

Systematic Review

Applications of Artificial Intelligence in Soil Characterization and Agriculture: A Systematic Review of Techniques, Models, and Applications

Cesar Augusto Navarro Rubio , Hugo Martínez Ángeles * , Mario Trejo Perea * , José Luis Reyes Araiza , Guillermo Ronquillo-Lomeli , Ivan Gonzalez-Garcia , Eusebio Ventura Ramos  and José Gabriel Ríos Moreno 

Facultad de Ingeniería, Universidad Autónoma de Querétaro, Santiago de Querétaro 76010, Mexico; cnavarro15@alumnos.uaq.mx (C.A.N.R.); lreyes@uaq.mx (J.L.R.A.); gronquillo@cidesi.edu.mx (G.R.-L.); ivan.glez@uaq.mx (I.G.-G.); eventura@uaq.mx (E.V.R.); riosg@uaq.mx (J.G.R.M.)

* Correspondence: hmartinez15@alumnos.uaq.mx (H.M.Á.); mtp@uaq.mx (M.T.P.)

Abstract

Artificial Intelligence (AI) has become a key enabler in soil science and agriculture, supporting advanced modeling, monitoring, and decision-making processes. This systematic review synthesizes recent developments in AI-based soil characterization and agricultural applications, with emphasis on soil physicochemical properties, digital soil mapping, irrigation management, and crop yield prediction. Following the PRISMA 2020 framework, a structured search of the Scopus database identified 196 eligible studies published between 2018 and 2026. The reviewed literature reveals a clear transition toward data-driven approaches, with machine learning and deep learning models dominating recent research. Random Forest, Support Vector Machines, gradient boosting methods, artificial neural networks, Convolutional Neural Networks, and Long Short-Term Memory architectures were the most frequently reported techniques. The primary data sources included in situ sensors, laboratory measurements, remote sensing imagery, and environmental covariates, often integrated through multi-source data fusion frameworks. The results indicate that tree-based ensemble models provide robust performance across diverse soil properties, whereas deep learning models are particularly effective for spatiotemporal prediction and remote sensing applications. AI-driven systems are increasingly used to support precision agriculture through irrigation optimization, crop yield forecasting, digital soil mapping, and soil health monitoring. However, challenges remain regarding data quality and availability, model transferability across regions, and the limited interpretability of complex models. The findings highlight current research trends, methodological challenges, and future opportunities for the development of reliable and scalable AI-driven soil and agricultural systems.



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1. Introduction

Soil is a fundamental component of terrestrial ecosystems and plays a critical role in agricultural productivity, environmental sustainability, and land management. The accurate characterization of soil properties such as moisture content, texture, salinity, temperature, and nutrient availability is essential for optimizing agricultural practices and ensuring

efficient resource utilization. These properties are inherently variable in both space and time, making soil systems highly complex and challenging to model using traditional analytical approaches.

Among the various soil parameters investigated in the literature, soil electrical resistivity (SER) has gained increasing attention due to its sensitivity to multiple physicochemical properties and its suitability for data-driven analysis. Electrical conduction in soils occurs primarily through the pore fluid and dissolved ions, making resistivity strongly dependent on moisture content, salinity, temperature, and soil structure. As a result, SER is widely used as an indirect proxy for assessing soil conditions in applications ranging from geophysical exploration to precision agriculture and environmental monitoring [1–3].

The relationship between soil electrical resistivity and environmental variables is highly nonlinear and influenced by complex interactions among multiple parameters. Moisture content has been consistently identified as the dominant factor controlling resistivity, exhibiting a strong inverse correlation ($r \approx -0.88$), while temperature and soil suction generally show weaker positive relationships [1–3]. In addition, soil properties such as clay content, plasticity, and dry unit weight significantly affect electrical conduction mechanisms, highlighting the need for multivariable modeling approaches capable of capturing these interactions [2,4]. Furthermore, electrical conductivity, which represents the inverse of resistivity, is closely linked to soil salinity and chemical properties such as pH and nutrient concentration, enabling its use in irrigation management and soil fertility assessment [3–5].

Traditional methods for soil characterization and resistivity measurement, including laboratory testing and field-based techniques such as the Wenner four-electrode method, provide reliable results but are often labor-intensive, time-consuming, and limited in spatial resolution. These limitations become particularly significant in agricultural contexts, where large-scale monitoring and real-time decision-making are required. Consequently, there has been a growing interest in developing data-driven approaches capable of estimating soil properties based on easily measurable variables.

In this context, Artificial Intelligence (AI) has emerged as a powerful tool for modeling complex soil systems. Machine learning (ML) and deep learning (DL) algorithms have demonstrated strong capabilities in capturing nonlinear relationships between soil variables and predicting key properties with high accuracy. Models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests (RF), and Extreme Gradient Boosting (XGBoost) have been widely applied for soil resistivity and property prediction. Some studies have reported coefficients of determination (R^2) values approaching 0.99 under specific experimental settings, controlled conditions, or dataset characteristics; however, model performance varies substantially depending on soil type, environmental conditions, data quality, and validation procedures [1,2,6]. In addition, advanced deep learning architectures, including Deep Neural Networks (DNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU), have shown strong performance in modeling temporal and spatial variability in soil systems, particularly for moisture prediction and hydraulic property estimation [7–9].

The integration of AI with sensing technologies has further enhanced soil characterization capabilities. Real-time monitoring systems based on electrical resistivity measurements, such as robotic Wenner arrays, enable rapid spatial mapping of soil properties across agricultural fields [3]. Similarly, Electrical Resistivity Tomography (ERT) combined with soil moisture measurements has been successfully applied to monitor irrigation processes and analyze wetting–drying cycles in crops such as cotton and tomatoes [10,11]. Moreover, multi-sensor platforms incorporating electrical, dielectric, optical (Vis–NIR), and acoustic

measurements, coupled with AI models, have enabled the development of high-resolution digital representations of soil systems, often referred to as “digital soil twins” [12].

Beyond resistivity-focused applications, AI techniques have been widely applied in broader agricultural contexts, including soil fertility mapping, crop yield prediction, crop recommendation systems, and smart irrigation management. These applications leverage large-scale datasets combining soil, climate, and remote sensing information to support data-driven decision-making in precision agriculture [4,13–17].

Despite these advances, several challenges remain in the application of AI to soil characterization and agricultural systems. Soil heterogeneity, environmental variability, and the dependence of models on site-specific conditions limit the generalizability of AI approaches [1,2]. Additionally, the availability of high-quality labeled data remains a major constraint, particularly when integrating field measurements, laboratory analyses, and remote sensing data at different spatial and temporal scales [12,14]. To address these issues, recent studies have explored synthetic data generation techniques, such as variational autoencoders, and multi-sensor data fusion strategies to improve model robustness and predictive performance [1,12,16]. Furthermore, there is a growing emphasis on the development of hybrid models that combine physical principles with AI techniques, as well as interpretable machine learning approaches, to enhance both predictive accuracy and model transparency [2,4,5].

Despite the rapidly expanding body of research in this field, the existing literature remains fragmented due to variations in datasets, modeling approaches, soil types, environmental conditions, and application domains. Many studies focus on specific regions or individual soil properties, while others emphasize particular AI techniques, making it difficult to establish a unified understanding of current advancements and limitations.

This fragmentation highlights the need for a systematic and comprehensive synthesis of the existing literature on AI applications in soil characterization and agriculture. A structured review is essential to identify dominant research trends, evaluate the performance of different AI models, and determine the most relevant soil parameters for predictive modeling.

Although several review studies have examined specific aspects of AI in agriculture, such as crop yield prediction, remote sensing applications, digital soil mapping, or precision agriculture technologies, a comprehensive synthesis integrating AI methodologies, soil properties, sensing technologies, and agricultural applications within a unified framework remains limited. Addressing these interconnected dimensions is essential to better understand how AI supports soil characterization and agricultural decision-making across multiple scales and application domains.

Accordingly, this study conducts a systematic review of the applications of Artificial Intelligence in soil characterization and agricultural systems, with particular emphasis on soil electrical resistivity, multivariable modeling approaches, and precision agriculture applications.

To structure this systematic analysis, the following research questions are defined. Addressing these questions provides insights into the current state of knowledge on AI-driven soil analysis and agricultural applications, while acknowledging that the findings are conditioned by the scope and characteristics of the selected studies.

- What types of AI models are most commonly used for soil characterization and agricultural applications?
- Which soil properties are most frequently modeled using AI techniques?
- What sensing technologies and data sources are employed in AI-driven soil studies?
- What are the main agricultural applications of AI in soil analysis, including precision agriculture and irrigation management?

- What limitations, challenges, and research gaps exist in current AI-based soil modeling approaches?

This systematic review is not hypothesis-driven; rather, it is structured around pre-defined research questions that provide a framework for synthesizing and analyzing the existing literature. The objective is to analyze and compare AI-based methodologies, identify key soil variables influencing predictive performance, and evaluate their applicability in agricultural systems.

This paper is structured as follows. Section 1 presents the Introduction, describing the importance of soil characterization, the role of electrical resistivity, and the emergence of AI techniques in agricultural applications. Section 2 describes the Materials and Methods, including the systematic review protocol, search strategy, and selection criteria. Section 3 presents the Results, summarizing the main AI techniques, soil properties, and application domains identified in the literature. Section 4 provides the Discussion, analyzing methodological trends, limitations, and future research directions. Finally, Section 5 presents the Conclusions, highlighting the main findings and contributions of this study.

2. Materials and Methods

2.1. Systematic Review Protocol

This systematic review was conducted following the principles established in the PRISMA 2020 framework [18], which provides a standardized methodology for identifying, screening, and selecting scientific literature. The application of this protocol ensures a transparent, structured, and reproducible workflow throughout the review process.

The methodological procedure was organized into four main phases: (i) identification of relevant studies through database searching, (ii) screening of records based on titles and abstracts, (iii) eligibility assessment through full-text evaluation, and (iv) final inclusion of studies that met the predefined criteria. This sequential approach allows for a clear traceability of the selection process while minimizing potential biases associated with subjective study selection.

The adoption of the PRISMA methodology enables a systematic synthesis of the existing literature on Artificial Intelligence applications in soil characterization and agricultural systems, with particular attention to soil electrical resistivity, multivariable soil analysis, and precision agriculture technologies. The PRISMA 2020 checklist is provided as Supplementary Material to ensure compliance with reporting standards.

To further support transparency and reproducibility, the review protocol was registered in the Open Science Framework (OSF) platform (registration DOI: <https://doi.org/10.17605/OSF.IO/6ACSK>, accessed on 30 March 2026). The literature search, screening, and study selection processes were completed prior to the final preparation of the manuscript, and the year 2026 represents the final time boundary defined in the search strategy. The OSF access date corresponds solely to the consultation and verification of the registered review protocol.

2.2. Search Strategy and Database Selection

The literature search was performed using the Scopus database, which was selected due to its extensive coverage of peer-reviewed journals, robust indexing system, and advanced search capabilities. Scopus offers a comprehensive representation of research across multiple disciplines, including soil science, agriculture, environmental engineering, and artificial intelligence, making it particularly suitable for the multidisciplinary scope of this study.

Although other databases such as Web of Science and Google Scholar also provide valuable sources of scientific information, Scopus was chosen to ensure consistency in

metadata, reproducibility of results, and reliable citation tracking. Nevertheless, it is acknowledged that relying on a single database may lead to the omission of some relevant studies, particularly those published in regional or non-indexed journals.

To mitigate this limitation, the search strategy was carefully designed to capture a broad range of relevant publications by combining keywords related to artificial intelligence, soil characterization, agricultural applications, and soil electrical resistivity.

The final search query used was as follows:

TITLE-ABS-KEY (("machine learning" OR "deep learning" OR "artificial intelligence") AND ("soil characterization" OR "soil properties" OR "soil moisture" OR "soil salinity" OR "soil electrical resistivity" OR "electrical conductivity") AND (prediction OR modeling OR estimation) AND ("precision agriculture" OR irrigation OR crop)) AND PUBYEAR > 2017 AND PUBYEAR < 2027 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English"))*

A temporal filter was applied to include publications from 2018 to 2026, ensuring that the analysis reflects recent advancements in artificial intelligence techniques and their applications in soil science and agriculture. Only peer-reviewed research articles and review papers written in English were considered to maintain scientific quality, consistency, and accessibility.

The final literature search was conducted on 30 March 2026. All records included in this review correspond to publications indexed in Scopus and available up to that date, consistent with the predefined search period from 2018 to 2026.

Review articles were included to provide a broader conceptual context and to identify general trends, methodologies, and key variables. However, the evaluation of modeling approaches, performance metrics, and application outcomes was primarily based on original research articles to avoid redundancy and ensure a consistent analytical comparison.

2.3. Inclusion and Exclusion Criteria

To guarantee the scientific relevance and methodological consistency of the studies considered in this review, a set of explicit eligibility criteria were established in alignment with the research objectives. These criteria were systematically applied during the screening and selection phases of the review process, following the PRISMA framework, through a detailed evaluation of titles, abstracts, and full-text documents.

The selection process was carried out through a structured multi-reviewer approach involving eight authors. Each identified record was independently examined by multiple reviewers to assess its compliance with the predefined inclusion and exclusion criteria. When discrepancies arose during the evaluation, the studies were subjected to a secondary assessment, and final decisions were reached through discussion and consensus. Formal inter-reviewer agreement statistics (e.g., Cohen's kappa) were not calculated because the screening process followed a collaborative consensus-based approach involving multiple reviewers rather than independent paired assessments. Disagreements were resolved through discussion and secondary evaluation until consensus was achieved. This collaborative procedure enhanced the reliability of the selection process and reduced potential subjectivity.

In addition to study selection, a standardized data extraction protocol was implemented to ensure uniformity in the information collected from each publication. A predefined data extraction form was designed specifically for this review, including key variables such as study objectives, type of artificial intelligence model employed, soil properties analyzed (e.g., moisture, salinity, electrical resistivity), data sources (e.g., sensors, laboratory measurements, remote sensing), and reported performance metrics (e.g., coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error

(MAPE)). This structured approach facilitated a consistent comparison of methodologies and outcomes across the selected studies.

By rigorously applying these eligibility criteria and standardized procedures, the review ensured that only studies directly relevant to artificial intelligence applications in soil characterization and agricultural systems were included. This methodological rigor contributed to minimizing selection bias and enabled a coherent synthesis of current advancements in AI-based soil analysis, predictive modeling, and precision agriculture applications.

2.3.1. Inclusion Criteria

Studies were considered eligible for inclusion when they met the following conditions:

Document type: Only peer-reviewed journal articles and review papers were included in order to ensure the scientific quality, reliability, and methodological soundness of the selected literature.

Publication period: The analysis was restricted to studies published between 2018 and 2026, allowing the review to focus on recent advances in artificial intelligence techniques applied to soil science and agricultural systems.

Language: Only publications written in English were considered to guarantee accessibility and consistency in the interpretation of the reported methodologies and results.

Subject area: Eligible studies were required to fall within relevant scientific domains, including Agricultural Sciences, Environmental Science, Earth and Planetary Sciences, Engineering, and Computer Science. These areas encompass the multidisciplinary nature of artificial intelligence applications in soil characterization and agriculture.

Thematic focus: Included studies had to explicitly address the application of artificial intelligence techniques such as machine learning, deep learning, or data-driven approaches for soil analysis, soil property estimation, or agricultural decision-making. Particular attention was given to studies involving soil electrical resistivity, electrical conductivity, or related soil physicochemical properties.

Modeling and analytical scope: Studies employing predictive, classification, regression, or mapping models based on AI techniques were included. This encompasses approaches aimed at estimating soil properties (e.g., moisture, salinity, fertility) or supporting agricultural applications such as irrigation management, crop monitoring, and precision agriculture.

Data and variables: Studies incorporating soil-related variables (e.g., moisture content, salinity, temperature, texture, nutrient levels) and/or sensor-based, laboratory, or remote sensing data were considered, as these variables are fundamental for AI-based soil characterization and agricultural analysis.

2.3.2. Exclusion Criteria

Publications were excluded from the review when one or more of the following conditions were identified:

Non-qualifying document types: Publications such as conference proceedings, book chapters, editorials, technical notes, short communications, and reports were not considered. These document types were excluded because they often present preliminary findings, limited methodological detail, or lack a rigorous peer-review process, which may compromise the consistency and comparability required for a systematic review.

Out-of-scope topics: Studies that did not explicitly address soil-related analysis or that lacked a clear connection to artificial intelligence applications in soil characterization or agricultural systems were excluded.

Unrelated application domains: Research focusing on electrical resistivity or conductivity in contexts not associated with soil systems such as solid-state materials, biomedical engineering, electronic devices, or purely geological rock studies without soil analysis was excluded to maintain thematic consistency.

Absence of AI-based methods: Studies that did not incorporate artificial intelligence, machine learning, deep learning, or data-driven modeling approaches were excluded, as they fall outside the core scope of this review.

Duplicate records: Redundant entries identified during the database search process were removed to avoid duplication in the analysis. Duplicate records were identified through the Scopus export process by comparing article titles, authors, publication years, and digital object identifiers (DOIs). Any duplicated entries detected during the screening stage were removed prior to title and abstract evaluation.

Unavailable or incomplete studies: Publications for which the full text was not accessible, or that lacked sufficient methodological or results-related information, were excluded to ensure the reliability of the extracted data.

Figure 1 illustrates the PRISMA 2020 flow diagram summarizing the study selection process for this systematic review focused on artificial intelligence applications in soil characterization and agriculture.

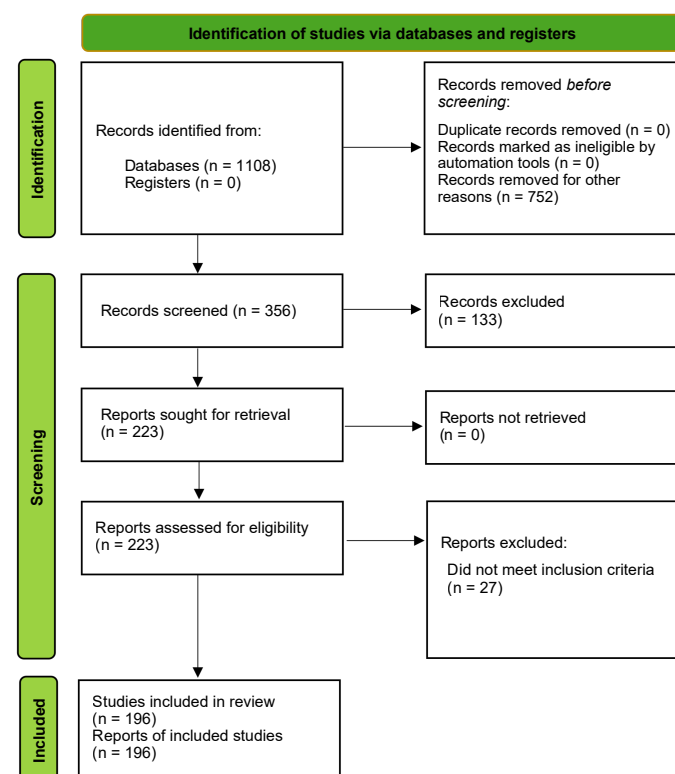


Figure 1. PRISMA 2020 flow diagram illustrating the study selection process for publications related to artificial intelligence applications in soil characterization and agricultural systems between 2018 and 2026.

The study selection process was conducted through a structured multi-phase filtering approach to progressively refine the dataset of relevant publications. In Phase 1 (identification), a total of 1108 records were retrieved from the Scopus database, reflecting the increasing research activity in artificial intelligence applications for soil analysis and agricultural systems. After applying initial filters related to publication year, document type, and language, 752 records were excluded, resulting in 356 studies remaining for further screening.

In Phase 2 (screening), the titles and abstracts of the 356 remaining records were evaluated to assess their relevance to the scope of this review. During this stage, 133 studies were excluded due to thematic misalignment, including works focused on general artificial intelligence applications without soil context, as well as soil-related studies lacking AI-based modeling approaches. Consequently, 223 articles were retained for full-text evaluation.

In Phase 3 (eligibility), the full texts of the 223 selected studies were carefully examined to verify compliance with the predefined inclusion criteria. At this stage, 27 additional publications were excluded, primarily due to insufficient methodological detail, absence of relevant soil variables, or lack of a clear artificial intelligence component.

Finally, in Phase 4 (inclusion), a total of 196 studies were selected that fully satisfied all eligibility criteria. These publications constitute the final dataset used for the qualitative synthesis and comparative analysis presented in this review.

The application of this multi-stage filtering strategy ensured a rigorous and systematic selection of the literature, allowing the identification of studies that are both methodologically robust and directly aligned with the objectives of this review.

Given the broad scope of the review and the large number of included studies, the synthesis was conducted at a thematic and methodological level. Consequently, the results emphasize common research trends, representative modeling approaches, sensing technologies, and application domains rather than providing a publication-by-publication analysis of all included studies.

It should be noted that a formal risk-of-bias assessment was not performed. The primary objective of this review was to provide a broad synthesis of research trends, artificial intelligence techniques, sensing technologies, soil properties, and agricultural applications reported in the literature. Given the substantial methodological diversity of the included studies including machine learning, deep learning, digital soil mapping, remote sensing, IoT-based monitoring, and decision-support systems a single standardized quality assessment framework was not considered appropriate for all study types.

Instead, the review emphasizes thematic synthesis, methodological comparison, and identification of emerging research directions. While this approach enables a comprehensive and integrative overview of the field, it may limit the ability to quantitatively assess the relative quality, reproducibility, or risk of bias of individual studies. Therefore, the findings should be interpreted as general patterns and trends across the literature rather than as definitive rankings of methodological quality or model performance. Future systematic reviews focusing on specific AI application domains may benefit from incorporating dedicated quality appraisal criteria, such as reporting transparency, validation strategies, reproducibility, external validation, and data quality indicators.

2.4. Conceptual Structure of Artificial Intelligence in Soil Characterization and Agriculture

The conceptual organization of the research field was examined through a bibliometric keyword co-occurrence analysis derived from the selected studies. This analysis was performed using VOSviewer software (version 1.6.20), which enables the visualization of relationships among frequently occurring terms and the identification of thematic clusters within a research domain. The resulting network provides a structured representation of the main research directions associated with artificial intelligence applications in soil characterization and agricultural systems (Figure 2).

ronmental conditions. This cluster also includes terms related to soil contamination and nutrient dynamics, indicating the role of AI in soil quality assessment.

The blue cluster is strongly linked to remote sensing and geospatial analysis. Keywords such as “remote sensing”, “satellite imagery”, “unmanned aerial vehicles (UAV)”, “Sentinel”, and “multispectral image” highlight the increasing use of satellite and drone-based data for large-scale soil monitoring. These technologies are often combined with machine learning models to generate spatial predictions of soil properties and support precision agriculture practices.

Another cluster (yellow) reflects soil mapping and data-driven modeling approaches, including terms such as “digital soil mapping”, “kriging”, “soil surveys”, and “mapping”. This group emphasizes the integration of statistical and machine learning methods for spatial interpolation and the generation of high-resolution soil information.

From the perspective of the research questions, the bibliometric network provides valuable insights into the structure and evolution of the field. The prominence of terms related to machine learning and prediction directly addresses the identification of commonly used AI techniques (Research Question 1). Similarly, the strong presence of keywords associated with soil moisture, salinity, and temperature highlights the most frequently analyzed soil variables (Research Question 2).

Furthermore, the integration of terms such as “remote sensing”, “IoT”, and “sensor-based systems” reflects the diversity of sensing technologies and data acquisition methods employed in AI-driven soil studies (Research Question 3). The clustering of agricultural and environmental terms also illustrates the wide range of application domains, including irrigation management, crop monitoring, and environmental assessment (Research Question 4).

While the present conceptual analysis focused on identifying thematic relationships and research clusters through keyword co-occurrence networks, future studies could complement this approach with temporal bibliometric analyses using tools such as CiteSpace. Such analyses may provide additional insights into the chronological evolution of research topics and the adoption of specific AI techniques, including Artificial Neural Networks (ANNs), Random Forest (RF), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, thereby enabling a more detailed assessment of the development of research hotspots within soil science and digital agriculture.

2.5. Analytical Framework for AI-Based Soil Characterization and Agricultural Modeling

Considering the wide range of methodologies reported in the literature for analyzing soil systems, an integrated analytical framework is presented to support the interpretation and comparison of the reviewed studies. This section does not introduce original results derived from the systematic review; instead, it consolidates fundamental theoretical relationships and modeling approaches commonly used to describe soil behavior and its interaction with artificial intelligence techniques. The framework serves as a conceptual reference that supports the research questions defined in this review by linking soil properties, sensing technologies, predictive modeling approaches, and agricultural applications.

The selected formulations represent widely accepted physical principles and data-driven modeling strategies that describe the relationships between soil properties such as moisture content, salinity, temperature, and electrical resistivity and their relevance in agricultural applications. These relationships provide a conceptual bridge between traditional soil science models and modern AI-based predictive approaches.

2.5.1. Fundamental Definition of Soil Electrical Resistivity

Soil electrical resistivity is defined as the intrinsic opposition of a soil medium to the flow of electrical current. This property depends on both the soil matrix and the conductive pathways provided by pore fluids and dissolved ions [2,19]. The classical expression is given by:

$$\rho = R \frac{A}{L} \quad (1)$$

where ρ represents soil resistivity ($\Omega \cdot \text{m}$), R represents the measured electrical resistance (Ω), A is the cross-sectional area (m^2), and L is the electrode spacing (m). This formulation underpins most field and laboratory measurement techniques and remains essential for linking physical measurements with predictive models.

2.5.2. Physicochemical Relationships in Soil Systems

The electrical behavior of soils is strongly governed by physicochemical properties, particularly moisture content, salinity, and porosity. Among these variables, moisture plays a dominant role due to its direct influence on ionic conduction pathways. The relationship between resistivity and volumetric water content is often represented through exponential or power-law expressions [20,21], such as:

$$\rho = \rho_0 e^{-k\theta} \quad (2)$$

where ρ_0 corresponds to the resistivity of dry soil, θ represents the volumetric moisture content, and k is an empirical coefficient dependent on soil type. This relationship reflects the rapid decrease in resistivity as water content increases.

In addition, electrical conductivity (EC), which is the reciprocal of electrical resistivity (SER), is closely associated with salinity and chemical composition, allowing indirect estimation of nutrient content and soil fertility. Although SER and EC are physically related, they represent distinct quantities and are often reported separately depending on the measurement technique and application domain. Temperature also affects resistivity through changes in ionic mobility, although its influence is generally secondary compared to moisture.

2.5.3. Multivariable and Regression-Based Models

To account for the complex and nonlinear interactions among soil variables, multivariate modeling approaches are frequently employed [22,23]. A generalized regression-based formulation can be expressed as:

$$\rho = \beta_0 + \beta_1\theta + \beta_2T + \beta_3S + \beta_4X + \varepsilon \quad (3)$$

where θ represents soil moisture, T temperature, S salinity, X includes additional soil parameters (e.g., texture or density), β_i are model coefficients, and ε is the residual error. These formulations provide a foundation for both traditional statistical models and modern machine learning approaches.

2.5.4. Artificial Intelligence Modeling Framework

Artificial intelligence techniques extend traditional regression approaches by enabling the modeling of highly nonlinear and multidimensional relationships [1,24–26]. In this context, soil characterization can be represented as a mapping function:

$$Y = f(X_1, X_2, \dots, X_n) \quad (4)$$

where Y represents the predicted soil property (e.g., moisture, salinity, or resistivity), and X_i corresponds to input variables derived from sensors, laboratory measurements, or remote sensing data.

Machine learning models such as Artificial Neural Networks, Random Forest, Support Vector Machines, and Extreme Gradient Boosting are widely used to approximate this function. Deep learning architectures further extend this capability by capturing temporal and spatial dependencies in soil systems, particularly when integrating time-series data and satellite imagery.

2.5.5. Integration with Agricultural Systems

Within agricultural contexts, the analytical framework extends beyond soil property estimation to include decision-support processes. AI models are used to link soil variables with agricultural outcomes such as crop yield, irrigation requirements, and nutrient management [27–31]. This integration can be conceptually represented as:

$$D = g(Y, C, E) \quad (5)$$

where D represents agricultural decisions (e.g., irrigation scheduling), Y corresponds to predicted soil properties, C includes crop-related variables, and E represents environmental conditions.

This formulation highlights the transition from soil characterization to actionable insights within precision agriculture systems, where AI-driven models support real-time decision-making and resource optimization.

2.5.6. Framework Interpretation

The analytical relationships presented in this section do not constitute new models developed in this study. Instead, they summarize established theoretical principles and widely adopted modeling approaches reported in the literature. These formulations provide a consistent reference framework that supports the interpretation and comparison of AI-based soil modeling techniques analyzed in this review.

The framework emphasizes the integration of physical soil processes, multivariable modeling, and artificial intelligence methods, illustrating how traditional soil science concepts are combined with advanced computational techniques to improve soil characterization and agricultural decision-making.

3. Results

The findings reported in this section are derived from the systematic evaluation of the studies included in this review. Unless otherwise specified, the observed trends, relationships, and model performances are based on the evidence documented in the analyzed literature.

3.1. Overview of Selected Studies and Research Trends

A general analysis of the literature reveals a significant increase in research activity, particularly after 2018, driven by advances in data availability, computational capabilities, and the growing demand for precision agriculture solutions [28,32–35]. Bibliometric and systematic reviews consistently highlight this expansion, especially in the application of machine learning (ML) and deep learning (DL) techniques for soil property estimation and remote sensing-based monitoring [28,32,33,36].

From a thematic perspective, the reviewed studies indicate that soil characterization research is strongly oriented toward predictive modeling. Soil moisture, temperature, nutrient content, soil organic carbon (SOC), soil organic matter (SOM), and electrical

conductivity/resistivity are among the most frequently analyzed variables [28,32,37–40]. In particular, SOC and SOM have gained prominence in studies based on remote sensing due to their importance in soil fertility and carbon cycle assessments.

Table 1 summarizes the main soil-related variables and research themes identified across representative studies.

Table 1. Main soil variables and research themes in AI-based soil characterization studies.

Variable/Theme	Example Focuses	References
Moisture and temperature	Soil temperature prediction using CNN–LSTM models across different climates; soil moisture depth profiles	[33,38,39]
Nutrients and SOC/SOM	Nutrient mapping; SOC prediction using CNN–LSTM; SOM monitoring via remote sensing	[6,17,28,32,37,41,42]
Electrical conductivity/resistivity	Prediction of soil electrical conductivity (SEC) and resistivity using ANN, XGBoost, and SVM models	[1,6,40,43,44]
Crop yield and phenotyping	Crop yield prediction using UAV-based deep learning; multisensory fusion for plant traits (e.g., maize)	[17,41,45–48]

Regarding methodological approaches, machine learning models dominate the field, with techniques such as Random Forest (RF), Support Vector Machines (SVM/SVR), Artificial Neural Networks (ANNs), and Extreme Gradient Boosting (XGBoost) frequently reported to achieve higher predictive performance than traditional linear and empirical models in soil and crop prediction tasks [1,6,17,28,38–40,42,44].

In parallel, deep learning approaches have experienced rapid growth, particularly for handling spatial and temporal variability in soil systems. Architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), CNN–LSTM hybrids, and 3D-CNN models have demonstrated strong performance in applications such as soil moisture prediction, soil temperature estimation, and crop yield forecasting [32,33,44–46,49]. Hybrid and optimized models, including combinations such as ANN–GA and XGBoost-based optimization frameworks, are also widely employed to capture complex nonlinear relationships in soil systems [6,38,40].

From a data perspective, the reviewed studies show a clear trend toward the integration of multiple data sources. In situ sensors and laboratory measurements remain fundamental, particularly for variables such as soil moisture, pH, electrical conductivity, and nutrient content [1,6,28,40,42,44,49]. However, there is a growing reliance on remote sensing technologies, including satellite platforms (e.g., Sentinel-1/2, MODIS, WorldView) and UAV-based systems equipped with hyperspectral, thermal, and LiDAR sensors [17,32–34,37–39,41,45–48].

The integration of multi-source data, including ground measurements, remote sensing, climate variables, and geographic information systems (GIS), has become a central component of modern AI-based soil analysis. This approach supports the development of advanced frameworks aligned with Agriculture 4.0, enabling improved irrigation management, fertilization strategies, and real-time monitoring [34,41,48,50].

In terms of applications, the reviewed studies are primarily focused on precision agriculture, irrigation and fertilization management, crop yield prediction, and digital soil mapping [28,34,40,41]. These applications highlight the role of AI as a key enabler for optimizing agricultural processes and improving resource efficiency.

Geographically, the selected studies cover a wide range of climatic and soil conditions, including regions in North America, Europe, China, Australia, and India [28,32,33,37,48]. This diversity enhances the generalizability of the observed trends but also introduces

variability associated with local soil characteristics, environmental conditions, and data availability.

The results indicate that research in this field is rapidly evolving toward integrated, data-driven approaches that combine artificial intelligence, multi-source data acquisition, and domain-specific knowledge. While these advancements have significantly improved soil characterization and agricultural decision-making, they also highlight ongoing challenges related to data heterogeneity, model transferability, and scalability across different environmental conditions.

3.2. Artificial Intelligence Techniques for Soil Characterization

The systematic analysis indicates that artificial intelligence (AI) has emerged as a prominent approach for modeling soil systems in agricultural contexts. Compared with conventional regression approaches, AI methods are more effective at representing the nonlinear and multivariate relationships linking soil properties, environmental covariates, and management practices [26,51–53].

Classical machine learning (ML). Algorithms such as Random Forest (RF), Support Vector Machines (SVM/SVR), Artificial Neural Networks (ANNs), and Extreme Gradient Boosting (XGBoost) are widely reported across the reviewed studies. These methods are routinely applied to estimate key soil variables including pH, electrical conductivity (EC)/salinity, moisture, temperature, hydraulic conductivity, and soil organic carbon (SOC) [26,52–58].

Among ML approaches, tree-based ensembles (e.g., RF, gradient boosting, XGBoost, LightGBM, and Extremely Randomized Trees) are consistently highlighted for their ability to handle high-dimensional predictors (climate variables, terrain attributes, and remote sensing indices) while maintaining robustness to noise and overfitting. These models frequently outperform linear and single-model baselines in soil prediction tasks [26,52–58].

Neural networks and deep learning (DL). ANN and deep neural network architectures are commonly employed when relationships are highly nonlinear and involve large sets of auxiliary variables or spectral inputs. These models have shown strong performance in predicting SOC, EC, and soil moisture, particularly when trained on large datasets [26,51,57–59]. However, their effectiveness is closely tied to data availability and hyperparameter optimization.

More advanced DL architectures including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, ConvLSTM, CNN–LSTM hybrids, and graph-based models have gained prominence in recent years. These models are particularly suited for spatio-temporal prediction tasks, such as soil moisture and temperature forecasting, satellite data gap-filling, and large-scale soil reanalysis [33,51,59–64]. In many reported studies, hybrid CNN–LSTM or 3D-CNN models achieve improved predictive performance compared with traditional ML approaches by capturing both spatial patterns and temporal dynamics.

Hybrid and ensemble strategies. An important trend identified in the literature is the increasing use of hybrid and ensemble approaches. These include voting and stacking ensembles of multiple ML algorithms, hybrid neural architectures, and optimization-enhanced models (e.g., ANN or XGBoost combined with genetic algorithms). Such strategies improve predictive accuracy and stability when modeling complex soil processes [26,54,55,65–68].

Interpretability and limitations. Despite their strong predictive performance, many AI models, particularly deep learning and ensemble approaches, are characterized by limited interpretability. This has motivated the adoption of explainable AI techniques such as SHAP and LIME to better understand model behavior and variable importance in soil and agricultural applications [60,65,69]. Additionally, model performance remains

highly dependent on data quality, representativeness, and spatial coverage, which can limit generalization across different regions and soil conditions [26,51,52,58].

The reviewed evidence demonstrates that AI techniques ranging from classical ML algorithms to advanced DL architectures and hybrid ensembles play a fundamental role in modern soil characterization. These approaches provide scalable and high-accuracy tools that underpin digital soil mapping and precision agriculture systems [26,33,51–54,59].

Table 2 provides a methodological overview of the principal AI techniques employed in soil characterization. Subsequent tables focus on specific soil properties and application domains, allowing a more detailed comparison of modeling approaches and performance within each thematic area.

Table 2. Main AI techniques and typical soil characterization applications reported in the literature.

Method Family	Typical Soil Targets/Tasks	References
Tree-based ML (RF, XGBoost, LightGBM, Extra Trees)	Soil pH, EC/salinity, SOC, ion content, hydraulic conductivity, spatial mapping	[26,54–56]
ANN/DNN	SOC prediction, spectral-based properties, EC estimation, soil moisture modeling	[26,51,60,61]
CNN, LSTM, ConvLSTM, CNN–LSTM	Soil moisture and temperature forecasting, satellite data gap-filling (SMAP, AMSR-E), spatio-temporal modeling	[33,51,60,61]
Hybrid and ensemble models (e.g., ANN–GA, stacking, voting)	SOC and pH/EC mapping, crop prediction, soil moisture estimation, model optimization	[54,55,65,66,68]

3.3. Soil Properties Modeled Using Artificial Intelligence

The literature analyzed in this review indicates that artificial intelligence techniques are extensively used to model a wide range of soil properties relevant to agricultural systems. Frequently studied variables include soil moisture, temperature, salinity, electrical conductivity/resistivity, nutrient content, and soil organic carbon, all of which play a key role in crop performance and soil health. The complexity and interdependence of these variables make them well-suited for AI-based approaches, which can capture nonlinear relationships across heterogeneous datasets. Consequently, predictive modeling of soil properties has emerged as a central focus of recent research, often integrating data from sensors, laboratory analyses, and remote sensing platforms to support precision agriculture and environmental decision-making.

3.3.1. Soil Moisture Estimation and Prediction

Soil moisture prediction has emerged as one of the most representative and extensively studied applications of artificial intelligence (AI) in soil characterization and agricultural systems. Its importance lies in its direct influence on crop growth, irrigation efficiency, and hydrological processes. As a result, soil moisture modeling has become a benchmark problem for evaluating the performance of machine learning (ML) and deep learning (DL) techniques across multiple spatial and temporal scales.

The reviewed studies consistently demonstrate that AI models can achieve high predictive accuracy by capturing the complex nonlinear relationships between soil conditions, climate variables, and remote sensing inputs. Among ML approaches, tree-based ensemble methods such as Random Forest (RF) are frequently reported among the highest-performing approaches, achieving very high accuracy in regional-scale applications (e.g., NSE values close to 0.98 and RMSE below 0.02 m³/m³) [70]. Similarly, gradient boosting methods have shown superior performance over traditional deep learning models in high-frequency, field-scale prediction tasks [71].

Deep learning approaches, particularly Long Short-Term Memory (LSTM) networks and deep neural networks (DNNs), have demonstrated strong capabilities in modeling temporal dynamics and sequential soil moisture variations. These models are especially effective for time-series forecasting and have shown robust performance across different crops, soil conditions, and climatic scenarios [7,8,71].

Hybrid architectures combining spatial and temporal learning, such as CNN–LSTM and ConvLSTM models, have frequently been associated with improved predictive performance by integrating spatial features from remote sensing data with temporal dependencies. These models have been successfully applied to tasks such as gap-filling between satellite observations and flood-related soil moisture monitoring [51,63]. Advanced configurations, including attention-based CNN–LSTM models with optimized hyperparameters, have demonstrated additional performance gains over conventional approaches [72].

Remote sensing data integration plays a critical role in large-scale soil moisture estimation. Satellite-based datasets, including Sentinel-1, SMAP, and ERA5, are commonly combined with climate variables, soil texture, and topographic information to improve prediction accuracy. LSTM-based models integrating these multi-source datasets have achieved strong performance (e.g., R^2 values around 0.87), although performance may vary depending on vegetation density and environmental conditions [73,74].

In addition to satellite data, unmanned aerial vehicles (UAVs) have been increasingly used for high-resolution soil moisture monitoring. Multi-modal UAV data, including RGB, multispectral, and thermal imagery, combined with AI models such as CNN and CNN–LSTM, have demonstrated high predictive accuracy (e.g., R^2 up to 0.88), particularly in orchard systems and shallow soil layers [75]. Hyperspectral data combined with optimized deep learning models have also achieved high accuracy levels exceeding 90% in soil moisture estimation [76,77].

Despite these advances, several methodological challenges persist. Soil moisture dynamics are influenced by complex interactions among climate, vegetation, and soil properties, making modeling highly sensitive to data quality and representativeness. Deep learning models, while effective, require large datasets and careful calibration to avoid overfitting. Additionally, model performance may decrease under certain conditions, such as high vegetation cover, highlighting limitations in generalization across environments [73].

The integration of multi-source data including in situ sensors, satellite products, and reanalysis datasets introduces further complexity, requiring careful preprocessing, feature selection, and calibration to ensure reliable predictions [25,78–80]. Transfer learning approaches have shown promise in improving model generalization across regions and datasets, particularly when local data availability is limited [63,81].

Table 3 presents representative examples of AI models and their performance across different scales and application contexts.

Table 3. Representative AI models and applications for soil moisture estimation and prediction.

Scale/Application	Representative High-Performing Approaches	References
Field-scale, high-frequency monitoring	XGBoost, LightGBM, deep learning regression; LSTM slightly lower performance	[71,82]
Regional-scale (monsoon conditions)	XGBoost and Random Forest outperform ANN, LSTM, and hybrid models	[70]
Multi-depth soil moisture prediction	LSTM with NDMI integration achieving very high accuracy ($R \approx 0.99$, $NSE \approx 0.996$)	[74]
Global soil moisture products	LSTM-based frameworks trained on large in situ datasets	[79]
Spatiotemporal gap-filling and flood monitoring	ConvLSTM and CNN–LSTM outperform standalone CNN or LSTM	[51]

3.3.2. Soil Salinity, Nutrients, and Chemical Properties

The modeling of soil salinity, nutrient content, and chemical properties has become a central focus in AI-based soil characterization due to its direct implications for soil fertility, crop productivity, and environmental sustainability [83–87]. Across the reviewed studies, key indicators such as electrical conductivity (EC), pH, macronutrients (N, P, K), and soil organic carbon (SOC) are consistently identified as essential variables for assessing soil health and agricultural potential [83,84,88–90].

Artificial intelligence techniques have demonstrated strong performance in predicting soil salinity and EC, particularly when integrating remote sensing data and environmental covariates. Deep learning and machine learning models, including feedforward neural networks (FFNN), Long Short-Term Memory (LSTM), Random Forest (RF), and gradient boosting methods, have been successfully applied using inputs such as spectral indices, elevation, pH, and vegetation indices. These approaches can achieve high predictive accuracy, with reported R^2 values up to approximately 0.84 for EC prediction [91].

Hyperspectral data combined with advanced ML algorithms such as XGBoost, LightGBM, RF, and Extremely Randomized Trees (ERT) have further improved EC estimation, reaching validation R^2 values as high as 0.96 when using optimized spectral and topographic features [58]. Similarly, the integration of active and passive remote sensing data (e.g., Sentinel-1 SAR and Sentinel-2 optical imagery) enhances salinity mapping performance, with RF-based models frequently achieving strong predictive performance in dryland environments [24]. Hybrid approaches combining RF and deep learning have also demonstrated strong performance in multi-class salinity classification tasks [92].

In the context of nutrient and SOC prediction, AI models are widely applied using hyperspectral and multispectral datasets. Machine learning and deep learning techniques including RF, SVM, ANN, and gradient boosting methods are commonly used to estimate macronutrients and soil organic matter, with particular emphasis on feature selection and spectral band optimization to reduce redundancy [93]. Neural network-based models, including multilayer perceptrons (MLP) and deep architectures such as CNN and LSTM, have shown strong performance in estimating SOC and related properties, often outperforming traditional regression approaches [94,95].

Large spectral datasets and advanced feature extraction techniques enable high-accuracy SOC prediction, with deep learning models achieving R^2 values close to 0.96 in some cases [95]. Additionally, low-cost approaches based on RGB or visible hyperspectral data combined with ML/DL models have demonstrated promising results for rapid soil testing applications, including estimation of nitrogen and organic carbon content [96].

The reviewed studies also highlight strong relationships among soil chemical properties. Field-based analyses show correlations between EC and nutrient levels, including positive relationships between EC and potassium or organic carbon, and negative correlations between EC and pH in certain soil conditions [85,88,89,97]. In saline-alkali soils, variables such as total nitrogen (TN), total phosphorus (TP), and soil texture (silt and clay fractions) are identified as key predictors of SOC variability, with RF models assigning high importance to these variables [83].

Remote and proximal sensing technologies play a crucial role in large-scale soil chemical mapping. Hyperspectral and multispectral platforms, including Sentinel-2 and AVIRIS-NG, are widely used to estimate salinity, SOC, and nutrient distributions. These data sources are typically combined with field measurements (EC, pH, SOC, nutrient content) to calibrate and validate AI models [24,58,91–96].

Despite these advancements, several challenges remain. Soil heterogeneity, salinity gradients, and site-specific management practices introduce variability that affects model performance and generalization [83–85,98]. Furthermore, remote sensing provides indirect measurements, particularly for subsurface properties, which can introduce uncertainty due to environmental noise and limited signal penetration [58,93,95,96].

To address these limitations, recent studies emphasize the importance of advanced preprocessing techniques, spectral transformations (e.g., derivatives, wavelets), and feature optimization to improve model accuracy and robustness [99]. These strategies are essential for enhancing the reliability of AI-based soil chemical predictions across diverse environmental conditions.

Table 4 summarizes the main AI approaches, data sources, and target properties identified in the reviewed studies.

Table 4. Representative AI methods and data sources for modeling soil salinity, nutrients, and chemical properties.

Target Property/Theme	Main Data Sources	Dominant AI Methods	References
EC/salinity mapping	Sentinel-2, AVIRIS-NG, hyperspectral, SAR	FFNN/LSTM ensembles, RF, ERT, GBM, DL	[24,58,91,92]
SOC and SOM	Laboratory spectra, simulated satellite spectra	LSTM, CNN, RF, PLSR, ANN	[93–95]
Multi-nutrient prediction (N, P, K, micronutrients)	Hyperspectral/multispectral data, field chemical analysis	RF, SVM, ANN, MLP, PLSR	[93,94,96]
Soil chemical status and indices	Field measurements (EC, pH, SOC, NPK)	RF importance analysis, regression models	[83,85,88,89]

3.3.3. Soil Texture, Structure, and Physical Properties

Soil texture, structure, and related physical properties are fundamental determinants of water flow, storage, root development, and nutrient dynamics in agricultural systems. Variables such as particle size distribution (sand, silt, clay), bulk density, porosity, and hydraulic conductivity directly influence soil functionality and are therefore essential for both agronomic management and environmental modeling.

Recent studies show a clear shift toward the use of artificial intelligence (AI) techniques for digital soil mapping (DSM), integrating ground measurements, remote sensing data, and proximal sensing technologies. Machine learning (ML) has become a core tool in DSM due to its ability to handle large datasets, nonlinear relationships, and highly correlated environmental covariates without strict statistical assumptions [100].

Among ML approaches, Random Forest (RF) is consistently reported as the most widely used algorithm for predicting soil texture, followed by Support Vector Machines (SVMs) and Quantile Regression Forest. These models generally outperform traditional linear regression methods, particularly in estimating sand, silt, and clay fractions [101]. Studies conducted in different regions confirm this trend; for example, RF and Cubist models outperform linear approaches when predicting clay content using terrain and satellite-derived variables [102]. Similarly, ensemble ML methods such as RF, SVM, and gradient boosting have demonstrated improved performance for mapping soil texture and related properties when combining remote sensing and terrain attributes [103].

Table 5 summarizes representative AI-based approaches for modeling soil texture and physical properties across different applications.

Table 5. Representative AI approaches for soil texture, structure, and physical property modeling.

Task/Property	Methods and Key Inputs	References
Direct vs indirect texture mapping	XGBoost, RF, GBDT, ExtraTrees with DEM and Sentinel-1/2 covariates	[104]
Sand, silt, clay prediction	RF, SVM, XGBoost using terrain and remote sensing variables	[105]
Texture and pH mapping	RF, SVM with Sentinel-2, SAR, and terrain attributes	[106]
Texture, OM, EC, CaCO ₃ estimation	SVM and ANN using multispectral reflectance data	[107]

Beyond classical ML, deep learning approaches are increasingly used to improve soil texture and structural characterization. Convolutional Neural Networks (CNNs) and hybrid deep learning models are particularly effective when working with image-based or spectral datasets, enabling the extraction of spatial patterns and improving classification accuracy [104,108]. Additionally, proximal sensing techniques such as visible and near-infrared (Vis–NIR) spectroscopy have been widely integrated with AI models to enable rapid and non-destructive estimation of soil physical properties [12,108].

Advanced multi-sensor systems have further expanded the capabilities of soil characterization. For instance, integrated probes combining measurements of friction, permittivity, resistivity, and spectral responses, along with AI models, allow high-resolution vertical profiling of soil physical, chemical, and biological properties, outperforming traditional sampling approaches [12].

From a physical perspective, soil texture and structure are strongly linked to hydraulic behavior. Studies demonstrate that particle size distribution influences bulk density, porosity, aggregate stability, and saturated hydraulic conductivity, suggesting that detailed modeling of these parameters can improve pedotransfer functions and predictive accuracy [109]. Furthermore, response-surface and ML-based models identify texture, porosity, and organic carbon as key drivers of hydraulic conductivity, often achieving high predictive performance (e.g., $R^2 > 0.85$) [110,111].

Advanced imaging techniques, such as X-ray computed tomography, highlight the importance of pore structure characteristics including pore size distribution and connectivity in controlling water retention and flow processes [112,113]. These structural indicators provide valuable inputs for AI models aimed at understanding soil physical behavior.

Despite these advances, several challenges remain. Many ML-based DSM approaches prioritize predictive accuracy while underrepresenting uncertainty quantification and spatial autocorrelation, which are critical for robust soil mapping [100]. Model transferability across regions is also limited due to variations in soil composition, topography, and environmental conditions [105]. Additionally, remote sensing data primarily capture surface characteristics, making the estimation of subsurface properties more complex and data-intensive [103,106].

3.4. Data Sources, Sensing Technologies, and Data Integration in AI-Based Soil Studies

The performance of artificial intelligence (AI) models in soil characterization and agricultural systems is closely linked to the availability and integration of diverse data sources and sensing technologies. Recent studies emphasize the increasing use of multi-source data, combining in situ measurements, laboratory analyses, remote sensing platforms, and proximal sensing techniques to capture soil variability across different spatial and temporal scales. This integration enables more robust and scalable modeling frameworks, enhancing the accuracy of soil property estimation and supporting a wide range of agricultural applications. In particular, the fusion of heterogeneous data within AI-based systems plays a

critical role in advancing precision agriculture, enabling improved monitoring, resource optimization, and data-driven decision-making.

3.4.1. In Situ Sensors and IoT-Based Soil Monitoring

In situ sensor networks and Internet of Things (IoT) platforms have become essential components of AI-driven soil characterization, enabling the continuous acquisition of high-resolution time-series data for key soil variables such as moisture, temperature, electrical conductivity (EC), pH, and nutrient content. These systems provide the data foundation required for both predictive modeling and real-time agricultural decision-making.

Recent studies highlight the widespread adoption of low-power wireless sensor networks that use communication technologies such as LoRaWAN, ZigBee, NB-IoT, GSM, and custom protocols to enable real-time monitoring of soil and environmental parameters [114–119]. These architectures typically consist of distributed sensor nodes deployed across agricultural fields, where measurements are transmitted through communication protocols such as MQTT to cloud-based platforms, virtual machines, or mobile applications [114,117–121].

In advanced implementations, IoT systems are structured in layered architectures that integrate sensing, communication, and cloud or edge computing components. Edge-level processing techniques, such as Kalman filtering and adaptive sampling, are used to improve data reliability, reduce noise, and optimize energy consumption [114,119]. These architectures support scalable and efficient monitoring frameworks suitable for precision agriculture applications.

Table 6 summarizes the main components and functionalities of IoT-based soil monitoring systems.

Table 6. Typical components and capabilities of IoT-based soil monitoring systems.

Component	Example Capabilities	References
Multi-sensor soil nodes	Measurement of moisture, temperature, pH, EC, NPK, and humidity	[114,115,119,120,122]
Wireless communication links	Real-time, low-power connectivity (LoRa, ZigBee, NB-IoT, GSM)	[114,117–119]
Cloud and application layer	Data visualization, alerts, decision support, and mobile access	[117,118,120]

The integration of IoT data streams with artificial intelligence models has enabled significant advancements in soil monitoring and prediction. Machine learning and deep learning techniques are widely used to process continuous sensor data for soil moisture and temperature prediction, as well as for irrigation scheduling and crop management decisions [42,123–127].

Time-series modeling approaches, particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong performance in multi-step prediction tasks, often outperforming traditional statistical models such as ARIMA and standard regression approaches [123,126,128]. More advanced models incorporate attention mechanisms, autoencoders, and reinforcement learning strategies to capture spatiotemporal dependencies and improve predictive accuracy [118,123,128].

An emerging trend is the development of virtual or soft sensors, where AI models are used to infer soil properties (e.g., moisture) from other sensor measurements, reducing hardware requirements and mitigating sensor failures [116,124,127].

In addition to distributed IoT systems, multi-sensor probes and embedded platforms provide advanced capabilities for soil characterization. For example, integrated probes

combining measurements of friction, dielectric permittivity, electrical resistivity, imaging, acoustics, and Vis–NIR sensing can generate high-resolution vertical profiles of soil properties, which are then analyzed using machine learning models such as partial least squares regression (PLSR), neural networks, and Random Forest [12]. Portable systems equipped with sensors for pH, moisture, EC, temperature, and nutrients also enable real-time soil fertility assessment and crop recommendation using AI-based models [122,129].

Despite these advances, several challenges remain in IoT-based soil monitoring. Calibration issues are common in low-cost sensors, particularly for soil moisture, where nonlinear behavior and environmental variability require careful correction and optimization [114]. Additionally, deployment constraints such as cost, energy consumption, and maintenance requirements limit spatial coverage and long-term reliability, especially in heterogeneous agricultural environments [114,119,130–132].

Data management also presents significant challenges, as IoT systems generate large volumes of continuous time-series data that require robust storage, synchronization, and quality control mechanisms. Integrating these datasets with external sources, such as weather data and remote sensing products, further increases system complexity [116,118,130,131].

3.4.2. Laboratory Data and Multi-Sensor Fusion

Laboratory measurements remain the reference standard for soil characterization and constitute a critical component in AI-based modeling frameworks. These data provide high-precision information on soil properties such as soil organic matter (SOM), soil organic carbon (SOC), pH, nutrients, and texture, and are widely used to calibrate and validate models based on proximal and remote sensing data [12,38,133]. The quality of laboratory measurements is particularly important, as inaccuracies or inconsistencies can directly propagate into AI models and degrade predictive performance [133].

Recent studies emphasize the increasing use of multi-sensor data fusion, where laboratory measurements are combined with proximal and remote sensing data to improve model accuracy and robustness. In these frameworks, laboratory data act as ground truth, enabling the evaluation of predictive models and the optimization of sensor combinations and algorithms [134–136]. For example, the integration of laboratory Vis–NIR spectra with satellite data (e.g., Sentinel-1 and Sentinel-2 time series) has been shown to significantly enhance SOC prediction compared to using satellite data alone [137,138].

Table 7 summarizes representative examples of laboratory data integration within multi-sensor fusion frameworks.

Table 7. Representative applications of laboratory data in multi-sensor fusion frameworks.

Fusion Type	Targets/Benefits	References
DSC multi-sensor probe + laboratory data	High-resolution soil profiling and modeling of scale effects	[12]
Proximal multi-sensor + laboratory data	Prediction of SOM, pH, LBC, Ca, Mg, Al with moderate to high accuracy	[134]
Laboratory Vis–NIR + Sentinel-1/2 imagery	Improved SOC mapping and reduced need for extensive lab sampling	[137,138]

Multi-sensor systems combine data from a variety of sensing technologies, including visible and near-infrared (Vis–NIR), mid-infrared, hyperspectral sensors, gamma-ray spectrometry, electrical conductivity probes, and mechanical or acoustic sensors. These sensors provide rapid, non-destructive measurements that are strongly correlated with laboratory-derived soil properties [25,134,136,139–141].

Advanced multi-sensor probes are capable of integrating multiple measurements such as dielectric permittivity, electrical resistivity, imaging, and spectral data to generate high-resolution vertical profiles of soil properties. When linked with laboratory data, these systems enable detailed characterization of soil physical, chemical, and biological conditions across depth profiles [142,143].

Machine learning and deep learning techniques play a central role in processing fused datasets. Algorithms such as Partial Least Squares Regression (PLSR), Random Forest (RF), Support Vector Machines (SVMs), Artificial Neural Networks (ANN/DNN), and more recently convolutional neural networks (CNNs) and Transformer-based models, are widely used to handle high-dimensional and heterogeneous data [137,139,144,145]. Feature selection, spectral transformations, normalization, and dimensionality reduction are essential preprocessing steps to reduce redundancy and improve model performance [25,136,140,146].

Deep learning architectures, particularly CNN and Transformer-based models, have shown strong potential in extracting complex patterns from large spectral datasets, significantly improving prediction accuracy for multiple soil properties when high-quality laboratory data are available [138,144,145].

Despite its advantages, multi-sensor data fusion presents several challenges. Differences in spatial resolution and measurement scale between laboratory samples and in situ or remote sensing data complicate model integration [12]. In some cases, combining multiple sensors may introduce redundancy and does not always lead to improved performance for certain properties [136].

Additionally, variability in data formats, sensor noise, and environmental factors such as the influence of soil moisture on spectral measurements require robust preprocessing, calibration transfer methods, and quality control procedures [133,140,141].

3.5. Applications of AI in Agricultural Systems

Artificial intelligence (AI) has become a key enabler of modern agricultural systems by facilitating the integration of soil, environmental, and crop data into advanced decision-support frameworks. The reviewed studies demonstrate that AI-driven approaches are increasingly applied to optimize agricultural processes, including precision farming, irrigation and fertilization management, crop yield prediction, and soil monitoring. These applications leverage the capacity of AI models to analyze large, heterogeneous datasets and capture complex interactions across spatial and temporal scales. As a result, AI technologies support more efficient resource management, improved crop performance, and the transition toward sustainable and data-driven agricultural practices.

3.5.1. Irrigation Management and Water Optimization

Artificial intelligence (AI)-driven irrigation systems have emerged as a key solution to address water scarcity and improve agricultural sustainability. These systems leverage predictive models to estimate soil moisture, evapotranspiration (ET), and crop water stress, translating these outputs into optimized irrigation schedules that enhance water use efficiency and crop productivity [147–153].

Machine learning (ML) techniques are widely applied in irrigation management, particularly within IoT-based systems that integrate soil sensors, weather data, and environmental variables. These systems use input data such as soil moisture, temperature, humidity, and weather forecasts to predict irrigation requirements and automatically control irrigation infrastructure, including pumps and valves, in real time [154–162]. Common algorithms include Random Forest (RF), Support Vector Machines (SVM/SVR), k-nearest neighbors (kNN), Artificial Neural Networks (ANN/MLP), gradient boosting, and de-

cision trees, which are used to classify irrigation states or predict the volume of water required [153,159,161,163].

Several studies report high predictive performance, with classification accuracies reaching up to 98–99% for irrigation decision tasks. In addition, simulation-based analyses indicate that AI-driven systems can achieve water savings of up to 27% and energy savings of up to 57% compared to conventional irrigation practices [159,163]. Machine learning models are also widely used to estimate ET and crop water stress indices (CWSI), with algorithms such as CatBoost and stacked ensembles achieving strong predictive accuracy (e.g., RMSE values between 0.06 and 0.72 mm d^{−1} depending on the variable and dataset) [152,153].

Table 8 summarizes the main AI approaches and their corresponding applications in irrigation management.

Table 8. Representative AI approaches and targets for irrigation management and water optimization.

Goal	Typical AI Methods/Setup	References
Soil moisture/irrigation need prediction	RF, SVM, kNN, ANN, gradient boosting with IoT sensors and weather data	[157,158,161–163]
ET and CWSI estimation	SVM, RF, CatBoost, stacked ensemble models	[152,153]
Irrigation decision (on/off control)	MLP, SVM, kNN classifiers, rule-based + ML systems	[159,161,163]

Deep learning (DL) and hybrid approaches have further enhanced irrigation modeling capabilities. Long Short-Term Memory (LSTM) networks are widely used for time-series prediction of soil moisture and irrigation requirements, often outperforming traditional ML models under variable climatic conditions [163]. Hybrid frameworks combining multiple algorithms, such as kNN, gradient boosting, and LSTM, have demonstrated significant improvements in predictive accuracy and water savings, with reported reductions of up to 31% in irrigation water use for specific crops [157].

More advanced approaches incorporate reinforcement learning (RL) and deep reinforcement learning techniques to dynamically optimize irrigation schedules based on continuous feedback from soil and environmental data. These systems can adapt to changing conditions and improve decision-making over time, achieving water-use reductions of approximately 20–25% while maintaining or improving crop yields [153,164,165].

The integration of IoT systems, remote sensing data, and AI models has enabled the development of fully or semi-autonomous irrigation solutions. These systems combine soil sensors, climate data, and satellite-derived information (e.g., ET estimates and vegetation indices) to support data-driven irrigation scheduling. Studies report water savings ranging from 10% to 40% without yield loss, with further improvements (up to 50%) when incorporating rainfall forecasts [152,153,166].

Despite these advancements, several challenges remain. The performance of AI-based irrigation systems is highly dependent on data quality, sensor calibration, and the spatial and temporal coverage of input data. Limited datasets and environmental variability can reduce model transferability across different crops, soils, and climatic conditions [148,153,165]. Additionally, many systems still require partial human intervention, and the development of fully autonomous, interoperable, and secure irrigation systems remains an active area of research [148,153,158].

3.5.2. Crop Yield Prediction and Decision Support Systems

Crop yield prediction represents one of the most impactful applications of artificial intelligence (AI) in agriculture, as it directly supports resource planning, input optimization, and food security strategies [27,167,168]. The reviewed literature consistently highlights the importance of integrating soil properties, climatic variables, crop characteristics, and remote sensing data within machine learning (ML) and deep learning (DL) frameworks to improve predictive performance [169–171].

A wide range of AI models has been applied for yield prediction. Classical ML algorithms such as Random Forest (RF), Support Vector Machines (SVM/SVR), Artificial Neural Networks (ANNs), and gradient boosting methods (e.g., XGBoost) are frequently reported to outperform traditional statistical approaches due to their ability to capture nonlinear relationships and interactions among heterogeneous variables [27,171,172]. Deep learning approaches, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Deep Neural Networks (DNNs), have gained increasing relevance, particularly when large datasets are available, often achieving superior predictive accuracy [167,173,174].

Key predictor variables include temperature, precipitation, soil moisture, soil type, nutrient content, and atmospheric conditions, as well as vegetation indices such as NDVI, EVI, LAI, and NDWI derived from remote sensing data [172,175,176]. Studies show that combining these variables significantly improves model performance. For instance, large-scale analyses demonstrate that integrating climate data, soil properties, and vegetation indices enables accurate yield forecasting with lead times of up to one to three months before harvest [170,171].

Table 9 summarizes representative AI approaches, data sources, and applications for crop yield prediction across different spatial scales.

Table 9. Representative AI approaches and data sources for crop yield prediction across different spatial scales.

Aim/Scale	Main Data Sources	Main AI Methods	Citations
Global/large-scale yield prediction	Weather data, soil properties, remote sensing indices	RF, ANN, SVM; CNN, LSTM, DNN	[27,167,174]
Regional yield prediction and lead time (China)	Climate variables, soil properties, vegetation indices, soil moisture	RF, ML ensemble methods	[170,171]
Field-scale yield prediction (soybean, potato)	Proximal sensing, remote sensing indices, soil properties, crop traits	SVR, CNN (2D/3D)	[172,177]
Yield estimation using SIF/NIRv (US wheat)	Solar-induced fluorescence (SIF), NIRv, climate data, soil properties	XGBoost, RF	[176]

Remote sensing has become a cornerstone of yield prediction, particularly for large-scale applications. Satellite platforms such as MODIS, Sentinel-2, and WorldView provide multi-temporal data that can be used to extract vegetation indices and phenological features [173,174,178]. Deep learning models, especially CNN-based architectures, have demonstrated the ability to predict crop yield directly from raw satellite imagery, with some studies reporting that up to 90% of yield variability can be explained using multitemporal data [177]. Moreover, the integration of multi-source satellite data, including vegetation indices, land surface temperature, solar-induced fluorescence, and vegetation optical depth, further enhances predictive accuracy [171].

Beyond prediction, AI-driven decision support systems (DSS) extend these capabilities by translating model outputs into actionable recommendations. These systems integrate yield predictions with soil data, weather forecasts, and crop requirements to support

decisions related to crop selection, fertilization strategies, irrigation planning, and pest management. For example, neural network-based systems can recommend crops and fertilizer application based on soil nutrient content and pH, while ML-based frameworks such as RF and XGBoost provide crop suitability assessments under specific environmental conditions [17,179]. More comprehensive platforms integrate predictive analytics, geographic information systems (GIS), and farm management tools into unified systems that support precision agriculture [180,181].

Despite these advances, several challenges remain. Model performance is highly dependent on data availability, quality, and representativeness, and models trained in one region or crop system may not generalize well to others [27,167,171]. Limited availability of labeled yield data remains a major constraint, motivating the use of data fusion, transfer learning, and advanced training strategies [27,169,174]. Additionally, the limited interpretability of complex deep learning models continues to hinder their adoption in decision-making contexts, highlighting the need for more transparent and explainable AI approaches [167,173,174].

3.5.3. Soil Mapping and Digital Soil Modeling

Digital soil mapping (DSM) has become a cornerstone of modern soil science and precision agriculture, enabling the transformation of sparse soil observations into spatially continuous maps of soil properties. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) approaches, plays a central role in this process by modeling complex relationships between soil variables and environmental covariates.

The reviewed literature consistently identifies tree-based ensemble methods, including Random Forest (RF), Quantile Regression Forest (QRF), Cubist, and Gradient Boosting algorithms, as some of the most effective techniques for DSM applications across different regions and soil properties [102,182–186]. These models outperform traditional approaches such as multiple linear regression and regression kriging due to their ability to capture nonlinear relationships and handle high-dimensional datasets [102,184,187]. Reviews emphasize that nonlinear ML models have become the standard in DSM, replacing classical statistical methods in many applications [100,188].

The most commonly mapped soil properties include soil organic carbon (SOC), soil organic matter (SOM), pH, texture (sand, silt, clay), cation exchange capacity (CEC), bulk density, and salinity-related indicators. Among these, soil pH and texture are generally predicted with higher accuracy, while properties such as SOC stocks, coarse fragments, and soil depth remain more challenging [182,188,189].

Table 10 presents representative AI approaches and their applications in DSM across different regions and soil properties.

Table 10. Representative AI approaches for digital soil mapping (DSM) across different soil properties and regions.

DSM Task/Property	Main AI Methods	References
SOC, CCE, clay (semi-arid Iran)	RF, Cubist	[102,189,190]
Sand, silt, clay, SOC, N, CEC (Burkina Faso)	RF, SVM, stochastic gradient boosting vs. MLR	[184]
pH, SOC, texture, bulk density (Swiss forests)	Quantile Regression Forest + model averaging	[185]
Multiple soil properties (low-relief regions)	RF, RF-regression kriging	[186]

Remote sensing and environmental covariates are fundamental inputs in DSM. Terrain attributes, vegetation indices (e.g., NDVI, EVI, MSAVI), soil indices, and climate variables are commonly used predictors, enabling large-scale mapping of soil properties [184,189,190]. Multitemporal remote sensing approaches, such as the generation of synthetic bare-soil

images, have been shown to significantly improve predictive performance and reduce uncertainty compared to models based solely on terrain variables [187,190]. The widespread availability of satellite data from platforms such as Sentinel and Landsat has played a crucial role in the operationalization of DSM [188,191].

Deep learning approaches have further advanced DSM by incorporating spatial context and multi-source data integration. Convolutional Neural Networks (CNNs) applied to stacked covariate images have demonstrated significant improvements in SOC mapping, reducing prediction errors by up to 30% at large spatial scales [192,193]. Multivariate CNN models are also capable of simultaneously predicting multiple soil properties and generating uncertainty maps, providing more comprehensive soil assessments [194]. Hybrid architectures, such as CNN–RNN models, have shown improved performance in capturing both spatial and temporal variability when integrating optical remote sensing, climatic, and topographic data [195].

The integration of multi-source data has become a defining characteristic of modern DSM. National and regional frameworks increasingly combine LiDAR-derived digital elevation models, climate datasets, multispectral satellite imagery, land-use information, and laboratory measurements within unified ML models [182]. Advanced fusion approaches explicitly incorporate uncertainty by weighting observations from different data sources, improving both prediction accuracy and model robustness [193]. The combination of static (terrain) and dynamic (multitemporal remote sensing) covariates has been shown to significantly enhance predictions of SOC, texture, and related properties [189,190].

Despite these advances, several limitations remain. Model performance tends to decrease with soil depth, and deep soil layers are often underrepresented in training datasets [188]. Challenges related to spatial autocorrelation, uncertainty quantification, and the integration of pedological knowledge persist, as many studies prioritize predictive accuracy over interpretability [100,188]. Data-related issues, including uneven spatial sampling, limited training data in certain regions, and scale mismatches between point measurements and raster covariates, further complicate model development and generalization [182,185,188].

3.6. Research Trends, Challenges, and Gaps Identified in the Literature

The reviewed literature reveals a rapid transition from traditional statistical approaches toward data-driven and hybrid artificial intelligence (AI) frameworks for soil characterization and agricultural decision-making [4,28,196]. Across domains such as soil analysis, crop yield prediction, and smart farming systems, recent studies consistently highlight the central role of machine learning (ML), deep learning (DL), multi-source data fusion, and emerging paradigms such as explainable AI (XAI) and IoT-enabled platforms [167,197–201].

3.6.1. Emerging Research Trends

A dominant trend is the widespread adoption of ML and DL techniques for modeling soil and agricultural systems. Classical ML algorithms such as Random Forest (RF), Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and gradient boosting methods continue to dominate applications in soil property prediction, digital soil mapping (DSM), and yield forecasting, consistently outperforming traditional statistical models [4,28,196].

In parallel, DL architectures including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and advanced architectures such as ResNet and VGG are increasingly applied to hyperspectral soil analysis, crop yield estimation from imagery, and precision agriculture tasks [200,202,203].

More recently, Transformer-based models have emerged as promising tools for spatiotemporal data fusion, improving feature integration and predictive performance in remote sensing-based agricultural applications [200].

Another key trend is the increasing reliance on multi-source data fusion. Studies emphasize the integration of soil data, climate variables, remote sensing (RS) imagery, and IoT sensor measurements to improve predictive accuracy and spatial coverage [198,200,204]. Multi-sensor RS fusion, including combinations of multispectral, LiDAR, and multi-platform data, has become common in crop monitoring and classification tasks, supported by advanced data harmonization techniques [198,204,205].

In addition, the expansion of IoT-based systems and wireless sensor networks (WSN) has enabled continuous soil monitoring and real-time data acquisition, supporting AI-driven decision support systems (DSS) for irrigation, fertilization, and soil health management [28,201]. This has contributed to the emergence of integrated “digital soil” and smart agricultural platforms that combine DSM, AI models, and sensing technologies into unified systems [196].

3.6.2. Key Challenges in AI-Based Soil and Agricultural Modeling

Despite these advancements, several critical challenges persist. One of the most significant limitations is related to data quality, availability, and bias. Many studies report that insufficient, noisy, or unevenly distributed datasets reduce model accuracy and reliability, particularly in soil property prediction and yield modeling [4,28,196]. Sampling bias and limited environmental representation can also lead to misleading predictions.

Model generalization and transferability represent another major challenge. AI models trained under specific environmental or geographic conditions often fail to perform well in new regions, seasons, or crop systems [28,81,206]. Although transfer learning and domain adaptation techniques are increasingly explored, their effectiveness remains context-dependent and requires further development [81,206,207].

The integration of heterogeneous data sources introduces additional complexity. Multi-sensor fusion requires careful handling of temporal alignment, spatial resolution differences, and radiometric consistency between datasets [200,205]. These processes can be computationally intensive and may limit the scalability of AI solutions, particularly in resource-constrained environments.

Model interpretability and computational complexity also remain important concerns. Many DL and ensemble models operate as “black boxes,” limiting their transparency and practical usability in agricultural decision-making [167,208]. Furthermore, the high computational cost and latency of advanced DL and Transformer-based models pose challenges for real-time applications and large-scale deployment [200,201].

Table 11 summarizes the main research trends, challenges, and identified gaps in AI-based soil and agricultural modeling.

Table 11. Summary of key research trends, challenges, and gaps in AI-based soil characterization and agricultural systems.

Category	Key Aspects	References
Emerging trends	ML/DL dominance, Transformer models, multi-source data fusion, IoT integration, digital soil platforms	[4,198,200,201,204]
Challenges	Data quality and bias, limited generalization, data integration complexity, computational cost, black-box models	[4,28,200,206,208]
Research gaps	Need for generalizable models, hybrid AI–physics approaches, uncertainty quantification, explainable AI, scalable solutions	[197,198,207,209]

3.6.3. Research Gaps and Future Directions

The literature highlights several important research gaps that define future directions. First, there is a clear need for more generalizable and transferable AI models capable of performing across diverse environmental conditions, crops, and geographic regions. This requires the development of standardized datasets, improved data-sharing practices, and multi-environment training strategies [81,197,207,210].

Second, the integration of domain knowledge into AI models remains limited. Most current approaches are purely data-driven, with limited incorporation of soil physics, crop models, or agronomic principles. Hybrid approaches that combine mechanistic understanding with AI techniques represent a promising direction for improving model robustness and interpretability [196,198].

Third, uncertainty quantification is still underdeveloped. Many studies focus on point prediction accuracy without explicitly addressing uncertainty, which is critical for decision-making in agricultural systems. Approaches based on ensemble methods, Bayesian frameworks, and probabilistic modeling are increasingly recognized as necessary for reliable predictions [200,206].

Finally, the development of explainable AI (XAI) and user-centered systems is essential for real-world adoption. Techniques such as SHAP, LIME, Grad-CAM, and interpretable models can provide insights into model behavior and improve trust among stakeholders [202,207–209]. Future research should also address issues of scalability, computational efficiency, and accessibility to ensure that AI-based solutions can be effectively implemented in diverse agricultural contexts, including resource-limited environments [200,205].

4. Discussion

The results synthesized in Section 3 demonstrate the rapid consolidation of artificial intelligence (AI) as a central paradigm in soil characterization and agricultural systems. The reviewed studies collectively indicate a clear transition from traditional statistical approaches toward advanced machine learning (ML), deep learning (DL), and hybrid frameworks capable of modeling complex, nonlinear interactions among soil, environmental, and agronomic variables. While these developments have significantly improved predictive capabilities, they also introduce new challenges related to data integration, model generalization, and interpretability. The following discussion provides a critical interpretation of these findings, emphasizing comparative performance, methodological trade-offs, and implications for practical agricultural applications.

Unlike the result-oriented tables presented in Section 3, the following synthesis tables summarize cross-cutting methodological trends, strengths, limitations, and future challenges identified across the reviewed literature.

4.1. Synthesis of AI Techniques for Soil Characterization

The reviewed literature highlights a progressive evolution in AI techniques used for soil characterization, ranging from classical ML algorithms to advanced DL and hybrid models. Tree-based ensemble methods such as Random Forest (RF) and gradient boosting consistently demonstrate strong performance across diverse soil properties, including moisture, salinity, organic carbon, and texture. Their robustness to high-dimensional data and noise makes them particularly suitable for applications involving heterogeneous environmental datasets [4,28].

Deep learning approaches, including CNN, LSTM, and hybrid CNN–LSTM architectures, have shown superior capability in capturing spatiotemporal dynamics, especially in soil moisture prediction, hyperspectral analysis, and remote sensing-based

applications [33,200]. These models outperform classical ML in scenarios involving large datasets and complex temporal dependencies, although their performance is strongly dependent on data availability and computational resources.

More recently, hybrid and ensemble strategies have emerged as effective solutions for improving prediction accuracy and stability. These approaches combine multiple algorithms or integrate optimization techniques, enabling better representation of nonlinear soil processes. However, the increasing complexity of these models often reduces interpretability, reinforcing the need for explainable AI techniques to better understand model behavior [201].

Beyond improving transparency, explainable artificial intelligence (XAI) techniques such as SHAP and LIME can also contribute to the scientific validation of AI-based soil models. By quantifying the relative importance and directional influence of input variables, these methods help determine whether model predictions are consistent with established soil processes. For example, XAI analyses can verify whether variables such as soil moisture, salinity, organic carbon, or texture are identified as dominant predictors in agreement with known physical and chemical relationships reported in soil science. Consequently, explainability tools provide a valuable link between data-driven predictions and domain knowledge, helping distinguish meaningful soil mechanisms from spurious statistical correlations.

Table 12 summarizes the main families of artificial intelligence techniques used in soil characterization, highlighting their strengths, limitations, and typical applications across soil-related variables.

Table 12. Synthesis of AI techniques applied to soil characterization, including their main characteristics, strengths, and limitations.

Model Family	Typical Applications in Soil Studies	Strengths	Limitations
Tree-based ML (RF, XGBoost, GBM)	Soil moisture, salinity, SOC, texture, nutrient mapping	High accuracy, robustness to noise, handles high-dimensional data, low preprocessing requirements	Limited temporal modeling capability, reduced interpretability compared to simple models
Classical ML (SVM, SVR, ANN)	Soil property estimation, regression tasks, spectral analysis	Good performance in nonlinear problems, flexible across datasets	Sensitive to parameter tuning, may struggle with very large datasets
Deep Learning (CNN, LSTM, RNN)	Soil moisture forecasting, hyperspectral analysis, remote sensing applications	Captures spatial and temporal patterns, high predictive performance with large datasets	High computational cost, requires large training data, low interpretability
Hybrid Models (CNN-LSTM, ANN-GA, ensembles)	Spatiotemporal soil prediction, multi-source data integration, irrigation and yield modeling	Combines strengths of multiple models, improved accuracy and stability	Increased complexity, difficult to interpret, higher computational demand
Ensemble and Optimized Models	Digital soil mapping, multi-variable prediction, agricultural decision support	Reduces overfitting, improves robustness and generalization	Requires careful design and validation, computationally intensive
Explainable AI (XAI) frameworks	Model interpretation, feature importance analysis, decision support systems	Improves transparency, supports trust and adoption	Does not directly improve prediction accuracy, adds methodological complexity

4.2. Integration of Multi-Source Data and Sensing Technologies

A key finding across the reviewed studies is the central role of multi-source data integration in improving AI-based soil modeling. The combination of in situ sensor data,

laboratory measurements, remote sensing imagery, and environmental covariates has become a standard approach in modern soil analysis and precision agriculture [198,204].

IoT-based systems and wireless sensor networks enable continuous monitoring of soil variables such as moisture, temperature, pH, and electrical conductivity, providing high-resolution temporal data streams that enhance predictive modeling and decision support systems [28]. At the same time, satellite and UAV data offer large-scale spatial coverage, allowing the development of scalable soil and crop models.

Despite these advantages, integrating heterogeneous data sources presents significant challenges. Differences in spatial resolution, temporal frequency, and data formats require advanced preprocessing and harmonization techniques to ensure consistency and reliability [200,205]. Additionally, multi-sensor fusion increases computational demands and may introduce redundancy if not properly managed.

The findings suggest that effective data fusion is not only a technical challenge but also a key determinant of model performance. Future advancements in this area will depend on improved data standardization, calibration methods, and scalable architectures capable of handling large, heterogeneous datasets.

Figure 3 illustrates a generalized framework for multi-source data integration in AI-based soil characterization, highlighting the flow from heterogeneous data acquisition to predictive modeling and agricultural applications.

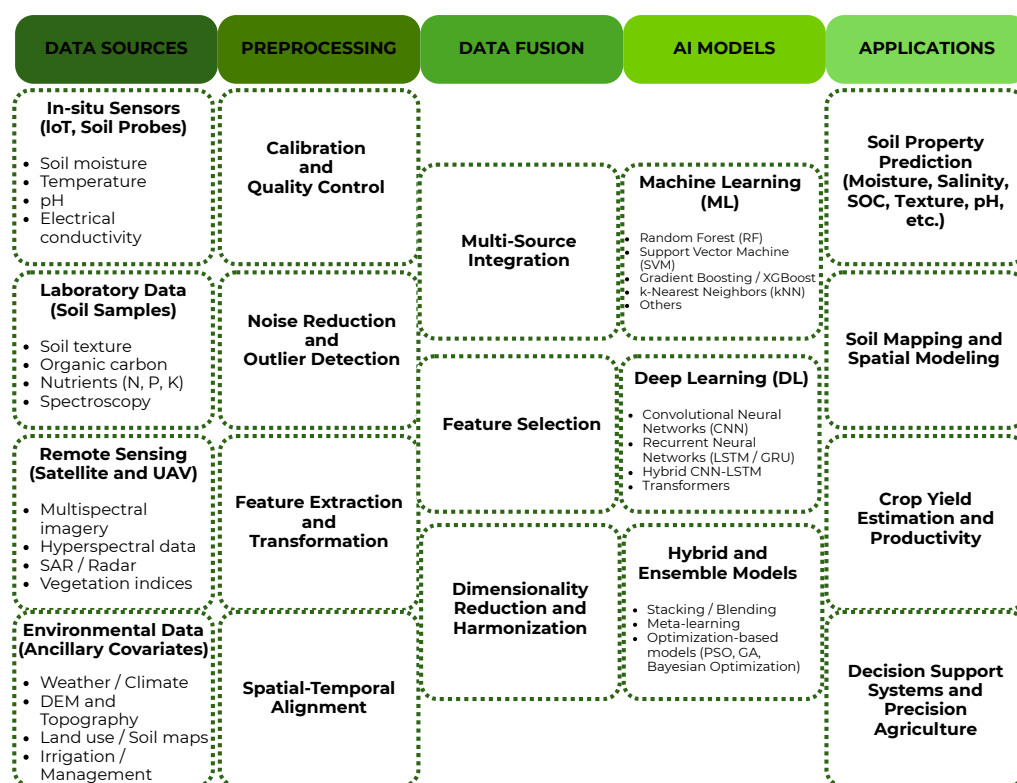


Figure 3. Conceptual framework of multi-source data integration for AI-based soil characterization and agricultural applications. The diagram illustrates the combination of in situ sensors, laboratory measurements, remote sensing platforms (satellite and UAV), and environmental datasets. These data sources undergo preprocessing steps such as calibration, normalization, and spatial–temporal alignment before being integrated through data fusion techniques. The fused datasets are then used to train machine learning and deep learning models, which support applications including soil property prediction, irrigation management, crop yield estimation, and decision support systems.

4.3. Comparative Performance of AI Models Across Soil and Agricultural Applications

The comparative analysis of AI models reveals clear performance differences depending on the modeling approach and application domain. Classical ML models such as RF, SVM, and gradient boosting are frequently reported to achieve higher predictive performance than traditional regression models in predicting soil properties and crop yield, primarily due to their ability to capture nonlinear relationships [4,167].

Deep learning models are frequently associated with improved performance in tasks involving spatiotemporal data, such as soil moisture forecasting and remote sensing-based yield prediction. Architectures such as LSTM and CNN–LSTM are particularly effective in modeling temporal dependencies and spatial patterns, often achieving higher accuracy than standalone ML models [7,33]. However, their advantages diminish when datasets are limited or lack sufficient variability.

Hybrid and ensemble models are frequently reported among the highest-performing approaches by combining the strengths of multiple algorithms. These approaches are particularly effective in complex applications such as irrigation optimization and digital soil mapping, where multiple interacting variables must be considered simultaneously.

Despite these advances, performance comparisons across studies remain challenging due to differences in datasets, evaluation metrics, and experimental conditions. Consequently, reported results should be interpreted as general trends rather than absolute benchmarks. This variability underscores the need for standardized evaluation frameworks and benchmarking datasets in future research.

Table 13 summarizes the comparative performance of the main AI model families across soil characterization and agricultural applications. The comparison highlights trade-offs between predictive accuracy, data requirements, and interpretability, illustrating that more complex models generally achieve higher accuracy at the expense of transparency and computational efficiency. It should be noted that the categories presented in the table (e.g., low, moderate, high, and very high) represent qualitative assessments derived from general trends reported in the reviewed literature and are intended as a conceptual comparison rather than as standardized quantitative benchmarks.

Table 13. Qualitative comparison of AI model families across soil characterization and agricultural applications based on general trends reported in the reviewed literature.

Model Type	Prediction Accuracy	Data Requirements	Interpretability	Typical Applications
Traditional regression	Low to moderate	Low	High	Simple soil relationships, baseline models
Classical ML (RF, SVM, XGBoost)	Moderate to high	Moderate	Medium	Soil property prediction, yield estimation, DSM
Deep learning (CNN, LSTM, CNN–LSTM)	High (with large datasets)	High	Low	Soil moisture forecasting, RS-based modeling, spatiotemporal analysis
Hybrid/ensemble models	Very high	High	Low to medium	Irrigation optimization, multi-source data modeling, precision agriculture

4.4. Implications for Precision Agriculture and Decision Support Systems

The integration of AI into soil characterization has significant implications for precision agriculture and decision support systems (DSS). The reviewed studies demonstrate that AI models can effectively support irrigation scheduling, crop yield prediction, soil fertility management, and resource optimization [148,153].

In irrigation management, AI-driven systems combine soil moisture predictions, weather data, and crop requirements to optimize water use, achieving substantial improvements in water efficiency and energy savings. Similarly, yield prediction models enable early forecasting and improved planning, contributing to more efficient agricultural practices and food security.

The integration of AI with IoT platforms and remote sensing technologies further enables real-time monitoring and adaptive decision-making. These capabilities are essential for developing smart agricultural systems that respond dynamically to changing environmental conditions.

However, the practical implementation of these systems depends on factors such as data availability, infrastructure, and user accessibility. Bridging the gap between advanced AI models and real-world agricultural applications remains a critical challenge, particularly in resource-limited settings.

Table 14 summarizes the main applications of AI-based soil characterization within precision agriculture and decision support systems. The comparison highlights how different AI techniques contribute to improving resource efficiency, enhancing predictive capabilities, and enabling real-time adaptive management in agricultural systems.

Table 14. Implications of AI-based soil characterization for precision agriculture and decision support systems.

Application Area	AI Techniques Used	Key Inputs	Main Benefits
Irrigation management	RF, SVM, LSTM, hybrid DL	Soil moisture, weather, ET, crop data	Water savings, energy efficiency, optimized scheduling
Crop yield prediction	RF, XGBoost, CNN, LSTM	Climate, soil properties, vegetation indices	Early forecasting, improved planning, yield optimization
Soil fertility management	ANN, RF, ensemble models	NPK, pH, SOC, EC	Precision fertilization, improved soil health
Smart monitoring systems (DSS)	ML/DL + IoT + RS integration	Sensor data, satellite imagery, environmental variables	Real-time decision-making, adaptive management

4.5. Limitations of Current Approaches and Methodological Challenges

The reviewed literature identifies several limitations that constrain the applicability and scalability of AI-based soil and agricultural models. Data-related issues, including limited availability, uneven distribution, and measurement uncertainty, remain one of the most significant challenges [4,196].

Model generalization is another critical limitation. AI models often perform well under specific conditions but struggle to adapt to different regions, soil types, or climatic conditions. This limitation highlights the need for more robust and transferable modeling approaches [81,206].

Another important methodological consideration concerns the validation strategies used to assess model performance. The reviewed studies employed a variety of validation approaches, including random train–test splits, cross-validation procedures, and independent validation datasets. However, validation methods were not consistently reported across all studies, preventing a systematic comparison within this review. This aspect is particularly relevant for spatial applications such as digital soil mapping and remote sensing-based modeling, where random data partitioning may overestimate predictive performance when spatial autocorrelation is present. More rigorous validation strategies, including spatial, temporal, and independent external validation, can provide a more realistic assessment of model generalization and transferability across environments.

Model interpretability also remains a key concern. Many advanced ML and DL models operate as black boxes, limiting transparency and practical usability in agricultural decision-making [208]. Although explainable artificial intelligence (XAI) techniques such as SHAP and LIME are increasingly being incorporated into agricultural AI workflows, their adoption remains limited compared with the rapid growth of predictive modeling approaches. Beyond improving transparency, XAI methods can help evaluate whether AI models are learning physically meaningful relationships. In soil characterization applications, for instance, explainability analyses may reveal whether variables related to soil moisture, texture, salinity, or organic matter exert influences that are consistent with established soil processes. Such capabilities are particularly important for increasing confidence in AI-assisted recommendations and facilitating the integration of data-driven models with agronomic and soil science knowledge.

Additionally, computational complexity and infrastructure requirements can restrict the adoption of AI technologies, particularly in small-scale or resource-constrained agricultural systems. Addressing these challenges is essential for ensuring equitable and scalable deployment of AI-based solutions.

Table 15 summarizes the main methodological challenges identified in AI-based soil and agricultural modeling. These challenges highlight critical barriers related to data, model design, and practical implementation, emphasizing the need for more robust, interpretable, and scalable solutions to enable wider adoption in real-world agricultural systems.

Table 15. Key limitations and methodological challenges in AI-based soil and agricultural modeling.

Challenge	Description	Impact on Models	Potential Solutions
Data availability and quality	Limited, noisy, or biased datasets; uneven spatial coverage	Reduced accuracy and unreliable predictions	Standardized datasets, improved sampling, data sharing
Generalization and transferability	Models trained in specific regions fail in new environments	Poor cross-region performance and scalability	Transfer learning, domain adaptation, multi-region training
Model interpretability	Black-box behavior of ML/DL models	Limited trust and adoption in decision-making	Explainable AI (SHAP, LIME), hybrid models
Integration of heterogeneous data	Differences in scale, format, and resolution across data sources	Increased complexity and potential inconsistencies	Data harmonization, feature selection, fusion strategies
Computational complexity and infrastructure	High processing and hardware requirements	Limited adoption in small-scale or low-resource systems	Efficient models, edge computing, cloud-based solutions

4.6. Future Research Directions and Emerging Opportunities

Future research in AI-based soil characterization should focus on improving model generalization, interpretability, and integration with physical knowledge. Hybrid models that combine data-driven approaches with soil physics and agronomic principles represent a promising direction for enhancing model reliability and applicability [196,198].

The development of standardized, large-scale datasets and open data-sharing frameworks is also critical for improving model performance and enabling cross-region comparisons [197]. Advances in transfer learning and domain adaptation are expected to play a key role in improving model transferability across different environments.

Explainable AI (XAI) will be essential for increasing trust and adoption of AI technologies in agriculture. Techniques such as SHAP, LIME, and Grad-CAM can provide insights into model behavior and support more transparent decision-making processes [201,209].

Finally, the integration of AI with emerging technologies such as IoT, edge computing, and digital agriculture platforms is expected to drive the development of fully autonomous and intelligent agricultural systems. These advancements have the potential to significantly improve sustainability, resource efficiency, and resilience in agricultural systems.

Table 16 outlines the main research directions and emerging opportunities in AI-based soil characterization and agricultural systems. The roadmap highlights how advances in data availability, model design, and enabling technologies are expected to drive the development of more robust, interpretable, and scalable AI solutions for precision agriculture.

Table 16. Future research directions and emerging opportunities in AI-based soil characterization and agriculture.

Research Direction	Key Approaches	Enabling Technologies	Expected Impact
Generalizable AI models	Transfer learning, domain adaptation, multi-region training	Large-scale datasets, cloud platforms	Improved cross-region applicability and robustness
Hybrid and physics-informed models	Integration of ML/DL with soil physics and crop models	Simulation tools, digital twins	Better interpretability and physical consistency
Explainable AI (XAI)	SHAP, LIME, Grad-CAM, interpretable models	Visualization tools, decision-support interfaces	Increased trust and adoption in agricultural systems
Multi-source data integration	Fusion of IoT, RS, lab, and climate data	IoT platforms, UAVs, satellite systems	More accurate and scalable soil and crop monitoring
Autonomous and smart agriculture systems	AI-driven DSS, reinforcement learning, automation	Edge computing, robotics, smart sensors	Real-time decision-making and resource optimization

4.7. Comparison with Representative State-of-the-Art Reviews on AI-Based Soil Characterization and Agricultural Applications

A critical comparison with recent state-of-the-art review studies reveals that research on artificial intelligence (AI) applied to soil characterization and agricultural systems has expanded significantly in recent years. Existing reviews typically focus on specific domains such as crop yield prediction, remote sensing applications, soil property estimation, or precision agriculture frameworks. While these studies provide valuable insights, they often address these topics in isolation, emphasizing particular methodologies, datasets, or application contexts rather than offering an integrated perspective.

Several recent reviews highlight the growing role of machine learning (ML) and deep learning (DL) techniques in agricultural systems, particularly for crop yield prediction, irrigation management, and remote sensing-based monitoring [27,167,173]. These studies emphasize the effectiveness of ML/DL models in handling large-scale datasets and extracting patterns from environmental and satellite data. However, their scope is frequently limited to crop-level outcomes, with less emphasis on the underlying soil properties that drive these processes.

Other review works focus specifically on soil characterization using remote sensing and digital soil mapping approaches, highlighting the importance of integrating environmental covariates and geospatial data for predicting soil properties such as organic carbon, texture, and moisture [100,198]. Although these studies provide detailed insights into soil mapping techniques, they often concentrate on specific modeling frameworks or data sources, without fully addressing the broader integration of AI, sensing technologies, and agricultural decision-making systems.

In parallel, reviews on precision agriculture and smart farming systems emphasize the integration of IoT, sensor networks, and AI-driven decision support systems for optimizing resource use and improving agricultural productivity [199,201]. These studies highlight the role of real-time monitoring and automated decision-making but tend to focus more on system-level implementations rather than the detailed modeling of soil processes.

In contrast, the present systematic review provides a comprehensive and integrated perspective by simultaneously addressing AI techniques, soil properties, sensing technologies, and agricultural applications within a unified framework. Unlike previous studies that focus on isolated components, this work synthesizes how soil physical, chemical, and biological properties are modeled using AI, how multi-source data are integrated, and how these models support practical agricultural applications such as irrigation management, yield prediction, and soil health monitoring.

Furthermore, this study emphasizes the interconnection between soil characterization and agricultural decision-making, highlighting soil as a central component of AI-driven agricultural systems rather than as a secondary variable. By linking soil properties, data sources, and AI methodologies across multiple scales, this review contributes to a more holistic understanding of digital agriculture and soil-informed decision support systems.

Table 17 summarizes the scope and focus of representative state-of-the-art reviews in comparison with the present study. The comparison highlights that most existing works concentrate on specific components such as crop prediction, remote sensing, or soil mapping, whereas this review integrates AI techniques, soil properties, sensing technologies, and agricultural applications within a unified analytical framework.

Table 17. Comparison of representative state-of-the-art reviews on AI-based soil characterization and agricultural applications.

Study	Main Focus	AI Techniques	Soil Properties	Applications	Scope
[27,167]	Crop yield prediction	ML, DL	Limited (indirect use)	Yield forecasting	Crop-centric
[173]	Remote sensing for agriculture	DL (CNN, LSTM)	Partial (via RS indices)	Monitoring, yield estimation	RS-focused
[100,198]	Digital soil mapping	ML, statistical models	SOC, texture, moisture	Soil mapping	Soil-centric
[199,201]	Precision agriculture systems	ML, DL, XAI	Limited (support variable)	DSS, irrigation, smart farming	System-level
This work	Integrated AI for soil and agriculture	ML, DL, hybrid models	Physical, chemical, biological properties	Irrigation, yield, soil monitoring, DSS	Holistic and integrative

5. Conclusions

This study presented a systematic review of artificial intelligence (AI) techniques applied to soil characterization and their integration within agricultural systems. The analysis demonstrates a clear transition from traditional statistical approaches toward data-driven methodologies, where machine learning (ML), deep learning (DL), and hybrid models play a central role in modeling complex soil processes. Across the reviewed literature, key soil properties such as moisture, salinity, organic carbon, nutrients, and texture were consistently identified as critical variables for agricultural applications. These properties are closely linked to crop productivity, water management, and soil health, reinforcing the importance of accurate soil characterization as a foundation for precision agriculture.

The results indicate that classical ML algorithms, particularly tree-based ensemble methods such as Random Forest and gradient boosting, provide robust and reliable performance across a wide range of soil-related tasks due to their ability to handle high-dimensional and heterogeneous datasets. Deep learning architectures, including CNN, LSTM, and hybrid CNN–LSTM models, demonstrate superior capability in capturing spatiotemporal dynamics, especially in applications involving remote sensing data and time-series analysis. Hybrid and ensemble approaches frequently achieve the highest predictive performance by combining complementary modeling strategies, although at the cost of increased computational complexity and reduced interpretability.

A key finding of this review is the fundamental role of multi-source data integration in AI-based soil analysis. The combination of in situ sensors, laboratory measurements, satellite and UAV data, and environmental covariates enables more accurate and scalable modeling frameworks. In particular, IoT-based monitoring systems and remote sensing technologies have significantly enhanced the spatial and temporal resolution of soil data, supporting real-time analysis and decision-making. However, challenges related to data heterogeneity, calibration, and harmonization remain critical barriers to effective data fusion and model reliability.

The reviewed studies also highlight the growing impact of AI in agricultural applications, including irrigation management, crop yield prediction, soil mapping, and decision support systems. AI-driven approaches have demonstrated significant potential to improve resource efficiency, optimize water and nutrient use, and support sustainable agricultural practices. Nevertheless, the practical implementation of these systems is often constrained by data availability, infrastructure limitations, and the need for user-friendly and interpretable solutions, particularly in resource-limited contexts.

Despite the substantial progress achieved, several challenges persist. These include limited data availability and quality, lack of standardized datasets and evaluation frameworks, reduced model generalization across regions and soil types, and the black-box nature of many advanced AI models. These limitations highlight the need for more robust, transparent, and transferable modeling approaches.

Future research should focus on the development of hybrid and physics-informed AI models that integrate soil science knowledge with data-driven techniques to improve interpretability and reliability. The creation of large-scale, standardized, and open-access soil datasets will be essential to enhance model generalization and enable cross-region comparisons. Additionally, advances in explainable AI (XAI), transfer learning, and domain adaptation are expected to play a key role in improving model transparency and applicability. Finally, the integration of AI with emerging technologies such as IoT, edge computing, and digital agriculture platforms will facilitate the development of fully autonomous and intelligent agricultural systems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy16131241/s1>, reference [18] is cited in the Supplementary Materials.

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