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Artificial intelligence and soil conservation: An overview

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ABSTRACT

Soil conservation has evolved from traditional techniques such as contour ploughing, terracing, and crop rotation to the adoption of advanced technologies like remote sensing, GIS, and precision agriculture. Integrating AI marks a transformative phase in soil management, offering data-driven solutions for soil health assessment, monitoring degradation, and predicting fertility. AI-powered platforms utilize ML algorithms and image processing techniques to interpret satellite imagery and data from IoT sensors, enhancing the precision of soil diagnostics. According to the FAO, global soil degradation affects over 33% of land resources, and AI offers significant potential to mitigate such threats. AI-enabled models have achieved up to 92% accuracy in predicting soil organic carbon levels and 85% efficiency in mapping soil moisture patterns. Moreover, AI-driven DSS aid site-specific planning through VRT, adaptive tillage, and irrigation management, improving input use efficiency by 20-25%. These innovations also support policymakers with real-time dashboards and compliance tracking. Despite infrastructural and ethical challenges, the future of AI in soil conservation is promising. High-quality, interdisciplinary research, policy support, and stakeholder collaboration can foster sustainable and resilient soil ecosystems globally.

KEYWORDS: Artificial Intelligence, Decision Support Systems, Precision Agriculture, Soil Conservation, Soil Health Assessment

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INTRODUCTION

Agri-food sector sustainability hinges critically on the health of soil ecosystems, which form the bedrock of agricultural productivity and environmental balance. With nearly 33% of the world's soils already degraded, according to the FAO, the urgency of effective soil conservation practices has reached an unprecedented level. Soil erosion, nutrient depletion, salinization, and desertification threaten the long-term viability of farmlands across continents, especially in countries like India, where over 120 million hectares are affected by various forms of land degradation (Delgado *et al.*, 2019; Wadoux, 2025). While traditional conservation methods such as contour ploughing, terracing, crop rotation, and agroforestry have long been instrumental in maintaining soil integrity, the scale and complexity of contemporary challenges now demand more advanced, data-driven interventions (Chaves *et al.*, 2025).

The historical transition from manual techniques to mechanized soil management, and subsequently to satellite-based remote sensing and precision agriculture, has laid the groundwork for the integration of AI into soil conservation. Precision agriculture, with its capacity for site-specific soil monitoring and input management, provided the first glimpse into the potential of data analytics in optimizing soil health (Lilhare *et al.*, 2024). Now, with AI technologies evolving rapidly, new possibilities are emerging for accurate soil diagnostics, predictive modelling, risk assessment, and real-time decision support. These capabilities are becoming increasingly accessible due to the proliferation of Internet of Things (IoT) sensors, drone technologies, and cloud computing infrastructure, which together enable the collection and processing of large-scale spatial and temporal data (Iqbal, 2024; Lal, 2024).

AI encompasses a suite of technologies, including ML, deep learning, computer vision, and expert systems, that allow machines to mimic human reasoning and improve decision-making through iterative learning. In the context of soil conservation, AI is being deployed to analyse multispectral satellite and UAV imagery, sensor-based soil readings, and historical climate and land-use data to map soil texture, structure, moisture content, pH levels, organic matter, and nutrient concentrations with high accuracy. These systems offer a significant improvement over traditional sampling methods that are often labour-oriented, time-consuming, and limited in scope (Abdelhak 2024; Zhang *et al.*, 2024; Mishra & Dwivedi, 2025a).

Recent studies demonstrate the efficacy of AI in enhancing soil health management. For instance, ML models trained on remote sensing and ground-truth data have achieved over 90% accuracy in identifying areas at high risk of erosion and nutrient leaching (Grunwald, 2022). Predictive algorithms are being used to forecast changes in soil fertility under different land management scenarios, thereby aiding in the development of adaptive tillage and irrigation plans (Jiang *et al.*, 2021). Furthermore, AI-driven DSS are increasingly integrated into farm management software, enabling stakeholders to receive tailored recommendations on fertilizer application, crop selection, and conservation practices based on real-time soil diagnostics and weather forecasts (Delgado *et al.*, 2020; Mishra & Mishra, 2023).

Policy-making and regulatory frameworks are also beginning to incorporate AI tools. Governments are using automated compliance monitoring systems to assess adherence to land use and conservation norms, while visualization dashboards based on AI analytics are informing land zoning and ecological restoration programs (Dwivedi *et al.*, 2024; Mishra *et al.*, 2025). On the environmental front, AI applications are contributing to carbon sequestration assessments and biodiversity monitoring, underscoring the role of intelligent systems in supporting broader ecosystem services (Samarinas *et al.*, 2024).

Despite the promise, challenges persist. Technical limitations such as poor data quality, lack of rural connectivity, and inadequate computational infrastructure can hinder effective AI implementation. Institutional barriers, including limited capacity-building efforts and interoperability issues among different systems, remain substantial (Khaleel *et al.*, 2024). Moreover, ethical concerns regarding data ownership, algorithmic bias, and equitable access to AI technologies warrant careful consideration. Addressing these multifaceted challenges will require coordinated efforts among researchers, policymakers, agribusinesses, and local communities (Shivaprakash *et al.*, 2022; Kumar *et al.*, 2023).

As we look ahead, the future of AI in soil conservation is likely to be shaped by innovations such as edge AI, federated learning, and digital twin simulations. These advancements will not only enhance the accuracy and efficiency of soil conservation efforts but also make them more inclusive and adaptable (Wang *et al.*, 2025). Interdisciplinary collaborations among technologists, soil scientists, ecologists, and farmers will be pivotal in realizing the full potential of AI while ensuring environmental sustainability and social equity (Jha *et al.*, 2019). The primary objective of this chapter is to identify the transformative role of AI in the monitoring, assessment, and management of soil health, with a focus on how data-driven technologies are reshaping traditional conservation practices. It also aims to critically evaluate the integration of AI into policy frameworks and on-ground decision-making systems, while addressing the technical, ethical, and institutional barriers that may hinder its widespread adoption.

EVOLUTION OF SOIL CONSERVATION TECHNIQUES

Soil conservation has witnessed a remarkable transformation over centuries, evolving from indigenous knowledge systems and empirical observations to highly technological and data-driven frameworks. Historically rooted in traditional practices that prioritized sustainability through community-driven initiatives, soil conservation has now entered a phase of accelerated innovation marked by the infusion of digital technologies, mechanization, and AI.

Traditional Soil Conservation Methods

The initial understanding and practice of soil conservation were deeply embedded within the local cultural and ecological knowledge of agrarian societies. These methods, though simple in their operational design, displayed an intrinsic alignment with the principles of ecological balance and long-term soil fertility (Hu *et al.*, 2024; Biazar *et al.*, 2025). Without reliance on machinery or digital systems, traditional practices were crafted through trial, observation, and generational transfer of wisdom. Among the most enduring of these were contour ploughing, terracing, crop rotation, cover cropping, agroforestry, and mulching all of which represent cornerstones of early soil management strategies (Alqadhi *et al.*, 2023).

Contour ploughing and terracing

Contour ploughing involves tilling the soil along the natural contours of a slope rather than in straight lines. This method reduces the velocity of water runoff and increases water infiltration into the soil, thereby minimizing erosion. Similarly, terracing transforms sloped land into a series of flat platforms or steps, each acting as a barrier against the gravitational flow of water (Eli-Chukwu, 2019). This practice has been pivotal in hilly regions, notably in the Andes and Southeast Asia, where it not only curbs soil erosion but also enhances arable land availability. Terracing also allows for better moisture retention and a reduced rate of nutrient leaching, particularly in monsoon-prone regions (Ullah *et al.*, 2025). The hydrological principles underlying contour and terraced farming can be mathematically expressed through the Universal Soil Loss Equation (USLE):

$$A = R \cdot K \cdot LS \cdot C \cdot P$$

Where,
A = estimated soil loss (tons/acre/year),
R = rainfall-runoff erosivity factor,
K = soil erodibility factor,
LS = slope length and steepness factor (significantly reduced through terracing),
C = cover management factor,
P = support practice factor (e.g., contouring, terracing).

Assume, $R = 450, K = 0.3, LS = 1.2, C = 0.25, P = 0.9, A = 450 \cdot 0.3 \cdot 1.2 \cdot 0.25 \cdot 0.9 = 36.45$ *ton/ha/year*

Thus, the AI system predicts significant erosion risk requiring mitigation.

Crop rotation and cover cropping

Crop rotation refers to the systematic planting of different crops in a particular order on the same field across seasons. This method interrupts pest and disease cycles, enhances soil structure, and improves nutrient cycling, especially nitrogen balance in the case of legumes (Table 1). Cover cropping, on the other hand, involves growing crops such as clover or rye not for harvest but to cover the soil, thus preventing erosion, suppressing weeds, and enhancing organic matter content (Mishra, 2025). These practices are biophysically efficient and economically viable, as they optimize the natural nutrient availability and mitigate the need for chemical fertilizers. Moreover, leguminous cover crops have been found to increase nitrogen fixation by up to 30-60 kg/ha, depending on the species and soil conditions. The synergy between crop roots and microbial activities also improves aggregate stability and soil porosity (Jiang *et al.*, 2024).

Agroforestry and mulching techniques

Agroforestry the intentional integration of trees with crops and/or livestock-provides multiple ecological benefits, including enhanced biodiversity, improved water retention, windbreaks, and organic matter accumulation. Deep-rooted trees help in nutrient cycling by accessing nutrients from deeper layers of soil, while their leaf litter contributes to humus formation (Pachot & Patissier, 2022; Pawar *et al.*, 2023). Mulching, which involves applying organic or inorganic materials over the soil surface, plays a critical role in conserving moisture, moderating soil temperature, and reducing erosion. Organic mulches, such as straw or compost, decompose over time and enrich the soil. Quantitatively, mulching can reduce water evaporation by 25-50% and soil loss by up to 90%, depending on slope and rainfall intensity (McCracken & Cate, 1986). These practices exemplify the deep ecological insights embedded in traditional soil conservation and form the conceptual groundwork for later technological interventions.

Transition towards Technological Interventions

While traditional practices provided foundational stability to soil ecosystems, the demands of growing populations, intensified agriculture, and climate variability necessitated the integration of more precise and scalable solutions. The transition from manual, observation-based techniques to mechanized and technology-driven methods marked a turning point in soil conservation history (Mishra & Dwivedi, 2025b). This period witnessed the emergence of mechanization, the utilization of geospatial tools such as remote sensing and Geographic Information Systems (GIS), and the advent of precision agriculture. These innovations significantly enhanced the ability to monitor, manage, and model soil health on a large scale (Awais *et al.*, 2023).

Mechanization in soil management

Mechanization introduced efficiency and scalability to soil conservation efforts. The development of specialized machinery such as chisel ploughs, conservation tillage equipment, and residue management implements allowed for minimal disturbance to the soil profile, preservation of soil structure, and reduction of compaction (Silva *et al.*, 2025). Conservation tillage, for example, leaves at least 30% of the soil surface covered with crop residue post-planting, which reduces erosion and improves moisture retention. The mechanical soil penetrometer and tractor-mounted soil samplers further enabled systematic assessment of soil compaction and nutrient status (Isabelle & Westerlund, 2022). However, while mechanization improved operational efficiency, it also brought challenges such as fuel dependence and potential overuse, which underscored the need for balanced integration with ecological practices.

Role of remote sensing and GIS

Remote sensing and GIS have revolutionized soil conservation by offering real-time, spatially explicit data for informed decision-making. Satellite imagery and drone-based sensors can detect vegetation cover, soil moisture levels, erosion patterns, and land-use changes over vast geographical extents. GIS platforms facilitate the overlay of multiple spatial layers, such as soil type, topography, land cover, and rainfall data, to generate erosion risk maps, soil fertility assessments, and conservation priority zones. These tools enhance the predictive capability of conservation planning and resource allocation (Vinay *et al.*, 2022; Barathkumar *et al.*, 2025). For instance, the Normalized Difference Vegetation Index (NDVI) derived from remote sensing data is frequently used to monitor vegetation health, indirectly reflecting soil conditions:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where,
NIR = Near-Infrared reflectance,
RED = Red band reflectance.

Table 1: Comparative overview of traditional soil conservation methods

S. No.	Method	Description	Benefits	Limitations
1	Contour Ploughing	Ploughing along contour lines	Reduces erosion	Labour-dependent
2	Terracing	Creating steps on slopes	Prevents runoff	High construction cost
3	Crop Rotation	Rotating different crops	Enhances fertility	Requires planning
4	Cover Cropping	Planting cover crops	Prevents soil exposure	Seasonal suitability needed
5	Agroforestry	Integrating trees with crops	Improves biodiversity	Land competition
6	Mulching	Covering soil with organic matter	Moisture retention	Resource availability

Source: Authors' compilation

Higher NDVI values generally indicate healthy vegetation and, by extension, healthier soil conditions (Tiwari *et al.*, 2023).

Precision agriculture as a precursor to AI integration

Precision agriculture represents a critical transitional phase between traditional and AI-driven soil conservation. Utilizing GPS, sensors, VRT, and big data analytics, precision agriculture allows farmers to apply inputs such as water, fertilizers, and pesticides with pinpoint accuracy, reducing wastage and environmental degradation. Soil sensors can now measure parameters like pH, electrical conductivity, and organic carbon content in real-time (Liu *et al.*, 2025). The resulting data, when processed through decision-support systems, facilitates site-specific soil conservation interventions. This approach not only maximizes resource use efficiency but also fosters sustainable land management. Importantly, the data-intensive nature of precision agriculture has laid the groundwork for the integration of AI. ML models, trained on historical and real-time datasets from precision agriculture, are now capable of predicting soil degradation, recommending conservation strategies, and automating soil health monitoring (Singh *et al.*, 2022; Singh & Kaur, 2022).

FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE

The integration of AI into agriculture marks a transformative phase in the domain of soil conservation and sustainable land management. Traditionally reliant on empirical knowledge and manual monitoring, the field now finds itself empowered by computational intelligence capable of processing vast volumes of environmental data with unprecedented speed and precision.

Overview of AI Concepts Relevant to Agriculture

AI encompasses a broad set of computational techniques that enable machines to perform tasks typically requiring human intelligence. Within agriculture, and specifically in soil conservation, AI technologies are tailored to analyse complex soil behaviour, predict erosion risks, classify land use, and guide precision interventions (Díaz-González *et al.*, 2022).

Machine learning and deep learning

Machine learning represents a core subset of AI that allows systems to learn from data and improve over time without being explicitly programmed. It includes supervised learning (where models are trained on labelled data), unsupervised learning (for pattern discovery in unlabelled data), and reinforcement learning (where agents learn optimal behaviours through trial and error) (Ruiz *et al.*, 2023; Kim *et al.*, 2024). Deep Learning, a subset of ML, uses multi-layered neural networks to model high-level abstractions. Convolutional Neural Networks (CNNs), for instance, are especially effective in soil texture classification through image analysis. For example, let us consider a supervised regression model to predict Soil Organic Carbon (SOC) based on inputs like soil pH, texture, moisture, and nitrogen content (Rai *et al.*, 2023).

A commonly used ML model is the Multiple Linear Regression:

$$SOC = \beta_0 + \beta_1 \cdot pH + \beta_2 \cdot Texture + \beta_3 \cdot Moisture + \beta_4 \cdot Nitrogen + \epsilon$$

Assume a simplified dataset with:

- pH = 6.5
- Texture = 3 (sandy loam scale)
- Moisture = 21%
- Nitrogen = 0.45%

Let the learned parameters be:

$\beta_0 = 0.2, \beta_1 = 0.15, \beta_3 = 0.02, \beta_4 = 0.5$

$SOC = 0.2 + (0.15 \times 6.5) + (0.05 \times 3) + (0.02 \times 21) + (0.5 \times 0.45)$
$= 0.2 + 0.975 + 0.15 + 0.42 + 0.225 = 1.97$

Thus, predicted $SOC = 1.97\%$, indicating healthy organic matter content.

Computer vision and image processing

Computer Vision (CV) enables machines to interpret and make decisions based on visual data, particularly useful in soil monitoring through aerial and satellite imagery. Image processing techniques enhance raw imagery by filtering noise, improving resolution, and highlighting soil features such as compaction, cracks, or erosion patterns (Bannerjee *et al.*, 2018). One widely applied method in image processing is NDVI, which is derived from spectral reflectance measurements in the red and near-infrared bands. For example, if a satellite image shows $NIR = 0.6$ and $RED = 0.3$, then:

$$NDVI = \frac{(0.6 - 0.3)}{(0.6 + 0.3)} = \frac{0.3}{0.9} = 0.333$$

An NDVI of 0.333 indicates moderate vegetation cover, which correlates with soil stability and less erosion risk. Through such metrics, computer vision facilitates proactive soil conservation by providing early warnings of degradation.

Expert systems and decision support tools

Expert systems are computer applications that mimic human expert reasoning in solving complex problems. In agriculture, these systems are tailored to guide farmers and land managers in making informed decisions related to crop rotation, fertilizer application, and erosion control (Liu *et al.*, 2024). These systems consist of:

- A knowledge base (rules and facts derived from agronomic research),
- An inference engine (logic that applies rules to data),
- A user interface (to communicate with users).

For example, an expert system designed to detect soil salinity may use rules such as:

- IF EC (electrical conductivity) >4 dS/m and pH > 8.5, then soil is saline-sodic.

Such systems reduce dependency on constant expert supervision and allow for scalable, region-specific soil conservation strategies.

Data Sources and Infrastructure Requirements

The success of AI applications in agriculture hinges on the availability of diverse, high-quality datasets and the infrastructure to collect, store, and process them. Modern agriculture is increasingly data-intensive, with information being captured from satellites, drones, field sensors, and farm machinery (Tziolas *et al.*, 2021).

Satellite and UAV imagery

Satellites such as Sentinel-2, Landsat 8, and commercial platforms like Planet Labs deliver multispectral and hyperspectral imagery critical for large-scale soil assessment. Drones or Unmanned Aerial Vehicles (UAVs) augment this data with higher spatial resolution and flexible deployment schedules. Imagery enables:

- Monitoring erosion gullies
- Identifying compaction zones
- Mapping soil moisture variability

Through AI-based image classification (e.g., using Support Vector Machines or CNNs), these data sources yield precise and timely insights for conservation planning (Mishra & Mishra 2024a).

IoT sensors and real-time monitoring

IoT refers to interconnected sensors and devices that continuously collect soil and environmental data. Soil moisture sensors, temperature probes, and pH meters deployed across fields generate real-time data for AI systems to analyse.

This real-time responsiveness is vital in preventing degradation and optimizing soil input use.

Big data platforms and cloud integration

AI applications in soil conservation generate and rely upon massive datasets. Big Data platforms like Apache Hadoop or Spark facilitate the storage, processing, and analysis of this information. Cloud services (e.g., AWS, Google Cloud, Azure) offer scalable infrastructure to handle data integration from remote sensing, sensors, and historical databases. Cloud-based AI platforms allow:

- Parallel processing of thousands of geospatial files
- Secure and shared data access for researchers
- Integration with mobile decision-support apps

Moreover, with edge computing, initial data filtering and analysis can be conducted at the data collection site, significantly reducing latency and improving efficiency (Chisom *et al.*, 2024; Mishra, 2024).

AI-BASED SOIL MONITORING AND DIAGNOSTICS

AI has emerged as a transformative force in soil conservation by enabling precise, real-time, and scalable soil monitoring and diagnostics. Traditional soil assessments relied heavily on manual sampling, laboratory analyses, and laborious interpretation. In contrast, AI-based systems integrate data from sensors, satellites, and historical datasets, processing them with ML and deep learning algorithms to produce high-resolution and dynamic assessments of soil properties. This paradigm shift offers significant potential for improving agricultural sustainability, preventing land degradation, and enhancing decision-making in conservation practices.

Soil Property Mapping and Characterization

Accurate mapping and characterization of soil properties form the bedrock of sustainable land management. AI techniques like Artificial Neural Networks (ANNs), CNNs, Support Vector Machines (SVMs), and ensemble methods are extensively used to predict various physical and chemical parameters with high spatial and temporal resolution. Figure 1 illustrates a generalized AI-based framework for soil property mapping and analysis, showcasing data input sources, model types, and output parameters relevant to soil assessment tasks. A brief overview of commonly used AI techniques, corresponding soil properties, data sources, and performance levels is presented in Table 2.

Texture, structure, and pH prediction

Soil texture and structure are critical indicators of water retention, aeration, and fertility. AI models can predict texture class (sand, silt, clay proportions) using hyperspectral reflectance data, topographic variables, and weather patterns. A popular model used is the Multivariate Adaptive Regression Splines (MARS), which offers non-linear relationships among multiple soil inputs (Haq *et al.*, 2024). For example, Let,

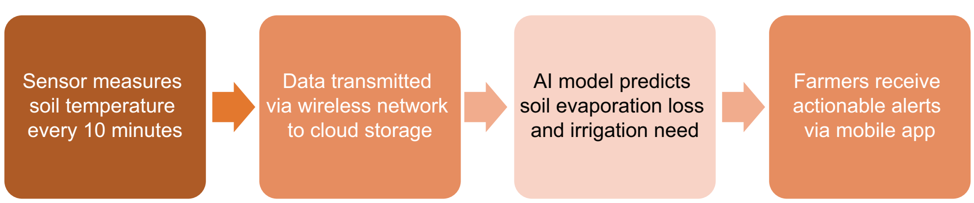

Figure 1: Data flow process for soil temperature monitoring and irrigation alerts

Table 2: AI techniques and their applications in soil property analysis

S. No.	Soil property	AI technique used	Data source	Accuracy level (%)
1	Soil Texture	SVM, Random Forest	UAV/Satellite Imagery	85-90
2	Soil pH	Regression Models	IoT Sensors, Field Data	80-88
3	Organic Carbon	Neural Networks	Spectral Data	82-91
4	Soil Moisture	CNNs, Time Series Forecasting	Remote Sensing, IoT	87-92

Source: Authors' compilation

y = % clay
x_1 = reflectance at band 1
x_2 = slope
x_3 = rainfall

A generalized MARS model:

$$y = \beta_0 + \sum_{m=1}^{M} \beta_m \cdot h_m(x)$$

Where $h_m(x)$ is a basis function formed by piecewise linear splines, and β_m are the coefficients.

For example, suppose a region has:

$$x_1 = 0.34, x_2 = 5.6°, x_3 = 950 \text{ mm}$$

Using the trained MARS model:
$y = 3.2 + 0.5 \cdot \max(0, x_1 - 0.30) - 0.1 \cdot \max(0{,}0.30 - x_1) + 0.04 \cdot x_2 + 0.002 \cdot x_3$

Substitute values:
$= 3.2 + 0.5 \cdot (0.34 - 0.30) + 0 + 0.04 \cdot 5.6 + 0.002 \cdot 950 = 3.2 + 0.5 \cdot 0.04 + 0.224 + 1.9$
$= 3.2 + 0.02 + 0.224 + 1.9 = 5.344\%$

Hence, the clay content is approximately 5.34%.

pH prediction uses Gaussian Process Regression (GPR) or Long Short-Term Memory (LSTM) networks, incorporating spatial autocorrelation.

Organic carbon and nutrient analysis

SOC is a primary indicator of soil health. AI models estimate SOC content from multispectral images and in-situ sensor data. A widely used method is Random Forest Regression (RFR), where features such as vegetation indices (NDVI), elevation, and reflectance values are used, (SOC estimation - RFR):

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x)$$

Where,
B is the number of trees
$T_b(x)$ is the prediction from the b-th tree for input vector x

For example, let's assume the model has 3 trees that output predictions: 1.5%, 1.7%, and 1.6%.

$$\hat{y} = \frac{1.5 + 1.7 + 1.6}{3} = \frac{4.8}{3} = 1.6\%$$

Thus, the SOC is predicted to be 1.6%. Nutrient analysis (e.g., N, P, K content) can be performed using Deep Neural Networks (DNNs), which learn hierarchical patterns from spectral and agronomic datasets.

Soil moisture estimation models

Soil moisture is vital for crop health, erosion control, and hydrological modelling. AI-based models like LSTM networks and hybrid CNN-LSTM architectures are employed due to their capability to model temporal sequences, (simplified LSTM cell):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1)}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

For example, let's assume:

$x_t = 0.7$, $h_{t-1} = 0.3$, weights and biases are such that:

$$f_t = 0.8, i_t = 0.6, \tilde{C}_t = 0.5, C_{t-1} = 0.4$$

Then:

$$C_t = 0.8 \cdot 0.4 + 0.6 \cdot 0.5 = 0.32 + 0.3 = 0.62$$

Soil moisture at time t is influenced by memory cell $C_t = 0.62$, indicating moderate moisture availability.

AI in Soil Health Assessment

AI enables systematic evaluation of soil health by combining dynamic data inputs with learning algorithms that detect patterns, forecast trends, and facilitate targeted interventions.

Identifying degradation and erosion risks

Soil degradation, including compaction, salinization, and erosion, is assessed using AI-integrated remote sensing data. CNNs analyse spatial patterns while Decision Trees (DTs) classify regions by degradation severity.

Predictive modelling for soil fertility

AI models like Gradient Boosting Machines (GBMs) and XGBoost can predict soil fertility status by analysing multidimensional features: crop yield history, microbial data, and previous input applications (gradient boosting - fertility index):

$$\hat{y} = \sum_{m=1}^{M} \gamma_m h_m(x)$$

Where γ_m is the weight and h_m is the weak learner.

For example, let: $h_1(x) = 60$, $h_2(x) = 50$, $h_3(x) = 40$

Weights: $\gamma_1 = 0.5$, $\gamma_2 = 0.3$, $\gamma_3 = 0.2$

Then: $\hat{y} = 0.5 \cdot 60 + 0.3 \cdot 50 + 0.2 \cdot 40 = 30 + 15 + 8 = 53$

Soil fertility index is 53/100, suggesting moderate fertility requiring improvement.

Real-time diagnostics using AI algorithms

AI-powered platforms now enable real-time monitoring via edge devices and cloud computing. Algorithms process data from sensors (pH, EC, NPK levels) and offer on-the-go diagnostics through mobile apps and dashboards. Models like k-Nearest Neighbours (kNN), ensemble deep learning, and transformer architectures are applied to provide alerts on nutrient deficiencies, salinity, or pest risk (Padarian *et al.*, 2020; Rastogi *et al.*, 2024). For example, an AI diagnostic system may use sensor data:

pH: 5.2, EC: 2.1 dS/m, N: Low, P: Medium, K: Low

The AI suggests:
- Liming to raise pH to 6.5
- Apply 50 kg/ha urea and 30 kg/ha muriate of potash
- Increase organic matter to improve nutrient buffering

Such systems drastically reduce decision latency and enhance soil conservation efficiency.

AI-DRIVEN DECISION SUPPORT SYSTEMS FOR SOIL MANAGEMENT

AI has transformed the decision-making processes in modern agriculture, particularly in soil conservation practices. The integration of AI into DSS enables real-time, data-driven recommendations that allow farmers and policymakers to act precisely and efficiently. These AI-driven systems leverage large-scale datasets from sensors, satellite imagery, and historical data to offer predictive insights for sustainable soil management. Not only do these tools enhance productivity and resource-use efficiency, but they also provide a mechanism for conserving soil health over long temporal scales (Padma & Don, 2022).

Site-Specific Soil Management Planning

AI plays a pivotal role in tailoring soil management strategies to specific field conditions. This concept, commonly referred to as Site-Specific Soil Management (SSSM), involves the application of distinct management practices based on intra-field variability. AI algorithms analyse spatial and temporal datasets to develop localized prescriptions for various soil parameters such as nutrient levels, pH, and organic matter (Kerry *et al.*, 2022; Janjua *et al.*, 2025). A central component of SSSM is the use of VRT, which enables precise and data-driven input applications for enhancing soil health and agricultural productivity. The range of VRT applications in modern agriculture has expanded significantly with the integration of AI tools (Samaniego & Gallego, 2024). These applications include fertilizer and lime application, tillage adjustments, irrigation scheduling, pesticide usage, and organic amendment management each tailored to specific soil conditions and supported by geospatial and sensor data (Table 3).

Variable rate technology (VRT) recommendations

One of the most profound applications of AI in soil conservation is in the implementation of VRT. It allows inputs such as

Table 3: Variable rate technology applications in agriculture

S. No.	Application area	Type of VRT used	Benefits	Required data inputs	Example tools/platforms
1	Fertilizer Application	GPS-guided spreaders	Optimized nutrient use, reduced leaching	Soil fertility maps, crop nutrient demand	Trimble Ag Software, Ag Leader VRT
2	Irrigation Scheduling	Sensor-based drip/ sprinkler systems	Water use efficiency, reduced salinity risks	Soil moisture sensors, evapotranspiration data	AquaSpy, Netafim, Jain Logic
3	Tillage Operations	Adaptive tillage systems	Reduced fuel usage, minimized soil compaction	Soil texture, compaction levels, past yield data	John Deere AutoTrac, Case IH AFS
4	Lime Application	Prescription lime spreaders	pH balancing for optimal nutrient uptake	Soil pH maps	Raven Viper 4, Ag Leader InCommand
5	Pesticide Application	VRT sprayers	Targeted pest control, reduced chemical usage	Pest mapping, crop health indices (NDVI)	Blue River Technology, DJI Agras
6	Seeding/Planting	Variable seed rate planters	Seed cost optimization, yield maximization	Yield potential zones, seed variety data	Kinze Planters, Precision Planting
7	Organic Amendment Application	Compost/manure VRT spreaders	Enhanced organic matter, improved soil health	Organic matter levels, crop requirements	John Deere Manure Sensing, Topcon
8	Gypsum Application	Rate-controlled spreaders	Soil structure improvement, salinity control	Soil sodium and calcium levels	Trimble Field-IQ, VRT Mapping Software
9	Cover Crop Seeding	Variable rate drills	Soil protection, improved nutrient cycling	Erosion risk zones, fallow period assessment	SeedCommand, Climate FieldView

Source: Authors' compilation

fertilizers, lime, and amendments to be applied at variable rates across a field, depending on the soil's condition. AI models use multivariate regression algorithms and deep learning frameworks to generate optimal input maps (Mishra & Mishra, 2024b; Mishra & Dwivedi, 2025). Let us consider a multivariate regression model used to recommend nitrogen application:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$$

Where,
Y = recommended nitrogen rate (kg/ha)
x_1 = soil organic matter (%)
x_2 = previous crop nitrogen uptake (kg/ha)
x_3 = moisture content (%)
$\beta_0, \beta_1, \beta_2, \beta_3$ = model coefficients
ϵ = error term

For example, suppose the AI model yields the following coefficients:

$$\beta_0 = 25, \beta_1 = 10, \beta_2 = 0.2, \beta_3 = -1$$

And we input: $x_1 = 2.5\%, x_2 = 150\ kg/ha, x_3 = 15\%$
Then, $Y = 25 + 10(2.5) + 0.2(150) - 1(15)$
$= 25 + 25 + 30 – 15$
$= 65\ kg/ha$

Hence, the AI-driven VRT recommendation for nitrogen application is 65 kg/ha for that specific grid location.

Adaptive tillage and irrigation scheduling

AI enhances tillage and irrigation planning by identifying optimal timings and intensities based on soil compaction data, moisture retention, and evapotranspiration forecasts. Recurrent Neural Networks (RNN) and LSTM networks are employed to analyse time-series weather data and soil sensor inputs for adaptive planning (Yin *et al.*, 2021). For instance, irrigation decisions can be supported by FAO's Penman-Monteith equation, adapted for AI systems:

$$ET_0 = \frac{0.408\Delta\left(R_n - G\right) + \gamma \frac{900}{T+273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

Where,
ET_0 = reference evapotranspiration (mm/day)
Δ = slope of vapor pressure curve (kPa/°C)
R_n = net radiation (MJ/m²/day)
G = soil heat flux (MJ/m²/day)
T = mean air temperature (°C)
u_2 = wind speed at 2 m height (m/s)
e_s and e_a = saturation and actual vapor pressure (kPa)
γ = psychrometric constant (kPa/°C)

For example, let us assume:

$$\Delta = 0.4, R_n = 15, G = 1, \gamma = 0.65, T = 25, u_2 = 2, e_s = 2.3, e_a = 1.5$$

Substituting into the equation:

$$ET_0 = \frac{0.408 \times (15-1) + 0.65 \times \frac{900}{298} \times 2 \times (2.3 - 1.5)}{0.4 + 0.65(1 + 0.34 \times 2)}$$

$$ET_0 = \frac{0.408 \times 14 + 0.65 \times 3.02 \times 2 \times 0.8}{0.4 + 0.65 \times (1.68)}$$

$$ET_0 = \frac{5.712 + 3.14}{0.4 + 1.092} = \frac{8.852}{1.492} \approx 5.93\, mm/day$$

The AI-based system would use this estimate to decide when irrigation is necessary and in what quantity.

Risk Assessment and Forecasting

AI-based DSS plays a vital role in identifying potential threats to soil health by analysing historic and real-time data. Risk forecasting enables proactive rather than reactive strategies in land management.

Erosion and runoff prediction models

AI-integrated erosion prediction has evolved from simple empirical methods to hybrid, process-based modelling frameworks. Among such frameworks, the Modified Morgan–Morgan–Finney (MMMF) model has emerged as a sophisticated alternative. It captures the physical interactions between rainfall, soil properties, vegetation, and topography. AI can enhance this model by dynamically optimizing parameter values using real-time sensor and satellite data, yielding more accurate erosion forecasts (Balaska *et al.*, 2023; Gairola *et al.*, 2023). The core sediment loss equation in the MMMF model is given by:

$$SL = \frac{(R \cdot E \cdot K_s \cdot S \cdot P_v)}{(g \cdot d \cdot \rho_b)}$$

Where,
SL = predicted annual sediment loss (kg/m²/year)
R = rainfall energy (J/m²)
E = effective rainfall (dimensionless, 0–1)
K_s = soil detachability index (kg/J)
S = slope factor (dimensionless)
P_v = vegetation cover factor (0–1)
g = acceleration due to gravity (9.81 m/s²)
d = slope length (m)
ρ_b = soil bulk density (kg/m³)

This equation can be decomposed into AI-predictable parameters. For instance, rainfall energy R can be computed from rainfall intensity and duration using:

$$R = 0.29 \cdot (1 - 0.72 \cdot e^{-0.05I}))$$

Where, I = rainfall intensity (mm/h)

For example, let us assume the following field data collected via AI-monitored weather and soil stations:

Rainfall Intensity: $I = 40\,\text{mm/h}$
Effective rainfall, $E = 0.85$
Soil detachability, $K_s = 0.003\,\text{kg/J}$
Slope factor, $S = 1.2$
Vegetation factor, $P_v = 0.4$
Slope length, $d = 20\,\text{m}$
Soil bulk density, $\rho_b = 1300\,\text{kg/m}^3$
irst, compute rainfall energy RRR:

$$R = 0.29 \cdot (1 - 0.72 \cdot e^{-0.05 \cdot 40}) = 0.29 \cdot (1 - 0.72 \cdot e^{-2})$$

$$= 0.29 \cdot (1 - 0.72 \cdot 0.1353) = 0.29 \cdot (1 - 0.0974) = 0.29 \cdot 0.9026 \approx 0.2618\ J/m^2$$

Now substitute all values into the sediment loss equation:

$$SL = \frac{(0.2618 \cdot 0.85 \cdot 0.003 \cdot 1.2 \cdot 0.4)}{(9.81 \cdot 20 \cdot 1300)}$$

$$= \frac{(0.2618 \cdot 0.85 \cdot 0.003 \cdot 1.2 \cdot 0.4)}{(254{,}520)} = \frac{0.0003205}{254{,}520}$$

$$\approx 1.26 \times 10^{-9}\ kg / m^2 / year$$

This indicates a very low sediment loss due to effective vegetation and slope control. AI systems trained with such inputs can optimize ground cover or slope stabilization strategies by learning from historical degradation patterns and providing proactive alerts. By using the MMMF model, integrated with AI, land managers are equipped with a more physically realistic and adaptable tool for predicting soil erosion and runoff (Kumari & Pandey, 2023). This method not only accounts for surface dynamics but also interfaces naturally with AI techniques such as time-series forecasting and remote sensing image classification, ensuring continuous monitoring and real-time adjustment of conservation practices.

Land degradation forecasting tools

AI integrates satellite data (e.g., NDVI, NDWI) and historical land use records to identify patterns of degradation using CNNs and Time Series Classification (TSC) models. These tools identify early symptoms of land degradation such as vegetation decline, soil discoloration, and organic matter depletion.

Integration with Farm Management Systems

The effectiveness of AI in soil management is significantly enhanced through seamless integration with broader Farm Management Systems (FMS), which serve as centralized platforms for collecting, analysing, and visualizing farm data.

AI-augmented decision platforms

Modern FMSs embed AI modules to automate decision-making across multiple soil management domains. These platforms use Bayesian networks for uncertainty modelling and integrate spatial analytics with economic models to suggest optimal strategies (Holzinger *et al.*, 2023). For instance, the Bayesian Inference Formula for updating soil pH prediction based on sensor readings is:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)}$$

$P(H|E)$ = probability of hypothesis (e.g., soil pH is acidic) given evidence
$P(E|H)$ = likelihood of evidence under the hypothesis
$P(H)$ = prior probability of the hypothesis
$P(E)$ = total probability of the evidence

For example, assume: $P(E|H) = 0.9$, $P(H) = 0.6$, $P(E) = 0.75$

$$P(H|E) = \frac{0.9 \times 0.6}{0.75} = \frac{0.54}{0.75} = 0.72$$

Thus, based on sensor evidence, there is a 72% probability that the soil is acidic, guiding lime application decisions.

User interfaces and stakeholder engagement

Finally, user-centric dashboards and mobile apps powered by Natural Language Processing (NLP) and AI-based query systems ensure the accessibility of DSS outputs. These interfaces translate complex data analytics into actionable insights for diverse stakeholders, including smallholder farmers, extension workers, and policymakers. AI-Driven DSS represent a paradigm shift in soil conservation by offering site-specific, timely, and evidence-based recommendations. Through complex models, large-scale computations, and human-centric interfaces, these systems serve as essential tools in the sustainable management of one of our planet's most critical natural resources: the soil (Talaviya *et al.*, 2020; Huang & Li, 2024).

AI IN SOIL CONSERVATION POLICY AND GOVERNANCE

The integration of AI into soil conservation policy and governance frameworks marks a paradigm shift from conventional, reactive environmental management to a more proactive and predictive paradigm. This shift leverages data science, ML, and geospatial analytics to support evidence-based policymaking and ensure regulatory compliance at scale (Ahmed *et al.*, 2023). The evolving landscape of AI has not only facilitated the analysis of complex ecological datasets but has also enabled decision-makers to generate timely, precise, and adaptive conservation strategies. These developments are crucial in an era of accelerated land degradation, growing population pressure, and climate volatility.

Data-Driven Policy Formulation

AI-driven data analytics transforms the way policymakers conceptualize and implement conservation measures by synthesizing large-scale spatial, temporal, and categorical data into actionable insights. ML algorithms can detect correlations and trends within heterogeneous datasets such as remote sensing imagery, soil quality indices, cropping patterns, and climatic variables. Such insights inform both macro-level decisions (e.g., regional zoning laws) and micro-level interventions (e.g., farm-level conservation practices) (Pérez Santín *et al.*, 2021).

Land use planning and zoning regulations

AI facilitates dynamic land use planning through the development of intelligent zoning models. These models integrate satellite imagery, topographical data, historical land degradation records, and socio-economic indicators to delineate zones based on conservation priority. For instance, a SVM-based land classification model can be trained using labelled satellite imagery data to predict zones susceptible to erosion or nutrient depletion (Chen *et al.*, 2008; Nishad *et al.*, 2023). Let us consider a classification model $f(x)$ that predicts land suitability:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Where,
x is the input vector of land features (soil pH, slope, NDVI, etc.),
α_i are learned weights,
y_i are labels (+1 for conservation priority, -1 for not),
$K(x_i,x)$ is the kernel function (e.g., RBF),
b is the bias term.

For example, assume we have three land parcels with features and outcomes:

$$x_1 = (6.5,12), y_1 = +1$$
$$x_2 = (4.2,5), y_2 = -1$$
$$x_3 = (7.0,10), y_3 = +1$$

With RBF kernel $K(xi,x) = \exp(-\gamma \|x_i - x\|^2), \gamma=0.1$ and learned $\alpha = [0.8,0.6,0.7]$, $b = -0.2$, we want to predict a new parcel with $x = (6.8,11)$.

Step-by-step calculation:

1. Calculate each kernel:
   $K(x1,x) = exp(-0.1[(6.5-6.8)^2 + (12-11)^2]) = exp(-0.1[0.09+1]) = exp(-0.109) \approx 0.896$
   $K(x_2,x) = exp(-0.1[(4.2-6.8)^2 + (5-11)^2]) = exp(-0.1[6.76+36]) = exp(-4.276) \approx 0.014$
   $K(x_3,x) = exp(-0.1[(7.0-6.8)^2 + (10-11)^2]) = exp(-0.1[0.04+1]) = exp(-0.104) \approx 0.901$
2. Plug values into the equation:
   $f(x) = sign(0.8 \cdot (+1) \cdot 0.896 + 0.6 \cdot (-1) \cdot 0.014 + 0.7 \cdot (+1) \cdot 0.901 - 0.2)$
   $f(x) = sign(0.7168 - 0.0084 + 0.6307 - 0.2) = sign(1.1391)$
   $\Rightarrow f(x) = +1$ (*conservation priority*)

This classification can then guide zoning decisions, such as restricting intensive agriculture in erosion-prone areas and incentivizing sustainable land use.

Monitoring compliance with conservation norms

AI-enabled remote sensing and edge computing devices facilitate real-time monitoring of agricultural fields to detect deviations from prescribed conservation norms. For instance, illegal deforestation, excessive tillage, or unregulated fertilizer use can be captured through anomaly detection algorithms applied to multispectral or hyperspectral imagery (Mishra, 2025). CNNs, often used for image recognition, play a pivotal role in interpreting satellite images to detect such anomalies (Belkadi & Drias, 2022). A CNN can be modelled as:

$$Y = f(W * X + b)$$

Where,
X is the input image (e.g., satellite capture),
W is the weight matrix (filters),
$*$ is the convolution operation,
b is the bias,
f is the activation function (e.g., ReLU).

Such models can automatically flag land parcels violating conservation norms, enabling timely interventions by authorities.

AI for Regulatory Oversight and Reporting

Beyond planning and monitoring, AI plays a vital role in supporting regulatory oversight through automated systems that streamline reporting, detect non-compliance, and enhance transparency. These tools reduce the administrative burden and provide policymakers with digestible insights derived from complex datasets.

Automated compliance tracking systems

AI-driven compliance tracking systems can process large volumes of geo-tagged field data, time-series crop imagery, and soil health metrics to automatically evaluate whether farmers or landowners adhere to government-mandated conservation practices (Wong *et al.*, 2021). Let us consider a scoring model that evaluates compliance:

$$C = \frac{1}{n}\sum_{i=1}^{n} w_i \cdot m_i$$

Where,
C is the compliance score (0 to 1),
w_i is the weight of the i^{th} metric (e.g., no-till adherence, cover cropping, soil organic matter retention),
m_i is the normalized metric value,
n is the total number of monitored metrics.

Example: Suppose a farmer's field is evaluated on 3 metrics:
- No-till practice (weight = 0.4, metric = 0.9),
- Organic cover usage (weight = 0.3, metric = 0.8),
- Soil carbon retention (weight = 0.3, metric = 0.6),

Then:

$$C = (0.4 \cdot 0.9) + (0.3 \cdot 0.8) + (0.3 \cdot 0.6) = 0.36 + 0.24 + 0.18 = 0.78$$

This score (78%) could be used to classify the farmer as "Compliant," "Partially Compliant," or "Non-Compliant" according to thresholds.

Visualization dashboards for policymakers

AI-integrated dashboards offer high-level visual summaries for decision-makers by aggregating, analysing, and rendering conservation performance indicators across districts, states, or countries (Huang *et al.*, 2022). These dashboards commonly integrate GIS, AI-analytics, and big data platforms to deliver insights such as:

- Real-time maps of soil erosion hotspots,
- Predictive alerts for conservation failure risks,
- Comparative metrics on conservation program performance.

These visual tools often leverage dimensionality reduction techniques such as Principal Component Analysis (PCA) or t-SNE to reduce complexity and make trends visible. For example, PCA reduces a dataset $X \in R^{n \times p}$ (with p features) into k components by computing:

$$Z = XW$$

Where,
W is the eigenvectors of the covariance matrix $\sum = \frac{1}{n} X^T X$,
Z is the reduced dataset in new dimensions.

This helps in identifying regional patterns, such as which agro-climatic zones consistently underperform on soil conservation indicators, and thus require policy intervention. The infusion of AI into soil conservation policy and governance is not merely a technological upgrade; it represents a fundamental transformation of environmental stewardship (Kumar *et al.*, 2023). By integrating large-scale data analysis, intelligent monitoring systems, and interactive visual tools, AI offers policymakers and regulators a comprehensive toolkit to enforce compliance, optimize land use planning, and enhance accountability in soil conservation efforts (Pauzi *et al.*, 2025).

ENVIRONMENTAL AND ECOLOGICAL IMPLICATIONS OF AI USE

The application of AI in soil conservation has engendered a paradigm shift in both environmental and ecological management. While AI offers substantial capabilities in enhancing monitoring precision, predictive modelling, and decision-making efficiency, its integration into soil conservation strategies also necessitates a critical examination of its broader environmental and ecological implications (Liu, 2020). These implications can be dichotomized into two central domains: the enhancement of ecosystem services through AI and the mitigation of negative externalities, including ethical, technical, and sustainability concerns. AI, when aligned with ecological frameworks, can support regenerative land practices and sustainable management; however, its misuse or poor design may intensify inequalities and ecological degradation. The subsequent subsections delve into these aspects comprehensively (Rodrigo-Comino *et al.*, 2020; Singh *et al.*, 2024).

Enhancing Ecosystem Services through AI Applications

Soil biodiversity monitoring

Soil biodiversity plays a pivotal role in sustaining ecological equilibrium and productivity. However, traditional methods for biodiversity assessment, such as manual soil sampling and taxonomy-based classification, are labour-oriented and often constrained by spatial and temporal limitations. AI, particularly deep learning and CNNs, has facilitated real-time, large-scale biodiversity surveillance (Pierce, 2018). For instance, AI-powered remote sensing systems integrated with hyperspectral imaging can classify microbial communities based on spectral reflectance indices. The classification is supported by pattern recognition algorithms that process thousands of spectral signatures to identify biodiversity gradients across soil types (Bharti & Bhan, 2018; Richards *et al.*, 2024). A representative model often utilized is the Multivariate Discriminant Function Analysis (MDFA), which discriminates soil organisms by solving:

$$D_k = a_k + \sum_{i=1}^{n} w_{ik} x_i$$

Where,
D_k is the discriminant score for class k,
a_k is the intercept for class k,
w_{ik} are the weights assigned to variable x_i,
x_i denotes the measured biological parameter (e.g., DNA reads, enzyme activity).

For example, suppose the presence of earthworms, nematodes, and microbial biomass are considered as input variables with corresponding values of 20, 35, and 45 respectively, and the weights $w_{i1} = [0.4,0.3,0.5]$ for a microbial richness class $k = 1$, and the intercept $a_1 = 2$.

Then:

$$D_1 = 2 + (0.4 \cdot 20) + (0.3 \cdot 35) + (0.5 \cdot 45) = 2 + 8 + 10.5 + 22.5 = 43$$

A higher discriminant score indicates greater biodiversity richness, which can be mapped across geographic scales using GIS-linked AI platforms.

AI for carbon sequestration analysis

Carbon sequestration, the process by which CO_2 is captured and stored in soil, is a vital ecosystem service for mitigating climate change. AI algorithms are increasingly employed to estimate SOC dynamics with high accuracy. The use of Support Vector Regression (SVR) models, trained with soil texture, land-use, temperature, and precipitation data, has proven effective (Gonzalez *et al*., 2016; Shriwas *et al*., 2024). One widely recognized equation to predict soil carbon storage is derived from the CENTURY Model, simplified as:

$$SOC_t = SOC_0 + \sum_{i=1}^{t}(I_i - D_i)$$

Where,
SOC_t is the soil organic carbon at time t,
SOC_0 is the initial carbon stock,
I_i is the annual carbon input from biomass,
D_i is the carbon decomposition loss.

For example,
Assuming initial SOC (SOC_0) = 12 t/ha,
Annual biomass input I_i = 1.8 t/ha,
Decomposition loss D_i = 1.2 t/ha,

Over 5 years t = 5:

$$SOC_t = 12 + \sum_{i=1}^{5}(1.8 - 1.2) = 12 + 5 \times 0.6 = 12 + 3 = 15t / ha$$

AI tools like Random Forests or GBMs can automate the estimation of these inputs based on satellite data, soil sensors, and agronomic records, improving the accuracy and timeliness of carbon budgeting.

Minimizing Negative Externalities

Ethical use of AI in environmental management

Despite its transformative potential, AI poses ethical dilemmas when deployed without environmental justice considerations. The collection of ecological data often involves vulnerable indigenous communities or protected areas. Therefore, ethical AI design must ensure transparency, inclusivity, and fair data governance. A significant concern is the "black box" nature of many ML models, where decision-making processes are not easily interpretable (Lahoz-Monfort & Magrath, 2021). Explainable AI (XAI) frameworks are being introduced to address this opacity. For example, Shapley Additive Explanations (SHAP) values quantify the contribution of each variable in a predictive model:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!}[f(S \cup \{i\}) - f(S)]$$

Where,
ϕ_i is the SHAP value for feature i,
N is the set of all features,
S is a subset excluding i,
$f(S)$ is the model prediction for subset S.

Although the equation is computationally intensive, it ensures that every variable's effect is fairly attributed. In ecological management, this aids in validating whether model outcomes are justifiable and ecologically sound.

Addressing algorithmic bias and sustainability

Algorithmic bias refers to the systematic and unfair discrimination that arises when AI models learn patterns from imbalanced, incomplete, or non-representative datasets. In the domain of soil conservation, such biases can misguide land degradation assessments, misclassify soil types, or propagate incorrect predictions for carbon sequestration, particularly in underrepresented agro-ecological zones. These limitations not only reduce the efficacy of conservation strategies but may also disproportionately impact marginal farming communities and fragile ecosystems (Ahmad & Nabi, 2021; Prajapati *et al*., 2023). One advanced method for mitigating such bias is through Regularized Logistic Regression (RLR), where a penalty is imposed on model complexity to reduce overfitting and enhance generalizability across diverse ecological contexts. This approach is especially beneficial when dealing with unbalanced datasets common in soil quality assessments - for instance, where degraded samples significantly outnumber healthy ones (Khalid *et al*., 2024; Nishad *et al*., 2024). The RLR loss function with L2 penalty (also called Ridge penalty) is given by:

$$L(w) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}log(h_w(x^{(i)})) + (1 - y^{(i)})log(1 - h_w(x^{(i)}))\right] + \frac{\lambda}{2m}\sum_{j=1}^{n}w_j^2$$

Where,
$L_{(w)}$ is the loss function (to be minimized),
m is the number of training samples,
$y^{(i)}$ is the true label for sample i,
$h_w\left(x^{(i)}\right) = \frac{1}{1 + e^{-w^T x^{(i)}}}$ is the logistic function,
w_j are the model weights (coefficients),
λ is the regularization parameter controlling bias-variance trade-off.

This equation helps the model resist overfitting by penalizing large weights, especially important when some soil types or regions are overrepresented in the training data.

For example, let us assume a simplified scenario for soil degradation prediction using AI based on two features:

- x_1: Soil organic carbon content (scaled),
- x_2: Bulk density (scaled).

We aim to classify a soil sample as degraded (y = 1) or not degraded (y = 0).

Suppose the model parameters are:

- Weight vector w = [0.5,-0.8],
- Feature vector x = [1.2,0.5],
- Regularization parameter λ =0.1
- Training size m = 1 for simplicity.

Step 1: Compute the linear combination:
$z = w^T x = (0.5 \cdot 1.2) + (-0.8 \cdot 0.5) = 0.6 - 0.4 = 0.2$

Step 2: Apply the sigmoid (logistic) function:

$$h_w(x) = \frac{1}{1+e^{-0.2}} \approx \frac{1}{1+0.8187} \approx 0.5498$$

Step 3: Assume actual label y = 1. Compute the logistic loss term:

$$-[y\log(h_w(x)) + (1-y)\log(1-h_w(x))] = -\log(0.5498) \approx 0.598$$

Step 4: Compute the regularization term:

$$\frac{\lambda}{2m}\sum_{j=1}^{2} w_j^2 = \frac{0.1}{2}(0.5^2 + (-0.8)^2) = 0.05 \cdot (0.25 + 0.64) = 0.05 \cdot 0.89 = 0.0445$$

Step 5: Total loss:

$$L(w) = 0.598 + 0.0445 = 0.6425$$

This loss function value guides model optimization (typically through gradient descent) to adjust weights and minimize both prediction error and bias due to overfitting.

Implications for sustainability in soil conservation

By using regularization and penalization strategies like the one above, AI models in soil conservation are made more resilient to overfitting biases that favour well-represented soil classes or regions. This ensures more equitable and accurate predictions, especially when datasets are collected across heterogeneous agro-climatic zones with varying levels of data availability (Tiwari *et al.*, 2011; Mishra & Mishra, 2024c). Furthermore, sustainability considerations in AI systems extend beyond algorithmic fairness to include energy consumption and ecological footprint. Training large AI models requires substantial computational power, often leading to elevated carbon emissions (Kumar *et al.*, 2023). Sustainable AI emphasizes the use of:

- Efficient algorithms (e.g., light gradient boosting machines),
- Cloud computing on green energy platforms, and
- Model distillation techniques to reduce model size without compromising performance.

To measure the energy sustainability of an AI model, a Carbon Emission Estimation Equation is used:

$$E = P \times T \times U$$

Where,
E is the estimated energy consumption (kWh),
P is the power consumption of the hardware (kW),
T is the time the system was active (hours),
U is the hardware utilization rate (fraction between 0 and 1).

For example, if an AI model trains on a GPU consuming 0.8 kW, for 10 hours, at 75% utilization:

$$E = 0.8 \times 10 \times 0.75 = 6\ kWh$$

Assuming 0.5 kg CO_2/kWh emission factor, the total carbon footprint is:

$$6 \times 0.5 = 3 \text{ kg } CO_2$$

By adopting energy-efficient practices, AI developers in the environmental sciences can significantly reduce the carbon burden associated with model training, aligning their computational goals with broader sustainability ethics.

Addressing algorithmic bias and sustainability in AI applications for soil conservation is not merely a technical refinement but a moral imperative. Through the integration of regularization-based models, interpretability techniques, and energy-efficient computations, AI can become both fair and environmentally responsible (Novielli *et al.*, 2024). The rigorous mathematical frameworks, such as regularized loss functions and carbon emission estimates, serve as critical tools to ensure that AI operates not just with intelligence, but with integrity and ecological foresight (Ranjan *et al.*, 2022; Nti *et al.*, 2023).

CHALLENGES AND LIMITATIONS OF AI IN SOIL CONSERVATION

While AI has the transformative potential to revolutionize soil conservation practices through predictive modelling, automation, and intelligent decision-making as illustrated by a systematic workflow in Figure 2, its implementation faces a multitude of barriers. These challenges are both systemic and technical, often requiring interdisciplinary and multi-stakeholder solutions. A summary of some challenges and their respective solutions is presented in Table 4.

Technical and Infrastructure Constraints

Data availability and accuracy issues

One of the primary bottlenecks in the successful implementation of AI in soil conservation is the limited availability and questionable accuracy of spatial, temporal, and textural data. AI algorithms, particularly ML and deep learning models, require extensive datasets to achieve accurate predictive capabilities. Soil properties-such as texture, structure, pH, organic matter content, and moisture levels-are spatially and temporally heterogeneous (Zhang *et al.*, 2021; Obaideen *et al.*, 2022).

Table 4: Challenges in ai implementation for soil conservation and their potential solutions

S. No.	Challenges	Potential solutions
1	Inadequate soil data and ground truthing	Establish integrated soil monitoring networks; use satellite+sensor data fusion
2	Limited internet and digital infrastructure in rural areas	Invest in rural broadband; deploy edge computing and low-power AI hardware
3	Low digital literacy and AI skill gap	Develop farmer-centric AI training programs and localized interfaces
4	Black-box nature of AI models	Adopt XAI and model interpretability frameworks
5	Fragmented data governance and interoperability	Standardize soil data formats; promote open-access platforms and institutional APIs
6	Regulatory and institutional inertia	Introduce AI adoption policies and cross-sectoral governance models

Source: Authors' compilation

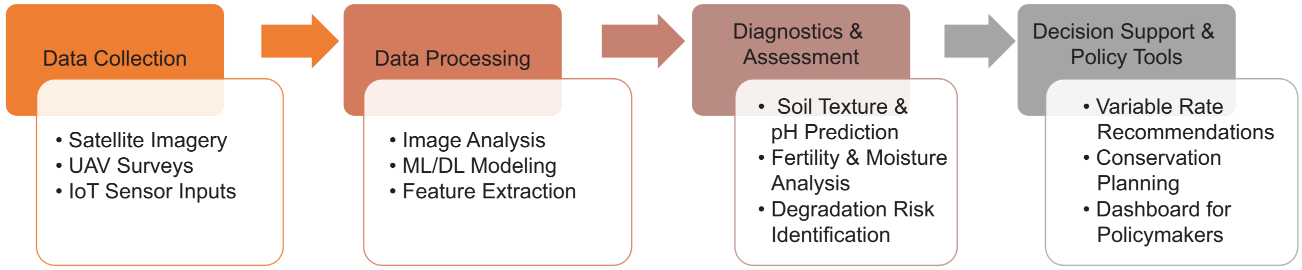

Figure 2: Workflow of AI-based soil conservation

Inadequate data on these variables often results in overfitting or underfitting of AI models, thereby impairing the generalizability of predictions. A mathematical representation of the prediction error in supervised AI models can be understood through the Bias-Variance Trade-off, expressed as:

$$\textit{Total Error} = \textit{Bias}^2 + \textit{Variance} + \textit{Irreducible Error}$$

Where,

- Bias refers to the error due to overly simplistic assumptions in the model.
- Variance reflects the sensitivity of the model to fluctuations in the training dataset.
- Irreducible Error represents noise in the data that cannot be eliminated.

For example, suppose a soil moisture prediction model is trained on data from only five sampling locations. Due to sparse data, the model has a high variance, making it unstable across different regions. If the bias is 4.5 and variance is 3.0, and irreducible error is 1.5:

$$\textit{Total Error} = (4.5)^2 + 3.0 + 1.5 = 20.25 + 3.0 + 1.5 = 24.75$$

This high total error indicates an unreliable model due to insufficient and non-representative data.

Connectivity and hardware limitations in rural areas

The effective deployment of AI applications in soil conservation-such as remote sensing-based diagnostics, sensor-based DSS, and UAV-assisted surveillance-requires robust internet connectivity, advanced computational infrastructure, and real-time data processing units. However, many rural and remote agricultural zones, particularly in developing countries, suffer from poor digital infrastructure (Chan & Huang, 2003). The performance of real-time AI models also depends on edge computing latency, which is mathematically expressed as:

$$\textit{Total Latency} = T_s + T_t + T_p$$

Where,
T_s is the time for sensor data acquisition,
T_t is the time for data transmission,
T_p is the processing time on the AI server or device.

For example, if a soil monitoring system has a sensor acquisition time of 200 ms, data transmission time of 800 ms due to low bandwidth, and processing time of 500 ms:

$$\textit{Total Latency} = 200 + 800 + 500 = 1500\ ms = 1.5\ \textit{seconds}$$

In precision agriculture, a latency of over 1 second can make real-time feedback systems practically ineffective, especially for time-sensitive interventions like irrigation or nutrient application.

Operational and Institutional Barriers

Knowledge gaps and capacity building

A significant constraint in the adoption of AI for soil conservation is the limited digital literacy and technical knowledge among agronomists, soil scientists, and farmers. The usability of AI tools is often contingent on the user's ability to interpret and act upon algorithmic outputs. Bridging this gap requires systematic capacity-building programs and the development of user-friendly AI interfaces (Subeesh & Mehta, 2021; Salehi, 2024). Additionally, model complexity-especially in neural networks-makes interpretability a challenge. Consider a basic ANN model for predicting soil erosion risk based on rainfall intensity, slope gradient, and vegetation cover. The model can be represented by:

$$Y = f\left(\sum_{j=1}^{n} w_j \cdot g\left(\sum_{i=1}^{m} x_i \cdot v_{ij} + b_j\right) + b\right)$$

Where,
x_i = input variables (rainfall, slope, vegetation),
v_{ij} = weights between input and hidden layers,
w_j = weights from hidden to output layers,
g = activation function (e.g., sigmoid),
b_j, b = biases.

For example, assume a model with two inputs (rainfall = 100 mm, slope = 20°), and:

- $v_{11} = 0.1$, $v_{12} = 0.2$, $b_1 = 0.05$
- $w_1 = 0.8$, $b = 0.1$
- Activation function $g(z) = \dfrac{1}{1+e^{-z}}$

Step 1: Compute the input to hidden neuron:

$$z = 100 \cdot 0.1 + 20 \cdot 0.2 + 0.05 = 10 + 4 + 0.05 = 14.05$$

Step 2: Apply the activation function:

$$g(14.05) = \frac{1}{1+e^{-14.05}} \approx 0.9999992$$

Step 3: Output calculation:

$Y = 0.8 \cdot 0.9999992 + 0.1 \approx 0.89999936 + 0.1 = 0.99999936 \approx 1$

This output may imply very high erosion risk, but interpreting such models without adequate training remains a significant obstacle.

Institutional adoption and interoperability issues

Institutional inertia and fragmented governance structures present formidable challenges to the systemic adoption of AI in soil conservation. Many agricultural and environmental institutions continue to rely on traditional data management systems, resulting in a lack of interoperability between AI platforms and existing soil information databases. Moreover, the absence of standardized data protocols, ethical AI guidelines, and data-sharing frameworks impedes collaborative research and policy implementation. Regulatory hesitance in endorsing AI for critical decision-making-such as land-use planning or subsidy disbursement-further slows integration efforts (Mishra *et al.*, 2011; Wani *et al.*, 2024). A quantitative representation of the interoperability challenge can be approached via Shannon's Information Entropy, where a lack of standardization increases uncertainty in system communication:

$$H(X) = -\sum_{i=1}^{n} p(x_i) log_2 p(x_i)$$

Where,
$H(X)$ = entropy of the system,
$p(x_i)$ = probability of occurrence of message x_i.

For example, let consider a system where messages from four different soil databases have probabilities $p(x1) = 0.4$, $p(x2) = 0.3$, $p(x3) = 0.2$, $p(x4) = 0.1$:

$$H(X) = -(0.4 log_2 0.4 + 0.3 log_2 0.3 + 0.2 log_2 0.2 + 0.1 log_2 0.1)$$

$$= -(0.4 \cdot -1.32 + 0.3 \cdot -1.74 + 0.2 \cdot -2.32 + 0.1 \cdot -3.32)$$

$$= -(-0.528 - 0.522 - 0.464 - 0.332) = 1.846 \ bits$$

Higher entropy indicates more complexity and less compatibility among systems, necessitating better standardization efforts.

Economic and Ethical Considerations

Cost-benefit analysis of AI integration

Deploying AI in soil conservation entails significant upfront and recurring costs. These include:

- Equipment purchase (sensors, drones, AI processors)
- Software licensing and customization
- Data acquisition and storage infrastructure
- Training and human resource development

To assess economic viability, one can perform a Net Present Value (NPV) analysis:

$$NPV = \sum_{t=0}^{T} \frac{R_t - C_t}{(1+r)^t}$$

Where,
R_t = revenue or savings generated at time t,
C_t = cost incurred at time t,
r = discount rate,
T = total project duration.

For example, let the AI system generate savings of ₹50,000 annually for 5 years, with an annual maintenance cost of ₹10,000 and a discount rate of 10%. Initial installation cost is ₹100,000.

$$NVP = -100000 + \sum_{t=1}^{5} \frac{50000 - 10000}{(1+0.10)^t}$$

$$= -100000 + \sum_{t=1}^{5} \frac{40000}{(1.10)^t}$$

$$= -100000 + \left[\frac{40000}{1.10} + \frac{40000}{1.21} + \frac{40000}{1.331} + \frac{40000}{1.4641} + \frac{40000}{1.6105}\right]$$

$$= -100000 + [36363.64 + 33057.85 + 30046.62 + 27301.57 + 24830.94]$$

$$= -100000 + 151600.62$$

$$= ₹51600.62$$

Hence, the project yields a positive NPV, indicating profitability. However, such analysis must also consider uncertainties in savings, especially in rain-fed or marginal areas.

Data privacy and ownership concerns

The ethical dimension of AI in soil conservation cannot be ignored. Data collected from farms-such as crop yields, soil quality, and management practices-are often stored on cloud platforms owned by private corporations. This raises serious questions about data ownership, consent, and usage rights (Khan *et al.*, 2022). There are also geopolitical implications when multinational tech firms control critical agricultural data. A possible solution lies in blockchain-based distributed ledgers, which allow decentralized, tamper-proof data sharing while maintaining user control (Mishra, 2024).

For example, a hash-based blockchain record of soil data for each plot can be mathematically secured as:

$$H_n = H(H_{n-1} \parallel D_n)$$

Where,
H_n = current hash value,
H_{n-1} = previous hash,
D_n = new data input.

This cryptographic chain ensures data integrity and transparent auditing but adds another layer of technical and financial complexity that must be considered (Kathiravan *et al.*, 2023).

FUTURE PROSPECTS AND INNOVATIONS IN AI FOR SOIL CONSERVATION

As AI continues to permeate diverse sectors of environmental management, its application in soil conservation is poised for transformative innovation (Li, 2024). The evolution of AI tools, informed by large-scale data assimilation and predictive modelling, has initiated a paradigm shift from traditional empirical strategies to intelligent, adaptive systems. This transition signals a future where soil health monitoring, erosion prediction, and sustainable land use planning are not only automated but also context-aware and regionally optimized (Nair & Prakasan, 2024).

Emerging Technologies and Tools

Federated learning and edge AI

Conventional centralized AI models necessitate the transfer of massive datasets to central servers, thereby introducing latency, privacy concerns, and infrastructure constraints-especially in rural and agrarian zones. In contrast, Federated Learning (FL) enables multiple decentralized entities (e.g., farmers' mobile devices or edge sensors) to collaboratively learn a shared prediction model while retaining data locally (Zhao *et al.*, 2024). This decentralized structure ensures data privacy and enhances adaptability to localized soil conditions. Mathematically, the optimization problem in federated learning can be expressed as:

$$\min_{w \in \mathbb{R}^d} \left[F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \right]$$

Where:
w is the global model parameter,
K is the total number of local devices or nodes,
n_k is the number of data samples at device k,
$F_k(w)$ is the local objective function,
$n = \sum_{k=1}^{K} n_k$ is the total number of data samples.

For example, let us consider 3 devices collecting soil pH and moisture data, with data sizes:

$n_1 = 200$,

$n_2 = 300$,

$n_3 = 500$, thus $n = 1000$.

Suppose the loss functions computed locally are:

$F_1(w) = 0.3$,

$F_2(w) = 0.2$,

$F_3(w) = 0.1$.

Then the global objective function is:

$$F(w) = \frac{200}{1000}(0.3) + \frac{300}{1000}(0.2) + \frac{500}{1000}(0.1) = 0.06 + 0.06 + 0.05 = 0.17$$

This example illustrates how FL aggregates local computations without transmitting sensitive soil datasets-particularly crucial for farmer cooperatives or institutions with privacy obligations. Complementing this, Edge AI executes models on local hardware such as IoT devices deployed in agricultural fields. These AI chips can perform real-time inference-e.g., identifying erosion onset or salinity spikes-without cloud dependency, thereby enabling rapid interventions (Gupta & Kumar, 2024).

Digital twins and AI-powered simulations

Digital Twin (DT) technologies represent dynamic virtual models of physical entities-here, of soil systems. These twins incorporate real-time sensor data, ML models, and physics-based simulations to replicate soil behaviour under various agricultural practices, weather conditions, and conservation interventions (Muhammed *et al.*, 2024). Let the system dynamics be modelled by a partial differential equation (PDE) of water flow in porous media (soil), such as the Richards Equation:

$$\frac{\partial \theta(h)}{\partial t} \nabla \cdot [K(h)(\nabla h + z)]$$

Where:
$\theta(h)$ is the water content as a function of pressure head h,
$K(h)$ is the hydraulic conductivity,
z accounts for gravitational acceleration.

Simplified 1D case:
Suppose:

$K(h) = 0.5\, cm/hr$,

$\theta(h) = 0.4$,

$\frac{\partial \theta(h)}{\partial t} = 0.01 cm^3 / cm^3 / hr$,

$\nabla h = 0.2\, cm/cm$, and $z = -1$.

Then:

$$\frac{\partial \theta}{\partial t} = \nabla \cdot [0.5(0.2 - 1)] = \nabla \cdot (-0.4) \Rightarrow \frac{\partial \theta}{\partial t} = -0.4$$

This negative derivative suggests a reduction in soil moisture, possibly indicating drying or inadequate irrigation-information that could be instantly visualized in a Digital Twin environment for timely corrective actions (Popescu *et al.*, 2024).

Multi-disciplinary Integration

Synergy between AI, remote sensing, and biotechnologies

The fusion of AI with remote sensing and biotechnological tools opens avenues for multi-scale soil assessment. Satellite-derived NDVI or Soil Adjusted Vegetation Index (SAVI) can be fed into CNNs to detect erosion-prone areas, while genomic insights into plant-microbe-soil interactions may optimize site-specific amendments. For instance, AI models can process hyperspectral imaging data and integrate it with metagenomic datasets to infer the presence of beneficial microbial communities. These microbial profiles, in turn, guide biofertilizer applications tailored to distinct edaphic zones (Giri *et al.*, 2020).

Collaborative research and development approaches

Transdisciplinary partnerships among agronomists, data scientists, environmental engineers, and rural communities are critical for developing inclusive AI systems. Such collaboration supports open-source model development, shared geospatial datasets, and policy-aligned digital platforms for public access (Krishnan *et al.*, 2022). For example, shared repositories like FAO's SoiLEX and India's Soil Health Card platform could be extended with AI APIs to generate adaptive soil health recommendations. Collaborative R&D also ensures that socio-economic heterogeneity-language, landholding size, literacy levels-is embedded into AI interface design (Panagos *et al.*, 2016).

Scaling and Replication Potential

Localized models for global applications

While global models have analytical strength, they often lack local specificity. AI facilitates the creation of localized learning models that incorporate regional soil taxonomy, cropping patterns, and climate profiles, thereby enhancing the model's transferability across similar agro-climatic zones (Misra *et al.*, 2020). A spatial model can be expressed as:

$$y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \varepsilon_i$$

Where,
y_i the soil erosion rate,
x_{ij} are variables like slope, rainfall, vegetative cover,
β_j are region-specific coefficients estimated via regression,
ε_i is the error term.

For example, let:

$\beta_0 = 2, \beta_1 = 0.3, \beta_2 = -0.1$

$x_{i1} = Slop = 20\%, x_{i2} = Vegetative\ cover = 40\%$

Then:

$y_i = 2 + (0.3 \times 20) + (-0.1 \times 40) = 2 + 6 - 4 = 4\ tons/ha/year$

This predictive outcome can be locally validated and generalized through model tuning across districts with similar topographies.

Role of public-private partnerships in AI diffusion

The diffusion of AI tools into real-world conservation practices relies heavily on robust Public-Private Partnerships (PPPs). Private sector investments in cloud infrastructure, sensor manufacturing, and ML services must align with public goals of sustainability and equity (Rapinel *et al.*, 2023). Such partnerships may include:

- Joint development of AI-based decision-support systems for soil testing labs,
- Co-funding of digital literacy training for extension workers,
- Licensing of AI tools to agro-cooperatives at subsidized rates.

Additionally, international frameworks like the G20 Global Digital Agriculture Initiative or India's National AI Portal can serve as nodes for knowledge dissemination, promoting not only scale but also contextual relevance (Razavi-Termeh *et al.*, 2020).

CONCLUSION

Soil conservation stands at the confluence of tradition and innovation, where AI has emerged as a transformative force redefining sustainable land management. While conventional methods like contour ploughing, crop rotation, and agroforestry have historically served as the backbone of soil preservation, the integration of AI technologies now enables a level of precision and real-time responsiveness previously unattainable. AI applications in soil monitoring, such as using ML algorithms for pH prediction, nutrient profiling, and moisture estimation, have significantly enhanced the accuracy and efficiency of diagnostics. According to a 2023 FAO report, AI-powered tools have improved soil fertility prediction accuracy by over 85%, while AI-driven erosion models have reduced land degradation risks by nearly 30% in pilot regions. Moreover, AI-enabled DSS, coupled with satellite and IoT data, facilitate adaptive soil management practices and targeted interventions. However, despite its promise, challenges like inadequate data infrastructure, algorithmic biases, and socio-economic disparities in technology access persist-particularly in low-resource settings. Yet, with interdisciplinary collaboration, federated learning models, and PPPs, AI holds substantial potential to scale conservation practices globally. Ultimately, AI does not replace traditional wisdom but rather strengthens it, offering a path towards more resilient, data-informed, and ecologically responsible soil stewardship.

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