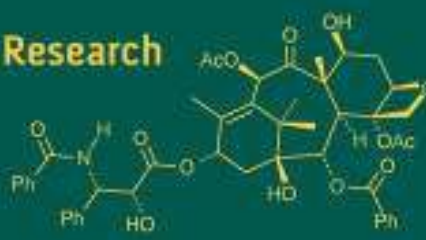
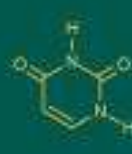
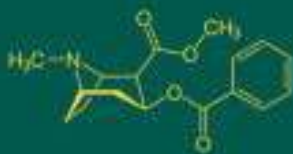


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Integration of soil spectroscopy and remote sensing for soil erodibility mapping: A review

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Abstract

Sustainable land management or environmental stability are significantly threatened by soil erosion, demanding effective methodologies for soil erodibility assessment. This review explores the integration of soil spectroscopy and remote sensing techniques to map soil erodibility. The rapid increase in the global population underscores the necessity for efficient monitoring and management of soil resources. Traditional methods of soil property evaluation are often time-consuming and limited in their spatial coverage. Integrating advanced technologies, including remote sensing and spectroscopy, presents a promising avenue for swift and comprehensive assessment.

To estimate soil properties like organic carbon, nitrogen, and phosphorus as well as physical factors like soil texture and structure, this review emphasizes the importance of soil spectroscopy, particularly visible-near infrared-short wave infrared (VIS-NIR-SWIR) spectroscopy. Additionally, it underscores potential of remote sensing in providing a broader spatial perspective, essential for mapping soil erodibility across diverse landscapes.

Various studies from different regions worldwide are examined, revealing the factors influencing soil erodibility and demonstrating the efficacy of integrating soil spectroscopy and remote sensing. The dynamic nature of soil erodibility, influenced by soil composition, climate, topography, and human activities, is elucidated through these studies. Furthermore, the review discusses the evolution of soil spectroscopy from lab-based instruments to portable devices and its role in enabling on-the-go soil analysis.

Ultimately, this review emphasizes critical role of integrating soil spectroscopy or remote sensing in advancing soil erodibility mapping, providing valuable insights for sustainable land management practices and conservation planning on a global scale.

Keywords: Soil Properties, spectroscopy, remote sensing

Introduction

Soil is a precious natural resource that provides a diverse and irreplaceable ecological environment for terrestrial organisms. However, with the global population steadily increasing at a rate "of 1.16% worldwide and 1.25% in South Asian nations, projections suggest that the global population, which is currently at 7.6 billion, will reach 8.6 billion via 2030, 9.8 billion via 2050, or 11.2 billion via 2100" (Chandan *et al.*, 2020) [15]. Therefore, assessing soil properties spatiotemporally for sustainable agricultural, hydrological, and environmental management is crucial. However, the rapid and reliable evaluation of soil characteristics has become a significant challenge in ecological monitoring.

Conventional techniques for analyzing soil properties through direct field sampling and laboratory analysis are undeniably precise but can be arduous and time-consuming. This is primarily because multiple samples are needed to factor in spatiotemporal variation. Additionally, these methods are typically restricted to local scales or small areas, which do not meet the needs of ecologists and land managers who require soil property estimations at the landscape level. Therefore, it is imperative to develop innovative methodologies for monitoring soil properties.

Remote sensing techniques provide rapid and comprehensive evaluations of soil properties across large areas. Elachi and Van Zyl (2006) [27] define remote sensing as using electromagnetic radiation to gather data about an object or phenomenon without making physical contact.

For evaluating soil chemical parameters like potassium (K), nitrogen (N), phosphorus (P), “cation exchange capacity, soil organic carbon (SOC), and pH, sensor-based laboratory-based Visible-Near Infrared-Short Wave Infrared (VIS-NIR-SWIR) spectroscopy” has become a competitive alternative to conventional laboratory analysis (Ji *et al.*, 2015). It can also be used to assess physical characteristics such as texture, bulk density, and soil structure (Bellon-Maurel *et al.*, 2010; Gholizadeh *et al.*, 2014) [8, 39].

Studying the spectral behavior of soil through remote sensors is a promising solution to the problem of class discrimination. Researchers have discovered that each soil type displays a unique spectral signature based on the absorption of specific wavelengths across the electromagnetic spectrum (Dematte, 2004) [18].

The scientific literature on soil erosion studies has used a variety of methods. Innovative methods that have shown significant potential for assessing different soil parameters include satellite remote sensing, geostatistics, geomorphology, field spectroscopy, machine learning, and combined in situ and laboratory soil reflectance measurements. Many researchers have used geostatistics, such as interpolation or spatial linear regression approaches, to monitor soil erodibility (K-factor), calcium carbonate (CaCO₃), and soil organic matter.

Collecting numerous well-distributed samples for further analysis can be costly and time-consuming, especially in extensive areas. Consequently, combining laboratory analysis with geostatistics and remote sensing might represent the optimal approach for enabling cost-effective and time-efficient monitoring of environmental changes. The extension “of local field studies to relatively large areas has been confirmed to be beneficial by Earth observation satellites. Satellite remote sensing is the only data source that enables continuous monitoring of the land degradation” processes.

The relationship among soil erosion and other soil erosion has been investigated using an integrated approach that combines geostatistics, geoinformatics, and field spectroscopy. Complex physical and chemical processes are influenced by “a variety of factors in the process of soil erosion by water. Soil erodibility, which denotes the soil surface's susceptibility to erosion, is essential for estimation of soil loss and implementation of soil conservation” practices (Wang *et al.*, 2014).

Previous “studies have often assumed that surface erodibility is static in time or space, but Geeves *et al.* (2000) [34] argue that this view can be misleading. Soil erodibility should be seen as a dynamic continuum, and more attention should be paid to the dynamic processes of soil erodibility” because of challenges associated with accurate measurement. According to Chappell *et al.* (2005) [16], measuring soil erodibility is challenging since several soil variables impact this indicator and can differ significantly over time and distance. Soil erodibility is impacted by a variety of soil variables, including clay mineralogy, soil chemistry, soil organic matter concentration, particle size distribution, structural stability, and water transmission characteristics (Lal, 1994).

Soil erodibility investigations have historically focused on agricultural lands, as noted by Zobeck (1991) [112]. Understanding the properties that influence soil erodibility is critical for accurate erosion estimates, effective conservation planning, and assessing the environmental

effects of agricultural practices. To delve deeper into these pivotal issues, we present a comprehensive review entitled “Integration of Soil Spectroscopy and Remote Sensing for Soil Erodibility Mapping: A Review.

2. Soil erodibility estimation

The following studies provide valuable insights into the influence of soil erodibility in different regions, highlighting the potential of advanced methods for accurate spatiotemporal mapping. Nandgude *et al.* (2014) [67] used the Soil-Plant-Air-Water (SPAW) model to estimate soil erodibility in the Dapoli region of Maharashtra. By considering soil properties namely sand, silt, clay, or organic matter content, the result found a significant inverse correlation between erodibility and organic matter, emphasizing the importance of organic content in erosion susceptibility. Baruah *et al.* (2019) [6] extended this knowledge to the Western Ghats and Coimbatore, estimating erodibility as per soil texture or organic matter. Their study underlines vulnerability of silt-rich soils to water erosion, with a correlation between silt content and erodibility. Yadav *et al.* (2005) [104] contributed to erodibility assessment in Delhi by linking soil characteristics, texture, and permeability to erodibility values. Their classification of soils into different erodibility categories provides a helpful framework for land management and conservation planning. Ezcabasil *et al.* examined erodibility indices in Anambra basin soils, highlighting the predictive power of dispersion and clay ratios. Their work supports the development of effective erosion prediction models and land use strategies. Zhu *et al.* (2019) [110] conducted a comprehensive study on spatial or temporal variations in soil erodibility across land use types and slopes in China. Their findings emphasize the influence of soil characteristics, topography, and climate on erodibility, with soil nitrogen and precipitation emerging as critical factors. Liu *et al.* (2020) [61] explored spatial variation of soil erodibility in “Yingwugou Watershed, Middle Dan River, China.” Their analysis underscores the impact of human activities on erodibility and emphasizes the need for tailored management approaches. Imani *et al.* (2014) [47] mapped soil erodibility in Iran's Yamchi Watershed using a combination of soil properties or geospatial techniques. Their results highlight its potential of remote sensing or spatial interpolation methods for generating comprehensive erodibility maps. Belasri *et al.* (2017) [9] extended erodibility mapping to Morocco's Oued El Makhazine watershed, revealing the role of soil particles and permeability in erosion susceptibility. Their study emphasizes the importance of soil stability and permeability in erosion control. Ostovari *et al.* (2021) explored soil erodibility in the Middle East, demonstrating correlations between soil particle types and erodibility. Their findings suggest the potential of pedo transfer functions for predicting erodibility at a regional scale.

3. Understanding Soil Spectroscopy: A Powerful Tool for Analyzing Soil Samples

Soil spectroscopy is an innovative technology used for soil testing, analysis, and health assessment. It provides an efficient way to manage plant nutrients or water resources. Compared to conventional wet chemistry soil analysis, which is expensive, time-consuming, and energy-intensive, soil spectroscopy is fast, cost-effective, sustainable, and repeatable. It was initially restricted to laboratories, but now it has transitioned to portable handheld devices.

An alternative to laboratory soil analysis, which uses a single spectrum to assess soil properties like organic or inorganic carbon, pH, total nitrogen, water retention qualities, texture, or mineralogy, is soil visible-infrared sensing. The measurements are very reproducible, and the cost of obtaining the data is significantly lower. Thus, large-scale, spatially intense examination of soil characteristics can benefit significantly from the use of soil spectroscopy.

Increased processing power, improvements in computer-based statistical and chemometric analytic tools, and developments in VIS, NIR, MIR spectrometers have all contributed to the growing interest in soil spectroscopy. To address the increasing demand for soil data to evaluate and track soil at different sizes, large databases of soil spectra are being developed.

MIR-based instruments are more accurate than NIR spectroscopy among infrared spectroscopic techniques. To quantitatively analyze soil spectral data, sophisticated statistical techniques are applied, revealing the relationship between spectral characteristics and soil attributes through reflectance spectroscopy. The preprocessed soil spectral data are then mathematically extracted using chemometric methods. To develop effective MIR calibration models, this data is empirically connected to conventional laboratory measurements.

It is essential to develop prediction models tailored to specific regions or soil types, utilizing regional soil spectral libraries together laboratory-analyzed soil parameter values to improve forecast accuracy. The spectral areas can be utilized to make cost-effective sensors for in situ and mobile soil status estimation, identifying significant spectral bands in the MIR and NIR regions that are relevant to the prediction of soil parameters is crucial. Proximal soil sensing is becoming easier as spectrometers become more accessible, affordable, and small because of developments in optics and electronic circuits.

Micro-electro-mechanical structures (MEMSs), thin-film filters, fiber optic assemblies, lasers, light-emitting diodes (LEDs), or high-performance detector arrays are among the new technologies being employed to create robust and efficient miniature handheld devices. By using handheld VIS-NIR-based spectroscopy, these devices enable measurements on moist soil in situ under typical field conditions, removing requirement for sample drying, grinding, and other labor-intensive preparations. Besides visible-IR-based spectrometers, X-ray fluorescence spectrometers contribute to the advancement of soil analysis.

3.1 Exploring the Advantages of Soil Spectroscopy - Soil spectroscopy offers the advantage of providing rapid results and requires only basic analytical infrastructure. In many soil assessment or monitoring applications, increasing the number of soil data points in terms of location, depth, and time can improve overall accuracy, even if individual measurements could be more accurate. A cost-benefit analysis of soil organic carbon (SOC) was carried out by (O'Rourke & Holden, 2011) [71]. The "Walkley-Black method, total organic carbon (TOC) analyzer, visible-near-infrared (Vis-NIR) diffuse reflectance spectroscopy, or lab hyperspectral imaging were all compared. Despite being less accurate than the TOC analyzer, Vis-NIR spectroscopy and laboratory hyperspectral imaging (800-1720nm) performed better because they were about 10 times cheaper. (Schwartz

et al., 2012) [82] Demonstrated that spectral analysis was a cost-effective means of monitoring petroleum contamination in" soils, yielding better results than traditional analytical chemistry methods used by certified laboratories. This cost difference becomes even more significant when applied to large-scale soil assessments involving many measurements. For "the African Soil Information System (AfSIS) project, the World Agroforestry Centre (ICRAF) stated that the cost of SOC analysis using spectroscopy was 1-3rd that of utilizing a C/N analyzer. As per Toth *et al.* (2013) [91], the European Commission's Joint Research Center employed a laboratory to examine about 20,000 samples for the land use/cover area frame survey (LUCAS) soil monitoring network. According" to data from the Soil Service of Belgium, the cost per sample for SOC analysis utilizing spectroscopic was < 1-3rd that of reference analyses.

Soil spectroscopy is an advanced method of soil analysis that has the potential to revolutionize soil information systems. Although there are various methods for soil classification, their implementation costs have hindered comprehensive data collection. Soil spectroscopy has emerged as a transformative tool for soil type classification, making it easier and more cost-effective to map soil types for land-use planning decisions.

By predicting essential properties like CEC and clay content using Vis-NIR spectroscopy, soil spectroscopy offers a practical way to enhance fertility recommendations and optimize fertilizer utilization. Wallonia's laboratories have embraced this approach since 2008. Initiatives like AfSIS use Vis-IR spectroscopy as the primary screening tool for characterizing a large volume of soil samples across Sub-Saharan Africa, and private-sector soil testing companies have also started using soil spectroscopy.

Standardizing the protocol for spectroscopic analyses can significantly enhance result reliability and comparability, thereby expanding spectral libraries and necessitating quality assessment and control measures for database integration. The widespread adoption of Vis-NIR or MIR spectrometers promises substantial benefits, particularly within farmers' consortia and agricultural organizations.

International organizations like the "Food and Agriculture Organization (FAO)" of the United Nations and the European Commission's JRC could play a important role in supporting projects that integrate established soil chemical analysis techniques with soil spectroscopy for comprehensive soil state assessment. The fusion of soil spectroscopy and remote sensing presents an invaluable approach for spatiotemporal soil erodibility mapping, addressing critical soil-related challenges within the broader context of sustainable land management.

3.3 Case Studies

In the case studies, advanced spectroscopic techniques are leveraged to enhance soil characterization and property prediction for various agricultural and environmental applications. These approaches offer rapid and cost-effective alternatives to traditional soil analysis methods, providing valuable insights for precision agriculture, land management, and ecological research. The common thread among these studies is the utilization of visible, near-infrared (VIS-NIR-SWIR) spectroscopy, which span electromagnetic spectrum from 350 to 2500 nm. Here, we summarize these case studies, highlighting their key findings and the potential of spectroscopic techniques for soil-related applications.

Case Study 1: Precision Viticulture Soil Characterization Using VIS-NIR-SWIR Spectroscopy

This study assesses effectiveness of VIS-NIR-SWIR reflectance spectroscopy for characterizing vineyard soils. Researchers collected soil samples from vineyards in Spain and employed portable spectroradiometers across VIS-NIR-SWIR range. By developing partial least squares regression (PLSR) models, they accurately predicted soil properties, including pH, electrical conductivity, and phosphorous. This study demonstrated the promise of spectroscopy in optimizing precision viticulture practices.

Case Study 2: Enhancing Soil Organic Matter Mapping in the Central Amazon Using VIS-NIR Spectroscopy

Accurate soil organic matter (SOM) mapping in the Central Amazon is essential for sustainable land management. In this case study, researchers utilized VIS-NIR spectroscopy as a covariate to improve spatial modeling for SOM mapping. Incorporating Vis-NIR spectra significantly enhanced map accuracy for SOM predictions, showcasing the potential of cost-efficient soil mapping in remote regions like the Central Amazon.

Case Study 3: Extending Soil Property Prediction Using Reflectance Spectroscopy

This case study investigates the predictive capabilities of Vis, NIR, and MIR reflectance spectroscopy for various soil properties. Researchers collected soil samples and measured reflectance spectra across these spectral ranges. Their findings revealed that Vis-NIR-MIR spectroscopy successfully predicted essential soil properties such as water content, texture, soil carbon, and cation exchange capacity. The success of these methods depends on factors like calibration quality and the specific property being predicted. These case studies demonstrate the potential of spectroscopic techniques in soil-related applications. The ability to rapidly and accurately assess soil properties and characteristics offers substantial benefits for agriculture, land management, and environmental research. These methods can transform traditional soil analysis and contribute to more sustainable and informed decision-making in various fields. (References: Zhu *et al.*, 2001^[111]; Corwin *et al.*, 2003^[17]; Wang *et al.*, 2018^[97]; Ma *et al.*, 2018^[63]; and others as cited in the case studies.

4. Remote Sensing Sensors

Remote sensing sensors are important devices that collect data about objects or scenes from a distance. Objects have unique spectral features, making them distinguishable in

remote sensing imagery based on spectral characteristics. Over “the past fifty years, a wide range of airborne and spaceborne sensors were used, ranging from multispectral to hyperspectral, covering wavelengths from visible to microwave, with spatial resolutions from sub-meter to kilometers and temporal frequencies from” 30min to weeks or months. Definitions of spatial resolution can be completely divided into categories as follows: (1) low or coarse resolution with a ground sampling distance (GSD) of at least 30m; (2) medium resolution with a GSD between 2.0 and 30m; (3) high resolution with a GSD between 0.5 and 2.0m; and (4) extremely high resolution with pixel sizes < 0.5m GSD (Navulur, 2006)^[68].

To obtain information about things or events without making physical contact, remote sensing uses electromagnetic radiation (Elachi & Van Zyl, 2006)^[27]. The spectrum resolution of optical sensors is mostly determined by the number, sampling, and location of the bands. Multispectral sensors provide 3 to 7 bands, seven to twenty bands by superspectral sensors, 20-500 hundred bands by hyperspectral sensors, and over a thousand bands by ultraspectral sensors (Gholizadeh *et al.*, 2018). The choice of imagery acquired by suitable sensors depends on four interrelated factors: (1) the mapping objective, (2) image cost, (3) climatic conditions, especially atmospheric conditions and (4) technical considerations for image interpretation.

What needs to be mapped and the expected level of mapping accuracy are determined by the mapping objectives. Relatively higher resolutions are required for detailed vegetation classification, while low-resolution images may be sufficient for identifying broad vegetation classifications. Image costs are high because distant sensing photos can be costly. Depending on the cost, low-resolution photos are utilized for large-scale mapping, while high-resolution images are utilized for small-scale mapping. Long-term cloud-free image series require atmospheric conditions, including cloud cover (Soudani *et al.*, 2006)^[87]. Finally, when choosing appropriate sensors, technical details like image quality, preprocessing, and interpretation are considered.

Commonly used sensors in vegetation mapping include “Landsat (especially T.M. or ETM+), SPOT, MODIS, NOAA-AVHRR, IKONOS, or QuickBird. The characteristics of” such sensors have been detailed, with many of them providing imagery for generating indices like NDVI computed from bands in visible or near-infrared regions.

Table 1: Different Sensors Used for Image Accusation

Sensors	Features	Mapping applications
Sentinel	Multispectral data with medium to coarse spatial resolution (30m for multispectral bands and 120m for thermal infrared bands)	Mapping vegetation and soil properties at the community level is usually capable of regional-scale mapping.
Landsat TM 8	Landsat 4 or 5 multispectral data with medium to coarse spatial resolution (30 m for multispectral bands and 120m for thermal infrared bands) from 1982 to the present. The area of each scene is 185*185km. 16 days is temporal resolution.	Mapping vegetation and soil properties at the community level is usually capable with regional scale mapping.
Landsat ETM+ (Landsat 7)	Multispectral data with “medium to coarse spatial resolution (15m for panchromatic band, 60m for thermal infrared, and 30m for multispectral bands) (1999 to present). The area of each scene is 185km via 185 km. 16 days is temporal resolution.	Mapping vegetation and soil properties at the community level is usually capable with regional scale mapping, or some dominant species can be determined.
SPOT	SPOT VGT has a coarse spatial resolution of 1 km and a full range of medium spatial resolutions from 20-2.5m. SPOT 1 through 5 were released in 1986, 1990, 1993, 1998, and 2002, respectively. Each scene spans 60 * 60 km for HRV/HRVIR/HRG and 1000 * 1000 km (or 2000 * 2000 km) for VGT. Data is currently not being provided by SPOT 1 and 3.	Usually, the regional scale can map soil and vegetation at the species or community level, or it can map land cover types (such as urban area, classes of vegetation, water area, etc.) at the global, national, or regional scale (from VGT).

MODIS	The Terra Satellite (2000-present) and Aqua Satellite (2002-present) provide multispectral data with low spatial resolution (250-1000 m). The period among revisits is around one to two days. Suitable for large-scale vegetation mapping. The swath measures 10 km (along-track at nadir) by 2330 km (cross-track).	mapping at the national or global scale. Appropriate for mapping different forms of land cover, such as urban areas, vegetation classifications, water areas, etc.
AVHRR	1-km GSD using multispectral NOAA satellite series data (1980 to the present). The scene is about 2400 by 6400km in size.	Mapping at the national, continental, or worldwide scale. Suitable for mapping different types of land cover, such as urban areas, vegetation classes, water areas, etc.
IKONOS	At 1 m (panchromatic) and 4 m (multispectral bands, including red, green, blue, and near infrared), it gathers high-resolution imagery. resolution. The revisit rate is 3-5 days (off-nadir).The single scene is 11 * 11 km.	Vegetation mapping at the species or community level at the local to regional scale might be utilized to confirm a different classification outcome.
QuickBird	Panchromatic "and multispectral images from a constellation of spacecraft with high resolution (2.4-0.6 m). The area of a single scene is 16.5 * 16.5 km. The frequency of revisits is between 1-3.5 days depending on latitude.	Vegetation mapping at the species or community level from local to regional scales, or utilized to verify vegetation cover obtained from other images
ASTER	Terra Satellite image with 14 spectral bands and medium spatial resolution (15-90m) from 2000 to the present. Visible to near-infrared bands have a spatial resolution of 15 m, short-wave infrared bands have a resolution of 30 m, and thermal infrared bands have a resolution of 90m.	Regional to national scale vegetation mapping at species or community level.
AVIRIS	Aerial sensors have recorded 224 spectral bands, from visible to near-infrared to short-wave infrared. Depending on the satellite platforms and the latitude of the data collected, the swath can range from several kilometers to dozens of kilometers, and the spatial resolution can range from meters to hundreds of meters.	At the local to regional scale, it is usually possible to map vegetation at the community or species level. Data are not easily accessible since they are acquired "as needed," and images are created as one-time operations.
Hyperion	With 220 bands ranging from visible to short-wave infrared, it gathers hyperspectral images. 30 meters is the spatial resolution. Data available since 2003.	Capable of mapping vegetation at the community or species level on a regional scale.

4.2 Assessing Soil Properties with Geospatial Techniques Organic Matter

Soil organic matter (SOC) is crucial in crop production, soil color, and quality. It is derived from plant residue and is the most important carbon source in the world. SOC affects agricultural "productivity and comprises around 75% of terrestrial ecosystems' total Carbon (T.C.) pool. Ecosystem functions, soil quality, nutrients, soil structure, nutrient supplies for soil microbial fauna, or water-holding capacity are" all enhanced by "high SOC. Increasing SOC levels improves the soil's ability to hold water for plants, improves plant nutrient" levels, availability, and storage, and improves the physical properties of the soil, all of which correlate to higher crop production. Mapping SOC content using various combinations of satellite imaging bands has

been a common use of geostatistical methods. GIS and RS approaches can be used to examine the different quantities of SOC content found in different slopes, soils, and land use categories. Geostatistics is an effective method for assessing soil properties, as it can precisely examine the spatial distribution of SOC. Researchers hold different opinions regarding various interpolation methods employed to assess the geographical variability of soil organic carbon. Ordinary kriging (OK) and co-kriging exceed the inverse distance weighting (IDW) approach. Empirical Bayes kriging (EBK) is the optimal method for estimating total dissolved solids (TDS) in water. The NDVI reflects vegetation condition and amount, and can be used to evaluate the organic carbon content.

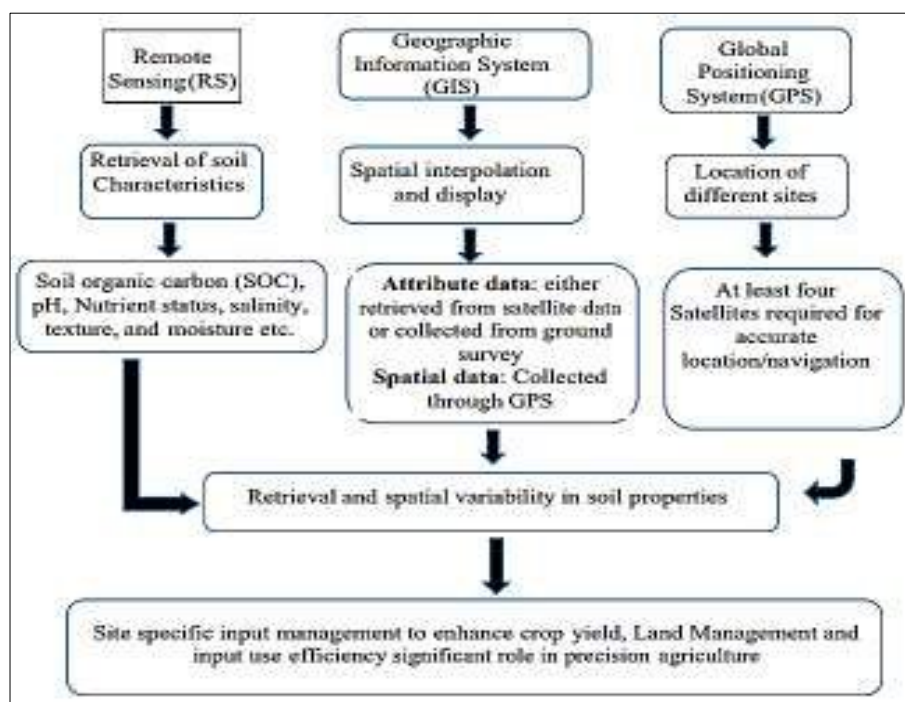


Fig 1: Geospatial techniques used in retrieval and spatial variability assessment of soil properties

Soil pH is crucial as it significantly impacts soil characteristics and various plant growth processes both chemically and biologically. A soil analysis conducted by (Denton *et al.*, 2017) ^[21] revealed no significant difference in pH ($p < 0.05$) at depths of 0-20cm and 20-40cm across three different locations. The researchers used kriging interpolation algorithms to map these pH values. Similarly, (Ghazali *et al.*, 2014) ^[35] integrated “soil data from surveys and laboratory analysis with Landsat 8 satellite imagery to

create a multiple regression model known as the soil pH Index (SpHI). With 4.66 for bare soil or 6.62 for paddy fields, this model” yielded soil pH values among 4.49 to 7.59. Goto (1985) ^[38] reported that the pH of the soil increased gradually from a starting point of 5.5. Regression analysis was used by (Pittman *et al.* 2014) ^[76] to connect field data to Landsat 8 band pixel values. They created models to determine the pH of soil and evaluated the models' accuracy to confirm their findings.

Table 2: Different spectral indices used for assessing soil properties through remote sensing

“Soil property	Vegetation Index	Formula	References
Soil organic matter	Modified Soil Adjusted Vegetation Index (MSAVI)	$\frac{\text{NIR}-\text{RED}(1+L)}{\text{NIR}+\text{RED}+L}$	Qi <i>et al.</i> , (1994) ^[77]
	Normalized Difference Vegetation Index (NDVI)	$\frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}}$	Rouse <i>et al.</i> ; (1974) ^[80] Tucker,
	Ratio Difference Vegetation Index (RDVI)	$\frac{\text{NIR}-\text{RED}}{(\text{NIR}+\text{RED})^{0.5}}$	Roujean and Breon, (1995) ^[81]
	Modified Non-Linear Vegetation Index (MNLI)	$\frac{(p2\text{NIR}-p\text{RED})(1+L)}{(p2\text{NIR}+p\text{RED}+L)}$	Gong <i>et al.</i> , (2003) ^[37]
Soil moisture	Soil Moisture Index (SMI)	$\frac{(\text{LST}_{\text{max}}-\text{LST})}{(\text{LST}_{\text{max}}-\text{LST}_{\text{min}})}$	Mohamed <i>et al.</i> ,
	Soil Moisture Index (SMI)	$\frac{(\text{LST}_{\text{mix}}-\text{LST})+1}{(\text{LST}_{\text{max}}-\text{LST}_{\text{min}})}$	van Leeuwen, (2015) ^[93]
	Moisture Stress Index (MSI)	$\frac{\text{MIDINFRARED}}{\text{NEAR INFRARED}}$	Zakir M, (2018) ^[106]
	Normalized Difference Water Index (NDWI)	$\frac{(\text{NIR}-\text{MIDIR})}{(\text{NIR}+\text{MIDIR})}$	Zakir M, (2018) ^[106]
	Soil Moisture Index (SMI)	$\frac{\text{TS}_{\text{max}}-\text{LST}}{\text{TS}_{\text{max}}-\text{TS}_{\text{min}}}$	Ghazali <i>et al.</i> , (2014) ^[35]
Soil salinity	Normalized Difference Vegetation Index (NDVI)	$\frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}}$	Ghazali <i>et al.</i> , (2014) ^[35]
	Ratio Vegetation Index (RVI)	$\frac{\text{NIR}}{\text{RED}}$	Major <i>et al.</i> ” (1990) ^[62]
	Normalized “Difference Salinity Index (NDSI)	$\frac{(\text{RED}-\text{NIR})}{(\text{RED}+\text{NIR})}$	Khan <i>et al.</i> , (2004) ^[114]
	Enhanced Vegetation Index (EVI)	$\frac{2.5(\text{NIR}-\text{RED})}{(\text{NIR}+\text{RED}+L) \times (1+L)}$	Liu and Huete, (1995)
	Soil Adjusted Vegetation Index (SAVI)	$\frac{(\text{NIR}-\text{RED})}{(\text{NIR}+\text{RED}+L) \times (1+L)}$	Huete, (1988)
	Salinity Index (S.I.)	$\sqrt{\text{BLUE}} \times \sqrt{\text{R}}$	Khan <i>et al.</i> , (2004) ^[114]
	Salinity Index (SI1)	$\sqrt{\text{GREEN}} \times \sqrt{\text{RED}}$	Khan <i>et al.</i> , (2004) ^[114]

To increase soil productivity, ensure food security, and enhance agricultural sustainability, geospatial technology assessment of soil nutrient status is crucial. Various soil variables, such as nutrient levels, water-holding capacity, or erosion-prone areas, can be derived from the spectral response of vegetation. Laboratory experiments using laser-induced fluorescence (LIF) and passive reflectance measurements have shown that differences in maximum fluorescence intensity at specific wavelengths are correlated with varying levels of nitrogen fertilization in corn. Soil samples can be collected using a soil probe, and soil cores can be extracted with a wooden rod to analyze micro and macronutrients comprehensively. The data can be processed and geo-referenced using ArcGIS software, with latitude and longitude information integrated into the map for enhanced clarity and information. Similarly, a method combining genetic algorithms and back propagation neural networks (GA-BPNN) can be used to enhance the accuracy of soil nutrient content estimation.

Soil moisture variability results from complex interactions among various environmental factors, including soil properties, land use, topography, precipitation, radiation, or vegetation. Remote sensing technologies, including thermal infrared, optical, passive, and active microwave methods,

have expanded the capabilities for studying land surface properties and parameters. While thermal infrared and optical sensors offer broad coverage and fine spatial resolution, they are limited by surface penetration and often obstructed via clouds or vegetation, weakening their relationship with soil moisture. Microwave sensors, with greater penetration depth, are less affected by clouds, allowing for more accurate and high-resolution measurements in all weather conditions.

Measuring soil moisture involves scattered point measurements at discrete intervals, requiring precise sample design and locations. Spatial interpolation and geospatial techniques serve as practical tools in this process and can create maps to reveal interactions between various soil attributes like soil type, geology, and vegetation cover. Geographic Information Systems (GIS) offer a comprehensive suite “of tools for geo-ecological monitoring, mapping, evaluation, or spatial analysis.

Researchers have used various methods, including Land Surface Temperature (LST) or soil reflectance, Normalized Difference Vegetation Index (NDVI) and” LST, thermal or optical remote sensing to estimate soil moisture. These methods combine thermal and optical remote sensing data and are as per thermal emissions or surface reflectance.

Synthetic aperture radar (SAR) and optical remote sensing were utilized in several studies to forecast total.

Table 3: Various geospatial techniques are utilized for assessment of soil properties.

Sr. No.	Soil properties studied	Data/tools used	Advantages/Limitations	References
1.	Soil organic carbon (SOC)	IRS P-6 satellite LISS III sensor	SOC was estimated using geographic methods, and its relation to soil pH and NDVI was examined. For other environmental variables, however, additional research is needed using a long-term multi-factor experimental approach.	Kumar <i>et al.</i> , (2015) [55]
2.	Soil salinity, moisture and pH	Landsat-8	The estimation of soil pH was successful; however, the relationship between soil pH and moisture, salinity, and temperature required enhancements in extraction methodologies to allow for uncertainties. However, the spectral and spatial resolution of Landsat-8 data is restricted; as a result, it is recommended to evaluate alternative data that exhibit better properties.	Ghazali <i>et al.</i> (2020) [35]
3.	Soil moisture	Radar Sentinel-1 and Landsat-8 optical and thermal band data	The spatial pattern of crops grown should also, it can be considered as soil moisture. It is related to the type of crops grown.	Mohamed <i>et al.</i> (2019)
4.	Soil organic carbon (SOC)	GIS, GPS, spatial interpolation techniques, etc. Radial basis function (RBF), empirical Bayes Inverse distance weighting (IDW), Local polynomial interpolation (LPI), kriging (EBK) and "ordinary kriging (OK)	OK was found superior over other methods, whereas IDW gave the worst results	Bhunia <i>et al.</i> , (2016) [10]
5.	Soil moisture	Landsat 4,5,8 satellites, Thematic mapper	Successfully predicted the moisture percent of areas where <i>in-situ</i> measurements are not available.	Zakir, (2008) [106]
6.	Soil salinity	Ikonos and Landsat-5 (3 visible bands (1,2&3), 2 NIR (4&5) and 1 MIR (7) band, ERDAS Imagine 8.7	Provided accurate methodology for estimating soil salinity using geospatial techniques.	Eldiery <i>et al.</i> , (2008)
7.	Soil moisture	GIS, Interpolation methods viz. inverse distance weighting, kriging, co-kriging	Co-kriging generated the most accurate soil moisture map	Gharechelou <i>et al.</i> , (2016)
8.	Soil salinity, pH and nutrient	Landsat 5 T.M., GIS	Analyzed the relationship between soil salinity and soil reaction, as well as the factors that affect soil properties" (e.g., land inclination and Na or K contents).	Gloweinka <i>et al.</i> , 2016

soil moisture. Geospatial models incorporating topographic and soil variables can calculate soil moisture potential over a watershed. Geo-environmental layers can be integrated into homogeneous land unit area (LUA) maps using geospatial processing techniques and geostatistical interpolation methods. This results in an accurate soil moisture database or map in an arid region. When merged with other databases, soil moisture data can provide valuable information for drought and flood indicators.

Soil Salinity

Soil salinization is a typical land degradation process that significantly reduces crop productivity and impacts soil health, water quality, and overall agricultural sustainability, leading to economic consequences (Zhu *et al.*, 2001; Corwin *et al.*, 2003) [17, 111]. Several variables, "such as soil type, land cover, climate, topography, vegetation, soil management methods, hydraulic conductivity, groundwater levels, and irrigation water quality, affect this complex procedure (Wang *et al.*, 2018; Ma *et al.*, 2018) [63, 97]. Soil salinity varies" spatially and temporally in agricultural fields, making it essential to have comprehensive information on its characteristics for effective soil reclamation and salinization prevention. In situ, soil sample extraction and laboratory analysis have traditionally assessed soil salinity to determine electrical conductivity. However, this method is both time-consuming and costly

due to requirements of dense sampling for accurate spatiotemporal characterization (Brunner *et al.*, 2007; Dehaan & Taylor, 2002) [12, 20]. Geophysical sensors, solute transport models, and modern geospatial technologies have demonstrated ability to surpass conventional methods. These methods enable quick evaluation and mapping of soil salinity, utilizing geophysical sensors to quantify electrical conductivity at a low cost (Nosetto *et al.*, 2013) [70].

For "monitoring and mapping soil salinity, remote sensing techniques have risen in popularity. The detection and mapping of soil salinity has been made easier by multispectral and hyperspectral data from satellites like Landsat, SPOT, IKONOS, QuickBird, Indian Remote Sensing" (IRS), EO-1 Hyperion, and HyMap (Farifteh, 2007; Weng *et al.*, 2008; Teggi *et al.*, 2012; Koshal, 2012; Dehni, 2012; Setia *et al.*, 2011; Dwivedi *et al.*, 2008) [23, 26, 32, 52, 84, 90, 102]. Various direct and indirect indicators can be used to detect soil salinity from remote sensing data. Direct indicators involve visible salt layers on soil surface, while indirect indicators include the presence of halophytes growing in salt-affected soil.

Salt crusts and efflorescence can complicate the direct method, as they may integrate with other soil components, making them less visible. Surface roughness and color can also interfere with reflectance measurements. However, it is possible to identify, monitor, and map salt-affected areas since the visible presence of halophytes acts as an indirect

indicator of soil salinity. To identify and map soil salinity based on the spectral properties of vegetation in varied contexts, researchers have employed a variety of vegetation indices, including SAVI, NDVI, SI, NDSI, RVI, GVI, SBI, and W.I. (Allbed *et al.*, 2014; Wang *et al.*, 2013) [5, 98]. Comprehensive coverage, cost-effectiveness, and the quick and timely delivery of soil salinity maps with medium to high resolutions are some benefits of using remote sensing data (Allbed and Kumar, 2013; Metternicht & Zinck, 1997) [66]. GIS/RS approaches have been used by researchers such as El (Bastawesy & Ali, 2013) and Wang *et al.* (2008) [99] for soil salinity estimation, groundwater rise, and salinity evaluation at the watershed scale.

Over the duration of four decades, spatial changes in soil attributes such as exchangeable sodium percentage (ESP) or electrical conductivity (E.C.) have been analyzed using GIS and R.S. (Güler *et al.*, 2014) [41]. By combining these technologies, soil salinity can be better understood. (Ren *et al.*, 2019) [78] used an integrated strategy to more accurately measure soil salinity dynamics, including solute transport modeling, GIS/RS analysis, and soil sampling at various scales.

5. Conclusion

The review underscores the significant progress in geospatial technology, mainly through satellite data and soil spectroscopy, enabling the assessment of soil characteristics at a regional scale. Various spectral indices and hyperspectral remote sensing have facilitated precise estimation and spatial mapping of soil properties, offering substantial benefits for site-specific agricultural management, enhancing input efficiency, and securing future food production. While hyperspectral spectroscopy shows moderate accuracy in estimating soil properties, there is potential for further development, especially in creating more robust spectral indices for different soil types. These findings emphasize the evolution of geospatial tools for better understanding and managing soil variability in agriculture.

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