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Research Article

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Detection of some soil properties using hyperspectral remote sensing of semi arid region of Tamil Nadu

■ RAJESHWAR MALAVATH **AND** S. MANI

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MEMBERS OF RESEARCH FORUM:

Corresponding author :
RAJESHWAR MALAVATH, Department of Soil Science and Agricultural Chemistry, College of Agriculture, Prof. Jayashankar Telangana State Agricultural University, Rajendranagar, HYDERABAD (TELANGANA) INDIA
Email: rajeshoct31naik@gmail.com

Co-authors :
S. MANI, Department of Soil Science and Agricultural Chemistry, Agricultural College and Research Institute, Tamil Nadu Agricultural University, COIMBATORE (T. N.) INDIA

Summary

Remote sensing with hyper spectral sensors can provide the fine resolution required for site-specific farming. The within-field spatial distribution of some soil properties was found by using multiple linear regressions to select the best combinations of wave bands, taken from among a full set of 512 narrow bands in the wavelength range of 350 to 1050 nm. The resulting regression equations made it possible to calculate the value of the soil property with a spatial resolution of 3.0 nm FWHM (Full Width Half Maximum). Both surface and subsurface samples of soil profile were taken from the three research stations. The soil samples were tested in a laboratory for 20 different properties. The per cent sand was found to be detectable with a reasonable degree of accuracy with R^2 = 0.851 for a three parameter model; the best combination of wavelengths was 426.81, 730.47 and 1037.7 nm. For silt, clay, field capacity, wilting point, Available water content, pH, electrical conductivity and $CaCO_3$ the results were ranges of degree of accuracy with R^2 from 0.609 to 826. The soil exchangeable properties such as Ca, Mg, Na and CEC, chemical composition such as SiO_2 and Fe_2O_3 R^2 values varied from 759 to 906. The poorest fit was for organic carbon with R^2 = 0.220 followed by Al_2O_3 (R^2 = 0.313). Available micronutrients (Fe and Mn) had R^2 0.491 and 0490. For all the properties except organic carbon and Al_2O_3, the correlation was statistically significant. The main findings were that some soil properties can be accurately detected using hyper spectral remote sensing.

Key words : Band selection, Soil profiles, Hyper spectral remote sensing, Multiple linear regression, Soil properties

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Introduction

Hyper spectral or imaging spectroscopy is defined as “the simultaneous acquisition of images in many narrow, contiguous spectral bands” (Goetz *et al*., 1985), which enables in constructing nearly complete spectral signatures of target surfaces. Hyper spectral Remote sensing, also known as imaging spectroscopy, is a relatively new technology that is currently being investigated by researchers and scientists with regard to the detection and identification of minerals, terrestrial vegetation, man-made materials and backgrounds. Under laboratory conditions, the spectral information of the visible, near-infrared and short wave infrared (VIS-NIR-SWIR; 0.4-2.5 mm) spectral regions provides a promising capability to identify soil, vegetation, rock and mineral materials. Because soil is a complex system, soil properties cannot be easily assessed directly from their reflectance spectra even under controlled (laboratory) conditions (Ben-Dor and Banin, 1994).

DeTar *et al*. (2008) reported that remote sensing with aircraft-based sensors can provide the fine resolution required for site-specific farming. The within-field spatial distribution of some soil properties was found by using multiple linear reggression to select the best combinations of wave bands, taken from full set of 60 narrow bands in the wavelength range of 429 to 1010 nm. Hyperspectral data being of larger volume, overlapping of weak overtones and fundamental vibrational bands, have been very difficult for its direct interpretation (Wetzel, 1993). Therefore, multivariate analysis is required for quantitative interpretation of soil parameters from hyperspectral reflectance data. A number of different calibration techniques are available and have been applied when relating measured spectra to measured values of soil properties. The choice of calibration technique will depend on the application of the data. Principal components regression (PCR) and stepwise multiple-linear regression are the most common (Wise *et al*., 2003). Different pre-processing transformations have been applied in numerous studies to transform soil spectral data, remove noise, accentuate features and prepare them for chemo metric modeling. Pre-processing transformations of spectral data constitute an important step in multivariate calibration and have been shown to improve the accuracy of prediction models (Dunn *et al*., 2002 and McCarty *et al*., 2002).

Keeping this in view, the information available on hyperspectral remote sensing is meagre for predicting physical, physico-chemical and chemical properties. The three research stations of TNAU *viz*., Maize Research Station, Vagarai of Dindigul district, Cotton Research Station, Veppanthatai of Perambalur district and Dryland Agricultural Research Station, Chettinad of Sivagangai district of Tamil Nadu to evaluate the accuracy and predictability of selected soil parameters derived by hyperspectral remote sensing.

Resource and Research Methods

The field portable spectroradiometer model: GER 1500 provides spectral measurements in either the stand alone mode or with a notebook computer interface. The GER 1500 instrument operates across the 350 nm to 1050 nm spectral range with accuracy and stability. It uses a diffraction grating with a silicon diode array. The silicon array has 512 discrete detectors that provide the capability to read 512 spectral bands. The Band width (nominal) is 1.5 nm, with resolution 3 nm FWHM (Full Width Half Maximum) and field of vision (FOV) Standard 4° Nominal. The spectroradiometer includes memory for standalone operation as well as capability for computer assisted operation through its COM2, RS232 serial port.

Collection of soil spectral data :

Air-dried, crushed and sieved (2 mm) soil samples were scanned using Field Portable Spectroradiometer Model: GER1500 covering wavelength ranging from 350 to 1050 nm in the laboratory condition. Fifty four soil samples of thirteen pedons of three different research stations were individually spread on white paper (29.7x 42.0 cm diameter) forming a layer of 1.8 cm (1.5 cm is considered as optically infinitely thick for soil). The sample surface was scraped plane with a ruler, as pressing can affect the porosity of the soil and result in a false measurement. Reflectance spectra were measured mid noon in between 11.30 am to 12.30pm, for allowing good sunlight as shown in Plate 1 and 2. The zenith angle of the Spectroradiometer was set to 45° by pointing the instrument at a distance of 30 cm above the soil surface. A panel coated with $BaSO_4$ paint was used as reference for the reflectance calibration. Each reflectance

Plate A : Recording spectral reflectance of black soils of CRS, Veppanthattai at 11.00 am to 12.30 pm

Plate B : Recording spectral reflectance of red and red laterte soils of MRS, vagarai and DARS, Chettinad

measurement produced a single spectrum.

Per cent spectral reflectance :

The instrument was optimized and calibrated before the first measurement and after every five minutes onwards to adapt to the changing atmospheric conditions. The incident spectrum was periodically obtained from the light reflected by a barium sulphate standard panel before each set of measurements. The per cent reflectance spectrum was calculated as the ratio between the reflected spectra from target and the incident spectra (reference) using the following formula.

$$\text{Per cent reflectance} = \frac{\text{Reflectance from target (soil surface)}}{\text{Reflectance from reference (barium sulphate panel)}} \times 100$$

The spectral reflectance data, both absolute and per cent reflectance values were transferred from the Spectroradiometer to a personal computer as ASCII files with extension utilizing a specific software supplied with the instrument. These files were later opened in a spreadsheet programme and further analyses were carried out. All the preliminary data preparation and calculations for soil parameter analysis were done using Microsoft Excel 2007 spreadsheet software. The 512 values of per cent spectral reflectance at approximately 1.5 nm bandwidth interval starting from 276.86 to 1093.50 nm (reflectance at 350 to 1050 nm ranges being more stable) were obtained for each soil samples. Two different methods were tested for selecting band-width that is best for prediction of soil properties *viz.*, 1. Correlation between each band and each soil property were worked out separately for spectral data sets and evaluated the relationship of correlation of reflectance with soil properties with the change in band-width. 2.Multiple regression models for each soil property were developed using each spectral data sets. Model predictability (Model R^2) was evaluated for selecting best band width for prediction of soil properties. Optimum band width found was to be used in the study for prediction of soil properties.

Band selection and development of prediction model :

Bivariate correlations analysis was done between soil properties and spectral data sets using SPSS software. Correlation analysis was performed for each soil property with each band. Best correlated bands from each reflectance related data sets were selected separately for each soil property, considering the absolute values of correlation co-efficients. The prediction model was developed for each soil properties considering all the bands as variable. Model predictability (R^2) was used for evaluating the spectral data sets for prediction of soil properties. Spectral data set with highest R^2 was selected for model development for each soil property. The correlation with each soil properties and reflectance data at different band width was computed and plotted against wavelength. Correlation between soil properties and reflectance at different wavelength for spectral data sets was evaluated for all soil properties.

Multiple linear regression is a common multivariate tool which, at its simplest level, forms a model that specifies the relationship between a response variable (Y) and a set of dependent variables (X). The soil property was considered the dependent variable and the various band reflectances were the independent variables. After a choice of the number of bands multiple linear regression was carried out for each soil parameter and best correlated bands from each spectral data set was selected. Best data set and optimum number of bands to be included in the model have been selected based on the highest R^2 value.

Research Findings and Discussion

Soil reflectance is affected by soil physical, physico-chemical and chemical properties. Correlation analysis of the spectral data with soil properties indicated that

Table 1: Description of physical, physico-chemical and chemical properties of the study area

Sr. No.	Soil property	Min.	Max.	Mean	Std. dev
1.	Sand (%)	19.7	73.7	56.7	16.6
2.	Silt (%)	4.7	20.0	11.2	4.73
3.	Clay (%)	16.5	64.3	32.0	13.5
4.	FC (kg kg^{-1})	8.5	61.5	25.7	15.9
5.	WP (kg kg^{-1})	4.5	38.5	14.6	11.8
6.	AWC (%)	4.3	23.0	11.2	7.83
7.	MWHC (%)	12.6	61.5	30.7	14.0
8.	pH (1:2.5)	4.40	9.13	6.51	1.64
9.	EC (dS m^{-1})	0.02	0.72	0.14	0.16
10.	OC (g kg^{-1})	0.70	6.5	3.31	1.50
11.	$CaCO_3$ (%)	0.20	15.5	4.0	8.43
12.	Ex. Ca [cmol (p^+) kg^{-1}]	0.99	29.8	8.11	10.0
13.	Ex .Mg [cmol (p^+) kg^{-1}]	0.39	10.3	3.07	3.40
14.	Ex .Na [cmol (p^+) kg^{-1}]	0.02	3.45	0.69	1.10
15.	CEC [cmol (p^+) kg^{-1}]	5.3	48.8	16.4	15.6
16.	Fe (mg kg^{-1})	1.45	26.96	10.5	6.60
17.	Mn (mg kg^{-1})	5.15	30.84	16.1	6.87
18.	SiO_2 (%)	49.6	66.56	57.0	4.94
19.	Al_2O_3 (%)	10.80	21.4	17.30	2.45
20.	Fe_2O_3 (%)	6.1	29.1	19.5	7.96

Table 2 : Wavelengths (nm) bands for the highest R^2 values for different soil properties

Soil property	One parameter (High correlated band)		Combination of two parameter		Combination of three parameter	
	WL	R^2	WL	R^2	WL	R^2
Sand (%)	730.47	0.433	426.81, 730.47	0.849	426.81, 730.47, 1037.7	0.851
Silt (%)	719.47	0.312	420.08, 719.47	0.561	420.08, 719.47, 888.44	0.700
Clay (%)	426.81	0.415	426.81, 719.47	0.762	426.81,719.47, 885.44	0.771
FC (kg kg^{-1})	426.81	0.429	426.81, 730.47	0.774	426.81, 730.47, 888.44	0.775
WP (kg kg^{-1})	423.45	0.476	423.45, 730.47	0.745	423.45, 730.47, 888.44	0.745
AWC (%)	730.47	0.436	426.81, 730.47	0.748	426.81, 730.47, 892.96	0.765
MWHC (%)	730.47	0.473	426.81, 730.47	0.764	426.81, 730.47, 888.44	0.816
pH (1:2.5)	730.47	0.458	426.81, 730.47	0.664	426.81, 730.47, 882.43	0.826
EC (dS m^{-1})	426.81	0.333	426.81, 730.47	0.560	426.81, 730.47, 8 92.96	0.616
OC (g kg^{-1})	943.88	0.026	943.88, 595.04	0.163	497.81, 595.04, 943.88	0.220
$CaCO_3$ (%)	421.77	0.340	421.77, 730.47	0.534	421.77, 730.47, 897.46	0.609
Ex. Ca [c mol (p^+) kg^{-1}]	426.81	0.503	426.81, 730.47	0.849	426.81, 730.47, 907.97	0.896
Ex .Mg [c mol (p^+) kg^{-1}]	426.81	0.429	426.81, 730.47	0.803	426.81, 730.47, 907.97	0.879
Ex. Na [c mol (p^+) kg^{-1}]	426.81	0.510	426.81, 730.47	0.821	426.81, 730.47, 888.44	0.841
CEC [c mol (p^+) kg^{-1}]	426.81	0.498	426.81, 730.47	0.860	426.81, 730.47, 888.44	0.906
Fe (mg kg^{-1})	730.47	0.334	426.81, 730.47	0.417	426.81, 730.47, 907.97	0.491
Mn (mg kg^{-1})	426.81	0.298	426.81, 730.47	0.437	426.81, 730.47, 892.96	0.490
SiO_2 (%)	719.47	0.251	445.18, 719.47	0.518	426.81, 719.47, 882.43	0.759
Al_2O_3 (%)	930.43	0.0195	615.97, 930.43	0.265	510.85, 615.97, 930.43	0.313
Fe_2O_3 (%)	426.81	0.387	426.81, 730.47	0.671	426.81, 730.47, 907.97	0.841

WL:Wave length; WLs: Wave lengths; R: Correlation co-efficient; R^2: Co-efficient of determination which parameter affects what part of the electromagnetic spectrum. The statistical summary of 20 properties of 54 soil samples of 13 pedons collected from the study area of 3 different Research Stations is given in the Table 1. Characterization of some selected soil parameter was detected with the spectral reflectance in the 350 to 1050 nm range using a multiple linear regression procedure for highly correlated bands (wave length) selection where every possible combination of bands by single, two and three parameter equations. The co-efficient of determination (R^2) obtained between the various soil properties and the multi-parameter spectral reflectance models are shown in Table 2. The best three combinations of three wavelength regression equations for each soil property are shown in Table 3.

The spectral reflectance of soils was decreased with increasing clay content whereas it increased with increasing sand. Sandy loam and sandy clay textured soil samples showed the highest reflectance than clayey soil samples (Fig.1). As per cent sand increased from 19.7 to 73.7 per cent spectral reflectance also increased. The wavelength region for highest correlation for sand was found at 730.47, 1037.7 and 426.81 nm which had an R^2 value of 0.851. The spectral correlation analysis for sand within lower wavelength region (400-500 nm)

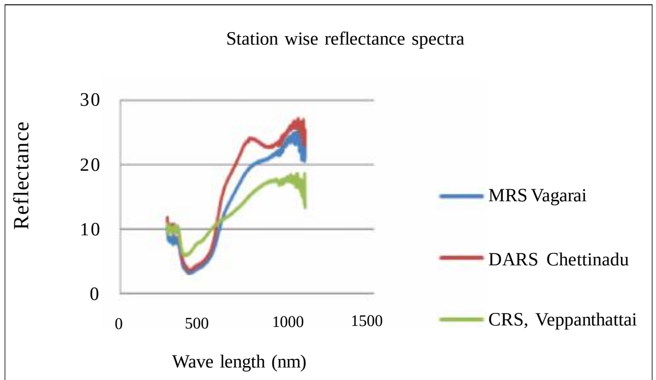

Fig. 1 : Representative station wise reflectance spectra of 3 research stations

was significantly negative and high at 426.81nm but beyond 600 nm, the correlation was significantly positive at 730.47 nm. The high positive correlation may be due to coarse texture of sand with high reflectance. The high negative correlation may be due to low sand with low reflectance. Similar result at VIS-NIR (400-2500nm) was reported Shepherd and Walsh (2002); Cozzolino and Morón (2003) and DeTar *et al*. (2008). The behaviour of soil due to change in texture depend up on the wave length and also influenced indirectly by changing other texture related parameters that affected reflectance.

Table 3 : Prediction equations for relating soil properties (best combination of three parameter model) from reflectance spectra

Model No.	Soil property	Regression equation	R^2
1.	Sand (%)	Y =53.20006-7.11239 (WL 426.81)+2.206842(WL 730.47)-0.43466 (WL1037.7)	0.851
2.	Silt (%)	Y =11.78008+0.985077(WL 420.08)-1.39128 (WL 719.47)+1.073886 (WL888.44)	0.700
3.	Clay (%)	Y =35.92889+5.62618 (WL 426.81)-1.13681 (WL 719.47)-0.27089 (WL885.44)	0.771
4.	FC (kg kg^{-1})	Y =27.55349+6.365475 (WL 426.81)-1.87273 (WL 730.47)+0.392196 (WL 888.44)	0.775
5.	WP (kg kg^{-1})	Y =12.8768+4.85415 (WL423.45)-0.90414 (WL730.47)-0.04257 (WL888.44)	0.745
6.	AWC (%)	Y =14.51789+1.648167 (WL426.81)-0.9579 (WL730.47)+0.419341 (WL892.96)	0.765
7.	MWHC (%)	Y =37.12787+3.044393 (WL 426.81)-2.78442 (WL 719.47)+1.612194 (WL 888.44)	0.816
8.	pH (1:2.5)	Y=7.437749+0.267034 (WL 426.81)-0.53786 (WL 730.47)+0.415557 (WL 8882.43)	0.826
9.	EC (dS m^{-1})	Y =0.090637+0.0479 (WL426.81)-0.03168 (WL730.47)+0.02295 (WL892.96)	0.616
10.	OC (g kg^{-1})	Y =1.5457+0.213428 (WL497.81)-0.43718 (WL595.05)+0.286207 (WL 943.88)	0.220
11.	$CaCO_3$ (%)	Y =0.339642+1.479387(421.77)-1.03555 (WL730.47)+0.816958 (WL897.46)	0.609
12.	Ex. Ca [c mol (p^+) kg^{-1}]	Y =5.313206+4.042192 (WL426.81)-2.088758 (WL730.47)+1.299697 (WL907.97)	0.896
13.	Ex .Mg [c mol (p^+) kg^{-1}]	Y =2.539982+1.187729 (WL426.81)-0.80879 (WL730.47)+0.551717 (WL907.97)	0.879
14.	Ex .Na [c mol (p^+) kg^{-1}]	Y =0.398243+0.432121 (WL426.81)-0.17646 (WL730.47)+0.093326 (WL888.44)	0.841
15.	CEC [c mol (p^+) kg^{-1}]	Y=13.62733+5.891817(WL426.81)-3.26959(WL730.47)+2.06187(WL888.44)	0.906
16.	Fe (mg kg^{-1})	Y =5.202437-0.70013 (WL426.81)+1.496735 (WL730.47)-1.03054 (WL907.97)	0.491
17.	Mn (mg kg^{-1})	Y =20.65049-2.1359 (WL411.62)+1.229098 (WL730.47)-0.96777 (WL892.96)	0.490
18.	SiO_2 (%)	Y=48.83549+1.039142 (WL445.18)-2.20124 (WL719.47)+1.897368 (WL882.43)	0.759
19.	Al_2O_3 (%)	Y=20.8177-0.27456(WL510.85)+0.80360(WL615.97)-0.6138(WL930.43)	0.313
20.	Fe_2O_3 (%)	Y=24.06959-2.23897(WL426.81)+2.491003(WL719.47)-2.04176(WL888.44)	0.841

Y=Predicted value of soil property

The per cent silt and clay in pedon samples were estimated with a reasonable degree of accuracy (R^2 = 0.700 and 0.771) with the combination of wavelengths *viz.*, 420.8, 719.47 and 888.44 nm and 426.81,719.47, and 885.44 nm, respectively. Spectral correlation analysis for silt and clay within lower wavelength region (400-500 nm) was significantly positive and high at 420.08nm and 426.81nm, respectively, but beyond 600 nm, the correlation was significantly negative at 719.47 nm. The high positive correlation at 426.81 nm may be due to finer nature of silt and clay. Similar result at VIS-NIR (400-2500nm) was reported earlier by Viscarra Rossel *et al.* (2006); Shepherd and Walsh (2002) and Cozzolino and Morón (2003). The correlation co-efficient for each constituent during the calibration model construction were found that combination of 3 individual wavelengths (bands), given better co-efficients than single individual wavelength (band) using multiple linear regression (MLR) technique. The goodness of fit in estimating sand, silt and clay from spectral reflectance values are shown in Fig.2, 3 and 4.

The field capacity, permanent wilting point, available water capacity and maximum water holding capacity in pedon samples were found to be detectable with a reasonable degree of accuracy with R^2 = 0.775, 0.745, 0.765 and 0.816, respectively with the reflectance around for the three best combinations of wavelengths at 426, 730, and 890 nm (Fig. 5, 6, 7 and 8). The spectral correlation analysis for correlation within lower wavelength region (400-600 nm) was positive but beyond 600 nm, the correlation was negative and gradually increases upto 730.47 nm. The high positive correlation and low reflectance at 426.81 nm was due to water adsorption bonds (O-H bonds) at lower wavelength region. The correlation was negative and high reflectance at 719.47 nm was due to coarse texture. The availability of field capacity, Permanent wilting point, available water capacity and maximum water holding capacity was obtained by the visible and a portion of near infrared region was mostly effective. Similar result at VIS-NIR

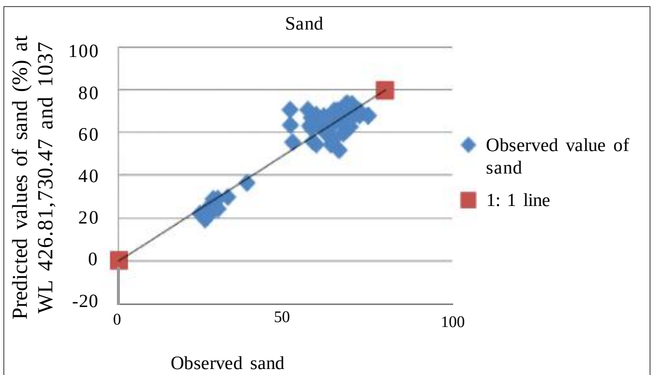

Fig. 2 : Correlation between measured and predicted values of sand

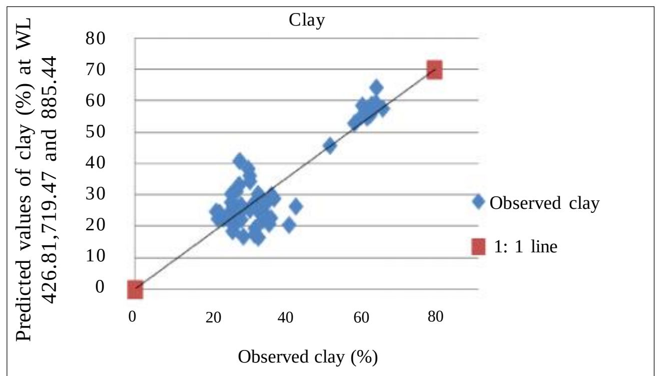

Fig. 4 : Correlation between measured and predicted values of clay

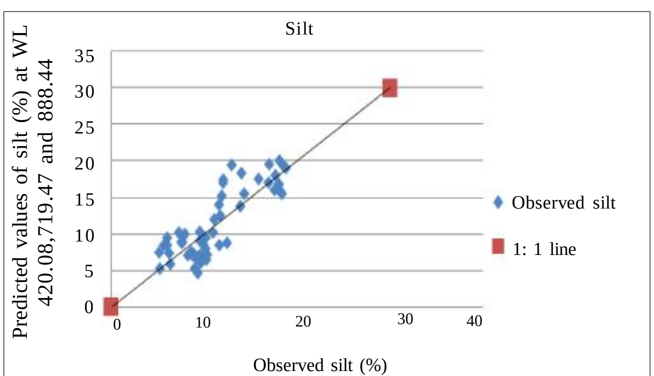

Fig. 3 : Correlation between measured and predicted values of silt

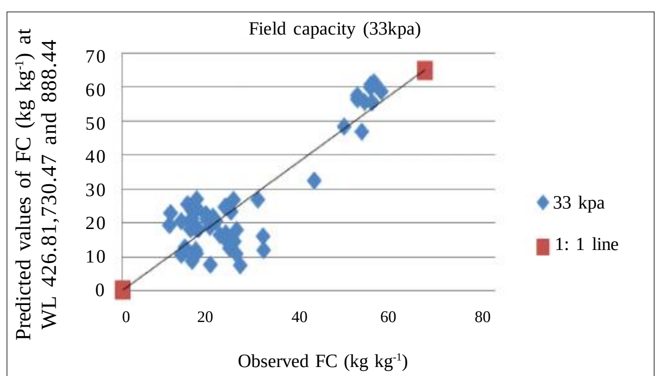

Fig. 5 : Correlation between measured and predicted values of FC

(400-2498 nm) was reported by Chang *et al*. (2001) and Islam *et al*. (2003).

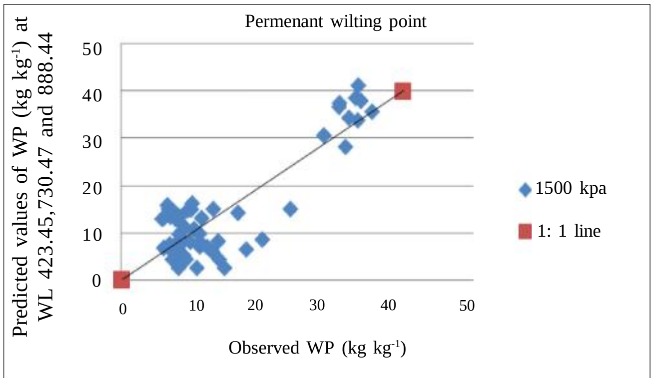

Fig. 6 : Correlation between measured and predicted values of WP

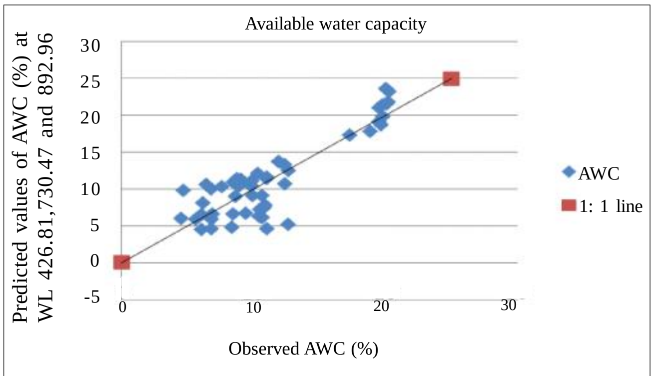

Fig. 7 : Correlation between measured and predicted values of AWC

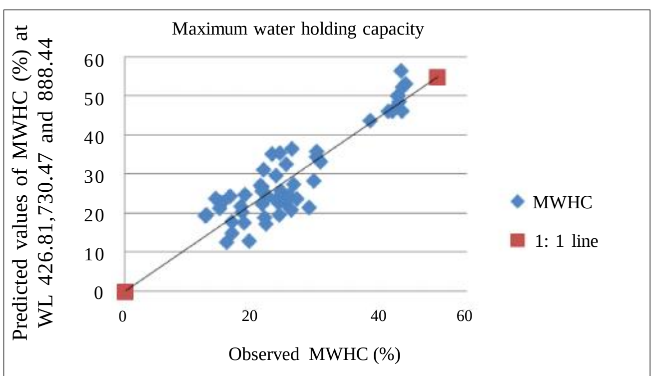

Fig. 8 : Correlation between measured and predicted values of MWHC

The pH is a critical soil property, which has important implications for soil fertility and has diagnostic value in terms of classifying soils. The soil pH was estimated with a reasonable degree of accuracy ($R^2 = 0.826$) from the reflectance of wavelengths around 426, 730 and 880 nm (Fig.9). The electrical conductivity (EC) can serve as an indirect indicator of important soil physical properties. The EC was estimated with a reasonable degree of accuracy ($R^2 = 0.616$) by the combinations of reflectance at 426, 730 and 890 nm (Fig.10). Spectral correlation analysis for soil pH revealed that within the lower wavelength region (400-500 nm) was positive. But beyond 600 nm, the correlation was negative and the highest correlation (-0.677) was obtained in visible region at 730.47nm. Similar result at VIS-NIR (350-2500nm) was reported by Shepherd and Walsh (2002). Spectral correlation analysis for soil EC revealed that the correlation within lower wavelength region (400-500 nm) was positive and highest correlation (0.577) was obtained in visible region at 426.81. But beyond 600 nm, the correlation was negative (-0.453) was obtained in visible region at 730.47nm. Similar result at VIS-NIR (350-2500nm) was reported by Kadupitiya *et al*. (2009) and Islam *et al*. (2003).

Soil organic carbon has unique spectral reflectance characteristics in the visible and near infrared regions.

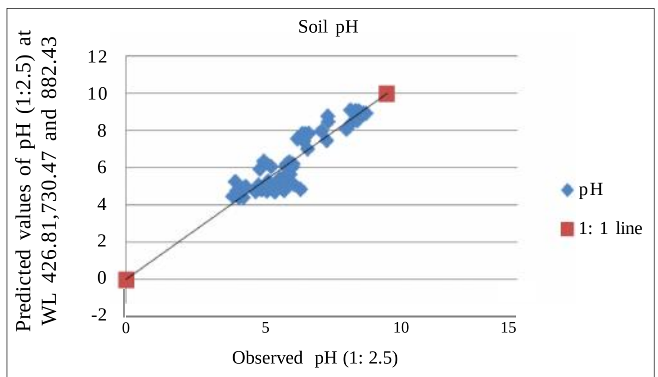

Fig. 9 : Correlation between measured and predicted values of pH

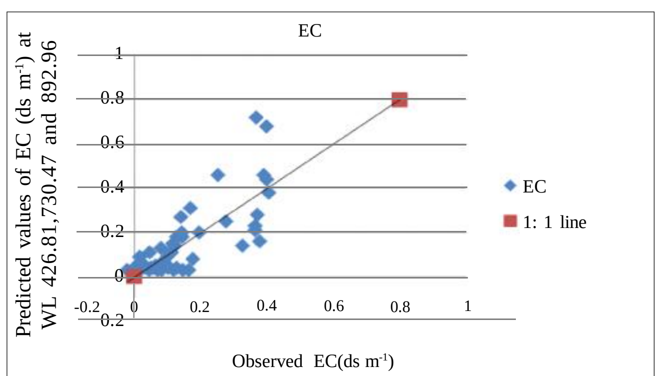

Fig. 10 : Correlation between measured and predicted values of EC

The organic carbon was estimated with poorest fit, with R^2 = 0.220 by the combinations of reflectance at 497, 595, and 943 nm (Fig.11). The spectral correlation analysis for correlation of soil organic carbon was not significant (r=0.020) with reflectance in the visible wavelength region (460-560 nm) at 497.81 nm as well as NIR (847-1030nm) at 943.88 nm (r=0.162). Spectral correlation analysis of organic carbon revealed that the correlation obtained at different wavelength was low which is due to the all the surface and subsurface soils of pedons were poor in availability of organic carbon and at this level no clear trend was established. The findings are in contrast to the work by Islam *et al.* (2003) and David (2009).

The correlation co-efficient of the spectra with calcium carbonate revealed that the higher correlation was estimated with a reasonable degree of accuracy (R^2 = 0.609) by combinations of reflectance at 420, 730, and 890 nm (Fig.12). The spectral correlation analysis for $CaCO_3$ within lower wavelength region (400-500 nm) was significantly positive and high at 421.77 nm. But beyond 600 nm, the correlation was negative at 730.47 nm. The high positive correlation at 421.81 nm was due to the higher reflectance characteristics of the lime content. Similar result at VIS-NIR (400-2500nm) was reported by Kadupitiya *et al*. (2009).

The exchangeable Ca, Mg and Na in samples were estimated with a high degree of accuracy with R^2 = 0.896, 0.879 and 0.841, respectively by the combinations of reflectance at 426, 730, and 900 nm. The prediction of data showing that VIS-NIR can predict the exchangeable Ca, Mg and Na in soil and statistically for predicted exchangeable Ca, Mg and Na are shown in Fig. 13, 14 and 15, respectively. Spectral correlation analysis for exchangeable Ca, within lower wavelength region (400-500 nm) was significantly positive (0.709) and high at 426.81 nm, but beyond 600 nm, the correlation was significantly negative (-0.560) at 730.47 nm. Similar result at VIS-NIR (350-2500nm) was reported by Viscarra Rossel *et al*. (2006) and Islam *et al*. (2003). Spectral correlation analysis for exchangeable Mg within lower wavelength region (400-500 nm) was significantly

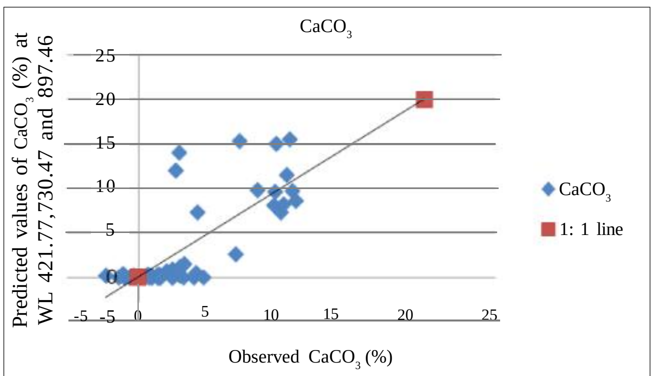

Fig. 12 : Correlation between measured and predicted values of $CaCO_3$

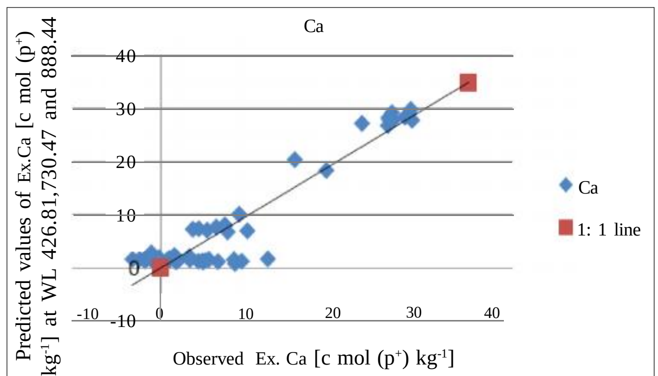

Fig. 13 : Correlation between measured and predicted values of exchangealbe Ca

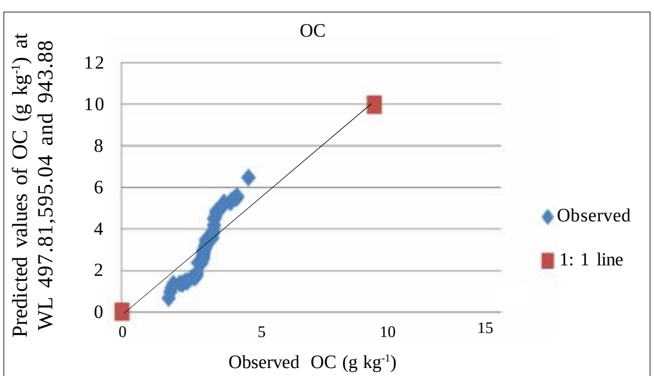

Fig. 11 : Correlation between measured and predicted values of OC

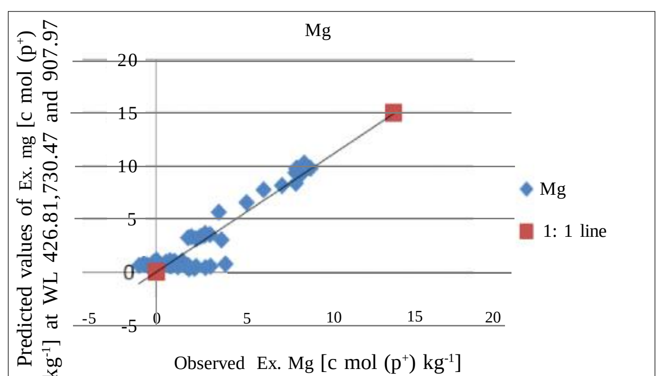

Fig. 14 : Correlation between measured and predicted values of exchangealbe Mg

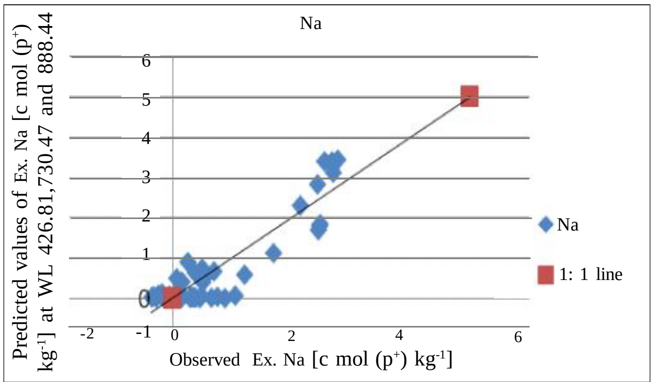

Fig. 15 : Correlation between measured and predicted values of exchangealbe Na

positive (0.653) and high at 426.81 nm, but beyond 600 nm, the correlation was significantly negative(-0.585) at 730.47 nm. Similar result at VIS-NIR (350-2500nm) was reported by Shepherd and Walsh (2002). Spectral correlation analysis for exchangeable Na within lower wavelength region (400-500 nm) was significantly positive (0.714) and high at 426.81 nm, but beyond 600 nm, the correlation was significantly negative (-0.529) at 730.47 nm. Similar result at VIS-NIR (400-2500nm) was reported by Chang *et al.* (2001).

The VIS-NIR can predict the exchangeable CEC in soil with high degree of accuracy with $R^2 = 0.906$ and statistically for predicted exchangeable CEC are shown in Fig. 16, which was highly significant by combination of reflectance at 426, 730, and 888 nm. Spectral correlation analysis for CEC within lower wavelength region (400-500 nm) was significantly positive (0.705) and high at 426.81 nm, but beyond 600 nm, the correlation was significantly negative (-0.573) at 730.47 nm. Similar result at VIS-NIR (350-2500nm) was reported by Chang *et al.* (2001); Shepherd and Walsh (2002) and Islam *et al.* (2003).

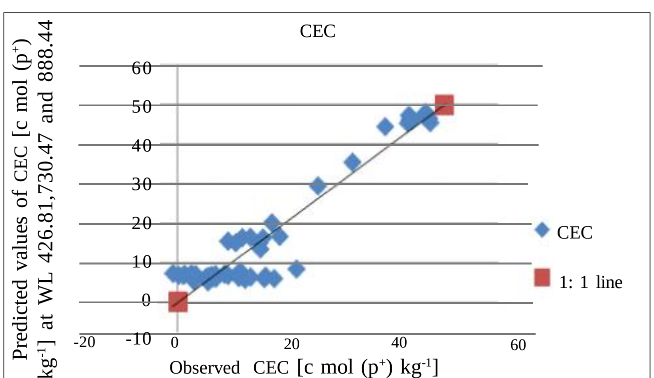

Fig. 16 : Correlation between measured and predicted values of exchangealbe CEC

The SiO_2 was estimated with a good degree of accuracy with $R^2 = 0.759$ by the combinations of reflectance at 426, 720 and 900 nm and statistically predicted SiO_2 is shown in Fig 17. Spectral correlation analysis for SiO_2 within lower wavelength region (400-500 nm) was significantly negative and high at 426.81nm, but beyond 600 nm, the correlation was positive and gradually increases upto 719.47 nm. The Al_2O_3 was estimated with the poorest fit ($R^2 = 0.313$) by the combinations of reflectance at 930.43 510.85 and 615.97 nm (Fig.18). The spectral correlation analysis for Al_2O_3 was negative within visible wavelength region at 510.85 nm and at NIR at 930.43 nm. The correlation was positive at 615.97 nm. The correlation was negative due to low Al_2O_3 content in surface horizons of all pedons and positive correlation which could be attributed due to high Al_2O_3 content in subsurface horizon. The Fe_2O_3 content of soils has been predicted from different spectral regions of the VIS-NIR, based on characteristic absorption features at 426, 730 and 888 nm. The

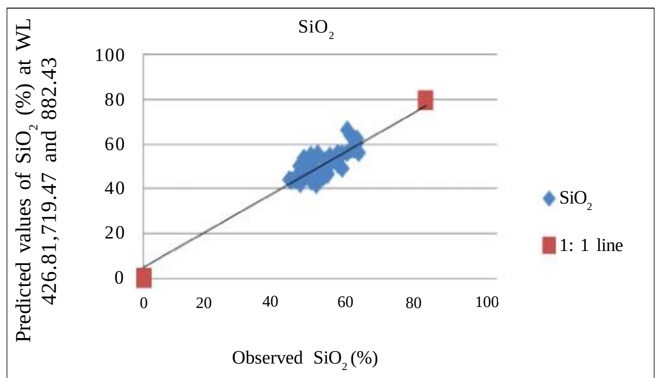

Fig. 17 : Correlation between measured and predicted values of SiO_2

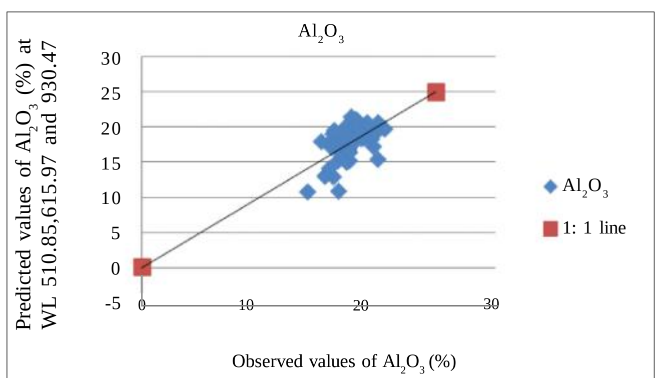

Fig. 18 : Correlation between measured and predicted values of Al_2O_3

prediction of data showing that Fe_2O_3 can estimated with a good degree of accuracy with R^2 = 0.841 (Fig.19). The spectral correlation analysis for Fe_2O_3 within lower wavelength region (400-500 nm) was significantly negative (-0.622) and high at 426.81nm which might be due to the absorption characteristics of the iron oxide. But beyond 600 nm, the correlation was positive (0.573) and gradually increased upto 730.47 nm (r =0.573). Similar result at UV-VIS-NIR (250-2500nm) was reported earlier by Islam *et al*. (2003) and David (2009).

The correlation co-efficient for available Fe and Mn were found to be estimated with reasonable accuracy (R^2= 0.491 and 0.490, respectively) by the combinations of reflectance at 426, 730, and 900 nm. The prediction

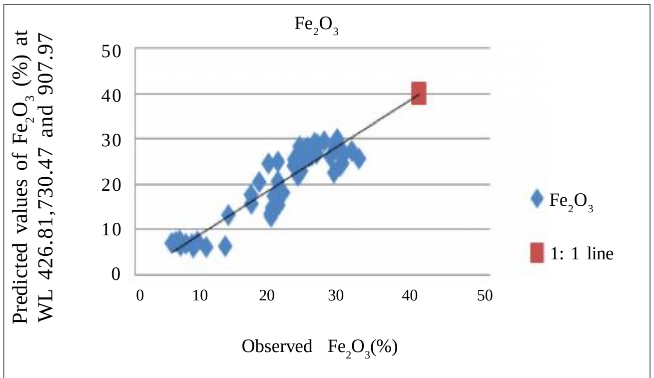

Fig. 19 : Correlation between measured and predicted values of Fe_2O_3

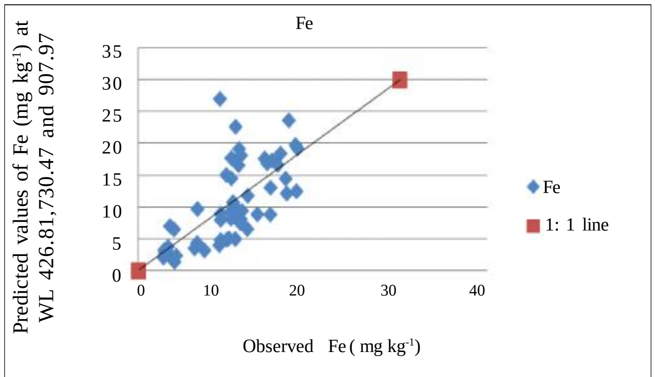

Fig. 20 : Correlation between measured and predicted values of Fe

Table 4 : Soil properties and sensitive spectral regions found from this study compared with past research information

Sr. No.	Soil properties	In this study: Most sensitive spectral region (nm)	In this study: Other sensitive spectral regions (nm)	Other studies: Found in literature (nm)
1.	Sand (%)	426.81,730.47	1037.7	440,540,640,720,860, 400-450
2.	Silt (%)	420.08,719.47	888.44	355-400, 520-620
3.	Clay (%)	426.81,719.47	885.44	355-400, 1500-1730, 902-1165
4.	FC (kg kg^{-1})	426.81,730.47	888.44	400-2498
5.	WP (kg kg^{-1})	423.45,730.47	888.44	400-2498
6.	AWC (%)	426.81,730.47	892.96	-
7.	MWHC (%)	426.81,730.47	892.96	-
8.	pH (1:2.5)	426.81,730.47	882.43	720, 1700, 1860, 700-1100
9.	EC (dS m^{-1})	426.81,730.47	892.96	390-400, 615-625, 685-695, 800-810, 950-960, 745-800, 350-400
10.	OC (g kg^{-1})	497.81,595.04	595.04	1530, 1870, 2180, 500-1200, 900-1200, 1700-2050, 745-815,
11.	$CaCO_3$ (%)	421.77,730.47	897.46	940, 706, 1470, 2260, 1800, 2380, 2340, 2320, 745-800
12.	Ex. Ca [c mol (p^+) kg^{-1}]	426.81,730.47	907.97	471-828
13.	Ex .Mg [c mol (p^+) kg^{-1}]	426.81,730.47	907.97	471-828
14.	Ex. Na [c mol (p^+) kg^{-1}]	426.81,730.47	888.44	400-2498
15.	CEC [c mol (p^+) kg^{-1}]	426.81,730.47	888.44	350-2500
16.	Fe (mg kg^{-1})	426.81,730.47	907.97	600-775, 640,700,900,1000-1100
17.	Mn (mg kg^{-1})	426.81,730.47	892.96	700-775
18.	SiO_2 (%)	445.18,719.47	882.43	960
19.	Al_2O_3 (%)	615.97, 930.43	510.85	-
20.	Fe_2O_3 (%)	426.81,730.47	888.44	550 - 650 , 750 – 950, 250-2500

of data showing that VIS-NIR can predict the Fe and Mn in soils and statistically predicted exchangeable Fe and Mn are shown in Fig.20 and 21. Spectral correlation analysis for correlation of Fe and Mn within lower wavelength region (400-500 nm) was negative at 426.81 nm which might be caused by paired and single Fe^{3+} electron transitions to higher energy state (Sherman and Waite, 1985). But beyond 600 nm, the correlation was positive at 730.47 nm which might be due to reflectance properties related to chemical composition of the soil material mainly based on specific absorption of spectrally active groups (known as chromophores), such as Fe, OH- in water and minerals, CO_3^{2-}, Al^{2+}, (Mg^+) OH, SO_4^{2-} in minerals (Mortimore *et al.*, 2004). The prediction of Fe and Mn was obtained at visible (400 - 500 nm) and near infrared region (700 – 900 nm). Similar result at VIS-NIR (400-2498 nm) was reported by Chang *et al.* (2001) and David (2009). The prediction of data of all the above soil property showing that using combinations of selected narrow bands of blue, green, red and NIR produced higher R^2 values than single narrow bands.The most sensitive spectral regions as found based on correlation for all the above properties are listed in tabular form in Table 4.

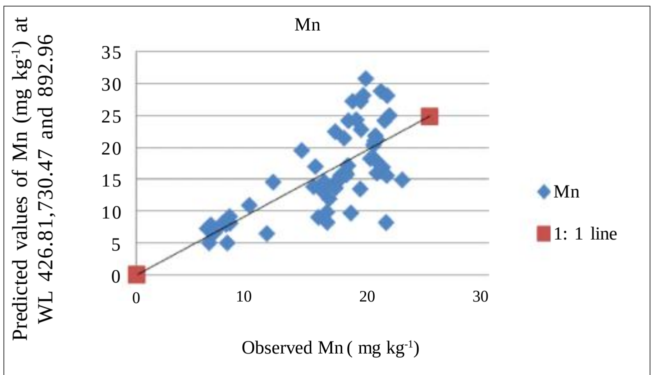

Fig. 21 : Correlation between measured and predicted values of Mn

Conclusion :

Stepwise regression approach was used and results revealed that models developed using spectral data were able to estimate the soil properties with reasonably higher accuracy. The sand, silt, clay, field capacity, permanent wilting point, available water capacity, maximum water holding capacity, $CaCO_3$, exchangeable cations, CEC, SiO_2 and Fe_2O_3 content were best predicted. Validation of R^2 was above 0.5 for all soil properties except organic carbon, Al_2O_3, available Fe and Mn. The highest accuracy (R^2=0.906) was found for CEC while lowest predictability (R^2=0.220) was for soil organic carbon.

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