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Artificial intelligence for sustainable soil systems: Advances in prediction, mapping and sustainable management of soil health and properties: A critical review

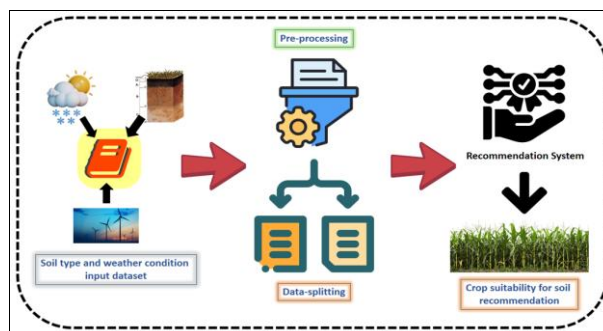
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Abstract

Soil is fundamental to food security, biodiversity and climate regulation, yet faces accelerating degradation from intensive agriculture, climate change and land scarcity. Artificial Intelligence (AI), encompassing Machine Learning (ML) and Deep Learning (DL), offers transformative capabilities for handling heterogeneous, high-dimensional soil data, enabling accurate prediction of properties (e.g., texture, organic carbon, moisture, nutrients), digital mapping, real-time monitoring via sensors/IoT, and precision management. This critical review synthesizes developments over the past decade, based on a systematic search across major databases (Google Scholar, Scopus, Web of Science, IEEE Xplore, ScienceDirect, MDPI, Nature). We evaluate dominant algorithms, Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), highlighting their ability to capture non-linear patterns while critiquing limitations in interpretability, data quality, regional bias and scalability for smallholder systems. AI consistently outperforms traditional methods in predictive accuracy (e.g., RF achieving 90-95% predictive accuracy for soil organic carbon across multiple studies), yet barriers persist: high costs, limited farmer training, infrastructure gaps in developing regions, and model opacity. Emerging solutions such as explainable AI, federated learning, digital twins, hybrid physics-informed models and edge computing promise greater accessibility and trustworthiness. We outline priorities for interdisciplinary collaboration to advance equitable, sustainable soil management aligned with global goals for food security and climate resilience.

Graphical Abstract



Keywords: Artificial intelligence, AI algorithms, soil health, soil properties, machine learning, precision agriculture

1. Introduction

Soil constitutes the foundational resource for terrestrial life, underpinning agricultural productivity, regulating water and nutrient cycles, sequestering carbon, supporting biodiversity and delivering essential ecosystem services. It is responsible for producing approximately 95%

of the world's food supply and hosts an estimated 25% of global biodiversity (FAO, 2020, 2022) ^[1, 2]. Despite its critical importance, soil faces unprecedented threats from intensive agricultural practices, deforestation, overgrazing, urbanization, pollution and accelerating climate change. Recent assessments highlight the scale of this crisis: human-induced land degradation affects vast areas, with up to 40% of the world's land already degraded, directly impacting more than 3 billion people through reduced ecosystem services, biodiversity loss and livelihoods (UNCCD, 2025) ^[3]. In agricultural contexts, more than 60% of human-induced degradation occurs on farmland, leading to diminished soil organic carbon, increased erosion, salinization, compaction and nutrient imbalances (FAO SOLAW, 2025) ^[4]. A pivotal 2025 FAO report (The State of Food and Agriculture) estimates that approximately 1.7 billion people worldwide live in regions where crop yields have declined by at least 10% due to human-driven land degradation. This includes 47 million children under five years of age experiencing stunting linked to malnutrition exacerbated by lower food production. Asian countries bear a disproportionate burden due to high population densities and accumulated degradation debt, while arid and semi-arid regions face compounded risks from drought and desertification. If current trends persist, projections suggest that up to 90% of global land could be degraded by 2050, with annual economic losses from degradation, desertification and drought reaching hundreds of billions of USD (UNESCO, 2024; UNCCD, 2025) ^[5, 3].

Compounding these environmental pressures is demographic growth: the global population, currently around 8.1 billion, is projected to reach approximately 9.6-9.8 billion by 2050 according to UN estimates (UN DESA, 2017) ^[6]. This trajectory demands a substantial increase in food production, potentially 50-70% more calories, to meet rising demand while minimizing further land conversion. However, arable land availability is finite and shrinking due to degradation and competing uses (e.g., urban expansion, bioenergy) (Kopittke *et al.*, 2025; Shokri *et al.*, 2025) ^[7, 8]. Alarmingly, conventional soil management and assessment approaches largely dependent on sporadic field sampling, labour-intensive laboratory analyses (e.g., hydrometer-based texture determination and wet chemistry for nutrient estimation), and statistical interpolation techniques (e.g., kriging) which are becoming increasingly inadequate to address the complexity and spatial variability of modern agro-ecosystems. These methods are labor-intensive, time-consuming, expensive, spatially limited and poorly equipped to capture the high spatial-temporal heterogeneity of soil properties influenced by climate variability, management practices and micro-topography. Artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), and related computational techniques, offers a paradigm shift by enabling the processing of large, heterogeneous, multi-source datasets from proximal sensors, remote sensing (satellites, UAVs), IoT networks and hyper spectral imagery (Chen *et al.*, 2022) ^[9]. AI excels at uncovering non-linear relationships, handling missing or noisy data, and providing scalable predictions for soil properties such as texture, organic carbon content, moisture dynamics, nutrient status, pH, and erosion risk (Pandey *et al.* 2023; Chen *et al.*, 2022) ^[10, 9].

Recent studies evidenced that AI has broader applications in managing soil health. For example, AI achieved notable accuracy in predicting soil properties, including soil carbon assessment, nutrients and physical, chemical and biological characteristics. Its use in soil mapping and resource optimization supports its adoption in soil management (Abdelhak, 2024) ^[11].

The availability of high-resolution datasets enables the development of data-driven models that can capture both nonlinear and complex data, thereby improving the prediction of soil parameters from diverse datasets (Bernardini *et al.*, 2024) ^[12]. Models like Random Forest and Convolutional Neural Networks often achieve R^2 values exceeding 0.85-0.95 across various pedoclimates (Wadoux, 2025; Schweng *et al.*, 2026; Kikis & Antoniadis, 2026) ^[13, 14, 15]. Beyond prediction, AI facilitates real-time monitoring, anomaly detection, digital soil mapping, precision fertilizer application and decision support systems that promote resource-efficient, site-specific management. This critical review synthesizes key developments in AI applications to soil science over the past decade (2015-2026), drawing from a systematic literature search across major databases. It evaluates dominant algorithms, their methodological strengths and limitations, performance in real-world contexts, and barriers to adoption, particularly in resource-constrained smallholder systems prevalent in regions like South Asia. Emphasis is placed on emerging solutions such as explainable AI, federated learning, digital twins and hybrid physics-informed approaches. The objectives are to: (i) provide a holistic, critical overview of AI methodologies and applications; (ii) highlight evidence-based performance gains and persistent gaps; and (iii) outline research and policy priorities to accelerate equitable, sustainable integration of AI for soil health restoration and global food-climate resilience.

2. Methodology

This study adopted a systematic review methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency, reproducibility and rigor in the selection of relevant literature. A comprehensive search was conducted across major academic databases, including Google Scholar, Scopus, MDPI, Web of Science, IEEE Xplore, Nature, and ScienceDirect. The primary search string used was “AI” in combination with soil-related keywords such as “soil science,” “soil properties,” “soil health,” “soil moisture,” “soil contamination,” and “agriculture.” To further refine the search, additional combinations were employed using computational terms such as “machine learning (ML),” “deep learning (DL),” “random forest (RF),” “support vector machine (SVM),” “modelling,” and “neural networks.” The initial search yielded 2,981 records. These were filtered to include only peer-reviewed articles published in English within the last 10 years, resulting in 633 records. Following this, duplicate entries were identified and removed, and a preliminary screening based on titles and abstracts was conducted to exclude studies not directly related to soil science or agricultural applications of artificial intelligence. Full-text articles ($n = 633$) were then assessed for eligibility. During this stage, studies that were not directly relevant to soil systems (e.g., general artificial intelligence applications in unrelated domains such as finance, medical diagnostics, or generic machine learning theory) were excluded. Additionally, duplicate publications and studies lacking sufficient methodological clarity were removed. After applying these criteria, approximately 104 studies were retained for final inclusion. These selected articles formed the basis for subsequent qualitative synthesis and bibliometric analysis. The analysis focused on identifying dominant research themes, frequently used methodologies and emerging trends in the application of artificial intelligence in soil science and agriculture. The PRISMA flow diagram illustrating the study selection process is presented in Figure 1.

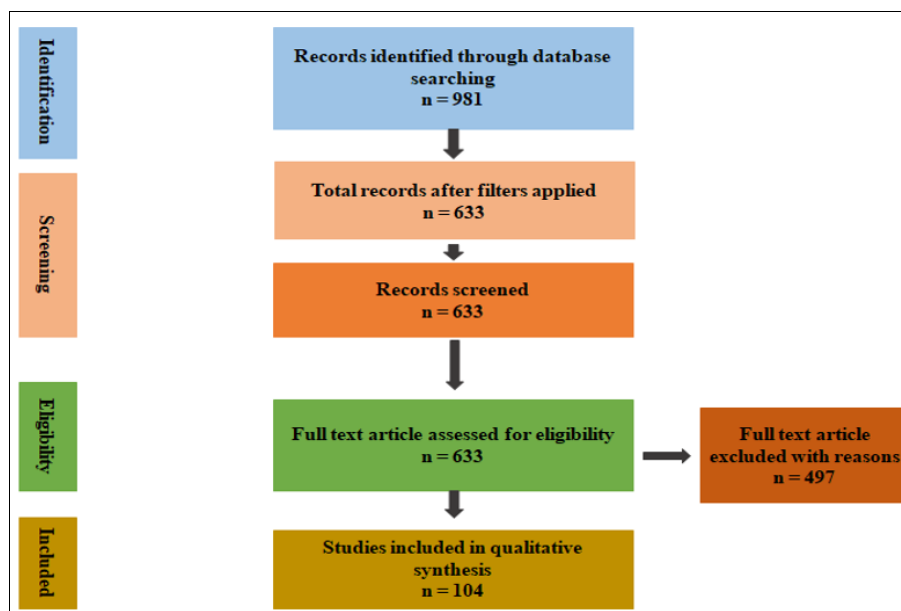


Fig 1: Literature Selection Workflow (Adapted from PRISMA 2020)

3. Overview of Key AI Techniques in Soil Science

Artificial intelligence techniques applied to soil science span a spectrum from classical machine learning to advanced deep learning architectures. Each approach offers distinct advantages depending on data type, task complexity and computational constraints. Ensemble methods, such as Random Forest (RF) and Gradient Boosting (including XGBoost), are widely favoured for tabular and sensor-derived data because of their robustness to overfitting, tolerance for missing values, and capacity to rank feature importance. Support Vector Machines (SVM) perform reliably on smaller or medium-sized datasets

with strong generalization capabilities. Artificial Neural Networks (ANN) effectively model non-linear relationships, while Convolutional Neural Networks (CNN) excel at extracting spatial and spectral patterns from imagery obtained via satellites or UAVs. Recurrent architectures, notably Long Short-Term Memory (LSTM) networks, are particularly suited for temporal data such as continuous sensor streams monitoring soil moisture or seasonal changes (Wadoux, 2025; Kikis & Antoniadis, 2026) [13, 15]. The following table provides a comparative overview of the dominant techniques, their strengths, limitations and representative performance in soil science applications.

Table 1: Comparative Overview of dominant techniques, their strengths, limitations and Performance

Technique	Category	Key Strengths	Main Limitations	Typical Applications
Random Forest (RF)	Ensemble ML	Robust to noise and missing data; interpretable feature importance	Computationally intensive for extremely large datasets	Soil organic carbon (SOC) prediction (often R^2 0.90-0.95); digital soil mapping
Support Vector Machine (SVM)	Supervised ML	Effective with small/medium datasets; strong generalization	Sensitive to hyperparameter tuning	Soil texture classification; moisture prediction
Artificial Neural Networks (ANN)	Neural Networks	Captures complex non-linear patterns	Black-box nature; requires substantial training data	Soil temperature and nutrient forecasting (R^2 frequently > 0.85)
Convolutional Neural Networks (CNN)	Deep Learning	Superior for multispectral/hyperspectral imagery	High computational demand; limited interpretability	SOC, nitrogen, and moisture mapping from remote sensing (outperforms RF on image data)
Long Short-Term Memory (LSTM)	Recurrent DL	Handles temporal dependencies effectively	Data-hungry; extended training times	Soil moisture time-series analysis and irrigation scheduling
Gradient Boosting (e.g., XGBoost)	Ensemble ML	High predictive accuracy; manages multicollinearity	Risk of overfitting if not properly tuned	Erosion risk and soil erodibility prediction

These models frequently surpass traditional geostatistical approaches (such as kriging) by 10-30% in key metrics like R^2 or RMSE when applied to heterogeneous soil datasets. Recent comprehensive reviews confirm that machine learning currently dominates AI applications in soil science, with the majority focused on prediction tasks, digital soil mapping and pedotransfer functions. However, challenges persist around incorporating domain-specific soil knowledge, ensuring interpretability and avoiding over-reliance on proprietary tools.

4. Integration of Artificial Intelligence in Earth System Science

Earth was not formed in a day and all life's needs are met

through it, but in recent days, it's facing major constraints, both natural and artificial. The natural resources of the Earth are silently being reduced. To manage and integrate with AI, this will achieve remarkable accuracy in predicting various conditions of the Earth (Mishra and Kayusi, 2025) [16]. However, the application of AI requires data that is reliable, of high quality and sufficient in quantity, but a gap and constraints still reduce real-world applicability. Machine learning models are widely used in earth science for their ability to identify complex, non-linear relationships. Model applicability can vary based on the nature of the application. For example, ANNs are used for modelling complex data, including soil moisture prediction from climate data or estimating soil features from spectral

measurements (Soni *et al.*, 2025) ^[17]. DNNs and CNNs are mainly applied to high-resolution drone and satellite data extraction (Al Masmoudi *et al.*, 2025) ^[18]. LSTMs are mainly applied to soil moisture and water loss predictions (Datta *et al.*, 2023) ^[19]. Groundwater contamination risk can be assessed using AI models such as ANN, SFL, MFL, and NF. NF and SFL produced acceptable performance, while ANN and MFL had poor prediction (Barzegar *et al.*, 2016) ^[20]. Most AI models consider only short-term datasets, leaving biological and climatic factors out. Most importantly, soil nature is heterogeneous, which creates uneven datasets that make reproduction or application elsewhere difficult.

4.1. Collection and processing of data

Collection and processing of data is a tedious process that requires enormous time and doesn't suit modern requirements. To overcome this problem, it has been automated with the help of AI, ML and other models. This makes it possible to manage larger samples and obtain quality data within a short period (Liu *et al.*, 2025) ^[21]. The collected data are processed to obtain quality results by integrating suitable parameters. Major global scientific problems can be solved by sharing the standardized collected data (Korean *et al.*, 2022) ^[22]. Data enrichment with the help of AI can extract meaningful and actionable information for researchers from abundant data and provide a stronger bond between science and society. Techniques like Diffusion Models (Yang *et al.*, 2023) ^[23] and Generative Adversarial Networks could generate reliable datasets even if the original dataset did not meet the coverage or frequency requirements (Goodfellow *et al.*, 2020) ^[24]. Drones, remote sensors, satellites and unmanned

aerial vehicles can also be used in the collection and processing of data. These help with the real-time monitoring of soil properties and provide significantly higher accuracy than traditional statistical approaches (Patil *et al.*, 2023) ^[25].

4.2. AI-based Anomaly Detection

After data collection and processing, some datasets do not follow the expected pattern, which is an anomaly. In the era of big datasets, detecting anomalies is a key task for both AI and other machine learning models, and it is also very challenging to differentiate useful anomalies from meaningless ones (Nassif *et al.*, 2021) ^[26]. From input data, relevant abstract features can be extracted layer by layer by deep belief networks, which are then fed into one-class support vector machines for anomaly detection (Xiong and Zuo, 2020) ^[27]. However, geoscience is a vast area and the field is changing fast, with many technologies emerging rapidly (Yang *et al.*, 2022) ^[28]. In recent days, large language models have shown promise in anomaly detection by leveraging their ability to analyze and understand data, enabling them to detect anomalies (Cao *et al.*, 2023) ^[29]. Similarly, to understand complex datasets and generate high-quality images from image- or video-based applications, diffusion models are now being explored (Tur *et al.*, 2023) ^[30]. With the help of AI, anomalies can be detected earlier and more accurately, providing better opportunities to act on natural hazards (Li *et al.*, 2021) ^[31]. The whale optimization algorithm was the most effective for predicting soil wind erodibility because of its accuracy, speed and efficiency, and its performance can be further increased by fitting it with a suitable model, especially MLP-WOA (Raei *et al.*, 2021) ^[32].

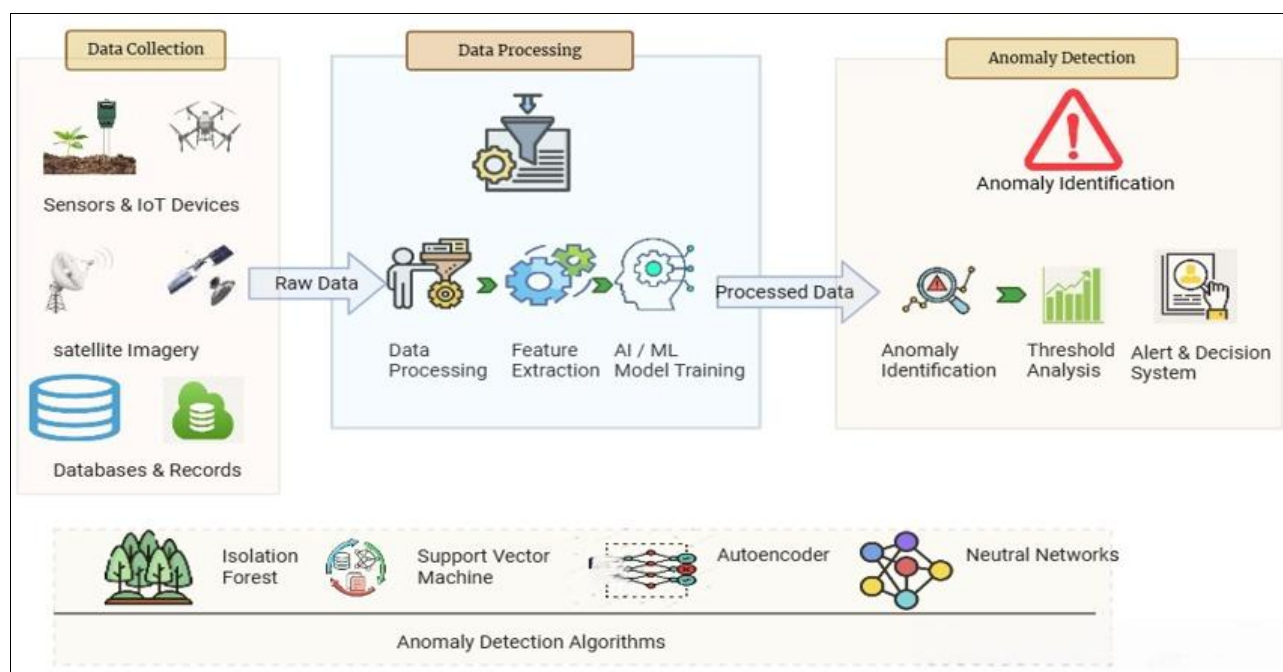


Fig 2: Framework of data collection, processing, and anomaly detection using AI [The three-stage anomaly detection architecture: transitioning raw data from sensors and databases through AI/ML processing to final anomaly identification and decision-making]

4.3. AI involvement in data monitoring and prediction

Unmanned vehicles can monitor larger areas and provide high-frequency datasets that enable direct data transfer and rule enforcement through AI. AI also supports scientists in managing observation and monitoring data through real-time synchronisation, delivering high-quality data. AI provides management strategies for problematic areas, helping scientists identify locations for measurements and the frequency of each

observation (Naresh *et al.*, 2024) ^[33]. Reinforcement learning models are used to find optimal routes and observations to achieve research goals, especially for scientists who can model different situations and develop efficient management strategies to achieve the expected output (Morchid *et al.*, 2024) ^[34]. Genetic algorithms can frame tasks as optimization problems and identify suitable models for scientists to fulfil their plans at low cost (Aijaz *et al.*, 2025) ^[35]. Data flow should be predicted

so that subsequent steps can be taken. Prediction comprises two types, namely short-term and long-term. Short-term prediction involves several hours or days and focuses more on trends. These trends may become unrecognizable within a limited time, and with the help of AI, this task can be tackled to provide improved values within a shorter period. It is most commonly used on a daily basis, especially in social sectors (Lee *et al.*, 2024) ^[36]. Forecasting (several days) or hindcasting (approximately six hours) are examples of short-term prediction. Rainfall forecasting with the help of generative models connected with radar has made it possible to get promising results compared with other models (Ravuri *et al.*, 2021) ^[37]. Different domains have different durations within long-term prediction and are used during strategic planning. Long-term prediction in geology may vary from several thousands to millions of years at the global as well as the regional level, and in meteorology it varies from several months to years. Forecasting changes in climate at the global level for the upcoming century is a typical example of long-term prediction.

5. AI interaction in soil health monitoring

Soil is part of our mother earth and plays a major role in supporting living beings. Ecological balance is only possible if soil is maintained healthy. AI has brought a significant revolution in soil health monitoring through data analysis, enabling extensive predictions and precise results. AI can predict soil health, offering greater power and flexibility to relate various factors and provide results that are more scalable, dynamic and actionable (Padhiary and Kumar, 2025) ^[38]. Soil types for possible problems can be categorized with the help of decision trees. With limited available data and low computational cost, decision tree interpretation is high (Piikki *et al.*, 2021). Soil nutrient content can be forecasted with regression models using soil and climatic variables, yielding high predictive accuracy and robust results for medium datasets (Canero *et al.*, 2024). Recent advances in neural networks, particularly deep learning models, are finding their way into soil health monitoring. Convolutional neural networks are mostly involved in analyzing satellite imagery, datasets related to the geography of earth, soil mapping using remote sensing, or image-based extraction of spatial features. They require high data and computational cost and have low interpretability (Yang *et al.*, 2020) ^[39]. Long Short-Term Memory models - a type of recurrent neural network - inspect time-series datasets from sensors, helping track soil destruction and seasonal variation trends. They can be used in irrigation scheduling and data requirements. The data requirement and computational cost are high, and they are applicable whenever soil dynamics are temporal (Wang *et al.*, 2023) ^[40]. To improve forecast accuracy and manage nonlinear interactions between soil properties, several algorithms are combined, such as Random Forest, Neuro-fuzzy logic and Gradient Boosting Trees. Random Forest uses multiple decision trees to solve classification and regression problems (each tree's own decision) and also uses labelled data to classify unlabelled data - Supervised learning. It is mostly utilized for soil fertility prediction and soil type classification, handling large and complex data and missing data (Wadoux, 2025) ^[13]. Neuro-fuzzy logic is a combination of ANN and Fuzzy logic and has the capacity to manage complicated data and give precise predictions about soil properties and behavior. One of the main applications of Gradient Boosting Trees is their capacity to predict complex outcomes, like the possibility of soil erosion or degradation trends (Shoib, 2023) ^[42].

6. Assessment and Monitoring of soil quality using AI

Soil quality is a complex, multidimensional attribute encompassing a wide set of factors influenced by management practices and the physical and chemical properties of soil. Traditional methods for assessing soil quality are time-consuming and expensive and they do not account for all parameters. Integrating soil data with real-time monitoring and AI-based tools will help in the optimal use of available resources (Padhiary and Kumar, 2025) ^[38]. Accurate, real-time data collection is enabled by sensor technology. Precise fertilizer application can be achieved by monitoring soil physical and chemical properties with sensors. Soil quality can be monitored using various sensors, including moisture, temperature, and pH sensors. In moisture sensors, real-time moisture levels can be predicted so that over- or under-watering can be avoided. Based on statistical indices, GA-ANN, ICA-ANN, ELM, and ORELM models have been used to predict groundwater levels and among these, the ORELM model is considered the most accurate (Mohammed *et al.*, 2023) ^[43]. Soil temperature affects all living activity and can be monitored using sensors, which helps in choosing suitable crops and management practices. Soil temperature can be measured using different models like XGBoost, CatBoost, LSTM, ANN, Ridge regression, Lasso regression, and ElasticNet. Among these, the ANN model can be used for monthly mean soil temperature prediction, and the LSTM model performs accurate predictions of soil temperature at 10 cm depth (Mampitiya *et al.*, 2024) ^[44]. In addition, pH also plays a major role in nutrient availability and crop growth. By monitoring pH levels with sensor technology, farmers can adopt suitable management strategies, understand soil health, recognize issues and take action (Gong, 2021) ^[45]. Soil management with resource optimization can be achieved through AI integration with real-time sensor data (Gul and Banday, 2024) ^[46]. Real-time data from sensors are transmitted to AI algorithms, which analyze trends and anomalies regarding soil health (Mohyuddin *et al.*, 2024) ^[47]. AI-based monitoring reduces labor, provides real-time feedback, increases precision, provides optimal soil conditions and enables proactive management (Sarkar *et al.*, 2022) ^[48]. In soil data collection, the arrangement of sensors at the field level plays a critical role in achieving efficiency (Yan *et al.*, 2021) ^[49]. To obtain valid information about soil, sensors are placed at varying depths. For moisture estimation, sensors are placed near the active root zones so that the real-time water requirement of the crop can be identified. Sensors are installed at the surface and at various depths to monitor soil temperature fluctuations. Acidity or alkalinity can be measured using pH sensors installed at the topsoil surface. The data collected periodically or continuously through sensors are transmitted to a central processing system via wireless networks, and some have self-calibration to ensure data accuracy and stable operation of the equipment (Ejiyi *et al.*, 2025) ^[50]. The collected data are transmitted to cloud storage, which offers advantages such as storing large datasets, strong adaptability, and robust security. Cloud storage data can be processed with AI technology, which helps perform real-time analysis, generate detailed reports and provide precise recommendations (Garah *et al.*, 2024) ^[51].

7. Soil health prediction using AI

Soil health is not just a word. All beings depend on soil, so the foremost goal should be maintaining soil health with the minimum available resources. All predictions depend on soil analysis. Manual analysis takes time, so integrating datasets with AI not only strengthens analysis but also yields optimum results

with minimal resource use (Shahriar *et al.*, 2025) [52]. Complete soil datasets can be established only through continuous data collection with the help of AI tools. The dataset contains not only current soil data but also historical data, including nutrients, temperature, moisture and other parameters. This continuous data collection helps understand soil quality, uncover important problems, and support improvement and management measures (Al Masmoudi *et al.*, 2025) [18]. AI analyses this dataset to identify patterns, parameter relationships, and trends, and to provide predictions. With the help of AI, prediction results inform farmers about environmental impacts on soil health and guide adoption measures, making soil health management scientific and efficient, leading to precision and sustainable agriculture (Al Khatib and Alshaib, 2025) [54]. Soil health conditions can be forecast with the help of AI predictive models (Wang *et al.*, 2022). To process and analyze data, these predictive models use algorithms such as regression analysis, time series analysis, and neural networks. These algorithms can handle complex, nonlinear datasets. Among these, time series analysis is used to evaluate changes in soil properties and enhance decision-making. Decision Tree, Generalized Linear

Model, Support Vector Machine, Artificial Neural Network, Deep Learning and Random Forest models have been used in drought prediction, and among these, the Generalized Linear Model outperformed (Oyoualsoud *et al.*, 2024) [55]. Site-specific soil management can be achieved with the help of regression models. Decision Support Systems, Theoretical mixture, empirical, and Feedforward Neural Network models have been developed for a wide range of applications in soil contamination management. Among these, the Feedforward Neural Network model outperformed in predicting contamination (Nimer *et al.*, 2024) [56]. Additionally, predictive models identify nutrient variations in soil and develop precise fertilization plans. They also forecast extreme weather events, reduce losses related to disasters, predict the effects of current agricultural practices on soil structure or erosion, and facilitate alternative practices that would counteract these degradations. Regression models, MLP models, and MLP-WOA models have been used to predict soil wind erodibility. Among these, the MLP-WOA model provided the best results because of its accuracy, speed, robust exploration method, and avoidance of local optima (Raei *et al.*, 2021) [32].

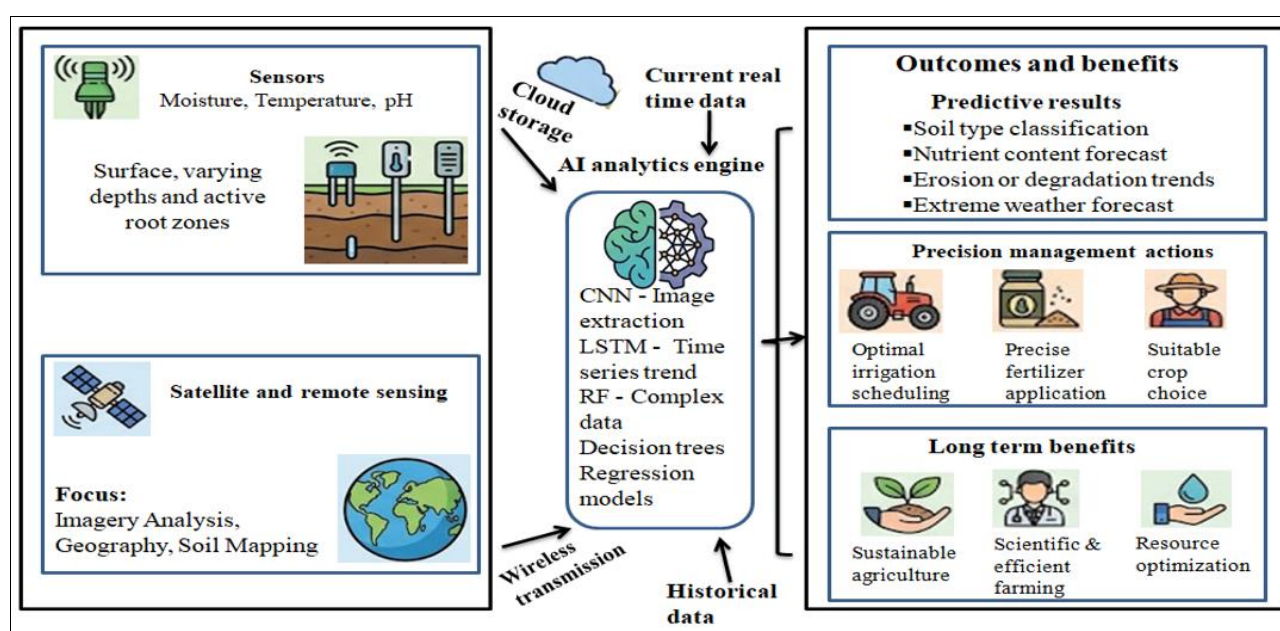


Fig 3: Leveraging Sensor and satellite data with ML for sustainable agricultural management [An overview of an AI-powered precision agriculture framework, detailing the flow from sensor and satellite data collection to predictive analytics and actionable farm management strategies]

8. AI-Driven Decision Support Systems in Agriculture

Real-time datasets are analyzed with the help of AI, and based on this analysis, reports on soil and crop conditions can be generated. By linking this information, the system can offer management suggestions (Zhao, 2023) [57]. This system not only improves decision-making efficiency but also reduces uncertainty, making management more precise and scientific. Fertilizer maps can be created by combining soil nutrient content with crop growth models through a decision support system (Mishra *et al.*, 2025). A decision support system is a smart system that supports decision-making and offers advantages such as automated explainability and accuracy, as it helps AI systems understand the reasons behind predictions and produce robust data (Confalonieri *et al.*, 2021) [59]; increased transparency, as it provides the logic behind the output (Knapic *et al.*, 2021) [60]; and enhanced collaboration, as it facilitates in-depth understanding so users can avoid biased predictions (Antoniadi *et al.*, 2021) [61]. An AI-based decision support

system operates through a hierarchical decision-making framework that integrates machine learning predictions with agronomic parameters. DSS is a rule-based system that draws on random forest to analyze real-time datasets that provide current conditions, and LSTM is used for short-term predictions, especially soil moisture availability. When a lower threshold is reached, it schedules irrigation and nutrient management. With the help of an AI-based DSS, rule-based expert systems can convert real-time sensor data into decisions. By integrating RF, LSTM and AI-DSS, predictive outcomes are translated into decisions for fertilization and irrigation scheduling, especially for nutrient and water management in sandy soils (Emara *et al.*, 2026) [62]. AI-DSS processes large datasets and delivers accuracy, reliability and efficiency in decision-making (Sai *et al.*, 2025) [63].

9. Artificial Intelligence in Fertilizer Management:

With the help of AI, soil nutrient deficiency and distribution can

be analyzed and application becomes scientific and targeted. Through real-time monitoring and data modelling, AI systems can make precise plans, preventing over- or under-application. Data modelling is crucial for generating fertilizer application models. Algorithms like RF, SVM and ANN can predict soil nutrient status and classify it into different fertility classes (Jain and Sethia, 2023) ^[64]. Scientific fertilizer fertilization plans can be made with the help of data modelling, which determines the current nutrient status and future nutrient trends. Soil organic carbon and nutrient status can be predicted through an RF model using soil colour, precipitation, EC and land shape, without sampling, still achieving 92% accuracy (Gunasekaran *et al.*, 2025) ^[65]. When spectral or satellite images are available, DL methods will outperform other approaches. In soil organic carbon prediction using RF, SVM and CNN models, the CNN model performed best (Ma *et al.*, 2022) ^[66]. Organic matter prediction using hyperspectral data, compared with CNN, SVM and hybrid CNN models, showed that the hybrid CNN outperformed other models, but required more data and training time (Deng *et al.*, 2025) ^[67]. For fertility prediction, DT and PLSR models were used because of their effectiveness in analyzing small datasets. These models understand how different models influence soil properties and relate them to soil fertility (Molnar *et al.*, 2022) ^[68]. To optimize future fertilization, AI will perform impact assessments to ensure long-term effectiveness, making nutrient management more scientific, stable, and sustainable. Several bio-inspired algorithms, such as Genetic Algorithms, Firefly and Bat Algorithms, Cuckoo Search, Particle Swarm Optimization, and Ant Colony Optimization, which are advanced forms of AI, are used in predicting soil fertility. These algorithms are inspired by natural phenomena and the behavior of animals, birds, ants, fishes, insects, etc., to tackle complicated and non-linear data problems (Mahmud *et al.*, 2024) ^[69]. Hybridization models like logistic regression, decision tree, decision tree + naive Bayes, and logistic regression + decision tree + naive Bayes are used in soil fertility prediction. Among these models, the logistic regression + decision tree combination performed well and predicted effectively (Senapaty *et al.*, 2024) ^[70]. Random Forest, Extra Trees and deep learning models like Multilayer Perceptron, Long Short-Term Memory networks were evaluated for soil fertility prediction. Among these models, the combination of Random Forest and Extra Trees gave higher accuracy (Gunasekaran and Sreevardhan, 2025) ^[65].

10. Artificial Intelligence applications in Soil Analysis and Texture Prediction

Artificial Intelligence have revolutionized soil analysis by enabling rapid, scalable and non-invasive assessment of soil health parameters, supporting precision agriculture and sustainable land management (Padarian *et al.*, 2020; Kumar *et al.*, 2024) ^[72, 73]. AI technologies process complex, high-dimensional data from sources such as satellite and drone imagery, proximal sensors, and spectral libraries to evaluate critical soil properties, including moisture, organic matter content, nutrient distribution, pH, and macro- and micronutrients (Ramaiah *et al.*, 2025; Lima *et al.*, 2025) ^[74, 75]. Deep learning models, particularly Convolutional Neural Networks, excel at analyzing high-resolution multispectral and hyperspectral imagery to detect spatial patterns linked to soil erosion, compaction, nutrient deficiencies and stress markers (Barathkumar *et al.*, 2024; Kumar *et al.*, 2024) ^[76, 73]. CNN effectively capture spectral variations for predicting soil organic carbon, nitrogen and moisture levels, even in remote or

heterogeneous areas where ground sampling is limited (Lima *et al.*, 2025; Padarian *et al.*, 2020) ^[75, 72]. Traditional ML algorithms such as Random Forest, Support Vector Machines and Gradient Boosting Trees perform robustly in regression and classification tasks, often achieving high accuracy and stability through ensemble methods (Shoaib, 2023; Araújo *et al.*, 2023) ^[42, 78]. RF is particularly effective for deriving soil quality indices and conducting risk assessments due to its resistance to over fitting, while SVM handles smaller datasets efficiently with strong generalization. A prominent application is soil texture prediction, which determines proportions of sand, silt and clay; a fundamental factor influencing water retention, nutrient availability, ecosystem health and agricultural productivity (Xing *et al.*, 2025) ^[79]. AI-driven methods uncover non-linear relationships in diverse inputs, including compositional data, spectral signatures, geospatial variables and environmental covariates (Johnson *et al.*, 2020) ^[80]. Deep learning frameworks and ensemble ML approaches have demonstrated superior performance over conventional laboratory techniques like hydrometer or pipette analysis, drastically reducing time, labour, and costs while enabling real-time or large-scale mapping (Kumar *et al.*, 2024; Lima *et al.*, 2025) ^[73, 75]. Despite these advantages, challenges persist: the requirement for high-quality, representative training data; limited interpretability of "black-box" models; risks of overfitting on small or noisy datasets; and the need for rigorous validation against ground-truth measurements (Wadoux, 2025) ^[13]. Environmental factors (e.g., cloud cover in optical remote sensing) and data integration issues further complicate deployment (Ramaiah *et al.*, 2025) ^[74]. Addressing these through explainable AI, hybrid models combining mechanistic soil knowledge with data-driven approaches, transfer learning, and fusion of multi-source data (e.g., UAVs with satellites) will enhance reliability, trust and adoption in farm management systems (Kumar *et al.*, 2024; Wadoux, 2025) ^[73, 13]. This integration of AI not only provides cost-effective insights but also paves the way for dynamic, site-specific soil management, contributing to sustainable agriculture amid climate variability.

11. Digital Soil Mapping Using Artificial Intelligence

Soil spatial mapping classifies heterogeneous soil based on properties to use resources precisely, and it represents basic pillar of soil and land management. AI has provided substantial support in the field of soil management and mapping through modelling non-linear, complex, and high-dimensional datasets that integrate soil and environmental parameters (Mohyuddin *et al.*, 2024) ^[47]. In different soil prediction areas, algorithms like RF, SVM, XGBoost, and ANN have performed well when compared to traditional interpolation techniques (Wadoux *et al.*, 2021) ^[83]. The primary reasons for selecting these algorithms were their adaptability to complex structures, ability to handle multicollinearity, and effective predictive performance. Multilayer Perceptron Regressor, Random Forest, Decision Tree, and Extreme Gradient Boosting models were applied to predict the soil erodibility factor. Among these, the Extreme Gradient Boosting model outperformed, and the predicted soil erodibility factor was mapped using GIS (Isik *et al.*, 2026) ^[84]. An AI-integrated soil mapping system uses algorithms like K-Means Clustering, Hierarchical Clustering, and predictive models to build maps that help divide the field area into homogeneous zones. K-Means Clustering separates the field into different zones based on soil properties. K-Means Clustering is a semi-supervised clustering model that is sensitive to outliers and is mostly used to handle unlabeled data with limited labeled data.

This method is mostly applied where practical application is challenging and is used in soil texture prediction (Zhu *et al.*, 2025) [85]. Hierarchical Clustering is used when samples show complex hierarchies. Soil property determination, estimation and mapping are based on two methodologies, including Spectral-based modeling and Digital Soil Mapping. In Spectral-based modeling, remote-sensed image data are used to estimate soil properties, and hyperspectral data are rich in information but data processing is a bit complicated. In Spectral-based modeling, hyperspectral data linked with satellites help collect spectral information in both visible and shortwave infrared, which is mostly used in soil organic matter content mapping (Yang *et al.*, 2022) [28]. Digital soil mapping is established based on

quantitative correlations of soil datasets taken from environmental data, including spatially explicit environmental data, measurements taken in the field and laboratory measurements. In digital soil mapping, environmental covariates are the key component because they help determine spatial variation and give accurate, precise results when compared to other soil mapping. Environmental covariates include SCORPAN factors of Jenny 1941 (Soil, Climate, Organisms, Relief, Parent material, Age and Location), which are used essentially in soil parameter mapping. Model validation is made by comparing the trained and original datasets and parameter optimization is usually done to increase model accuracy (Sun *et al.*, 2023) [86].

Table 2: Substantiation of best ML model in soil property prediction

S. No.	ML models	Area of study	Property assessed	Best ML model	Used Validation measure	Author Reference
1.	CNN, LSTM, RF and CNN-LSTM	Hainan island, China	SOC	CNN-LSTM	R ² , RMSE and RPIQ	Dong <i>et al.</i> , 2024 [98]
2.	RF, OK and RF-OK	Gijang-gun, South Korea	Soil contamination	BRT	R ² and RMSE	Han and Suh, 2024 [99]
3.	RF, XGBOOST and STACKING METHOD	Dhamtari, Chattisgarh	SOC	XGBOOST	R ² , RMSE and sMAPE	Mundada and Jain, 2025 [100]
4.	XGBoost, CatBoost, LSTM, ANN, Bi LSTM, Ridge regression, Lasso regression, ElasticNet	Nukus, Uzbekistan	Soil temperature	LSTM	RMSE, MAE, MSE and R ²	Mampitiya <i>et al.</i> , 2024 [44]
5.	Theoretical physics-based models, Mixture theory models, Statistical empirical models, ANN models and FFNN models	Jordan	Soil Complex Permittivity and Diesel Pollution Content	FFNN models	MSE, R	Nimeret <i>et al.</i> , 2024 [56]
6.	GA-ANN, ICA-ANN, ELM and ORELM models	Sonqor plain in western Iran	Groundwater level	ORELM	RMSE, NRMSE, NASH and R	Mohammed <i>et al.</i> , 2023 [43]
7.	Ridge, Lasso and Elastic regression models	Diyarbakir, Turkey	Soil fertility index	Lasso	R ² and RMSE	Aciret <i>et al.</i> , 2025 [101]
8.	Regression tree and boosted tree algorithms	Eastern Thailand	Soil moisture content	boosted tree	R ² , MAE and RMSE	Panyavarapon <i>et al.</i> , 2025 [102]
9.	SVM, ANN and RF	Eastern China	SOC	RF	R ² , RMSE and PRD	Yu, 2026 [103]
10.	RF model	Eastern China	Soil heavy metal prediction	RF	R ² , MAE and RMSE	Nieet <i>et al.</i> , 2024 [104]

CNN - Convolutional Neural Network; LSTM - Long Short-Term Memory; RF - Random Forest; OK - Ordinary Kriging; RF-OK - Random Forest-Ordinary Kriging; BRT - Boosted Regression Trees; XGBoost - Extreme Gradient Boosting; ANN - Artificial Neural Network; Bi-LSTM - Bidirectional Long Short-Term Memory; Ridge - Ridge Regression; Lasso - Least Absolute Shrinkage and Selection Operator; ElasticNet - Elastic Net Regression; FFNN - Feedforward Neural Network; GA-ANN - Genetic Algorithm-Artificial Neural Network; ICA-ANN - Imperialist Competitive Algorithm-Artificial Neural Network; ELM - Extreme Learning Machine; ORELM - Online Regularized Extreme Learning Machine; SVM - Support Vector Machine; SOC - Soil Organic Carbon; R² (R²) - Coefficient of Determination; RMSE - Root Mean Square Error; MAE - Mean Absolute Error; MSE - Mean Squared Error; NRMSE - Normalized Root Mean Square Error; NASH - Nash-Sutcliffe Efficiency; RPIQ - Ratio of Performance to Interquartile Range; sMAPE - Symmetric Mean Absolute Percentage Error; PRD - Prediction Residual Deviation; R - Correlation Coefficient.

12. Challenges and Limitations of AI Adoption

While AI-powered tools hold transformative potential for agricultural sustainability, several challenges impede their effective adoption, particularly in developing countries. These limitations include high initial setup and training costs, making them unsuitable for small farm holdings (Schroeder *et al.*, 2024; Schweng *et al.*, 2026) [87, 14]. The practical application of AI tools is further constrained by the existence of uneven datasets, which can reduce prediction accuracy. Moreover, models trained for specific parameters, such as those for tropical climates, may not yield accurate results in temperate or other climatic regions (Gavilán-Acuna *et al.*, 2024) [88]. Model over-fitting is another significant concern, especially in ecosystems with fewer variables, such as desert environments, compared to forest ecosystems. The use of suitable AI models is crucial to avoid uncertainties arising from sampling bias, model limitations, and variations (Gavilán-Acuna *et al.*, 2024) [88]. AI models heavily rely on the data they are trained on; incomplete training data can

lead to unfair or inaccurate outcomes. Continuous updating and the addition of algorithms increase dataset requirements and costs, making large-scale implementation challenging (Jia *et al.*, 2025) [89]. Different agricultural fields often require distinct AI models. For instance, in yield estimation through fertilizer application, selecting the most appropriate model is difficult due to variations in accuracy among models, complicating their application in soil fertility studies.

Another significant difficulty is the regional specificity of AI models; models trained with specific soil and environmental datasets may not be universally applicable to other regions without a loss of accuracy. To overcome this, multi-regional, standardized, and broader data collection efforts, facilitated by researchers, may offer a pathway to universal AI model adoption (Schweng *et al.*, 2026) [14]. Dynamic soil and climatic conditions pose a challenge for static model applications. Furthermore, agricultural automation intensity is uneven, and infrastructure defects, such as the unavailability of skilled labor and limitations

in electricity accessibility, hinder adoption (Schroeder *et al.*, 2024) ^[87]. In rural areas, a lack of training, connectivity, accessibility to digital tools, and language interfaces continue to limit usability among farmers (Naseri&Idris, 2025) ^[91]. Policy frameworks for large data services are still developing, with deficiencies in data sharing and collaboration among stakeholders (Yu *et al.*, 2025) ^[92]. Government support through funding subsidies, fostering partnerships between private and public bodies, and regulatory measures are essential to ensure that public and rural areas benefit from these advancements (Kopańska *et al.*, 2024) ^[93].

13. Future Directions and Prospects of Artificial Intelligence in Soil Science

The progression of Artificial Intelligence in soil science indicates a profound transformation for precision agriculture, soil health monitoring, and sustainable land management. While current AI applications already provide highly accurate predictions for soil texture, nutrient status, moisture levels, carbon content, and contamination (Kumar *et al.*, 2024; Kikis and Antoniadis, 2026) ^[73, 15], the coming decade is expected to prioritize enhancing the accessibility, trustworthiness, scalability, and ethical responsibility of these technologies. Key emerging trends include real-time, on-device data processing, collaborative privacy-preserving methods, virtual simulation, and improved model interpretability, all aimed at overcoming existing limitations such as data scarcity, model opacity, and restricted generalizability (Kikis & Antoniadis, 2026) ^[15]. To circumvent reliance on cloud infrastructure, which is often inaccessible in rural agricultural settings, there is a growing shift towards deploying lightweight neural networks and machine learning models directly onto farm equipment, drones, handheld spectrometers, and IoT soil sensors, using fewer resources (Mohyuddin *et al.*, 2024) ^[47]. This localized processing capability facilitates immediate decision-making. Coupled with advancements in affordable multispectral sensors, these edge computing solutions are set to standardize high-resolution soil texture mapping and moisture forecasting, even in regions with limited data availability. Decentralized federated learning offers another transformative pathway by solving data-privacy and regional bias issues. Farms and research institutions can collaboratively train shared models without exchanging raw soil data. This approach allows models trained on diverse global datasets (temperate, arid, tropical) to improve predictions for soil organic carbon, texture, and contamination while preserving farmer data ownership (Kikis & Antoniadis, 2026) ^[15].

The evolution of digital twins for soil-crop systems signifies a paradigm shift towards advanced predictive simulation. A digital twin functions as a dynamic virtual replica of an actual agricultural field, continuously updated with real-time data from sensors, satellites, and weather stations (Petroselli *et al.*, 2024; Melesse *et al.*, 2024) ^[95, 96]. This technology will empower farmers and scientists to conduct hypothetical “what-if” analyses, such as evaluating the impact on soil moisture and carbon sequestration if irrigation is reduced by 20% and cover crops are introduced, prior to implementing physical changes. These hybrid AI twins, integrating physics-informed models with data-driven machine learning, are expected to significantly improve long-term forecasts of soil health trends in the context of climate change (Kikis & Antoniadis, 2026; Melesse *et al.*, 2024) ^[15, 96]. Explainable AI (XAI) is emerging as a crucial facilitator across all future AI applications. As AI models, including CNNs, LSTMs, and Transformers, become increasingly complex, their ‘black-box’ nature can impede

adoption by farmers and policymakers. In the short term (3-5 years), several advancements are anticipated: more affordable portable spectrometers, higher-resolution satellite constellations, widespread IoT sensor networks, and hybrid cloud-edge platforms will collectively democratize AI-driven soil analysis. Proximal sensing, when combined with ML, will enable on-site texture classification and nutrient recommendations, potentially reducing the need for traditional laboratory testing (An, 2024; Kikis & Antoniadis, 2026) ^[97, 15]. Looking further ahead, quantum computing holds promise for resolving highly intricate soil biogeochemical interactions that currently exceed classical computational limits. Quantum-enhanced machine learning could accelerate global-scale digital soil mapping and uncertainty quantification, although practical applications are estimated to be 10-15 years away (Kikis & Antoniadis, 2026) ^[15]. Ultimately, realizing the full potential of AI in soil science necessitates robust interdisciplinary collaboration among soil scientists, AI engineers, farmers, and policymakers. A strong emphasis must be placed on developing user-friendly, cost-effective and ethically governed tools that augment, rather than replace, human expertise. By proactively addressing challenges related to data standardization, model interpretability and equitable access, AI is poised to not only enhance soil texture prediction, mapping and health assessment but also to significantly contribute to global objectives of food security, climate resilience and regenerative agriculture (Kikis & Antoniadis, 2026; Lima *et al.*, 2025; Xing *et al.*, 2025) ^[15, 75, 79].

14. Conclusion

Addressing critical global issues such as soil health degradation, soil organic carbon depletion and climate change necessitates the development and strategic application of suitable AI models. This review had overviewed the significant role of AI in enhancing soil health management and highlighted how the selection criteria of optimal models can substantially increase decision-making efficiency. AI applications have significantly enhanced the efficiency of soil health assessment, nutrient management, and erosion risk evaluation, enabling more precise, data-driven, and sustainable agricultural practices. However, the widespread adoption of AI in soil science faces several limitations, including high implementation costs, a lack of technical skills among farmers, insufficient training infrastructure and inadequate datasets, which collectively hinder broader utilization. To bridge these gaps, concerted efforts are required, including providing comprehensive training to farmers, fostering collaborations between public and private entities, securing government financial support and encouraging developers to create affordable and user-friendly interfaces. The continuous ongoing development of hybrid AI models, advancements in data collection technologies, and improved accessibility to AI tools will further strengthen AI's role in soil analysis, crop production and decision support. Ultimately, these advancements will contribute significantly to environmental sustainability, food security, and the resilience of agricultural systems in the face of evolving global challenges.

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17. Abbreviations

This manuscript contains the following abbreviations:

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
SVM	Support Vector Machine
MFIS	Mamdani Fuzzy Inference System
ANFIS	Adaptive Neuro-Fuzzy Inference System
DNN	Deep Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
SFL	Single Fuzzy Logic
MFL	Multi Fuzzy Logic
NF	Neuro-Fuzzy
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLP-WOA	MLP with Whale Optimization Algorithm
GA-ANN	Genetic Algorithm-ANN
ICA-ANN	Imperialist Competitive Algorithm-ANN
ELM	Extreme Learning Machine
ORLEM	Online Regularized Extreme Learning Machine
XGBoost	Extreme Gradient Boosting
CatBoost	Categorical Boosting
DSS	Decision Support System
RF	Random Forest
AI-DSS	Artificial Intelligence-Decision Support System
DL	Deep Learning
DT	Decision Tree
DLSR	Deep Learning-based Super Resolution / Sparse Representation
UAV	Unmanned Aerial Vehicle
R ²	Coefficient of Determination
RMSE	Root Mean Square Error
RPIQ	Ratio of Performance to Interquartile Distance
sMAPE	Symmetric Mean Absolute Percentage Error
MAE	Mean Absolute Error
MSE	Mean Square Error
R	Correlation Coefficient
NRMSE	Normalized Root Mean Square Error
NASH	Nash-Sutcliffe Efficiency
PRD	Percentage Root Mean Square Difference

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