

Potential of Hyperspectral Remote Sensing in Predictive Soil Health Monitoring under Climate-Induced Stress Scenarios

Mukesh Kumar¹, Rajeev Kumar², Rekha Jangra³, Balkar Singh⁴ and Neetu Kataria⁵

^{1,5}*Department of Botany, Government College Bahadurgarh, Jhajjar 124 507, Haryana, India*

²*Department of Geography, Government College Bahadurgarh, Jhajjar 124 507, Haryana, India*

³*Department of Botany, Pt. Chiranji Lal Sharma Government College Karnal 132 001, Haryana, India*

⁴*Department of Botany, Arya P.G. College Panipat 132 103, Haryana, India*

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ABSTRACT

Soil health is a key factor in agricultural production, environmental sustainability, and climatic resilience. As climate change increases the frequency and intensity of stressors including drought, salinization, and heat extremes, there is an urgent need for better methods to monitor and predict soil deterioration. Hyperspectral remote sensing (HRS) has developed as a breakthrough technology capable of detecting minor spectral signatures of important soil parameters with high precision and spatial detail. This paper investigates the expanding importance of hyperspectral imaging in soil health monitoring, with a focus on its use in climate-stressed areas. The paper proposes a conceptual framework for predicting soil health, analyzes hyperspectral soil property indicators, and emphasizes the need of temporal monitoring and change detection. The integration of hyperspectral data with vegetation and atmospheric factors is being examined in order to gain a better understanding of the continuity of soil, vegetation, and atmosphere. Deep learning, data fusion, and artificial intelligence (AI) developments are examined as enabling real-time, scalable, and precise soil health forecasting. There are still issues with sensor calibration, data complexity, ground truth requirements, and accessibility, despite the technology's enormous potential. A plan for future study is provided in the paper's conclusion, which calls for interdisciplinary cooperation, technological advancement, and legislative backing to mainstream hyperspectral soil monitoring in light of climate change. The way we evaluate, predict, and manage soil health in the twenty-first century could be completely changed by hyperspectral remote sensing combined with AI-driven analytics and larger environmental databases.

Key words: *Hyperspectral remote sensing, Soil health monitoring, Climate induced stress & Artificial intelligence.*

Introduction

Soil health, a cornerstone of sustainable agriculture, is increasingly threatened by climate-induced stressors such as droughts, heat waves, flooding, and altered precipitation patterns. Traditional soil moni-

toring techniques are usually labor-intensive, time-consuming, and lack the spatial and temporal precision necessary to address large-scale environmental dynamics, despite their effectiveness on small scales (Bhargava *et al.*, 2024, Kumar *et al.*, 2024). As a result, remote sensing methods-in particular,

(¹Assistant Professor, ²Professor, ³Assistant Professor, ⁴Associate Professor, ⁵Associate Professor)

hyperspectral remote sensing, or HRS—are becoming more and more popular as a way to improve soil health management and monitoring in real time over large geographic areas. The detection of minute variations in soil characteristics that are invisible to multispectral sensors or the human eye is made possible by hyperspectral imaging, which records a broad spectrum of spectral information across hundreds of small, continuous bands (Aroca-Fernandez, *et al.*, 2025 and Lu *et al.*, 2020).

The advent of HRS technologies has revolutionized the way soil parameters are monitored, enabling the identification of biochemical and physical changes induced by climatic stresses. Unlike conventional remote sensing platforms, hyperspectral sensors provide high-resolution data that can be effectively used to detect soil degradation, nutrient depletion, moisture variation, salinity, and organic matter fluctuations—all vital indicators of soil health (Audebent *et al.*, 2019). With the pressing challenges posed by global climate change, including shifts in soil temperature and hydrological regimes, the role of hyperspectral remote sensing in predictive soil health monitoring is emerging as a critical field of study and useful for various crops monitoring (Figure 1.)

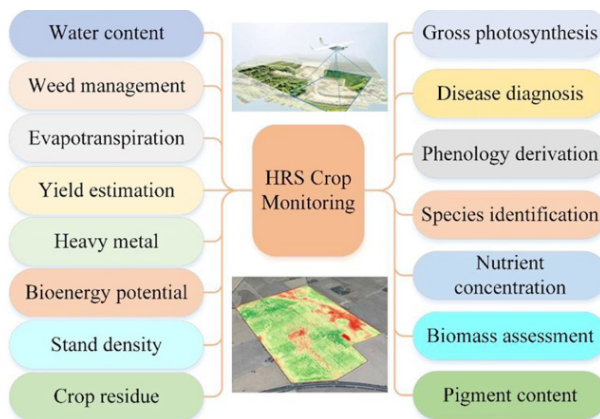


Fig. 1. Role of Hyperspectral crop monitoring

In the context of climate-induced stress scenarios, the integration of hyperspectral data into predictive models can enhance early warning systems, guide sustainable land management practices, and inform policy decisions. These capabilities are particularly important in agrarian economies where soil fertility directly affects food security. Moreover, coupling HRS with machine learning algorithms, AI-driven analytics, and soil-vegetation-atmosphere simula-

tion models offers unprecedented opportunities to forecast soil health conditions with high precision (Kamarudin *et al.*, 2021).

The objective of this paper is to present a thorough analysis of the developing application of hyperspectral remote sensing in predictive soil health monitoring. Predictive soil health assessment, hyperspectral characterization of soil properties, temporal dynamics under climate variability, integration with hydrological and ecological processes, data fusion approaches, limitations, and future research directions are all covered in detail in the following sections. This study highlights the revolutionary potential of HRS technologies in tackling the complex problems of soil health monitoring under climate change stressors by integrating current developments.

Conceptual Framework of Predictive Soil Health Monitoring

The proactive evaluation and forecasting of soil conditions through the use of historical data, real-time observations, and predictive analytics is known as predictive soil health monitoring (Lu *et al.*, 2020). Soil science, climate modeling, sensor technologies, geospatial data analytics, and ecological feedback mechanisms are all integrated into the conceptual framework for such a system. Fundamentally, by changing the focus from reactive soil evaluation to anticipatory management, this strategy enables stakeholders to stop degradation before it becomes irreparable (Hauser *et al.*, 2024).

The foundation of predictive soil health monitoring lies in understanding the interactions between soil properties (physical, chemical, and biological), climatic variables (temperature, rainfall, humidity), and anthropogenic activities (land use changes, fertilizer application, irrigation practices). These interactions are inherently complex and non-linear, requiring sophisticated models capable of capturing dynamic feedbacks. Hyperspectral remote sensing fits into this framework as a critical observational tool that supplies high-resolution, continuous spectral data essential for parameterizing and validating soil health models (Aroca-Fernandez, *et al.*, 2025). The framework's identification and measurement of soil health indicators is one of its main features. These consist of microbial activity, salinity, moisture content, nutrient levels, pH, texture, and soil organic carbon. Hyperspectral sensors offer a non-invasive monitoring technique by detecting spectral reflec-

tance patterns that match these markers. For instance, changes in organic matter or clay content can be indicated by differences in reflectance at particular wavelengths, and thermal and shortwave infrared bands can be used to infer moisture stress (Keller *et al.*, 2018).

The predictive aspect involves the integration of hyperspectral data with environmental datasets, including climate projections, land surface temperature, and vegetation indices (Shaw *et al.*, 2003). Machine learning models, such as Random Forest, Support Vector Machines, and Deep Learning Networks, are increasingly employed to extract meaningful patterns from the voluminous and high-dimensional data generated by hyperspectral sensors. These models can predict future soil conditions under different climate scenarios, providing early warnings and decision-support tools for farmers and policymakers (Keller *et al.*, 2021 and Hauser *et al.*, 2024).

Furthermore, the framework incorporates spatial and temporal scalability. It enables localized assessments at the farm level as well as broader regional and national-scale evaluations. Data from satellite-based hyperspectral missions, airborne sensors, and proximal field instruments can be integrated to provide multi-scale insights (Archibald *et al.* (1999). Temporal dynamics are captured through continuous monitoring, facilitating the detection of trends, anomalies, and abrupt shifts in soil conditions linked to climatic extremes. Ultimately, the conceptual framework of predictive soil health monitoring emphasizes a systems approach merging observational technologies with process-based and statistical models to anticipate and address soil degradation in a rapidly changing climate (Kumar *et al.*, 2024)

Hyperspectral Signatures of Key Soil Properties

Hyperspectral remote sensing excels at detecting and quantifying subtle spectral signatures associated with various soil properties. Each soil constituent has a unique spectral reflectance profile across the visible, near-infrared (VNIR), and shortwave infrared (SWIR) regions, allowing for their identification and mapping with high precision. These spectral fingerprints serve as the foundation for developing predictive models of soil health (Li *et al.*, 2022 and Li *et al.*, 2025). Soil organic matter (SOM), a critical indicator of soil fertility, exhibits distinct absorption features in the VNIR region, typically

around 400–700 nm. These features arise due to the presence of chromophoric compounds such as humic acids and fulvic acids. Hyperspectral imaging can detect even minor variations in SOM, facilitating spatially detailed assessments of soil carbon content. Similarly, soil texture components—sand, silt, and clay—affect reflectance patterns primarily in the SWIR region (1100–2500 nm), where clay minerals show diagnostic absorption bands due to overtone and combination vibrations of OH, Al-OH and Mg-OH groups (Li *et al.*, 2025).

Soil moisture content significantly influences spectral reflectance, as water absorbs strongly in both the VNIR and SWIR regions. As soil moisture increases, overall reflectance decreases due to the absorption of incoming radiation by water molecules. Hyperspectral sensors are sensitive to this change, enabling precise estimation of soil water content. This capability is particularly important in drought-prone regions where soil moisture is a limiting factor for crop productivity and ecosystem stability (Piccoli *et al.*, 2025). Salinity and pH are other crucial soil health indicators that exhibit identifiable spectral characteristics. Salt-affected soils often show elevated reflectance in the visible region due to salt crusts, while pH-related changes in soil mineralogy can be detected through shifts in absorption features. For instance, soils with high pH often have carbonate minerals that manifest spectral signatures around 2300 nm. Hyperspectral imaging can thus support the classification and mapping of saline and alkaline soils with high spatial accuracy (Audebert *et al.*, 2019).

In addition to these properties, hyperspectral sensors can detect soil contamination by heavy metals and hydrocarbons. Contaminants alter the chemical and physical structure of soil, leading to changes in spectral reflectance. Advanced processing techniques, such as continuum removal and derivative analysis, enhance the ability to identify these subtle alterations. In summary, hyperspectral signatures provide a rich source of information on key soil properties. The ability to extract and analyse these signatures enables continuous, non-invasive, and large-scale assessment of soil health, laying the groundwork for predictive monitoring under climate-induced stress conditions (Piccoli *et al.*, 2022).

Temporal Dynamics and Change Detection in Soil Health

Temporal dynamics in soil health are changes in soil

attributes that occur over time as a result of natural processes and human activities, particularly those worsened by climatic variability. Monitoring these dynamics is critical for early identification of soil deterioration, directing land management methods, and determining the influence of climate change on soil systems. Hyperspectral remote sensing (HRS), with its high spectral resolution and continuous monitoring capability, provides a potent tool for detecting these temporal changes with unparalleled accuracy (Bhargava *et al.*, 2024). One of the primary advantages of HRS is its ability to capture multi-temporal data, allowing for the assessment of how soil characteristics evolve under stress conditions such as drought, flooding, or temperature extremes (Vairavan *et al.*, 2024). For instance, repeated hyperspectral observations can identify declining trends in soil organic carbon or increasing salinity levels over cropping seasons or years. This capability is particularly valuable in arid and semi-arid regions, where soils are highly sensitive to climatic perturbations (Shaw *et al.* (2003).

Temporal change detection approaches based on hyperspectral data include comparing spectral signatures at several time points. These techniques range from simple image differentiation to more advanced multivariate statistical approaches like principal component analysis (PCA), change vector analysis (CVA), and time-series modeling with machine learning algorithms. Such approaches can reveal both rapid changes, such as soil disturbance caused by tillage or erosion, and long-term patterns, such as nutrient depletion or organic matter loss (Zhang *et al.*, 2023).

Moreover, temporal analysis enables the differentiation between seasonal variability and long-term degradation trends. For example, moisture-related spectral changes might be seasonal, corresponding to rainfall patterns, while a consistent decline in specific spectral bands over multiple seasons could indicate permanent soil degradation. This distinction is crucial for designing adaptive land management strategies. The integration of HRS data with ground truth observations enhances the reliability of temporal change detection. Ground-based measurements of soil parameters at different time intervals can be used to calibrate and validate hyperspectral models, increasing their predictive power. In addition, combining hyperspectral data with meteorological and hydrological datasets facilitates a more comprehensive understanding of the drivers behind soil

changes (Selci, 2019).

Soil Moisture and Thermal Stress Indicators via Hyperspectral Imaging

Soil moisture and temperature are fundamental variables that govern a wide array of soil biochemical and physical processes. Under climate-induced stress scenarios—especially drought and heat waves—monitoring these parameters becomes critical for assessing soil health and its capacity to support agricultural productivity and ecosystem functions. Hyperspectral remote sensing offers a non-invasive and efficient way to estimate both soil moisture content and thermal stress indicators by capturing detailed spectral information across the VNIR and SWIR regions (Aroca-Fernandez, *et al.*, 2025).

The estimation of soil moisture using hyperspectral imaging is based on the absorption features of water in the 1400 nm, 1900 nm, and 2200 nm regions. As soil moisture increases, the depth of these absorption features becomes more pronounced due to the higher water content absorbing more radiation. This property allows hyperspectral sensors to detect even slight variations in soil moisture, which is crucial for early drought detection and irrigation planning. Unlike microwave-based moisture sensors that are more effective in detecting surface moisture, hyperspectral sensors can provide information about moisture at slightly deeper soil layers, especially when combined with radiative transfer models. (Zhang *et al.*, 2023). Thermal stress in soils is associated with elevated surface temperatures, which influence microbial activity, nutrient cycling, and plant root health. Hyperspectral imaging, while primarily focused on the reflective portion of the electromagnetic spectrum, can be complemented with thermal infrared (TIR) data to provide a comprehensive assessment of thermal conditions. Additionally, some studies have shown that thermal stress can alter the spectral characteristics of soils indirectly through changes in organic matter decomposition, crust formation, or soil colour due to oxidation all of which can be detected using hyperspectral sensors (Patange *et al.*, 2024).

An emerging approach involves integrating hyperspectral and thermal imaging to create indices that capture the synergistic effects of moisture and heat stress. For instance, combined indices such as the Soil Adjusted Vegetation Index (SAVI) and Normalized Difference Water Index (NDWI) derived from hyperspectral bands can be used alongside

thermal data to identify hot spots of soil stress (Figure 2). This multi-dimensional analysis provides deeper insights into how climate stressors interact to affect soil health (Chen *et al.*, 2019; Kumar *et al.*, 2024).

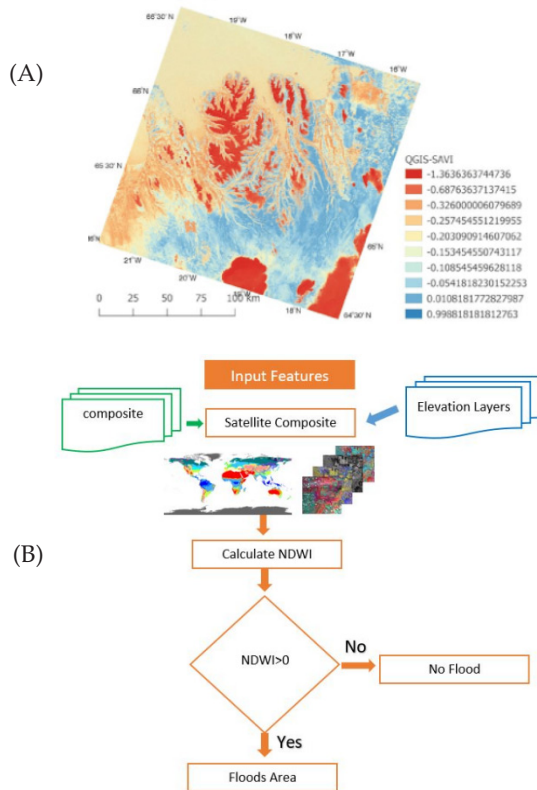


Fig. 2. A general image of Soil Adjustment Vegetation Index (SAVI) (B) A view of flow chart of NDWI (Normalized Difference Water Index (NDWI))

Integration of Hyperspectral Data with Soil–Vegetation–Atmosphere Interactions

The soil–vegetation–atmosphere continuum represents a complex system of energy, water, and nutrient exchanges that are highly sensitive to climate variations. Understanding and monitoring this continuum is essential for evaluating soil health and its response to environmental stressors. Hyperspectral remote sensing, with its ability to simultaneously capture data related to soil, vegetation, and atmospheric influences, plays a pivotal unravelling these interactions under climate-induced stress scenarios (Bhargava *et al.*, 2024, Shaw *et al.*, 2003). One of the key strengths of hyperspectral data is its capability to assess both soil and plant conditions in tandem. Vegetation reflectance, especially in the red edge

and near-infrared regions (680–750 nm), is highly sensitive to plant health, chlorophyll content, and stress levels. Since vegetation health is often directly linked to soil conditions particularly moisture and nutrient availability changes in canopy spectra can serve as indirect indicators of soil degradation. For example, a decline in vegetation vigour, as evidenced by hyperspectral vegetation indices like the Red Edge Position (REP) or Chlorophyll Index, may point to underlying soil salinity or nutrient deficiencies (Lu *et al.*, 2020).

Simultaneously, soil surface characteristics including organic matter, texture, and wetness can be directly determined via hyperspectral photography. A more comprehensive understanding of soil–plant interactions is made possible by the combination of this dual study with vegetation indices. Furthermore, ecohydrological models that describe water fluxes between soil, plants, and the atmosphere can be parameterized and validated using hyperspectral data. Atmospheric conditions, including humidity, radiation, and temperature, also play a role in influencing both soil and plant reflectance (Arachibold *et al.*, 1999 and Lu *et al.*, 2020). Hyperspectral sensors account for atmospheric effects through calibration and correction techniques, enabling more accurate interpretation of ground conditions. In precision agriculture, integrating atmospheric data (e.g., from weather stations or satellite-based atmospheric sensors) with hyperspectral soil and vegetation data supports better decision-making on irrigation, fertilization, and crop selection under changing climate conditions (Singh *et al.*, 2010).

Advances in Data Fusion and AI for Soil Health Forecasting

The predictive potential of hyperspectral remote sensing in soil health monitoring has been greatly improved by the development of data fusion techniques and artificial intelligence (AI). AI technologies like machine learning (ML) and deep learning (DL) are essential for identifying significant patterns, cutting down on noise, and creating reliable prediction models because of the high dimensionality and complexity of hyperspectral datasets. A more thorough and precise representation of soil health under climate-induced stress conditions is achieved when these technologies are used in conjunction with data fusion strategies that combine hyperspectral data with supplementary sources such as LiDAR, thermal infrared, microwave, and

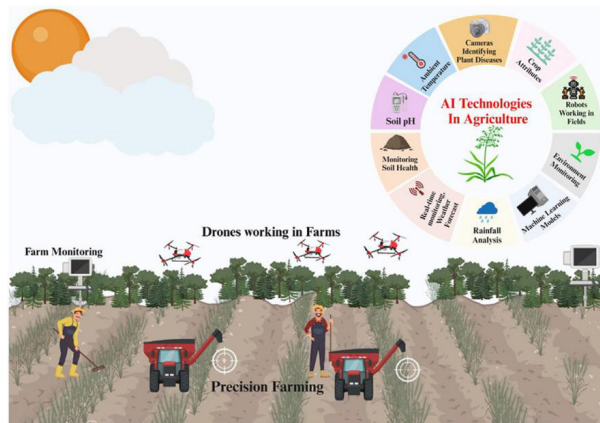


Fig. 3. Role of AI technologies in agriculture for soil health forecasting

temperature data Figure 3.

Data fusion refers to the integration of information from multiple sources to produce more consistent, accurate, and useful information. In the context of soil health monitoring, hyperspectral data is often fused with multispectral imagery, digital elevation models (DEMs), soil sample datasets, vegetation indices, and climate data (temperature, rainfall, humidity) (Bajcsy and Groves 2004). For instance, fusing hyperspectral reflectance with soil texture maps or vegetation health indices enhances the ability to identify degraded patches and predict soil nutrient availability more accurately. Fusion with thermal data also helps assess soil moisture and heat stress synergistically.

AI algorithms are particularly well-suited for processing hyperspectral data due to their ability to handle non-linear relationships, high-dimensional feature spaces, and noisy inputs. Supervised learning algorithms like Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting Machines (GBMs) are frequently used for soil property classification and regression tasks. Meanwhile, unsupervised techniques such as k-means clustering and self-organizing maps (SOMs) assist in exploratory data analysis and soil type classification. Deep learning, especially convolutional neural networks (CNNs), has emerged as a powerful tool for hyperspectral image analysis. CNNs can learn spatial and spectral features simultaneously, making them highly effective for tasks such as soil moisture estimation, organic matter prediction, and detection of contamination. Recurrent neural networks (RNNs), particularly Long Short-Term Memory

(LSTM) networks, are increasingly used for time-series forecasting of soil health variables, leveraging the temporal dimension of remote sensing data.

AI-powered frameworks are also being embedded into decision support systems and agricultural management platforms. These systems can provide real-time alerts, recommend site-specific interventions, and simulate soil responses to various climate scenarios. Cloud computing platforms and open-source AI libraries (e.g., Tensor Flow, PyTorch) have democratized access to these technologies, allowing researchers and practitioners to build scalable solutions. Moreover, the use of explainable AI (XAI) techniques is gaining traction, offering transparency in model outputs and facilitating stakeholder trust. Understanding the 'why' behind model predictions is crucial when dealing with critical land management decisions, especially in regions vulnerable to climate change. In essence, the integration of AI and data fusion in hyperspectral remote sensing represents a paradigm shift in soil health forecasting. These innovations enable more accurate, scalable, and timely predictions, empowering sustainable agricultural practices and climate resilience planning.

Limitations, Challenges, and Calibration Needs

Despite the promising capabilities of hyperspectral remote sensing in soil health monitoring, several limitations and challenges persist that hinder its widespread adoption and operational use. These issues span technical, methodological, and infrastructural domains, necessitating a careful assessment of calibration needs, data quality, and interpretation accuracy. One of the foremost challenges is the high dimensionality of hyperspectral data. With hundreds of spectral bands, these datasets are computationally intensive and require significant storage and processing power. The presence of redundant or highly correlated bands complicates model building, increasing the risk of overfitting in predictive algorithms. Dimensionality reduction techniques such as principal component analysis (PCA), minimum noise fraction (MNF), and band selection algorithms are necessary to streamline the data without losing critical information. Another critical challenge lies in sensor calibration and standardization. Variations between sensors (airborne, satellite, proximal), atmospheric interference, and differing acquisition conditions can result in inconsistencies in spectral data. Accurate calibra-

tion, including radiometric, geometric, and atmospheric correction, is essential for ensuring the reliability and comparability of hyperspectral images across time and space. This is particularly important when performing change detection or building time-series models. Soil surface conditions, such as roughness, vegetation cover, and residue, can also influence spectral reflectance, leading to inaccuracies in property estimation. While spectral unmixing techniques can separate soil signals from vegetation or litter, these approaches add complexity to the processing chain and often require ancillary data or field validation.

Ground truthing remains a fundamental bottleneck. While hyperspectral data can offer detailed spectral insights, it must be validated against field-based soil measurements to establish accurate predictive relationships. Collecting such reference data is labour-intensive, expensive, and often limited in spatial and temporal scope, especially in developing regions. Moreover, soil heterogeneity poses a challenge to model generalization, as localized models may not perform well across different soil types, land uses, or climatic zones. There is also a lack of standard methodologies and protocols for hyperspectral soil analysis. Discrepancies in pre-processing steps, band selection, and model evaluation criteria can lead to inconsistent results across studies. Establishing standardized procedures would facilitate replication, comparison, and integration of research findings. In addition, access to hyperspectral data is still limited. While satellite missions such as EnMAP and PRISMA are helping bridge this gap, many operational users still rely on airborne or costly proprietary sensors. Data accessibility, affordability, and user training are crucial factors that need to be addressed to scale up the application of hyperspectral technologies in soil monitoring. Finally, ethical and policy considerations, including data privacy, geospatial sovereignty, and equitable technology access, must be integrated into the broader discourse on hyperspectral soil monitoring. As the technology matures, addressing these challenges through coordinated research, international collaboration, and open data initiatives will be vital to harness its full potential.

Roadmap for Future Research and Technological Innovation

The future of hyperspectral remote sensing in predictive soil health monitoring hinges on concerted

research, technological innovation, and policy integration. As climate change continues to alter soil systems worldwide, there is an urgent need to evolve remote sensing methodologies, build interdisciplinary frameworks, and create accessible tools that can transform soil health forecasting from a niche research topic to a mainstream practice in sustainable land management. One of the key research priorities is the development of next-generation hyperspectral sensors with improved spatial, spectral, and temporal resolution. The upcoming Surface Biology and Geology (SBG) mission by NASA and enhanced sensors aboard Cube Sats and drones offer promising avenues for high-frequency, high-resolution monitoring (Zhang *et al.*, 2021). These platforms can provide dynamic soil assessments at both local and global scales, helping bridge the gap between proximal sensing and satellite observation. Advances in sensor miniaturization and UAV integration can democratize access to hyperspectral technologies, especially in resource-constrained settings. Light-weight hyperspectral sensors mounted on drones enable flexible, cost-effective data collection, particularly for precision agriculture and field experimentation. Continued innovation in this domain will empower farmers and extension agents with on-the-spot diagnostic capabilities Shaw *et al.*, 2003 and Singh *et al.*, 2010).

Research must also focus on improving the robustness and transferability of hyperspectral models. Creating large, open-access spectral libraries representing diverse soil types, climatic zones, and management systems can facilitate model calibration and validation across broader geographies. Collaborative platforms such as the Global Soil Spectral Library (GSSL) are vital steps in this direction. From a computational standpoint, integration of cloud-based processing, edge computing, and AI-driven automation will streamline data analysis and decision support (The use of federated learning and decentralized data models could offer privacy-preserving solutions for sharing and processing geospatial data (Green *et al.*, 2018). Real-time dashboards and mobile applications powered by AI models could bring soil health predictions directly to the end-users. Interdisciplinary research is also necessary to refine soil-vegetation-atmosphere interaction models using hyperspectral inputs. Collaborations between soil scientists, ecologists, remote sensing experts, and data scientists will enhance the scientific foundation of predictive soil health models. Incon-

porating socio-economic data into predictive models can also support more holistic decision-making, particularly in vulnerable agro ecosystems (Kumar *et al.*, 2024 and Bhargava *et al.*, 2024).

Policy support and institutional capacity-building are equally important. Governments and international bodies must invest in hyperspectral infrastructure, data dissemination systems, and user training programs. Establishing national and regional soil health monitoring networks using hyperspectral data could form the basis for climate-smart agricultural policies and land degradation neutrality goals under frameworks like the UNCCD.

Conclusion

Hyperspectral remote sensing represents a transformative advancement in the field of soil health monitoring, particularly under the growing threat of climate-induced stressors. By capturing high-resolution spectral data across hundreds of bands, it enables detailed, non-invasive assessments of key soil properties such as moisture, organic matter, salinity, and contamination levels. When integrated with AI and data fusion techniques, hyperspectral imaging not only enhances the accuracy of soil diagnostics but also contributes to the development of robust predictive models capable of forecasting degradation trends and informing proactive land management. This review has explored the conceptual and technological underpinnings of hyperspectral remote sensing in predictive soil health monitoring, highlighting its potential in assessing temporal dynamics, supporting soil-vegetation-atmosphere interaction models, and advancing early warning systems for soil stress. However, the successful deployment of these technologies at scale demands overcoming several challenges, including calibration issues, data accessibility, model generalization, and the need for comprehensive ground truth datasets. Looking ahead, continued innovation in hyperspectral sensor design, AI integration, and computational efficiency will play a critical role in expanding the applicability of this technology. Collaborative initiatives that foster interdisciplinary research, open data platforms, and policy integration are essential to create sustainable, climate-resilient soil monitoring frameworks. Ultimately, hyperspectral remote sensing offers not just a window into the current state of soil health but a forward-looking tool to navigate the challenges of land

degradation and food security in an era of global environmental change.

Conflict of Interest- None

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