International Journal of Plant & Soil Science

Volume 35, Issue 18, Page 1386-1394, 2023; Article no.IJPSS.104362
ISSN: 2320-7035

Geo-spatial Tools for Assessing Soil Fertilty: A Review

Sangya Singh [a++*], Vishakha Rai [a++], Sunil Upadhyay [a++] and Shubham Singh [b++]

[a] Jawaharlal Nehru Krishi Vishwa Krishi Vishwa Vidyalaya, Jabalpur, 482008, India.
[b] Rajmata Vijayaraje Scindia Krishi Vishwa Vidyalaya, Gwalior, 474002, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJPSS/2023/v35i183480

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/104362

Review Article

Received: 26/05/2023
Accepted: 01/08/2023
Published: 02/08/2023

ABSTRACT

Soil, as a precious non-renewable resource, plays a pivotal role in agricultural productivity, making the improvement of soil fertility a paramount objective. To ensure soil health and optimize resource utilization for food production while mitigating negative environmental impacts in the face of climate change, it is crucial to gather geographical information on soil and its fertility levels. This is where remote sensing (RS) and Geographic Information System (GIS) technologies, particularly high-resolution satellite data and geostatistical methods, have proven highly effective.

Historically, most studies focused on evaluating a limited set of soil properties to gauge quality or fertility levels. However, it is now evident that adopting a holistic approach by integrating multiple soil indicators encompassing chemical, biological, and physical aspects is essential. Such a comprehensive assessment can offer valuable insights into specific land management techniques and environmental conditions, enabling better decision-making.

In light of this necessity, the utilization of high-resolution remote sensing data in conjunction with ground observations has become pivotal in mapping and tracking soil fertility. RS and GIS

[++] PhD Scholar;
**Corresponding author: E-mail: sangyasingh8183@gmail.com;*

technologies provide detailed, spatially explicit information, facilitating large-scale soil assessments and identifying trends and patterns over time. This integration empowers researchers and land managers to implement sustainable agricultural practices and conservation efforts, ultimately maximizing food production while preserving the environment.

By harnessing the power of RS and GIS technologies, researchers can gain a deeper understanding of soil health, facilitating the development of effective land management strategies and resource utilization practices.

In conclusion, the amalgamation of high-resolution remote sensing data and ground observations is crucial for comprehensive soil fertility assessment. This approach contributes significantly to sustainable land management, ensuring food security, and safeguarding our invaluable soil resource amidst the challenges posed by climate change.

Keywords: Remote sensing; GIS; soil fertility; soil properties; spectral reflectance.

1. INTRODUCTION

In order to meet the rising demand for food commodities, the increasing population growth necessitates agricultural expansion [1]. Crops must be produced in environments that are highly favorable for them in order to attain food security and enhanced food output. To use natural resources responsibly and increase their productivity, it is necessary to evaluate the spatiotemporal dynamics of soil quality and fertility. Crop residue management, nutrient management, soil tillage, and pest management are examples of agricultural practices that have an impact on ecosystem goods and services as well as soil quality and fertility [29,17].

In terms of environmental quality, soil quality refers to a soil's capacity to preserve ecosystem functions while also producing economic goods and services [38,36]. Both soil quality and fertility are influenced by a variety of soil factors, including pH, texture, soil structure, soil organic matter, and the amount of water and nutrients that are available to plants. These factors, in turn, are influenced by soil processes like erosion, leaching, aeration, nutrient cycles, and anaerobiosis. The biological, chemical, and physical characteristics of the soil, the soil process, and the environmental quality are all combined to form soil quality [54,36]. The foundation of input-based high agricultural production systems is the soil fertility state. The optimization and sustainability of agricultural ecosystems depend on the determination and assessment of soil fertility [5,64]. To formulate and carry out national agricultural policies, decision-makers need a precise measurement of the spatiotemporal variability of soil fertility and degradation. As a result, during the past few decades, remote sensing has emerged as a crucial tool in soil research due to its capacity to characterize soil heterogeneity in both the spatial and temporal domains and conduct nondestructive analyses of soil properties. The information gathered by the remote sensors is analyzed in relation to the characteristics of the soil. Soil spectral reflectance is crucial for obtaining information about various soil types and for use in soil mapping, land degradation mapping and monitoring, soil fertility management, and watershed management.

The advantages of Remote Sensing (RS) are its extensiveness, non-invasiveness, speed, and adaptability. RS involves employing electromagnetic energy to assess attributes of targeted objects from a distance. Ecology, oceanography, climatology, geology, and agriculture are just a few of the environmental-related fields to which it has already seen widespread application. The advances in the observatory systems such as remotely sensed data of fine-to-coarse spatiotemporal resolutions, and in the process-based and data-driven modelling techniques have facilitated the collection, storage, analysis, visualisation, and interpretation of non-spatial data for soil fertility index (SFI) [40,20,45,52,63,48].

Continuous soil mapping and monitoring is a possibility with remote sensing data. If the soils are exposed at the surface and the technologies are accurate enough to produce the information required, they can offer an effective and affordable method to determine the composition of the surface soil. Since the 1970s, when databases of mineral spectra were built in the lab [27,26] there has been interest in using non-invasive sensing techniques, such as reflectance spectroscopy, to remotely determine the mineralogical composition of planetary surfaces.

The information gathered by the remote sensors is analysed in relation to the characteristics of the soil. Soil spectral reflectance is crucial for obtaining information about various soil types and for use in soil mapping, land degradation mapping and monitoring, soil fertility management, and watershed management. In terms of geographical, radiometric, temporal, and spectral resolutions, data interpretation techniques have recently undergone a profound transformation on par with satellite capabilities.

2. REMOTE SENSING AND GEO-STATISTICAL TECHNIQUES IN SOIL STUDIES

According to Ravisankar and Sreenivas [51], remote sensing techniques are crucial for soil and land degradation mapping, monitoring of degraded lands, soil moisture evaluation, soil fertility, soil water conservation measures, and soil suitability investigations. Additionally, soil scientists personally examine less than one thousandth of the soil below the surface to precisely designate soil bodies on the landscape. They are able to do this because to the validity of the soil-landscape model, a potent paradigm that allows soil scientists to predict the soil properties with accuracy [25].

The study of events that change in space and/or time is known as geostatistics. It provides a method of employing conventional regression techniques to describe the spatial continuity of natural events.The geographical variability of soil nutrients is investigated using remote sensing and geostatistical approaches [65]. It focuses mostly on spatially autocorrelated data.

3. SPECTRAL REFLECTANCE OF SOILS

Many applications of remote sensing in soils depend on the spectral reflectance characteristics of soils. Data on soil reflectance can be collected in a lab, on the outside, and from the air or space. According to [9], the study of soil spectral reflectance has the potential to forecast soil physical, chemical, and biological parameters quickly and non-destructively. Additionally, different soil characteristics, such as water-holding capacity, eroded areas, and nutritional variations, can be inferred from the vegetation spectrum response.

The majority of passive remote sensors may gather data on soil properties from reflectance spectra in the visible (0.40 to 0.70 m), near-infrared (0.70 to 1.10 m), and short-wave infrared (1.10 to 2.50 m) areas of the electromagnetic spectrum. In addition, thermal infrared wavelengths between 3.0 and 5.0 m and 8.0 and 12.0 m do offer diagnostic data on soils. The form and nature of the reflectance curve determine the physical and chemical characteristics of the soil, including its colour [49], texture, structure, moisture content [58], surface conditions, roughness, and iron oxide content [30], among others.

Table 1. Spectral reflectance of different soil parameters that determine soil fertility

SNo	Soil Property	Spectral reflectance band (μm)	Characteristics	Reference
1	Soil color	0.45-0.70	RS sensors capable of sensing blue, green and red are very important	[18]
2	Soil texture	0.45-2.00	An increase in particle size causes a decrease in reflectance	[7]
3	Organic matter	1.70,2.18,2.31	An increase in Organic matter decreases reflectance	[7,54]
4	Iron oxides	0.40,0.43,0.45, 0.51,0.55,0.70, 0.87,0.90,1.0	An increase in iron oxide decreases reflectance	[59]
5	Clay minerals	1.40-2.20	Respond by the presence of hydroxyl bands at these bands	[35]
6	Sulphates, carbonates, hydroxyl combinations	1-2.50	Responds at these bands	[28,13]
7	Soil crusting	0.40-2.50	Spectral changes due to size distribution and mineralogical composition	[8]

(Source- [34])

Spectral analysis can be used in laboratories to determine a variety of soil characteristics. However, atmospheric influences [21,53] structural effects, lower spectral and spatial resolution, geometric distortions, and the spectral mixture of features [33,53] complicate the measurement when using airborne or spaceborne spectroscopy. Lichens, non-photosynthetic vegetation, and photosynthetic vegetation (PV, NPV), which can cover up to 100% of the soil in highly vegetated areas, can also be a constraint for soil applications. Lichens and mosses can cover up to 70% of the surface in tundra and open woodland ecosystems [56,57].

4. SOIL QUALITY/ FERTILITY ASSESSMENT

Designing sustainable agricultural practices (optimal agricultural usage) that can assist in bridging the current gap between food production and demand and addressing the issue of food security depends critically on the assessment of soil quality. New opportunities for measuring/evaluating soil quality at various spatial scales are made possible by the accessibility of RS datasets and GIS spatial modelling tools [46,60]. Digital soil maps were created by combining the physical, chemical, and biological characteristics of the soil with a digital elevation model and a Sentinel-2 satellite picture in order to create a spatially explicit soil quality model, according to [55].

The application GIS-enabled web-based soil information system that offers a descriptive, quantitative, and geographic soil database via a straightforward interface is described by Abdelfattah [2]. The technique was used to evaluate the soil's capacity for managing and growing plants. Abdell A et al. [3] created a spatial model for the evaluation of soil quality using GIS and RS technologies. To map the soil quality index, his model used GIS conventional kriging spatial interpolation and four major soil quality indicators (soil fertility index, soil physical index, soil chemical index, and geomorphological characteristics Index). Applying these GIS-based models offers approaches to control soil quality that are supported by data. This would make it possible for decision-makers, those who create policies, planners of land use, and agriculturalists to effectively manage soil resources so that agricultural lands can be used sustainably and to the best of their ability [58,50,43]. In order to achieve food security and sustainable agricultural policies and practices, it is crucial to evaluate soil quality indicators.

4.1 Chemical Aspect Affecting Soil Fertility

In addition to other characteristics of soil fertility, RS can be used to analyse the levels of organic carbon, NPK, and micronutrients (Fe, Mn, Zn, and Cu). The ability of soil to hold onto chemical components or compounds that are damaging to the environment or plant growth is related to its chemical properties. For instance, [4] emphasises the significance of soil chemical characteristics in plant growth, particularly C and nitrogen N levels, which enhance plant growth, soil structure, and water penetration, boost soil biological activity, regulate erosion, and prevent surface sealing.

One of the most important plant nutrients for optimising crop yields and farmer profits is nitrogen. The spatial variance in nitrogen content has been handled using crop vigour as a stand-in indicator and spatial interpolation of soil analytical data using RS data as the interpolation's guiding force [51]. It has been discovered that hyperspectral remote sensing is a crucial tool for identifying plant nutrient stress, which also serves as a measure of soil fertility. When comparing nitrogen and phosphorus levels at the leaf and canopy levels, Osborne et al. [47] demonstrated the value of hyperspectral data, although the connections were not constant across all stages of plant growth. Derivative analysis of spectrum reflectance spectra was shown to be a useful method for stress detection, and it produced spectral reflectance peaks. Utilising remote sensing and GIS to identify nutritional challenges enables us to implement site-specific nutrient management, which lowers cultivation costs and improves the effectiveness of fertiliser use for crops.

The colour of the soil is one of the markers used in remote sensing to map soil organic carbon; darker soils often have more soil organic matter than lighter soils. According to Viscarra Rossel et al. [61], saturated organic matter, variations in the composition and amount of black humic acid, and soil moisture all contribute to the darker of soil with higher levels of organic carbon. This is why it's common practise to map SOC by soil colour using the visible portion of the spectrum. The correlations, however, are not strong enough to be applied practically in a wide range of soils [60].

Soils that are degraded due to presesnce of salt content or by any other factor are also identified using Remote sensing techniques. In general, quantitative mapping of organic carbon, salt concentrations, clay minerals, and nutrients can be done using hyperspectral remote sensing data. The mapping of the salt-affected soils has made extensive use of the hyperspectral data. DAIS - 7915 hyper-spectral aerial sensor data were evaluated by BenDor et al. [10] for the quantification and production of maps of soil characteristics, including organic matter, soil moisture, and soil salinity. They used the Visible and Near Infrared Analysis (VNIRA) method, which produces an empirical model for forecasting soil properties. The hyper-spectral remote sensing (HSR) domain was utilised to determine its viability based on spectral laboratory data that demonstrate a considerable ability to anticipate the aforementioned soil attributes and populations utilising the VNIRA technique. Using the physical and chemical characteristics of the soil as well as image components (such as absorption-reflectivity profiles, band combinations, the greytones of the pictures under investigation, and the textures of the soil and vegetation covers as seen in images), soil salinity groups were constructed. Results from spectral measurements on salt-affected soils were presented by [19], indicating spectral alterations in the soil for varying degrees of salt concentration. Relationships between different salinity levels, spectral features, and geophysical properties of salt-affected soils are demonstrated in laboratory experiments.

4.2 Physical aspect affecting Soil Fertility

In a wide variety of naturally occurring surface soils, Stoner and Baumgardner [58,7] discovered five distinctive soil spectral reflectance curve morphologies that they deemed typical of the diversity of soil reflectance. Curve shape, the presence or absence of absorption marks signifying different organic matter and iron content, as well as texture, were used to identify these curve forms. Many soil characteristics can be assessed by spectral analysis of soil samples under laboratory settings, it was shown a few decades later. Examples include soil organic matter [10,22,41], soil moisture, Fe_2O_3, SiO_2, and Al_2O_3 [23,42,44], as well as sand, silt, and clay.

In proximate sensing, partial least-squares regression or multiple linear regression are generally used to estimate soil texture. These models are mostly calibrated using sample data. The findings demonstrate that these techniques are effective for predicting soil texture, but because the models' calibration is dependent on the local environment, they are often inapplicable beyond the study locations [16,42].

The development of microwave remote sensing has made it possible to determine the amount of soil moisture present in a field. Using data from remote sensing, it is possible to learn about crop water demand, water use, soil moisture conditions, and related crop growth at various stages. For instance, Bandara [6] evaluated the effectiveness of three large irrigation projects in Sri Lanka using NOAA satellite data. In order to provide soil moisture and soil temperature at four soil depths and vegetation root zones at 1 km spatial resolution in near real-time (few hours' latency), Das *et al*. [14] developed a soil moisture and temperature map for India using the high-resolution land data assimilation system (HRLDAS) as a computing tool.

Another important physical property affecting soil fertility is its surface roughness. The highest gradient of the water's surface slope (gradient) defines the surface roughness, which describes the surface's undulating condition. Increased surface roughness may reduce soil erosion and soil losses by up to 31%, according to earlier research [24,39]. As a result, it can enhance biological quality, soil structure, and fauna and flora development. Soil surface roughness is a crucial component of study on the soil erosion process that cannot be overlooked, as well as a crucial indicator of the degree of surface change and soil erosion [32]. One of the key elements affecting a soil's spectral properties is the surface roughness brought on by the presence of soil particles and aggregates [31]. Since the imperfections on the surface may create shadows, which might be identified and displayed by RS imageries, it is frequently a good predictor of soil degradation, especially for soil erosion [12,15]. According to numerous research [37,62], the effects of soil surface roughness are entirely similar to or even superior to those of moisture content.

Individual RS platforms, whether optical or microwave, have just been found to be ineffective at separating the combined effects of soil roughness and moisture content [66]. Therefore, a novel approach to the inversions of soil surface roughness has been developed by merging these two various platforms.

4.3 Biological Aspect Affecting Soil Fertility

Soil Biological Indicators (SBI) give information about the living component of the soil and are crucial to maintaining vital soil health processes like the breakdown of organic matter in the soil, nutrient cycling, pollutant degradation, and stability formation of the soil structure. One of the most prominent soil biological indicators is soil organic matter (SOM) [11]. Additionally, soil organic carbon is regarded as a crucial factor in determining soil quality since it typically correlates favourably with crop output and soil fertility, which in turn interacts with chemical, physical, and biological soil qualities. The majority of soil is made up of SOM, which is a complex mixture of organic chemicals produced by humification as well as by plants, living microbes, and their metabolism.

Soil spectral reactions could be hidden in bare soil areas with a lot of residues left over from the previous crop. In order to evaluate the surface soil organic matter content, high spatial digital terrain models (DEM) created by remote microwave or laser techniques can help with understanding how soil forms and how surface moisture moves. Researchers have evaluated various spectral responses in distinct bands in terms of observable soil properties such as sand, silt, clay, iron oxides, magnesium oxides, and organic carbon to explore the precise impacts of organic carbon on soil reflectance. Separable bands from soils that have not been fractionated are compared to separable bands from inorganic fractions, in which extractable organic matter and humic acid have been eliminated.In the sets of bands in question, there is a direct correlation between soil organic carbon and reflectance: as soil organic carbon rises, reflectance falls. The physical cause causing spectral changes in this group of bands is the organic matter present in the soil [29]. Zhang, Ding, et al. [65] developed various methods for effectively assessing SOM by NIR spectroscopy while taking salt-affected soils into consideration. These innovative approaches offer fresh ways and trustworthy assistance for precisely estimating SOM.

5. CONCLUSION

High-resolution remote sensing data, in conjunction with ground observations, emerges as a crucial tool for mapping and monitoring soil fertility, especially at the village level. By combining remote sensing technologies, such as satellite imagery, with on-site measurements, researchers can obtain detailed spatial information that aids in understanding the variability of soil nutrients and other key parameters across large areas. Geostatistics, GIS, and remote sensing together form a powerful trio for comprehending the spatial variability of soil nutrients. These technologies enable researchers to analyze data in a spatial context, identifying patterns and trends that might be missed with traditional point-based measurements. This spatially explicit information is instrumental in making informed decisions about soil management strategies and resource allocation to maximize agricultural productivity while minimizing environmental impacts.

Looking ahead, future research will likely focus on enhancing the integration of proximal (ground-based) and remote sensing data. Scaling-based approaches will be employed to optimize the use of all available data sources, ensuring a more comprehensive understanding of soil fertility and its spatial distribution. By combining data from various sources, researchers can leverage the strengths of each technology, creating a more robust and reliable assessment of soil health.

Overall, the integration of high-resolution remote sensing data, geostatistics, and GIS will play a pivotal role in advancing our understanding of soil fertility and quality. This integrated approach will contribute to more sustainable land management practices and resource utilization, ultimately leading to increased food production with reduced environmental impacts. By harnessing the power of these technologies, we can ensure the preservation and optimal use of one of our most valuable non-renewable resources - soil.

ACKNOWLEDGEMENT

I am thankful to National Agriculture Higher Education Projecr, Centre for Advanced Agricultural Science and Technology on “Skill development to use spatial data for natural resources management in agriculture”, Department of Soil and Water Engineering, JNKVV, Jabalpur for providing financial and other support.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Abdel R, Arafat SM. An approach of agricultural courses for soil conservation

based on crop soil suitability using geomatics. Earth Syst Environ. 2020;4: 273–285.

2. Abdelfattah MA, Kumar AT. A web-based GIS enabled soil information system for the United Arab Emirates and its applicability in agricultural land use planning. Arab. J. Geosci. 2015;8:1813-1827.
3. Abdell A, El Baroudy AA, Arshad M, Mahmoud EK, Saleh AM, Moghanm FS, Shaltout KH, et al. A GIS-Based Approach for the Quantitative Assessment of Soil Quality and Sustainable Agriculture. Sustainability. 2021;13:13438.
4. Abdul KH, Hossain MS, Rosamah E, Azli N, Saddon N, Davoudpoura Y, Islam MN, Dungani R. The role of soil properties and it's interaction towards quality plant fiber: a review. Renew. Sustainable Energy Rev. 2015;43:1006–1015.
5. Antonio D, Gomez AJ. Principles of agronomy for sustainable agriculture. In Villalobos, Francisco J,Fereres E. In chapter,the soil, Physical, Chemical and Biological properties; 2017.
6. Bandara KMPS. Monitoring irrigation performance in Sri Lanka with high frequency satellite measurements during the dry season. Agricultural Water Management. 2003;58(2):159 170.
7. Baumgardner MF, Silva LF, Biehl LL and Stoner ER. Reflectance properties of soils. Advances in Agronomy. 1985;38:1-44.
8. Ben-Dor, E, Goldishiegr N, Benyamini Y, Agassi M and Blumberg DG. The spectral reflectance properties of soil structural crusts in the 1.2 to 2.5 m spectral region. Soil Science Society of America Journal. 2003;67:289-299.
9. Ben-Dor, E, Inbar Y And Chen Y. The reflectance spectra of the organic matter in The visible near infra red and short wave infra red region (400-2500 nm) during a Combine decomposition process. Remote Sensing of Environment. 1997; 61:1-15.
10. Ben-Dor, E, Patkin K, Banin A, Karnieli A. Mapping of several soil properties using DAIS 7915 hyperspectral scanner data — a case study over clayey soil in Israel. Int. J.Remote Sens. 2002;23(6):20.
11. Celestina C, Hunt JR, Sale PW, Franks AE. Attribution of crop yield responses to application of organic amendments: A critical review. Soil Tillage Res. 2019; 186:135–145.
12. Chabrilla S, Ben-Dor E, Cierniewski J, et al. Imaging Spectroscopy for Soil Mapping and Monitoring. Surv Geophys 2019;40, 361–399.
13. Clark RN. Spectroscopy of rocks and minerals, and principles of spectroscopy. In:Remote Sensing for the Earth Sciences: Manual of Remote Sensing, Third. ed. New York: (A.N. Rencz , Ed.) John Wiley and Sons, Inc. 1999;3-58.
14. Das DK, Singh G. Estimation of evapotranspiration and scheduling irrigation using remote sensing techniques. Proc. Summer Inst. On agricultural remote sensing in monitoring crop growth and productivity, IARI, New Delhi. 1989; 113-17.
15. Davidson MWJ, Thuy Le, Mattia F, Satalino G, Manninen T,d Borgeaud M. On the characterization of agricultural soil roughness for radar remote sensing studies. IEEE Transactions on Geosciences and Remote Sensing. 2000; 38:630-640.
16. Demattê JAM, Nanni MR, Formaggio AR, Epiphanio, JCN. Spectral reflectance for the mineralogical evaluation of Brazilian low clay activity soils. Int. J. Remote Sens. 2007;28(20):4537-4559.
17. El-Naggar A, Sang Soo Lee, Rinklebe J, Muhammad F, Hocheol So, Sarmah AK, Andrew R. Mahtab A, et al. Ok.Biochar application to low fertility soils: A review of current status, and future prospects.Geoderma. 2019;337:536-554.
18. Escadafal R. Remote sensing of soil color: Principles and applications. Remote Sensing Reviews. 1993;7:261-279.
19. Farifteh J, Van der Meer F. Spectral characteristics of salt-affected soils; Impact on Imaging Spectroscopy. 4th Workshop on Imaging Spectroscopy. 2005;27-29.
20. Feizizadeh B, Blaschke T. Land suitability analysis for Tabriz Count, Iran: A multi-criteria evaluation approach using GIS. J. Environ. Plann. Manag. 2013;56(1):1–23.
21. Gail PA et al. In: David, K.L. (Ed.), History of one family of atmospheric radiative transfer codes. SPIE. 1994;170–183.
22. Gomez C, Viscarra Rossel RA, McBratney AB. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: an Australian case study. Geoderma. 2008;146(3–4): 403–411.
23. Hahn C, Gloaguen R. Estimation of soil types by non linear analysis of remote sensing data. Nonlinear Processes Geophys. 2008;15(1):115–126.
24. Herodowicz K, Piekarczyk J. Effects of soil surface roughness on soil processes and remote sensing data interpretation and its measuring techniques - A review. Polish Journal of Soil Science. 2018;51, 229.

25. Hudson BD. The soil survey as paradigm-based science. Journal of Soil Science Society of America. 1992;56:836-841.
26. Hunt GR, Salisbury JW. Visible and near-infrared reflectance spectra of minerals and rocks, I: Silicate minerals. Mod. Geol. 1970;1:219–228.
27. Hunt GR. Spectral signatures of particulate minerals in the visible and near infrared. Geophysics. 1977;42:501–513.
28. Hunt GR. Spectroscopic properties of rocks and minerals. In: Handbook of Physical Properties of Rocks. (R.S. Camichael, Ed.), CRC Press, Boca Raton. 1982;295-385.
29. Hunter M, others. Agriculture in 2050: Recalibrating targets for sustainable intensification. BioScience. 2017;67(4): 386–391.
30. Irons JR, Weismiller RA, Peterson GW. Soil reflectance. In: Theory and Application of Optical Remote Sensing (G. Asrar, Ed.), Wiley Series on Remote Sensing, Wiley, New York. 1989;66-106.
31. Jiang C, Hongliang F, Shanshan W. Review of land surface roughness parameterization study. Advances in Earth Science. 2012;27.3:292.
32. Krenz J, Greenwood P, Kuhn NJ. Soil degradation mapping in drylands Using Unmanned Aerial Vehicle (UAV) Data. Soil Syst. 2019;3:33.
33. Kriebel KT. Average variability of the radiation reflected by vegetated surfaces due to differing irradiations. Remote Sens. Environ. 1978;7(1):81–83.
34. Krishan G, Saha S, Kumar S, Patel R. Remote sensing in soil fertility evaluation and management bioresources for sustainable plant nutrient management. 2014;509-533.
35. Kruse FA, Thiry M, Hauff PL. Spectral identification (1.2-2.5 mm) and characterization of Paris Basin kaolinite/smectite clays using a filed spectrometer.In: Physical Measurements and Signature in Remote Sensing. Proceedings of the 5th International Colloquium, Courchevel, France. 1991; 1:181-184.
36. Kumar U, Nayak AK, Mohammad S, Vadakattu VSR, Gupta P, Panneerselvam, Mohanty S, Kaviraj M, Kumar A, Chatterjee D, B Lal, Gautam P, et al. Continuous application of inorganic organic fertilizers over 47 years in paddy soil alters the bacterial community structure and its influence on rice production. Agriculture, Ecosystems & Environment. 2018;262: 65-75.
37. Labarre S, Jacquemoud S, Ferrari C, Delorme A, Derrien A, Grandin R, et al. Retrieving soil surface roughness with the Hapke photometric model: Confrontation with the ground truth,Remote Sensing of Environment. 2019;225:1-15.
38. Lal R. Restoring soil quality to mitigate soil degradation. Sustainability. 2015;7(5):5875-5895.
39. Li L, Nearing MA, Polyakov VO, Nichols MH, Pierson FB, Cavanaugh ML. Evolution of rock cover, surface roughness, and its effect on soil erosion under simulated rainfall. Geoderma. 2020;379.
40. Li ZW, Huang JQ, Li YY, Guo W, Zhu JF. Assessment on fertility of dongting lake wetland area (China) based on GIS and fuzzy evaluation. J. Cent. S. Univ. Technol. 2011;18(5):1465- 1472.
41. Metternicht GI. Categorical fuzziness: A comparison between crisp and fuzzy class boundary modelling for mapping salt-affected soils using Landsat TM data and a classification based on anion ratios. Ecol. Modell. 2003;168 (3), 371–389.
42. Minasny B, McBratney AB. Regression rules as a tool for predicting soil properties from infrared reflectance spectroscopy. Chemom. Intell. Lab. Syst. 2008;94(1):72–79.
43. Hunter M, others, Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. BioScience. 2017;67(4):386–391.
44. Mokarram M, Hojati M. Using ordered weight averaging (OWA) aggregation for multi-criteria soil fertility evaluation by GIS (case study: Southeast Iran). Comput. Electron. Agric. 2017;132:1–13.
45. Nanni MR, Demattê JAM. Spectral reflectance methodology in comparison to traditional soil analysis. Soil Sci. Soc. Am. J. 2006;70(2):393–407.
46. Nie Y, Yu J, Wu Y, Yu L, Jing Y, Zhou Y. A comprehensive evaluation of soil fertility of cultivated land: a GIS- based soil basic Niche- Fitness Model. Commun. Soil Sci. Plant Anal. 2016;47(5),670–678.
47. Osborne SL, Scheper JS, Francis DD, Schlemmer MR. Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. Agronomy Journal. 2002;94:1215-1221.
48. Özyazici AM, Dengiz O, Sağlam M, Erkoçak A, Türkmen F. Mapping and assessment based modeling of soil fertility differences in the central and eastern parts of the Black Sea region using GIS and geostatistical approaches. Arabian Journal of Geosciences. 2017;10:1-9.
49. Post DF, Horvath EH, Lucas WM, White SA. Ehasz MA, Batchily EK. Relations between

soil color and Landsat reflectance on semi-arid rangelands. Soil Science Society of America Journal. 1994;58: 1809-1816.

50. Rahman AM, Hega BR, Yossif T. Soil fertility assessment for optimal agricultural use using remote sensing and GIS technologies. Appl. Geomatics. 2021;13: 605–618.
51. Ravisankar T, Sreenivas K. Soils and land degradation in Remote Sensing Applications (P.S. Roy, R.S. Dwivedi and D.Vijayan, Eds.), NRSC publication, NRSC, Hyderbad; 2011.
52. Ren Y, Chen J, Chen L, Zhang H, Zhang K. Research and implementation of a universal workflow model to evaluate the soil fertility based on OGC Web Service. Geo Spatial Inf. 2018;21(4):346–357.
53. Richter R, Schläpfer D. Geo-atmospheric processing of airborne imaging spectrometry data. Part 2: Atmospheric/ topographic correction. Int. J. Remote Sens. 2002;23(13):2631 2649.
54. Shen W, Ni Y, Gao N, Bian B, Zheng S, Lin X, Chu H. Bacterial community composition is shaped by soil secondary salinization and acidification brought on by high nitrogen fertilization rates. Appl. Soil Ecol. 2016;108:76–83.
55. Shepherd KD, Walsh MG. Development of reflectance spectral libraries for characterization of soil properties. Soil Science Society of America Journal. 2002; 66:988-998.
56. Shokr MS, Abdellatif MA, El Baroudy AA, Elnashar A, Ali EF, Belal AA, Attia W, Ahmed M, Aldosari AA, Szantoi Z, et al. Development of a Spatial Model for Soil Quality Assessment under Arid and Semi-Arid Conditions. Sustainability. 2021;13:2893.
57. Solheim I, Engelsen O, Hosgood B, Andreoli G. Measurement and modeling of the spectral and directional reflection properties of lichen and moss canopies. Remote Sens. Environ. 2000;72(1):78–94.
58. Stoner ER, Baumgardner MF. Characteristics variation in reflectance of surface soils. Soil Science Society of America Journal. 1981;45:1161-1165.
59. Tunçay T, Kılıç Ş, Dedeoğlu M, Dengiz O, Başkan O, Bayramin İ. Assessing soil fertility index based on remote sensing and gis techniques with field validation in a semiarid agricultural ecosystem. J. Arid Environ. 2021;190:104525.
60. Vincent RK. An ERTS multi spectral scanner experiment for mapping iron compounds. In: Proceedings of the 8th International Symposium on Remote Sensing of Environment. University of Michigan, Annual Arbor. 1973;1239-1247.
61. Viscarra R, Minasny RA, Roudier B, McBratney P. Colour space models for soil science. Geoderma 133. 2006;(3–4): 320–337.
62. Wen J, Dou B, You D, Tang Y, Liu Q, et al. Forward a small – timescale BRDF/ albedo by multisensory combined BRDF inversion model. IEEE Transactions on Geoscience and Remote Sensing. 2017;55:683-697.
63. Williams H, Colombi T, Keller T. The influence of soil management on soil health: an on farm study in southern Sweden. Geoderma. 2020;360:114010.
64. Zhang Q, Yang Z, Yong Li, Chen D, Zhang J, and Chen M. Spatial variability of soil nutrients and GIS based nutrient management in Yongji County, China. International Journal of Geographical Information Science. 2010;24(7):965-981.
65. Zhang Z, DingJ, Zhu C, Wang J, Ma G, Ge X, et al. Strategies for the efficient estimation of soil organic matter in salt-affected soils through Vis-NIR spectroscopy: Optimal band combination algorithm and spectral degradation, Geoderma. 2021;382.
66. Zheng X, Feng Z, Li L, Li B,Jiang T, Li X, Chen S. Simultaneously estimating surface soil moisture and roughness of bare soils by combining optical and radar data. International Journal of Applied Earth Observation and Geoinformation. 2021;100.

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/104362