



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.

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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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MLR, PCR and PLSR are also used for prediction of several soil properties such as pH, soil organic carbon content, nitrogen, phosphorus, potassium, calcium, magnesium, sodium, iron, manganese, zinc, copper, boron, molybdenum, sand silt, clay and soil moisture. Some commonly used spectral indices are also applied for prediction of soil properties. Some of the soil physical properties viz. sand, silt and clay as well as chemical properties viz. pH and organic carbon could be estimated with good to very good prediction using pure spectra of soil. However, contrasting results of prediction of soil properties using multivariate analysis techniques have also been reported. The content of this review article will be helpful for researchers who are working on alternate methods of estimation of soil properties.

Keywords: Hyperspectral spectroscopy; multiple linear regression; partial least square regression; principal component regression; soil spectra; spectral indices.

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 spectro-radiometer, 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].

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⁻ in water and minerals, CO₃²⁻, Al²⁺, Mg²⁺, SO₄²⁻ 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 entire spectra of EMR [27]. Therefore, sharp reflection and/ or absorption peaks might be attributed to presence or absence of chemical chromophores. 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 used 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 the 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)

[33]. Absorption peaks occurring due to presence of SOM and its intermediate decomposition products are weak which may not be 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 used 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 influences the spectral reflectance of soil in the form of Fe²⁺ and Fe³⁺ oxides or its impurities [37]. Spectral reflectance of dominant clay minerals has been studied adequately by Clark [30] (Fig. 3).

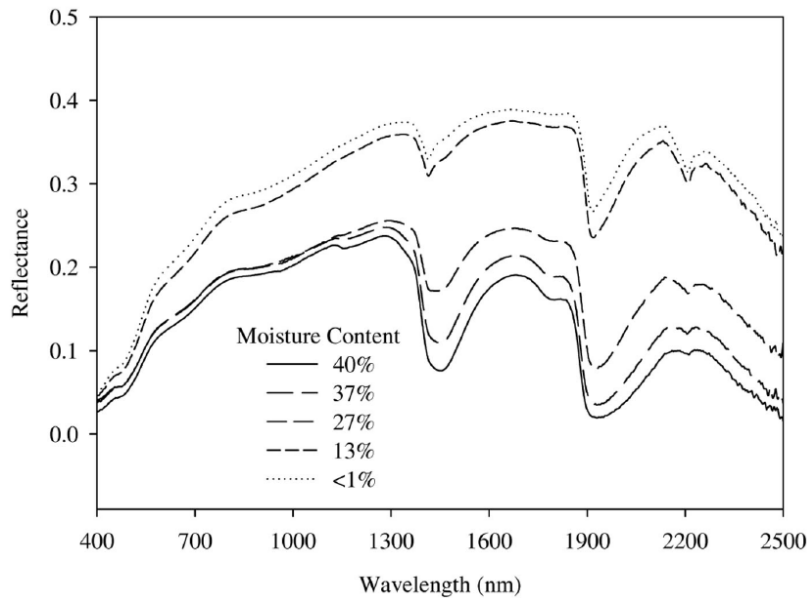


Fig. 1. Spectral reflectance of soil with different levels of moisture [28]

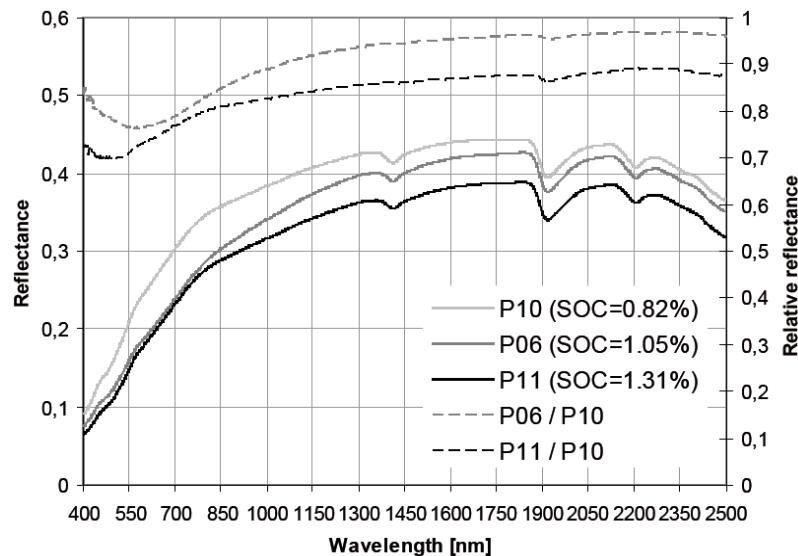


Fig. 2. Spectral reflectance of soil with different levels of organic carbon [33]

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

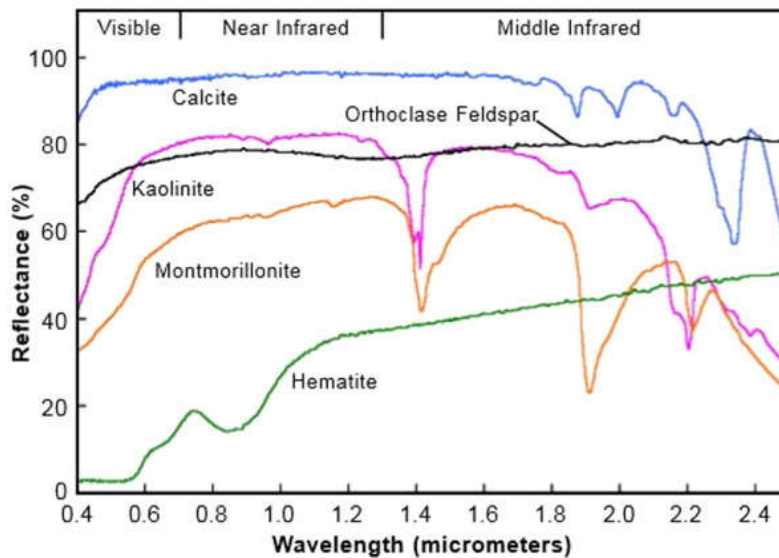


Fig. 3. Spectral signature of dominant clay minerals [30]

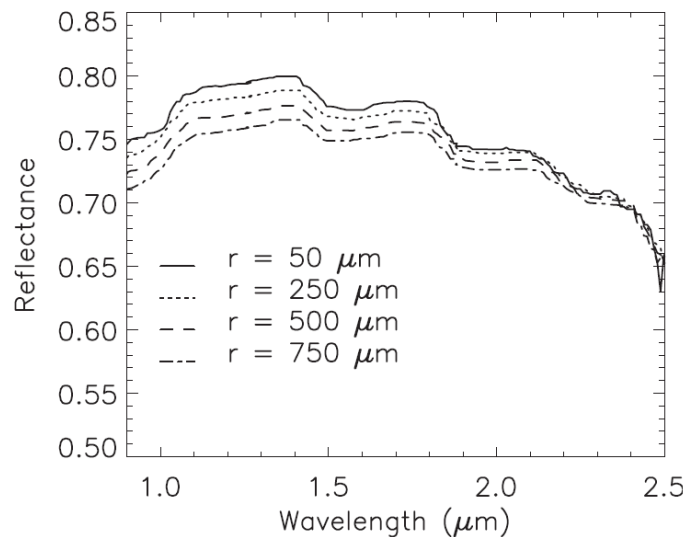


Fig. 4. Spectral reflectance from different particle size [38]

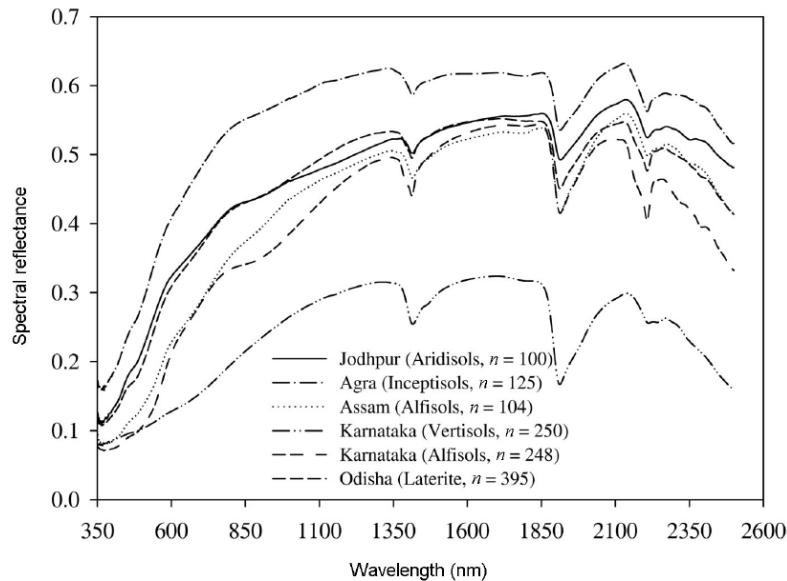


Fig. 5. Spectral signature of major soil orders of India [28]

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), Normalized Difference Vegetation Index (NDVI), 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.

REFERENCES

1. World Bank. Population Growth (Annual %). The World Bank IBRD-IDA; 2017. Available:<http://data.worldbank.org/indicator/sp.pop.grow> [Accessed 20 February 2019]
2. United Nations. World Population Projected to reach 9.7 billion by 2050. United Nations DESA; 2015. Available:<http://www.un.org/development/desa/en/news/population/world-population-prospects-2017.html>. [Accessed 20 February 2019]
3. Tao DL, Singh NJ, Goswami C. Spatial variability of soil organic carbon and available nutrients under different topography and land uses in Meghalaya, India. *International Journal of Plant and Soil Science*. 2018;21(4):1-16. DOI: 10.9734/IJPSS/2018/39615
4. Hunt G, Salisbury J. Visible and near infrared spectra of minerals and rocks II: carbonates. *Modern Geology*. 1971;2:23-30.
5. Sahoo RN, Ray SS, Manjunath KR. Hyperspectral remote sensing of agriculture. *Current Science*. 2015;108(5): 848-859.
6. Curran PJ, Dungan JL, Peterson DL. Estimating the foliar biochemical concentration of leaves with reflectance

- spectroscopy: Testing the Kokaly and Clark methodologies. *Remote Sensing of Environment*. 2001;76(3):349-359.
7. Davey MW, Saeys W, Hof E, Ramon H, Swennen R, Keulemans J. Application of visible and near-infrared reflectance spectroscopy (VIS/NIRS) to determine carotenoid contents in banana (*Musa* spp.) fruit pulp. *Journal of Agricultural and Food Chemistry*. 2009;57(5):1742-1751.
 8. Schlerf M, Atzberger C, Hill J, Buddenbaum H, Werner W, Schüler G. Retrieval of chlorophyll and nitrogen in Norway spruce (*Picea abies* L. Karst.) using imaging spectroscopy. *International Journal of Applied Earth Observation and Geoinformation*. 2010;12:17-26. DOI:10.1016/j.jag.2009.08.006.
 9. Curran PJ. Remote sensing of foliar chemistry. *Remote Sensing of Environment*. 1989;30(3):271-278.
 10. Skidmore AK, Ferwerda JG, Mutanga O, Van Weiren SE, Peel M, Grant RC, Prins HH, Balci FB, Venus V. Forage quality of savannas-simultaneously mapping foliar protein and polyphenols for trees and grass using hyperspectral imagery. *Remote Sensing of Environment*. 2010; 114:64-72.
 11. Bowers SA, Hanks RJ. Reflection of radiant energy from soils. *Soil Science*. 1965;100:130-138.
 12. Dalal RC, Henry RJ. Simultaneous determination of moisture, organic carbon, and total nitrogen by near infrared reflectance spectrophotometry. *Soil Science Society of America Journal*. 1986;50:120-123.
 13. Barnes EM, Sudduth KA, Hummel JW, Lesch SM, Corwin DL, Yang C, Daughtry CST, Bausch WC. Remote and ground-based sensor techniques to map soil properties. *Photogrammetric Engineering and Remote Sensing*. 2003;69:619-630.
 14. Mouazen AM, Maleki MR, De Baerdemaeker J, Ramon H. On-line measurement of some selected soil properties using a VIS-NIR sensor. *Soil and Tillage Research*. 2007;93:13-27.
 15. Sudduth KA, Hummel JW. Soil organic matter, CEC, and moisture sensing with a portable NIR spectrophotometer. *Transactions of American Society of Agricultural Engineers*. 1993;36:1571-1582.
 16. Adamchuk VI, Hummel JW, Morgan MT, Upadhyaya SK. On-the-go soil sensors for precision agriculture. *Computer and Electronics in Agriculture*. 2004;44:71-91.
 17. Stevens A, Van Wesemael B, Bartholomeus H, Rosillon D, Tychon B, Ben-Door E. Laboratory, field and airborne spectroscopy for monitoring organic carbon content in agricultural soils. *Geoderma*. 2008;144:395-404.
 18. Udelhoven T, Emmerling C, Jarmer T. Quantitative analysis of soil chemical properties with diffuse reflectance spectrometry and partial least-square regression: A feasibility study. *Plant and Soil*. 2003;251:319-329.
 19. Ben-Dor E, Heller D, Cudnovsky A. A novel method of classifying soil profiles in the field using optical means. *Soil Science Society of America Journal*. 2008;72:1113-1123.
 20. Chen F, Kissel DE, West LT, Adkins W. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. *Soil Science Society of America Journal*. 2000;64:746-753.
 21. Galvao LS, Pizarro MA, Neves Epiphanyo JC. Variations in reflectance of tropical soils: Spectral-chemical composition relationships from AVIRIS data. *Remote Sensing of Environment*. 2001;75:245-255.
 22. Ben-Dor E. Quantitative remote sensing of soil properties. *Advances in Agronomy*. 2002;75:173-243.
 23. Baumgardner MF, Silva LF, Biehl LL, Stoner ER. Reflectance properties of soils. *Advances in Agronomy*. 1986;38(1):1-44.
 24. Mulder VL, Bruin SDE, Schaepman ME, Mayr, TR. The use of remote sensing in soil and terrain mapping- A review. *Geoderma*. 2011;162:1-19.
 25. Stoner ER, Baumgardner MF. Characteristic variations in reflectance of surface Soils. *Soil Science Society of America Journal*. 1981;45(6):5.
 26. Ben-Dor E. Characterization of soil properties using reflectance spectroscopy. In: Thenkabail PS, Lyon JG, Huete A editors. *Hyperspectral remote sensing of vegetation*. CRC Press, Florida. 2011;513-558.
 27. Hill J, Udelhoven T, Vohland M, Stevens A. The use of laboratory spectroscopy and optical remote sensing for estimating soil properties. In: Oerke EC et al editors. *Precision crop protection- the challenge and use of heterogeneity*. Springer, Dordrecht. 2010;67-86.

28. Das BS, Sarathjith MC, Santra P, Sahoo RN, Srivastava R, Routray A, Ray SS. Hyperspectral remote sensing: Opportunities, status and challenges for rapid soil assessment in India. *Current Science*. 2015;108(5):860-868.
29. Clark RN, King TVV, Klejwa M, Swayze GA, Vergo N. High spectral resolution reflectance spectroscopy of minerals. *Journal of Geophysical Research*. 1990; 95:12653-12680.
30. Clark RN. Spectroscopy of rocks and minerals and principles of spectroscopy. In: Rencz AN editor. *Remote sensing for the earth sciences: manual of remote sensing*. American Society for Photogrammetry and Remote Sensing, Maryland. 1999;3-58.
31. Lobell DB, Asner GP. Moisture effects on soil reflectance. *Soil Science Society of America Journal*. 2002;66:722-727.
32. Aber JD, Wessman CA, Peterson DL, Melillo JM, Fownes JH. Remote sensing of litter and soil organic matter decomposition in forest ecosystems. In: Hobbs RJ, Mooney H editors. *Remote sensing of biosphere functioning*. Springer-Verlag, New York. 1990;87-103.
33. Cierniewski J, Kusnierek K. Influence of several soil properties on soil surface reflectance. *Quaestiones Geographicae*. 2010;29(1):14-25.
34. Stenberg B, Viscarra Rossel RA, Mouazen AM, Wetterlind J. Visible and near infrared spectroscopy in soil science. *Advances in Soil Science*. 2010;107:163-215.
35. Ben-Dor E, Irons JR, Epema GF. Soil reflectance. In: Rencz NA editor. *Remote sensing for the earth sciences: manual of remote sensing*. John Wiley, New York; 1999;111-188.
36. Shepherd KD, Walsh MG. Development of reflectance spectral libraries for characterization of soil properties. *Soil Science Society of America Journal*. 2002; 66:988-998.
37. Ben-Dor E. Quantitative remote sensing of soil properties. *Advances in Agronomy*. 2002;75:173-243.
38. Okin GS, Painter TH. Effect of grain size on remotely sensed spectral reflectance of sandy desert surfaces. *Remote Sensing of Environment*. 2004;89:272-280. DOI: 10.1016/j.rse.2003.10.008
39. Sarathjith MC, Das BS, Vasava HV, Mohanty B, Anand SS, Wani SP, Sahrawat KL. Diffuse reflectance spectroscopic approach for the characterization of soil aggregate size distribution. *Soil Science Society of America Journal*. 2014;78:369-376.
40. Baldrige AM, Hook SJ, Grove CI, Rivera G. The ASTER spectral library version 2.0. *Remote Sensing of Environment*. 2009; 113(4):711-715.
41. Viscarra Rossel RA. The soil spectroscopy group and the development of a global soil spectral library. *NIR News*. 2009;20(4):14-15.
42. Viscarra Rossel RA, Behrens T, Ben-Dor E, et al. A global spectral library to characterize the world's soil. *Earth-Science Reviews*. 2016;155:198-230.
43. NBSS&LUP. Annual report 2013-14. National Bureau of Soil Survey and Land Use Planning, Nagpur, India. 2014;28-29.
44. Viscarra Rossel RA, Walvoort DJJ, McBratney AB, Janik LJ, Skjemstad JO. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma*. 2006;131(1-2): 59-75.
45. Dardenne P. Stability of NIR spectroscopy equations. *NIR News*. 1996;7(5):8.
46. Pinheiro EFM, Ceddia MB, Clingensmith CM, Grunwald S, Vasques GM. Prediction of soil physical and chemical properties by visible and near-infrared diffuse reflectance spectroscopy in the Central Amazon. *Remote Sensing*. 2017;9(293):1-22. DOI: 10.3390/rs9040293
47. Islam K, Singh B, McBratney AB. Simultaneous estimation of various soil properties by ultra-violet, visible and near-infrared reflectance spectroscopy. *Australian Journal of Soil Research*. 2003; 41:1101-1114.
48. Janik LJ, Merry RH, Skjemstad JO. Can mid infra-red diffuse reflectance analysis replace soil extractions? *Australian Journal of Experimental Agriculture*. 1998;38(7): 681-696.
49. Shibusawa S, Imade Anom SW, Sato S, Sasao A, Hirako S. Soil mapping using the real-time soil spectrophotometer. In: Grenier G, Blackmore S editors. *Proceedings of third european conference on precision agriculture*. Sup Agro, Montpellier. 2001;1:497-508.
50. Chang CW, Laird DA. Near-infrared reflectance spectroscopic analysis of soil C and N. *Soil Science*. 2002;167(2):110-116.

51. McCarty GW, Reeves III JB, Reeves VB, Follett RF, Kimble JM. Mid-infrared and near-infrared diffuse reflectance spectroscopy for soil carbon measurements. *Soil Science Society of America Journal*. 2002;66:640-646.
52. Chang CW, Laird DA, Mausbach MJ, Hurburgh CRJ. Near-infrared reflectance spectroscopy - principal components regression analyses of soil properties. *Soil Science Society of America Journal*. 2001;65:480-490.
53. Daniel KW, Tripathi NK, Honda K. Artificial neural network analysis of laboratory and in situ spectra for the estimation of macronutrients in soils of Lop Buri (Thailand). *Australian Journal of Soil Research*. 2003;41:47-59.
54. Cozzolino D, Moron A. The potential of near-infrared reflectance spectroscopy to analyse soil chemical and physical characteristics. *Journal of Agricultural Sciences*. 2003;140:65-71.
55. He Y, Huang M, Garcia A, Hernandez A, Song H. Prediction of soil macronutrients content using near-infrared spectroscopy. *Computers and Electronics in Agriculture*. 2007;58(2):144-153.
56. Nduwamungu C, Ziadi N, Tremblay GF, Parent LE. Near-infrared reflectance spectroscopy prediction of soil properties: Effects of sample cups and preparation. *Soil Science Society of America Journal*. 2009;73:1896-1903.
57. Wetterlind J, Stenberg B, Soderstrom M. Increased sample point density in farm soil mapping by local calibration of visible and near infrared prediction models. *Geoderma*. 2010;153(3-4):152-160.
58. Ji W, Shi Z, Huang J, Li S. *In situ* measurement of some soil properties in paddy soil using visible and near-infrared spectroscopy. *Public Library of Science One*. 2014;9(8):1-11. DOI:10.1371/journal.pone.0105708
59. Bilgili AV, van Es H, Akbas F, Durak A, Hively W. Visible-near infrared reflectance spectroscopy for assessment of soil properties in a semi-arid area of Turkey. *Journal of Arid Environment*. 2010;74(2): 229-238.
60. Wetterlind J, Stenberg B. Near-infrared spectroscopy for within-field soil characterization: Small local calibrations compared with national libraries spiked with local samples. *European Journal of Soil Science*. 2010;61(6):823-843.
61. Vendrame PRS, Marchao RL, Brunet D, Becquer T. The potential of NIR spectroscopy to predict soil texture and mineralogy in Cerrado Latosols. *European Journal of Soil Science*. 2012;63(5):743-753.
62. Yang XM, Xie HT, Drury CF, Reynolds WD, Yang JY, Zhang XD. Determination of organic carbon and nitrogen in particulate organic matter and particle size fractions of Brookston clay loam soil using infrared spectroscopy. *European Journal of Soil Science*. 2012;63(2):177-188.
63. Dick WA, Thavamani B, Conley S, Blaisdell R, Sengupta A. Prediction of β -glucosidase and β -glucosaminidase activities, soil organic C, and amino sugar N in a diverse population of soils using near infrared reflectance spectroscopy. *Soil Biology and Biochemistry*. 2013;56:99-104.
64. Vasques GM, Grunwald S, Harris WG. Spectroscopic models of soil organic carbon in Florida, USA. *Journal of Environmental Quality*. 2010;39(3):923-934.
65. Rabenarivo M, Chapuis-Lardy L, Brunet D, Chotte JL, Rabeharisoa L, Barthes BG. Comparing near and mid-infrared reflectance spectroscopy for determining properties of Malagasy soils, using global or local calibration. *Journal of Near Infrared Spectroscopy*. 2013;21(6):495-509.
66. Amare T, Hergarten C, Hurni H, Wolfram B, Yitafaru B, Selassie YG. Prediction of soil organic carbon for Ethiopian highlands using soil spectroscopy. *International Scholarly Research Notices Soil Science*. 2013;11:720589.
67. Ji W, Viscarra Rossel RA, Shi Z. Accounting for the effects of water and the environment on proximally sensed Vis-NIR soil spectra and their calibrations. *European Journal of Soil Science*. 2015; 66(3):555-565.
68. Nocita M, Kooistra L, Bachmann M, Muller A, Powell M, Weel S. Predictions of soil surface and topsoil organic carbon content through the use of laboratory and field spectroscopy in the Albany Thicket Biome of Eastern Cape Province of South Africa. *Geoderma*. 2011;167:295-302.
69. Leone A, Viscarra Rossel RA, Amenta P, Buondonno A. Prediction of soil properties with PLSR and Vis-NIR spectroscopy: Application to Mediterranean soils from

- Southern Italy. *Current Analytical Chemistry*. 2012;8(2):283-299.
70. Xie HT, Yang XM, Drury CF, Yang JY, Zhang XD. Predicting soil organic carbon and total nitrogen using mid and near infrared spectra for Brookston clay loam soil in Southwestern Ontario, Canada. *Canadian Journal of Soil Science*. 2011; 91(1):53-63.
 71. Stevens A, Nocita M, Toth G, Montanarella L, van Wesemael B. Prediction of soil organic carbon at the European scale by visible and near infrared reflectance spectroscopy. *Public Library of Science One*. 2013;8(6):1-13. DOI: 10.1371/journal.pone.0066409
 72. Lee KS, Lee DH, Sudduth KA, Chung SO, Kitchen NR, Drummond ST. Wavelength identification and diffuse reflectance estimation for surface and profile soil properties. *Transactions of American Society of Agricultural and Biological Engineers*. 2009;52:683-695.
 73. Sudduth K, Kitchen N, Sadler E, Drummond S, Myers D. VNIR spectroscopy estimates of within-field variability in soil properties. In: Viscarra Rossel RA et al. editors. *Proximal soil sensing, progress in soil science*. Springer, Dordrecht, the Netherlands; 2010.
 74. Awiti AO Walsh MG, Shepherd KD, Kinyamario J. Soil condition classification using infrared spectroscopy: A proposition for assessment of soil condition along a tropical forest- cropland chronosequence. *Geoderma*. 2008;143:73-84.
 75. Curcio D, Ciraolo G, D'Asaro F, Minacapilli M. Prediction of soil texture distributions using VNIR–SWIR reflectance spectroscopy. *Procedia Environmental Science*. 2013;19:494-503.
 76. Ramirez-Lopez L, Behrens T, Schmidt K, Stevens A, Dematte JAM, Scholten, T. The spectrum-based learner: A new local approach for modeling soil vis-NIR spectra of complex datasets. *Geoderma*. 2013; 195:268-279.
 77. Sankey JB, Brown DJ, Bernard ML, Lawrence RL. Comparing local vs. global visible and near-infrared (VisNIR) diffuse reflectance spectroscopy (DRS) calibrations for the prediction of soil clay, organic C and inorganic C. *Geoderma*. 2008;148(2):149-158.
 78. Genot V, Colinet G, Bock L, Vanvyve D, Reusen Y, Dardenne P. Near infrared reflectance spectroscopy for estimating soil characteristics valuable in the diagnosis of soil fertility. *Journal of Near Infrared Spectroscopy*. 2011;19(2):117-138.
 79. Waruru BK, Shepherd KD, Ndegwa GM, Kamoni PT, Sila AM. Rapid estimation of soil engineering properties using diffuse reflectance near infrared spectroscopy. *Biosystems Engineering*. 2014;121:177-185.
 80. Geladi P. Chemometrics in spectroscopy-part-1: Classical chemometrics. *Spectrochimica Acta Part B: Atmospheric Spectroscopy*. 2003;58:767-782.
 81. Burns DA, Ciurczack EW. *Handbook of Near-Infrared Analysis*. Marcel Dekker, New York; 2001.
 82. Albrecht R, Joffre R, Gros R, Le Petit J, Terrom G, Perissol C. Efficiency of near-infrared reflectance spectroscopy to assess and predict the stage of transformation of organic matter in the composting process. *Bioresource Technology*. 2008;99:448-455.
 83. Kawamura K, Mackay AD, Touhy MP, Betteridge K, Sanches ID, Inoue Y. Potential for spectral indices to remotely sense phosphorus and potassium content of legume-based pasture as a means of assessing soil phosphorus and potassium fertility status. *International Journal of Remote Sensing*. 2011;32(1):103-124. DOI: 10.1080/01431160903439908

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