Hyperspectral remote sensing: opportunities, status and challenges for rapid soil assessment in India

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Rapid and reliable assessment of soil characteristics is an important step in agricultural and natural resource management. Over the last few decades, diffuse reflectance spectroscopy (DRS) has emerged as a new tool to obtain both qualitative and quantitative information on soil in a non-invasive manner. The DRS approach is attractive because both the proximal and remote mode of measurements may be adopted to estimate multiple attributes of soil such as physical and chemical soil properties and nutrient contents from a single reflectance spectrum. Hyperspectral imaging cameras onboard remote sensing platforms are already providing hundreds of narrow, contiguous bands of reflectance values and the technology is becoming popular as the hyperspectral remote sensing (HRS) approach. The main objective of this review is to summarize the preparedness and opportunities for using the HRS approach for soil assessment in India. Detailed literature review suggests that the HRS approach requires large spectral databases and robust spectral algorithms in addition to the capability to interpret HRS images. Over the last decade, few efforts have been made to create spectral libraries for Indian soils. However, most of these libraries are very small, precluding the development of robust spectral algorithms. Specifically, the availability of HRS data and robust retrieval algorithms for soil properties from HRS data through unmixing procedures require special attention. With several global initiatives to make HRS data available, coordinated efforts are needed in India to build comprehensive spectral libraries, algorithms and create trained human resources to take full advantage of this emerging technology. Specifically, a dedicated spaceborne mission will provide quality hyperspectral data for the effective application of HRS for soil assessment in India.

Keywords: Hyperspectral remote sensing, reflectance spectroscopy, soil assessment, spectral databases and algorithms.

Introduction

RAPID and reliable assessment of soil characteristics is an important step in agricultural and natural resource management. In general, soils are opaque to most sensing methods. For example, microwave radiations penetrate only a few centimetres of the topsoil; visible (VIS) and infrared radiations can barely penetrate through the soil surface. Consequently, most soil assessments are performed under laboratory conditions. Laboratory methods used for estimating soil chemical properties are based on wet chemistry with tedious and time-consuming sample preparation and analyses steps. Assessment of soil physical attributes generally takes a longer time than chemical attributes. Soil properties widely vary both in time and space[1]. Consequently, rapid and *in situ* assessment of soil properties even in near-real time remains a formidable task despite decades of research and development in soil testing.

Over the past few decades, remote sensing approaches provide some solution for rapid soil assessment[2]. These approaches are fast, nondestructive and have large spatial coverage. There are four factors that influence the remote sensing (especially optical) signature of soil – mineral composition, organic matter, soil moisture and texture[3]. Remote sensing data have been used for soil classification, soil resources mapping[4,5], soil moisture assessment[6] and soil degradation (salinity) mapping[7] among many others. Particularly, hyperspectral remote sensing (HRS) is emerging as a promising tool for its capability to measure the reflectance of earth surface features such as soil, water, vegetation, etc. at hundreds of contiguous and narrow wavelength bands. Availability of such a large pool of spectral information offers an opportunity to estimate multiple soil attributes from the same reflectance

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spectra with greater specificity than their multispectral counterpart.

Diffuse Reflectance Spectroscopy (DRS) in the VIS, Near-Infrared (NIR), and Shortwave-Infrared (SWIR) regions (350–2500 nm) forms the basis of HRS. Chemical bonds of different molecules vibrate at characteristic frequencies when exposed to electromagnetic energy. Energy absorbed, reflected and scattered in the process may, therefore, be related to specific wavelengths[8]. Such specificity (reflectance at characteristic wavelength) may be treated as a unique spectral feature in unique correspondence to the composition of the end-member. In particular, the specificity allows for the assessment of different soil attributes once spectral reflectance is known and a relationship between the spectral feature and soil attribute is known a priori. Thus, spectral signatures are often considered as inherent soil properties that vary across different soils[9].

Laboratory-scale studies have clearly shown that the DRS approach may be used for estimating several soil properties such as soil texture[10], organic carbon (OC) content[11–13], nutrient content such as nitrogen (N)[14], phosphorus (P), potassium (K)[15], electrical conductivity (EC)[16], cation exchange capacity (CEC)[17], iron (Fe) content[11], soil moisture content[18], carbonates[19] and hydraulic properties[20]. Recently, the DRS approach was shown to be successfully used for estimating the parameters (median aggregate diameter and standard deviation) of lognormal aggregate size distribution function of soils[21]. Several reviews demonstrate the potential of the DRS approach as an emerging technology in soil assessment[9,22].

To utilize the HRS technology, high-resolution optical and thermal sensors are used to first create a spectral repository of reflectance spectra under controlled laboratory conditions with associated soil properties. Such spectral libraries are then used for developing spectral algorithms, for transforming processed hyperspectral signals into meaningful soil attributes. Although a few spectral libraries exist in developed countries, regional databases on basic soil properties and soil reflectance spectra are still being created in different parts of the world. Recently, a global spectral library with 3768 soils was developed in which only 104 soils were from the whole of Asia[23]. In India, only a fewer spectral libraries with different soil properties exist[20,60,61]. With a large variation in soil properties across our country, there is a requirement for developing more extensive spectral libraries representing specific regions and rightly there are initiatives to expand existing spectral libraries into a national soil spectral library[24,25]. In this article, fundamentals of DRS technology as applied to soil studies have been presented. Spectral libraries for typical Indian soils have been summarized. The preparedness and opportunities for combining the developed spectral libraries with the remotely sensed hyperspectral data are highlighted.

Spectral features of selected soils of India

Figure 1 shows the average spectral reflectance of some selected soils from different parts of India. It may be noted that the reflectance characteristics varies across soil types. As expected, darker Vertisols of Karnataka show minimum soil reflectance at all wavelengths compared the lighter Inceptisols of Uttar Pradesh (soils of Agra region) and Aridisols of Rajasthan (soils of Jodhpur region); deep red Alfisols of lateritic origin show intermediate reflectance values. Such distinct variations in spectral reflectance show promise of distinguishing major soil orders across large landscapes. With regard to different spectral bands, the VIS spectral features generally account for the electronic transitions (ET) associated with the iron-bearing minerals such as hematite and goethite[26]. The NIR absorptions (700–2500 nm) are associated with the overtones and combination bands of covalent bonds between O–H, C–H and N–H atoms[27]. The O–H functional groups in minerals and all the above functional groups in organic matter (OM) are responsible for the characteristic absorptions in the NIR reflectance spectra[28].

Typically, all soil spectra show three prominent absorption peaks around 1400, 1900 and 2200 nm. The absorption peaks at 1400 and 1900 nm indicate the first overtone of O–H stretches and the combination of H–O–H bending with O–H stretching[29] and are generally termed as water absorption peaks. The absorption between 2200 and 2300 nm is mainly due to the combination of metal–OH bending and O–H stretching associated with the clay content mineral[30]. Other absorption bands in the NIR region are due to iron oxides between 870 and 1000 nm and carbonates between 2200 and 2500 nm. Carbonates have a strong overtone band between 2300 and 2350 nm and three weaker combination bands near 2120–2160, 1970–2000 and 1850–1870 nm (ref. 31).

Factors influencing soil reflectance

Soil reflectance is a collective response of different soil factors (chromophores) to electromagnetic radiation. Soil chromophores are classified as chemical and physical chromophores[32] based on their nature of influence on the soil spectrum. The chemical chromophores absorb incident energy at discrete wavelengths, while the physical chromophores influence the entire spectrum[33]. Thus, any variation with regard to absorption features may indicate the presence or absence of chemical chromophores, while a change in the shape of the reflectance spectra accounts for the influence of physical chromophores. The chemical chromophores in the soil consist of moisture content, organic matter, clay minerals and iron oxides. Similarly, particle size and sample geometry are considered as physical chromophores[32].

Inverse relationship exists between soil moisture content and spectral reflectance[34]. Spectral reflectance decreases

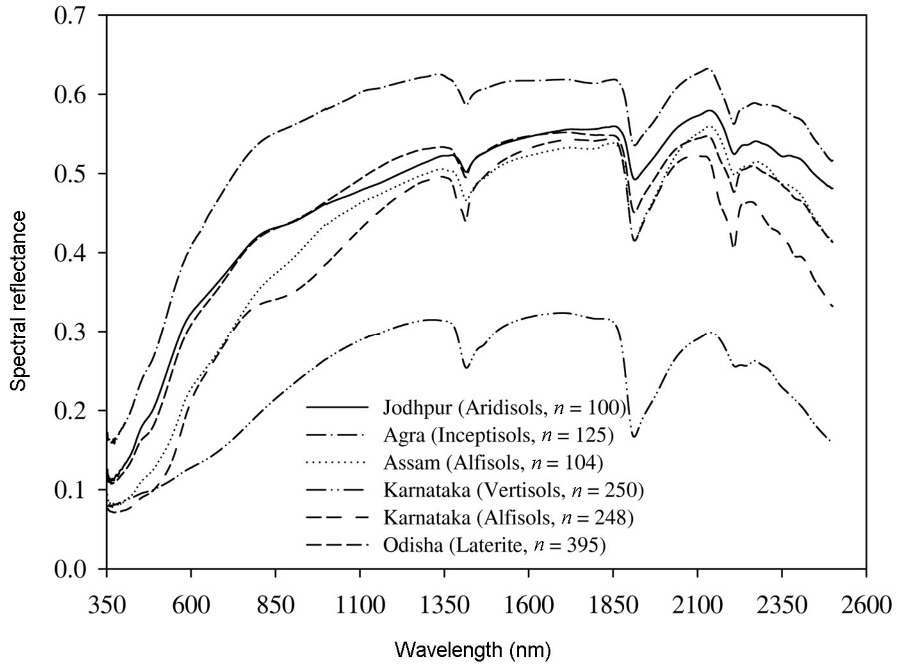

Figure 1. Average spectral reflectance for the selected soils of India.

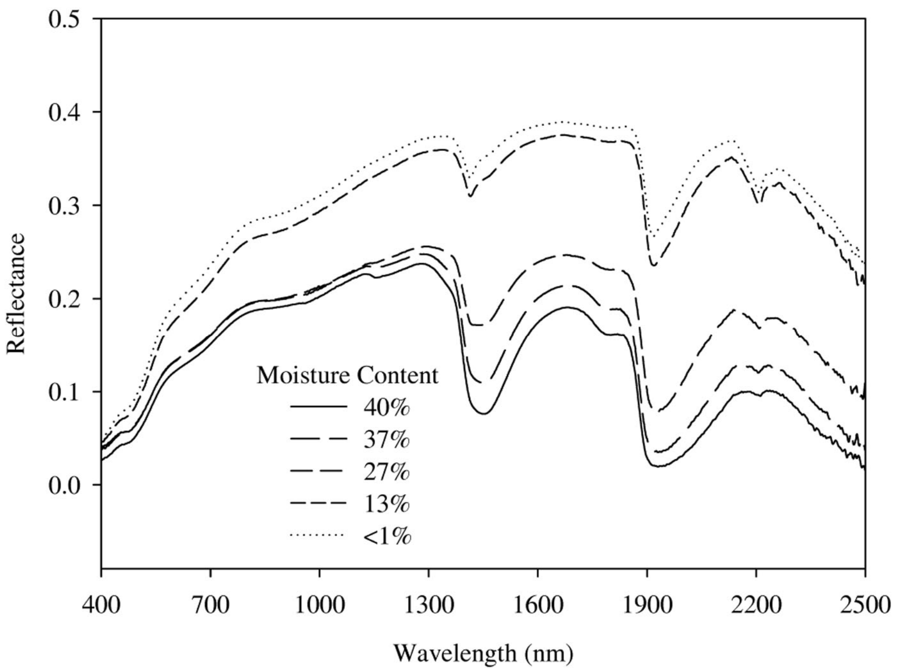

Figure 2. Typical soil spectral reflectance curves under varying soil wetness conditions.

with increase in gravimetric soil moisture content[35], as shown in Figure 2. The O–H bond present in water is the strongest absorber of NIR radiation. Fundamental absorption of water in the liquid phase occurs at 3106, 6079 and 2903 nm associated with the symmetric O–H stretching, H–O–H bending and asymmetric O–H stretching respectively[31]. The overtones of O–H stretching occur near 1400 nm and a combination of the H–O–H bending and O–H stretching occurs around 1900 nm (ref. 29).

A combination of metal–OH bending and O–H stretching occurs near 2200 to 2300 nm (ref. 31). Soil moisture has a dramatic influence on soil albedo and may influence other chromophores[36]. Soil OM and its products after decomposition appear to have noticeable influence on the spectral reflectance of mineral soils[37]. Remarkable increase in the spectral reflectance may be observed if OM is removed from the soil[34]. The absorption features associated with OM in the VNIR wavelength are often weak and may not be readily perceptible to the naked eye[38]. But a broad and clear distinction in the overall reflectance with OM content is generally seen in the VIS region[39]. Similarly, clay minerals have a major influence on the VNIR portion of spectral reflectance[13,40]. The OH functional group is associated with the mineral structure (lattice water), mostly in 2 : 1 type octahedral sheets or with the water molecules adsorbed to the mineral surface[41]. Thus, all the absorption features related to OH may also be linked to explain the influence of clay minerals on spectral reflectance of the soil. Iron content has a significant role in defining the shape of the reflectance spectra due to the ET of Fe^{2+} and Fe^{3+} present in the soil as iron oxides or impurities[3]. Spectral reflectance decreases with the increase in particle size. Bowers and Hanks[34] verified that the spectral reflectance of the soil increases exponentially with the decrease in particle size and the increment was found to be rapid below 0.4 mm diameter. They observed that the soil surface becomes smooth as the particle size decreases and thus they related the soil reflectance as a function of its surface roughness. As the soil surface roughness increases, major portion of the incident energy gets trapped in the inter-aggregate spaces resulting in lower reflectance[21,39].

Spectral libraries and spectral algorithms

A spectral library is an essential component in the analysis of HRS data for the prediction of soil properties[42], soil classification[43] and digital mapping[28]. Bellinaso *et al.*[44] summarized that (a) a spectral library should have sufficient number of samples representing the variability of soils found in the region to which it refers, (b) samples must be carefully sub-sampled, handled, prepared, stored and scanned, and (c) the reference data from the samples to be used in the calibrations must be acquired through recognized and trusted analytical procedures. Table 1 lists the major soil spectral libraries across the world[45]. The spectral library of soils developed by The Soil Spectroscopy Group was collected from 43 countries across the world. The soils in the International Centre for Research in Agroforestry and International Soil Reference and Information Centre (ICRAF–ISRIC) library were collected from 785 soil profiles across the five continents. The world soil spectral library[23] contains information on 3768 samples from USA and two tropical territories and an additional 416 samples from 36 different countries in Africa (125), Asia (104), America (75) and Europe (112). It may be noted that very little information on the soils of Asia is available. Recently, several studies have reported the use of regional or national spectral libraries in characterizing local-scale soil properties[46].

Spectral algorithms are developed using a combination of data-mining algorithms for feature extraction and multivariate regression for the calibration and validation of spectral algorithms[23,30,40]. Spectral reflectance consists of information on both the composition (absorption) and scattering (Rayleigh and Lorentz-Mie) of incident EMR. The scattering component is of least significance in the context of soil compositional analysis, as it does not have energy transfer with the soil sample. But it may cause undesirable variations (baseline shifts and nonlinearity) in the spectra[47]. Thus, the scattering component has to be effectively eliminated from the reflectance signal. Also, accuracy of prediction may improve with pre-processing. The pre-processing techniques may be categorized under scatter correction methods and spectral derivatives[47]. The scatter correction methods consist of multiplicative scatter correction (MSC), detrending (DT), standard normal variate (SNV) and normalization. The spectral derivative method consists of first derivatives (FD) and second derivatives (SD) of the reflectance spectrum. SNV and DT eliminate the multiplicative interferences of scatter and particle size and account for the variation in baseline shift and curvilinearity in diffuse reflectance spectra[48].

One of the important steps in DRS data modelling is the selection of an appropriate subset for calibration and validation. The adoption of a suitable data-partitioning scheme depends on the type of method used for modelling. Generally, linear models entail even distribution of samples, whereas the nonlinear models are sensitive to specific distribution of samples over the entire measurement space. The most common method used by soil spectroscopic scientists for subset selection is that of random selection[49]. The other major challenge in spectroscopic studies is the number of samples required for calibration. Effects of calibration sample size on the predictive performance have been examined[40]. The rate of performance degradation was less for large calibration size. But a rapid decrease in the performance was noted for calibration size between 100 and 200 samples. Recently, adequate prediction of soil OC and texture properties at

Table 1. Soil spectral libraries across the world (compiled from Stevens *et al.*[45])

Spatial scale	*N*
Global	5,223
Global	4,436
Global	4,184
Eastern and southern Africa	1,000
Sub-Saharan Africa	17,000
Australia	10,677
Europe	20,000

N, Number of soil samples.

the farm-scale was shown with just 79 samples[50]. Although there are many studies with less than 50 samples in calibration[51], it is difficult to draw general conclusions about the minimum sample size required for calibration.

The early phases of soil spectroscopic studies used multiple linear regression (MLR) for model development[51]. The drawback of the MLR approach is that it cannot account for the multi-collinearity associated with the reflectance signal. Limited studies have attempted to use stepwise multiple linear regression (SMLR) for model calibration[52]. With the ability to resolve the multi-collinearity issue and dimension reduction, the principal component regression (PCR) technique of eigen value decomposition gained importance in soil spectroscopic studies[53]. A method similar to PCR is the partial least square regression (PLSR) approach[54], where both the predictor and response variables are used to build scores with the greatest predictive power. The PLSR algorithm integrates the compression and regression steps and selects successive orthogonal factors that maximize the covariance between predictor and response variables[26]. Majority of the soil spectroscopic studies conducted so far used PLSR[55] or modified PLSR[56] for model calibration. The other advanced regression methods used in soil spectroscopic studies are multivariate adaptive regression splines[40], regression tree[23] and committee trees[57]. The performances of nonlinear techniques such as artificial neural networks, support vector machine and genetic algorithm in soil spectroscopy have also been examined.

Generally, the simple linear relationship between the observed and model-predicted values is evaluated based on R^2 and the root-mean-squared error (RMSE). Both R^2 and RMSE are range-dependent[58]. Thus, most of the spectroscopic studies use standardized form of RMSE such as the residual prediction deviation (RPD) criterion[53]. Table 2 lists performance statistics for several soil properties.

HRS utilization for soil assessment in India

Building a national soil spectral library

In India, limited efforts have been made for spectral library generation. The National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Nagpur, developed a spectral database of 128 surface soils collected from different physiographic/climatic regions of India[59]. Spectral reflectance properties (350–1800 nm) of some dominant soils occurring at different altitudinal zones in Uttaranchal Himalayas have also been examined[60].

The spectral characteristics were explained with regard to the shape of the spectral curve and reflectance percentage at different wavebands. The correlation of selected soil properties such as pH, OC, FeO, Fe_2O_3, dry soil moisture, clay, silt and sand with the reflectance for limited number ($n = 40$) of soil samples was also examined[60]. Based on the correlation coefficient values it was concluded that the soil spectral reflectance decreased with increase in OC ($r = –0.91$) and soil moisture content ($r = –0.68$). Srivastava *et al.*[61] studied the spectral reflectance (350–2500 nm) properties of some shrink–swell soils ($n = 135$) of Central India. The soil properties analysed in the study include soil colour, sand, silt, clay, pH, EC, OC, $CaCO_3$, exchangeable Ca, Mg, K, Na, CEC, exchangeable sodium percentage and CEC : clay ratio. They noticed significant correlation of soil albedo (average of the relative reflectance) with soil Munsell colour value ($r = 0.505$), chroma ($r = 0.496$), OC ($r = –0.39$), clay ($r = –0.263$) and CEC ($r = –0.405$). Spectral data modelling using SMLR was done for the prediction of soil properties. The SMLR model was calibrated with a dataset of 65 soil samples, whereas the remaining 70 samples were used for validation. Good calibrations were obtained for pH ($R^2 = 0.87$), OC ($R^2 = 0.71$), CEC ($R^2 = 0.77$) and clay ($R^2 = 0.61$) and R^2 for validation lay between 0.56 and 0.77 for these soil properties.

Santra *et al.*[20] characterized soil hydraulic properties by means of proximal spectral reflectance in 350–2500 nm wavelength range using 100 soils from a micro-watershed near Chilika Lake, Odisha. The hydraulic properties such as saturated hydraulic conductivity and the parameters of water retention model were estimated by pedotransfer functions (PTFs) and spectrotransfer functions (STFs). The PTFs/STFs were developed using MLR with basic soil properties, proximal spectral reflectance, integrated band reflectance, continuum removal (CR) factor and a combination of integrated band reflectance and CR factors separately as predictor variables and the individual hydraulic property as the response variable. Results in terms of RMSE revealed that STFs had similar accuracy as PTFs for estimating hydraulic properties. Gulfo *et al.*[62] assessed soil moisture content using hyperspectral reflectance (350–2500 nm) data of 240 samples collected from 80 sampling points at three different depths from the Indian Agricultural Research Institute farm, New Delhi. The results of the regression approaches suggest that both the SMLR ($R^2 = 0.799$) and the principal component analysis approach ($R^2 = 0.805$) may be used for the estimation of soil moisture from reflectance. Divya *et al.*[63] used hyperspectral reflectance (350–2500 nm) to analyse the textural and compositional characteristics of 36 sand samples with varying clay contents collected from a river and beach near Chennai city. Several samples were prepared with varying proportions of sand and clay to examine the influence of clay on the spectral characters of a sand–clay admixture. Spectral separability based on Euclidean distance in various wavelength regions for the different mixtures was computed. Results indicated that sand and clay can be easily discriminated because of high spectral separability between them, especially in the 450–1100 nm region. The study

Table 2. Regression statistics of prediction for selected soil properties using diffuse reflectance spectroscopy

Property	Pretreatment	R^2	RMSE	RPD	Reference
Basic soil properties					
Sand (%)	FD	0.60	9.46	1.60	55
Clay (%)	SNV	0.82	3.93	2.38	55
OC (%)	SG + FD	0.29	4.60	1.12	2
pH	ABS	0.79	0.10	3.23	49
pH	SNV + FD	0.62	0.35	1.69	55
EC (dS/m)	SNV	0.51	0.03	1.34	55
Nutrient content					
P (mg/100 g)	MaxN + FD + SG	0.69	1.35	1.80	15
P (mg/kg)	Raw	0.47	22.57	1.34	55
K (mg/kg)	ABS	0.62	44.60	1.59	49
S (mg/kg)	SNV	0.50	2.21	1.31	55
Zn (mg/kg)	ABS	0.78	0.25	2.08	49
Zn (mg/kg)	FD	0.18	10.74	1.10	55
Fe (%)	ABS	–	2.61	1.81	73

R^2, Coefficient of determination; RMSE, Root mean square error; RPD, Residual prediction deviation; ABS, Absorbance; FD, First derivative; SNV, Standard normal variate; SG, Savitzky–Golay smoothing; MaxN, Maximum normalization; DT, Detrending.

identified reliable spectral parameters such as depth, slope, position, peak reflectance, area under the curve and radius of the curve for the estimation of compositional and textural characteristics based on the correlation between them.

Recently, under a NAIP project, laboratory-measured soil spectral reflectance data (350–2500 nm) of the Indo-Gangetic Plains covering parts of Punjab and Haryana were calibrated with soil properties of agronomic importance using PLSR technique for rapid prediction of soil properties[25,64,65]. The application of calibration models on validation datasets (those not used for calibration) resulted in very good prediction of OC content ($n = 320$, $R^2 = 0.81$, RMSEP = 0.116, RPD = 2.30) and available K ($n = 320$, $R^2 = 0.78$, RMSEP = 0.243, RPD = 2.13), ECe ($n = 402$, $R^2 = 0.94$, RMSE = 5.33, RPD = 3.99), saturation extract $Ca^{2+} + Mg^{2+}$ ($n = 401$, $R^2 = 0.81$, RMSE = 1.51, RPD = 2.40), saturation extract Na^+ ($n = 402$, $R^2 = 0.88$, RMSE = 2.45, RPD = 2.89), saturation extract Cl^- ($n = 402$, $R^2 = 0.92$, RMSE = 2.16, RPD = 3.44), saturation extract SO_4^{2-} ($n = 402$, $R^2 = 0.67$, RMSE = 2.21, RPD = 1.60) and $CaCO_3$ ($n = 436$, $R^2 = 0.66$, RMSE = 0.79, RPD = 1.72).

Kadupitiya *et al.*[66] assessed some of the soil properties such as mineralizable N, available P and K, extractable Mn, Fe, Cu, Zn, $CaCO_3$, OC, EC, pH, soil texture, bulk density, particle density and hydraulic conductivity (K_s) using DRS of 85 pre-processed soil samples collected from farmers' fields of Jalandhar, Punjab, India. Based on adjusted R^2 of the predicted models, FD of absorbance was found suitable for the model predicting N, while its SD of absorbance was best for Mn, Fe and Zn prediction models. Similarly, SD of reflectance yielded good prediction for P and Cu and its FD for K prediction. The highest predictability (adjusted R^2) was 0.93 recorded for $CaCO_3$, while the lowest of 0.68 was obtained for N. Based on RPD and range error ratio (RER), these authors confirmed that N, P, K, Mn, Fe, $CaCO_3$, OC, pH, EC, sand, silt and clay were predicted well. Sarathjith *et al.*[21] extended the utility of DRS approach to estimate aggregate size characteristics of soils. The geometric mean diameter (GMD) and median aggregate diameter of the aggregate size distribution function were accurately estimated for Vertisols ($n = 247$) and Alfisols ($n = 249$) of Karnataka.

Ray *et al.*[13] used ground-based hyperspectral data for soil discrimination and parameter estimation. Two visibly similar soil types (sandy loam and loamy sand) were selected for the study. Spectral data were collected using ASD ground spectroradiometer. Five spectral indices [brightness index = $((B^2 + G^2 + R^2)/3)^{0.5}$; saturation index = $(R - B)/(R + B)$; hue index = $(2*R - G - B)/(G - B)$; colouration index = $(R - G)/(R + G)$ and redness index = $R^2/(B*G^3)$] 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. The results showed that saturation index was the best to separate sandy loam and loamy sand soils. The regression equations developed between soil parameters and spectral indices were highly significant for OC ($R^2 = 0.785$), available K ($R^2 = 0.812$), sand ($R^2 = 0.819$), silt ($R^2 = 0.783$) and clay ($R^2 = 0.644$) content, suggesting that these parameters may be estimated from reflectance data.

Soil resources study in using hyperspectral imaging data

Extending laboratory-level spectroscopic studies for larger areas or spatially distributed phenomena is now possible with the introduction of imaging spectroscopy or

HRS image data. Retrieval of soil properties in spatial scale from image spectroscopy would facilitate digital soil mapping and understanding soil processes in spatio-temporal scale. However, the transfer of relationships established at the laboratory level up to higher scales poses several problems associated with possible factors of confusion, such as (i) changes in soil roughness, moisture, illumination and view conditions; (ii) sensor characteristics like spectral and spatial resolution, radiometric calibration which may also change relationships between measured reflectance and actual soil characteristics, and (iii) possible atmospheric effects[19,67]. There are detailed studies on atmosphere correction of the HRS image[68,69]. Due to atmospheric influences and mixed pixel effects on the signals, application of HRS image data is still challenging to the research community[30]. There have been a few studies of using HRS imaging data for soil classification and parameter estimation. Most of these studies have been carried under a national-level project on hyperspectral remote sensing applications of Space Applications Centre (SAC), ISRO, Ahmedabad[70].

A comprehensive study was carried out over the Jalandhar region of Punjab to evaluate the HRS approach for measuring soil properties such as available N, P, K, OC, $CaCO_3$, sand, silt and clay using the Hyperion hyperspectral satellite remote sensor data and *in situ* data collected under field and laboratory conditions[71]. Spectral reflectance, absorbance and their first and second derivatives were used to develop models to find a suitable one for assessing soil properties. It was found that irrespective of sensor and platforms, derived spectral parameters such as FD and SD of reflectance and absorbance were found to better suited than original reflectance data for developing prediction models for soil properties. Prediction models in the case of laboratory condition were better (having adjusted R^2 for all eight parameters ranging from 0.65 to 0.87) compared to field condition (adjusted R^2 ranging from 0.39 to 0.7) and were found to be worst for models from satellite-derived reflectance (adjusted R^2 ranging from 0.28 to 0.52). Two major attributes to such low model accuracy are: (i) poor signal-to-noise-ratio, and (ii) aggregate effect of pixel-covered area ($30 \times 30\ m^2$) on spectral value of Hyperion pixel. An attempt was made to compare the satellite-derived soil OC map and conventionally generated OC map using geostatistical technique. Predicted and measured had good agreement with a R^2 value of 0.61.

Similarly, a joint study undertaken by NBSS&LUP, Nagpur and SAC, Ahmedabad showed significant negative correlation between soil OC and soil reflectance data of 139 bands of Hyperion image. SMLR was used to develop a spectral model ($R^2 = 0.51$) for the prediction of OC from soil reflectance data[24]. Ghosh *et al.*[72] used Hyperion data over Udaipur city to estimate soil fertility parameters (OC, available N, available P, available K, exchangeable Ca, exchangeable Mg and available S). Statistical analysis was performed to optimize the number of spectral bands and spectral parameter to be used for estimating soil nutrient content for the unknown pixels of the image. Spectral bands were optimized using correlogram and spectral parameters were optimized using multiple regression analysis. Similarly, the PLSR analysis on soil OM, sand, silt, clay and N, P, K contents carried out with the Indian hyperspectral imager (HySI) data in Jalandhar district, Punjab showed the RPD values ranging from 0.95 for available P to 4.9 for clay content[69].

Conclusions

Currently, most soil analyses in India are done through chemical analysis. There are about 1049 soil testing labs operating in the country with an annual analysing capacity of 10.7 million samples. The country has approximately 121 million agricultural fields (a bounded piece of land) and the capacity of soil testing labs simply lags far behind the requirement. Moreover, almost no efforts are made to monitor soil physical properties or soil water-holding attributes at a national scale and hence water resource management in India is based on the distribution and supply of water instead of actual crop requirement. Under such a scenario, very high spectral, spatial and temporal resolutions of HRS technology offer an attractive alternative for soil testing in a rapid and non-invasive fashion. However, there are technological challenges to accomplish the HRS utility. First, high-resolution HRS data and the technical skills to analyse such data must be available. Secondly, national and regional spectral libraries with proven spectral algorithms should also be in place to derive farmer-friendly HRS data products. Third, the HRS data are highly collinear with inherently low signal-to-noise ratio and are a mixed signal. Data analytics and robust algorithms to analyse such 'near-big data' must be developed in-house to make the technology affordable. Fourth, like any remote sensing data, HRS is also limited for getting information about the surface soil. There is a need to develop models to extend the surface soil information to profile parameters. Also, soil assessment by remote sensing is marred by the vegetation cover. Hence, it is essential to identify typical plant signatures from hyperspectral reflectance to indirectly infer the soil properties. However, with improvement in data availability (including India's proposal to launch hyperspectral sensors in GISAT-1 and Cartosat-3), multivariate analysis techniques and modelling tools, it is expected that hyperspectral data, in near future, may be used for operational soil health monitoring. Specifically, a dedicated spaceborne mission from polar orbits would provide further impetus to the application of HRS for soil assessment by providing quality hyperspectral data.

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