

## Geo-Spatial tools for assessing Soil Fertility- A review

### 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 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*

### 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 [38], [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 [33],[32]. 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 [50],[32]. 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 characterise soil heterogeneity in both the spatial and temporal domains and conduct nondestructive analyses of soil properties. 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.

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) [34], [20],[41],[48],[59],[43].

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 [26],[25] 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.

## **REMOTE SENSING AND GEO-STATISTICAL TECHNIQUES IN SOIL STUDIES**

According to Ravisankar and Sreenivas [47], 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 [24].

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.

## 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 [10], 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 [45], texture, structure, moisture content [54], surface conditions, roughness, and iron oxide content [28], among others.

Spectral analysis can be used in laboratories to determine a variety of soil characteristics. However, atmospheric influences [21],[49] structural effects, lower spectral and spatial resolution, geometric distortions, and spectral mixture of features [29],[49] 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 [52].

**Table 1 : Spectral Reflectance of different Soil parameters that determine Soil Fertility (Source- [30])**

SNo	Soil Property	Spectral reflectance band ( $\mu\text{m}$ )	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 decrease in reflectance	[8]
3	Organic matter	1.70,2.18,2.31	Increase in Organic matter decreases reflectance	[8]; [50]
4	Iron oxides	0.40,0.43,0.45, 0.51,0.55,0.70, 0.87,0.90,1.0	Increase in iron oxide decreases reflectance	[55]
5	Clay minerals	1.40-2.20	Respond by presence of hydroxyl bands at these bands	[31]
6	Sulphates, carbonates, hydroxyl combinations	1-2.50	Responds at these bands	[27];[13]
7	Soil crusting	0.40-2.50	Spectral changes due to size distribution and mineralogical composition	[9]

## SOIL QUALITY/ FERTILITY ASSESSMENT

Designing sustainable agricultural practises (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 [15],[56]. 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 [51].

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 soils' capacity for managing and growing plants. Abdell A *et al.* (2021) [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 [54],[46],[39]. In order to achieve food security and sustainable agricultural policies and practises, it is crucial to evaluate soil quality indicators.

### **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 [47]. 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.* (2002) [42] 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.* (2006), 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 [56].

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.* (2002) [11] 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 greytone 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.

### **Physical aspect affecting Soil Fertility**

In a wide variety of naturally occurring surface soils, Stoner and Baumgardner (1981) [13] 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 [11], [22], [36], soil moisture,  $\text{Fe}_2\text{O}_3$ ,  $\text{SiO}_2$ , and  $\text{Al}_2\text{O}_3$  [23], [37], [40], 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],[37].

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 (2003) [7] 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.* (1989) [14] developed a soil moisture and temperature map for India using the high resolution land data assimilation system (HRLDAS) as a computing tool.

### **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) [12]. 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 [30].

## 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.

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