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REVIEW ARTICLE

Emerging trends in AI-based soil health assessment: A review

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Abstract

The application of artificial intelligence (AI) in soil health assessment presents significant advancements over conventional methods by enabling more efficient and precise measurements. This review examines and supports how AI monitors soil health and its significance for sustainable land management. AI technologies, including machine learning, remote sensing and big data analytics, enable researchers and practitioners to analyse diverse data sources, model soil-plant relations and predict soil health trends with greater accuracy. AI-integrated soil health monitoring enables tracking of key soil parameters, facilitating efficient nutrient management, soil erosion control and overall ecosystem sustainability. AI-driven precision agriculture helps stakeholders predict the long-term impacts of farming practices, optimize resource use, enhance crop yields and reduce environmental impacts. This review also demonstrates how updated highlights recent research, case studies and best practices that demonstrate how AI-based soil health monitoring contributes to agricultural sustainability, conservation and food security.

Keywords: artificial intelligence (AI); agricultural sustainability; environmental risk mitigation; soil health monitoring

Introduction

Over the years, a major focus has been on understanding soil quality, sustainable food production and food security (1). Soil health assessment uses an ecosystem-based approach that evaluates the soil's biological, chemical and physical components to estimate its functional capacity. It integrates the soil's textural, biological and chemical properties for effective management and sustainability. Although there are specific guidelines for air and water pollution monitoring, there are limited standard protocols for assessing the soil and its condition concerning the landscape (2). Sometimes, analyzing the soil data using the traditional methods involves using many exhaustive tools, hence producing a soil data set that is often incomplete and does not present real-time information (3). Artificial intelligence (AI) has recently emerged as a promising tool for soil quality evaluation, capable of analyzing large datasets and generating highly accurate results. Farmers and land managers are increasingly adopting AI technologies, including machine learning algorithms (MLAs) and image processing, to obtain precise and timely insights into soil health and nutrient availability. These technologies can potentially revolutionize how scientists and farmers assess and manage soil health for improved productivity (4). Machine learning algorithms (MLAs) play a crucial role in AI-based soil health assessment by efficiently processing large-scale data from sensors, satellite imagery and archives (5). AI-based analysis not only assists farmers in making informed decisions on fertilization, Irrigation, crop rotation and seed selection, but also helps identify issues such as soil erosion, nutrient imbalances and water stress (either excess or deficit) (5). Further, AI technologies can analyze the condition of the soil and can aid the farmers in identifying the first signs of pest and disease infections, which will, in turn, assist the farmers in reducing crop losses and applying sustainable farming practices by optimizing the use of resources and minimal use of chemicals (4). The AI-based system to evaluate soil health for agricultural purposes is yet to be developed, but there is great potential to develop the application of this system because of employing advanced AI technology and easy data collection in the future. The current situation offers a vast opportunity to construct and progress the AI-based approaches in soil health assessment (6). This study hypothesizes that integrating artificial intelligence with soil health measurement is key to revolutionising sustainable land management's accuracy, efficiency and cost-effectiveness. The urgency of the research stems from the mounting environmental issues soil erosion and climate stress that necessitate smarter, data-driven solutions. Concurrently, the economic necessity of reducing input usage while maximizing output at the expense of minimal environmental loss makes AI a necessary ingredient. Bridging this environmental-economic divide, the hypothesis lies in the potential of AI to make soil management an even more accurate, lucrative and sustainable.

Overview of the soil health assessment

Soil health is fundamental to sustainable agriculture and is crucial for crop productivity, environmental sustainability and ecosystem resilience (7). A major limitation of current soil assessment methods is their partial subjectivity, making large-scale monitoring less reliable and consistent. Advancements in AI have significantly improved knowledge and approaches to soil health management. This is a unique opportunity to transform agriculture because the measurement of soil health using artificial intelligence results in actual and inexpensive monitoring systems. AI allows researchers to make meaningful conclusions about the data of soil properties based on MLA, deep learning techniques and big data analysis of chemical, physical and biological characteristics. The soil health is shown in the diagrammatic representation in the overview of the soil health assessment in Fig. 1. This includes physical properties such as soil texture and structure, chemical indicators like pH and nutrient content and biological aspects such as microbial activity and organic matter levels. The figure serves as a visual summary of how these diverse indicators influence overall soil health. Understanding these relationships is crucial for making informed decisions in agriculture, land management and environmental conservation, as healthy soils are foundational to sustainable plant production, water filtration and ecosystem resilience.

Importance of AI-based soil health assessment

AI-based soil health assessment is becoming increasingly important in modern agriculture, as it provides accurate and real-time data on soil fertility and quality (4). Traditional soil testing techniques, including laboratory analysis and the whole hand sample approach, are typically utilized to determine soil quality. The entire hand sample technique requires physically testing soil by hand and appearance-farmers or agronomists will use their hands to assess texture, moisture and structure, usually by rubbing the soil between their fingers or moulding it into forms to determine characteristics. Although fast and inexpensive, it only gives approximate, subjective estimations versus accurate laboratory testing. On the other hand, an AI-based soil health assessment entails data mining from sensors, drones, satellites and other sources with the aid of empirical and mechanistic algorithms and other machines. This technology enables a more detailed analysis of soil organic matter, moisture levels and nutrient status compared to traditional methods (8). Thus, there are AI prospects of farmers or land managers deciding on which crop to cultivate, when to irrigate crops and if to apply fertilizers. This is also well suited for using AI to assess the possible problems or even anomalies of the soil that may hinder the yield of crops. The preparation gets easier early enough and failure is averted, boosting crop production and the practices in use in agriculture. Additionally, AI supports sustainable land management by providing accurate assessments of soil and land conditions. The Applications of Artificial intelligence in soil health assessment are shown in Fig. 2. It illustrates various applications of Artificial Intelligence in soil health assessment, including nutrient prediction, soil texture classification and disease detection. These applications highlight the potential of AI to enhance precision and efficiency in sustainable agriculture. AI-based evaluations enable land managers to assess the long-term

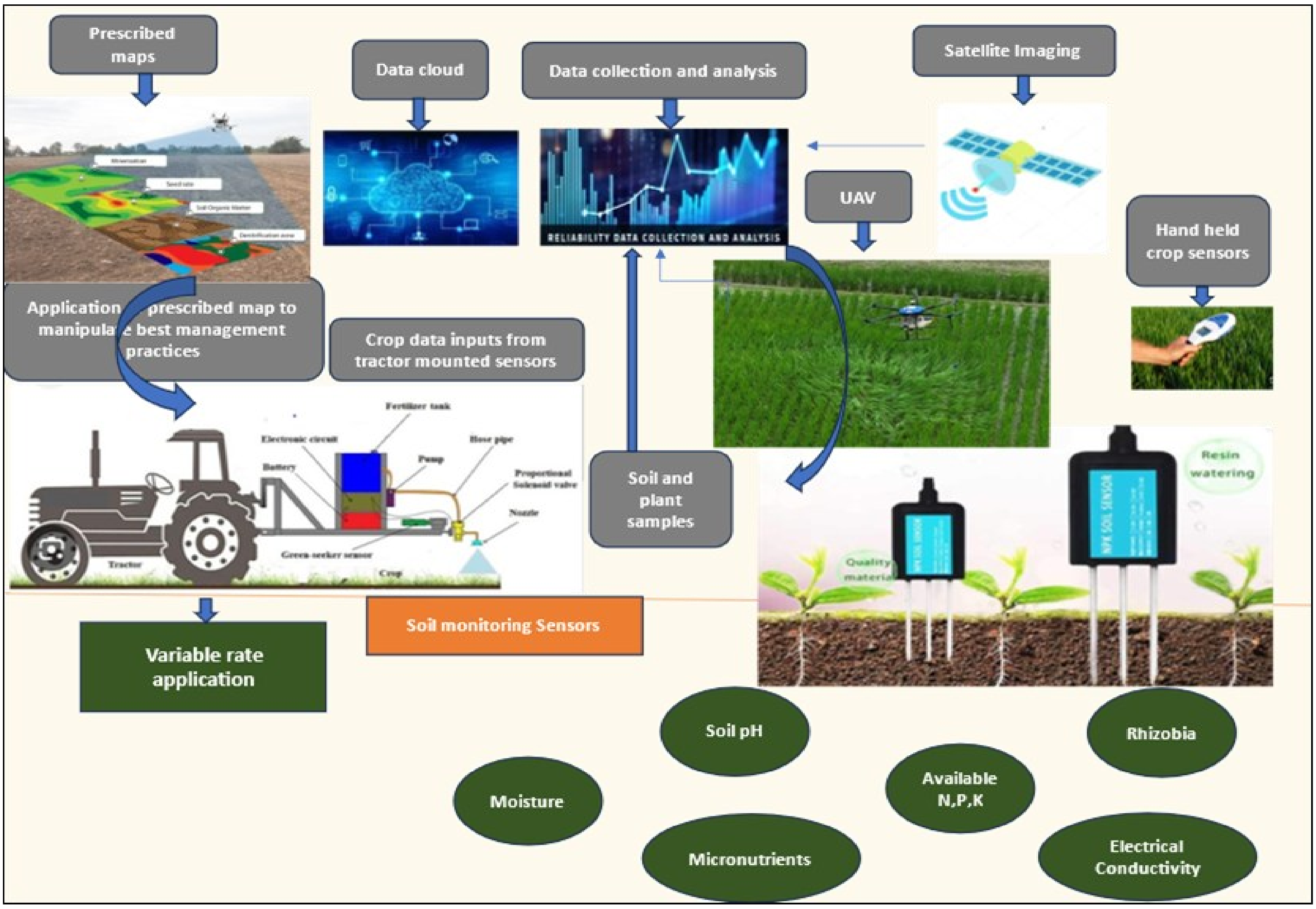

Fig. 1. Diagrammatic representation of the overview of soil health assessment.

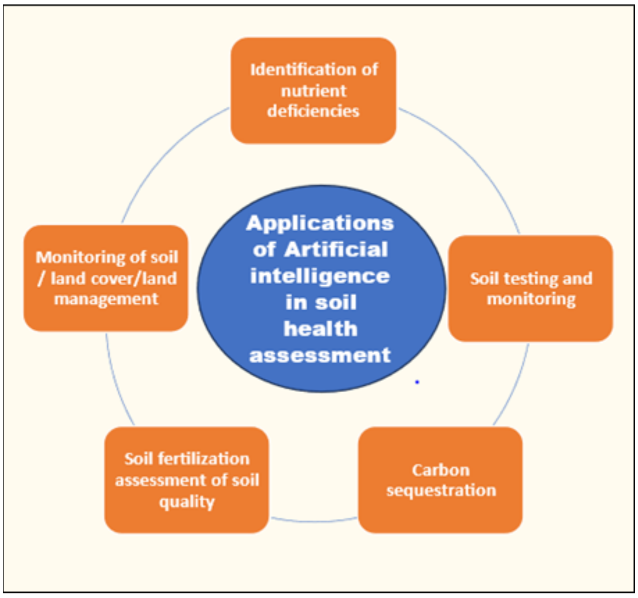

Fig. 2. Applications of artificial intelligence in soil health assessment.

impact of their practice on soil quality by providing insights into soil fertility and health (9). This technological advancement empowers land managers and farmers to make data-driven decisions, enabling them to evaluate the long-term impacts of agricultural practices on soil quality. By leveraging AI, they can detect early signs of degradation, optimize input use and support sustainable land management strategies, making AI a critical tool for enhancing both productivity and environmental stewardship.

Role of Artificial Intelligence in agriculture

Accurate weather forecasting is increasingly vital in today's rapidly changing world, especially as agriculture must adapt to unpredictable climate conditions. Agriculture businesses cannot afford to ignore the role of weather forecasts, particularly in areas related to planting, irrigation water issuing and even harvest time. However, conventional agricultural practices may no longer be sufficient to address the increasing challenges posed by climate volatility and the pressure to produce more food on limited land. These methods often lack the adaptability and data-driven precision needed to respond effectively to unpredictable weather patterns, soil degradation and resource scarcity issues that are intensified by growing population demands (10). AI systems can forecast weather patterns with greater accuracy, monitor soil and crop conditions through sensors and satellite imagery and optimize Irrigation, fertilization and planting schedules ultimately improving productivity, reducing waste and making farming more resilient to climate-related stresses (4). The next revolution in agriculture is already in sight as AI solves a few problems that this sector has even today: plant recognition, plant disease identification and precision agriculture. AI can analyze vast data and offer precise predictions because of machine learning, deep learning, image processing, artificial neuron networks and many other technologies (11). The first one is precision farming, which is the main advantage of using artificial intelligence in the agricultural industry. AI technologies are integrated for precise farming based on climate, growing and soil conditions data.

For AI applications in soil management to be truly sustainable, they must first demonstrate economic profitability. Sustainability in this context extends beyond environmental impact, it also encompasses the financial viability necessary to ensure long-term adoption and scalability. From an investor's perspective, profitability is the primary indicator of value, influencing both short-term funding decisions and long-term strategic commitment. As highlighted in "The Analysis of Investment into Industries Based on Portfolio Managers," portfolio managers prioritize sectors that offer a strong return on investment, guided by risk-adjusted performance indicators. Similarly, "The Dynamic Effect of Micro-Structural Shocks on Private Investment Behavior" reveals that private investors are highly sensitive to structural shifts in market dynamics, favoring industries where innovation such as AI-driven solutions, leads to measurable productivity gains and cost efficiencies. Therefore, AI in soil management must improve agronomic outcomes and demonstrate financial returns to attract and retain investment. Establishing this profitability is a prerequisite for sustainable development and wider adoption within agricultural systems. AI-driven data analysis enhances pest control, optimizes fertilizer application and improves irrigation planning, ultimately increasing crop yields while minimizing environmental impact (12). The breakthrough lies in integrating AI and IoT for real-time soil monitoring, enabling data-driven farming that can boost crop yields by up to 25 %, potentially saving billions in global agricultural losses. Farmers, agri-tech firms and policymakers will directly benefit through enhanced productivity and resource efficiency. AI-driven agriculture fosters job creation by integrating expertise from computer science, agronomy, plant science and related fields, promoting social mobility and economic development (13).This work enables AI-IoT-driven soil monitoring with up to 90 % accuracy, increasing yield by 20-25 % and reducing input costs by 15 %, translating to ~$200B in potential global agri-tech value. Beneficiaries include precision farming platforms, sensor manufacturers and large-scale producers.

Traditional methods vs. AI-based soil health assessment

Overview of conventional soil testing techniques

Precise and reliable soil testing techniques are required to make well-informed decisions about crop selection, fertilizer management and general soil health (14). Traditional soil testing methods include soil sampling, which involves collecting samples from various field parts for laboratory analysis. Physical analysis entails the structure, which is how the parts are arranged, the soil structure, the smallest division of itself and the compaction, which is the health state of the soil. The physical tests are prioritized to determine the nutrient status of the soil and its soil pH and other chemical properties. Biological analysis examines soil bacterial, fungal and microbial activity to assess their role in nutrient cycling and soil fertility (15). To overcome these limitations of these indices, some other indices like enzymes, microbial biomass and soil respiration are well illustrative of the soil and nutrient status as an integrated system. Recent trends in soil management include biochar applications for N_2O emission reduction through enhanced denitrifier activity (16) and silica nanoparticles improving seed germination efficiency and input economics, offering sustainable, cost-effective alternatives to conventional fertilizers. Soil management trends today revolve around using biochar as a soil amendment for enhanced water holding and structure. As shown in "Changes in Soil Water Retention Following Biochar Amendment," biochar is very efficient at raising the soil's moisture-holding capacity, which is critical in drought resilience. However, as discussed in "Cost Breakdown Indicates That Biochar Production from Microalgae in Central Europe Requires Innovative Cultivation Procedures," cost feasibility remains problematic, necessitating the creation of low-cost and scalable production technologies for optimal use of biochar in sustainable soil management. (17). Accurate and reliable soil testing methods are essential for making informed decisions in agricultural systems. These methods provide valuable information about soil health, nutrient levels and microbial activity, which are commonly used Conventional soil testing techniques shown in Table 1. The importance of precise physical, chemical and biological analysis is not emphasized in today's quickly evolving world. The data from these analyses is crucial for managing soil health, maximizing crop yields and guaranteeing sustainable farming methods (18).

Challenges and limitations

Evaluation of the soil is an important decision tool in agricultural management since it gives details concerning the fertility and quality of the soil. Historically, common qualitative ways to evaluate the state of health of the soils have included resorting to chemical analysis through wet chemistry carried out in the laboratory or spectroscopy (19). Despite their effectiveness, conventional soil assessment methods have several limitations. First of all, standard approaches can be quite time- and labour-consuming. The time required for traditional soil testing often delays crucial farming decisions (20). Furthermore, traditional methods can be costly (21). Many smallholder farmers may not afford to purchase tools and reagents to enable them to carry out tests on the soil as they used to do to check on the health of their soil. The second disadvantage is the low throughput, a drawback in learning with the implementation of traditional procedures. Therefore, using a conventional approach to study this area and a limited number of samples of soil, may prove quite challenging or even impossible to gather an overall picture of the whole agricultural field (22). Despite the limitations of traditional methods, AI presents a promising solution for evaluating soil health by offering faster, more accurate and scalable assessments. Through machine learning models and remote sensing technologies, AI can identify nutrient deficiencies, detect soil degradation and recommend corrective actions addressing many of the challenges faced by conventional approaches.AI incorporates assessment of soil health using a data analysis process along with the application of artificial intelligence to a large pool of data comprising data on soil (19). Conventional soil health methods, such as manual sampling and lab-based analysis, provide highly accurate, site-specific data on physical and chemical properties like pH, nutrient levels and organic matter. These techniques are backed by decades of research and standardized protocols, making them reliable and well-understood, but it is labor-intensive, time-consuming and often too costly for large-scale or frequent monitoring. In contrast, AI-driven techniques leverage remote sensing, machine learning and big data to offer scalable, real-time insights across vast areas, enabling predictive modeling and early problem detection. These systems can analyze patterns not easily detected by human observation, such as subtle changes in soil moisture or crop stress. However, their accuracy heavily depends on data quality and quantity and they require substantial technical expertise to implement and maintain. Additionally, AI models can sometimes lack transparency, making it difficult to interpret results without domain knowledge. A hybrid approach using AI for large-scale monitoring and conventional methods for calibration and validation offers the most comprehensive solution for sustainable soil management (23).

Introduction to AI-based approaches

Artificial Intelligence (AI) transforms traditional agricultural practices by providing innovative solutions for monitoring and managing soil health. Unlike conventional methods, which rely heavily on manual sampling and lab analysis, often time-consuming, labour-intensive and limited in scale, AI-based approaches offer faster, more accurate and cost-

Table 1. Commonly used conventional soil testing techniques

Aspect	Techniques used	Source
Soil sampling	Essential step in soil testing	(9)
Physical analysis	Assessing soil texture, structure and compaction	(9)
Chemical analysis	Determining nutrient levels, pH and chemical properties	(9)
Biological analysis	Examining presence and activity of microorganisms	(47)
Integrated indicators	Soil enzymes, microbial biomass, soil respiration	(28)
Soil testing services	Available to farmers for soil analysis	(49)
Importance of methods	Essential for informed decision making in agriculture	(59)

effective assessments. Employing machine learning, computer vision and remote sensing technologies, AI can process enormous amounts of data from satellite images, drone surveys and soil sensors. These systems can identify patterns and anomalies in soil conditions that cannot be seen by the naked eye, including moisture levels, nutrient deficiencies, pH imbalances and early signs of degradation. AI models can also forecast future soil health trends using weather forecasts, land use patterns and crop cycles, allowing for proactive decision-making. By incorporating AI into soil health assessment, farmers and agricultural professionals obtain real-time, data-driven insights to help their work become more sustainable, maximize input efficiency and ultimately boost productivity, particularly under climate volatility and increasing food pressures.

Advantages of AI-based soil health assessment

AI-powered soil health assessment provides several benefits that can significantly improve the accuracy and efficiency of this critical task. AI can recognize patterns and correlations within the data that are not readily apparent to humans (24). AI models can identify soil health trends by analyzing historical data alongside real-time inputs from IoT devices and sensors and generate actionable insights that support smarter decision-making for farmers and agronomists (2). Methods with AI have a set of specific benefits over conventional soil quality testing methods. The major benefits are efficiency and speed. Artificial intelligence systems are capable of processing vast amounts of data gathered by sensors, satellites, or drones much faster than laboratory testing. This enables farmers to make soil care and crop planting decisions faster. High Accuracy: Machine learning algorithms trained on diverse datasets can detect subtle differences in soil properties that would go undetected by manual testing. AI can test complex interactions between many variables, such as soil texture, nutrient and water, to give extremely accurate assessments. Real-Time Monitoring, with the assistance of IoT-based soil sensors and remote sensing technologies, AI enables continuous soil health monitoring. This offers real-time information on moisture, temperature and salinity, enabling timely interventions. Predictive Capabilities AI not only examines present conditions it can also examine future trends as well. By superimposing historical statistics, weather maps and cultivation patterns, AI can predict potential problems like nutrient deficiency, erosion vulnerability, or crop stress and enable farmers to implement preventive measures before they happen. Scalability and Cost-Effectiveness After deployment, AI-based solutions can scan vast fields of crops at a relatively lower cost than frequent on-field sampling. Such scalability is especially advantageous for large farms and areas with poor laboratory access. Decision Support AI platforms are likely to come with simple-to-use dashboards along with recommendations that help farmers and policymakers make informed, data-driven decisions on fertilization, Irrigation, crop rotation and soil conservation practices.

Components of AI-based soil health assessment

Sensor technologies

AI has a pivotal role in contemporary soil health evaluation by interpreting data gathered from a range of advanced sensor technologies. The sensors electrical conductivity sensors, moisture sensors, pH sensors and nutrient sensors, capture real-time measurements of soil characteristics. AI algorithms convert this data into patterns, trends and actionable information on sustainable land use. Through integrating AI and sensor technologies, evaluation becomes more precise, efficient and scalable. Soil health is essential in agriculture because it directly affects crop productivity, nutrient availability and overall ecosystem sustainability (11). Sensor data refer to the soil's measurable physical and chemical parameters, as illustrated by the quantity and diversity of water present in the soil, the soil temperature, pH, nutrients and organic matter. The AI process for soil health assessment entails using various sensors ready to measure a specific parameter. Physical sensors measure parameters such as soil temperature and moisture. Soil moisture sensors measure volumetric water content, which can be used in irrigation scheduling and temperature sensors measure soil heat content that influences microbial activity and plant growth. Temperature sensors help monitor the soil temperature, essential for understanding microbial activity and nutrient uptake (25). Chemical sensors measure parameters such as soil pH and nutrient content. pH sensors are utilized to assess the acidity or alkalinity of soil, a key factor in evaluating nutrient availability and identifying the ideal pH levels for supporting plant growth (26). Nutrient sensors, such as ion-selective electrodes and optical sensors, are employed to monitor the concentrations of essential nutrients in the soil. They offer critical insights into nutrient imbalances, helping farmers optimize fertilizer use.

Additionally, specialized sensors for measuring soil organic matter, including infrared spectroscopy and carbon-nitrogen sensors, leverage advanced technology to estimate organic matter levels by analyzing the reflectance or absorption of specific light wavelengths (27). pH sensors measure soil alkalinity or acidity, which influences the availability of nutrients. In contrast, nutrient sensors measure the concentration of the main elements such as nitrogen, phosphorus and potassium. Biological sensors are a recent technology that analyze microbial activity or detects biological indicators in the soil, providing information on the soil's biological health and fertility. Biological sensors are designed to identify and measure the presence and activity of microorganisms and other soil organisms. Examples of biological sensors include DNA-based microbial sensors and enzyme activity detectors (27). Moisture sensors provide essential information about the soil's water content, helping determine when and how much to irrigate. They work by measuring soil conductivity or estimating the potential water availability in the soil (28). Integrating advanced sensor technologies and artificial intelligence offers a groundbreaking approach to assessing soil health in modern agriculture. Furthermore, combining chemical sensor arrays with chemometric data analysis enables the simultaneous evaluation of multiple soil parameters. This innovation broadens the scope of sensory applications, extending beyond soil classification and quality assessment to include quantitative analysis and comprehensive evaluations of human impacts on soil conditions (29).

Remote sensing

Remote sensing technology and artificial intelligence have revolutionized soil health assessment in agriculture. Their combined application has significantly advanced soil health assessment, improving how soil conditions are monitored and managed (30). Soil plays a crucial role in agricultural systems by supplying essential nutrients and fostering crop growth. However, assessing soil health has traditionally been a time-consuming and labour-intensive (31). In order to make measurements based on sensors more efficient, modern techniques, particularly artificial intelligence and remote sensing, have significantly improved the accuracy and efficiency of soil health diagnosis. Remote sensing uses satellite images or aerial photographs to gather information about the Earth's surface, while AI uses one or many algorithms to analyze or process the data collected effectively (32). Combining RS and AI benefits researchers and farmers by helping them understand the state of soil without conducting physical sample collection or time-consuming field studies (4). AI-driven soil health assessment tools provide real-time, high-resolution data for better decision-making. For example, suppose the data has been gathered on previous applications and different forms of weather or climate. In that case, the developed AI algorithms can predict the likelihood of soil erosion or nutrient leaching (24). This data empowers farmers to act early and adopt good farming practices to minimize risks. That way, farmers become empowered and can make better choices and adopt better practices that are organized for sustainability (33). Schematic framework of remote sensing techniques, data analysis and soil measurement applications, shown in Fig. 3. The integration of remote sensing and AI technologies in the assessment of agricultural systems has yielded significant advancements in understanding crop status, improving soil quality and optimizing farming practices. Overall, the integration of remote sensing and AI technologies in the assessment of agricultural systems has yielded significant advancements in understanding crop status, improving soil quality and optimizing farming practices (34).

Internet of things

Traditionally, soil health assessment has been a labour-intensive and time-consuming process (35). Advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) have revolutionized soil health assessment methods. By continuously monitoring key variables, IoT devices offer farmers valuable insights and recommendations to optimize soil health and boost crop yield (36). Integrating IoT devices and AI has made soil health assessment more efficient and accurate. Additionally, access to both historical and real-time data has greatly expanded the potential of using Artificial intelligence in precision agriculture (11). The ICT monitoring system combines AI algorithms and IoT devices to handle the

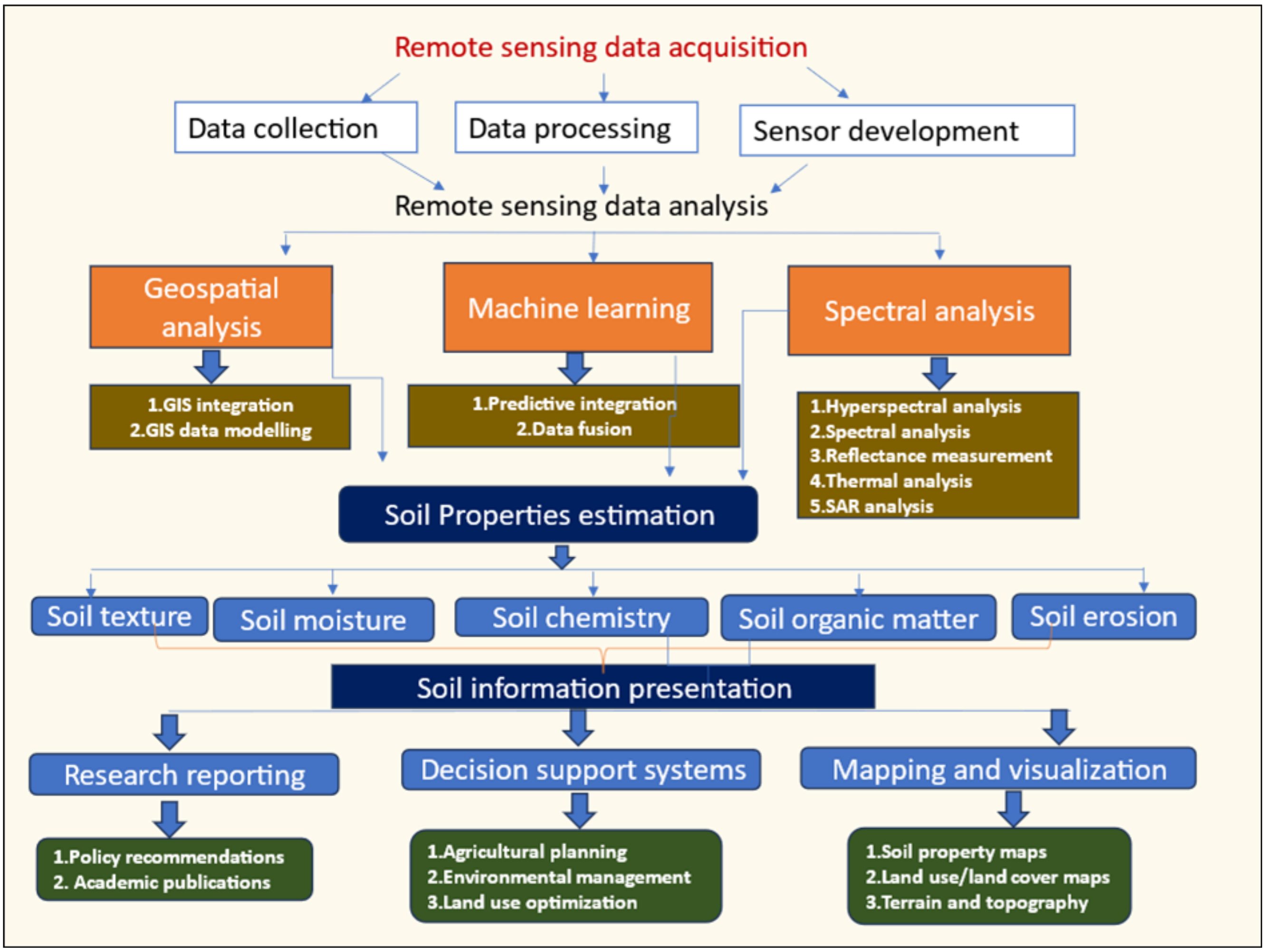

Fig. 3. Schematic framework of remote sensing techniques, data analysis and applications in soil measurements.

actual risk of soil and irrigation water contamination in real time. IoT sensors record real-time environmental data and AI uses this data to identify anomalies, estimate the contamination levels and offer actionable information for farm planning. Farmers can make data-driven decisions to prevent nutrient deficiencies, water pollution and crop diseases by leveraging IoT and AI. IoT systems utilize electrical conductivity (EC) sensors to monitor soil texture and salinity changes continuously. Additionally, soil insects and pests are detected using optoelectronic, acoustic, impedance sensors and nanostructured biosensors (35).

Data processing and analysis techniques

Machine Learning Algorithms (MLA)

In recent years, there has been growing interest in creating AI-based systems for soil health assessment. Machine learning algorithms (MLA) have become valuable tools in this field, allowing researchers to assess and predict soil health parameters (36) accurately. These algorithms utilize advanced data processing and analysis techniques to extract valuable insights from soil data, helping farmers and agricultural professionals make informed decisions regarding land management and crop production (37). The application of machine learning algorithms is shown in Fig. 4. This technique, used in machine learning for soil health assessment, is feature selection, which helps identify the most relevant soil parameters for accurate predictions. Data preprocessing is vital for preparing soil data for analysis. This process includes several steps: data cleaning, normalization and feature selection. A key technique in machine learning algorithms for soil health assessment is data preprocessing, vital for preparing soil data for analysis. This process includes several steps: data cleaning, normalization and feature selection. Data preprocessing, a crucial step in machine learning for soil health assessment, includes data cleaning to remove inconsistencies, errors and missing values and normalization, transformation and feature selection to prepare the data for accurate analysis and modelling. Normalization standardizes the data, bringing it onto a common scale to ensure that all variables contribute equally to the analysis. Feature selection helps identify the data's most relevant and informative features, which are then used to train the machine learning model (38).

Supervised learning algorithms rely on labeled training data, where input variables (such as soil characteristics) are linked to the corresponding output variables (soil health parameters) to learn the relationship between them. Once the algorithm has learned this mapping, it can use it to predict outcomes on new, unseen data (39). Commonly used supervised learning algorithms for soil health assessment include Bayesian estimation, random forest and support vector regression. Bayesian estimation is a probabilistic approach that updates predictions as new soil data becomes available, making it effective for dynamic soil health assessments (40). Random forest is an ensemble learning technique that builds a model for soil health assessment using multiple decision trees. It is great for assessing soil health because it can handle the complex relationships between different soil properties and environmental factors without overfitting. It's beneficial for analyzing large datasets with many variables, helping predict key soil quality indicators like nutrient levels, moisture and microbial activity (41). Support vector regression is a supervised learning algorithm that links input variables to the corresponding soil health parameters by identifying the optimal hyperplane that maximizes the margin between data points (42).

In contrast, unsupervised learning algorithms do not rely on labeled training data. They are designed to identify patterns and relationships within the data without prior knowledge or guidance. These algorithms are especially valuable in soil health assessment as they can reveal hidden trends and connections in the data. Common unsupervised learning algorithms for soil health evaluation include k-means clustering for grouping similar soil samples and principal component analysis (PCA) for reducing data dimensionality while preserving essential patterns (43). Deep Learning Models As soil condition estimation involves the

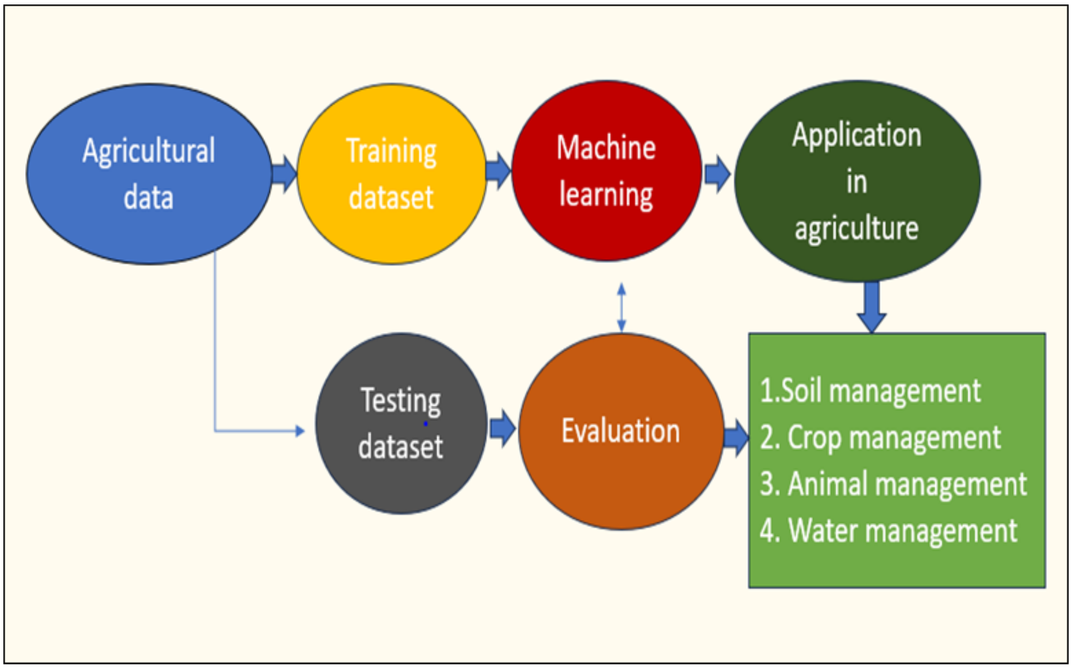

Fig. 4. Machine learning algorithm framework.

analysis of complex, high-dimensional and mostly non-linear information from multiple heterogeneous sources, deep learning models are a suitable solution. Deep models such as CNNs and RNNs are well-suited for pattern discovery and relationship detection in large data sets. Deep learning offers improved prediction accuracy by learning hierarchical representations of the soil data and facilitates improved decision-making through the aid of precision agriculture. In recent years, there has been an increasing interest in applying artificial intelligence techniques for soil health assessment in agriculture. Deep learning transforms soil health assessment by helping researchers and farmers make sense of vast data. Here are some key models making an impact: Convolutional Neural Networks (CNNs) analyze satellite and drone images to assess soil properties like moisture, organic matter and texture, making remote sensing more precise. Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTM) Networks track changes in soil conditions over time, helping monitor moisture levels, temperature shifts and seasonal variations. Autoencoders detect irregularities in soil health, such as contamination or nutrient imbalances, by recognizing patterns in large datasets and flagging anomalies. Generative Adversarial Networks (GANs) create synthetic soil data to fill in gaps, improving predictions in regions with limited historical records. Transformer Models, like BERT and Vision Transformers (ViTs), are being explored for analyzing soil health reports and classifying soil types based on images. By integrating these deep learning techniques, precision agriculture is becoming more efficient, enabling better soil fertility management, smarter irrigation strategies and early detection of soil degradation. Deep learning (DL) models are increasingly being used in AI-driven soil health assessment due to their ability to analyze large datasets and extract meaningful patterns (44). A key challenge in soil health assessment is the precise measurement and prediction of ground and surface water availability, which is essential for guiding agricultural practices and optimizing crop production (45). Traditionally, predicting hydrological response features like soil moisture was done using physics-based and empirical hydrological models, which demanded substantial computational time and expertise (46) Deep learning models integrate multi-source data, including remote sensing imagery, weather patterns, irrigation records and historical yields, to enhance soil health assessment accuracy (47). By integrating various data sources, these models can capture the complex spatiotemporal correlations in soil moisture variations, resulting in more accurate predictions and a deeper understanding of soil health in agriculture.

Additionally, deep learning models can address the limitations of traditional physics-based and empirical hydrological models, which often require extensive computational time and expertise. With the ability to learn complex patterns and relationships from large datasets, deep learning models are well-suited for analyzing and interpreting diverse agricultural data (48). By accurately forecasting soil moisture, deep learning aids in precision irrigation, optimizing resource use and enhancing crop yields.

Parameters and indicators for soil health assessment

Soil fertility evaluation

Soil fertility assessment is crucial for evaluating soil health, as it determines the soil's ability to support plant growth (49).Soil fertility can be assessed using conventional methods, such as chemical soil analysis and advanced techniques, including molecular biology and remote sensing (50). These include conventional methods, such as chemical analysis of soil samples and advanced techniques like molecular biology and remote sensing. Chemical analysis of soil samples remains one of the most commonly used methods for evaluating soil fertility levels, as it provides precise information on nutrient availability and composition Table 2 (51). It includes measuring the levels of key nutrients like nitrogen, phosphorus and potassium, along with other important factors such as pH and organic matter content. Molecular biology techniques, like DNA sequencing and gene expression analysis, help us better understand soil fertility by studying the microbes that support nutrient cycling. For example, metagenomic sequencing identifies beneficial bacteria that boost nitrogen levels, making soil more productive. RNA sequencing shows how microbes react to different soil conditions, helping farmers fine-tune fertilization methods. By analyzing microbial diversity, these techniques help detect imbalances, assess soil health and develop strategies to improve nutrient availability for healthier crops (22). On the other hand, remote sensing uses satellite imagery and other technologies to collect data on soil fertility through soil reflectance and vegetation indices. These advanced techniques hold great potential to complement and improve traditional methods of soil fertility assessment (48). In conclusion, assessing soil fertility for soil health evaluation requires a blend of traditional and advanced methods (52).

Soil moisture content and irrigation management

Soil moisture content is a critical factor influencing plant growth, nutrient uptake and microbial activity. Effective irrigation management plays a vital role in maintaining optimal moisture levels by ensuring water is applied when and where it's needed most. By monitoring soil moisture data, farmers can avoid both under- and over-irrigation, which helps conserve water, reduce leaching of nutrients and promote healthier crop development. Integrating this data with AI-driven irrigation systems further enhances efficiency and sustainability in agricultural practices.

Table 2. Soil fertility range

Element	General range (%)	Critical level (%)
N	2.0 - 4.0	<2
P	0.2 - 0.5	<0.1
K	1.5 - 3.0	<1.0
Ca	0.5 - 3.0	<0.1
Mg	0.2 - 0.5	<0.2
S	0.2 - 0.5	<0.15
Fe	50 - 150 ppm	<5 ppm
Cu	05 - 20 ppm	<4 ppm
Zn	20 - 100 ppm	<15 ppm
Mn	20 - 500 ppm	<20 ppm
B	02 - 100 ppm	<20 ppm
Mo	01 - 2.0 ppm	<0.1 ppm
Cl	0.2 - 2.0 ppm	-

Soil condition is a critical factor influencing crop yield, productivity and stability. Soil condition assessment involves testing of moisture content and efficient policies on the use of water in Irrigation (53). Different parameters and indicators require use to assess the soil's condition with regards to moisture and approaches towards Irrigation. Such factors provide important data that encompasses the ability of a soil to retain water; its capacity to retain nutrients; and the soil's fertility and state of health (54). They include: Crop yield per unit area and time; Crop biomass per unit area and time; Legume: non-legume ratio; Water use efficiency over time; Nutrient use efficiency; and; Quality of produce per unit area, such as concentration of toxic elements in food crops. In addition, the following parameters are important to consider: The three key factors of soil health are soil texture, which is the proportion of sand, silt and clay that affects water retention and drainage. Soil Aggregation -The formation of stable microstructures that improve water infiltration and retention. Soil Moisture -The amount of water present in the soil. (55)Soil Depth to a Root-Restricting Layer: This parameter indicates the extent a layer in the soil restrains root penetration thus affecting plants' access to water and nutrients. Available Water-Holding Capacity: This parameter measures how much water within the soil is available to plants for growth and development after retention by the soil. Bulk Density/ Penetration Resistance: The following are indices that assess the compaction of the soil about water intake and root penetration (56). Hydraulic Conductivity: This parameter measures how well the soil accepts water and how drainable it is because of the ability to either transmit or hold water well (57). Aggregate Stability: This indicator evaluates the soil aggregates' ability to withstand breakdown, which is crucial for preventing erosion and preserving soil structure to ensure effective water infiltration (58). Organic Matter: The presence of organic matter in the soil enhances its structure, boosts water retention, improves nutrient storage and supports microbial activity (26). Nutrient Availability/Retention Capacity: This parameter evaluates the soil's ability to provide and retain key nutrients necessary for plant growth, which is vital for maximizing crop productivity (53) pH: Soil pH affects nutrient availability and microbial activity, as various plants have specific pH needs. Irrigation management is essential in maintaining the right soil moisture content, a critical factor in soil health assessment. Effective irrigation management ensures that plants get the required amount of water without leading to waterlogging or dehydration.

Nutrient cycling and microbial activity

Soil status evaluation is very important for estimating production systems' sustainability and yield capacity. Soil quality can be assessed using both qualitative and quantitative methods, considering physical, chemical and biological properties. Physical soil properties such as soil texture, structure, moisture content, porosity and bulk density are key indicators of soil health. These indicators influence water retention, root penetration and nutrient availability (58). Key chemical indicators of soil fertility include total carbon and nitrogen content, mineral nutrients, organic matter and cation exchange capacity. However, these indicators generally take more time than biological indicators such as soil health based on the presence, abundance and activity of living organisms within the soil. Unlike chemical indicators, which measure nutrient levels and pH, biological indicators reflect the biological functioning and fertility of the soil ecosystem. These include microbial biomass, soil respiration rates, enzyme activities and the diversity of soil fauna such as earthworms and nematodes. Because they respond sensitively to environmental changes, biological indicators provide valuable insights into the long-term sustainability of soil management practices. Both sets of indicators give important information on the intensity of microbial turnover and the nutrient cycling, which are critical for sustaining the health of soils. Furthermore, the measures in this subcategory include the ability of soil macro and meso fauna like; worms and insects (52). A comprehensive soil quality assessment requires, multiple indicators rather than relying on a single parameter.

Predictive models for soil health

The forecast and models for monitoring and understanding the changes in soil health in agriculture in the contemporary world are critical due to the fast-evolving nature of the environment and land usage. Soil condition influences food production, crop yield, quality and overall ecosystem stability: Improving soil fertility is essential for enhancing food quality, environmental sustainability and overall human and animal well-being (53). One approach to assessing and predicting soil health in agricultural systems is using integrative indicators (58). Key health indicators include nutrient levels, organic matter content, microbial activity and physical properties such as aggregate stability. Aanthropogenic activities, such as deforestation and intensive farming, contribute to soil degradation, including desertification, biodiversity loss and nutrient depletion. Activities such as afforestation, using organic matter to rehabilitate degraded lands and replanting programs of trees, soil fauna and microorganisms are fundamental in rejuvenating the soils and enhancing their capability to handle vicious forces in the environment (59). Predicting and evaluating the health of the soil in agriculture is quite a daunting task because of the nature of the soil. For this purpose, several indicators and indices have been formulated, but they are distinguishable from each other by sensitivity to changes in soil conditions. For instance, microbial biomass C and N, diversity, enzymes and respiration rates will likely change rapidly, while other soil properties may take longer to respond to change. Using multiple indicators provides a more comprehensive soil health assessment, reducing reliance on a single parameter (60).

Integration with precision agriculture practices

The integration of AI with precision agriculture enables farmers and researchers to collect crucial data on soil properties, pest management, Irrigation and post-harvest crop handling (36). AI-powered soil testing provides real-time data on soil moisture, nutrient content and pH levels, enabling precise soil management. Additionally, AI can reduce the usage of chemicals in farming by providing the right advice on the number of fertilizers and pesticides to use (13). Some of the emergent themes include soil factors, pest management, water and crop handling, farmers' knowledge and access to innovation and technology (2). AI addresses these challenges by providing accurate, timely and predictive data analysis as for informed decision-making. AI algorithms can analyse large, complex datasets, identifying patterns and relationships that may not be apparent to human observers. These ideas can be extended to improve soil management and resource utilization as well as raise production levels in agriculture (61). AI enhances disease management by detecting early symptoms of plant diseases and recommending appropriate treatments. Also, it can be used to monitor and predict the right time to harvest, preserve storage conditions and prevent damage. Integrating AI with prone-specific agriculture techniques that will be used for status determination of the soil is a potential solution to the challenges in agriculture. By integrating AI into precision agriculture, farmers can optimize resource use, improve yields and promote sustainable farming practices (24).

Economic benefits and cost-effectiveness

In modern-day agriculture, many problems exist like soil types and their properties, pest control, Irrigation, storage after harvesting, farmers ignorance and even embracing new technology (24). Artificial intelligence has emerged as a useful solution to deal with these issues. AI-based soil health assessment is one of the most cost-effective innovations in modern agriculture, offering multiple economic benefits. It can be stated that one of the key economic benefits of the AI-based approach to soil health assessment increased profitability. AI-driven recommendations help farmers adjust their practices, leading to increased profitability (62). In particular, the AI models assist in avoiding the gross over-application of fertilizers by offering recommendations based on ground conditions at that time. Targeted fertilization reduces unnecessary costs while promoting eco-friendly farming practices. Moreover, an assessment of soil health through AI systems can also anticipate uncertainties like diseases based on plants, livestock and others allowing the farmers to undertake prophylactics thereby reducing crop vulnerability It is also important to note that when the soil quality is assessed in different ways, it can also be used predicting how the soil will respond to vegetation (24).

Moreover, soil conditions can be monitored by AI to detect any problems, such as nutrient deficiency or pH imbalance early on before they occur. Addressing such concerns at this early stage can help farmers stop yield loss, thereby improving their productivity. The economic benefits of AI-based soil health assessment could lead to inclusive growth in developing economies. Providing access to AI-based agricultural technologies and data-sharing platforms in developing economies could help farmers elude market asymmetries and information asymmetries. By doing so, better market opportunities, better access to information and greater profits for small-scale farmers can be achieved (62). New technologies based on Artificial Intelligence have helped farmers access real-time data, enabling them to plan their farming through accurate weather forecasts and consequently reducing the risk of crop failure due to unpredictable weather conditions (4).

Policy implications and agricultural decision-making

AI-based tools have the potential to revolutionize agricultural decision-making and carry major policy implications. Precision agriculture and resource optimization: AI can analyze the vast amount of soil data (Nutrient levels, moisture content, spatial variability) to provide farmers with precise recommendations for fertilization, Irrigation and other inputs leading to efficient resource use and reduced waste. While favourable weather conditions are essential for successful crop production, they must be complemented by healthy soil to achieve optimal yields. Soil health particularly its moisture retention and nutrient availability directly influences how effectively crops can benefit from rainfall, temperature and sunlight. In other words, good weather creates the opportunity for growth, but the condition of the soil determines how well that opportunity is realized. Therefore, understanding the interplay between weather patterns and soil health is crucial for informed agricultural decision-making.

Soil degradation is a major challenge for farmers, often caused by deforestation, over-cultivation and improper land management. AI-based soil health assessment tools enable real-time soil quality monitoring, supporting targeted interventions and policies promoting sustainable land management (13). Beyond soil health, AI offers insights into water management, crop rotation, pest control and nutrient optimization (2). In short, it will help farmers better anticipate and adapt to changing climatic conditions, reducing the risks associated with unpredictable weather patterns (36). Thus, AI would assist in situation analysis, with pests and diseases being held responsible (24). This image recognition technology-based AI can monitor potential soil defects and nutrient deficiencies, allowing farmers to act promptly before further damages are inflicted on the crops (63). Integrating the AI-soil health assessment into agricultural decision-making will enable policymakers to promote sustainable land management practices, enhance resource efficiency and increase crop productivity (36).

Planetary Intelligence: The future of regenerative agro-technological convergence:

Industrial applications are poised to evolve beyond site-specific prescriptions toward *autonomous agro-ecological stewardship*. In this emerging paradigm, decentralized AI agents could continuously monitor, predict and optimize soil conditions across entire landscapes, interfacing with autonomous machinery and bio-sensor networks. This level of integration may catalyse a shift from reactive soil treatment to proactive soil design, where soil is curated, not merely managed. More profoundly, this AI-soil symbiosis may redefine what we mean by "health" in ecological terms. Future systems may encode ethical and ecological parameters into their assessments, enabling a shift from yield-centric models to *ecological intelligence systems* that optimize for biodiversity, carbon sequestration and long-term fertility factors traditionally marginalized in industrial frameworks.

Crucially, the role of AI in soil health opens avenues for an *inclusive knowledge regime*, wherein localized and indigenous soil knowledge can be integrated, codified and scaled through machine learning frameworks, thus democratizing agronomic innovation across the globe. This fusion of AI and pedology is not an endpoint but a point of origin: an inflection in the agricultural-technological continuum. The challenge ahead lies not in perfecting models but in ensuring that they operate as instruments of planetary intelligence-scalable, interpretable and fundamentally regenerative

Open issues in AI-based soil health assessment

Data quality and quantity

- Data scarcity and heterogeneity: Acquiring high-quality, representative soil data across diverse regions and depths is challenging due to variations in soil composition, climate and land use.
- Data labelling: Accurate labelling of soil health parameters (nutrient levels, microbial activity) for AI training is labour-intensive and requires expertise from soil scientists.
- Sensor limitations: Existing sensors may struggle to measure critical soil properties such as microbial activity and organic matter quality and may be affected by environmental conditions like temperature fluctuations and moisture levels.

Model development and validation

- Model complexity**:** Developing AI models capable of accurately predicting soil health requires accounting for diverse factors such as soil type, climate variations and land-use patterns, which influence nutrient availability and microbial activity.
- Model interpretability: Ensuring transparency in AI predictions is essential for building trust, reducing bias in soil assessments and enabling farmers to make informed decisions.
- Model validation: AI models must be tested against independent datasets and real-world soil conditions to evaluate accuracy, generalizability and long-term reliability.

Integration with agricultural practices

- Decision-making: For AI-based soil health assessments to be widely adopted, they must be supported by user-friendly tools and clear guidelines from policymakers and agricultural organizations.
- Scalability: Large-scale implementation of AI-based solutions faces challenges in data management, computational power and infrastructure, particularly in regions with limited connectivity and sensor access.
- Economic feasibility: Demonstrating the cost-effectiveness of AI-based soil health assessment is essential to drive adoption among farmers and agricultural stakeholders, requiring support from researchers and policymakers.

Ethical and societal considerations

- Artificial Intelligence (AI) continues to prove itself as a powerful tool for addressing multifactorial techno-economic problems, especially where data, timing and decision-making intersect. Recent research highlights this impact: In "Artificial intelligence-based predictive maintenance, time-sensitive networking and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things", AI plays a central role in enhancing operational efficiency, reducing costs and improving real-time decision-making across industrial networks. Meanwhile, "The impact of corporate reputation and social media engagement on the sustainability of SMEs: Perceptions of top managers and the owners “shows how AI and digital analytics help small and medium-sized enterprises (SMEs) navigate market dynamics, maintain sustainability and adapt reputational strategies using real-time social insights.
- Data privacy: Safeguarding farmers' data and ensuring ethical usage is critical to prevent misuse and unauthorized access by third parties.
- Equity: AI-based tools should be accessible and affordable to all farmers, particularly smallholder farmers, regardless of their technical expertise or financial resources.
- Environmental impact: The sustainability of AI-based agricultural technologies must be evaluated, considering factors such as energy consumption and cloud computing, sensor production and long-term resource use.
- Overcoming these challenges requires collaboration among researchers, policymakers, farmers and technology providers to ensure the development of scalable, sustainable and widely accessible AI-based solutions for soil health assessment.

The research hypotheses are primarily confirmed, indicating that AI applications in soil management are not only feasible However, shows strong potential for industrial adoption, with promising signs of long-term economic sustainability.

Conclusion

The review explores the integration of artificial intelligence (AI) in soil health assessment, examining its applications in monitoring and management. It highlights the promise of AI-driven technologies like machine learning, remote sensing and data analytics in transforming the evaluation and management of soil health. AI-based soil health monitoring is crucial in advancing agricultural sustainability, environmental conservation and food security. It underscores the necessity of accurate and timely soil health assessments, pointing out the advantages of AI in optimizing farming practices, enhancing sustainability and reducing environmental risks. Additionally, it addresses the challenges and limitations of traditional soil testing methods and the transformative potential of AI-based soil health assessment in modernizing agricultural practices. Assessing soil health is essential for sustainable agriculture and food security. This assessment faces challenges and limitations with traditional methods, which can be time-consuming and labour-intensive. However, AI emerges as a promising solution for evaluating soil health. This review examines key AI-based soil health assessment aspects, including data acquisition, processing techniques and evaluation parameters. This review examines key AI-based soil health assessment aspects, including data acquisition, processing techniques and evaluation parameters. It also explores how AI can be integrated with precision agriculture practices. Similarly, research like "Generative artificial intelligence of things systems, multisensory immersive extended reality technologies and algorithmic big data simulation and modelling tools in digital twin industrial metaverse" highlights the growing power of immersive tech and big data in forecasting performance and success in virtual industrial environments. The review also discusses ethical and environmental considerations, emphasizing data privacy, farmer livelihoods and the ecological impact of chemical inputs. The necessity for technological advancements in AI-based soil health assessment is highlighted, along with the potential benefits while considering ethical and ecological factors. Ultimately, AI-driven technologies have the potential to revolutionize agricultural sustainability, environmental conservation and global food security.

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Authors' contributions

GP contributed to the conception, literature survey, data collection and writing of the original draft. MD collected the data and curation and processing of the collected data were performed. PS validated the data collected and contributed to the literature survey. KR participated in the literature survey and checked the quality of the manuscript. KP participated in writing the original draft of the manuscript. PC helped in the study's conception and helped revise the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interest regarding the publication of this paper.

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AI Declaration : During the preparation of this work, the authors used Chat GPT by Open AI to enhance language clarity and readability. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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