reliability and the model did not estimate available N with reasonable accuracy at unobserved sites in study area.

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