



AI-Based Soil Fertility Management Review: Challenges And Opportunities

Atin Kumar^{1*}, Himani Sharma², Satendra Kumar³

¹School of Agriculture, Uttaranchal University, Dehradun – 248007, Uttarakhand, India. Email – atinchaudhary0019@gmail.com, ORCID ID: <https://orcid.org/0000-0002-1653-2146>

²School of Agriculture, Uttaranchal University, Dehradun – 248007, Uttarakhand, India. Email – himanis831@gmail.com

³Department of Soil Science and Agricultural Chemistry, College of Agriculture, Sardar Vallabhbhai Patel University of Agriculture & Technology, Meerut – 250110, Uttar Pradesh, India. Email – drskk1@gmail.com

***Corresponding Author:** Atin Kumar
atinchaudhary0019@gmail.com

Abstract

Agriculture is vital for global food security but faces challenges meeting growing demand. Soil fertility management is a major challenge, impacting crop yields and environmental sustainability. Effective strategies providing timely soil nutrient information and fertilizer recommendations are needed. Machine learning offers promise in analyzing large datasets to predict soil properties and crop yield based on factors like nutrient levels, soil pH, and climate conditions. AI-based soil fertility management can improve crop yield, reduce fertilizer waste, and minimize environmental impact but requires accurate data on soil nutrients, weather conditions, and other relevant factors for training machine learning models. In conclusion, AI-based soil fertility management offers a promising solution to the challenges of meeting growing agricultural demands while ensuring environmental sustainability. By using machine learning to analyze large datasets and provide fertilizer recommendations, this approach has the potential to improve crop yield, minimize fertilizer waste, and reduce environmental impact. However, its success relies heavily on accurate and comprehensive data for training machine learning models. As technology advances, the integration of AI in soil fertility management holds great opportunities for sustainable agriculture.

Keywords: AI-based soil fertility management, machine learning, crop yield, soil nutrient prediction, fertilizer recommendations, environmental sustainability.

Introduction to AI-Based Soil Fertility Management

AI-based soil fertility management refers to the use of artificial intelligence technologies and data analytics to optimize and improve the management of soil fertility in agriculture. This approach involves utilizing various AI techniques, such as machine learning, deep learning, image processing, and computer vision, to analyze data on soil composition and quality, plant nutrient requirements, and environmental factors (Singh et al., 2020), (Naresh et al., 2020). The aim is to develop intelligent systems that can make accurate predictions and recommendations for optimizing soil fertility and crop productivity. AI-based soil fertility management has gained significant attention in recent years due to its potential to revolutionize agricultural practices. By integrating AI technologies with soil science, farmers can make data-driven decisions to maximize crop yield while minimizing the use of fertilizers and other inputs. One of the key challenges in this field is the availability and quality of data. Efforts are being made to collect comprehensive soil data through remote sensing and on-site sensors, which will be essential for training AI models to provide accurate recommendations. Additionally, there is an opportunity to develop user-friendly AI interfaces that can be easily adopted by farmers with varying levels of technical expertise (Chlingaryan et al., 2018). These interfaces can provide personalized recommendations and insights, making it easier for farmers to implement precision soil management practices. Overall, AI-based soil fertility management holds great promise for sustainable and efficient agriculture. One of the key challenges in AI-based soil fertility management is model training, validation, and deployment. This requires access to high-quality and representative data, as well as developing robust algorithms that can accurately analyze and interpret the data.

Understanding Soil Fertility: A Primer

Soil fertility refers to the ability of soil to provide essential nutrients and conditions necessary for plant growth and productivity. This includes factors such as the availability of macro and micronutrients, pH level, organic matter content, and soil structure. In order to effectively manage soil fertility, it is crucial to understand the complex interactions between these factors and their impact on crop health and yield. AI-based soil fertility management aims to leverage artificial intelligence technologies, such as machine learning, deep learning, image processing, and computer vision, to analyze data on soil characteristics and crop performance in order to make accurate predictions and recommendations for optimizing soil fertility. AI-Based soil fertility management has emerged as a promising approach for optimizing agricultural practices and improving crop productivity. By integrating AI technologies with soil science, farmers can make informed decisions to maximize crop yield while minimizing the use of fertilizers and other inputs. AI-based soil fertility

management has the potential to revolutionize the way farmers approach soil management. It can provide real-time insights and recommendations based on the specific needs of each field, helping farmers optimize nutrient application, irrigation, and crop rotation strategies. Additionally, AI-based soil fertility management can also help identify and address nutrient deficiencies or imbalances in the soil, leading to more targeted and efficient fertilization practices. Overall, AI-based soil fertility management has the potential to revolutionize agriculture by enabling precision and sustainable farming practices. However, there are several challenges and opportunities associated with AI-based soil fertility management. Some of the challenges include:

1. Data collection and standardization: AI-based soil fertility management relies on access to accurate and representative data. This data includes information on soil characteristics, crop performance, weather patterns, and other relevant factors. Collecting and standardizing this data is a significant challenge, as it requires extensive field sampling and data collection efforts. Furthermore, ensuring the quality and consistency of the collected data is crucial for accurate analysis and predictions.

2. Quality and availability of data: The success of AI-based soil fertility management relies heavily on access to high-quality, reliable, and diverse data. This includes data on soil characteristics, crop performance, weather patterns, and other relevant factors. However, the availability and quality of such data can vary greatly across regions and farms.

3. Limited adoption and access: The adoption of AI-based soil fertility management practices may be limited due to various factors such as lack of awareness, cost constraints, and limited access to technology and internet connectivity in rural areas.

4. Interpretation and decision-making: While AI can provide valuable insights and recommendations, it is ultimately up to the farmer to interpret and make decisions based on the AI-generated information (Pathan et al., 2020). Furthermore, trust and understanding of AI technology among farmers may pose a challenge in the adoption and implementation of AI-based soil fertility management.

5. Integration with existing farming practices: Incorporating AI-based soil fertility management into existing farming practices may require significant changes in workflows and decision-making processes.

6. Lack of technical expertise: Implementing AI-based soil fertility management requires a certain level of technical expertise and knowledge. Farmers and agricultural professionals may need training and support to effectively utilize AI technologies for soil fertility management. Developing AI-based soil fertility management systems poses several challenges in terms of data collection and standardization, ensuring the quality and availability of data, limited adoption, and access to technology, interpretation and decision-making, integration with existing farming practices, and the lack of technical expertise. Overall, AI-based soil fertility management presents both challenges and opportunities in the field of agriculture.

The Role of Artificial Intelligence in Agriculture

Artificial Intelligence is transforming agriculture by enabling precision farming through data-driven insights into soil conditions, plant health, and climatic factors, leading to more accurate irrigation and fertilization. Predictive analytics powered by AI can forecast crop yields, weather trends, and potential pest or disease threats, allowing farmers to proactively address issues and make data-informed decisions. Soil and crop monitoring, leveraging AI with sensors and remote sensing, track changes in real-time, aiding in maintaining optimal growing conditions. Harvesting robots and autonomous tractors can perform tasks such as picking produce and tilling fields, reducing the need for manual labor. AI-driven agricultural robots are capable of identifying, classifying, and treating weeds, thereby reducing herbicide usage and supporting sustainable practices. Supply chain management benefits from AI through improved tracking, demand forecasting, and distribution planning, leading to less waste. Finally, AI models can optimize the breeding process by predicting the best plant and animal traits, accelerating the development of higher-yielding and more resilient crop varieties and livestock breeds. AI-based soil fertility management presents both challenges and opportunities in agriculture (Zha, 2020). AI can revolutionize the way we manage soil fertility by leveraging data-driven insights and advanced algorithms.

Current Challenges in AI-Based Soil Fertility Management

Collaboration and knowledge sharing among researchers, farmers, technology developers, and policymakers are essential for addressing these challenges. Developing standardized protocols and best practices for AI-based soil fertility management is crucial. Additionally, ensuring data privacy and ownership, as well as making AI-based solutions accessible and affordable for farmers of all scales, are important steps in overcoming the associated challenges (Peters et al., 2020).

The potential benefits of AI-based soil fertility management in agriculture are significant. Providing personalized recommendations and insights for precision soil management practices has the potential to revolutionize the way soil fertility is managed. Through data-driven insights and advanced algorithms, AI-based soil fertility management can optimize agricultural practices improve crop productivity, and promote sustainable farming methods (Sharma et al., 2022). As stakeholders collaborate in this field, the integration of AI technologies with soil science shows promise to drive positive change efficiencies in ag navigate industry agricultural sector by driving innovation and creating a more sustainable and productive agricultural sector. However, there are several challenges that need to be addressed for successful implementation of AI-based soil fertility management. These challenges include obtaining representative and high-quality data, ensuring data privacy and ownership, developing robust algorithms that can analyze complex soil data accurately and make appropriate recommendations, and making AI-based solutions accessible and affordable for farmers

of all scales. Furthermore, model training, validation, and deployment are also unique challenges in developing AI-based soil fertility management systems. Moreover, there is a need to establish a collaborative framework that brings together researchers, farmers, technology developers, and policymakers to develop standardized protocols and best practices for AI-based soil fertility management. Furthermore, addressing the scepticism and lack of trust among farmers regarding the benefits of data sharing is crucial. Overall, the development and implementation of AI-based soil fertility management present both challenges and opportunities. The challenges of developing AI-based soil fertility management include obtaining representative and high-quality data, ensuring data privacy and ownership, developing robust algorithms, and making solutions accessible and affordable. However, if these challenges are overcome, there are numerous opportunities for AI-based soil fertility management to revolutionize agriculture by improving productivity, sustainability, and profitability. The implementation of AI-based soil fertility management can bring about significant benefits for the agricultural sector. These benefits include optimized nutrient management, reduced fertilizer and water use, improved soil health, enhanced crop yield and quality, and minimized environmental impact. AI-driven soil fertility management has the capacity to transform the agricultural industry by enhancing productivity, sustainability, and financial viability. Additionally, AI-based soil fertility management can contribute to addressing the global challenges of food security and sustainability.

Addressing AI Challenges in Agriculture: Proposed Solutions

To address the challenges of developing AI-based soil fertility management, several solutions can be proposed. Firstly, there is a need for data collection and sharing mechanisms that ensure the privacy and ownership rights of farmers while still allowing for the gathering of valuable data. This can be achieved through the development of secure and transparent data platforms, where farmers have control over their data and can choose to share it with researchers and stakeholders based on agreed-upon terms and conditions. Secondly, it is important to invest in research and development efforts to improve the accuracy and reliability of AI algorithms used in soil fertility management. This can involve refining existing algorithms and developing new ones that can effectively analyze and interpret diverse soil data. Thirdly, there should be efforts to make AI-based soil fertility management solutions accessible and affordable for farmers of all sizes. This can be achieved through partnerships between technology companies, agricultural organizations, and government agencies to provide training, resources, and incentives for farmers to adopt AI technologies in their soil fertility management practices. Finally, it is crucial to prioritize interdisciplinary collaboration and knowledge sharing among researchers, agronomists, data scientists, and farmers. This collaboration can facilitate the exchange of expertise, insights, and best practices in AI-based soil fertility management, leading to more effective solutions that are tailored to local agricultural contexts and challenges. To address the challenges of developing AI-based soil fertility management, several solutions can be proposed. Firstly, there is a need for data collection and sharing mechanisms that ensure the privacy and ownership rights of farmers while still allowing for the gathering of valuable data. This can be achieved through the development of secure and transparent data platforms, where farmers have control over their data and can choose to share it with researchers and stakeholders based on agreed-upon terms and conditions. Secondly, it is important to invest in research and development efforts to improve the accuracy and reliability of AI algorithms used in soil fertility management. This can involve refining existing algorithms and developing new ones that can effectively analyze and interpret diverse soil data. Thirdly, there should be efforts to make AI-based soil fertility management solutions accessible and affordable for farmers of all sizes. This can be achieved through partnerships between technology companies, agricultural organizations, and government agencies to provide training, resources, and incentives for farmers to adopt AI technologies in their soil fertility management practices. Finally, it is crucial to prioritize interdisciplinary collaboration and knowledge sharing among researchers, agronomists, data scientists, and farmers. This collaboration can facilitate the exchange of expertise, insights, and best practices in AI-based soil fertility management, leading to more effective solutions that are tailored to local agricultural contexts and challenges. In conclusion, AI-based soil fertility management holds great potential for addressing the challenges of monitoring and improving soil fertility. By leveraging AI algorithms and advanced technologies, farmers can make informed decisions about nutrient management, irrigation schedules, and crop selection, leading to improved yields, reduced input costs, and more sustainable agronomic practices.

Opportunities for AI in Soil Fertility Management

Firstly, AI can enhance precision farming techniques by accurately analyzing soil data and providing real-time recommendations for fertilization and irrigation. This can lead to more efficient use of resources and increased crop productivity. Secondly, AI can assist in early detection and management of soil-borne diseases and pests. By analyzing data from sensors and satellite imagery, AI algorithms can identify early signs of disease or pest infestation, allowing farmers to take preventive measures and mitigate potential crop losses (Pathan et al., 2020). Additionally, AI can play a crucial role in optimizing nutrient management. AI algorithms can analyze soil data, crop characteristics, and environmental factors to determine the optimal amount and timing of nutrient application, ensuring that crops receive the necessary nutrients for healthy growth while minimizing nutrient losses and environmental impacts. Furthermore, AI can contribute to soil mapping and analysis. By integrating data from various sources such as satellite imagery, soil sensors, and historical data, AI algorithms can create detailed soil maps that provide valuable information about soil composition, nutrient levels, and potential fertility. This information can help farmers make informed decisions about soil management practices and identify areas that require specific attention or interventions. Lastly, AI can facilitate the development of predictive models for soil fertility. These models can analyze historical data, weather patterns, and crop performance to

predict future soil fertility trends. By understanding how soil fertility may change over time, farmers can proactively adjust their management practices to optimize crop production and reduce environmental impacts.

More opportunities for AI-based soil fertility management include the integration of AI with precision farming technologies, such as drones and autonomous vehicles, to enable targeted and efficient application of nutrients and other inputs. Additionally, AI can be used to develop decision support systems that provide farmers with customized recommendations for soil fertility management based on their specific conditions and goals. Furthermore, AI can play a crucial role in addressing the challenges of soil fertility management. For instance, by helping to overcome the uneven distribution of mechanization by automating tasks that would otherwise require heavy machinery. Furthermore, AI has the potential to address the challenge of processing large sets of data accurately and quickly. Moreover, AI can enhance data security and privacy by implementing robust encryption and authentication measures (Zha, 2020). Another challenge that AI-based soil fertility management faces is the availability and quality of data (Li, 2023). However, with advancements in sensor technologies and data collection methods, AI can help overcome these challenges by improving data quality through data fusion techniques and developing algorithms to analyze and interpret complex soil data. With the advancement of AI technology, soil fertility management in agriculture can be revolutionized through the accurate and real-time analysis of soil data (Pathan et al., 2020). AI-based soil fertility management has the potential to transform agricultural practices by providing real-time analysis of soil data, optimizing resource use, detecting and managing soil-borne diseases and pests, optimizing nutrient management, creating detailed soil maps, and developing predictive models. Additionally, it can integrate with other emerging technologies in agriculture like precision farming and autonomous vehicles for improved efficiency and productivity.

Real-World Applications of AI in Soil Fertility Management

Some real-world applications of AI in soil fertility management include: - Predicting soil fertility using visible-near-infrared spectroscopy and machine learning models like support vector machines, random forest, and convolutional neural networks.

Apologies for the confusion earlier. Based on the information provided from the article itself, the real-world applications for soil fertility assessment include:

Using UV-Vis-induced fluorescence sensors can determine soil fertility in real-time, saving time compared to traditional laboratory analyses that may take days or weeks. The study assessed if induced fluorescence of soil can estimate soil chemical properties such as organic matter, nitrogen, phosphorus, potassium, and various micronutrients vital to plant growth. It also suggests that soil samples can be classified into different fertility classes based on their fluorescence readings, informing farmers about the fertility status of different parts of their fields. Additionally, the study aimed to predict the recommended rate of nitrogen fertilizer application for maize cultivation based on the fluorescence data, potentially guiding more precise nutrient management (Longchamps et al., 2022).

Musanase et al. 2023 implemented a Machine Learning-based Crop and Fertilizer Recommendation System for real-world testing in an agricultural setting in Rwanda. Here are the applications used:

IoT sensors were deployed in cropland to monitor and collect data on soil nutrient levels such as nitrogen, phosphorus, potassium, and soil pH, providing real-time data necessary for their analysis. A neural network ML model was utilized to recommend crops based on the collected data. This model was trained on major Rwandan crops and key growth parameters. For fertilizer recommendations, a rule-based system that uses pre-compiled tables to determine the right amount and type of fertilizers based on soil conditions was employed. Additionally, a conceptual architecture for CFRS deployment on a cloud server was presented to offer real-time, effective, and data-driven agricultural recommendations by monitoring soil conditions and nutrient dynamics over time. This combination of applications formed the core of their real-world application in this study with the aim of enhancing decision-making for Rwandan farmers regarding crop selection and fertilizer usage (Musanase et al., 2023).

Folorunso et al reported the Digital Soil Mapping and Machine Learning for Soil Fertility Prediction; various machine learning models are used to predict and map soil properties and fertility status, which can guide farmers on appropriate fertilization strategies and land management practices. Tools like quantitative regression forests, cubist models, and self-organizing maps are employed to assess soil fertility status by analyzing soil datasets.

Crop Yield Prediction: The review cites studies where machine learning models are used to relate soil nutrients to yield of specific crops like maize, cassava, and yam. Adjusting soil nutrient levels based on ML predictions can optimize crop outputs.

Soil Quality Improvement: Organic manures and inorganic fertilizers are used to enhance soil nutrients, and their effects on crop growth are analyzed through experiments. ML can help predict the outcomes of various soil amendment strategies.

Soil moisture prediction using multi-sensor data: Advanced hybrid models integrating feature selection algorithms are employed to predict soil moisture levels, which is a crucial aspect of real-time monitoring.

Nutrient Deficiency Identification: ML models help identify deficiencies of certain nutrients such as nitrogen, phosphorus, potassium, endashcalcium, and so on, enabling targeted interventions for soil and growth improvement. These applications collectively support decision-making in agriculture, improve productivity. In today's rapidly changing world, the significance of accurate predictions and recommendations for soil fertility management cannot be overstated. (Folorunso et al., 2023)

Future Prospects of AI in Soil Fertility Management

The systematic review insights into the current state of AI and machine learning applications in soil fertility management and suggests several future prospects. Here are some potential future directions for AI and ML in this field:

1. Advanced Predictive Models:

- Developing more sophisticated ML and deep learning models that can more accurately predict soil properties across diverse environmental conditions and different soil types.
- Integration of multi-sensor data from remote sensing technologies to enhance the spatial and temporal resolution of soil fertility assessments.
- Exploring ensemble learning techniques, such as combining multiple ML models to improve prediction accuracy and reliability.

2. Hybrid and Ensemble Techniques:

- Employing hybrid machine learning models that combine multiple algorithms to improve prediction accuracy.
- Utilizing ensemble methods that aggregate the strengths of various models to provide more robust predictions of soil properties.
- Integrating ML models with IoT technologies for real-time monitoring and data collection, allowing for more accurate and timely soil fertility predictions.

3. Big Data Analytics:

- Leveraging big data analytics to process large volumes of soil data from varied sources to uncover intricate patterns and insights into soil health and fertility.
- Enhanced data mining techniques to discover new relationships between soil characteristics and their impact on crop growth.
- Exploring the use of advanced statistical techniques, such as clustering and pattern recognition, to identify hidden patterns in soil data and optimize fertilizer application strategies.

4. Internet of Things and Sensor Technology:

- Incorporating IoT devices and sensor networks for continuous monitoring of soil conditions, providing real-time data for ML models.
- Development of smart sensors that can detect a wide range of soil nutrients and biological indicators for more comprehensive soil health assessments.

5. Precision Agriculture:

- Further integration of machine learning into precision agriculture practices for site-specific soil management, fertilizer application, and crop health monitoring.
- Automated systems that use ML predictions to control the application of inputs like water, nutrients, and pesticides based on soil fertility status.

6. Data-Driven Decision Support Systems:

- Creating intelligent decision support systems that provide actionable recommendations for farmers and agronomists based on ML analyses.
- User-friendly interfaces and applications that translate complex soil data and ML predictions into practical guidance for soil management.

7. Global Soil Information Systems:

- Expanding the development of smart soil information systems that incorporate ML models for use in both developing and developed countries.
- International collaboration and sharing of soil data and ML models to benefit a broader range of agricultural stakeholders.

8. Addressing Data Quality and Coverage:

- Ensuring high-quality and representative soil data for training and testing ML models, overcoming challenges of data scarcity and quality in some regions.
- Initiatives to close the data gaps, especially in developing countries where soil data might be sparse or inaccessible.

9. Sustainability and Climate Change Adaptation:

- Using AI and ML to develop resilient agricultural.
- Systems that can adapt to changing climate conditions and mitigate the impacts of soil degradation.
- Promoting sustainable soil management practices, such as conservation agriculture and organic farming, through AI-based recommendations for soil health improvement.

Conclusion:

In conclusion, AI's application in soil fertility management has the potential to revolutionize agriculture by leveraging machine learning algorithms and data-driven decision support systems. This innovation enables more informed decisions regarding fertilizer application, irrigation, and crop rotation, thereby enhancing overall productivity and resource efficiency in agriculture. Despite challenges like data quality and user-friendly interfaces, the integration of AI with IoT technologies allows for real-time data collection, offering precise soil management practices. While addressing issues such as global information systems and collaboration is crucial, the substantial benefits make AI-based soil fertility management a promising avenue for accurate analysis, real-time monitoring, and improved sustainability in agriculture.

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