Hyperspectral Spectroscopic Study of Soil Properties - A Review

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Authors' contributions

This work was carried out in collaboration among all authors. Author NJS searched literature for the study. Author CG studied the literature and wrote the manuscript. Author BKH assisted in preparation of the manuscript. All authors read and approved the final manuscript.

ABSTRACT

Soil analysis is required for efficient use of inputs viz. seeds, fertilizers, irrigation water and other agricultural planning. However, there are several disadvantages of soil analysis such as they are time consuming, expensive and labour intensive. Many approaches are developed to overcome these difficulties. Hyperspectral spectroscopy is emerging as a promising tool for studying soil, water and vegetation. Therefore, an attempt has been made to review the scope of using hyperspectral reflectance spectroscopy for estimation of soil properties as an alternative to traditional laboratory soil analysis methods.

Spectral signature of soil can be used for fast and non-destructive estimation of soil properties. Diffuse reflectance in 350-2500 nm range of electromagnetic spectra forms the basis of hyperspectral spectroscopy. An object is characterized by the characteristic absorptions and peaks in the electromagnetic spectra. A number of calibration techniques are applied for establishing relationship between reflectance spectra and soil properties. Multiple Linear Regression (MLR), Principal Component Regression (PCR) and Partial Least Square Regression (PLSR) are most commonly used techniques.

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1. INTRODUCTION

Soil is the most vital natural resource for all the productive activity of the world. Soil provides all the basic requirements of human being i.e. food, feed, fodder, fibre and fuel. Thousands of years are required to produce one centimeter of soil through natural process (weathering of rocks and minerals). On the other hand, human population of the world is increasing at the rate of 1.16% and this rate is even more (1.25%) for South Asian Countries [1]. This has been projected that the human population of the world will reach 8.6 billion in 2030, 9.8 billion in 2050 and 11.2 billion in 2100 from the current population of 7.6 billion [2]. The increasing human population has put tremendous pressure on the natural resources including the soil; most vital natural resource.

Nutrient status of soil is very dynamic (with respect to time) and diverse (with respect to space). Hence, periodic monitoring of nutrient status of soil and inventory of spatial variability map of soil is the need of the hour [3]. Though soil analysis is essential for agricultural planning, this has several disadvantages such as they are expensive, time consuming, and often cause environmental pollution. Therefore, alternative techniques may be developed which are rapid, repeatable, cost effective and environment friendly. This can be achieved through the use of new technologies such as mass spectroscopy, X-Ray diffraction, nuclear magnetic resonance, hyperspectral spectroscopy etc.

2. HYPERSPECTRAL REMOTE SENSING OF SOIL

Hyperspectral sensors are instruments that acquire reflectance in several, narrow, contiguous spectral bands in the visible, near infrared (NIR), mid infrared (MIR) and thermal infrared (TIR) regions of the electromagnetic radiation (EMR). Laboratory and field studies have revealed that certain soil characteristics exhibit characteristic absorption band, which could be used for their identification. For instance, soil water exhibit weaker absorption bands at 970 nm, 1200 nm and 1770 nm and prominent absorption bands at 1400 nm and 1900 nm. Similarly, gypsum and montmorillonite exhibit absorption bands at 1800 nm and 2300 nm, and between 520 nm and 1000 nm, respectively [4]. Most of the currently operating optical sensors have coarse spectral resolution on the order of 50 to 200 nm. As a result, such measurements are not adequate to resolve subtle variations in soil units arising due to variation in chemical composition. This has led to the development of high spectral resolution spectrometers capable of providing several spectral bands of typically 1 to 5 nm bandwidths. Hyperspectral remote sensing in large continuous narrow wavebands provides significant advancement in understanding the subtle changes in biochemical and biophysical properties of the crop plants and their different physiological processes, which otherwise are indistinct in multispectral remote sensing [5]. Hyperspectral remote sensing techniques have been developed from a laboratory-based near infrared spectroscopy (NIRS) technique [6]. The narrow sensitive band range (10 nm or less) makes it possible to detect subtle variations in the reflectance spectra, which are caused by differences in biochemical composition and physiology of vegetation [7,8]. In recent years, researchers have extended the technique of reflectance spectroscopy to measure biochemical parameters by field spectroradiometer, airborne and space borne sensors, trying to explore the variation in chemical composition in a spatial context [8,9, 10]. The potential of hyperspectral spectroscopy has been recognized by soil scientists since a few decades [11,12].

Keywords: Hyperspectral spectroscopy; multiple linear regression; partial least square regression; principal component regression; soil spectra; spectral indices.
Hyperspectral spectroscopy can be divided into three distinguished types of measurements for soils viz. laboratory measurements, proximal sensing measurements and remote sensing measurements. The two latter techniques are able to collect spectral data in-situ and are therefore usually exploited to map soil properties [13]. Many authors reported the development of spectral sensors mounted on tractors [14,15]. These systems are generally used in precision agriculture to manage the quantity of nutrient inputs into soils [16]. Proximal sensing may also include hand-held measurements, which is used as a fast tool to monitor soil properties in-situ [17, 18]. Ben-Door et al. [19] presented a hyperspectral reflectance device able to collect in-situ 3D spectral data through an entire soil profile, allowing a rapid and objective soil classification. Remote sensing of soil properties has also been attempted using aerial photographs [20], multispectral [21] and hyperspectral images (imaging spectroscopy) [22]. Imaging spectroscopy differs from multispectral imaging in its contiguous number of wavebands, enabling precise recording of the spectrum and a detailed analysis of spectral properties of the soil surface. 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.

Reflection spectra have been used for many years as one of the source of information about variation in earth surface composition. A wide range of information can be obtained from natural and chemical properties of soil [23]. This is mainly based on specific absorption of spectrally active groups known as chromophores such as Fe, OH ions in water and minerals, CO$_3$$^2$-, Al$^{3+}$, Mg$^{2+}$, SO$_4$$^2$- in minerals and other organic matters.

### 3. SPECTRAL SIGNATURE OF SOIL

The spectral reflectance of soil varies with a range of chemical and physical properties which facilitates discrimination of different soils [13,24]. The most important characteristics of a soil influencing properties are: Moisture (inversely proportional to reflectance; wet soils appear darker than dry soils), organic matter (inversely proportional to reflectance; increasing organic matter content gives darker soils), texture (sandy soils are more reflective than clay soils), surface roughness (inversely proportional to reflectance; decrease in surface roughness slightly increases reflection), iron content (increase in iron oxide changes soil colour towards brick-red resulting in increased reflection in the red and a decreased reflection in green region) [22,24,25].

The soil properties influencing the spectral reflectance are known as chromophores. Soil chromophores may be chemical chromophores or physical chromophores based on their nature of influence on the soil spectrum [26]. The incoming EMR is absorbed at discrete wavebands by the chemical chromophores. On the contrary, physical chromophores influence the shape of the reflectance spectra. Soil moisture, organic matter, clay minerals and iron oxides are dominant chemical chromophores influencing reflection and absorption peaks of soil spectra. On the other hand, sand, silt, clay and geometry are dominant physical chromophores influencing the shape of reflectance spectra [28].

Spectral reflectance decreases with increase in gravimetric soil moisture content (Fig. 1) [28]. This is attributed to presence of O-H bond which is the strongest absorber of EMR. For stretched O-H bond, absorption peak use to occur in 3106 nm, for H-O-H bending, absorption peak occurs in 6079 nm and for asymmetric O-H stretching, absorption peak occurs in 2903 nm spectral band in EM spectra [29]. Again, clear absorption peak occurs in 1400 nm due to presence of O-H overtone stretching. Absorption peak in the 1900 nm is due to combination of H-O-H bending and O-H stretching [30]. On the other hand, absorption peak in 2200 to 2300 nm occurs due to combined influence of metal-OH bending and O-H stretching [29]. Soil moisture is the most dominant chromophore which may influence all other chromophores in the reflectance spectra of soil [31].

Soil Organic Matter (SOM) and its intermediate decomposition products significantly influence the spectral reflectance of mineral soils [32]. SOM has inverse relation with spectral reflectance of soil, removal of SOM results in increase in spectral reflectance of soil (Fig. 2)
Absorption peaks occurring due to presence of SOM and its intermediate decomposition products are weak which may not able to distinguish with naked eye [34]. However, influence of SOM on the overall spectral signature of soil is distinct in the visible region of electromagnetic spectra [23].

Clay minerals are also found to have significant influence on the spectral signature of soil [35]. The OH functional group use to be associated with the 2:1 type octahedral sheets or with the water molecules adsorbed to the mineral surface (lattice water). Therefore, all the absorption characteristics shown by OH group are shown by the clay minerals in the reflectance spectra [36]. Again, iron content also significantly influence the spectral reflectance of soil in the form of Fe$^{2+}$ and Fe$^{3+}$ oxides or its impurities [37]. Spectral reflectance of dominant clay minerals has been studied adequately by Clark [30] (Fig. 3).

**Fig. 1.** Spectral reflectance of soil with different levels of moisture [28]

**Fig. 2.** Spectral reflectance of soil with different levels of organic carbon [33]
Among the physical chromophores, particle size of soil is the most dominant factor influencing the spectral signature of soil. Spectral reflectance of soil increases exponentially with the decrease in particle size, particularly when particle size is smaller than 0.4 mm diameter (Fig. 4) [38]. Soil surface becomes smoother as the particle size decreases and thus they reflect more part of the incident EMR. On the contrary, increase in particle size increases the surface roughness, thus major portion of the incident EMR gets trapped in the spaces between the soil particles resulting in lower reflectance [23,39].

Stoner and Baumgardner [25] identified five characteristic soil spectral reflectance curves which they considered representative of the diversity of soil reflectance found in wide ranges of naturally occurring surface soils. These curve forms were identified by curve shape and the presence or absence of absorption features representing distinctive organic matter and iron content, as well as texture. Das et al. [28] studied the spectral signature of major soils of India and it was found that the spectral reflectance varied across soil types. Vertisols of Karnataka showed lower soil reflectance in the entire

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**Fig. 3. Spectral signature of dominant clay minerals [30]**

**Fig. 4. Spectral reflectance from different particle size [38]**
electromagnetic spectra compared to the Inceptisols of Uttar Pradesh (soils of Agra region) and Aridisols of Rajasthan (soils of Jodhpur region). This was due to darker colour of Vertisols in comparison to Inceptisols of Agra region and Aridisols of Jodhpur region. On the other hand, deep red Alfisols of lateritic origin showed intermediate spectral reflectance values (Fig. 5).

The analysis of mineralogy with spectral proximal sensing has made great progress over the years. Nowadays, several institutes provide spectral libraries with comprehensive collections of a wide variety of materials. For example, the ASTER spectral library version 2.0, which is a collection of contributions from the Jet Propulsion Laboratory, Johns Hopkins University and the United States Geological Survey, is a widely used spectral library which contains over 2400 spectra of a wide variety of minerals, rocks, vegetation and manmade materials covering the wavelength range of 400 to 1540 nm [40]. Partial Least Square Regression (PLSR) can be used to match collected spectral samples to those in the spectral libraries [41].

Global spectral library with 23631 soils representing 92 countries have been developed in which only 67 soils were from India [42]. There is no reported study on spectral signatures of soil and its correlation with soil properties for the North Eastern hill region of India. With a large variation in soil properties across our country, there is a requirement for developing more extensive spectral libraries representing specific regions and there are initiatives to expand existing spectral libraries into a national soil spectral library [43].

Reflectance data have been successfully used for study of soil properties such as moisture, soil organic carbon (SOC), inorganic carbon, total nitrogen (N), cation exchange capacity (CEC), pH, potassium (K), magnesium (Mg), calcium (Ca), zinc (Zn), iron (Fe) and manganese (Mn) with various levels of accuracies [44]. Since spectral signature of soils reflect a set of soil properties like organic matter content and some chemical and biological properties, some researchers have hypothesized that spectral signature could probably be used to discriminate clusters of soil samples differing in their quality.

4. MULTIVARIATE ANALYSIS FOR PREDICTION OF SOIL PROPERTIES

Hyperspectral data being of large volume, overlapping of weak overtones with fundamental vibrational band makes it difficult for direct interpretation. Therefore, a number of calibration techniques are applied for establishing relationship between spectra and soil properties. Multiple Linear Regression (MLR), Principal Component Regression (PCR) and PLSR are most commonly used techniques [45]. A number of indicators are used for validation of prediction of soil properties such as coefficient of
determination ($R^2$), Root Mean Square Error (RMSE), Ratio of Performance to Deviation (RPD), Ratio of Performance to Inter Quartile (RPIQ) and Bias [46].

For quantitative prediction of chemical soil properties such as pH, PCR has been reported to be best multivariate method [47], followed by PLSR [48] and Stepwise Multiple Linear Regression (SMLR) [49]. Again, PLSR has been found to be most suitable multivariate method for quantitative prediction of soil carbon [50,51] followed by PCR [52]. Similarly, for quantitative prediction of total soil nitrogen, PLSR has been observed to be the most suitable multivariate method [50]. However, PCR has been found to be most suitable for quantitative prediction of mineralized soil nitrogen [52]. On the contrary, Neural Network (NN) was found to be most suitable quantitative prediction of available soil phosphorus and available potassium [53]. However, PCR is most suitable for quantitative prediction of exchangeable potassium [52]. MARS [35] and PCR [52] have been found to be most suitable multivariate method for quantitative prediction of CEC, Ca$^{2+}$ and Mg$^{2+}$. For prediction of micronutrients such as Cu and Fe, modified PLSR has been reported as most suitable for quantitative prediction [54]. On the other hand, PCR was found to be most suitable multivariate method for quantitative prediction of Zn and Mn.

For quantitative prediction of physical soil properties such as sand (%), PCR has been reported to be best multivariate method [52] followed by Multivariate Adaptive Regression Spline (MARS) [35] and modified PLSR [54]. Similarly, PCR has been reported to be best multivariate method for quantitative prediction of silt [52] followed by modified PLSR [54] and MARS [35]. On the other hand, modified PLSR has been reported to be the best multivariate method for quantitative prediction of clay [54] followed by MARS [35] and PCR [47,52]. Again, PCR and SMLR have been found to be most suitable multivariate method for quantitative prediction of moisture content of soil [47,49].

Soil pH has been predicted with $R^2$ value of more than 0.8 at local level [55,56] and at regional level [57,58]. However, at global level, pH has been predicted with $R^2$ value of more than 0.7 [35]. On the other hand, this has been observed that pH has been predicted with $R^2$ value of less than 0.5 at local level [59,60] and at regional level [61]. SOC has been predicted with $R^2$ value of more than 0.9 at local level [62,63] and regional level [62,64,65,66,67,68, 69,70]. However, at global level SOC has been predicted with $R^2$ value of more than 0.8 [71]. On the contrary, $R^2$ value of less than 0.5 has been reported for predicted SOC at local level [60]. Macro nutrients of soil such as N, P, K, Na, Ca, Mg and micro nutrients such as Fe, Mn, Zn, Cu, B and Mo has been found to be predicted with $R^2$ value of less than 0.5 [72,73].

Soil physical properties such as sand content was also predicted with $R^2$ value of more than 0.8 at local level [59,60], $R^2$ value of more than 0.9 at regional level [57] and $R^2$ value of more than 0.7 at global level [35]. On the contrary, $R^2$ value of less than 0.5 was predicted at the local level [60] as well as at the regional level [61,69]. Silt content with $R^2$ value of more than 0.7 was predicted at the local level [45,74] as well as at the regional level [57]. At the global level, $R^2$ value of more than 0.6 was predicted for silt [35]. On the contrary, $R^2$ value of less than 0.3 was predicted at the local level [59,60] and $R^2$ value of less than 0.4 was predicted at the regional level [61,69]. On the other hand, clay content has been predicted with $R^2$ value of more than 0.9 at the local level [59], more than 0.8 at the regional level [69,75] and $R^2$ value of more than 0.7 at the global level [76]. On the contrary, $R^2$ value of less than 0.3 was reported at the local level [73,77], while $R^2$ value of less than 0.5 was reported at the regional level [78,79].

5. SPECTRAL INDICES FOR ESTIMATING SOIL PROPERTIES

Although a qualitative interpretation of hyperspectral spectra through visual analysis can be achieved [25], direct quantitative prediction of soil characteristics is almost impossible because soil constituents interact in a complex way to produce a given spectrum. Statistical models are usually used for quantification of the property of interest which is known as Chemometrics. Geladi [80] has reported the overview of the use of chemometrics in spectroscopy. The quantitative analysis of HRS data may be conducted in two ways, both requiring the implementation of multivariate statistics [81]. Firstly, clustering techniques can be used to discriminate samples or to detect changes in sample properties [82]. On the other hand, regression methods can be used for prediction of unknown properties using calibration equations which relate spectral information to sample properties [52].
An increasing number of studies emphasize the ability of hyperspectral spectroscopic analysis for quantitative prediction of soil physical, chemical and biological properties [43]. Most hyperspectral regression models are based on laboratory measurements under controlled conditions, which avoid disturbing factors characterizing field measurements like soil moisture content, soil roughness and vegetation cover [17]. Some of spectral indices used for estimating soil properties using spectral reflectance are Simple Ratio Index (SRI), Relative Vigour Index (RVI), Renormalized Difference Vegetation Index (RNDVI), Modified Simple Ratio Index (MSRI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index with self adjustment factor (MSAVI), Photochemical Reflectance Index (PRI), Normalized Phaeophytinization Index (NPI), Green Ratio Index (GRI), Water Index (WI), Structure Independent Pigment Index (SIPI), Short Wave infrared Water Index (SWWI), Normalized Difference Water Index (NDWI), Triangular Vegetation Index (TVI), Modified Triangular Vegetation Index (MTVI), Simple Ratio Water Index (SRWI), Modified Chlorophyll Absorption in Reflectance Index (MCARI), Transformed Soil Adjusted Vegetation Index (TSAVI), Optimized Soil Adjusted Vegetation Index (OSAVI), Transformed Chlorophyll Absorption in Reflectance Index (TCARI), Cellulose Adsorption Index (CAI) and Shortwave Infrared Water Stress Index (SIWSI) [83].

### 6. CONCLUSION

Assessment of soil physical and chemical properties is important for understanding the spatial variability of soil. Traditionally, soil samples are collected and analyzed in the laboratory for the soil fertility properties for assessment of spatial variability. Spectral signatures of soil reflect variation in some of the important soil properties viz. moisture content, organic carbon content, particle size and type of clay minerals. Hyperspectral spectroscopy has been found to be useful in estimation of soil properties with moderate accuracy level. Some authors have reported encouraging results for prediction of soil physical (sand, silt & clay) and chemical properties (pH & OC). On the contrary, many authors have reported contradictory results on prediction of soil properties using the multivariate analysis techniques. However, the regression models will be useful for researchers who are working on alternate methods for estimation of soil properties. Spectral indices are found to predict soil properties with low level of confidence. Therefore, there is a scope for development of spectral indices capable of assessing and predicting soil properties for major soil types.

### DISCLAIMER

The products used for this research are commonly and predominantly used products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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