HYPERSPECTRAL MODELLING FOR PREDICTION OF SOIL TEXTURE USING ASD SPECTRORADIOMETER DERIVED SOIL SPECTRA

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ABSTRACT: Hyperspectral Remote sensing or Reflectance spectroscopy provides an alternate method for non-destructive characterization of key soil properties. Different approaches, including chemometrics techniques or using specific absorption features, have been proposed to estimate various soil properties from visible and near infrared (VNIR, 400-1200 nm) reflectance data. The study was aimed at generation of soil spectral library in the laboratory conditions and predictive modelling of soil texture using various reflectance transformations. 133 soil samples collected from two different sites of Telangana i.e ICRISAT and Shadnagar and covering a wide range of soil textures were pre-processed and analysed in the laboratory for their textural composition (sand silt and clay %). Laboratory spectra of all soil samples were collected using ASD spectroradiometer (covering range of 350-2500 nm), after pre-processing. Spectral library of all soil samples were generated by taking averaging of 5 spectra. Fourteen distinct reflectance transformations were generated for each sample from lab generated spectra. Partial Least Square Regression (PLSR) modelling was used for prediction of soil texture using these reflectance transformations, employing Unscrambler software. Many of these reflectance transformations showed accurate predictions (high R^2 values) for sand, silt and clay textural fractions. The PLSR modelling revealed best results for the Root R transformation of reflectance where (R^2= 0.47, RMSE= 6.67) for clay, (R^2= 0.73, RMSE =10.33) for sand and (R^2= 0.54, RMSE= 9.59) for silt particle sizes. Similarly, R, log R and 1/R transformations also yielded satisfactory predictions for soil particle size. The study showed us the potential of hyperspectral modelling employing PLSR technique for predicting soil texture and may help us in the spatial mapping of soil texture types using airborne and space borne hyperspectral remote sensing data.

1. INTRODUCTION

Soil texture is an inherent property of any given soil which is rarely altered by land management practices but plays a key role in moderating almost all other soil properties. From nutrient supplying capacity to infiltration rate, soil aeration to water holding capacity, an array of such soil properties are heavily dependent on soil texture. Thus capturing the spatial variability of texture over a large scale is an important prerequisite for adoption of suitable land management practices. However, the present laboratory methods of soil texture estimation (international pipette method, hydrometer method) are labour intensive and time consuming and requires large number of samples. These complexities associated with the conventional methods of texture determination are currently driving the scientific community to develop indirect estimation methods based on proximal and remote sensors (ground based, airborne or satellite based), including reflectance spectroscopy. Remotely sensed data are useful when they are combined with numerical modelling and ground based information. For studying the soil properties of large area through remote sensing we need to extract and process the small ground based information. By applying the ground based modelling over the satellite data we can predict the soil properties of whole area covered by satellite.

Chemometric techniques, which utilizes visible and near infrared and shortwave infrared reflectance domains to predict various soil properties can be effective alternative to the conventional texture determination procedures. These techniques are low cost, less time and labour intensive and helps in prediction of soil properties with reasonable accuracy based on their reflectance characteristics in 400 – 2500 nm wavelength range. Of the various multivariate statistical techniques used to relate the soil spectrum to soil attributes, the partial least- Squares Regression (PLSR) technique is most prominent and widely adopted by researchers across the globe (Chang and Laird, 2002; McCarty *et al*, 2002; Conforti *et al*, 2015; Viscarra Rossel, 2008). PLS regression is particularly suited when the matrix of predictors has much more variables than the number of observations, and when multicollinearity exists among predictors (X variables). Compared to other multivariate statistical techniques, PLSR is generally preferred because it is more understandable and the algorithm is computationally faster (Curcio et al, 2013). The present study was aimed to generate spectral library of the soil samples and do predictive modelling of soil texture using various spectral transformations employing PLSR technique.

2. STUDY AREA

This study was carried out at two sites namely ICRISAT and Shadnagar sites in the state of Telangana, located at the southern portion of India (Fig 1). ICRISAT site is located in and around Patancheru in Sangareddy District, whereas Shadnagar site is located in Ranga Reddy District of Telangana. Both the study areas were approximately 20km x 10km (Total swath covered by airborne survey). The swath covered includes large stretches of agricultural fields, where variety of crops are cultivated throughout the year and thus was identified for crop and soil related studies using AVIRIS data. Major crops cultivated in both the areas are rice, maize, cotton, Bengal gram, red gram and various vegetables like cabbage, tomato, brinjal etc at various locations. Shadnagar site had much more fallow area compared to ICRISAT site and was found to be much drier than ICRISAT site. Majority of the area is under rice based cropping systems. During the field survey, various crops at different growth stages and conditions were identified. The major soil types present in both the sites are red soil, black soil and mixed soil.

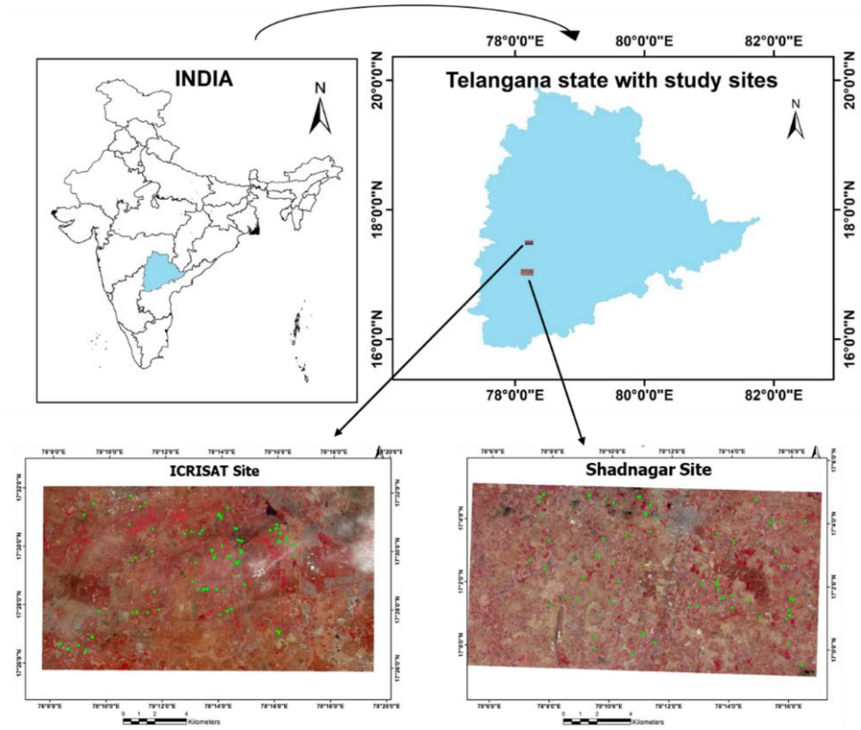

Fig 1: Study site locations within Telangana state and the FCC of both sites indicating GPS locations of sampling locations

3. METHODOLOGY

The overall methodology adopted in the study is depicted in the Fig 2

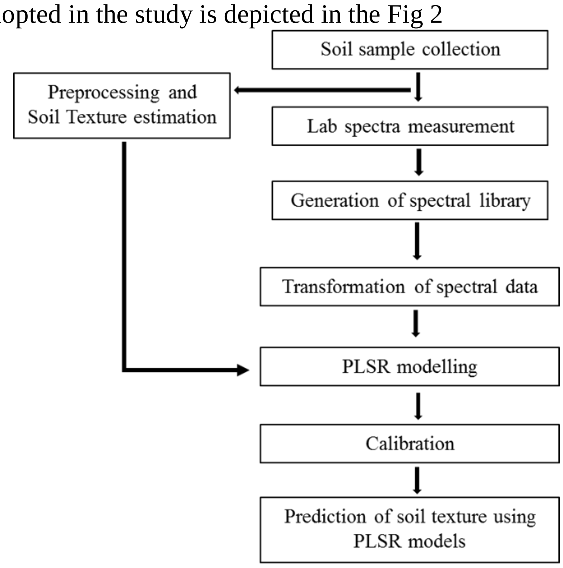

Fig 2: Flow chart of the overall methodology adopted in the study

3.1 Sampling Strategy

The sampling areas and sites were determined by interpretation of high resolution image (LISS IV and Cartosat) of the study area, which helped us to identify large agricultural patches and even helped us in identification of fallow as well cropped fields. The entire area was traversed with the help of satellite image and GPS. In the field, local variations were given importance, including change in soil colour, crop type and growth variations, land use land cover type etc. The study area was divided into grids for sampling purpose. The coordinates of each sampling location was recorded using GPS as well as the data was collected and uploaded using format described in Bhuvan Crop AVIRIS android app.

3.2 Soil Sample Collection, Pre-Processing and Soil Texture Analysis

Soil samples were also collected from various sampling locations, depending on the local variability and soil characteristics. The soil samples were collected by quartering process by mixing soil from different points in the area and then dividing them into required quantity (400 gm each). Thus during the field campaign at both sites, 133 soil samples were collected along with their GPS locations from various sampling locations including different cropping systems, depending on the local variability and soil characteristics.

These samples were carried to the laboratory and were pre-processed for sample preparation. The samples were air dried in the laboratory, then crushed gently using a mortar and pestle to break down larger aggregates. Afterwards, visible plant roots and other debris were removed and each sample was sieved through 2 mm sieve to obtain homogenized samples and were then quartered. These procedures were aimed to homogenize the moisture as well as roughness of various soil samples, thus reducing their adverse effects on soil spectroscopic measurements, to a large extent. These homogenized soil samples were divided into two parts, one part for analysis of soil texture as well as other soil properties and other part for the generation of reflectance spectra in the laboratory.

Soil texture i.e., the relative proportion of primary soil particles (sand: 2-0.05mm, silt: 0.05-0.002 mm and clay: <0.002 mm) was determined by dispersing soil samples in distilled water using sodium hexametaphosphate followed by Bouyoucos hydrometer method (Bouyoucos, 1962). Later the textural classes of samples were determined using the United States Department of Agriculture soil texture triangle (USDA, 2010).

3.3 Lab Spectra Measurement/Laboratory VNIR spectroscopy

The laboratory reflectance spectra (in the wavelength range of 350 – 2500nm) of pre-processed and 2m sieved soil samples were measured using Analytical Spectral Device (ASD) FieldSpec IV Spectroradiometer (Analytical Spectral Devices Inc., Boulder, Colorado, USA), under controlled dark room conditions. Precautions were taken to avoid stray light as well as dark current generated within the instrument and instrument was calibrated using white reference panel (Spectralon diffuse reflectance panel, provided along with the instrument) at the start as well as after every five successive reflectance measurements. The sieved soil samples were subjected to ASD spectrometer in a 9 cm diameter petri plate painted black and then kept over a dark piece of cloth. The surface of soil samples was levelled using the edge of a spatula to obtain a smooth and uniform surface. The spectra were collected from nadir with the help of a contact probe with in-built illumination source, at 1nm spectral resolution, after real time viewing. Each soil reflectance spectra were recorded using the instrument as the average of 25 consecutive scans, in order to minimize the noise levels of spectral signature. Besides, the measurement was repeated 5 times, by rotating each sample 90 degrees (0, 90, 180, 270 and 360 degrees) in order to avoid any possible spectral anomalies and errors due to measurement geometry and stray light. Thus for each soil sample, five spectra were collected and averaged out to generate spectral library, during pre-processing.

The reflectance spectra collected in ASD binary file format was converted into ASCII format using View SpecPro software (Analytical Spectral Devices, Inc., Boulder, CO, 80301). The ASCII files were then imported into ENVI 5.0 version software and spectral libraries were created.

3.4 Generation of Reflectance Transformations

Before doing hyperspectral modelling for soil texture prediction using statistical techniques, spectral pre-processing was done to reduce noise and enhance absorption features (Naes et al., 2004). Various reflectance transformations sensitive to different soil properties were identified by a thorough literature survey. He *et al* (2008), Wang *et al* (2013), Curcio et al (2013), Li *et al* (2014) and Conforti *et al* (2015) have given a detailed account regarding the generation of various reflectance transformations and their use in quantitative modelling of various soil properties including soil organic matter as well as soil texture. On the basis of all these studies, 15 different reflectance transformations (Table 1) were identified and used in the present study to evaluate their potential for quantitative prediction of soil texture. The spectral libraries generated for each sample was used for the generation of reflectance transformation.

Table 1: Different reflectance transformations used in the study and their formulae

Different Transformations and formulas	
Description	**Formula**
Reflectance	R
Logarithm of R	Log R
Square root of R	$\sqrt{R}$
Reciprocal of R	1/R
Reciprocal of Log R	1/log R
Reciprocal of root R	$1/\sqrt{R}$
First derivative of R	R’
First derivative of log R	(log R)’
First derivative of root R	$\sqrt{R}$’
First derivative of 1/ R	(1/R)’
First derivative of 1/log R	(1/log R)’
First derivative of $1/\sqrt{R}$	$(1/\sqrt{R}$)’
Second derivative of R	R”
Second derivative of root R	$\sqrt{R}$”
Second derivative of Log R	(log R)”
Second derivative of 1/R	(1/R)”

Different transformations of reflectance value aids us in hyperspectral modelling for soil properties prediction by means of removing the noises (linear or linear-like as well as multiplication noise), removing the additive baseline (“offset”) as well as linearizing the correlation (originally non-linear) between measured reflectance and soil physico-chemical properties (He *et al*., 2008 and Curcio et al., 2013). In the study, not only the reflectance derivative was calculated, but also the first order and second order derivative of four transforms of reflectance (logarithm, reciprocal, square root and logarithmic reciprocal) were also calculated.

3.5 Multivariate statistical modelling

Among the various multivariate statistical methods available for chemometric analysis, Partial Least Square Regression (PLSR) technique was used for predictive modelling of soil texture using various reflectance transformations. PLSR is a common Vis-NIR calibration technique, which is known for its simplicity, precision, predictability and clearly quantitative explanations (Martens and Naes, 1989; Naes et al., 2004; Viscarra Rossel et al., 2006). PLSR generalizes and combines features from PCA and multiple regression and is particularly useful to predict a set of dependent variables from a (very) large set of independent variables (i.e., predictors). PLSR is generally preferable because the algorithm is computationally faster and it is more understandable. PLSR tries to find a few components or factors (linear combinations) of the spectral data (original X values) and use them in regression equations for predicting observed variable (soil properties). The PLSR technique uses data compression to reduce the large number of measured collinear spectral variables to derive a few statistically significant non-correlated factors or latent variables. These latent variables are orthogonal factors which maximize the covariance between dependent (y) and independent (x) variables and explain majority of the variations in predictors and responses. Thus PLS regression is suited and widely used in cases when the predictor matrix (eg: spectra) has more variables than the total number of observations and multicollinearity exists among X variables.

The latent variables were chosen by a random cross-validation procedure using the same samples. Pre-treatment of data, regression calculations and PLSR modelling using all the reflectance transformations for soil textural prediction was performed using the Unscrambler X 10.5 software (Camo Inc. 2006). In order to know the accuracy of the PLSR regression models, entire dataset of 133 observations was randomly split into two: the calibration dataset (comprising 80 samples, i.e., 60% of total data set) for prediction model development and the validation dataset (comprising 53 samples, i.e., 40% of total data set) for testing the accuracy of the developed model. Random cross-validation was done to test the predictive significance of each PLSR component and to determine the total number of factors (latent variables) to be retained in the final calibration model. The goodness of prediction of the cross validated models were checked using the coefficient of determination (R^2) and the root mean square error (RMSE), with the cross validated models having highest R^2 and lowest RMSE values chosen as the best. The chosen models were later independently tested using the validation data set, and the overall prediction accuracy was checked using various statistical parameters like coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean absolute Difference (MAD), Efficiency Coefficient (E), using the observed (O_i) and predicted (P_i) values (Curcio *et al.*, 2013).

4. RESULTS AND DISCUSSION

The basic descriptive statistics of sand, silt and clay textural fractions of complete, calibration as well as validation data sets are given in Table 2. The sand content for the complete data set has a mean value of 53.68% and ranges from 27.16 to 85.16 %. Most of the soil samples had higher sand content in comparison to silt and clay. The silt content of complete data set varied from 1.28 to 55.28 % with a mean value of 23.11%, whereas the clay content was found to vary from 6.84 to 38.84 % with a mean value of 23.19%. The data appeared to follow quite symmetric frequency distribution, as revealed by low skewness values (Table 2). The textural fraction distributions at the two sampling locations are depicted in Fig 3. The soil samples from Shadnagar site had higher sand content in comparison to ICRISAT site, whereas silt and clay contents were found to be higher in samples collected from ICRISAT area (Fig 3). The soil samples were found to belong to various soil textural classes mainly loam, sandy clay loam, clay loam, sandy loam, sandy clay and silt loam, with majority of samples belonging to first four classes.

Table 2: Descriptive statistics values of complete, calibration and validation data sets for different textural fractions

Soil Textural Fractions	Data set	Count	Mean	Median	Standard deviation (%)	Minimum	Maximum	Skewness
Sand (2-0.05mm)	Complete	133	53.68	53.16	14.28	27.16	85.16	0.19
	Calibration	80	49.64	47.16	12.77	28.80	77.16	0.38
	Validation	53	59.79	59.88	14.38	27.16	85.16	-0.25
Silt (0.05 - 0.002mm)	Complete	133	23.11	23.28	12.11	1.28	55.28	0.21
	Calibration	80	26.68	29.28	12.28	3.64	55.28	-0.12
	Validation	53	17.73	15.28	9.70	1.28	41.28	0.49
Clay (<0.002mm)	Complete	133	23.19	23.56	6.32	6.84	38.84	-0.06
	Calibration	80	23.68	23.56	5.57	6.84	37.56	-0.37
	Validation	53	22.47	22.48	7.30	8.84	38.84	0.27

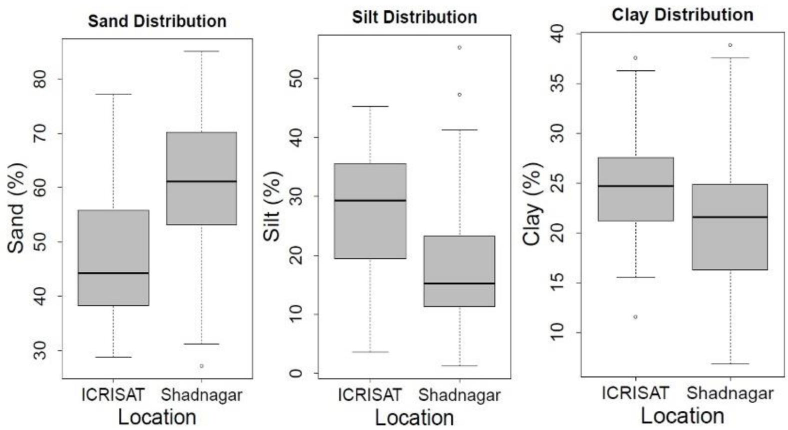

Fig 3: Textural fraction distributions at the two sampling locations

4.1 Spectral Analysis and PLSR modelling for soil textural fractions

Reflectance spectra generated by laboratory measurements was used for the spectra library generation and further spectra analysis including reflectance transformations. All the soil samples exhibited characteristic reflectance spectra in the Vis-NIR region in corresponding to various molecular groups or chemical and/or mineralogical components (Dematte and Terra, 2014). Lower reflectance values were observed in the visible region (400-700nm) increasing gradually in the near infrared region (700-2500nm), with prominent absorption peaks/regions around 1400, 1900 and 2200nm wavelengths. The peaks at 1400 and 1900 nm is associated with the hydroxyl group of free water while the 1400 and 2200 nm absorption features are associated with clay minerals and lattice –OH features (Ben-Dor, 2002; Viscarra Rossel et al., 2006). Additionally, the 2200nm feature is also associated with various organic functional groups like CH_2, CH_3 etc, SiOH bond or cation-hydroxyl bonds in the various clay mineral (Clarke et al, 1990).

Visual analysis of the reflectance curves revealed that the shapes of the curves and the intensity variations can be attributed to the textural differences because of the strong correlation between soil texture and shape of spectra

(Mouazen et al, 2005). Fig 4a clearly shows the differences in the mean spectral curves of dominant soil textural classes. The red soil samples showed higher reflectance in the red wavelength region of visible range.

The sandy loam and sandy clay loam soils were found to have relatively higher reflectance in comparison to other classes. This may be attributed to the higher sand content and thus the dominance of quartz fraction, which increased the overall spectral reflectance intensity (White et al, 1997).

The various reflectance transformations done using the average spectral library of dominant textural classes are given in Fig 4b onwards. The various transformations helped to reduce the various types of noises in spectra in addition to their effects in enhancing the different absorption features.

A statistical summary of the PLSR models developed using various spectral transformations for soil textural prediction is given in Table 3. The transformations which yielded models with moderate to high values for coefficient of determination (*R^2>0.5*) during calibration and cross-validation are only included here. The latent variables/prediction factors used in the development of final calibrated models were 03 for sand, 02 for silt and 05 for clay textural fractions. These were selected on the basis of the results of cross-validation procedure i.e., highest R^2 and lowest RMSE values.

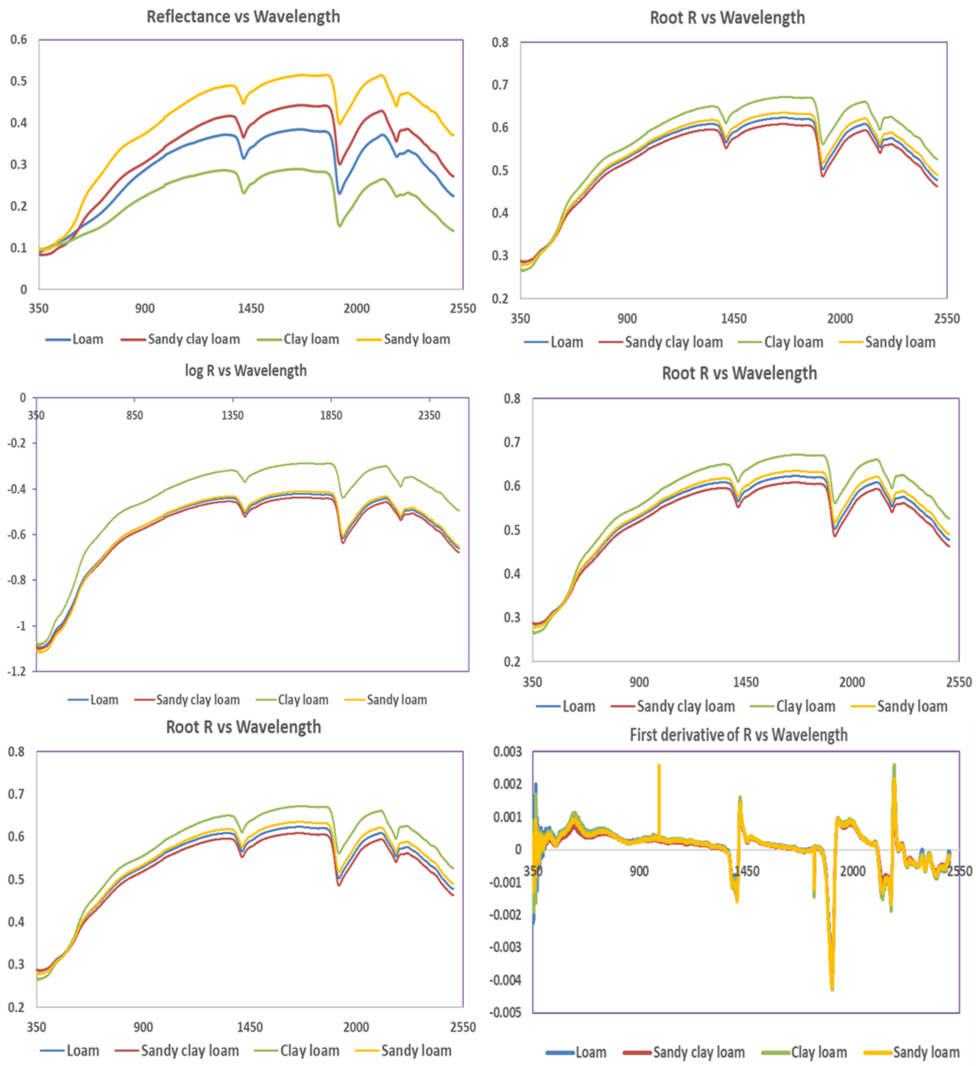

Fig 4: Mean reflectance spectra of dominant soil textural classes and various reflectance transformations

Among the 15 reflectance transformations along with reflectance spectra, 08 yielded satisfactory results during model calibration and validation phases (Table 3), whereas the first and second derivative spectrum of root R, reciprocal of R, reciprocal of log R and reciprocal of root R failed to yield well calibrated models.

In case of sand fraction, all the 08 transformations yielded satisfactory calibration models with R^2 > 0.6, which were later validated using an independent dataset and the statistical parameters. Model developed using root R was found to give most accurate prediction among them, with R^2 = 0.73 and RMSE value of 10.33. Reflectance model also yielded a similar result during validation, with a slightly lower R^2 value of 0.71 and an RMSE value of 10.63, followed by the models using 1/root R (R^2 = 0.67 and RMSE = 10.33) and log R (R^2 = 0.67 and RMSE = 12.31). All the other models exhibited lower R^2 (<0.65) and higher RMSE values during validation (Table 3). These results were confirmed by the MAD (root R: 11.13%, R: 11.49%, 1/root R: 13.15% and log R: 13.42%) and E values (root R: 0.67, R: 0.65, 1/root R: 0.56 and log R: 0.53).

Table 3: Statistics of various soil textural prediction models developed using spectral transformations employing PLSR technique

Soil textural fractions using PLSR approach							
Spectral transformation	**Soil texture**	**Calibration (N=80)**		**Prediction (N=53)**			
		R^2	**RMSE**	**R^2**	**MAD**	**RMSE**	**E**
R statistics	Sand	0.66	7.36	0.71	11.49	10.63	0.65
	Silt	0.53	8.30	0.49	9.69	9.69	0.36
	Clay	0.34	4.85	0.45	7.24	6.89	0.43
Log R statistics	Sand	0.65	7.47	0.67	13.42	12.31	0.53
	Silt	0.52	8.44	0.46	11.93	11.08	0.17
	Clay	0.50	4.54	0.40	7.38	7.09	0.40
Root R statistics	Sand	0.68	7.09	0.73	11.13	10.33	0.67
	Silt	0.54	8.22	0.54	9.97	9.59	0.37
	Clay	0.51	4.48	0.47	6.89	6.67	0.47
1st Derivative R	Sand	0.62	7.8	0.55	14.35	13.37	0.45
	Silt	0.59	7.79	0.49	10.26	10.34	0.30
	Clay	0.63	3.36	0.14	8.64	8.51	0.14
1st Derivative Log R	Sand	0.63	7.69	0.49	15.7	8.39	0.34
	Silt	0.65	7.42	0.37	12.42	12.06	0.2
	Clay	0.47	4.0	0.16	8.73	8.39	0.16
1/R statistics	Sand	0.64	7.55	0.64	14.09	10.33	0.50
	Silt	0.52	8.49	0.53	11.17	9.59	0.30
	Clay	0.29	5.45	0.14	8.49	6.67	0.14
1/Log R statistics	Sand	0.64	7.5	0.57	13.69	12.24	0.54
	Silt	0.30	10.5	0.36	12.18	11.40	0.12
	Clay	0.49	5.3	0.12	8.55	8.59	0.12
1/ Root R	Sand	0.69	7.05	0.67	13.15	10.33	0.56
	Silt	0.53	8.32	0.51	11.16	9.59	0.28
	Clay	0.57	5.37	0.25	8.01	6.67	0.25

In case of silt fraction, we could generate moderately accurate models (R^2>0.5) during calibration using seven out of the eight transformations (except 1/log R) listed in Table 3. But when these calibrated models were tested for their prediction ability using the validation dataset, models developed using log R and first derivative log R failed to give good prediction accuracies compared to others (low R^2, high RMSE and low E values). Model developed using root R was found to give most accurate prediction among them, with R^2 = 0.54 and RMSE value of 9.59 and subsequently confirmed by low MAD (9.97) and high E (0.37 values). Models developed using 1/R and 1/root R also yielded similar results during validation, with slightly lower R^2 values (0.53 and 0.51 respectively) and similar RMSE value (9.59 for both models) followed by the models developed reflectance and first derivative reflectance spectra. These findings were confirmed by the MAD as well as E values of respective models.

During the model calibration for clay fraction, we could generate moderately accurate models (R^2 > 0.5) using four out of the eight transformations (except R, first derivative of log R, 1/R and 1/log R) listed in Table 3. When these four selected models were tested for their prediction ability using the validation dataset, only two models i.e., log R and root R gave good results. Model developed using root R was found to give most accurate prediction among them, with R^2 = 0.47 and RMSE value of 6.67 followed by log R with R^2=0.40 and RMSE value of 7.09. Both of these models showed low MAD and high E values in comparison with others. In case of model developed using reflectance data, even though the model showed lower R^2 value (0.34) during calibration, the prediction accuracy using validation dataset was found to be quite satisfactory at par with root R model, with an R^2 value of 0.45, RMSE of 6.89 and an E value of 0.43.

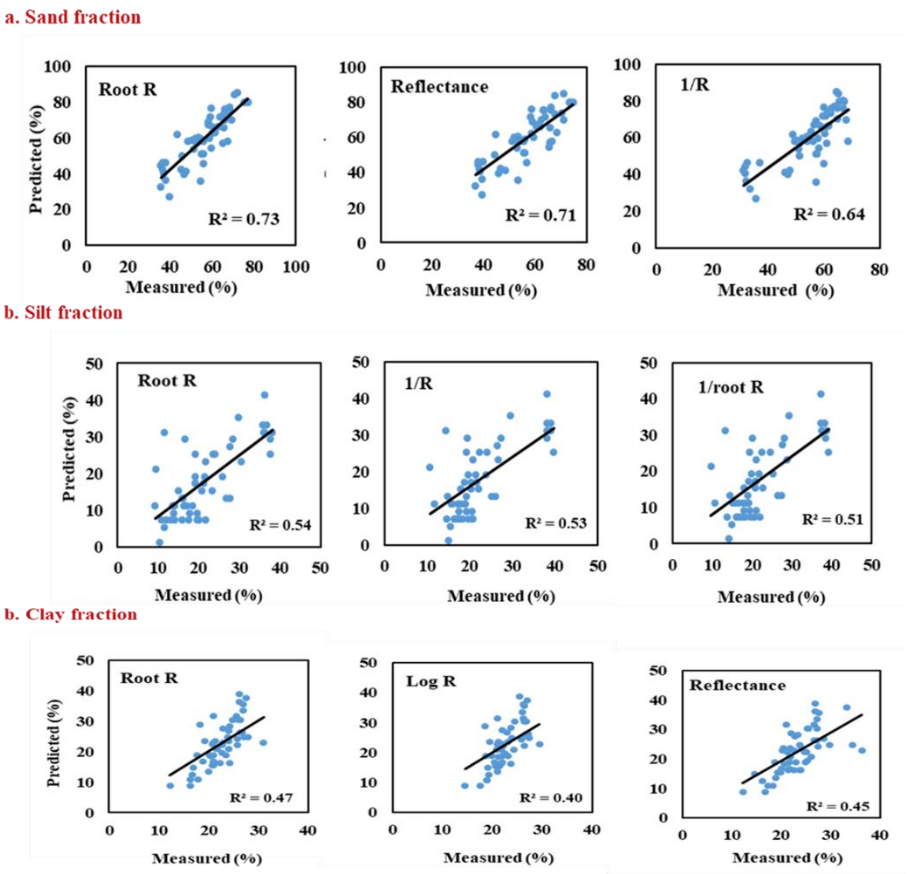

Fig 5: Measured vs Predicted scatter-plots of the three best performing models for different soil textural fractions (R^2: coefficient of determination)

5. CONCLUSION

Soil texture is a vital inherent property of any given soil which plays a key role in moderating almost all other soil properties. The main objectives of this study were to generate various spectral transformations using the laboratory based spectral libraries of different soil samples and predictive modelling using them for soil textural prediction in the semi-arid tropical region of India. PLSR, a prominent multivariate statistical technique was used for developing soil textural prediction models using various spectral transformations along with reflectance data. The sandy loam and sandy clay loam soils were found to have relatively higher reflectance in comparison to other textural classes. Root R transformation was found to give the best satisfactory results for prediction of various soil textural classes during calibration and validation phases of model development. Various other spectral transformations like 1/R and log R also gave good prediction results along with reflectance data for different textural classes. These results may help us in developing techniques and optimal settings for various airborne as well as space borne hyperspectral sensors for accurate mapping of soil texture as well as other soil properties on a large spatial domain.

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