



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2025): 5.20
www.agronomyjournals.com
2025; SP-8(11): 448-454
Received: 02-10-2025
Accepted: 03-11-2025

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Integrating remote sensing and GIS for soil health monitoring: A comprehensive review

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DOI: <https://www.doi.org/10.33545/2618060X.2025.v8.i11Sf.4301>

Abstract

Soil health underpins sustainable agriculture, ecosystem integrity, and food security. Conventional soil monitoring relies on field sampling and laboratory analysis, which are often time-consuming, labour-intensive, and spatially limited. Recent developments in remote sensing (RS), geographic information systems (GIS), and digital soil mapping (DSM) offer efficient, scalable alternatives enabling frequent, large-area assessment of soil physical, chemical, and biological properties. This review synthesises state-of-the-art methods integrating RS, GIS, and machine learning (ML) to monitor soil health indicators—such as soil organic carbon (SOC), bulk density, texture, moisture, and nutrient status. We examine successes and limitations, explore case studies (including in India), and highlight recent advances in high-resolution mapping, spatio-temporal monitoring, and predictive modelling. We also discuss how RS-GIS integration supports land-use planning, soil degradation assessment, and targeted soil restoration interventions. The review concludes with a summary of research gaps and recommendations for operational soil-health monitoring systems.

Keywords: Soil health, remote sensing, GIS, Digital Soil Mapping (DSM), soil organic carbon

1. Introduction

Soil constitutes a dynamic, living resource that sustains plant growth, cycles nutrients, regulates water, and supports biodiversity. Monitoring soil health—its capacity to function as a living ecosystem that sustains productivity, environmental services, and resilience—has never been more critical. Traditional soil assessment methods rely on point-based sampling and laboratory analyses. While these methods remain foundational, they suffer from limited spatial coverage, high cost, and infrequent application, rendering them inadequate for timely landscape-scale soil health management.

Advances in remote sensing (RS), geographic information systems (GIS), and computational modelling over the past few decades provide a powerful alternative. These tools enable spatially continuous, temporally frequent, and cost-effective assessments over large areas. When integrated with in situ measurements and statistical or machine learning models, RS-GIS frameworks can estimate soil properties at unsampled locations, enabling near-real-time monitoring of soil health.

This review examines how the integration of RS and GIS has been used to monitor soil health. We synthesise methods (spectral, radar, multispectral, thermal, digital soil mapping), discuss key soil health indicators mapped so far, evaluate performance and limitations, and highlight relevant applications. We give special attention to research in India and similar agro-ecological zones to illustrate how RS-GIS-based soil health monitoring can support sustainable land management and agriculture ^[1, 2].

2. Soil Health: Definition, Key Indicators, and Need for Monitoring

Soil health refers to the capacity of soil to function as a dynamic living system that sustains plant and animal productivity, maintains or enhances water and air quality, and supports human health and habitation. Effective monitoring involves assessing multiple physical, chemical, and biological soil properties. Important indicators often include soil organic carbon (SOC), bulk

density, texture (clay, silt, and sand content), soil moisture, nutrient content (nitrogen and phosphorus), pH, aggregate stability, and biological activity ^[2, 3].

- **Soil Organic Carbon (SOC):** A fundamental indicator of fertility, structure, moisture retention, nutrient cycling, and carbon sequestration. SOC influences soil porosity, aggregate stability, water retention, and microbial biomass.
- **Bulk Density and Texture:** Indicators of soil compaction, porosity, drainage capacity, and capacity to hold water and nutrients. High bulk density or coarse sandy texture may impair root growth and water/nutrient retention ^[3, 4].
- **Soil Moisture and Water Holding Capacity:** Essential for plant available water, affecting crop yield, drought resilience, and irrigation needs.
- **Nutrient Content:** Nitrogen, phosphorus, and other macro/micronutrients are critical for plant growth; their

spatial variability influences fertiliser application and soil fertility management ^[4, 5].

- **Aggregate Stability and Biological Activity:** Indicators of soil structure, erosion resistance, aeration, root penetration, and microbial life—essential for long-term soil health ^[5, 6].

Given spatial heterogeneity in soils, land use, topography, and management history, soil health can vary widely even within a small region. Repeated monitoring across space and time is crucial to detect degradation (erosion, nutrient loss, compaction), plan interventions (restoration, fertilisation, conservation tillage), and track recovery or decline. Traditional point-based monitoring fails to capture such variability across landscapes—creating a need for scalable, spatially continuous methods.

Table 1: Soil Health Indicators and Their Measurement Techniques

Soil Health Indicator	Measurement Technique	Advantages	Limitations
Soil Organic Carbon (SOC)	Field sampling, RS	Accurate at field level, scalable with RS	Difficult to assess depth variation in SOC
Bulk Density	Soil coring, Field sampling	Direct measurement of soil compaction	Time-consuming, point-based sampling
Soil Moisture	Remote sensing (SAR), RS	Large-scale, frequent monitoring	Surface moisture only, limited by vegetation cover
Aggregate Stability	Laboratory testing	Direct measurement, accurate	Time-intensive, limited spatial coverage
Nutrient Content (N, P)	Field sampling, Laboratory analysis	Precise, standardized analysis	Requires laboratory analysis, expensive

3. Remote Sensing and GIS: Tools for Soil Health Assessment

Remote sensing (RS) and GIS provide mechanisms for inferring or mapping soil properties over large areas. Combined with field sampling and modelling, they enable estimation of soil health indicators across space with acceptable accuracy ^[6, 7].

3.1 Remote Sensing Techniques

- **Spectral Multispectral/Hyperspectral Imagery:** Reflectance data from soil surface (visible, near-infrared, shortwave infrared) can correlate with surface soil properties like organic carbon, texture, moisture, colour, and soil mineralogy. Hyperspectral sensors provide acceptable spectral resolution, enabling the detection of subtle soil chemical and physical differences.^(7,8) A recent critical review of RS-based SOC research concluded that RS offers a viable alternative for SOC estimation in precision agriculture systems. However, reliability depends on soil exposure, absence of dense vegetation cover, and proper calibration.
- **Radar / Microwave / SAR (Synthetic Aperture Radar):** Radar penetrates the soil surface and is sensitive to dielectric constant, which varies with moisture and, to some extent, soil texture and roughness. Radar-based backscatter can support soil moisture estimation and, under certain conditions, serve as a proxy for other soil properties, especially when combined with ancillary data ^[8, 9].
- **Thermal and Thermal Infrared Data:** Surface temperature and emissivity data provide indirect information that can be related to soil moisture, soil thermal properties, surface roughness, and evapotranspiration. When combined with energy-balance models (e.g., surface energy balance algorithms), they help infer soil moisture or stress conditions. Methods such as surface energy balance (e.g., in ET estimation) can complement soil moisture and water-stress monitoring ^[9, 10].
- **Land Cover / Land Use Change Monitoring:** Vegetation cover, crop patterns, bare soil exposure, erosion exposure,

and land degradation can be monitored via multitemporal RS data (e.g., satellite imagery). Changes in land cover influence soil exposure to erosion, organic matter input, nutrient cycling, soil compaction, and microbial activity—key aspects of soil health. Integration with soil property maps helps link land-use change to soil health outcomes ^[10, 11].

3.2 GIS Integration

GIS provides a spatial framework for integrating heterogeneous data, including remote sensing outputs, field sampling data, soil maps, topography (DEM), land use/land cover (LULC), climate, hydrology, and management history. Using GIS, soil health indicators can be mapped continuously across landscapes, enabling spatial analysis, temporal monitoring, and correlation with environmental or anthropogenic variables.

GIS supports

- Overlay analysis (soil maps, land cover, slope, erosion risk)
- Spatial interpolation of point-based soil data using proximity or geostatistical methods
- Digital Soil Mapping (DSM) by integrating RS-derived variables and ancillary data to predict soil properties in unsampled areas ^[12, 13].
- Temporal change detection by comparing multitemporal RS/GIS layers (e.g., land cover shifts, vegetation changes, surface exposure) to infer soil degradation or recovery

Together, RS and GIS reduce the reliance on exhaustive sampling, cut costs, and enable scalable soil health monitoring—vital for large or remote regions, frequent assessments, and policy-level planning ^[13, 14].

4. Digital Soil Mapping (DSM) and Machine Learning Approaches

Digital Soil Mapping (DSM) combines RS, GIS, environmental covariates (climate, topography, land use), and statistical or machine learning (ML) models to predict soil properties across

landscapes. DSM greatly enhances spatial coverage, resolution, and efficiency compared to classical soil survey.

Recent studies have demonstrated high predictive performance for key soil health indicators using DSM. For example, a 2025 systematic review found that remote-sensing data combined with ML and deep learning models can estimate soil organic carbon (SOC) with reasonable accuracy, offering significant potential for large-scale soil health monitoring [15, 16].

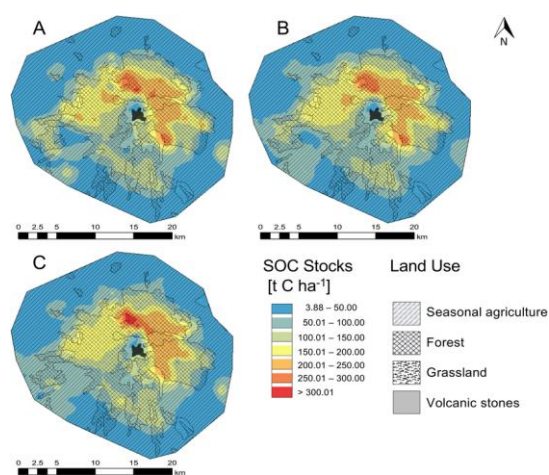
In a study of a hilly Himalayan region, DSM using legacy soil data combined with RS and ML produced SOC maps at 30 m spatial resolution. The maps revealed spatial variability in SOC across land-use types: evergreen forests had higher SOC than other land covers.

Another example: soil aggregate stability—a key measure of soil structure and erosion resistance—has been mapped using RS-based models. A 2021 study used remote sensing data, topography, organic matter, and geology to predict aggregate stability across a landscape, achieving strong performance ($R^2 > 0.92$ in training, acceptable $R^2 > 0.65$ in testing). Such mapping is critical for assessing soil susceptibility to erosion, compaction, and degradation [17, 18].

DSM workflow typically involves

1. Collection of field sample data for target soil properties (SOC, bulk density, texture, etc.).
2. Compilation of environmental covariates: RS-derived indices, DEM/topographic variables, land use/cover, climate parameters, parent material, and soil maps.
3. Selection and training of statistical or ML models (e.g., Random Forest, SVM, regression, deep learning) using sample data.
4. Prediction of soil properties across the entire study area (grid) to generate continuous spatial maps.
5. Validation and uncertainty assessment using cross-validation, independent validation points, error metrics (R^2 , RMSE, MAE) [18, 19].

DSM offers several advantages: acceptable spatial resolution, ability to estimate multiple properties simultaneously, scalability, repeatability, and cost-effectiveness. It supports soil health monitoring over time, hotspot detection, and intervention planning.



Spatial distribution of Soil Organic Carbon (SOC) mapped using RS-GIS-DSM frameworks for improved soil health assessment.

Source; Fusaro C, Sarria-Guzmán Y, Chávez-Romero YA, Luna-Guido M, Muñoz-Arenas LC, Dendooven L, Estrada-Torres A, Navarro-Noya YE. 2019. Land use is the main driver of soil organic carbon spatial distribution in a high mountain ecosystem. PeerJ 7:e7897 <https://doi.org/10.7717/peerj.7897>

5. Applications: Soil Quality Monitoring, Degradation Assessment, and Land Management

Integration of RS, GIS, and DSM enables diverse applications relevant to soil health, environmental management, agriculture, and policy. Key applications include:

- **Soil Quality / Soil Health Mapping and Monitoring:** Soil health indicators (SOC, bulk density, texture, moisture, aggregate stability) can be mapped across regions to identify zones of high fertility and zones at risk of degradation. RS-GIS-based soil health maps support periodic monitoring without exhaustive field sampling [20, 21].
- **Land Degradation and Soil Erosion Assessment:** By linking soil properties, topography, land cover, and rainfall data, GIS and RS allow identification of erosion-prone areas, degradation hot spots, and land-use change impacts. For instance, combining soil maps with land cover dynamics and slope information helps locate zones vulnerable to soil loss [21, 22].
- **Sustainable Land-use Planning and Management:** Soil health maps inform decisions about crop suitability, land-use allocation, fertilisation regimes, soil conservation measures, and restoration efforts. They support precision agriculture and site-specific nutrient management by identifying spatial variability.
- **Soil Fertility and Nutrient Management:** RS (especially hyperspectral) and DSM can help estimate nutrient-related proxies (e.g., SOC, organic matter, clay content) and infer fertility, enabling targeted fertilisation and reduced input waste [23, 24].
- **Monitoring Land-cover Change and Its Impact on Soil Health:** Multitemporal RS images detect changes in land use, forest cover, cropping patterns, and urban expansion. When combined with soil property maps, these analyses reveal how land-use change affects soil degradation, fertility loss, compaction, or soil organic carbon decline.
- **Policy and Conservation Planning:** Soil health data at the landscape scale supports watershed management, reforestation programs, soil restoration policies, carbon sequestration initiatives, and compliance with sustainable land management goals.

These applications make RS-GIS-based soil health monitoring a powerful tool for governments, researchers, land managers, and farmers [25, 26].

6. Case Studies with Emphasis on Indian Context

Emerging research from India demonstrates practical applications of RS, GIS, and DSM for soil health monitoring and land management.

6.1 Soil Quality Assessment in the Lower Mahanadi Basin

A recent study (2025) applied geospatial techniques to analyse soil quality and land-cover change in the Lower Mahanadi Basin (eastern India) over 2011–2020. The authors used RS-based land use/land cover (LULC) data (MODIS MCD12Q1), global soil databases (e.g., SoilGrid 250 m), and GIS to compute a Simple Additive Soil Quality Index (SQI). Key indicators—bulk density, organic carbon, nitrogen content, clay, sand, silt percentages, and pH—were layered to map soil quality spatially [27, 28].

Findings: from 2011 to 2020, cropland area decreased by 5.1%, forests increased by 11.5%, grassland expanded, and wastelands shrank. SOC stocks improved in many places (> 48.8 t/ha), bulk

density decreased, and overall SQI improved in parts of the basin. Areas with clay-rich soils exhibited higher nutrient retention and fertility, whereas sandy soils in the south remained more vulnerable to leaching and fertility loss.(29,30) The study demonstrates how RS-GIS-based analysis can reveal spatial-temporal soil health trends over a decade. This case underscores RS-GIS's capacity to monitor land-use change, soil quality, and ecosystem health at the basin scale, facilitating sustainable land management and restoration planning.

6.2 Digital Mapping of Soil Organic Carbon in Himalayan Terrain

A 2025 study applied the DSM, combining legacy soil data, RS-derived environmental covariates, and machine learning to map the distribution of soil organic carbon (SOC) in a hilly Himalayan region. Resulting maps at 30 m spatial resolution indicated higher SOC values in evergreen forest zones, lower values in agricultural or degraded lands. Given the fragile ecology of the Himalayan terrain—susceptible to erosion, deforestation, and soil degradation—this spatial SOC mapping provides critical baseline information. It enables

prioritisation of conservation, afforestation, soil restoration, and sustainable land-use policies. It also provides a model for mountain-region soil health monitoring, where field sampling is challenging and resource-intensive [31, 32].

6.3 Soil Physical Degradation Assessment via RS and GIS

In a recent Indian district-level study (Jamtara, Jharkhand), researchers used RS and GIS to assess key physical and chemical soil properties across the region to evaluate soil health. The study mapped soil texture, organic matter, nutrient content, and degradation indicators using satellite data and geospatial modelling [33, 34]. Such assessments allow the identification of degraded land, compaction zones, and nutrient-poor areas, and inform targeted interventions—such as nutrient management, liming, crop rotation, or soil amendments. Collectively, these studies illustrate how RS-GIS integration supports soil health monitoring across diverse Indian agroecological zones (plains, river basins, hills), offering scalable tools for soil conservation, sustainable agriculture, and land management policies.

Table 2: Case Study Examples of RS and GIS Integration for Soil Health Monitoring

Study Location	Soil Properties Monitored	Methods Used	Key Findings
Lower Mahanadi Basin, India	Soil Organic Carbon, Bulk Density, pH	MODIS LULC, SoilGrids, GIS	SOC improved by 48.8 t/ha, bulk density decreased
Himalayan Region, India	Soil Organic Carbon (SOC)	DSM, RS, ML	Evergreen forests had higher SOC than other land covers
Jamtara, Jharkhand, India	Soil texture, Organic matter, Nutrient content	Satellite data, GIS, Geospatial modeling	Degraded zones identified, targeted interventions proposed
Mesa Verde, USA	Soil Organic Carbon, Soil Erosion	DSM, Remote sensing, GIS	Erosion-prone areas mapped for conservation planning

7. Challenges, Limitations, and Uncertainties

While RS-GIS and DSM offer powerful tools, they face significant challenges and limitations when used for soil health monitoring:

7.1 Surface-only sensitivity and sampling constraints

Many RS methods (especially spectral, optical, and radar-based) are sensitive only to the uppermost soil layer (a few centimetres). Soil health indicators relevant to root-zone functioning (e.g., nutrients, bulk density, structure) at depth remain hard to capture. For example, SOC varies with depth; surface SOC alone may not represent total SOC stock or root-zone carbon storage. A recent study cautioned that depth-induced variation must be addressed when using RS to estimate SOC stocks [35, 36]. Thus, RS-GIS-based maps may misrepresent subsurface soil health conditions—limiting their utility for deep-rooted crops or long-term carbon sequestration assessment.

7.2 Dependence on vegetation cover, land-use, and soil exposure

The accuracy of spectral or radar-based methods depends heavily on soil exposure, minimal vegetation cover, and stable surface conditions. In vegetated fields or forested areas, canopy cover, plant residues, crop phenology, and moisture content obscure soil reflectance or radar backscatter, reducing reliability. Hyperspectral or SAR methods require careful calibration and may still struggle under dense vegetation [37, 38].

7.3 Need for extensive ground-truth data and ancillary environmental layers

DSM models rely on representative, high-quality ground-truth samples—soil laboratory analyses across diverse land uses, soil types, depths—and on reliable ancillary data (DEM, land cover, climate, geology, parent material, soil maps). In many regions, especially developing countries, such data are incomplete, outdated, or spatially uneven. This limits model accuracy and generalizability.

7.4 Temporal dynamics and monitoring frequency limitations

Soil properties change with management practices, land-use changes, erosion, organic matter addition or removal, cropping cycles, climate variability, and land disturbances. RS-based soil health assessment often produces snapshots rather than continuous monitoring. Frequent, repeated sampling (RS) is needed for meaningful temporal tracking, but this increases costs and complexity [39, 40].

7.5 Uncertainty, model transferability, and validation difficulties

Machine learning or statistical DSM models may overfit to specific regions or datasets. Their performance may degrade when transferred to different soil types, climates, land uses, or seasons. Validation requires independent ground data; lack of such data often leads to uncertain predictions. Soil heterogeneity and complex interactions among soil properties, climate, and land use make robust modelling challenging.

8. Future Directions and Recommendations

To realise the full potential of integrating RS, GIS, and DSM for soil health monitoring, future research and implementation should focus on:

- **Depth-aware soil health mapping:** Combine surface RS data with in-situ deep soil sampling, soil profile databases, and soil hydraulic or pedogenic models to estimate subsoil properties (e.g., deeper SOC, bulk density, moisture, nutrients). Use data assimilation techniques, geo-statistical models, or inversion models that incorporate depth variation [41, 42].
- **Multi-sensor, multi-temporal, multi-scale approaches:** Fuse data from multispectral, hyperspectral, radar (SAR), thermal, LiDAR, and DEM sources; integrate seasonal and inter-annual RS datasets to monitor soil health changes over time.
- **Integration of microbial and biological indicators:** Explore remote-sensing proxies or surrogate indicators (e.g., vegetation vigour, crop performance, land cover dynamics) combined with limited soil biological sampling to infer biological soil health [43, 44].
- **Regional calibration and robust modelling using machine learning:** Build region-specific DSM models using diverse soil, land use, climate, and topography data. Use ML algorithms (e.g., Random Forest, SVM, deep learning) with careful cross-validation, uncertainty quantification, and independent validation datasets [46, 47].
- **Policy-oriented, operational soil health monitoring systems:** Develop national or regional soil health monitoring frameworks using RS-GIS-DSM methods. (48,49)Use open-access satellite data (e.g., from publicly available sensors), cloud computing, and web-based platforms to deliver soil health maps to policymakers, land managers, and farmers [50, 51].
- **Combination with land-use planning, conservation, and agricultural management tools:** Use soil health maps to guide land-use decisions, soil restoration, nutrient management, reforestation, crop rotations, soil conservation practices, payment-for-ecosystem-services schemes, and carbon sequestration initiatives [52, 53].
- **Capacity building and data infrastructure in developing regions:** Invest in soil sample databases, ground-truth networks, soil mapping, training, and institutional frameworks (e.g., national agencies, research institutions) to support regular, consistent soil health monitoring.(54,55) In India, leveraging institutions working in RS/GIS (e.g., national or regional remote sensing centres) can accelerate adoption [53, 56].

9. Conclusion

Integration of remote sensing, GIS, and digital soil mapping offers a transformative pathway for large-scale, cost-effective, and spatially continuous soil health monitoring. Recent studies demonstrate that key soil health indicators—soil organic carbon, bulk density, texture, soil quality indices, and aggregate stability—can be reliably mapped across landscapes, even in complex terrains such as Himalayan hills and river basins. Indian case studies show that such approaches can detect temporal changes, land-use impacts, and spatial heterogeneity in soil quality across agricultural and forested landscapes [57,58].

However, limitations remain. Remote sensing rarely captures subsurface soil properties; dense vegetation and land cover complicate spectral or radar-based assessments; robust ground-truth data remain scarce; temporal monitoring is limited; and model transferability and uncertainty persist. Overcoming these challenges requires combining surface data with soil profile information, adopting multi-sensor and multi-temporal approaches, integrating biological soil health indicators, and building regionally calibrated machine-learning models.

Scaling up these methods into operational soil health monitoring systems can support sustainable land management, soil conservation, fertiliser and water-use planning, restoration initiatives, and climate-smart agriculture. For countries like India with diverse agro-ecological zones and high population pressure on land resources, RS-GIS-DSM-based soil health monitoring offers a vital tool to ensure soil sustainability, agricultural productivity, and environmental resilience [59].

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