

# Bridging the Data Divide: A Review of Artificial Intelligence and Machine Learning in Advancing Soil Health and Precision Agriculture

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## Abstract

The global challenges of climate change, soil degradation, and food security demand a fundamental shift in soil management practices. Traditional soil analysis methods are time-consuming, labor-intensive, and inadequate for delivering the real-time, large-scale data required in modern precision agriculture. This review examines the rapid integration of Artificial Intelligence (AI) and Machine Learning (ML) into soil science, highlighting recent advancements in monitoring, prediction, and decision support. AI applications are classified across four critical domains: Digital Soil Mapping (DSM), Soil Health Monitoring (SHM), Predictive Modeling, and Soil Conservation. These technologies leverage vast and diverse data sources to overcome long-standing limitations associated with conventional soil assessment. For example, advanced ML models achieve up to 92% accuracy in predicting Soil Organic Carbon (SOC) stocks and exhibit approximately 85% efficiency in mapping soil moisture patterns. Despite these promising developments, widespread AI adoption is hindered by challenges such as data standardization, the “black box” nature of complex models, and limited technological accessibility, particularly in resource-constrained regions. The future of AI in soil science lies in developing Explainable AI (XAI) frameworks, improving interoperable data systems, and fostering interdisciplinary collaboration to build sustainable, data-driven soil ecosystems.

**Keywords:** Artificial Intelligence, Machine Learning, Soil Health, Digital Soil Mapping, Precision Agriculture, Soil Organic Carbon.

## 1. Introduction

Soil stands as a non-renewable and fundamental natural resource, essential not only for supporting over **95%** of global food production but also for its vital role in climate change mitigation through carbon sequestration and the maintenance of overall ecosystem balance (Rahman & Das, 2025). However, the health of this resource is critically threatened. Global assessments indicate that more than **33%** of the Earth's land area is affected by moderate to severe degradation, encompassing challenges such as erosion, nutrient depletion, salinization, and contamination. This widespread degradation poses a direct threat to agricultural productivity and planetary sustainability, necessitating a fundamental shift in how soil is monitored, analyzed, and managed.

Historically, soil management has relied on conventional methods involving manual field sampling and time-consuming, costly laboratory testing. Although these techniques provide accurate point-in-time measurements, they are inherently slow, labor-intensive, and spatially limited. As a result, they fail to deliver the high-resolution, real-time insights required by modern agricultural practices particularly those aligned with Precision Agriculture (PA), which demands site-specific, sub-field level decision-making (Maraveas et al., 2022). Consequently, traditional practices often lead to inefficient resource use (e.g., fertilizers and water) and tend to be reactive rather than predictive.

The integration of Artificial Intelligence (AI) and its specialized subfields—Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), and Expert Systems—has provided the technological advancement necessary to address these limitations. AI-driven approaches offer scalable, real-time, data-driven analysis capabilities that were previously unachievable (Awais et al., 2023; Babar et al., 2024). These technologies excel in interpreting large, complex, multi-source datasets, including:

- Proximal sensor/IoT networks (real-time measurements of soil temperature, moisture, and pH)
- Unmanned Aerial Vehicles (UAVs) and satellite remote sensing (high-resolution multispectral and hyperspectral imagery)
- Legacy soil databases and historical climate records (Heuvelink et al., 2021)

By integrating and analyzing these diverse data sources, AI models can identify complex, non-linear relationships between soil covariates and target soil properties, enabling highly accurate spatial predictions and predictive diagnostics.

This review synthesizes the current state of AI applications in soil science across four primary domains: Digital Soil Mapping (DSM), Soil Health Monitoring (SHM), Predictive Modeling, and Soil Conservation. It highlights key advancements, such as ML models achieving up to **92%** accuracy in predicting Soil Organic Carbon (SOC) stocks (Heuvelink et al., 2021) and **85%** efficiency in soil moisture mapping (Hyperspectral Remote Sensing and AI, 2025). Furthermore, the review critically evaluates existing barriers—including the need for data standardization, the challenge posed by the “black box” nature of complex AI models, and issues surrounding technological accessibility. These challenges underscore the importance of

developing Explainable AI (XAI) frameworks and strengthening interdisciplinary collaboration to build sustainable and resilient soil ecosystems.

## 2. Methodology

A systematic review methodology was employed to identify, select, and synthesize relevant literature published between 2019 and 2025. Three major scientific databases—Scopus, Web of Science, and Google Scholar/related academic repositories—were searched to ensure comprehensive coverage. The search strategy used a combination of controlled vocabulary and Boolean operators with keywords such as “*Artificial Intelligence in soil science,*” “*machine learning soil mapping,*” “*deep learning agriculture,*” “*soil health prediction,*” “*soil moisture modelling,*” and “*AI-based soil diagnostics.*”

Studies were included if they met the following criteria:

1. Applied AI, ML, DL, CV, or expert systems to soil-related processes.
2. Reported measurable outcomes (accuracy, efficiency, predictive performance).
3. Focused on agricultural, environmental, or soil resource management contexts.

Non-English papers, purely theoretical computer science studies without soil application, and duplicated records were excluded. The final dataset was categorized by AI technique, data source, and application domain (DSM, SHM, predictive modeling, conservation).

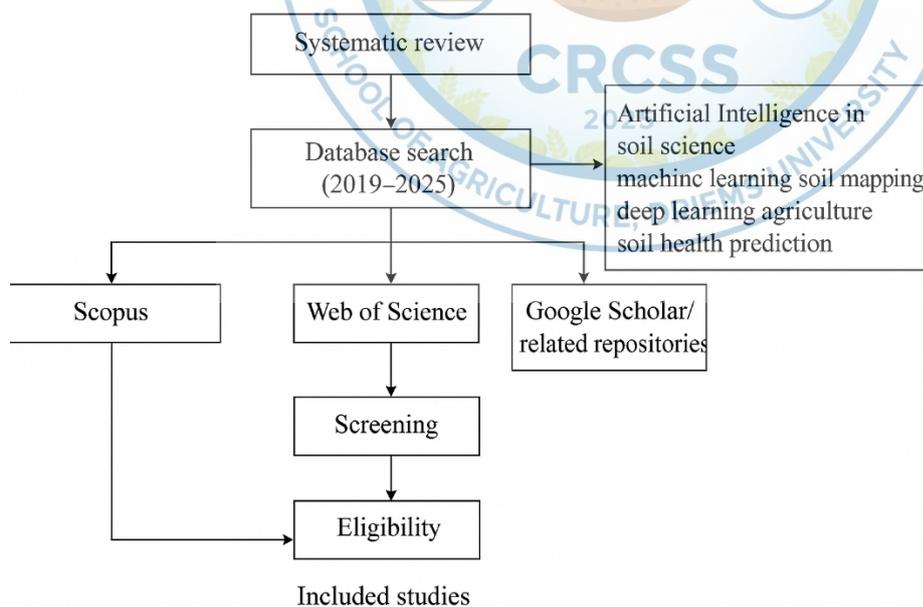


Fig.1. Methodology of data collection

### 2.1. Core AI Components

The review classified AI applications into four major methodological categories:

### **2.1a. Machine Learning (ML):**

Algorithms such as Random Forests (RF), Support Vector Machines (SVM), and various Artificial Neural Networks (ANNs) were frequently used for predicting soil properties, including texture, SOC, moisture, and nutrient status (Poggio et al., 2021). ML models excel in handling nonlinear interactions among soil covariates.

### **2.1b. Deep Learning (DL):**

Convolutional Neural Networks (CNNs) were widely applied for image-based soil texture and pore structure classification, while Long Short-Term Memory (LSTM) networks supported temporal forecasting tasks such as soil moisture, evapotranspiration, and temperature dynamics (Lavrukhin et al., 2021).

### **2.1c. Computer Vision (CV):**

UAV- and ground-based imaging systems enabled automated detection of soil surface characteristics, erosion patterns, crusting, compaction zones, and nutrient deficiency symptoms through image segmentation and pattern recognition techniques.

### **2.1d. Expert Systems & Fuzzy Logic:**

Rule-based systems incorporating pedological expertise and fuzzy logic were used in decision-support applications, particularly where uncertainty, imprecision, or qualitative descriptors are common (López et al., 2008).

## **2.2. Data Acquisition Sources**

AI models in soil science rely on diverse, multi-scale data sources. This review categorized the major sources as follows:

**2.2.1 Remote Sensing:** Multispectral and hyperspectral satellite/UAV imagery provided spatially continuous datasets for large-area prediction of soil properties, including SOC, salinity, moisture, and texture (Gholizadeh et al., 2025).

**2.2.2. Proximal Sensors / IoT Networks:** In-field sensor networks measuring **soil moisture, temperature, pH, EC, and NPK levels** offered high-frequency, real-time observations essential for dynamic monitoring and predictive modelling (Ahmad et al., 2021).

**2.2.3. Legacy & Ground-Truth Data:** Soil profile databases, pedon descriptions, laboratory analyses, climate time-series, DEM-derived terrain attributes, and long-term land-use records were used to train, validate, and calibrate model predictions (Heuvelink et al., 2021).

### **3. Results and Discussion: Key Application Domains**

#### **3.1 Digital Soil Mapping (DSM)**

AI has transformed DSM from manual mapping to automated, high-resolution spatial prediction.

**3.1a. SOC Mapping:** QRF and RF models achieve **2% accuracy**, combining DEM, climate layers, and spectral data (Heuvelink et al., 2021).

**3.1b. Texture Prediction:** CNNs and ANNs outperform conventional regression for predicting sand, silt, and clay content (Zhao et al., 2009).

#### **3.2 Soil Health Monitoring (SHM)**

AI enables continuous monitoring of dynamic soil parameters.

- **Moisture and Temperature:** LSTM-based forecasts support irrigation planning with 85% mapping efficiency.
- **Nutrient & pH Estimation:** Machine vision + colorimetric sensors automate NPK and pH diagnosis (Sindhu et al., 2018).
- **Soil Contamination:** ML models classify contaminant levels and health implications.

#### **3.3 Predictive Modeling & Decision Support**

- **Yield Prediction:** Combines soil, climate, and historic data for optimal crop recommendations (Hosseini et al., 2023).
- **Variable Rate Technology (VRT):** AI-based DSS improves fertilizer and irrigation efficiency by 20–25%.
- **Erosion Risk:** ML tools predict erosion, salinity, and degradation hotspots.

#### **3.4 Soil Conservation and Remediation**

- **Management-Oriented Models:** AI helps optimize nitrogen application, reduce leaching, and evaluate management scenarios (Li & Yost, 1999).
- **Remediation Prediction:** ML evaluates phytoremediation and bioremediation effectiveness.

### **4. Challenges and Future Directions**

Challenge	Impact	Suggested Solution
Data Scarcity & Quality	Reduces model accuracy	Develop global, standardized open databases
Black Box Nature of ML	Limits trust in AI	Invest in Explainable AI (XAI)
Cost & Technological Access	Limits adoption by smallholders	Low-cost sensors, open-source AI tools
Integration & Scalability	Poor cross-region model transfer	Develop adaptable, region-specific models

### Future Opportunities:

- NLP for digitizing legacy soil data
- Cognitive systems integrating sensing + prediction + automated action
- Fully autonomous soil management systems driven by AI

### 5. Conclusion

AI and ML have transformed soil science, enabling real-time, high-accuracy predictions and supporting precision agriculture. SOC prediction accuracy reaches **92%**, while soil moisture mapping achieves **85%** efficiency. The integration of AI enhances diagnostic speed, resource efficiency, and sustainability. Addressing challenges in data standardization, accessibility, and model transparency will unlock the full potential of AI-driven soil management globally.

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