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## **INTEGRATING AI TECHNOLOGIES FOR SUSTAINABLE RESTORATION OF TROPICAL SOILS AND FOOD PRODUCTION**

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### **Abstract**

*Soil is increasingly solicited for multiple crops to achieve food self-sufficiency; as such, it's directly impacted by the growing human population's demand for increased agricultural production and crop yields. Thus, unsustainable practices such as intensive cropping, excessive fertilizer use, organic matter (OM) mismanagement, and depletion of organic carbon (OC) from agricultural soil have negatively impacted soil health, leading to soil degradation. This paper explores the role of Artificial Intelligence (AI) in rehabilitating degraded soils, AI-integrated agricultural practices that support sustainable soil and food production, and barriers to adopting AI-based soil restoration strategies, particularly among smallholder farmers. Furthermore, the study emphasized the critical need for smallholder farmers to be trained to improve their digital literacy and capacity to use AI-enabled advisory platforms. The need for policymakers to collaborate with telecommunication companies in enhancing mobile network coverage in rural areas, and for the government to address the challenge of limited access to AI tools by introducing grants and financing schemes to enable farmers to purchase essential AI-enabled devices at a lower cost. Addressing the challenges faced by smallholder farmers in adopting AI-technologies fosters the restoration of degraded soils, improving food production within the tropical regions.*

**Keywords: Artificial intelligence, sustainable restoration, food production**

### **Introduction**

Food security is a challenge for millions of people worldwide, especially in developing regions, as many nations depend on agriculture for food security and economic stability. By the end of 2050, the world's population is predicted to have grown from 8.1 billion (year 2024) to 9.1 billion, requiring 3 billion tons of grain to feed everyone—roughly 50% more food production than is currently needed (Adamchuk et al., 2020). The same is applicable in the tropics, as population is constantly growing and it's estimated to hit 401 million by 2050 (FAO, 2018), requiring an increase in food production to feed the expected population. Population growth is associated with increased pressure on natural resources such as water, soil, and climate conditions (Oberle *et al.*, 2019), which are mainly the foundation of agricultural production. In fact, soil is increasingly solicited for multiple crops to achieve food self-sufficiency. As such, it's directly impacted by the growing human population's demand for increased agricultural production and crop yields. However, productive land is decreasing due to declining land fertility, urbanization, pollution, and salinization. Unsustainable practices such as intensive cropping, excessive fertilizer use, organic matter (OM) mismanagement, and depletion of organic carbon (OC) from

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agricultural soil have negatively impacted soil health, leading to land degradation. These practices disrupt the natural soil ecosystem, reducing fertility and overall land productivity (Mamatha *et al.*, 2024). Soil health and quality are critical to sustainable agriculture as they are the most essential components of agriculture and food production. Notably, it also has a direct impact on environmental quality and ecosystem services. Soil quality can be defined as the capacity of a soil to host and provide ecosystem services (Cannavacciuolo *et al.*, 2017). Soil is said to be healthy when it can withstand stress and disturbance, recycle nutrients, transform organic matter, and support microbial life (Calvaruso *et al.*, 2021). Unfortunately, soil health can deteriorate either due to anthropogenic reasons, such as human activities and natural causes or climate change and other related factors (Drake *et al.*, 2020). The strain from rapid demographic growth is evident in declining soil fertility in tropical regions as soils are overexploited, resulting in soil degradation characterized by wind and water erosion, pollution, loss of soil nutrients, and biodiversity. Soil degradation reduces ecosystem services, such as decline in soil quality and productivity which threatens food security, and increases vulnerability to environmental impacts, especially in tropical regions with developing economies where livelihoods are directly tied to land productivity. Tropical soils are often characterized by high temperatures, high rainfall, and intense weathering. However, due to extensive agricultural practices, deforestation, and other land use changes to which soils in the tropical zone are often subjected, they are particularly complex and challenging to manage; as a result, they are often degraded and low in agricultural productivity. Soil plays a crucial role in sustaining agriculture and maintaining environmental balance. Hence, it's imperative and expedient to have more healthy soil, by exploring alternative ways of restoring degraded soils, such as the use of Artificial Intelligence (AI) and Machine Learning (ML). The restoration of degraded tropical soils entails stopping existing degradation processes and restoring the soil's physiochemical properties to recover arable land, curb deforestation, and protect soils and forests threatened by overexploitation. This process can be achieved more effectively and within a shorter time frame through the application of Artificial Intelligence (AI), compared with conventional restoration methods. Artificial intelligence (AI) and Machine Learning (ML) are two of the most well-known and powerful emerging technologies that have produced ground-breaking solutions for managing soil health (Maraveas *et al.*, 2022). A revolutionary strategy that encompasses machine learning, deep learning, large data analytics, and decision support systems that can analyze vast datasets to detect patterns, predict degradation trends, and recommend adaptive soil management strategies (Liakos *et al.*, 2018). Remote sensing platforms and Geographic information systems that are AI-powered are mostly used to monitor land use changes, soil moisture levels, erosion hotspots, and nutrient status with high spatial and temporal precision (Zhang *et al.*, 2021). Furthermore, AI-driven models support precision agriculture by optimizing the use of fertilizers, water, and other resources, thereby reducing environmental impacts while enhancing crop productivity (Shamshiri *et al.*, 2018). In tropical regions, where heterogeneity is high, AI provides a cost-effective and scalable solution for restoring soil functions and achieving sustainable food production. This review synthesizes the recent literature on the potential of integrating AI technologies into the restoration of tropical soils to improve agricultural productivity and food security. To this end, this literature review aims to;

- i. Explore the role of artificial intelligence technologies in rehabilitating degraded soils.
- ii. Identify AI-integrated agricultural practices that support sustainable soil and food production in the tropics.
- iii. Identify barriers to adopting AI-based soil restoration strategies, particularly among smallholder farmers.

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### **Role of artificial intelligence technologies in rehabilitating degraded soils.**

Climate change, population growth, land use and cover changes, and soil erosion are major contributors to soil degradation process and, as such, are raising global concerns. Soil erosion is a natural process activated by human activities and natural forces and poses a significant threat to the environment, land management, agricultural production, and sustainability (Lal, 2020). It is a natural phenomenon that involves the natural removal of the soil's surface layer due to natural forces. Furthermore, there are many causes of soil erosion: water erosion (i.e., rainfall and runoff), wind erosion (i.e., strong winds), gravity erosion (i.e., soil movement induced by steep slopes), and ice erosion (i.e., glaciers and frost). These soil erosion types result in the loss of fertile soils, reduced crop yields, pollution sedimentation, increased floods, and climate change impact (Zhao *et al.*, 2023). Therefore, a comprehensive understanding of soil erosion monitoring is critical for future decision-making (Radočaj *et al.*, 2020). Given the shortcomings of traditional methods for identifying, analyzing, and interpreting the soil erosion phenomenon, there is an essential need for new, rapid, accurate, eco-friendly, and non-destructive approaches to achieve these tasks. On the other hand, Artificial intelligence (AI) is rapidly expanding in the field of research, with applications including characterizing, estimating, and predicting soil erosion levels (Avand *et al.*, 2023). Techniques in AI, including machine learning (ML) and deep learning (DL), are being utilized to enhance the detection, characterization, prediction, and understanding of soil erosion (Mosavi *et al.*, 2020). Popular algorithms that estimate and predict soil erosion include random forests (RF), conventional neural networks (CNNs), and artificial neural networks (ANNs). The AI algorithms can process and classify hyperspectral and multispectral satellite images to identify various land use and land cover changes (LULC) units, including vegetation cover, bare soils, water bodies, urban areas, and others (Dahiya *et al.*, 2023). AI approaches can also be used to detect land use and land cover changes (LULCC) by analyzing historical satellite images (time series) for quantifying soil erosion. Furthermore, AI is employed to create prediction models for quantifying soil erosion as well as other land parameters such as vegetation, slope, moisture, and soil properties. AI is also used to select soil erosion features and parameters using various spectral indices derived from data obtained by satellites and other platforms or instruments which can be used by land managers, policymakers, stakeholder groups, and researchers to estimate soil erosion levels, categorize different areas (vulnerable and non-vulnerable), and implement successive soil erosion mitigation plans (Panagos *et al.*, 2020; Emadi *et al.*, 2020). Hence, the utilization of AI in detecting and modeling soil erosion makes it possible to cover large-scale areas and provide detailed spatial information, which is beneficial for mapping and monitoring extensive regions (Radočaj *et al.*, 2020), and eliminates the need for physical efforts like traditional ground surveying and sampling, which can harm ecosystems.

### **AI-integrated agricultural practices that support sustainable soil and food production in the tropics.**

Agriculture faces several critical challenges, which include climate change, water scarcity, environmental degradation, and dependence on conventional energy sources (Mana *et al.*, 2024). According to Liu, (2024), sustainable agriculture is an agricultural practice that permanently meets the essential conditions of environmental health, economic viability, and social equity while ensuring long-term productivity and resource conservation for future generations. Recently, a key challenge for the agriculture industry has been feeding a rapidly growing population. There is a growing consensus that transforming the global food system is essential to ensure safe and nutritious food for all while



maintaining ecological balance within the earth's limits, which is certainly unattainable with conventional agricultural practices (Stringer *et al.*, 2020). Moreover, FAO, (2021) reported that the use of natural resources in recent days has been highly stressed, as 25 % of all farmland is highly degraded, and about 80 % of deforestation is driven by agriculture globally. Thus, about 720–800 million people globally are suffering from food insecurity (Mana *et al.*, 2024). However, Sub-Saharan Africa bears the most considerable portion (22 %) annual cost of land degradation in the world, as the world's most serious land degradation has been occurring in the region for the past ten years (Byaro *et al.*, 2023). Nearly 70 % of the tropics region's soil resources are affected by soil erosion and nutrient depletion, and 40 % of the soils are characterized by low nutrient reserves (Tully *et al.*, 2015), which is attributed to low suitability for agricultural production. All the above-mentioned challenges lead to poverty and hunger, as SSA is already classified in the "serious category" on the Global Hunger Index (GHI) severity scale (Grebmer *et al.*, 2023). As such, a worldwide agricultural transformation is needed to switch from conventional to modern automated approaches. The essence of farming always involves strategies for increasing crop production without sacrificing quality. Productive farms exhibit maximum utilization of natural resources like soil, water, and air, and allocate natural resources for the future to deal with formidable challenges like climate change, labor shortages, urbanization leading to the shrinkage of land for farming, poor soil fertility of the available land, declining water resources, etc. (Kusumavathi *et al.*, 2025). Pandey and Mishra (2024), also opined that accuracy and robustness achieved through the use of AI technologies are critical in this farming perspective, as they direct the way for precise use of natural resources and ultimately bring about a massive change in the field of agriculture. Various tasks are included in agricultural activities, such as crop-relevant decisions, irrigation control, soil health assessment, and fertilizer selection. The major key challenges in the agricultural sector are to prepare the soil to cultivate, select the crop and seed according to the location, and finally harvest, which is becoming increasingly challenging due to climate change (Ennouri *et al.*, 2021). One of the tedious tasks in intelligent farming is to determine important parameters for the selection of crops and their management. But the application of artificial intelligence in agriculture eliminates the farming scenario, thereby increasing crop productivity on a large scale. Henceforth, Artificial Intelligence (AI) is considered a game-changer in the field of agriculture. Every plant requires specific soil nutrients and moisture for proper growth and development. Low moisture content within the soil can limit the availability of soil nutrients, which results in low crop productivity. Artificial Intelligence-based technological recommendations have enabled farmers to produce supplementary output with reduced input, especially in irrigation practices, and even improved output quality, ensuring a quick go-to-market for yielded crops.

### **Soil management with the use of AI**

An integral part of agricultural activities is soil management, as soil acts as a reservoir of nutrients, water, minerals, and diverse microbes. The health and productivity of the "cornerstone of life" or "magic carpet" (soil) beneath our feet help us attain the climate and biodiversity targets, build a clean and circular economy, reverse biodiversity loss, and protect human health. Balanced applications of both organic sources in large quantities and inorganic sources in small quantities are very important for sustaining soil health. The application of organic materials like compost and manure improves the soil's quality, porosity, and aggregation, preventing soil crust formation. Soil-test-based fertility management is a valuable tool for building up the productivity of agricultural soils that have extremes in spatial

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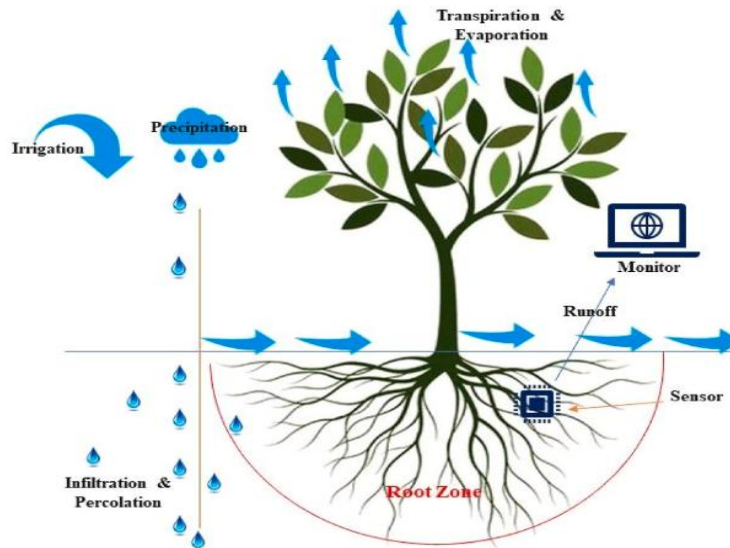
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variability. International Business Machines (IBM) created a microfluidic chip inside a card that performs chemical analysis of soil and an AI-driven machine vision algorithm that estimates the colorimetric test value better than the normal human eye. An artificial neural network (ANN) estimates field capacity and soil moisture content (Bhattacharya *et al.*, 2018). An artificial neural network (ANN) model forecasts soil texture information using characteristics derived from existing coarse-resolution soil map and hydrographic parameters derived from a digital elevation model (DEM) (Zhao *et al.*, 2009). Sarkar *et al.* (2021) reported that the soil risk characterization decision support system (SRC-DSS) is useful for identifying contaminated soils. The AI technologies can also be useful for estimating biological parameters like soil enzyme activity. One of such is the multiple linear regression (MLR), and a digital terrain model (DTM) attached to ANN, effective in mapping soil enzyme activity (Tajik *et al.*, 2011). In the north-central lateritic region of Kerala, India (Suchithra *et al.*, 2020) Extreme Learning Machine (ELM) technique is useful not only for sorting but also for predicting soil fertility indices and pH levels.

### **Crop management with the use of AI**

Crop management begins with seed sowing and continues with examining growth, harvesting, and storage. Physical monitoring of large farms by farmers is highly impossible. Thus, Crop monitoring by AI technologies is very much required, thereby reducing human interventions in the consciousness of AI, leading to automation would have a big impact on saving water loss in agriculture. Several AI technologies have been used by different researchers to prevent water loss and enhance optimum utilization in crop fields. An estimation of soil moisture in paddy fields using less meteorological data was made possible with two ANN models (Arif *et al.*, 2012). Arvind *et al.* (2017) developed a model using an Arduino microcontroller and ZigBee technology for analyzing the water requirements of a crop planted in a field for its entire lifecycle. Furthermore, an automated irrigation system with an Arduino microcontroller for reducing manpower and time spent in the process of irrigation was developed (Jha *et al.*, 2019). Dai *et al.* (2011) developed an ANN model for predicting the response of crops to soil moisture and salinity, but considered only soil temperature and texture as factors. A smartphone application named Cotton Smart Irrigation App (Cotton App) and IG Droid were developed to schedule irrigation in the cotton crop and other crops (Vellidis *et al.*, 2016). Bartlett *et al.* (2015) developed Water Irrigation Scheduling for Efficient Application (WISE), a smartphone application for better use of water resources. Perea *et al.* (2016) implemented a multiplatform application for precision irrigation scheduling for the strawberry production sector in 2016, using both PC and Android devices. Blueleaf, a smartphone irrigation scheduling tool by Saab *et al.* (2019) uses crop, soil, weather, and irrigation system data to support farmers in the water application process and scheduling irrigations. Even though AI has significantly improved precision agriculture, several structural, technical, and social barriers hinder its widespread adoption in different environments, especially among smallholder farmers. These barriers can be categorized into four major groups: technological, economic, social, and regulatory challenges (Adebayo and Salusi, 2021). Technological barriers are among the most significant. AI technologies require a lot of digital infrastructure, such as access to smartphones, reliable internet connectivity, and cloud-based platforms, which might be expensive and out of reach for small-scale farmers in rural areas (Eke *et al.*, 2022).



**Fig. 1. Water inflow and losses, and detection of water stress by sensor.**

**Barriers to adopting AI-based soil restoration strategies, particularly among smallholder farmers.**

Another technological constraint is the absence of localized datasets for training AI models. Most AI models used in agriculture are trained on datasets from Western or Asian contexts, which do not accurately reflect the specific agro-climatic conditions of tropical ecosystems (Ojo and Lawal, 2020; Oyediji *et al.*, 2024). AI-based tools and technologies, such as sensors, drones, and AI-enabled mobile applications, require substantial investment in hardware, software, and technical support (Adeniran *et al.*, 2022). Smallholder farmers, who represent a significant proportion of the agricultural workforce, in most developing countries within the tropics operate on small profit margins and may lack the financial resources to adopt AI-powered advisory services (Chukwu *et al.*, 2021). In effect, without targeted government subsidies, financial incentives, or loan schemes, it is unlikely that smallholder farmers will adopt AI-driven advisory tools on a large scale (Adegbite *et al.*, 2023). Additionally, social and cultural barriers also play a significant role in hindering AI adoption. Many smallholder farmers perceive AI technology as a foreign and complex concept, leading to skepticism regarding its effectiveness (Ibrahim *et al.*, 2021). Farmers often have greater trust in traditional and experience-based farming methods, especially when AI-generated recommendations contradict long-standing indigenous knowledge (Olaniyi, 2021). Agricultural extension officers may also resist the adoption of AI, viewing it as a threat to their roles and livelihoods (Bamigboye *et al.*, 2022). Since AI systems are often advertised as "automated advisory tools," some extension agents believe they will be replaced by AI-based chatbots and remote advisory systems, creating resistance to technology adoption (Olowo *et al.*, 2023). Lastly, regulatory and policy barriers present significant challenges. Nigeria does not have a clear legal or policy framework for

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the use of AI in agriculture, which creates uncertainty for both farmers and private-sector actors (Chukwu *et al.*, 2021).

## Conclusion

Food security is a challenge for millions of people worldwide, especially in developing regions, as many nations depend on agriculture for food security and economic stability. In recent years, issues of food insecurity have intensified due to global increases in population growth, requiring more food production than is currently needed. These have led to the intensification of agricultural activity and the cultivation of the soil beyond its capacity, thus resulting in soil degradation. To overcome all these challenges, the use of modern technology for sustainable farming through efficient resource utilization remains a great necessity. Undoubtedly, artificial intelligence, being a revolutionary innovation, brings prosperity to agriculture by promoting sustainable agricultural production, environmental preservation, and restoring degraded tropical soils. The advanced technologies, such as computer vision, machine learning, and predictive analytics, enable precise decision-making in crop management, soil health monitoring, and resource optimization. It facilitates smart farming practices by automating labor-intensive tasks, decreasing input wastage without compromising quality. AI can provide a cheaper and sustainable solution to soil degradation in tropical regions. Thus, AI technologies can be adopted in solving soil degradation and food security in the region.

## Recommendations

Based on the literature reviewed, the following recommendations are proposed to enhance the adoption of AI technologies in the sustainable restoration of tropical soils and food production:

- i. Smallholder farmers should be trained to improve their digital literacy and technical capacity to use AI-enabled advisory platforms through on-site demonstrations, workshops, and mobile-based tutorials. Training initiatives should target farmers with lower education levels to ensure inclusivity and wider adoption.
- ii. To address the challenge of limited access to AI tools, subsidies, grants, and financing schemes should be introduced to enable farmers to purchase essential AI-enabled devices such as smartphones, sensors, and drones. Partnerships with tech companies and financial institutions can facilitate access to these tools at lower costs.
- iv. Policymakers should collaborate with telecommunication companies to enhance mobile network coverage in rural areas. Investments in broadband infrastructure will support seamless connectivity, enabling farmers to receive timely AI-based advisory services.

## References

- Adamchuk, V. I and Hossain, A. (2020). Machine learning in soil science: A review. *Soil Science Society, American Journal of Medicine*, 84(3): 561- 78.
- Adebayo, S. O., and Salisu, Y. (2021). Overcoming barriers to AI adoption in agricultural extension: Lessons from Nigeria. *African Journal of Agricultural Research*, 16(8): 1123-1145.



- Adegbite, T. A., Ajayi, B. O., and Lawal, S. M. (2023). The future of agricultural advisory services: AI-driven platforms for Nigerian smallholder farmers. *International Journal of Agricultural Innovations and Research*, 21(2): 78-101.
- Adeniran, T. A., Yusuf, L. K., and Eke, J. E. (2022). Exploring the economic impact of AI adoption in agricultural extension: Evidence from smallholder farmers in Nigeria. *Nigerian Journal of Agricultural Economics*, 15(1): 34-59.
- Arif, C., Mizoguchi, M., Setiawan, B.I and Doi, R. (2012). Estimation of soil moisture in paddy field using Artificial Neural Networks, *International Journal of Advanced Research in Artificial Intelligence*, 1(1): 17–21, <https://doi.org/10.14569/IJARAI.2012.010104>.
- Arvind, G., Athira, V.G., HariPriya, H., Rani, R.A. and Aravind, S. (2017). Automated irrigation with advanced seed germination and pest control. *IEEE Technology and Innovation ICT Agricultural and Rural Development (TIAR)*, <https://doi.org/10.1109/tiar.2017.8273687>.
- Bamigboye, A. A., Lawal, S. M., and Ibrahim, K. T. (2022). AI-based chatbots and advisory services: Transforming agricultural extension for smallholder farmers. *African Journal of Technological Advancement*, 9(4): 67-89.
- Bartlett, A., Andales, M., Arabi, T and Bauder, A. (2015). Smartphone app to extend use of a cloud-based irrigation scheduling tool, *Computers and Electronics in Agriculture*, 111, 127–130. <https://doi.org/10.1016/j.compag.2014.12.021>.
- Bhattacharya, P., Pramanik, P., Ray, M and Krishnan, P. (2018). Comparison of artificial neural network and multi-linear regression for prediction of field capacity soil moisture content. *Journal Agricultural Physics*, 18 (2): 173–180
- Byaro, M., Nkonoki, J and Mafwolo, G. (2023). Exploring the nexus between natural resource depletion, renewable energy use, and environmental degradation in sub-Saharan Africa. *Environmental Science and Pollution Research*, 30(8): 19931–19945. Doi: 10.1007/s11356022-23104-7.
- Calvaruso, C., Blanchart, A., Bertin, S., Grand, C., Pierart, A and Eglin, T. (2021). Quels paramètres du sol mesurer pour évaluer les fonctions et les services écosystémiques associés? *Étud. Gest. Sols*, 28, 3–29.
- Cannavacciuolo, M., Cassagne, N., Riou, V., Mulliez, P., Prévost-Bouré, N.C., Dequiedt, S., Villenave, C., Cérémonie, H., Cluzeau, D and Cylly, D. (2017). Validation d'un tableau de bord d'indicateurs sur un réseau national de fermes en grande culture et en viticulture pour diagnostiquer la qualité biologique des sols agricoles. *Innovation in Agronomy*, 55, 41–54. [CrossRef]
- Chukwu, E. J., Olaniyi, T. J., and Okafor, C. A. (2021). Identifying the cost implications of AI- driven agricultural advisory services in Nigeria. *Agricultural Economics and Policy Journal*, 14(3): 56-78.



- Dahiya, N., Singh, S., Gupta, S., Rajab, A., Hamdi, M and Elmagzoub, M. A. (2023). Detection of multitemporal changes with artificial neural network-based change detection algorithm using hyperspectral dataset. *Remote Sensing*, 15(5):1326. DOI: 10.3390/rs15051326
- Dai, X., Huo, Z and Wang, H. (2011). Simulation of response of crop yield to soil moisture and salinity with artificial neural network, *Field Crops Research*, 121(3): 441–449. <https://doi.org/10.1016/j.fcr.2011.01.016>
- Drake, T. W., Podgorski, D. C., Dinga, B., Chanton, J. P., Six, J and Spencer, R. G. (2020). Land-use controls on carbon biogeochemistry in lowland streams of the Congo Basin. *Global Change Biology*, 26, 1374–1389. [CrossRef] [PubMed].
- Eke, J. E., Ojo, S. K and Olaniyi, T. J. (2022). Overcoming digital infrastructure challenges for AI-driven agricultural extension in rural Nigeria. *Information and Communication Technology for Development*, 8(2): 56-78.
- Emadi, M., Taghizadeh-Mehrjardi, R., Cherati, A., Danesh, M., Mosavi, A and Scholten, T. (2020). Predicting and mapping of soil organic carbon using machine learning algorithms in Northern Iran. *Remote Sensing*, 12(14): 2234. DOI: 10.3390/rs12142234
- Ennouri, K., Smaoui, S., Gharbi, Y., Cheffi, M., Braiek, O.B., Ennouri, M and Triki, M.A. (2021). Usage of artificial intelligence and remote sensing as efficient devices to increase agricultural system yields, *Journal of Food Quality*, 6242288. <https://doi.org/10.1155/2021/6242288>.
- FAO, (2021). FRA 2020 Remote Sensing Survey. Brows on 31.08.2024.
- Ibrahim, K. T., Okafor, C. A., and Eke, J. E. (2021). Enhancing agricultural productivity through AI-driven advisory platforms in Nigeria. *International Journal of Agricultural Science and Technology*, 19(3): 78-101
- Jha, K., Doshi, A., Patel, P and Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, 2, 1–12. <https://doi.org/10.1016/j.aiia.2019.05.004>.
- Kusumavathi, K., Konatala, R., Lal P., Sarkar, S., Banerjee, H., Bandopadhyay, P., Debadatta Sethi, D and Uppendar, K. (2025). Artificial intelligence for fostering sustainable agriculture. *Current Plant Biology*, 42, 100476. [www.elsevier.com/locate/cpb](http://www.elsevier.com/locate/cpb)
- Lal, R. (2020). Soil erosion and gaseous emissions. *Applied Sciences*, 10(8): 2784. DOI: 10.3390/
- Liakos, K. G., Busato, P., Moshou, D., Pearson, S and Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensor*, 18(8): 2674. <https://doi.org/10.3390/s18082674>
- Liu, S. (2024). Towards a sustainable agriculture: achievements and challenges of Sustainable Development Goal Indicator 2.4.1, *Global Food Security*, 37, 100694. <https://doi.org/10.1016/j.gfs.2023.100694>.



Mamatha, B., kadalli, G.G., Manjunath, R., Chandana Mudigiri, C and Vilakar, K. (2024). Effect of Long term Fertilization and Manuring on Nutritional Quality of Maize Grain. *International Journal of Plant and Soil Science*, 36(6): 749-762. Article no.IJPSS.116609

ISSN: 2320-7035

Mana, A.A., Allouhi, A., Hamrani, A., S. Rehman, S., el Jamaoui, I and Jayachandran, K. (2024). Sustainable AI-based production agriculture: exploring AI applications and implications in agricultural practices. *Smart Agricultural Technology*, 7, 100416. <https://doi.org/10.1016/j.atech.2024.100416>.

Mosavi, A., Sajedi-Hosseini, F., Choubin, B., Taramideh, F., Rahi, G and Dineva, A. A. (2020). Susceptibility mapping of soil water erosion using machine learning models. *Water*, 12(7):1995. DOI: 10.3390/w12071995

Oberle, B., Bringezu, S., Hatfield-Dodds, S., Hellweg, S., Schandl, H and Clement, J. (2019). *Global Resources Outlook; International Resource Panel, United Nations Environment*. Paris, France.

Olaniyi, T. J. (2021). The impact of digital literacy on AI adoption in Nigerian agricultural extension. *Journal of Agricultural Education and Development*, 17(2), 71-102.

Olaniyi, T. J., Yusuf, L. K., and Adebayo, S. O. (2022). Language barriers in AI advisory platforms: Implications for smallholder farmers in Nigeria. *Journal of Language and Communication in Agriculture*, 11(2), 89-112.

Olowo, F. T., Chukwu, E. J., and Bamigboye, A. A. (2023). Bridging the gap in AI adoption for agricultural extension: Insights from Nigerian smallholder farmers. *Agritech Research Journal*, 15(2): 67-89.

Oyediji, B. I., Yekinni, T. O., Sennuga, S. O., Bamidele, J. and Eleke, U. P. (2024). Constraints faced in the utilization of credit for poultry enterprise in developing countries. *Journal of Agriculture and Allied Sciences*, 4(2): 106-119.

Panagos, P., Ballabio, C., Poesen, J., Lugato, E., Scarpa, S and Montanarella, L. (2020). A soil erosion indicator for supporting agricultural, environmental and climate policies in the European Union. *Remote Sensing*, 12(9): 1365. DOI: 10.3390/rs12091365

Pandey, D.K and Mishra, R. (2024). Towards sustainable agriculture: harnessing AI for global food security, *Artificial Intelligence in Agriculture*, 12, 72–84. <https://doi.org/10.1016/j.aiia.2024.04.003>.

Perea, R.G., García, I.F., Arroyo, M.M., Díaz, J.R., Poyato, E.C. and Montesinos, P. (2016). Multiplatform application for precision irrigation scheduling in strawberries, *Agriculture and Water Management*, 183, 194–201. <https://doi.org/10.1016/j.agwat.2016.07.017>.

Radočaj, D., Obhodaš, J., Jurišić, M and Gašparović, M. (2020). Global open data remote sensing satellite missions for land monitoring and conservation: A review. *Land*, 9(11): 402. DOI: 10.3390/land9110402.

Corresponding Author: O.E. ONWUDIWE

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- Saab, M.T.A., Jomaa, I., Skaf, S., Fahed, S and Todorovic, M. (2019). Assessment of a Smartphone Application for Real-Time Irrigation Scheduling in Mediterranean Environments. *Water*, 11(2): 252. <https://doi.org/10.3390/w11020252>.
- Sarkar, A., Maity, P.P and Mukherjee, A. (2021). Application of AI Soil Science. *Food Scientific and Report*, 2 (2): 38–39.
- Shamshiri, R. R., Kalantari, F., Ting, K. C., Thorp, K. R., Hameed, I. A., Weltzien, C and Shad, Z. M. (2018). Advance in greenhouse automation and controlled environment agriculture: A transition to plant factories and urban agriculture. *International Journal of Agricultural and Biological Engineering*, 11(1): 1-22. <https://doi.org/10.25165/j.ijabe.20181101.3210>
- Stringer, L.C., Fraser, E.D.G., Harris, D., Lyon, C., Pereira, L., Ward, C.F.M and Simelton, E. (2020). Adaptation and development pathways for different types of farmers, *Environmental Science Policy*, 104, 174. <https://doi.org/10.1016/j.envsci.2019.10.007>.
- Suchithra, M.S and Pai, M.L. (2020). Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters, *Information Processing in Agriculture*, 7 (1): 72–82, <https://doi.org/10.1016/j.inpa.2019.05.003>
- Tajik, S., Ayoubi, S and Nourbakhsh, F. (2011). Prediction of soil enzymes activity by digital terrain analysis: comparing artificial neural network and multiple linear regression models, *Environmental Engineering Science*, 29(8): 798–806. <https://doi.org/10.1089/ees.2011.0313>.
- Tully, K., Sullivan, C., Weil, R and Sanchez, P. (2015). The State of Soil Degradation in Sub-Saharan Africa: Baselines, Trajectories, and Solutions. *Sustainability*, 7(6): 6523–6552. Doi: 10.3390/su7066523.
- Vellidis, G., Liakos, V., Andreis, J., Perry, C., Porter, W., Barnes, E., Morgan, K., Fraisse, C and Migliaccio, K. (2016). Development and assessment of a smartphone application for irrigation scheduling in cotton, *Computer and Electronics in Agriculture*, 127, 249–259. <https://doi.org/10.1016/j.compag.2016.06.021>.
- Zhang, C., Liu, F and Hu, D. (2021). Deep learning for remote sensing data. A technical tutorial on the state of the art. *IEE Geoscience and Remote Sensing Magazine*, 9(2): 27-47. <https://doi.org/10.1109/MGRS.2021.3059891>
- Zhao, H., Lin, Y., Zhou, J., Sun, Q., Yang, L and Delang, C. O. (2023). Quantifying the dynamic processes of soil erosion and lake sediment deposition in the Holocene in China. *Quaternary Science Reviews*. 304:107993. DOI: 10.1016/j.quascirev.2023.107993
- Zhao, Z., Chow, T.L., Rees, H.W., Yang, Q., Xing, Z and Meng, F. R. (2009). Predict soil texture distributions using an artificial neural network model, *Computer Electronic in Agriculture*, 65 (1): 36–48, <https://doi.org/10.1016/j.compag.2008.07.008>.