JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Leveraging Artificial Intelligence (AI) for Soil Management: A Comprehensive Overview

Sanjay Lilhare[1*], Pratik Sanodiya[2], Vineet Kumar Dwivedi[1], and T. Singh[1]

[1]Department of Agronomy, AKS University, Sherganj, Satna - 485001 (M.P.), India

[2]Department of Agronomy, Institute of Agricultural Sciences, BHU, Varanasi (U.P.) - 221005, India

Abstract

In recent years, the integration of artificial intelligence (AI) technologies into agricultural practices has revolutionized soil management strategies. This paper provides a comprehensive examination of AI's multifaceted role in managing soil health, productivity, and sustainability. AI-driven precision agriculture techniques offer unprecedented insights into soil composition, moisture levels, nutrient content, and crop performance. Through the analysis of data from various sources including sensors, drones, and satellites, farmers can make informed decisions to optimize irrigation, fertilization, and pest control, thereby enhancing crop yields while minimizing environmental impact. Moreover, AI-powered soil health monitoring systems enable real-time monitoring of key soil parameters, allowing for timely interventions to prevent degradation and promote sustainable soil management practices. Advanced predictive modeling algorithms forecast soil erosion, nutrient depletion, and disease outbreaks, empowering farmers to implement proactive measures for soil conservation and resilience. Lastly, AI-driven robotics and automation streamline soil remediation processes, offering precise and efficient solutions for restoring degraded soils and mitigating the impact of contaminants.

Keywords: Integration, artificial intelligence, soil health, sustainability, soil conservation.

Introduction

Artificial Intelligence (AI) has emerged as a transformative force across various industries, revolutionizing the way we approach problem-solving and decision-making. In recent years, the application of AI has extended its reach to the realm of agriculture, specifically in soil management. Soil, a fundamental component of the agricultural ecosystem, plays a crucial role in determining crop productivity, nutrient content, and overall ecosystem health. As the global population continues to grow, the demand for food also rises, making efficient and sustainable soil management practices imperative. The integration of AI into soil management brings forth a paradigm shift in traditional farming methods, allowing for precision agriculture and data-driven decision-making. AI technologies, such as machine learning, data analytics, and robotics, are being harnessed to optimize soil health, maximize crop yields, and minimize environmental impact. This marks a significant departure from conventional approaches, providing farmers with valuable insights and tools to address challenges associated with soil degradation, nutrient depletion, and climate change. The need for robust, quick, and accurate soil analysis using AI technology holds a great and promising future for sustainable agricultural practices and efficient natural resource management (Pandey *et al.* 2023).

The main functions of AI in soil management

1. **Precision Farming:**

Precision agriculture is made possible by AI by utilizing data from a variety of sources, including sensors, satellite imaging, and historical data. Farmers may customize their agricultural operations to certain locations within a field by using the precise maps of soil conditions that are produced once this information is processed and evaluated. By maximizing the use of resources like water, fertilizer, and pesticides, this focused strategy reduces environmental impact while increasing efficiency.

2. **Predictive Analytics:**

Machine learning algorithms can analyze vast amounts of historical data to predict soil conditions, crop performance, and pest outbreaks. By identifying patterns and trends, AI helps farmers make informed decisions about planting times, crop selection, and pest control strategies, ultimately improving yields and reducing the reliance on chemical inputs.

3. **Soil Health Monitoring:**

AI-powered sensors and IoT devices can continuously monitor soil health parameters such as moisture levels, temperature, and nutrient content. Real-time data collection allows for proactive decision-making, enabling farmers to address issues promptly and prevent soil degradation. This approach facilitates the implementation of sustainable farming practices.

4. **Autonomous Farming Machinery:**

Robotics and AI are transforming farming machinery into smart, autonomous systems. These machines can perform tasks like planting, harvesting, and weeding with precision and efficiency. By automating these processes, farmers can optimize resource use, reduce labor costs, and enhance overall productivity.

5. **Data-Driven Decision-Making:**

AI facilitates data-driven decision-making by analyzing complex datasets and providing actionable insights. Farmers can access information on soil conditions, weather patterns, and market trends, allowing them to make informed choices that enhance productivity and profitability.

The Indian government is now starting to utilize these innovations in its development of the agriculture industry before understanding the significance of AI, which has modified the way people play in other sectors as well. As an essential component of agriculture, and soil science, AI has additionally influenced this. Soil testing and monitoring, fertilization of the soil, evaluations for the quality of the soil, finding deficiency nutrient levels, and carbon sequestration, along with many different fields relevant to it are just a few of the many fields that it comes into contact with in the fields of soil science. The robotics industry, drones, predictive analysis, sensor-based soil monitoring equipment, images from satellites, automatic systems for irrigation, etc. are among the many AI-based technologies that possess the possibility to fundamentally change how Indian agriculture works. With the assistance provided by these advances in technology, growers will soon be able to evaluate crop, soil, and weather conditions for improved yields (Rai *et al*.,2023).

(1) **Soil testing**

To make it easier to analyze soil, (IBM,2018) designed a compact soil testing device that makes use of a colorimetric technique to effectively evaluate five characteristics. An artificial recognition engine enabled by AI can estimate the predictive value of a colorimetric evaluation far more accurately than the average human eye thanks to the micro-fluidic chip within the card that does the chemical analysis. By integrating monitors into cloud computing services and permitting remote utilization of results stored on IoT (internet of Things) cloud servers, the IoT may additionally have an essential part in testing the soil (Sindhu *et al*., 2018). The implementation of AI to information collected through remote sensing has widened. A vital approach for classifying surface area is grounded truth-based training under a supervision model. Comparing two sets of data collected by remote sensing from two separate dates to find changes is another strategy; this is commonly referred to as the substance method for classification (Karpatne, 2016). According to (Saiz-Rubio *et al*.,2020), the administration of soil, land cover, and land is an additional application for AI-driven autonomous automobiles.

(2) Soil and Irrigation management

As surveillance and management applications, numerous IoT and ML (machine learning) related agricultural irrigation systems have already been created. One developing irrigation system includes sensors and an energy module situated on the sprinkler's top. For measuring the moisture in the soil, a different technique attaches a sensor that senses soil moisture to an internet connection (Abba *et al*., 2019). Another irrigation system utilizes ML for handling information and air temperature, humidity, and quality parameters for scheduling irrigation (Vij *et al*., 2020). In agriculture, issues regarding soil and management of irrigation are crucial. Crop loss and poor quality of crops are brought on by inadequate watering and managing the soil. The present chapter includes multiple research projects on soil and irrigation management that employ AI arrives at in conjunction with an expert system built on rules (Brats *et al*., 1993) in evaluating the efficiency of a micro irrigation system design. (Sicat *et al*.,2015) developed a fuzzy-based system utilizing farmers' specialization to suggest products based on the suitability of land maps produced by the fuzzy system. (Tremblay *et al*.,2010). Based on data about weather conditions and the amount of water content of the soil, (Valdes-Vela *et al*., 2015) employed a Takagi Sugeno Kang fuzzy inference technique to estimate the stem water holding capacity of a plant. (Arif *et al*., 2013) designed an artificial neural network (ANN) oriented method for evaluating moisture in the soil in paddy. (Broner and Comstock,1997) represent two more widely recognized systems that use artificial neural networks for irrigation and soil management. (Song and He. Zhai *et al*.,2006), (Patil *et al*.,2009), (Hinnell *et al*.,2010), (Junior *et al*.,2016), and (Antonpoulos *et al*.,2017) represent a few examples. Considering four atmospheric inputs, (Manek and Singh, 2016) evaluated various neural network design concepts to predict rainfall. According to this study, neural networks with radial basis function outperformed various other approaches.

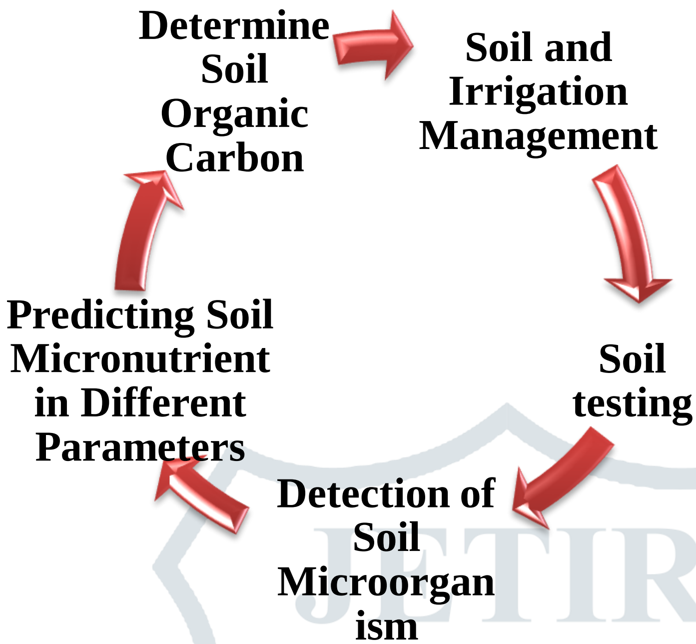

Fig 1. - Role of AI in soil management

(3) Predicting soil micronutrients in different parameter

(Jeong *et al*., 2017) employed a variety of vegetation indicators with particular features obtained from computerized elevation maps to forecast the spatial nutrients of the soil. The results of the study indicate that support vector regression, or SVR, is a useful technique for predicting the nutrients N and P. Geographical factors and the ANN-based pedotransfer functions may both improve the system's ability to forecast soil P levels, claim Keshavarzi *et al*. (2015). ANN artificial neural network models with thermal images helped (Safaa and Maxwell, 2015) assess the N content of pastures. According to their findings, ANN models could have been effectively adapted for pasture N content. When attempting to assess cation exchange capacity (CEC) employing soil particle size distribution (PSD) and soil organic matter (SOM), (Zolfaghari *et al*.,2016) used the k-NN (k-Nearest Neighbor) approach. The results they obtained suggested that the accuracy of the ANN and k-NN methods used for calculating soil CEC is comparable. A vital component of the fertility of the soil and its ecological effects is soil nutrients. Conventional approaches for evaluating nutrients in soils are challenging to use and, therefore presents major difficulties for applications in practice. Using the methods of support vector machines (SVM), multiple line regression (MLR), and artificially intelligent neural networks (ANNs), respectively, we propose several detailed methods for assessing the nutrients in soil during this study (E. W. Russell, 1997). In certain studies, farmers are employing soil methods for cultivation (Reddy, 2011). The vast majority of their methods are the result of their extensive understanding of local conditions and numerous years of experience. Mixed cropping and planting of legumes were other common methods, as was the administration of FYM and chemical fertilizers. This suggests that farmers have an understanding of the economic importance of FYM along with additional organic manures, according to (Hosier and Bradley,1999).

(4) Detection of soil microorganisms

For instance, the general composition of the soil fauna and microbial community is thought to be crucial in every ecosystem for initiating responses that have global ramifications related to reducing the cycling of atmospheric carbon (Glassman et al., 2018). Microbiological reactions to management can happen in a matter of hours or days, depending on the situation (Landesman et al., 2019). Consequently, it was discovered that non-biological indicators of chemical quality, such as total organic carbon in the soil (SOC), were more sensitive to changes in the management of soil or land use than biochemical responses, such as microbial production of extracellular binding agents (Redmile-Gordon *et al.*, 2020). Through the process of micro aggregate subsequent generations from microbiological extracellular polymeric compounds (EPS; Krause *et al*., 2019) and retaining in fungal hyphae, which in turn offer protection from erosion (Tang *et al*., 2011), soil biota are directly linked to soil structural stability. These microorganisms act on nutrient delivery and plant protection, and they're important for plant survival (Crossa *et al*., 2017). On the varied nature of soil microbial characteristics, we have a dearth of complete information. The gathering of extensive and robust data regarding terrestrial ecosystems and their utilization has substantial potential in facilitating the development of precise gauges for soil health since microbial activities' exceptionally sensitive processes are simple to recognize.

(5) Determine soil organic carbon

Numerous soil research made use of AI. Examples of these kinds of research involve the measurement of dryland salinity (Spencer *et al*., 2004), forecasting riverbed salinity (Maier and Dandy,1998), and estimating pH and the amount of clay in the soil (Henderson *et al*. 2004). A sample of the ground must be obtained and investigated in a controlled environment to find out the amount of organic carbon present. The process of collecting the sample is, unfavorably tedious and costly. Instead of directly detecting carbon inorganic from samples of dirt, researchers are looking toward more affordable estimation approaches. Determining the relationship between carbon from organic matter and weather conditions as well as soil site variables became the subject of research. Organic carbon levels have been observed to be correlated with variables such as precipitation, temperature, clay content, and soil texture (Hontoria *et al*., 1999; Parton *et al*., 1987). The purpose of this research is to establish a rapid and inexpensive approach for calculating organic carbon levels employing data from soil surveys and automated instruments. In a study carried out in America (Nichols,1984), organic carbon was determined using linear regression. It was believed that an estimate of organic matter in soil might be calculated with a regression model and yearly precipitation given the strong association between soil organic carbon and clay content. Results demonstrated that, under certain circumstances, organic carbon may be effectively anticipated. Another American study (Parton *et al*., 1987) evaluated the highest and lowest limits of the biological carbon content considering the yearly precipitation as a factor. (Hontoria *et al*.,1999) they estimated the total quantity of carbon dioxide from organic sources in Spain using the method of linear regression. It was demonstrated that the general level of biological carbon may be identified by employing annual rainfall in in addition to temperature. For evaluating the amount of naturally occurring carbon, several linear regression techniques that consider into account soil taxonomy, texture, drainage, slope, and elevation have been created and developed (Tan *et al*., 2004). It was discovered that there existed a connection. Could have been established, particularly for agriculture, between carbon from organic materials and those factors. Other characteristics of the soil, such as dryland salinity, were successfully categorized using AI neural networks (Spencer *et al*., 2004). AI neural networks have been considered to represent an appropriate tool for challenging issues like determining the amount of organic matter in the soil since they possess an ability to tackle complex or noisy situations.

Conclusion

In conclusion, using AI in soil management has great potential to help solve the problems that face contemporary agriculture. AI has the potential to significantly impact the long-term health and production of our soils and, consequently, the global food chain by promoting sustainability, improving resource management, and providing farmers with useful information. To fully utilize AI for soil management, further study and cooperation between the tech and agriculture industries will be essential as technology develops.

Reference

A. C. Hinnell, et al., "Neuro-Drip: estimation of subsurface wetting patterns for drip irrigation using neural networks," *Irrigation science*, vol. 28 no.6, pp. 535-544, 2010.

A. H. Manek, and P. K. Singh, ―Comparative study of neural network architectures for rainfall prediction, In proc. Technological Innovations in ICT for Agriculture and Rural Development (TIAR), 2016, pp. 171-174, 2016, July, IEEE.

A. Vij, S. Vijendra, A. Jain, S. Bajaj, A. Bassi, and A. Sharma, "IoT and machine learning approaches for automation of farm irrigation system," *Procedia Computer Science*, vol. 167, pp. 1250–1257, 2020

C. Arif, M. Mizoguchi, and B. I. Setiawan, ―Estimation of soil moisture in paddy field using Artificial Neural Networks, ‖ arXiv preprint arXiv: 1303.1868, 2013.

Crossa, J., P´erez-Rodríguez, P., Cuevas, J., Montesinos-Lopez, ´ O., Jarquín, D., de los Campos, G., … Varshney, R. K. (2017). Genomic selection in plant breeding: Methods, models, and perspectives. *Trends in Plant Science*, 22(11), 961–975.

E. W. Russell "The Management of Inputs for Yet Greater Agricultural Yield and Efficiency" Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences Vol. 281, No. 980, (Nov. 25, 1977), pp. 209-219

H. Song and Yong He, "Crop nutrition diagnosis expert system based on artificial neural networks," in Proc. Third International Conference on Information Technology and Applications, 2005. ICITA 2005. Vol. 1. IEEE, 2005.

Henderson, B., E. Bui, C. Moran, and D. Simon (2004), Australia-wide predictions of soil properties using decision trees, Geoderma, 124, 383–398.

Hontoria, C., J. Rodriguez-Murillo, and A. Saa (1999), Relationships between soil organic carbon and site characteristics in peninsular Spain, *Soil Science Society of America Journal*, 63, 614–621.

Hosier, S., and L. Bradley. 1999. Guide to Symptoms of Plant Nutrient Deficiencies. Arizona Cooperative Extension Publication AZ1106. Tucson: University of Arizona Extension

IBM (2018) Agropad-AI-powered technology will help farmers health-check soil and water, https://www.ibm.com/blogs/research/2018/09/agropad/

Israel Broner and Carlton R. Comstock, "Combining expert systems and neural networks for learning site-specific conditions," *Computers and electronics in agriculture*, vol. 19 no.1, pp. 37-53, 1997.

J. da Silva, et al., "Comparison of mapping soybean areas in Brazil through perceptron neural networks and vegetation indices," *African Journal of Agricultural Research*, vol.11 no.43, pp. 4413-4424, 2016.

Jeong G, Oeverdieck H, Park SJ, Huwe B, Ließ M, 2017. Spatial soil nutrients prediction using three supervised learning methods for assessment of land potentials in complex terrain. Catena 154: 73-84. https://doi.org/10.1016/j.catena 2017.02.006

Karpatne, A., Jiang, Z., Vatsavai, R. R., Shekhar, S., & Kumar, V. (2016). Monitoring land-cover changes: A machine-learning perspective. *IEEE Geoscience and Remote Sensing Magazine*, 4(2), 8-21.

Keshavarzi A, Sarmadian F, Omran ESE, Iqbal M, 2015. A neural network model for estimating soil phosphorus using terrain analysis. *Egypt J Remote Sens Space Sci* 18: 127-135. https://doi.org/10.1016/j.ejrs.2015.06.004

Krause, L., Biesgen, D., Treder, A., Schweizer, S. A., Klumpp, E., Knief, C., & Siebers, N. (2019). Initial microaggregate formation: Association of microorganisms to montmorillonite-goethite aggregates under wetting and drying cycles. Geoderma, 351, 250–260

Landesman, W. J., Freedman, Z. B., & Nelson, D. M. (2019). Seasonal, sub-seasonal and diurnal variation of soil bacterial community composition in a temperate deciduous forest. *FEMS Microbiology Ecology*, 95(2). fiz002.

M. Valdés-Vela, et al., "Soft computing applied to stem water potential estimation: A fuzzy rule-based approach," *Computers and Electronics in Agriculture*, vol. 115, pp. 150-160, 2015.

Maier, H., and G. Dandy (1998), Understanding the behavior and optimizing the performance of backpropagation neural networks: an empirical study, *Environmental Modelling and Software*, 13(2), 179–191.

Nichols, J. (1984), Relation of organic carbon to soil properties and climate in the southern great plains, *Soil Science Society of America Journal*, 48, 1382–1384.

Pandey DK, Hunjra AI, Bhaskar R, Al-Faryan MA. Artificial intelligence, machine learning and big data in natural resources management: a comprehensive bibliometric review of literature spanning 1975–2022. *Resour Policy*. 2023;86:104250. doi: 10.1016/j.resourpol.2023. 104250. [CrossRef] [Google Scholar]

Parton, W., D. Schimel, C. Cole, and D. Ojima (1987), Analysis of factors controlling soil organic matter levels in great plains grassland, *Soil Science Society of America Journal*, 51, 1173–1179.

Rai, S., Lilhare, **S.,** Tiwari, A. S., and Jaiswal, R.V. (2023). Role of artificial intelligence (AI) in soil management. Book *food security*. Mahima Research Foundation and Social Welfare. ISBN: 978-81-965883-2-8. 49-54.

Redmile-Gordon, M., Gregory, A. S., White, R. P., & Watts, C. W. (2020). Soil organic carbon, extracellular polymeric substances (EPS), and soil structural stability as affected by previous and current land use. Geoderma, 363, 114143.

S. Abba, J. Namkusong, J.-A. Lee, and M. Crespo, "Design and performance evaluation of a low-cost autonomous sensor interface for a smart IoT-based irrigation monitoring and control system," Sensors, vol. 19, no. 17, p. 3643, 2019.

S. S. Patil, et al., "Web-based expert system for diagnosis of micronutrient deficiencies in crops," in Proceedings of the World Congress on Engineering and Computer Science. Vol. 1. 2009.

Safaa M, Maxwellb TMR, 2015. Predicting pasture nitrogen content using ANN models and thermal images. 21st Int Congr on Modelling and Simulation, Gold Coast, Australia.

Saiz-Rubio, V., andRovira-Más, F. (2020). From smart farming towards agriculture 5.0: a review on crop data management. Agronomy, 10(2), 207.

Sindhu, P., & Indirani, G. (2018). IoT-enabled soil testing. *Asian Journal of Computer Science and Technology*, 7(S1), 54-57

Spencer, M., T. Whitfort, and J. McCullagh (2004), Mapping dryland salinity using neural networks, AI 2004, *Springer-Verlag*, 1233– 1238.

Tan, Z., R. Lal, N. Smeck, and F. Calhoun (2004), Relationships between surface soil organic carbon pool and site variables, Geoderma, 121, 187–195.

V. Z. Antonopoulos, and A. V. Antonopoulos, ―Daily reference evapotranspiration estimates by artificial neural networks technique and empirical equations using limited input climate variables, *Computers and Electronics in Agriculture*, vol. 132, pp. 86-96, 2017.

Y. Zhai, et al. "Soil texture classification with artificial neural networks operating on remote sensing data," *Computers and Electronics in Agriculture*, vol. 54 no. 2, pp. 53-68, 2006.

Zolfaghari A, Taghizadeh-Mehrjardi R, Moshki A, Malone B, Weldeyohannes A, Sarmadian F, Yazdani M, 2016. Using the nonparametric k-nearest neighbor approach for predicting cation exchange capacity. Geoderma 265: 111- 119. *https://doi.org/10.1016/j.geoderma*.2015.11.012.