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Artificial Intelligence in Soil Science: Advancing Soil Health and Quality Assessment

Mahala DM*, Jat SL, Singh AK and Jat HS

ICAR-Indian Institute of Maize Research, India

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***Corresponding author:** Deep Mohan Mahala, Scientist (Sr. Scale)-Soil Science, ICAR-Indian Institute of Maize Research, Ludhiana, Punjab, India

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Abstract

Maintaining ecological services, biodiversity, and sustainable crop productivity all depend on the health and quality of the soil. Traditionally, soil quality assessment has been time-consuming. However, Artificial Intelligence (AI) is reshaping the way we think about soil science, particularly the assessment of soil quality. The soil quality assessment is now quicker and more efficient thanks to AI. AI assisted Soil monitoring, modelling, and management is creating new opportunities for environmental protection, carbon management, and sustainable farming. In this article, we will look at a few specific AI tools and methods are being used in soil science.

Keywords: Machine learning; Artificial intelligence; Soil health; Soil quality; Soil Science

Introduction

Soil health and quality are critical to sustainable agriculture. Because it has a direct impact on agricultural production, environmental quality and ecosystem services. Healthy soil helps maintain biological productivity, maintain water and air quality and promote plant and animal health [1]. With agricultural evolution, the importance of soil health is increasing, particularly in global food security and environmental sustainability [2]. The soil health assessment through the traditional soil testing methods has limitations due to their time-consuming, labor-intensive, and costly nature. The collection, transportation, and subsequent chemical analyses require extensive field work and can take days or weeks to produce results [3,4]. This long process can potentially delay crucial decisions for optimizing soil management practices. Agriculture is on the cusp of a revolution with the incorporation of Artificial Intelligence (AI), which optimizes tons of processes, and enhances accuracy, efficiency, and scalability. AI can fast process huge amounts of data with precision to aid decision-making processes that help enhance productivity and lessen resource use [5]. Such developments have increased the usage of AI in the agriculture, including crop monitoring, disease diagnosis, automated harvesting, and precision irrigation [6,7]. The incorporation of AI into soil science is a crucial advancement in evaluating and monitoring soil health and quality. This review synthesizes the recent literature on AI and Machine Learning (ML) applications in soil science; in particular, in soil health and quality assessment.

Applications of AI in soil health and quality assessment

In soil science, the primary or most significant application of AI is the evaluation and monitoring of soil quality. With ML algorithms and deep learning models, AI allows for the real-time monitoring of soil properties like moisture, organic matter, levels of nutrients, and microbial composition [8]. These insights help in decision-making of farmers and in the end aids in crop production and soil health. ML algorithms has shown great promise in how soil properties like Soil Organic Carbon (SOC), moisture content, and level of nutrients can be estimated. For example, techniques such as Support Vector Machines (SVM), Artificial

Neural Networks (ANN) and Random Forests (RF) are able to predict changes in SOC combining such predictions with the data on environmental variables and soil nutrients [9,10]. These models provide significantly higher accuracy than traditional statistical approaches and thus contribute to the sustainable management of soils [11]. The added advantage of having large datasets is also a plus when it comes to ML owing to the fact that agricultural processes that are based on these systems require soil analysis within a specific period of time and precision due to the need to maximize crop productivity along with resource use [12].

Convolutional Neural Networks (CNNs) are becoming more widely used in the study and evaluation of soil images, especially in the evaluation of soil quality. This is because CNNs are designed to process visual information and are capable of retrieving features that are associated with soil properties. For example, Bryk and Kołodziej evaluated the possibilities of applying image processing techniques for predicting the bulk density of soils and showed that image processing with the use of CNNs can improve pedo transfer functions based on soil images [13]. Zong [14] successfully used Deep Convolutional Neural Networks (DCNNs) to predict a wide range of soil properties, including SOC, which shows that such models can outperform traditional approaches in terms of accuracy and efficiency. Moreover, integration of remote sensing technologies with ML has further advanced the assessment of soil quality. Such examples of remote sensing integration with ML include the use of passive microwave and optical data to retrieve soil moisture with high temporal consistency, as which have shown AI has effectively improved the monitoring of soil moisture [15]. Studies prove that the use of landsat-8 and sentinel-2, among other satellite data in estimation of soil salinity properties in arid regions can be achieved [16-18]. Such studies thus illustrate how remote sensing can offer otherwise inaccessible and critical information about soil conditions that might otherwise not be accessible by conventional means, which are in the first place reliant on localized sampling that may not represent broader trends [19]. In addition to the above, AI can predict spatial variation of soil nutrients through hyperspectral remote sensing and analyze complicated datasets to improve management strategy for soil nutrients [20]. All these techniques assist in improved assessment of soil and also contribute to the development of digital soil maps that are essential to effective land management [21]. Moreover, application of AI in soil science encompasses soil fertility prediction as well as the identification of vital characteristics of soils that influence agricultural yield. The ML techniques have been applied to build models that explain relationships between soil properties and fertility so as to focus interventions that enhance soil health [11,22]. Studies have focused on the suitability of using decision trees as well as gradient boosting machines in predicting soil nutrient indices, thus demonstrating the potential of AI to informed agronomic decisions and improve crop management techniques [23]. Such predictive capability is particularly critical in view of climate change and the increasing demand for food, where proper soil management becomes imperative. Beyond predictive modeling, AI has prominently been used in the classification and assessment of soil quality. Recent studies have used ML algorithms to classify the soils based on their physical and chemical properties, which has provided key information about healthiness and potential risks of the soils being contaminated [24]. For effective remediation strategies as well as sustainable land use, accurate soil classification is crucial [25]. Moreover, hybrid ML models that tend to combine many algorithms have shown great promise in improving prediction accuracy [26]. Furthermore, it is hypothesized that knowledge of soil could be incorporated into ML algorithms with the benefits of both accuracy in prediction and model interpretability, bridging the gap between empirical data and theoretical knowledge [27].

Challenges and opportunities

The understanding and management of soil health is about to take a great leap forward thanks to the development of new ML and AI techniques. There are areas including data quality, model validation, integration of domain knowledge which need to be looked into. Once these are sorted out, AI can be utilized to promote sustainable agricultural practices and ensure that the health of the soils globally improves. It can provide an extra dimension to precision agriculture by presenting information in real-time using sensors and remote sensing devices, allowing farmers to carry out processes such as fertilization, irrigation, and crop management with intelligence. This puts less strain on the soils and it increases food production as well. It can also create soil management practices that sustainability will dictate. The implementation of AI in soil science faces a number of issues, which include the heterogeneous nature of soil data, the requirements for bigger database to support the training process as well as the interpretability of AI models. It is still difficult to explain the rationale behind such predictions, and integration of domain knowledge into AI models is essential. Soil science is a complex field that encompasses various biological, chemical, and physical processes, so incorporating expert knowledge into AI algorithms is crucial. Therefore, soil and data scientists need to work side by side to create models that not only predict soil characteristics but also explain processes responsible for the state of soil health. In spite of these hurdles, the combination of AI and soil science is likely to be key to improvement of the health and quality of soils. By addressing these challenges and fostering collaboration between disciplines, the field can harness the full potential of AI to promote sustainable soil management and improve food security.

Conclusion

In conclusion, the combination of artificial intelligence and soil science holds great promise for improving soil health and quality assessment. Although there are significant challenges but the potential benefits of improved soil management practices and increased agricultural yields make it a worthwhile endeavor. By addressing these challenges and promoting collaboration between disciplines, the field can harness the full potential of AI to promote sustainable and improved soil management.

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