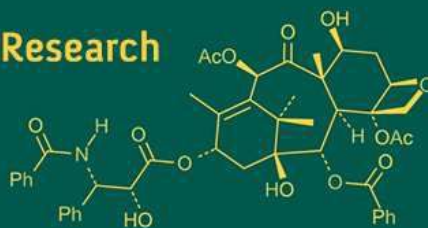
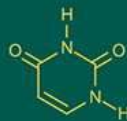


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Artificial intelligence and machine learning in soil analysis innovations for sustainable agriculture: A review

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Abstract

Soil analysis is one important tool in sustainable agriculture since they represent information in terms of soil health and fertility to farmers; hence, there is an optimum resource management. Conventional methods of soil analysis though effective are normally time-consuming, expensive, and often labor-intensive. With the appearance of Artificial Intelligence (AI) and Machine Learning (ML), it has been no more than a transformative innovation in the field of soil analysis. This paper addresses some recent innovations of AI and ML application for soil analysis, focusing on techniques such as remote sensing, spectral analysis, predictive modeling, and precision agriculture, all of which help sustain farming practices.

Keywords: Soil analysis, AI tool, machine learning, sustainable agriculture

1. Introduction

Soils are one of the determinants in agricultural productivity as their health would dictate yield, quality, and production (Khanna *et al.* 2019) ^[44]. Sustainable management of the soil also requires correct analysis to ensure that the soil has fertility to support crop cycles (Bai *et al.* 2020) ^[11]. AI and ML-based technologies present a more advanced alternative for the traditional testing methods on soil (Awais *et al.* 2023) ^[9], which can provide real-time understanding and predictive capability aiding efficient and sustainable management of the soil (Hosseini *et al.* 2023) ^[40].

This is the basic foundation of agriculture; it has a direct relationship with the crop yield and quality in relation to ecological stressors. It is essentially important in the long-term sustainability of soil fertility in sustaining the practices of high-yield farming and ecosystems, and also for food security globally (Panduranga, *et al.* 2024) ^[61]. The traditional approaches for soil testing are excellent but usually involve a great deal of time, mainly because they require manual sampling of soils, operations performed in a laboratory, and the use of heavy labor resources, which have significant limitations, such as being relatively unfeasible at large scales or even in resource-poor areas.

Two of the most prominent emerging technologies that have given birth to revolutionary solutions for soil health management are AI and ML (Maraveas *et al.* 2022) ^[46]. These technologies empower data-driven insights by enabling real-time, accurate, and scalable soil analysis (Babar *et al.* 2024) ^[10]. They bring actionable insights on nutrient levels, moisture content, pH, and more to farmers and agricultural scientists. Artificial intelligence and machine learning help in predictive capabilities and empower the adoption of proactive soil management practices by farmers for optimal crop cycles and sustainable agriculture (Senoo *et al.* 2024) ^[71] and (Mana *et al.* 2024) ^[45].

The applications of soil analysis AI and ML facilitate the precision agriculture approach to farming wherein the application of resources is tailored to individual soils in order to avoid the use of chemicals and save natural resources (Li, X. 2024) ^[35]. It only increases the fertility of the soil but also reduces impact on the environment through fertile agricultural produce that shares coherence with the programs of sustainability (Pandey *et al.* 2024) ^[60]. This paper reports and discusses the present applications, case studies, challenges, and future

directions toward sustainability in agriculture for AI and ML in enhancing soil analysis techniques.

2. Machine Learning in Soil Analysis

This has basically switched soil analysis from being manually, time-consuming to one that is data-driven to predict sustainable agriculture. Advanced ML algorithms now speed up and are more accurate than soil analyses, making precision farming possible; hence, the optimization of inputs and the improvement of soil health over a long-time scale is possible (Alazzai *et al.* 2024) ^[6]. Putting together the ML trends and other technologies, such as the IoT and satellite imaging, gives an impactful approach to the challenges of modern agriculture.

Machine learning is a vital technology to be explored to innovate soil analysis, driven by data, focusing on soil health and nutrient flow dynamics. Machine learning has applications in quality prediction, nutrient and moisture analysis, crop yield forecasting, and many more aspects of soil analysis and (Akkem *et al.* 2023) ^[5]. Key primary machine learning approaches and specific tasks that advance both the analysis and management of soil are discussed below.

2.1 Data-Driven Soil Quality Prediction

There is validated supervised learning in some algorithms for regression and classification for soil quality parameters analysis. For instance, some such algorithms include Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting Trees (GBT) (Shoaib M.M. 2023) ^[78] and Araújo *et al.* 2023) ^[7]. These can be used in large amounts of data resulting from the soil, such as pH, organic matter, and nutrient levels, to reveal patterns underlying those that can predict soil quality correspondingly.

This has actually been successful in prediction in soil attributes containing factors like pH, organic matter, and nutrients through supervised learning-based ML algorithms. After large data sets, the performance of RF SVM and GBT algorithms was good in classifying the soil types and for quality indices (Hanoon *et al.* 2022) ^[36]. These models can analyze tiny trends and relationships among soil properties and help farmers to determine nutrient deficiencies and the health risks of the soil.

This is because Random Forest achieves very high accuracy in soil property classification, being an ensemble learning technique that pools together the results of many decision trees towards an ultimately more stable and generalizable model.

Support Vector Machines also do well on smaller datasets and tend to classify various soil samples as per a few known parameters.

One application of Gradient Boosting Trees is the ability to predict complex outcomes- like the probability of soil erosion or degradation trends-by learning from error in each successive iteration.

2.2 Deep Learning for Soil Nutrient and Moisture Analysis

Thus, deep learning models such as Convolutional Neural Networks, CNN have been successful in the extraction of features from the soil images and spectral data in order to predict soil nutrient and moisture levels (Bharadiya *et al.* 2023) ^[17]. CNNs do very well with complex patterns within unstructured data and that might allow for an accurate

analysis about the soil's composition through remote sensing and hyperspectral imaging (Attri *et al.* 2023) ^[8].

Useful tools in analyzing unstructured soil data, such as images of the soil or remote sensing data, forecast nutrient contents and moisture levels through deep learning methods, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (Hassan *et al.* 2023) ^[38]. For instance, CNN is able to process the high resolution of soil imagery; hence the ability to evaluate composition and structure of soils would emerge through patterns of pixel intensity and color variation (Muruganatham *et al.* 2022) ^[55].

Convolutional Neural Networks (CNNs): CNNs are particularly well-suited for spectral soil analysis, since variations in wavelength correspond to specific nutrients or moisture levels. It identifies and measures micronutrients and organic matter contents from spectral characteristics.

Recurrent Neural Networks (RNNs): RNNs identify seasonal patterns of soil holding moisture and nutrient depletion through time-series soil monitoring based on analyzing historical data to facilitate proactive management of the soil (Han *et al.* 2024) ^[35] and (Chintamaneni *et al.* 2024) ^[22].

2.3 Crop Yield and Soil Husbandry Predictive Models

AI prediction models based on soil and crop data, forecasting crop yields based on historical data, can be used in real-time management of conditions in the soil. Among ML techniques, are time-series analysis evaluating changes in soil properties that influence yield, enhancing farmer decision-making on fertilization, irrigation, crop rotation, among other factors, for sustainable longer-term crop production.

One of the primary applications of ML in soil analysis is predictive modeling (Malashin *et al.* 2024) ^[42]. This would help farmers determine decisions about crop yield as well as soil management practices based on predictions. This could be established based on historical data from both soil and crop analysis through an ML model that predicts crop yield beforehand based on some quality metric of soil. Such models would provide insight for farmers to determine optimum planting times, amendments, and fertilizations needed. Time-Series Analysis and Regression Models are some of the common algorithms that make such predictions.

Time-Series Analysis: The method helps in the investigation on how seasonal factors affect the health of soil and crop yield. The researchers can make use of time-series models to identify the cycles of availability of soil nutrient and moisture retention so that specific changed conditions may be used in changing the treatment of the soil by farmers (Elavarasan *et al.* 2020) ^[28] and Akkem *et al.* 2023) ^[54].

Regression Models: Simple and multiple linear regression models as well as nonlinear regression models can accurately map the interaction relationships of soil properties, for example, levels of nitrogen, pH, and crop yield (Shatar *et al.* 1999) ^[77] and (Hara *et al.* 2021) ^[37]. These models are indispensable for making suggestions on site-specific strategies for soil management, including

optimal levels of fertilizers and timing of irrigation based on projected yield outcomes.

2.4 Soil Classification and Mapping

Soil classification and mapping is an important application in precision agriculture. By using ML models, one can classify the types of soils and map the spatial variability in agricultural fields, indicating a site-specific management approach. Techniques like K-Means Clustering and Hierarchical Clustering divide the field into homogenous zones and help to understand the areas for specific treatment (Metwally *et al.* 2019) ^[49].

K-Means Clustering: This algorithm helps in the sectioning of fields into zones depending on the properties of the soil in which the variable fertilization for farmers will be applied to avoid waste of resources and to prevent contamination of the environment (Nawar *et al.* 2017) ^[57] and Fard *et al.* 2023) ^[32].

Hierarchical Clustering: This is helpful when soil samples of the region have complex hierarchies. In this method, the varying textures and types of soils can be realized that affect the holding capacity of the water as well as the extent of penetration of roots through it (Rabot *et al.* 2018) ^[65].

Benefits of ML in Soil Analysis

High Accuracy: Ensemble and deep learning approaches in ML deliver highly accurate predictions of soil health metrics (Radočaj *et al.* 2022) ^[66].

Cost-effective

The ease of data acquired either through ground collection or remote sensing using ML offers instant health status insights of soil without expenditure incurred in traditional soil sampling and subsequent laboratory testing (Abdullahi *et al.* 2023) ^[1].

Scalability

ML algorithms can effectively handle large data generated from sources such as satellites, drones, and soil sensors to conclude intensive analytical assessments of soils across vast regions (Ahmad M.B. 2023) ^[4].

3. Applications of AI and ML in Soil Analysis

The emergence of new horizons of AI and ML technologies has expanded the capabilities of soil analysis, which is now providing handy tools for farmers and agricultural scientists in managing soil health for optimal resource allocation and informative choices towards sustainable agriculture. This section deals with key applications of AI and ML in soil analysis, including remote sensing, spectral analysis, soil mapping, and IoT-based soil monitoring (Padarian *et al.* 2020) ^[59].

AI and ML applications in soil analysis transform the way farmers monitor, manage, and maintain soil health efficiently to make proper usage of resources and to obtain sustainable agriculture (Padarian *et al.* 2020) ^[59]. By using AI in soil analysis, it is possible to use remote sensing, precision mapping, IoT-based monitoring, and predictive modeling for proper preservation and enhancement of soil integrity as well as its productivity (Sharma *et al.* 2020) ^[76]. Increasingly, such technologies will provide a clear solution in the future (Malashin *et al.* 2024) ^[42].

3.1 Remote Sensing and Spectral Analysis

Integrating soil health monitoring into large-scale monitoring applications is made possible by the convergence of technologies in remote sensing and AI. Using algorithms for AI, analysis can now be possible using photographs from satellites and drones in finding out soil moisture, organic matter, and nutrient distribution (Shoshany *et al.* 2013) ^[79]. Real-time monitoring is also possible by applying spectral analysis integrated with ML models, thus decreasing manual soil sampling.

Such monitoring through the use of remote sensing coupled with AI-driven analysis is the current base for large-scale soil monitoring. Nutrient levels, moisture, organic matter, and other such parameters are analyzed by the AI models using satellite images, drone images, and hyperspectral images over vast areas without the need for physical Berger *et al.* 2022) ^[16].

Spectral Analysis: Soil reflectance across many wavelengths is collected with spectral imaging sensors, which allows for information on composition and health. AI algorithms, especially deep learning models, process this spectral data to develop quantitative soil organic carbon, nitrogen content, and moisture levels and can determine assessments accurately even in inaccessible locations (Nanni *et al.* 2006) ^[56] and Ben-Dor *et al.* 1999) ^[14].

Machine Learning in Image Analysis: High-resolution imagery is utilized by ML models similar to CNNs to identify features typical of soil erosion, compaction, or nutrient deficiencies. These models can further analyze spectral variations to detect soil stress markers and forecast soil health trends (Barathkumar *et al.* 2024) ^[12] and (Sharma *et al.* 2024) ^[75].

Benefits

Soil condition can be monitored over large areas by using remote and time-effective inspection techniques that include remote sensing and spectral analysis. With the aid of remote sensing, there is a possibility of persistent soil quality and health with very little impact on the environment.

3.2 Soil Mapping for Precision Agriculture

AI-based soil mapping makes fields segmented according to the characteristics of the soil, so precision agriculture benefits from this segmentation. It shows spatial variability within a field mapped by ML algorithms into selective applications of fertilizers, pesticides, and irrigation, thereby reducing waste and environmental impact on soil health (Mohamed, M. 2023) ^[51].

So, soil mapping refers to the delineation of agriculturally significant areas into soil zones based on soil properties to guide resource application precisely where needed. AI-powered soil mapping uses clustering algorithms and predictive models to analyze spatial soil variability and thus makes precision agriculture practiced possible (Mohyuddin *et al.* 2024) ^[52] and (Sharma *et al.* 2020) ^[76].

This includes the application of Machine Learning algorithms like K-Means Clustering and Hierarchical Clustering to build maps of soil properties, thus enabling one to divide fields into homogeneous areas on the basis of nutrient levels, pH, and moisture. Variable rate application of fertilizers, pesticides, and water saves resource wastage and improves crop health and Mathur *et al.* 2023) ^[47].

Site-Specific Recommendation: Soil maps provide tangible information for optimal planting periods, crop rotation, and fertilizer application. Coupling historical and current soil data, AI models provide site-specific recommendations that are friendly to the environment, allowing sustainability (Mana *et al.* 2024)^[45].

Advantages

Soil mapping maximizes the input usage, reduces environmental influence, and elevates yield through the spotlight of variability at a granular level in the soil.

3.3 IoT and Sensor-Based Soil Monitoring

Coupled with AI, it has become possible for IoT to provide the soil with real-time analysis through sensors that assess soil parameters such as temperature and pH or moisture, among others. The AI algorithms consume sensor data to get real-time recommendations on soil management and ways for the farmer to optimize resource usage (Gul *et al.* 2024)^[34].

Integration of IoT with AI-based analytics made it possible to offer continuous real-time monitoring of soil parameters. The IoT device with sensor modules deployed in the field collect data on various soil parameters such as pH, temperature, moisture, and salinity. AI models then analyze these datasets for actionable information regarding soil health (Huang *et al.* 2021)^[18] and (Khan *et al.* 2024)^[52].

IoT-based real-time monitoring with sensors: All the soil data are transmitted from the IoT sensors to central systems wherein AI algorithms analyze trends and anomalies. This enables farmers to make instant responses to the soil conditions-for example, by altering their irrigation during drought periods or adding nutrients in real-time depending on a deficiency found (Chowdury *et al.* 2019)^[23].

Automated Decision-Making: AI-based systems can implement specific decisions based on sensor data such as changing the water application schedule or configuring a threshold below which the nutrient levels are considered low to send alert for active amendment. These automated decisions reduce labor, increase precision, and provide optimal soil conditions and Sarker *et al.* 2022)^[79].

Advantages

IoT-based monitoring of soil avoids routine manual testing, provides real-time feedback, and enables proactive management of soil-assuring sustainability.

3.4 Soil Health Prediction and Crop Yield Forecast

In general, applications of AI and ML for soil health prediction support long-term sustainability by predicting the degradation, depletion of nutrients, and potential yield. Predictive models are generally developed using past data collected from the soil, environment variables, and weather forecasts to predict future soil conditions as well as crop yields and Meenakshi *et al.* 2022)^[48].

Yield prediction models are ML models. There are yield prediction models based on parameters such as soil quality, which further predict crop yield. Yield predictions help farmers to change their strategies toward soil treatment and optimize fertilization and prepare for different crop cycles with the forecast of soil health and Sharif A. (2021)^[73].

Long-Term Soil Health Prediction: AI models can predict long-term trends in soil fertility and degradation based on historical soil data. For instance, predictive analytics may predict the effect of the agricultural practices currently being employed on soil structure or erosion versus nutrients and facilitate the implementation of practices that would counteract these degradations over time.

Benefits

Farmers will be equipped with the decision-making data that promotes productivity and sustainability while reducing dependency on chemical inputs-increasing long-term soil conservation through yield and soil health predictions and (Bhogal *et al.* 2024)^[19].

Case Studies and Practical Implementations

Case Studies and Practical Applications This section is based on some case studies and practical applications of AI and ML in soil analysis, which have real-world applications explaining exactly how these technologies help in sustainable agriculture. As this is a multi-agriculture region-based application area, the study then further elaborates on the effectiveness of AI-powered soil analysis to enhance soil health, optimize resource usage, and improve crop productivity (Awais *et al.* 2023)^[9].

4.1 Case Study: India's Precision Agriculture Initiative

Recent developments in India have involved launching a string of AI-based soil analysis initiatives targeting the enhancement of productivity for smallholder farmers. It has partnered with agricultural technology companies to develop mobile and web-based platforms that provide customized soil health reports. These utilize AI-based algorithms that process soil sensor data, remote sensing imagery, and satellite data towards producing actionable insights for the farmer and Miranda *et al.* 2019)^[50].

In India, such AI-based platforms have been integrated with the use of soil sensors and remote sensing to give the farmer customized reports on the health of their soil, which provide insight into the nutrients required and the optimal times of planting. Such platforms are driving predictive analysis in reducing fertilizer usage, thus helping farmers keep their soils fertile in a sustainable manner.

Soil Health Cards: With sensor data collected and analyzed using AI, soil health cards provide a snapshot of nutrient levels, pH, and organic content in given fields. There would be a reduction in the use of chemicals and balanced feed for the soil with recommendations for fertilizer, planting dates, and harvesting.

Predictive Analytics for Crop Management: With AI-driven soil analysis, it predicts yield potential with a given amount of soil health and climate data. Historical soil data combined with current soil health can be used to recommend crop rotation and planting time, among others, with the view of maximizing yields while ensuring soil fertility (Miranda *et al.* 2019)^[50] and Bhat *et al.* (2021)^[18].

Outcome

It has reduced the input costs of smallholder farmers by about 20% and increased the crop yields by 15%, thus demonstrating the feasibility of AI in sustaining and

economically viable agriculture in resource-poor environments.

4.2 Case Study: AI-Based Soil Health Management, United States

The United States also applied AI-based platforms in large-scale soil health monitoring to assess soil degradation. These models, by referencing the historical data on soils and crop yields, can provide predictive information on future soil degradation and thus scope for proactive conservation measures to minimize soil erosion and nutrient depletion (Shalini *et al.* 2024)^[72].

AI-based soil analysis platforms have been actively used in the management of soil health for large farms in the United States. This program employs ML algorithms, IoT sensors, and remote sensing to track and predict a set of soil health indicators such as moisture levels, nutrient content, and erosion risks.

Soiler Moisture Monitoring for Water Conservation: A soil moisture sensor takes the principle of IoT to capture real-time data and allow AI algorithms to make recommendations based on precise information on soil moisture. Since AI feeds farmers with accurate current data concerning ideal irrigation timetables, they are better positioned to conserve water resources (Fernandez *et al.* 2020)^[33] and Zhou *et al.* 2023)^[21].

Erosion Risk Prediction: AI uses historical soil data as well as observed weather patterns to predict erosion risks. Predictions by AI allow the farmer to apply methods like cover cropping or contour plowing for the potential prevention of erosion. These do not only protect the soil structure but also prevent nutrient runoffs.

Results

These implementations have helped large farms save water use up to 30% and soil erosion up to 40%, which is why AI is important because it complements other aspects of economic and environmental sustainability.

4.3 Case Study: AI in Soil Fertility Management in Sub-Saharan Africa

Restoration and maintenance of soil health in Sub-Saharan Africa, where soil fertility decline is a headache, is being brought about by AI-based soil analysis platforms. Organizations are partnering with tech companies to develop mobile applications that will help to appraise soil properties; hence offering nutrient management strategies tailored to specific regions.

Mobile Soil Testing and Fertilization Recommendation:

Farmers enter soil information through mobile apps or use data analyzed by AI from external remote sensing sources. In that case, AI will give on-the-spot insights into the soil fertility level and recommend organic or synthetic fertilizers considering the local soil conditions and nutrient deficits (Rao *et al.* 2009)^[67] and Dimkpa *et al.* 2017)^[27].

Soil quality prediction for land management: AI models embrace long-term risks in soil health; basically, these are acidity and loss of organic matter through the regional profile of soil and environmental factors. These models give farmers a basis for recommendations on soil amendments

and conservation for healthy soil (Hermans *et al.* 2020)^[39] and Park *et al.* 2005)^[62].

Outcomes

The use of these tools has improved matters concerning soil fertility and productivity by an estimated increase of up to 25% more yield per hectare. This is how AI can enhance agricultural productivity in regions that lack the capabilities of a normal soil-analysis resource.

4.4 Case Study: Drone-Based Soil Analysis in Brazil's Agribusiness Sector

Brazil, with one of the largest agribusiness sectors in the world, has stepped into AI and ML to develop precision agriculture. Brazilian agriculture widely adopts the utilization of drones in combination with AI in their soil analysis tools to observe soil health and optimize resource allocation.

AI-Powered Drone Spectral Analysis: Drones equipped with spectral sensors take data regarding the soil characteristics across immense agricultural spaces. The AI algorithms that come out of the spectral data will unveil where nutrient deficiencies, compaction, and erosion are occurring (Chen *et al.* (2023)^[21] and Agrawal *et al.* 2024)^[2].

Precision Fertilization and Irrigation: AI models based on drone-collected data help provide recommendations for variable-rate application of fertilizers and irrigation. Mapping soil variation on the farming side means the application of resources precisely where needed; thereby averting overuse and lowering environmental impact (Lu *et al.* 2022)^[41].

Outcomes

Such yields have been known to rise by 15%, and at the same time, as levels of fertilizer and water have been reduced by 20%, this is what an AI-based analysis in soils can make happen in large-scale farming while encouraging sustainability.

Summary of Key Highlights

Case studies reveal that AI and ML in soil analysis reap an immense benefit for all farms, regardless of their size and different geographic or economic contexts. By providing accurate and up-to-date information to farmers, AI-based tools in soil health management enable the monitoring of the efficient use of resources with resulting improvement in soil fertility, thus bringing about higher crop production. The case studies demonstrate how AI and ML, taking into account the whole arc of food production, can bring about a significant impact on the global agriculture context related to food security and sustainability concerns.

5. Challenges and Future Directions

While the application of AI and ML in soil analysis produces significant benefits toward sustainable agriculture, it still poses certain considerable challenges. Discussions of key challenges, such as limitations of data, an inability to adapt algorithms, potential scalability, and most importantly, accessibility for farmers, are important to consider so that innovations can be maximized with more

AI-driven soil analysis accessibility and effectiveness (Araújo *et al.* 2023)^[7] and Sharma *et al.* 2020)^[76].

5.1 Data Collection and Quality Challenges

The ability and quality of data required to feed AI and ML models is a major drawback (Whang *et al.* 2023). Typically, the data on the soil varies in terms of inconsistency, region-based data, and lack of applicability to optimize the model accuracy or generalizability. This calls for high investment in collecting soil data and developing a standard protocol (Munappy *et al.* 2022)^[54] and Deekshith, A. (2021)^[26].

The principal challenge for AI-driven soil analysis will be the quality and variability of data. Soil data, in general, varies very significantly around different geographical regions due to the types of soils available, climate, and farming techniques. Furthermore, it is capital-intensive to conduct systematic collection of accurate soil data using sensors and drones or remote sensing technologies Barrena *et al.* 2023)^[13].

Data Scarcity in Developing Regions: In most developing regions, consistent soil health data are either non-existent or severely limited, precluding the ability to train robust, region-specific models for AI. Such data scarcity leads to less accurate predictions and generalized recommendations that may not effectively translate to other contexts - anything but beneficial to agriculture diversity across regions (Ahad *et al.* 2020)^[3].

Standardization Problems: Because of differences in measurement practices and reporting structures, it makes the aggregation of data coming from different sources a problem since the metrics for soil health can vary. Unstandardized protocols also minimize the success chances of models trained on diverse.

Possible Solutions

The development of standardized soil sampling protocols and opening up institutions to share data improves the quality and access to data. Other initiatives could be considered as subsidizing soil monitoring tools in low-resource areas to address the scarcity of data and generate stronger datasets on which AI models can be trained.

5.2. Algorithm generalization and adaptability

The AI models that have been trained on region-specific data may fail when transferred to another climate or soil condition. The research in transfer learning and model generalization should enhance the applicability of AI solutions to smallholder farmers in different agricultural regions (Malashin *et al.* 2024)^[42].

AI models designed on specific soil data could not be generalized across different types of soils, climates, or agricultural practices. Such models that work perfectly fine in one region do not work well in another region due to variable characteristics of the soil as well as other environmental conditions. This, hence, limits the adoption of AI-enabled soil analysis at a more universal level (Zhang *et al.* 2023)^[9] and (Espinel *et al.* 2024)^[31].

Transfer Learning and Domain Adaptation: Transfer learning proves useful in making models adapted to other regions, but the training of such models with limited data from similar regions remains challenging. Domain-specific

tuning may lead to higher implementation costs and reduced scalability.

Potential Solutions

Advances in transfer learning and domain adaptation techniques will help with model generalization, making AI models learn better and more suitably to new soil types and conditions. Further, collaboration between local research institutes and AI developers can also bring regionally adapted models to meet the needs of soil analysis in the locality (Persello *et al.* 2022)^[63] Vanlauwee 63t.

5.3 Accessibility for Smallholder Farmers

Despite its high potential, the smallholder farmer in the developing world may not have the necessary infrastructure or resources that would allow them to implement AI-driven soil analysis. Policymaking and other stakeholders should work together to develop accessible and affordable AI tooling.

Many AI-based soil analysis tools entail significant investments in IoT sensors, drones, and remote sensing, that most smallholder farmers in low-resource settings could not afford. Moreover, complex AI models, along with data interpretation tools, would be of little use to the farmer without technical training (Eli-Chukwu, N. C. 2019)^[30].

High Cost of Deployment: Many high-tech AI solutions are too costly to deploy, as the costs incurred at setup are enormous, and subsequent maintenance costs remain high. Mostly, such costs discourage the most susceptible resource users- small-scale farmers-from accessing cheap insights into the soil health (Sharma *et al.* 2020)^[76].

Usability Challenges: Most of the AI-based platforms rely on technical expertise for interpretation, which remains a constraint for users with limited formal education in technology or data science (Sarker *et al.* 2021)^[70].

To increase accessibility, partnerships between government, NGOs, and private companies can underwrite AI-based tools for soil analysis that will be accessible to smallholder farmers. Some of the effective interface's simplification and intuitive as well as most importantly low-cost sensors could unlock the use of AI-driven soil analysis. On-the-job training programs reaching the farmer will be equipped with skills and craft basic interpretations data to help them utilize tools such as AI and Sarker, I. H. (2022)^[70].

5.4 Ethical and Environmental Concerns

As AI expands its reach in agriculture, issues such as data privacy, environmental consequences, and resource use start to pose significant ethical challenges. Gathering and sharing soil data, especially of small holder farms, raises concerns over ownership of data and privacy issues Senoo *et al.* 2024)^[71].

Data Privacy: Smallholder farmers are not likely to open their soils' data due to issues of data privacy or suspicion that they are being used at will for other motives.

Environmental Impact: Heavy reliance on AI-based soil analysis equipment, such as drones and IoT sensors, is likely to introduce issues concerning the environmental footprints of those technologies. The devices are likely to consume more energy to function; this energy could be derived from

unsustainable sources erasing any environmental benefits in sustainable agriculture practices (Awais *et al.* 2023)^[9].

Possible Solutions

Clear data privacy policies that will establish ownership of soil data by farmers will encourage the sharing of data while at the same time keeping the rights of the farmers intact. Investing in energy-friendly AI tools such as solar sensors will reduce the environmental impact of technologies used in agricultural.

5.5 Future Directions

The future of AI and ML may make the analysis of soil accurate, accessible, and sustainable. Below are just some of the avenues for further development.

Hybrid Approaches of AI Models: Hybrids of the traditional soil science with AI method, incorporating hybrid models that combine physical properties of soils with predictions from AI, enhance the model's accuracy and adaptability. For example, physics-informed neural networks based on the principles of both soil and environmental science may provide more accurate predictions regarding the behaviors of soils under different conditions (Rabbani *et al.* 2023)^[64].

Edge AI: Edge AI refers to processing on devices, such as sensors, out of clouds, instead of cloud servers. It has the potential of providing real-time soil analysis with lower latency and energy usage. Since it reduces dependence on constant internet connectivity, it is very beneficial for remote or low-connectivity areas (Singh *et al.* 2022)^[43].

Open-source platforms development: Open-source AI tools and datasets to analyze soil can diminish the limitations of entry for smaller-scale organizations and individual farmers. The open collaboration of research and development can not only catalyze innovation but also ensure equal access to AI-driven soil analysis technologies, including algorithms, data, and insights from researchers and developers (Cox *et al.* 2023)^[25].

Integration with Regenerative Agriculture Practice: Through advancement in AI, its tools can be integrated with the practices of regenerative agriculture, emphasizing long-term vitality in soil and biodiversity and nutrient cycles. AI can input predictive insights for no-till practices, cover cropping, and organic amendments tailored to specific conditions in the soil.

6. Conclusion

AI and ML have demonstrated a lot of potential to improve soil analysis, mainly through efficiency, precision, and scalability. They support sustainable agriculture since they enlighten a farmer on health-related matters around soils while reducing environmental impact and improving resource management. Future advances in AI and ML will likely address the challenges found at the moment and create a robust framework for sustainable agriculture. Indeed, the implementation of AI and ML in soil analysis is a giant leap towards sustainable realization of agriculture. The data-driven inputs regarding the health status of the soils, the nutrient content that is present therein, the moisture status, and, thus, the potential for erosion provide

substantial insight into the assessment of soil, thereby allowing farmers to make better choices that boost crop productivity through optimum resource usage and minimal environment impact. From smallholder farms to large-scale agribusiness, AI-based tools support more precise soil management, reducing dependency on chemical inputs and inducing regenerative practices that will build up soil vitality over time.

Despite promising these technologies have shown to be, data scarcity, high costs, and accessibility barriers still limit their wide usage. At the same time, such technologies will require addressing serious obstacles and challenges in terms of the development of cost-effective solutions, models corresponding to various regions, and user-friendly interfaces so that they become accessible for all farmers, particularly those in low-resource regions. Advances in edge AI as well as hybrid models, along with standardization of data collection and open data sharing, will also make such adaptable and scalable.

The future of AI and ML in soil analysis relies on cross-disciplinary collaboration. In terms of technological progress, we can merge the latest developments in machine learning, soil science, and environmental conservation together to transform agriculture into a far more resilient, sustainable, and data-driven industry. Such support to informed, resource-friendly practices by AI-driven soil analysis does not only benefit agricultural productivity but further goes in efforts towards addressing the challenges of climate change, natural resources conservation, and food security for generations to come.

7. References

1. Abdullahi AY. Benefits and drawbacks of different soil types. TMP Universal Journal of Research and Review Archives. 2023, 2(2).
2. Agrawal J, Arafat MY. Transforming farming: A review of AI-powered UAV technologies in precision agriculture. Drones. 2024;8:664.
3. Ahad MA, Paiva S, Tripathi G, Feroz N. Enabling technologies and sustainable smart cities. Sustainable Cities and Society. 2020;61:102301. DOI:10.1016/j.scs.2020.102301.
4. Ahmad MB. Benefits and drawbacks of different soil types. IPHO-Journal of Advance Research in Agriculture and Environmental Science. 2023;1(07):1-8.
5. Akkem Y, Biswas SK, Varanasi A. Smart farming using artificial intelligence: A review. Engineering Applications of Artificial Intelligence. 2023;120:105899.
6. Alazzai WK, Obaid MK, Abood BSZ, Jasim L. Smart agriculture solutions: Harnessing AI and IoT for crop management. In: E3S Web of Conferences. Vol. 477. EDP Sciences; c2024. p. 00057.
7. Araújo SO, Peres RS, Ramalho JC, Lidon F, Barata J. Machine learning applications in agriculture: Current trends, challenges, and future perspectives. Agronomy. 2023;13(12):2976.
8. Attri I, Awasthi LK, Sharma TP, Rathee P. A review of deep learning techniques used in agriculture. Ecological Informatics. 2023;102217.
9. Awais M, Naqvi SMZA, Zhang H, Li L, Zhang W, Awwad FA, *et al.* AI and machine learning for soil analysis: An assessment of sustainable agricultural

- practices. *Bioresources and Bioprocessing*. 2023;10(1):90.
10. Babar AZ, Akan OB. Sustainable and precision agriculture with the internet of everything (IoE). arXiv preprint arXiv:2404.06341. 2024.
 11. Bai C, Dallasega P, Orzes G, Sarkis J. Industry 4.0 technologies assessment: A sustainability perspective. *Int J Prod Econ*. 2020;229:107776. DOI:10.1016/j.ijpe.2020.107776.
 12. Barathkumar S, Sellamuthu KM, Sathyabama K, Malathi P, Kumaraperumal R, Devagi P. Advancements in soil quality assessment: A comprehensive review of machine learning and AI-driven approaches for nutrient deficiency analysis. *Commun Soil Sci. Plant Anal*. 2024;1-26.
 13. Barrena-González J, Gabourel-Landaverde VA, Mora J, Contador JFL, Fernández MP. Exploring soil property spatial patterns in a small grazed catchment using machine learning. *Earth Sci Informatics*. 2023;16(4):3811-3838.
 14. Ben-Dor E, Irons JR, Epema GF. Soil reflectance. In: *Remote sensing for the earth sciences: Manual of remote sensing*. Vol. 3. 3rd ed. New York: Wiley; c1999. p. 111-188.
 15. Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: A comprehensive updated review. *Sensors*. 2021;21(11):3758.
 16. Berger K, Machwitz M, Kycko M, Kefauver SC, Van Wittenberghe S, Gerhards M, *et al.* Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review. *Remote Sens Environ*. 2022;280:113198.
 17. Bharadiya JP, Tzenios NT, Reddy M. Forecasting of crop yield using remote sensing data, agrarian factors, and machine learning approaches. *J Eng Res Reports*. 2023;24(12):29-44.
 18. Bhat SA, Huang N. Big data and AI revolution in precision agriculture: Survey and challenges. *IEEE Access*. 2021;9:110209–110222. DOI:10.1109/access.2021.3102227.
 19. Bhogal A, Griffiths O, Lewis-Reddy L, Newell-Price P, Nicholson F, Williams J. Review of evidence: Sustainable management of soils in England. 2024.
 20. Chen C, Pan J, Lam SK. A review of precision fertilization research. *Environ Earth Sci*. 2014;71:4073-4080.
 21. Chen J, Zhou J, Li Q, Li H, Xia Y, Jackson R, *et al.* CropQuant-Air: An AI-powered system to enable phenotypic analysis of yield-and performance-related traits using wheat canopy imagery collected by low-cost drones. *Front Plant Sci*. 2023;14:1219983.
 22. Chintamaneni V, Janipalli A, Rajaram J, Devi TA, Vajjala KVK, Vivekanandhan V. Revolutionizing farming: An analysis of IoT-based smart agriculture monitoring systems. In: 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC). IEEE; c2024. p. 486-492.
 23. Chowdury MSU, Emran TB, Ghosh S, Pathak A, Alam MM, Absar N, *et al.* IoT based real-time river water quality monitoring system. *Procedia Comput Sci*. 2019;155:161-168.
 24. Coates RW, Delwiche MJ, Brown PH. Precision irrigation and fertilization in orchards. In: 2005 ASAE Annual Meeting. American Society of Agricultural and Biological Engineers; c2005. p. 1.
 25. Cox D, White C. The great regeneration: Ecological agriculture, open-source technology, and a radical vision of hope. Chelsea Green Publishing; c2023.
 26. Deekshith A. Data engineering for AI: Optimizing data quality and accessibility for machine learning models. *Int J Manag Educ Sustain Dev*. 2021;4(4):1-33.
 27. Dimkpa C, Bindraban P, McLean JE, Gatere L, Singh U, Hellums D. Methods for rapid testing of plant and soil nutrients. *Sustainable Agric Rev*. 2017;1-43.
 28. Elavarasan D, Vincent PD. Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. *IEEE Access*. 2020;8:86886-86901.
 29. Elbasi E, Mostafa N, AlArnaout Z, Zreikat AI, Cina E, Varghese G, *et al.* Artificial intelligence technology in the agricultural sector: A systematic literature review. *IEEE Access*. 2022;11:171-202.
 30. Eli-Chukwu NC. Applications of artificial intelligence in agriculture: A review. *Eng Technol Appl Sci Res*. 2019, 9(4).
 31. Espinel R, Herrera-Franco G, RivadeneiraGarcía JL, Escandón-Panchana P. Artificial intelligence in agricultural mapping: A review. *Agriculture*. 2024;14(7):1071.
 32. Fard KG, Mokarram M. Investigating the pollution of irrigated plants (*Rosmarinus officinalis*) with polluted water in different growth stages using spectrometer and K-means method. *Environ Sci Pollut Res*. 2023;30(35):83903-83916.
 33. Fernandez SG, Vijayakumar K, Kalyanasundaram V, Vidyasagar S, Selvabharathi KSD, Palanisamy R. Smart soil monitoring and water conservation using irrigation on technology. *Indones J Electr Eng Comput Sci*. 2020;19(1):99-107.
 34. Gul D, Banday RUZ. Transforming crop management through advanced AI and machine learning: Insights into innovative strategies for sustainable agriculture. *AI, Comput Sci Robot Technol*. 2024.
 35. Han H, Liu Z, Li J, Zeng Z. Challenges in remote sensing based climate and crop monitoring: Navigating the complexities using AI. *J Cloud Comput*. 2024;13(1):34.
 36. Hanoon MS, Abdullatif BA, Ahmed AN, Razzaq A, Birima AH, El-Shafie A. A comparison of various machine learning approaches performance for prediction suspended sediment load of river systems: A case study in Malaysia. *Earth Sci Informatics*. 2022;1-14.
 37. Hara P, Piekutowska M, Niedbała G. Selection of independent variables for crop yield prediction using artificial neural network models with remote sensing data. *Land*. 2021;10(6):609.
 38. Hassan M, Kowalska A, Ashraf H. Advances in deep learning algorithms for agricultural monitoring and management. *Appl Res Artif Intell Cloud Comput*. 2023;6(1):68-88.
 39. Hermans SM, Buckley HL, Case BS, Curran-Cournane F, Taylor M, Lear G. Using soil bacterial communities to predict physico-chemical variables and soil quality. *Microbiome*. 2020;8(1):79.

40. Hosseini FS, Seo MB, Razavi-Termeh SV, Sadeghi-Niaraki A; c2023.
41. Lu Y, Liu M, Li C, Liu X, Cao C, Li X. Precision fertilization and irrigation: Progress and applications. *AgriEngineering*. 2022;4(3):626-655.
42. Malashin I, Tynchenko V, Gantimurov A, Nelyub V, Borodulin A, Tynchenko Y. Predicting sustainable crop yields: Deep learning and explainable AI tools. *Sustainability*. 2024;16(21):9437.
43. Singh A, Mehrotra R, Rajput VD, Dmitriev P, Singh AK, Kumar P, *et al.* Geoinformatics, artificial intelligence, sensor technology, big data: emerging modern tools for sustainable agriculture. In: *Sustainable Agriculture Systems and Technologies*. 2022. p. 295-313.
44. Khanna A, Kaur S. Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture. *Computers and electronics in agriculture*. 2019 Feb 1;157:218-31
45. Mana AA, Allouhi A, Hamrani A, Rahman S, el Jamaoui I, Jayachandran K. Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices. *Smart Agric Technol*. 2024;100416.
46. Maraveas C. Incorporating artificial intelligence technology in smart greenhouses: Current state of the art. *Appl Sci*. 2022;13(1):14.
47. Mathur R, Katyal R, Gunwal I, Chandra S. Artificial intelligence in sustainable agriculture. *Int J Res Appl Sci Eng Technol*. 2023;11(June):4047-4052.
48. Meenakshi M, Naresh R. Soil health analysis and fertilizer prediction for crop image identification by Inception-V3 and random forest. *Remote Sens Appl Soc Environ*. 2022;28:100846.
49. Metwally MS, Shaddad SM, Liu M, Yao RJ, Abdo AI, Li P, *et al.* Soil properties spatial variability and delineation of site-specific management zones based on soil fertility using fuzzy clustering in a hilly field in Jianyang, Sichuan, China. *Sustainability*. 2019;11(24):7084.
50. Miranda J, Ponce P, Molina A, Wright P. Sensing, smart and sustainable technologies for Agri-Food 4.0. *Comput Ind*. 2019;108:21-36.
51. Mohamed M. Agricultural sustainability in the age of deep learning: Current trends, challenges, and future trajectories. *Sustain Mach Intell J*. 2023;4:2-1.
52. Mohyuddin G, Khan MA, Haseeb A, Mahpara S, Waseem M, Saleh AM. Evaluation of machine learning approaches for precision farming in smart agriculture system-A comprehensive review. *IEEE Access*. 2024.
53. Motia S, Reddy SRN. Exploration of machine learning methods for prediction and assessment of soil properties for agricultural soil management: A quantitative evaluation. *J Phys Conf Ser*. 2021;1950(1):012037.
54. Munappy AR, Bosch J, Olsson HH, Arpteg A, Brinne B. Data management for production quality deep learning models: Challenges and solutions. *J Syst Softw*. 2022;191:111359.
55. Muruganantham P, Wibowo S, Grandhi S, Hoque N, Samrat, Islam N. A systematic literature review on crop yield prediction with deep learning and remote sensing. *Remote Sens*. 2022;14(9):1990.
56. Nanni MR, Demattè JAM. Spectral reflectance methodology in comparison to traditional soil analysis. *Soil Sci Soc Am J*. 2006;70(2):393-407.
57. Nawar S, Corstanje R, Halcro G, Mulla D, Mouazen AM. Delineation of soil management zones for variable-rate fertilization: A review. *Adv Agron*. 2017;143:175-245.
58. Ouazaa S, Jaramillo-Barrios CI, Chaali N, Amaya YMQ, Carvajal JEC, Ramos OM. Towards site-specific management zones delineation in rotational cropping system: Application of multivariate spatial clustering model based on soil properties. *Geoderma Reg*. 2022;30:e00564.
59. Padarian J, Minasny B, McBratney AB. Machine learning and soil sciences: A review aided by machine learning tools. *Soil*. 2020;6(1):35-52.
60. Pandey DK, Mishra R. Towards sustainable agriculture: Harnessing AI for global food security. *Artif Intell Agric*. 2024.
61. Panduranga KM, Ranganathasharma RH. Sustainability insights on learning-based approaches in precision agriculture in internet-of-things. *Int J Electr Comput Eng*. 2024, 14(3).
62. Park SJ, Hwang CS, Vlek PLG. Comparison of adaptive techniques to predict crop yield response under varying soil and land management conditions. *Agric Syst*. 2005;85(1):59-81.
63. Persello C, Wegner JD, Hänsch R, Tuia D, Ghamisi P, Koeva M, *et al.* Deep learning and earth observation to support the sustainable development goals: Current approaches, open challenges, and future opportunities. *IEEE Geosci Remote Sens Mag*. 2022;10(2):172-200.
64. Rabbani A, Samui P, Kumari S. A novel hybrid model of augmented grey wolf optimizer and artificial neural network for predicting shear strength of soil. *Model Earth Syst Environ*. 2023;9(2):2327-2347.
65. Rabot E, Wiesmeier M, Schlüter S, Vogel HJ. Soil structure as an indicator of soil functions: A review. *Geoderma*. 2018;314:122-137.
66. Radočaj D, Jurišić M, Antonić O, Šiljeg A, Cukrov N, Rapčan I, *et al.* A multiscale cost-benefit analysis of digital soil mapping methods for sustainable land management. *Sustainability*. 2022;14(19):12170.
67. Rao AS, Muralidharudu Y, Lakaria BL, Singh KN. Soil testing and nutrient recommendations. *J Indian Soc Soil Sci*. 2009;57(4):559-571.
68. Saleem MH, Potgieter J, Arif KM. Automation in agriculture by machine and deep learning techniques: A review of recent developments. *Precis Agric*. 2021;22(6):2053-2091.
69. Sarker IH. AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems. *SN Comput Sci*. 2022;3(2):158.
70. Sarker IH, Hoque MM, Uddin MK, Alsanoosy T. Mobile data science and intelligent apps: concepts, AI-based modeling and research directions. *Mob Networks Appl*. 2021;26(1):285-303.
71. Senoo EEK, Anggraini L, Kumi JA, Luna BK, Akansah E, Sulyman HA, *et al.* IoT solutions with artificial intelligence technologies for precision agriculture: Definitions, applications, challenges, and opportunities. *Electronics*. 2024;13(10):1894.

72. Shalini VT, Neware R, Kumari T, Kumar M. Soil health management using artificial intelligence for smart agriculture systems. 2024.
73. Sharifi A. Yield prediction with machine learning algorithms and satellite images. *J Sci Food Agric*. 2021;101(3):891-896.
74. Sharma A, Jain A, Gupta P, Chowdary V. Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access*. 2020;9:4843-4873.
75. Sharma NA, Kumar K, Chand RR, Kabir A. Utilizing hyperspectral imaging with machine learning techniques for soil analysis. *Comput Intell Hyperspectral Image Anal*. 2024.
76. Sharma R, Kamble SS, Gunasekaran A, Kumar V, Kumar A. A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Comput Oper Res*. 2020;119:104926.
77. Shatar TM, McBratney AB. Empirical modeling of relationships between sorghum yield and soil properties. *Precis Agric*. 1999;1:249-276.
78. Shoaib MM. Exploring machine learning in deep foundation and soil classification application [master's thesis]. Baton Rouge: Louisiana State University; 2023.
79. Shoshany M, Goldshleger N, Chudnovsky A. Monitoring of agricultural soil degradation by remote-sensing methods: A review. *Int. J Remote Sens*. 2013;34(17):6152-6181.