www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2023; SP-12(9): 2426-2431

www.thepharmajournal.com
Received: 20-06-2023
Accepted: 24-07-2023

Devid Kumar Sahu
Department of Soil Science and Agricultural Chemistry, JNKVV, Jabalpur, Madhya Pradesh, India

Homeshvari
Department of Fruit Science, JNKVV, Jabalpur, Madhya Pradesh, India

Vishakha Rai
Department of Soil Science and Agricultural Chemistry, JNKVV, Jabalpur, Madhya Pradesh, India

Vivek Singh
Department of Soil Science and Agricultural Chemistry, JNKVV, Jabalpur, Madhya Pradesh, India

Sunil Kumar Upadhyay
Department of Soil Science and Agricultural Chemistry, JNKVV, Jabalpur, Madhya Pradesh, India

Corresponding Author:
Devid Kumar Sahu
Department of Soil Science and Agricultural Chemistry, JNKVV, Jabalpur, Madhya Pradesh, India

Use of hyperspectral remote sensing as advanced tools for study in soil characteristics: A review

Devid Kumar Sahu, Homeshvari, Vishakha Rai, Vivek Singh and Sunil Kumar Upadhyay

Abstract
Minimizing environmental consequences and enhancing crop yield are based on soil chemical, physical, and mineralogical properties. Traditional procedures, on the other hand, are time consuming and costly. Soil property mapping must be done quickly and accurately for agricultural, forestry, and environmental management. In addition to mapping and classifying soil, hyperspectral remote sensing can also be utilized for texture descriptions. The aim of this work is to extend and analysis an alternate approach for assessing soil parameters utilizing UV-Vis-NIR spectroscopy to existing soil analysis methods. Optical remote sensing analyzes variable electromagnetic radiation (spectral characteristics) reflected from various targets on the Earth's surface in the visible spectral area, namely near infrared, shortwave infrared, and thermal infrared (0.4 to 14 microns). The analysis and evaluation of reflected radiation detected by a large number of narrow, contiguous, and continuous spectral bands is the basis of hyper spectral remote sensing. It is also known as imaging spectroscopy. Imaging spectrometers' detailed spectrum characterization of surface absorption patterns allows robust inversion methods to be utilized to recover biological and geochemical information about the captured area.

Keywords: Hyperspectral remote sensing, soil characteristics, mapping

Introduction
Soil is a valuable natural resource that provides an irreplaceable and diversified environment for all eco-system (Breemen and Buurman *et al*. 2003 and Osman *et al*. 2014) [68, 75]. Soil quality management both globally and temporally is crucial for agro ecological sustainability (Hively *et al*. 2011 and Lagacherie *et al*. 2013) [27, 37]. However, one of the major challenges in environmental monitoring is the timely and accurate measurement of soil attribute. Traditional methods for analysis are accurate for identify and observe of soil attribute, but they require a more number of samples to detect spatial variability, which takes time and labor (Jaber *et al*. 2011 and Ciampalini *et al*. 2015) [28, 14]. Furthermore, the applications of these techniques are limited to local or small areas, whereas scientists and researchers need estimates of soil quality at a larger scale (Psomas *et al*. 2011) [50]. As a result, novel techniques for monitoring soil parameters are required.
Many contiguous narrow spectrum bands of electromagnetic radiation (EMR) in the visible, near-infrared, mid-infrared and thermal infrared regions are measured by hyperspectral sensors. Certain soil features have a specific absorption band that can be used to identify them, according to laboratory and field investigations. Soil water, for example, has lesser absorption bands at 970, 1200, and 1770 nanometer and more significant absorption bands at 1400 nm and 1900 nm. Similarly, gypsum and montmorillonite have absorption bands at 1800 and 2300 nm, as well as between 520 and 1000 nm. Soil spectral signatures that may be measured quickly can aid in the development of algorithms for estimating soil parameters (Shepherd *et al*. 2002, Brown *et al*. 2006, Rossel *et al*. 2016, Katuwal *et al*. 2017) [60, 9, 71, 32]. These created methods can also be used by unmanned aircraft and remote sensor devices to rapidly generate a map of a soil's attributes. A rapid scan of geocoded soil samples were estimated using spectral based algorithms however; this may require a large library of soil spectra representing diverse soil types in India.

Application of hyper spectral remote sensing in soil mineral identification
Geological surveys based Traditional mineral mapping is labor intensive, expensive and ineffective. Traditional investigations entail substantial structural mapping, landform study, petrology, mineralogical and soil chemical analysis (Kusuma *et al*. 2012, Ramakrishnan *et al*.

2015) [36, 52-53]. RS, on the other hand, provides significantly more affordable method of quickly finding and collecting mineral information across entire geographical area. This is because spectral data obtained by remote sensing might be utilized to infer hydrothermally altered mineral or altered mineral area, which have been linked various kinds of mineralize systems (Carrino *et al*. 2018) [11].

155 bands were evaluated using hyper spectral data to identifying and mapping the key altered minerals by absorption bands between VNIR and SWIR areas. SAM and SFF methods are utilized to determine the mineral are presents. Five minerals, kaolinite-5, kaolinite-2, muscovite, hematite, and kaosmec, are identified and used to create a mineral map using the SAM classifier on a Hyperion data (Rani *et al*. 2015) [54]. Despite the low signal to noise ratio of the Hyperion image they are capable to detect dolomite and dolomite with chlorite from the data. Spectroscopic studies are appropriate for identifying minerals and rocks (Govil *et al*. 2018) [23]. Significant discrepancies are noted for quartz-rich sediments, with SWIR overestimating their distribution and LWIR producing more consistent results when compared to current maps. Longwave infrared (LWIR) and shortwave infrared (SWIR) pictures were both influenced by widespread lichen coatings on mafic rocks (basalts and gabbros), with SWIR providing better findings than LWIR (Feng *et al*. 2018) [17]. Significant correlation between iron oxide concentration with near-infrared absorption feature depth and width across different empirical models, with root mean square error (RMSE) (Shaik *et al*. 2021) [58]. Mineral identification and mapping using airborne hyperspectral data employing methods such as spectral angle mapper (SAM), spectral feature fitting (SFF), and mixture tuned matched filtering (MTMF). The visible and near-infrared spectral reflectance of minerals is used to identify them. A total of 13 minerals were detected and a mineral map was created using various methods. The mineral map created by the MTMF method is more convenient and accurate than other algorithms (Jain *et al*. 2019) [29]. Vertical stripes are removed using a local split removal algorithm. Absolute area inversion was performed using the FLAASH module. Spectral information is reduced using minimal noise refraction techniques and applying quiet bands to the pixel purity index and the purest pixels on Earth's surfaces (Vigneshkumar *et al*. 2017) [70]. AVIRIS-NG hyperspectral data can and may be used to identify and determine hydrothermally changed, weathered, and clay minerals (Tripathi *et al*. 2017) [67]. A thorough examination of reflectance spectroscopy for identifying of minerals from rare earths in carbonatite samples from throughout the world (Neave *et al*. 2016) [44]. Short range hyperspectral image is helpful for detecting absorption features caused by base metal (Boesche *et al*. 2015) [8]. More advanced techniques of RS by implementing the resonant microwave cavity concept in hyperspectral SAR images. Beyond the mineral explorations, the authors used the hyperspectral imaging technique to corroborate its rapid capacity as an application in food safety. (Morrison *et al*. 2016) [30].

Application of hyperspectral remote sensing in soil nutrient prediction

Soil nutrients are important for assessing soil fertility and play an important role in soil productivity, food safety, and to sustain agro-ecological (Nowak *et al*. 2015) [45]. Soil nutrient mapping that is timely and precise can be very beneficial in minimizing nutrients losses and thus enhancing fertilizer management. Hyperspectral remote sensing data has become an essential source of information for modeling soil nutrients due to its capacity to detect even the tiniest spectrum changes in soil nutrients (Song *et al*. 2018) [63].

Stepwise regression models based on spectral images formed from increased spectral variables produced good geographic distributions, indicating that this method has a high potential for predicting soil attributes. (Yu *et al*. 2017) [74]. The suggested machine learning method has the ability to efficiently determine soil nutrient spectral characteristic indices, improve the accuracy of results. LASSO and GBDT algorithms were used to increases the precision of soil total N, P and K estimation, which is important for managing agricultural land (Peng *et al*. 2021) [48]. A combination of SWIR, NIR, and visible region was found to be more useful for assessing plant nutrient levels (Mahajan *et al*. 2014) [40]. Computer vision hyperspectral remote sensing have been excellent assessment accuracy and efficient reflection for organic carbon, nitrogen, phosphorus and potassium content (Ma *et al*. 2022) [39]. Multiple linear regression (MLR), random forest regression (RFR), support vector machine for regression (SVR), and gradient boosting (GB) were used to analysed for N, P, K and organic carbon content using optical remote sensing data, terrain/climate data and real soil value. Suggest that GB and RFR performed superior than other sMAPE models (Kaur *et al*. 2020) [33]. Assessing soil nutrients the DWT-SVR (discrete wavelet transformation-support vector regression) method may be a good data mining strategy. (Sarathjith *et al*. 2016) [56]. The spectral region 993.2 nm has a distinct characteristic. As a result, a model for estimating N, P and K fractional abundance in soil samples is developed (Patel *et al*. 2019) [47]. The RF model outperformed the SVR model in reproducing micronutrient heterogeneity as well as extreme values in the resulting maps (Keshavarzi *et al*. 2022) [34]. Apply neural network model for predicting status of soil nutrients using principal wavelet components (Gulhane *et al*. 2017) [25].

Application of hyperspectral remote sensing in soil organic carbon estimation

SOC is an important source of plant nutrients, stimulates particle aggregation, improves soil structure, enhances water holding capacity, and gives habitation for soil microorganism. (Schoonover and Crim 2015) [57]. The impact of SOC on agricultural productivity has driven interest in digital soil mapping technologies (Chen *et al*. 2000, Frazier *et al*. 1989, Mishra *et al*. 2009 and Mulder *et al*. 2011) [13, 19, 42, 43]. Spectroscopy is utilized digital soil mapping systems since it have been shown to precisely and effectively relate spectral reflectance to soil characteristics (Bachofer *et al*. 2015, Gomez *et al*. 2008) [2, 22].

Soil organic carbon index (SOCI) had the potential to be used for forecast and map SOC using Worldview-2 satellite spectra data to the same range as the Rapid Carbon evaluation laboratory spectra (Thaler *et al*. 2018) [65]. The multiple regression equation among SOM content and spectral index was significant and the color index was greater significance in estimating soil organic carbon (Mandal *et al*. 2016) [41]. A statistical relationship between soil organic carbon content and image brightness value in the blue, red and green of an aerial image and a logarithmic equation was developed for prediction organic carbon status. After completing a spectral test on laboratory soil, the amount of organic matter in the soil in the range of 0.35 μm to 1.4 μm was assessed and the form of the reflectance spectrum was calculated. The coefficient of the polynomial of degree 3 was used as a parameter to determine the shape of the continuous spectral curve for soil. Obtaining the spectral reflect values to calculate the polynomial coefficients is necessary for this method of predicting the organic matter content in TM or ETM images (Sharma *et al*. 2015) [59]. High organic matter content in soils its increases soil color changes light to dark the reflectivity of the soil spectra decreases and to predict model built using remote sensing technique becomes more precise (Xie *et al*. 2018) [72]. In an independent data set containing field spectroscopic data, random forest regression can more accurately estimate status of soil organic carbon. The PLSR model on the other hand, over fits the calibration data set. The visible range was the most critical wavelength for predicting soil organic content (Bangelesa *et al*. 2020) [3]. Soil organic carbon (SOC) content was evaluated and compared using ordinary kriging and cokriging geostatistical approaches with hyperion data as an independent variable. In general CK methods outperformed OK in the geographical to predict of SOC content (Saha *et al*. 2011) [55]. The artificial neural network (ANN) model was potential technique to predict the distribution of SOC using hyperspectral data in the agricultural field (Tiwari *et al*. 2015) [66]. Remote sensing (RS)-based indices using multiple linear regression stepwise (MLR- stepwise), partial least squares regression (PLSR) and principal component analysis-regression (PCA-R). The MLR-stepwise model was found to be superior in performance with high and minimal RMSE compared to PLSR and PCA-R and RMSE models for SOC prediction (Yami *et al*. 2023) [73]. SOC and spectral indices (NDVI and BSI) were found to have a statistically significant (Bhunia *et al*. 2017) [6].

Application of hyperspectral remote sensing in soil moisture estimation

Soil moisture is a vital phase in the hydrological system and their evaluations are to predict changes in a region's water balance. Direct soil moisture measurements are frequently expensive, time consuming, invasive, and technology dependant. RS data has been brought out as a promising technique for measuring soil moisture characteristics in various landscapes and sampling points as an alternative to point data in soil by providing a regional description of water redistribution at various temporal and geographical resolutions.

The NIR wavelength spectral reflections is high sensitive to soil moisture fluctuation than the visible and bands in this range were addressed while creating empirical models for soil moisture estimate (Gulfo *et al*. 2012) [24]. Metric learning-based soil moisture estimation methods outperform traditional methods that use principal component analysis for feature reduction (Tang *et al*. 2022) [64]. Precision agriculture can make better use of high resolution soil moisture data for irrigation scheduling (Lakhankar *et al*. 2009) [38]. In the laboratory, a recently developed model multilayer radiative transfer model of soil reflectance provides a good fit to measured soil moisture content (Eon *et al*. 2021) [16]. A significant statistical correlation between hyperion data and soil moisture probe data (Finn *et al*. 2011) [18]. We used Landsat 8 optical and thermal sensors to retrieve soil moisture using random forest (RF), support vector machine (SVM), artificial neural network (ANN) and elastic net regression (EN) techniques. The RF model outperforms the SVM, ANN and EN algorithms in terms of soil moisture predictions (Adab *et al*. 2020) [1]. This study's objective was to determine whether SMI from Landsat 8 could be utilized to monitor soil moisture in agricultural fields and comprehend its link with soil temperature and crop growth (Sholihah *et al*. 2021) [61]. Passive microwaves have a greater probability of detecting soil moisture condition on a large scale, but have a low spatial resolution. The active microwave has a very high spatial resolution, but it has a relatively low return frequency and is more susceptible to vegetation and ground hardness. SAR is critical for retrieving regional soil moisture maps. Radar data (SAR) is considered the best tool to obtain information on soil moisture at the field level, but it also presents serious problems such as the presence of surface roughness, crop cover and variation in soil texture over large agricultural area (Snehlata *et al*. 2021) [62]. The hyperspectral imaging (HIS) technology can detect soil type and moisture content. (Haijun *et al*. 2017, Rajitha *et al*. 2022) [26, 51].

Application of hyperspectral remote sensing in soil texture

The most important soil factors is a soil texture, which is described as the mixture of three particle sizes such as sand, silt and clay. Because soil texture correlates with physical attributes such as consistency, rooting capacity and water and air retention capacity, it is an important criterion to define soil characteristics and plant growing conditions (Blume *et al*. 2010) [7]. Soil textural mapping at various scales is required; however the traditional method requires a greater number of samples and analysis to adequately determine the spatial diversity of soil texture (Curcio *et al*. 2013) [15]. Because standard techniques and field surveys are costly users are now developing indirectly estimating methods using proximal and remote sensors, especially reflected spectrometer (Brown *et al*. 2006) [10]. As input data for PLSR model, hyperion image data and soil information were used to successfully assess soil texture and generate maps containing regions of similar soil characteristics (Kanning *et al*. 2016) [31]. CHRIS was able to perform better than MIVIS in terms of its accuracy and ability to predict the texture of soil (Casa *et al*. 2013) [12]. Sentinal-2 imagery data are accurate and useful for detect and map variation in clay but don't for silt and sand (Gholizadeh *et al*. 2018) [21]. Soil classification using Support Vector Machine (SVM) is more significance for soil analysis of very complex region without reduction of dimensionality in satellite data (Vibhute *et al*. 2015) [69]. The PLSR technique has potential for forecast and assist us in geographical mapped of soil textural using hyperion data (George *et al*. 2015) [20].

Conclusion

HRS technology offers an attractive alternative for simple and fast soil analysis. However, there are technology constraints to get around in order achieving HRS utility.

- High resolution HRS data must be available, as well as the technological skills to analyze such data.
- To obtain farmer friendly HRS data products, there should also be national and regional spectral library databases with validated spectral algorithms.
- HRS, like any other type of remote sensing data, is confined to gathering information about the ground surface. Models must be developed to extend information from the surface soil to the profile parameters. Furthermore, the vegetation cover influences the evaluation of the soil by distant sensors.

In addition to the complexity mentioned above, it is predicted that hyperspectral data will be employed for operational monitoring of soil health in the near future. As a result, a dedicated space broadcast from polar orbits is critical for ground assessment by giving high-quality hyperspectral data.

Acknowledgements
The authors would like to thank to National Agriculture Higher Education Project (NAHEP), Centre for Advanced Agriculture Science and Technology on “Skill development to use data for natural resources management in agriculture”, College of Agricultural Engineering, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur for providing financial and other support.

References
1. Adab H, Morbidelli R, Saltalippi C, Moradian M, Ghalhari GAF. Machine Learning to Estimate Surface Soil Moisture from Remote Sensing Data, Water. 2020;12(11):3223
2. Bachofer F, Quénéhervé G, Hochschild V, Maerker M. Multisensoral topsoil mapping in the semiarid Lake Manyara region, northern Tanzania. Remote Sens. 2015;7:9563-9586.
3. Bangelesa F, Adam E, Knight J, Dhau I, Ramudzuli M, Mokotjomela TM. Predicting Soil Organic Carbon Content Using Hyperspectral Remote Sensing in a Degraded Mountain Landscape in Lesotho, Applied and Environmental Soil Science; c2020.
4. Ben Dor E, Chabrillat S, Dematte JAM, Taylor GR, Hill J, Whiting ML, *et al*. Using imaging spectroscopy to study soil properties. Remote sensing of environment. 2009;113(1):S38-S55.
5. Ben-Dor E, Banin A. Near-infrared analysis as a rapid method to simultaneously evaluate several soil properties. Soil Sci. Soc. Am. J. 1995;59:364-372.
6. Bhunia GS, Shit PK, Pourghasemi HR. Soil organic carbon mapping using remote sensing techniques and multivariate regression model, Geocarto International; c2017. DOI: 10.1080/10106049.2017.1381179.
7. Blume HP, Brümmer G, Horn R, Kandeler E, Kögel-Knabner I, Kretzschmar R, *et al*. Scheffer / Schachtschabel Lehrbuch der Bodenkunde, 16th ed.; Spectrum Akademischer Verlag: Heidelberg, Germany; c2017.
8. Boesche N, Rogass C, Lubitz C, Brell M, Herrmann S, Mielke C, *et al*. Hyperspectral REE (rare earth element) mapping of out crops applications for neodymium detection. Remote Sensing. 2015;7:5160-5186.
9. Brown DJ, Shepherd KD, Walsh MG, Dewayne Mays M, Reinsch TG. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma. 2006;132:273-290.
10. Brown DJ, Shepherd KD, Walsh MG, Mays MD, Reinsch TG. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma. 2006;132:273-290.
11. Carrino TA, Crósta AP, Toledo CLB, Silva AM. Hyperspectral remote sensing applied to mineralexploration in southern Peru: A multiple data integration approach in the Chapi Chiara gold prospect. Int. J Appl. Earth Obs. Geoinf. 2018;64:287_300.
12. Casa R, Castaldi F, Pascucci S, Palombo A, Pignatti S. A comparison of sensor resolution and calibration strategies for soil texture estimation from hyperspectral remote sensing. Geoderma. 2013;197(198):17-26.
13. Chen F, Kissel DE, West LT, Adkins W. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Sci. Soc. Am. J. 2000;64:746-753.
14. Ciampalini A, André F, Garfagnoli F, Grandjean G, Lambot S, Chiarantini L, *et al*. Improved estimation of soil clay content by the fusion of remote hyperspectral and proximal geophysical sensing. J Appl Geophys. 2015;116:135-145.
15. Curcio D, Ciraolo G, Asaro FD, Minacapilli M. Prediction of soil texture distributions using VNIR/SWIR reflectance spectroscopy. Proc. Environ. Sci. 2013;19:494-503.
16. Eon RS, Bachmann CM. Mapping barrier island soil moisture using a radiative transfer model of hyperspectral imagery from an unmanned aerial system. Sci Rep. 2021;11:3270.
17. Feng J, Rogge D, Rivard B. Comparison of lithological mapping results from airborne hyperspectral VNIR_SWIR, LWIR and combined data. Int. J. Appl. Earth Obs. Geoinf. 2018;64:340-353.
18. Finn MP, Lewis M, Bosch D, Giraldo M, Yamamoto K, Sullivan DG, *et al*. Remote Sensing of Soil Moisture Using Airborne Hyperspectral Data, GIScience & Remote Sensing. 2011;48(4):522-540.
19. Frazier B, Cheng Y. Remote sensing of soils in the eastern Palouse region with Landsat Mhematic mapper. Remote Sens. Environ. 1989;28:317325.
20. George KG, Kumar V, Danodia A, Kumar S, Kumar AS. Hyperspectral modelling for prediction of soil texture using asd spectroradiometer derived soil spectra; c2015.
21. Gholizadeh A, Zizala D, Saberioon M, Boruvka L. Oil organic carbon and texture retrieving and mapping using proximal, airborne and Sentinel-2 spectral imaging, remote sensing of environment; c2018. p. 89-103.
22. Gomez C, Rossel RAV, McBratney AB. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study. Geoderma. 2008;146:403-411.
23. Govil H, Gill N, Rajendran S, Santosh M, Kumar S. Identification of new base metal mineralization in Kumaon Himalaya, India, using hyperspectral remote sensing and hydrothermal alteration. Ore Geol. Rev. 2018;92:271-283.
24. Gulfo E, Sahoo RN, Sharma RK, Khanna M. Soil moisture assessment using hyperspectral remote sensing. In Proceedings of the Second National Workshop on Challenges and Opportunities of Water Resources Management in Tana Basin, Upper Blue Nile Basin, Ethiopia. Blue Nile Water Institute, Bahir Dar University, Ethiopia; c2012. p. 69-77.
25. Gulhane VA, Rode SV, Pande CB. Wavelet for Predicting Soil Nutrients using Remotely Sensed Satellite Images. International Journal of Computer Applications. 2017;174(4):35-38.
26. Haijun Q, Xiu J, Liu Z, Maxime DI, Shaowen L. Predicting sandy soil moisture content with hyperspectral imaging, Int J Agric & Biol Eng. 2017;10(6):175.
27. Hively WD, McCarty GW, Reeves JB, Lang MW, Oesterling RTA, Delwiche SR. Use of airborne hyperspectral imagery to map soil properties in tilled agricultural fields. Appl Environ Soil Sci. 2011;358193:1-13.

28. Jaber SM, Lant CL, Al-Qinna MI. Estimating spatial variations in soil organic carbon using satellite hyperspectral data and map algebra. Int J Remote Sens. 2011;32:5077-5103.
29. Jain R, Sharma RU. Airborne hyper spectral data for mineral mapping in southeastern Rajasthan, India, International journal of applied earth observation and geoinformation. 2019;81(1):137-145.
30. Morrison K. Hyperspectral 10-50GHz SAR imaging of building materials, IEEE Radar Conference (Radar Conf). 2016. p. 1-5. DOI: 10.1109/RADAR.2016.7485116.
31. Kanning M, Siegmann B, Jarmer T. Regionalization of uncovered agricultural soils based on organic carbon and soil texture estimations. Remote Sens. 2016;8:927.
32. Katuwal S, Hermansen C, Knadel M, Moldrup P, Greve MH, de Jonge LW. Combining X-ray computed tomography and visible nearinfrared spectroscopy for prediction of soil structural properties. Vadose Zone Journal; c2017. DOI:10.2136.
33. Kaur G, Das K, Hazra J. Soil Nutrients Prediction Using Remote Sensing Data in Western India: An Evaluation of Machine Learning Models, International geosciences and remote sensing symposium; c2020.
34. Keshavarzi A, Kaya F, Başayiğit L, Gyasi Agyei Y, Rodrigo Comino J, Caballero Calvo A. Spatial prediction of soil micronutrients using machine learning algorithms integrated with multiple digital covariates, research square; c2022. p. 1-42.
35. Kumar S, Gautam G, Saha SK. Hyperspectral remote sensing data derived spectral indices in characterizing saltaffected soils: A case study of Indo-Gangetic plains of India. Environ Earth Sci. 2015;73:3299-3308.
36. Kusuma KN, Ramakrishnan D, Pandalai HS. Spectral pathways for effective delineation of highgrade bauxites: a case study from the Savitri River Basin, Maharashtra, India, using EO-1 Hyperion data. Int. J Remote Sens. 2012;33(22):7273_7290.
37. Lagacherie P, Sneep AR, Gomez C, Bacha S, Coulouma G, Hamrouni MH, *et al*. Combining Vis-NIR hyperspectral imagery and legacy measured soil profiles to map subsurface soil properties in a Mediterranean area (Cap-Bon, Tunisia). Geoderma. 2013;209-210:168-176.
38. Lakhankar T, Krakauer N, Khanbilvardi R. Applications of microwave remote sensing of soil moisture for agricultural applications International Journal of Terraspace Science and Engineering. 2009;2(1):81-91.
39. Ma L, Li A, Yu H, Chen G. Hyper spectral remote sensing estimation of soil nutrients in the black soil region based on computer vision model, Science Asia. 2022;48(2022):287-293.
40. Mahajan G, Sahoo RN, Pandey RN, Gupta VK. Using hyperspectral remote sensing techniques to monitor nitrogen, phosphorus, sulphur and potassium in wheat (*Triticum aestivum* L.), Precision Agriculture, 2014, 15(5).
41. Mandal UK. Spectral color indices based geospatial modeling of soil organic matter in Chitw and Istrict, Nepal, Remote Sensing and Spatial Information Sciences, Volume XLI-B2; c2016.
42. Mishra U, Lal R, Slater B, Calhoun F, Liu D, Van Meirvenne M. Predicting soil organic carbon stock using profile depth distribution functions and ordinary kriging. Soil Sci. Soc. Am. J. 2009;73:614-621.
43. Mulder V, De Bruin S, Schaepman M, Mayr T. The use of remote sensing in soil and terrain mapping: A review. Geoderma. 2011;162:1-19.
44. Neave DA, Black M, Riley TR, Gibson SA, Ferrier G, Wall F, *et al*. On the Feasibility of Imaging Carbonatite-Hosted Rare Earth Element Deposits Using Remote Sensing. Economic Geology. 2016;111:641-665.
45. Nowak B, Nesme T, David C, Pellerin S. Nutrient recycling in organic farming is related to diversity in farm types at the local level. Agric. Ecosyst. Environ. 2015;204:17-26.
46. Sharma AK, Dr. Sarup J, Dr. Gupta DC. A review paper synergistic approach to evaluate the mineral resources: A new perspective. Int. J Geogr Geol. Environ 2021;3(1):06-13.
47. Patel AK, Ghosh GK. Soil Fertility Status Assessment Using Hyperspectral Remote Sensing, Proc. SPIE, Remote Sensing for Agriculture, Ecosystems, and Hydrology. 2019;XXI:11149
48. Peng Y, Wang L, Zhao L, Liu Z, Lin C, Hu Y, *et al*. Estimation of Soil Nutrient Content Using Hyperspectral Data, Agriculture. 2021;11(11):1129
49. Peón J, Recondo C, Fernández SF, Calleja J, De Miguel E, Carretero L. Prediction of topsoil organic carbon using airborne and satellite hyperspectral imagery. Remote Sens. 2017;9:1211.
50. Psomas A, Kneubühler M, Huber S, Itten K, Zimmermann NE. Hyperspectral remote sensing for estimating aboveground biomass and for exploring species richness patterns of grassland habitats. Int J Remote Sens. 2011;32:9007-9031.
51. Rajitha A, Bhargavi P, Jyothi S. a Survey on Soil Classification Using Hyperspectral Images, Webology. 2022;19(2):7667-7684.
52. Ramakrishnan D, Bharti R. Hyperspectral remote sensing and geological applications. Curr. Sci. 2015;108(5):879-891.
53. Ramakrishnan D, Nithya M, Singh KD, Bharti R. A field technique for rapid lithological discrimination and ore mineral identification: results from Mamandur polymetal deposit, India. J Earth Syst. Sci. 2013;122(1):1-14.
54. Rani N, Mandla VR, Singh T. Spatial distribution of altered minerals in the gadag schist belt (GSB) of Karnataka, Southern India using hyperspectral remote sensing data. Geocarto Int. 2017;32(3):225-237.
55. Saha SK, Tiwari SK, Kumar S. integrated Use of Hyperspectral Remote Sensing and Geostatistics in Spatial Prediction of Soil Organic Carbon Content, Journal of the Indian Society of Remote Sensing. 2022;50(1):129-141.
56. Sarathjith MC, Das BS, Wani SP, Sahrawat KL, Gupta A. Comparison of data mining approaches for estimating soil nutrient contents using diffuse reflectance spectroscopy. Current Science. 2016b;110(6):1031-1037.
57. Schoonover JE, Crim JF. An introduction to soil concepts and the role of soils in watershed management. J Contemp. Water Res. Educ. 2015;154(1):21-47.
58. Shaik I, Begum SK, Nagamani PV, Kayet N. Characterization and mapping of hematite ore mineral classes using hyperspectral remote sensing technique: a case study from Bailadila iron ore mining region, SN Applied Sciences. 2021;3:182.
59. Sharma A, Weindorf DC, Wang D, Chakraborty S. characterizing soils via portable X-ray fluorescence spectrometer, Cation exchange capacity (CEC),

Geoderma. 2015;239:130-134.

60. Shepherd KD, Walsh MG. Development of reflectance spectral libraries for characterization of soil properties. Soil Science Society of America Journal. 2002;66:988-998.
61. Sholihah R, Karyati NE, Trisasongko BH, Panuju DR, Iman LOS, Nadalia D. Estimating soil moisture condition of paddy fields by using optical remote sensing imagery, IOP Conf. Ser.: Earth Environ. Sci. 2021, 1109.
62. Snehlata K. Soil moisture estimation using microwave remote sensing: A literature review, SGVUJ climate change water. 2021;8:55-72.
63. Song YQ, Zhao X, Su HY, Li B, Hu YM, Cui XS. Predicting spatial variations in soil nutrients with hyperspectral remote sensing at regional scale. Sensors. 2018;18:3086.
64. Tang B, Xie W, Meng Q, Moorhead RJ, Feng G. Soil Moisture Estimation Using Hyperspectral Imagery Based on Metric Learning, International conference on machine learning and application; c2022.
65. Thaler EA, Larsen IJ, Yu Q. A New Index for Remote Sensing of Soil Organic Carbon Based Solely on Visible Wavelengths, Soil Science Society of America Journal. 2018;83:1443-1450.
66. Tiwari SK, Saha SK, Kumar S. Prediction Modeling and Mapping of Soil Carbon Content Using Artificial Neural Network, Hyperspectral Satellite Data and Field Spectroscopy, Advances in Remote Sensing. 2015;4:63-72.
67. Tripathi MK, Govil H. Evaluation of AVIRIS-NG hyperspectral images for mineral identification and mapping, heliyon. 2019;5(11):e02931.
68. Van Breemen N, Buurman P. Soil formation. New York: Kluwer Academic Publishers; c2003.
69. Vibhute AD, Kale KV, Dhumal RK, Mehrotra SC. Soil type classification and mapping using hyperspectral remote sensing data, International Conference on Man and Machine Interfacing (MAMI); c2015.
70. Vigneshkumar M, Yarakkula K. Nontronite mineral identification in nilgiri hills of tamil nadu using hyperspectral remote sensing, IOP Conf. Series: Materials Science and Engineering. 2017;263:032001.
71. Viscara Rossel RA, Behrens T, Ben Dor E, Brown DJ, Dematte JAM, Shepherd KD, *et al*. A global spectral library to characterize the world’s soil. Earth- Science Reviews. 2016;155:198-230.
72. Xie R, Xieo H. Application of remote sensing in the estimation of soil organic matter content, Chemical Engineering Transactions. 2018;66:469-474.
73. Yami B, Singh NJ, Handique BK, Swami S. Mapping and monitoring of soil organic carbon using regression analysis of spectral indices, Current Science. 2023;124(12):1431-1444.
74. Yu H, Kong B, Wang GX, Du RX, Qie GP. Prediction of soil properties using a hyperspectral remote sensing method. Arch. Agron and Soil Sci. 2017;64(4):546-559.
75. Osman KT. Soil degradation, conservation and remediation. Dordrecht: Science & Business Media; c2014.