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Research Article

Soil Discrimination and Parameter Estimation using Hyperspectral Data and Multivariate Analysis Techniques

S.S. RAY[1]*, J.P. SINGH[2] AND J.S. PARIHAR[1]

[1]*Space Applications Centre, ISRO, Ahmedabad-380 015, Gujarat*
[2]*Central Potato Research Station, Jalandhar-144 003, Punjab*

ABSTRACT

Soil discrimination and estimation of soil parameters are essential for site specific management. Estimation of soil parameters using conventional techniques is cumbersome and time-consuming. This study has been carried out to understand the utilization potential of spectral data for soil discrimination and parameter estimation. Two visible similar soil types (sandy loam and loamy sand) were selected for the study. Spectral data were collected using ASD ground spectroradiometer. Large number of spectral indices were computed using both narrow band and simulated broad-band spectral data. Stepwise discriminant analysis was carried out to find out the optimum indices for soil discrimination. Results showed that saturation index was best to separate sandy loam and loamy sand soils. The regression equations developed between soil parameters and spectral indices were highly significant for organic carbon (R^2 =0.78), available K (R^2 = 0.81), sand (R^2=0.82), silt (R^2=0.78) and clay (R^2=0.64) content.

Key words: Organic carbon, soil texture, available N, hyperspectral data

Introduction

Soils exhibit continuous variation in space and time as a result of natural and anthropogenic factors. Monitoring small changes in soil property is difficult because of the high spatial variability. Spectroscopy has been used for a long time to differentiate highly divergent soil types. However, the challenge for imaging spectrometry is to discriminate among soils having similar chemical and physical properties (Palacios-Orueta and Ustin, 1996). Soil reflectance spectra in the VIS-NIR-SWIR (400-2500 nm) region are known to be rather complex and often do not permit utilization of simple spectral analysis routines (Ben-Dor, 2002). One important task in utilization of spectral data for soil studies is to estimate soil properties using high spectral resolution data (Baumgardner *et al*., 1985). In the quantitative soil spectroscopy, the most common technique used is called Near-Infrared-Reflectance-Analysis (NIRA) where empirical relationships are developed using absorption features and chemical component of soil (Ben-Dor and Banin, 1995).

Several soil properties, namely, surface condition, particle size, organic matter, soil colour, moisture content, iron and iron oxide content and mineralogy have been found to affect their spectral behaviour (Dwivedi, 2001). According to Ben-Dor (2002) the three major chemical chromophores (materials in soil system that absorb incident radiation in discreet energy levels) in soil can be roughly categorized as: minerals (mostly clay and iron oxides), organic matter (living and decomposing), and water.

*Corresponding author,
Email: shibendu.ray@gmail.com
Current address: Mahalanobis National Crop Forecast Centre, New Delhi- 110012

Organic matter is the dominant factor in determining soil spectral behaviour when it is present in quantities more than 2 per cent (Baumgardner *et al*., 1970). Sudduth and Hummel (1993) have been able to estimate organic matter in the using reflectance spectroscopy. In general, the increase in contents of organic matter, soil moisture, iron oxides and clay fraction produces a decreases in soil reflectance (Stoner and Baumgardner, 1981). Coleman and Montgomery (1987) showed that near infra red bands (0.76-0.90 mm) were best related to organic matter. Similarly, soil texture also significantly influences the reflectance pattern. Fine textured clay soil generally show lower reflectance than coarse textured sandy soil (Horvath *et al*., 1984; Galvao *et al*., 2001) because they usually have less amounts of organic matter, iron oxides and clay minerals (Galvao *et al*., 1997). Ben-Dor *et al* (1997) found that the reflectance pattern in the VIS-NIR-SWIR region was a promising tool for monitoring the composting process of organic matter. Ben-Dor (2002) adopted Visible and Near Infrared Analysis approach, in which they selected 38 most reliable bands based on the correlogram spectrum for each soil property. Then they followed a forward stepwise multiple regression analysis to generate empirical equations relating soil properties (field moisture, saturated moisture, organic matter, electrical conductivity and pH) with reflectance at different bands. The R^2 varied from 0.53 (pH) to 0.83 (organic matter). The wavelengths whose reflectance were significantly related with soil parameters included 689, 739 and 1650 nm for field moisture; 705, 722, 1678 and 2328 nm for organic matter; 739, 1650 and 2166 nm for EC and 722 and 2118 nm for pH.

Soil colour is a key feature in identification and classification of soils. Although soil colour has littler direct influence on the functioning of soil, one may infer a great deal of about a soil from its colour if it is considered with other observable features (Mattikalli, 1997). Soil colour is influenced by parent material, organic matter, iron oxides, limestone and water content. Traditionally, Munsell colour charts are used to describe soil colour visually, by assigning hue, value and chroma. Leone and Escadafal (2001), while relating soil chemical and physical properties, found that colour hue was significantly realted to manganese content, colour value was highly influenced by $CaCO_3$ and CEC; while colour chroma showed a significant dependence upon soil texture, and particularly on the percentages of clay (negative correlation) and sand (positive correlation) content. Soil reflectance have been found to be correlated with soil colour (Mattikalli, 1997). Leone and Escadafal (2001) used the visible bands of the MIVIS hyperspectral sensor to estimate Munshell colour components through single and multiple regression analysis. The R^2 values for hue, value and chroma were 0.58, 0.81 and 0.87, respectively. Many radiometric indices have been developed, such as the Saturation Index or the Hue Index (Escadafal *et al*., 1994), Redness Index (Madeira *et al*. 1997), Brightness Index (Mathieu *et al*., 1998), which have been related to soil colour (Mathieu *et al*., 1998). The details of these indices are presented in Table 1. Ray *et al*. (2002 & 2004) showed that these indices, derived using

Table 1. Soil colour related radiometric indices

Sl. No.	Index	Formula	Index properties	References
1	Brightness Index	$((B^2+G^2+R^2)/3)^{0.5}$	Average reflectance magnitude	Mathieu et al., 1998
2	Saturation Index	(R-B)/(R+B)	Spectra slope	Escadafal et al. (1994)
3	Hue Index	(2*R-G-B)/(G-B)	Primary colors	Escadafal et al. (1994)
4	Coloration Index	(R-G)/(R+G)	Soil color; Hematite/(hematite+ goethite) ratio	Escadafal and Huete (1991)
5	Redness Index	$R^2/(B*G^3)$	Hematite content; Redness	Madeira et al. (1997)

where R=red band; G=green band and B=blue band high spatial resolution Ikonos data and hyperspectral could be related soil parameters like organic matter.

Palacio-Orueta and Ustin (1998) applied multivariate analysis, specifically principal component analysis and canonical discriminant analysis, as well as band depth analysis to AVIRIS (Advanced Visible/Infrared Imaging Spectrometer) bands simulated from laboratory spectra to test their performance in analyzing soil properties. Results showed that total iron and organic matter contents were the main factors affecting spectral shape, although sand content significantly affected the spectral contrast of the absorption features. The study carried out by Leone *et al*. (1995) showed that organic matter was significantly related to brightness index. Similarly, Suk *et al*. (2002) in their study has showed how the principal component 2 and 4 were strongly correlated to soil chemical properties like organic matter, magnesium (Mg), and potassium (K) contents. For applications like site-specific crop management, estimation of soil nutrient status is highly essential. Daniel *et al*. (2003) found soil nutrient sensitive bands in hyperspectral data using Artificial Neural Networks and nutrient prediction model. The bands were 410, 460 and 480 nm (for OM), 1030, 1120 and 1160 nm (for P), 450, 470 and 650 nm (for K). Daniel *et al*. (2006) developed empirical models to estimate soil nutrient parameters from spectral reflectance of various narrow bands.

In this context, this study was carried out with two objectives, i) to study optimum spectral indices to discriminate between two closely related soil types, and ii) to develop empirical models for estimation of soil parameters from spectral indices.

Data and Methods

Study area

The study was carried out in the farm of Central Potato Research Station (31.16^{0}N latitude and 75.32^{0}E longitude) in Jalandhar, Punjab state of India. IKONOS multi-spectral data of 30th April shows the layout of the farm (Figure 1).

Fig. 1. Location of two fields in CPRS Farm, Jalandhar whose soil separability was studied

The farm follows potato-wheat crop rotation. The study was carried out during wheat crop growing period in two fields (numbers 3 and 19), where potato had been harvested and the land was fallow.

Soil parameter estimation

Eighteen and thirty-five soil samples (surface soil) were collected from the field at regular intervals from field 3 and 19, respectively. The samples were analyzed for soil organic carbon (%), available nitrogen (ppm), available phosphorus (ppm), available potassium (ppm) and soil texture (sand, silt and clay percentage). The methodology for determining soil parameters is given in Table 2. The mean surface soil parameters of these two fields are presented in Table 3. The texture of soil field 3 is sandy loam, while that of field 19 is loamy sand. Field 19 has higher sand content and lower clay and organic matter content compared to field 3.

Spectral data collection

Spectral data for soil were collected at the above grid locations, using a 512 channel spectroradiometer with a range of 350 nm to 1800 nm (FieldSpec®Pro, 2000 Analytical Spectral Devices, Inc). The instrument acquires hyper-spectral data at the spectral resolution of 3 nm at 700 nm and 10 nm at 1400 nm. The sampling

Table 2. Methodology for determining soil chemical parameters

Parameter	Method	Reference
Organic carbon	Chromic acid titration	Walkley and Black (1934)
Available N	Alkaline permanganate extractable	Subbiah and Asija (1956)
Available P	Sodium bicrabonate extractable	Olsen et al. (1954)
Available K (Exch.+ Soluble)	Ammonium acetate extractable	Muhr et al. (1965)
Mechanical composition (Soil texture analysis)	Day's hydrometer	Day (1965) Gee and Bauder, (1986)

Table 3. The average values of parameters of surface soil for two fields in CPRS farm

Field No	O.C. (%)	Available N (ppm)	Available P (ppm)	Available K (ppm)	Sand (%)	Silt (%)	Clay (%)	Texture
3	0.45 (0.04)	112.5 (11.4)	21.4 (17.2)	211.6 (43.5)	70.9 (1.9)	16.5 (2.5)	12.6 (2.3)	Sandy loam
19	0.25 (0.06)	103.2 (14.2)	28.5 (8.6)	100.3 (20.7)	82.6 (2.2)	8.0 (1.7)	9.4 (1.3)	Loamy Sand
F Value	164.3**	5.7*	4.1*	160.6**	142.1**	80.1**	15.7**	

**Significant at the 0.01 level; * Significant at the 0.05 level
Figures within parentheses are standard deviation values

interval was 1.4 nm for the spectral region 350-1000 nm and 2 nm for 1000-1800 nm. Gathering spectra at a given location involved optimizing the integration time (typically set at 17 ms), providing foreoptic information, recording dark current, collecting white reference reflectance and finally, obtaining the target reflectance. The target reflectance is the ratio of energy reflected off the target to the energy incident on the target (measured using $BaSO_4$ white reference). Since the dark current varies with time and temperature, it was gathered for each integration time (virtually for each new reading). The instrument comes with a window-based software ViewSpec Pro (Ver. 2.10) for viewing, analysing and exporting the spectral data. For each grid point two reflectance measurements were collected, along a transect, with a nadir view from a height of 1.3 m above ground for crop and soil using 25^0 FOV (Field of View). We got 35 (for field 19) and 18 (field 13) spectral profiles (after averaging the two-three measurements of each point) and each profile contained 1471 data points. The data between 1350 and 1430 nm was removed because of noise in the data. Previous studies (Thenkabail, 2002) have shown that spectral bands in the immediate neighborhood of one another provide similar information, and are essentially redundant. Based on these facts, we averaged the spectral data over 10 nm to reduce the number of bands to 69 wavelengths. There are several ways to compress the data from 1 nm to 10 nm. However, we did simple averaging, assuming a square wave spectral response function within a 10 nm range. We found that within any 10 nm range, the coefficient of variation of reflectance was less than 2 %. Hence an average can represent the reflectance values of that range appropriately.

Soil spectral analysis

Soil reflectance spectra can be visually analyzed and grouped on the basis of their characteristic form (e.g., brightness, shape, absorption features) (Valeriano *et al*., 1995). Visual analysis of the spectroscopic data is certainly time consuming, particularly when the data set is very large, and may become fairly subjective (Leone and Sommer, 2000). Hence, we have used different statistical techniques to analyse the above-mentioned characteristics.

Towards determining the shape of the curve, a minimal set of sixteen fundamental narrow-bands were selected, appropriately positioned in the frequency axis, in such a way as to represent the general shape and slopes of all the curves in the data set. This was done following the procedure suggested by Galvao and Vitorello (1995).

Absorption features were analysed using the continuum removal technique. Continuum removal is a common technique employed in the interpretation of reflectance spectra in order to analyse the absorption band depth (Clark, 1999). The continuum-removed absorption depths were estimated for 945, 1125 and 1436 nm. These absorption bands were decided based on the studies of Palacios-Orueta and Ustin (1998) and Leone and Sommer (2000). Though Leone and Sommer (2000) had applied band depth analysis both in visible and near-infrared bands, Palacios-Orueta and Ustin (1998) were of the opinion that, since absorption features of soil are broader in the visible region, it is better to apply band-depth analysis to NIR region. The soil components responsible for absorption in 945, 1125 and 1436 nm were goethite, hydroxyl ions and bound water, respectively (Leone and Sommer, 2000). In our study the continuum between 915-995 nm, 1065-1185 nm and 1285-1556 nm were fitted, for each reflectance spectrum using straight-line equation. The reflectance at continuum was estimated for a particular wavelength using the fitted equation. The band depth after removal of continuum were computed as

$$D = 1 - R_b / R_c$$

where R_b is the reflectance at the band bottom, and R_c is the reflectance of the continuum at the same wavelength as R_b (Clark and Roush, 1984).

Computation of radiometric indices

Five soil colour related radiometric indices, namely Brightness Index (Mathieu *et al.*, 1998), Saturation Index (Escadafal *et al.*,1994), Hue Index (Escadafal *et al.*, 1994), Coloration Index (Escadafal and Huete, 1991), Redness Index (Madeira *et al.*, 1997), were computed using the reflectance values obtained using the spectroradiometer. The radiometric indices were computed using both narrowband and broadband reflectance.

The broadband reflectance was generated from the narrowband data. The reflectance for different broadbands, as per IRS LISS 1, was computed using the spectral response function (Figure 2) as follows (Liang, 2004).

$$R_b = \frac{\int_{\lambda_{\min}}^{\lambda_{\max}} R_\lambda f(\lambda) d\lambda}{\int_{\lambda_{\min}}^{\lambda_{\max}} f(\lambda) d\lambda}$$

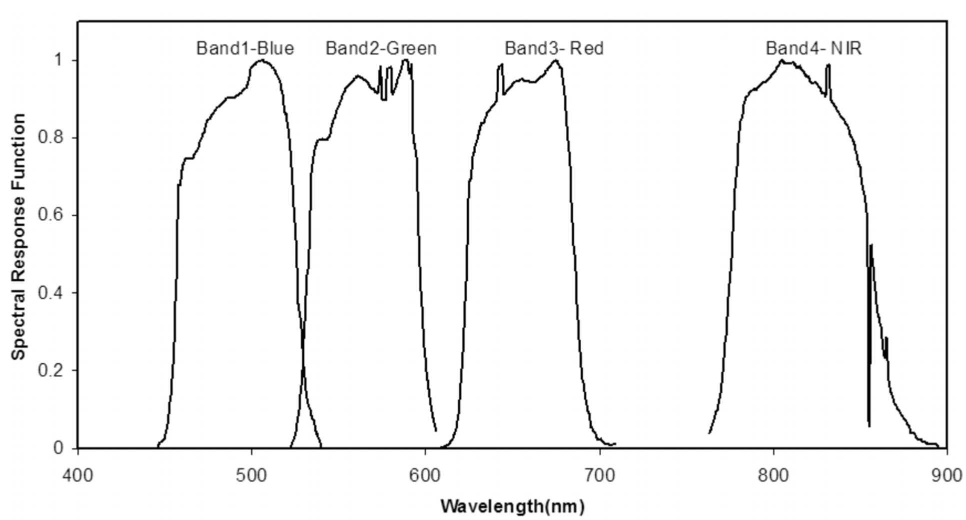

Fig. 2. Spectral response function for IRS LISS 1 sensor

where R_b is the reflectance of broadband, is the wavelength and f(λ) is the spectral response function.

For computing the corresponding narrowband indices, Levin *et al.*, (2005) had used the reflectance of 640 nm (red), 510 nm (green) and 460 nm (blue). However we used the reflectance corresponding to the central wavelength of IRS LISS 1 bands. The central wavelengths (l_c) were computed by moment method as suggested by Palmer (1984).

$$\lambda_c = \frac{\int_{\lambda_{min}}^{\lambda_{max}} f(\lambda)\lambda d\lambda}{\int_{\lambda_{min}}^{\lambda_{max}} f(\lambda) d\lambda}$$

Multivariate statistical analysis

Two types of multivariate statistical analyses are commonly carried out to analyse soil spectra (Palacios-Orueta and Ustin, 1998). The Principal Component Analysis (PCA) is applied to define the shape and the contribution of each eigen vector to the overall reflectance spectra, whereas step-wise discriminant analysis (SDA) is carried out to select the minimum number of feature to be required for separating different soil types. The PCA was performed both on the full spectral range and also selected bands. The SDA was performed using following twenty parameters as input: reflectance in blue, green, red and NIR (both narrowband data and computed broadband data); ten radiometric indices, five each for narrowband and broadband; four principal components (two each for full spectral range and the selected sixteen bands); and band depths for 945, 1125 and 1436 nm (Table 4). The separability was tested using Wilks' Lambda, F value and canonical correlation. The SDA was carried out using SPSS V11.5 with following options (Maximum number of iterations= 50, minimum partial F to enter= 3.84, and maximum partial F to remove= 2.71)

Results and Discussion

Reflectance difference

The average reflectance spectrums of two fields are presented in Figure 3. The loamy sand soil had higher reflectance than the sandy loam soil. The loamy sand soil had higher organic matter content and higher clay content. In general, the increase in contents of organic matter, soil moisture, iron oxides and clay fraction produces a decrease in soil reflectance (Stoner and Baumgardner, 1981).

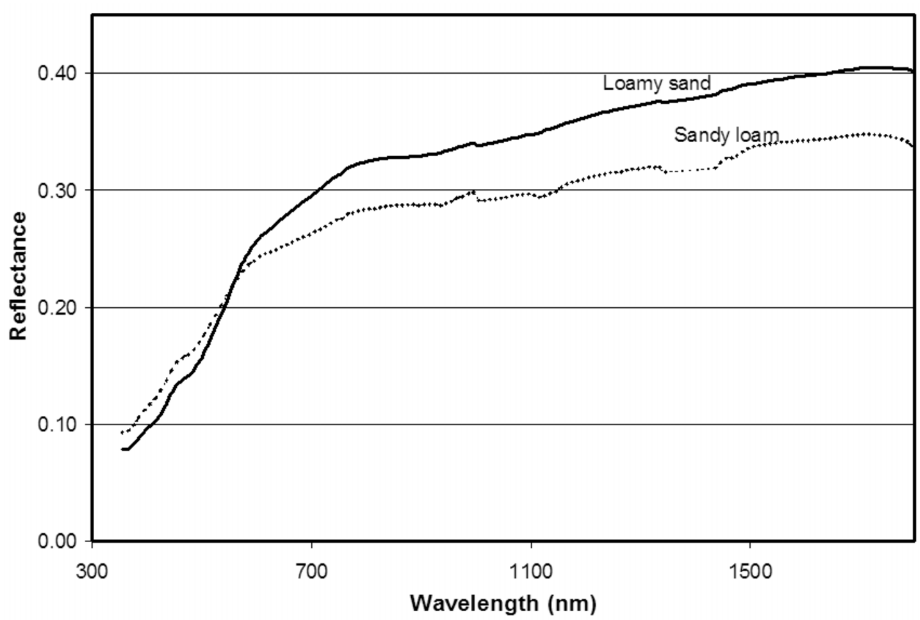

Fig. 3. Average reflectance spectra of two soil types in CPRS field

Table 4. The indices used for step-wise discriminant analysis

Indices/Bands	Explanation
BLUE	Reflectance of broadband-Blue
GREEN	Reflectance of broadband-Green
RED	Reflectance of broadband-Red
NIR	Reflectance of broadband-NIR
BI	Brightness Index from broadband reflectance
SI	Saturation Index from broadband reflectance
HI	Hue Index from broadband reflectance
CI	Coloration Index from broadband reflectance
RI	Redness Index from broadband reflectance
BLUE492	Blue Reflectance at 492nm
GREEN565	Green Reflectance at 565nm
RED655	Red Reflectance at 655nm
NIR816	NIR Reflectance at 816nm
BIN	Brightness Index from narrowband reflectance
SIN	Saturation Index from narrowband reflectance
HIN	Hue Index from narrowband reflectance
CIN	Coloration Index from narrowband reflectance
RIN	Redness Index from narrowband reflectance
DEPTH945	Band Depth at 945 nm
DPTH1125	Band Depth at 1125 nm
DPTH1436	Band Depth at 1436 nm
PC1ALL	First PC of full spectrum (400-1800 nm)
PC2ALL	Second PC of full spectrum (400-1800 nm)
PC1SEL	First PC of sixteen selected bands
PC2SEL	Second PC of sixteen selected bands

Principal component analysis

The first principal component occupied more than 98% of the variability in dataset for both whole spectrum and selected 16 bands (Table 5). The similarity of cumulative variance in both cases showed that these selected 16 bands could represent the variability available in the whole spectrum. Galvao and Vitorello (1995) showed that the first and second principal components were related to the albedo and slope characteristics of the spectra, while the absorption bands were related to the remaining components. They also found that PCA using a small number of narrow bands to represent the spectrum was an adequate mathematical approach for spectral analysis.

Table 5. Results of Principal Component Analysis of soil reflectance (350-1800 nm) of all bands and selected sixteen bands, representing the shape of the curve

Factor	Eigenvalue	Percent variance	Cumulative variance
	All bands		
1	134.84	98.43	98.43
2	1.94	1.42	99.84
3	0.15	0.11	99.95
	16 bands		
1	15.71	98.19	98.19
2	0.26	1.64	99.83
3	0.02	0.10	99.93

The first principal component is related to the brightness variation of the spectrum (Leone and Sommer, 2000). Palacios-Orueta and Ustin (1998) found that soils with high reflectance have high weights on this PC. In our case we found that for loamy sand soil, the eigen vector loadings of PC1 is more than 0.9 for all wavelengths (Figure 4). The PC2 loading ranged from positive (0.367) to negative values (-.074). This could be interpreted as an expression of slope variation of the reflectance curves in the VIS-NIR region (Leone and Sommer, 2000). Palacios-Orueta and Ustin (1998) showed that first PC was related sand content, while the second PC showed a negative correlation with the organic matter content.

Stepwise discriminant analysis

It was attempted to study the separability of the two soils by using step-wise discriminant analysis (SDA). The discriminant analysis was carried out to find out the most optimal parameters to discriminate (separate) between

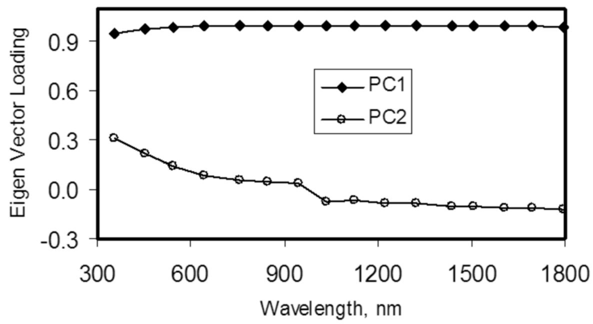

Fig. 4. Eigen vectors related to the first and second principal components derived from the application of PCA to 16 representative bands (Plot F19)

different samples using multivariate separability measures, such as Wilks' lambda, F Value etc. (Thenkabail, 2002). The SDA selected those indices which were significantly different for different soil types, and also which were not much related to each other. In this analysis, at each step, the variable (narrow band index) that minimizes the overall Wilks' Lambda was entered. High Wilks' lambda indicates less separability and high F value means more separability. The analysis stops when Wilks' Lambda gets saturated. The final five indices that were selected for soil separability included saturation index (narrow band), PC2 of sixteen selected bands, NIR reflectance at 816 nm, Blue reflectance at 492 nm, Hue Index (broadband), Coloration Index (narrow band) with final Wilks' Lambda 0.043 and F value 168.8 (Table 6). The saturation index and PC2 are related soil slope and hence related to the organic matter content (Palacios-Orueta and Ustin, 1998). The hue Index and coloration index are related to soil colour.

The reason for these variables getting selected in SDA can be seen from the one way analysis of variance presented in Table 7. Higher F value indicated, the between-group variability for that parameter was higher than within-group variability. SIN had the highest F value (219.8) and hence got selected. However, the next variable, SI with very high F value (217.0) did not get selected, as it was highly correlated with SIN (Table 8). The PC2SEL had very low F value, however it could get selected in SDA, as its correlation with all other spectral parameters was very low, except with PC2ALL. The reason for blue band getting selected was that it had significant correlations with all other spectral parameters except for absorption depths and PC2s. Since none of the radiometric indices used NIR band reflectance, It must have been got selected to add a new component.

The correlation analysis also showed that in case of soil spectrum, there was very high correlation (>0.99) between narrow band and their corresponding broad band. Similarly narrow band radiometric indices were very closely related to their broad band counterparts. This was because the visible part of the soil spectrum is mostly featureless, i.e. there was no typical absorption feature. Hence converting narrow band to broad band for soil spectrum might not reduce the information content.

As the indices SIN, CIN and HI had high F value in ANOVA analysis and also were part of the output of SDA, these indices were used to classify the soil. K-means classification approach was followed. This procedure identified relatively homogeneous groups of cases based on selected characteristics, using an algorithm that could handle large numbers of cases. However, the algorithm required to specify the number of

Table 6. Stepwise Discriminant Analysis for selection of best indices for separation two different soil types

Step	Variables	Wilks' Lambda	F
1	SIN	0.188	219.8
2	SIN, PC2SEL	0.091	250.2
3	SIN, PC2SEL, NIR816	0.058	267.2
4	SIN, PC2SEL, NIR816, Blue492	0.053	214.7
5	SIN, PC2SEL, NIR816, Blue492, HI	0.047	188.5
6	SIN, PC2SEL, NIR816, Blue492, HI, CIN	0.043	168.8

Table 7. Analysis of variance of different spectral indices/bands for two different soil types

Indices/Bands	Mean (Std. Dev)		F	Sig.
	Plot 3 (Sandy loam)	Plot 19 (Loamy sand)		
BLUE	0.172 (0.048)	0.155 (0.050)	1.3	0.259
GREEN	0.223 (0.062)	0.227 (0.070)	0.1	0.812
RED	0.253 (0.067)	0.280(0.081)	1.4	0.238
NIR	0.286 (0.073)	0.326 (0.090)	2.6	0.113
BI	0.179 (0.054)	0.183 (0.064)	0.0	0.834
SI	0.196 (0.019)	0.288(0.023)	217.0	0.000
HI	2.152 (0.166)	2.456 (0.116)	60.5	0.000
CI	0.063 (0.012)	0.103 (0.012)	129.5	0.000
RI	40.499 (18.058)	53.617 (26.805)	3.5	0.068
BLUE492	0.171 (0.048)	0.154 (0.049)	1.4	0.246
GREEN565	0.225 (0.061)	0.228 (0.070)	0.0	0.867
RED655	0.253 (0.067)	0.280 (0.082)	1.4	0.239
NIR816	0.285(0.074)	0.326 (0.090)	2.8	0.102
BIN	0.179(0.054)	0.183 (0.064)	0.0	0.860
SIN	0.200 (0.020)	0.294 (0.023)	219.8	0.000
HIN	2.047 (0.165)	2.365 (0.132)	57.9	0.000
CIN	0.062 (0.010)	0.103 (0.012)	152.1	0.000
RIN	40.249 (17.928)	53.753 (27.077)	3.6	0.062
DEPTH945	0.011 (0.017)	-0.019 (0.151)	0.7	0.409
DPTH1125	-0.008 (0.142)	-0.010 (0.076)	0.0	0.948
DPTH1436	-0.041(0.223)	0.009 (0.021)	1.7	0.193
PC1ALL	5.6E-04 (1.001)	-9.5E-18 (1.000)	0.0	0.998
PC2ALL	-6.2E-18 (1.000)	-5.1E-17 (1.000)	0.0	1.000
PC1SEL	0.0006 (1.000)	0.0003 (0.999)	0.0	0.999
PC2SEL	-0.0011 (1.001)	-0.0011 (1.000)	0.0	1.000

Table 8. Correlation between spectral parameters

Indices/Bands	BLUE	GREEN	RED	NIR	BI	SI	HI	CI	RI
BLUE	1	.977**	.937**	.911**	.975**	-.378**	-.507**	-.424**	-.878**
GREEN	.977**	1	.987**	.974**	.997**	-.190	-.343*	-.244	-.832**
RED	.937**	.987**	1	.996**	.987**	-.045	-.205	-.102	-.769**
NIR	.911**	.974**	.996**	1	.975**	.022	-.136	-.034	-.731**
BI	.975**	.997**	.987**	.975**	1	-.185	-.332*	-.237	-.819**
SI	-.378**	-.190	-.045	.022	-.185	1	.933**	.986**	.537**
HI	-.507**	-.343*	-.205	-.136	-.332*	.933**	1	.963**	.661**
CI	-.424**	-.244	-.102	-.034	-.237	.986**	.963**	1	.594**
RI	-.878**	-.832**	-.769**	-.731**	-.819**	.537**	.661**	.594**	1
BLUE 492	.998**	.975**	.933**	.906**	.972**	-.387**	-.515**	-.433**	-.882**
GREEN565	.979**	.999**	.985**	.971**	.997**	-.202	-.356**	-.259	-.837**
RED655	.937**	.987**	1.0**	.995**	.987**	-.046	-.207	-.103	-.771**
NIR816	.908**	.972**	.995**	1.0**	.973**	.029	-.130	-.027	-.728**

Contd...

Indices/Bands	BLUE	GREEN	RED	NIR	BI	SI	HI	CI	RI
BIN	.976**	.997**	.986**	.973**	.999**	-.191	-.338*	-.244	-.819**
SIN	-.372**	-.185	-.040	.026	-.182	.995**	.932**	.984**	.528**
HIN	-.474**	-.311*	-.173	-.105	-.300*	.930**	.995**	.966**	.648**
CIN	-.408**	-.227	-.085	-.018	-.222	.990**	.955**	.995**	.582**
RIN	-.874**	-.828**	-.764**	-.725**	-.814**	.543**	.665**	.600**	1.0**
DEPTH 945	.153	.140	.108	.097	.125	-.192	-.184	-.202	-.309*
DPTH 1125	-.115	-.097	-.080	-.088	-.081	.090	.155	.121	.170
DPTH 1436	-.524**	-.476**	-.427**	-.412**	-.462**	.248	.266	.239	.372**
PC1ALL	.970**	.988**	.977**	.968**	.988**	-.178	-.307*	-.221	-.787**
PC2ALL	.173	.137	.081	.041	.112	-.330*	-.488**	-.406**	-.405**
PC1SEL	.970**	.987**	.977**	.967**	.988**	-.179	-.310*	-.222	-.788**
PC2SEL	.173	.137	.082	.040	.112	-.331*	-.489**	-.407**	-.406**

	BLUE 492	GREEN565	RED655	NIR816	BIN	SIN	HIN	CIN
BLUE	.998**	.979**	.937**	.908**	.976**	-.372**	-.474**	-.408**
GREEN	.975**	.999**	.987**	.972**	.997**	-.185	-.311*	-.227
RED	.933**	.985**	1.0**	.995**	.986**	-.040	-.173	-.085
NIR	.906**	.971**	.995**	1.0**	.973**	.026	-.105	-.018
BI	.972**	.997**	.987**	.973**	.999**	-.182	-.300*	-.222
SI	-.387**	-.202	-.046	.029	-.191	.995**	.930**	.990**
HI	-.515**	-.356**	-.207	-.130	-.338*	.932**	.995**	.955**
CI	-.433**	-.259	-.103	-.027	-.244	.984**	.966**	.995**
RI	-.882**	-.837**	-.771**	-.728**	-.819**	.528**	.648**	.582**
BLUE492	1	.977**	.933**	.903**	.973**	-.380**	-.483**	-.417**
GREEN565	.977**	1	.985**	.969**	.997**	-.197	-.325*	-.241
RED655	.933**	.985**	1	.995**	.986**	-.041	-.175	-.085
NIR816	.903**	.969**	.995**	1	.972**	.034	-.099	-.012
BIN	.973**	.997**	.986**	.972**	1	-.188	-.306*	-.229
SIN	-.380**	-.197	-.041	.034	-.188	1	.929**	.986**
HIN	-.483**	-.325*	-.175	-.099	-.306*	.929**	1	.958**
CIN	-.417**	-.241	-.085	-.012	-.229	.986**	.958**	1
RIN	-.879**	-.833**	-.766**	-.722**	-.815**	.534**	.653**	.587**
DEPTH945	.151	.142	.107	.096	.124	-.174	-.193	-.201
DPTH1125	-.099	-.091	-.081	-.077	-.082	.086	.175	.112
DPTH1436	-.533**	-.467**	-.427**	-.412**	-.462**	.214	.232	.224
PC1ALL	.966**	.986**	.977**	.967**	.988**	-.171	-.269	-.207
PC2ALL	.191	.147	.085	.034	.114	-.327*	-.523**	-.379**
PC1SEL	.966**	.985**	.976**	.966**	.988**	-.173	-.272*	-.208
PC2SEL	.190	.148	.085	.034	.114	-.327*	-.525**	-.379**

	DPTH 1436	PC1ALL	PC2ALL	PC1SEL	PC2SEL
BLUE	-.524**	.970**	.173	.970**	.173
GREEN	-.476**	.988**	.137	.987**	.137
RED	-.427**	.977**	.081	.977**	.082

Contd...

	DPTH 1436	PC1ALL	PC2ALL	PC1SEL	PC2SEL
NIR	-.412**	.968**	.041	.967**	.040
BI	-.462**	.988**	.112	.988**	.112
SI	.248	-.178	-.330*	-.179	-.331*
HI	.266	-.307*	-.488**	-.310*	-.489**
CI	.239	-.221	-.406**	-.222	-.407**
RI	.372**	-.787**	-.405**	-.788**	-.406**
BLUE492	-.533**	.966**	.191	.966**	.190
GREEN565	-.467**	.986**	.147	.985**	.148
RED655	-.427**	.977**	.085	.976**	.085
NIR816	-.412**	.967**	.034	.966**	.034
BIN	-.462**	.988**	.114	.988**	.114
SIN	.214	-.171	-.327*	-.173	-.327*
HIN	.232	-.269	-.523**	-.272*	-.525**
CIN	.224	-.207	-.379**	-.208	-.379**
RIN	.368**	-.782**	-.408**	-.783**	-.409**
DEPTH945	.000	.105	.196	.105	.196
DPTH1125	.029	-.074	-.252	-.075	-.231
DPTH1436	1	-.543**	.077	-.544**	.082
PC1ALL	-.543**	1	.000	1.0**	.000
PC2ALL	.077	.000	1	.000	.998**
PC1SEL	-.544**	1.0**	.000	1	.000
PC2SEL	.082	.000	.998**	.000	1

**Significant at 0.01 level, *at 0.05 level

clusters. The classifications showed out of total 53 samples, 46 were classified correctly, showing a classification accuracy of 86.7 per cent.

The scatterplot between the hue index (broad band) and saturation index (narrow band) could clearly show the separability of almost all data points in sandy loam and loamy sand soil (Figure 5). The loamy sand soil had lower SIN and HI compared to sandy loam soil. The spread of the data points in SIN axis was more than the HI axis.

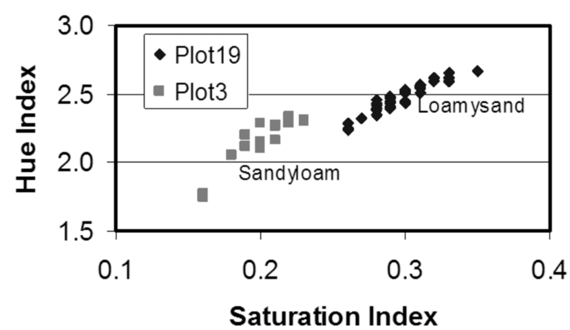

Fig. 5. Scatter plot of two soil types (two fields) when two best indices for soil discrimination plotted against each other.

Estimation of soil parameters

All the spectral parameters, which have been defined in Table 4, were evaluated to estimate soil parameters like organic carbon, available nutrients (N, P, and K) and soil texture. The correlation between soil parameters and spectral parameter showed that organic carbon significantly and negatively related to the three radiometric indices (both narrowband and broadband), namely saturation index, hue index and coloration index (Table 9). Other nutrients like available nitrogen because of its correlation with organic matter (available nitrogen is generally organically available nitrogen) had shown significant correlation with radiometric indices. The correlation among the soil parameters

Table 9. Correlation between spectral and soil parameters

Indices/ Bands	OC	AVLN	AVLP	AVLK	Sand	Silt	Clay
BLUE	.181	0.025	0.166	0.164	-0.239	0.269	0.095
GREEN	.006	-0.047	0.204	-0.007	0.019	0.021	-0.094
RED	-.114	-0.094	0.237	-0.128	0.232	-0.187	-0.241
NIR	-.161	-0.105	0.255	-0.173	0.297	-0.239	-0.312
BI	.014	-0.041	0.202	0	0.014	0.028	-0.093
SI	-.818**	-.331*	0.222	-.825**	.820**	-.801**	-.577**
HI	-.702**	-.276*	0.171	-.649**	.618**	-.595**	-0.451
CI	-.781**	-.300*	0.225	-.758**	.744**	-.725**	-.525*
RI	-0.246	-0.144	-0.069	-.273*	0.178	-0.235	-0.002
BLUE492	0.185	0.026	0.155	0.17	-0.237	0.268	0.094
GREEN565	0.022	-0.042	0.196	0.004	0.013	0.023	-0.082
RED655	-0.113	-0.091	0.24	-0.127	0.226	-0.182	-0.236
NIR816	-0.166	-0.104	0.26	-0.176	0.307	-0.258	-0.3
BIN	0.018	-0.036	0.199	0.005	0.006	0.037	-0.091
SIN	-.820**	-.331*	0.241	-.826**	.824**	-.802**	-.582**
HIN	-.700**	-.274*	0.185	-.645**	.605**	-.587**	-0.434
CIN	-.797**	-.326*	0.24	-.786**	.779**	-.759**	-.551*
RIN	-0.251	-0.146	-0.065	-.279*	0.182	-0.239	-0.005
DEPTH945	0.103	0.144	-0.091	0.129	0.176	-0.22	-0.027
DPTH1125	0.027	0.139	-0.13	0.067	0.149	-0.307	0.218
DPTH1436	-0.159	0.099	-.317*	-0.168	0.106	-0.173	0.065
PC1ALL	0.041	-0.043	0.234	0.025	-0.041	0.083	-0.058
PC2ALL	-0.021	-0.008	-0.134	-0.012	0.07	-0.046	-0.094
PC1SEL	0.043	-0.041	0.237	0.025	-0.043	0.085	-0.057
PC2SEL	-0.021	-0.011	-0.13	-0.008	0.071	-0.058	-0.072

** Significant at the 0.01 level, *At the 0.05 level

is presented in table 10. Sand had significant positive correlation with the radiometric indices, whereas clay and silt had negative correlation. Available K, which is also known as exchangeable clay, is related to silt and clay content (Table 10). Because of this, it had significant correlation with radiometric indices. Other spectral parameters did not significant correlation with any soil parameter, except for absorption depth at 1436 nm having significant relation with available phosphorus. Leone and Escadafal (2001) have found that soil colour was related to soil chemical and physical properties and (Mathieu *et al*., 1998) have shown that the radiometric indices were related soil colour. Thus we could relate the soil nutrient and physical parameters to radiometric indices. Ray *et al*. (2004) also had shown that these indices, derived using high resolution Ikonos data could be related to soil parameters like organic matter. We also generated empirical models for soil parameter estimation from spectral parameters using stepwise regression analysis technique (Table 11). We could generate highly significant models for organic matter (R^2=0.78), available K (R^2=0.81) and soil texture (R^2=0.64-0.81). The empirical models for available nitrogen and phosphorus had low R^2 though statistically significant.

Table 10. Correlation among the soil parameters

Soil parameters	OC	AVLN	AVLP	AVLK	Sand	Silt	Clay
OC	1	.450**	-.197	.851**	-.802**	.798**	.535*
AVLN	.450**	1	-.015	.483**	-.480*	.515*	.245
AVLP	-.197	-.015	1	-.162	-.024	.023	.018
AVLK	.851**	.483**	-.162	1	-.882**	.888**	.567*
Sand	-.802**	-.480*	-.024	-.882**	1	-.947**	-.763**
Silt	.798**	.515*	.023	.888**	-.947**	1	.513*
Clay	.535*	.245	.018	.567*	-.763**	.513*	1

**Significant at the 0.01 level, *At the 0.05 level

Table 11. Regression equations between soil parameters and reflectance indices

Parameter	Equation	R^2	N	F value
OC	0.855-2.191*SIN-0.031*PC2SEL+0.001RI	0.785	53	59.7**
AVLN	130.726-92.976*SIN	0.110	53	6.29*
AVLP	9.813-37.309*DPTH1436+180.004*CIN	0.202	53	6.33*
AVLK	142.333-1837.471*SIN+202.737*HI-11.187*PC2ALL	0.812	53	70.36**
Sand	50.504+131.255*SIN-0.130*RIN	0.819	19	36.1**
Silt	0.507-152.354*SIN+21.387*HI	0.783	19	28.8**
Clay	19.528 -43.570*SIN +0.051*RIN +6.540*DPTH1125	0.644	19	9.02**

**Significant at the 0.01 level, *At the 0.05 level

Conclusions

This study was carried out for detailed analysis of ground-based spectral data towards understanding its utilization for related soil type discrimination and soil parameter estimation. Many spectral indices, based on soil colour, reflectance at different bands, principal components, and continuum removed spectra were used in the study. The spectral indices were computed both using narrow band and broad band data. The results showed significant role of spectral indices, not only for discrimination of soil types but also for estimating soil parameters.

Since, site specific soil management needs precise information on soil variability, the study could be used for precision farming. The results will also be useful in developing procedures for soil mapping and assessment using space-based remote sensing data.

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