NIPES-Journal of Science and Technology, Research Vol. 7, Special Issue: Landmark University International Conference SEB4SDG 2025, pp. 2186–2191

NIPES - Journal of Science and Technology Research
www.nipes.org

Emerging Trends in Food Security: The Critical Role of Artificial Intelligence in Agricultural Productivity Systems

Aremu, Charity
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
aremu.charity@lmu.edu.ng

Abolusoro, Stephen
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
abolusoro.stephen@lmu.edu.ng

Ige Sunday
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
ige.sunday@lmu.edu.ng

*Wale Ayojimi
Department of Agriculture
Landmark University,
Omu-Aran, Nigeria
ayojimi.wale@lmu.edu.ng

Oyekale, Solomon
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
oyekale.solomon@lmu.edu.ng

Oshagbemi, Taylor
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
oshagbemi.tailor@lmu.edu.ng

Alori, Elizabeth
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
alori.elizabeth@lmu.edu.ng

Adegbite, Kehinde
Department of Agriculture
Obafemi Awolowo University,
Ile-Ife, Nigeria
adegbite.kehinde@gmail.com

*Aniobi Mathias Maduakolam
Agricultural & Biosystems Engineering
Landmark University
Omu-Aran, Nigeria
aniobi.mathias@lmu.edu.ng

Oke, Funmilayo
Department of Agriculture
Landmark University
Omu-Aran, Nigeria
oke.funmilayo@lmu.edu.ng

Correspondence emails: aniobi.mathias@lmu.edu.ng +2347037663044, ayojimi.wale@lmu.edu.ng +2348072757577

Abstract—Due to inefficiencies in production and distribution systems, resource constraints, and environmental degradation, traditional agricultural methods are becoming diminishingly capable and effective in addressing food security challenges. The most important global concern of the twenty-first century research is promoting food security even as the world's population grows, and climate actions increase. Agricultural productivity thrives on timely, optimum and acceptable weather elements. In response, Artificial intelligence has become a trending strategy and tool that uses cutting-edge technologies to improve food systems' sustainability, productivity, and efficiency. To facilitate real-time farming and decision-making, artificial intelligence in precision agriculture incorporates data-driven technologies like, the Internet of Things (IoT), satellite imaging, tensiometer, geographic information systems (GIS), remote sensing etc. With the use of these technologies, farmers can efficiently and promptly use farm inputs including water, liquid macro and micro-nutrients (fertilizers), and pesticides based on the unique requirements of the soil and crop. Engaging Artificial Intelligence will promote seamless and smart agricultural production processes, and reduction in environmental hazards with resultant effect on improved food systems. Smart irrigation systems, blockchain-enabled supply chain transparency, AI-based disease and pest detection, and the use of unmanned aerial vehicles (UAVs) for crop monitoring are some of the major emerging trends in Precision agriculture as facilitated by AI. To maintain sustainability, efficiency, and productivity, agriculture must change as environmental pressures, and global food demands also change in the upward direction. Artificial intelligence provides requisite tools to support smart farming. Precision in agriculture does not only promote food availability, and sustainability, but also provide data and statistics for informed and intentional steps towards enhanced productivity. The study concludes that AI is essential in attaining a sustainable agricultural future after discussing the advantages, difficulties, and potential future of AI-powered farming.

Keywords—AI, precision farming, food security, emerging trends, agricultural productivity

https://doi.org/10.37933/nipes/7.4.2025.SI256
eISSN-2682-5821| pISSN-2734-2352

I. Introduction

The need for sustainable resource use, environmental concerns, and the rising demand for food worldwide are all causing a major shift in the agricultural sector. This is to say that in the recent, the agricultural sector has been at a threshold as orchestrated by man-made and natural challenges such as rising population, climate actions, and uncontrollable fall in natural resources [1].

Undoubtedly, as the name suggests, the challenges of traditional farming methods are fueled by tools that are frequently ineffective in addressing the demands of environmental degradation and food security. Precision agriculture, a data-driven strategy that optimizes farming practices, is being used by industries to address and revolutionize agricultural activities for outstanding timely produce/product performance [2,3]. Adoption of Artificial Intelligence (AI), which permits real-time data analysis and decision-making, is essential to this evolution [4].

There has never been more pressure on agriculture to produce more with less input, as the world's population is expected to approach 10 billion people by 2050 [5,6]. Despite the long-standing years of traditional farming practices, the demand for modern food systems in terms of quantity, quality and sustainability is yet achieved. Noting this, precision farming and artificial intelligence (AI), empirically called "smart farming," has created a hope and future for food security. This topic examines how AI tools like machine learning which include, GP- guided tractors, Soil sensors, automatic weeders, robotics, crop scouting robots, AI-smart irrigation platforms according to [7] etc, and Internet of Things (IoT) devices are embraced and accepted as instruments for transforming agricultural practices in order to satisfy the world's need for food security.

Predictive analytics can forecast extreme weather events, suggest crop varieties that can withstand stress, and direct planting schedules. These innovations are critical in African regions (Sub-Saharan Africa and South Asia) where food insecurity is most vulnerable [8,9]. Agricultural productivity is constrained by subsistence farming. Precision farming and artificial intelligence (AI) support smart farming, which offers a revolutionary approach to contemporary agriculture. It encompasses the application of AI to agricultural productivity processes like crop monitoring, forecasting, nutrient applications, yield predictions, updating and evaluating soil health, and automation of processes such as feeding regime, date and time for planting and harvesting, etc. Machine learning, computer vision, big data analytics, and the Internet of Things (IoT) are examples of AI technologies used in smart farming that gather, process, and interpret data from multiple sources to enable real-time, data-driven informed decision for better agricultural practices. According to Food and Agriculture Organization [5], the increase in food production must not be less than 70% by 2050 in order to meet global food demands. This review, therefore, analyzes through internet search, the fundamental applications and uses, challenges and future prospects of artificial intelligence and its incorporation into precision agriculture through crop monitoring, yield prediction, pest control, irrigation management, and automating machinery towards advancing agricultural practices for food security in the Sub-Saharan nations.

II. Connecting Food security and Artificial intelligence

One of the most urgent global issues of the twenty-first century is food security. [5] defines food security as the state in which all people, at all times, have physical, social, and economic access to enough food that is safe and nourishing. Globally, by 2050, it is expected that there will be more than 9.7 billion people (see fig. 1). It is expected that the increase in food production from agricultural systems will be hugely overwhelmed arising from the pressure from the natural ecosystem and resources as well the non-dependable climate actions which hitherto has bewildered the expectations on global food security. The use of digital technologies and data-driven instruments like artificial intelligence (AI), machine learning, and the Internet of Things (IoT) in smart agriculture is becoming more widely acknowledged as a practical way to improve global food security, even in the ravaging climate actions against seamless traditional farming operations.

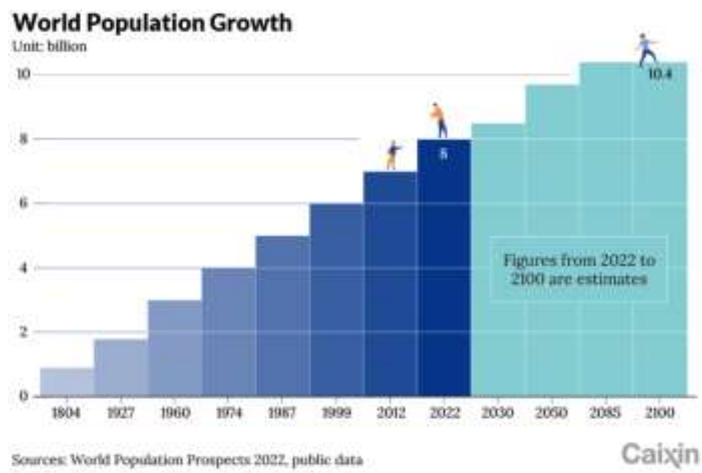

Figure 1: World Population Growth

III. A. The Role of AI in enhancing Precision in Agricultural Productivity

The fundamental pillar of food security is food availability, which depends on agricultural productivity. Smart agriculture improves productivity through the integration of precision farming techniques. Better still, other productivity activities include smart irrigation, weed, pest and disease control, yield optimization, etc which ensure optimized use of inputs like water, fertilizers, and pesticides for enhance output (Table 1). AI-driven systems use data from satellite imagery, weather sensors, and soil health monitors to make real-time decisions that maximize crop yields while minimizing waste [10]. For example, variable rate technology (VRT) allows for the precise application of nutrients and irrigation, which enhances the efficiency of farming operations and leads to higher yields [11].

In order to improve planning and resource allocation, machine learning models are also essential for forecasting crop yields and determining the best times to plant. Particularly in areas susceptible to food shortages as a result of environmental stressors or unstable economies, these innovations are essential to guaranteeing steady food production and supply.

3b. Crop Health Assessment and Monitoring AI-powered systems gather high-resolution photos of crops using drones, satellites, and ground-based sensors. To find indications of illness, dietary inadequacies, or water stress, these photos are examined using machine learning algorithms, specifically convolutional neural networks (CNNs) [9]. Significant yield losses are avoided, and prompt interventions are made possible by early detection.

3c. Insect and Management of plant diseases and pest infestations result in significant crop losses. AI systems can use image recognition and sensor data to identify particular pests and disease symptoms. [8] showed how deep learning can accurately identify 58 distinct plant diseases. By applying pesticides more precisely, these insights lessen the impact on the environment and the use of chemicals. Further details on use of AI for precision Agriculture is presented in Tables 1.

Table 1: Agricultural productivity activities and role of Artificial intelligence

S/N	Agricultural activity	Role of AI	Benefits of AI	Reference 1
1	Precision irrigation	AI smart irrigation optimal prediction systems to provide predictions on when to apply irrigation water.	Water conservation, improved performance	[13]
2	Pest and disease early detection	AI-powered computer vision systems to provide robotics for monitoring and identifying plant diseases.	Early detection and treatment prevents loses and makes for protection.	[8]
3	Weed control	Use of AI enabled drones robots to detect and destroy targeted emerging weeds.	Reduced undue competition among plants, chemical usage, and prevent secondary infestation through weeds harbouring pests.	[14]
4	Yield prediction	AI models (CNNs, RF) for yield forecasting.	Improved crop management strategies	[15]
5	General precision practice	Use of IBM Watson decision platform for prompt and proactive decision making on all-inclusive activities (farm input, logistics and sales.	Optimal agricultural input utilization and cost reduction. Proactive logistics in marketing and produce sales.	[10,16]

IV. Promoting Climate Resilience

The ultimate challenge to global food security is climate change, which affects crop production by making droughts, floods, and other extreme weather events more frequent (Table 2). To increase resilience against weather threats, smart agriculture is essential. AI can assist farmers in anticipating weather anomalies and modifying their practices in response by using climate models and predictive analytics [1]. For example, based on future weather forecasts, AI systems can suggest different sowing schedules or crop varieties that are resistant to drought. This flexibility is crucial for maintaining food production in the face of adversity. Furthermore, smart agriculture encourages sustainable methods like conservation tillage and effective water management, which contribute to ecosystem protection and the long-term sustainability of agricultural land [4].

This may however be expensive and seemingly unpracticable, especially by pro-poor farmers who are small-holder farmers and hence the cost of AI application may be farfetched. The role of extension agents and the development of simple AI tools for such local community-based farmers is worth giving prominent attention.

TABLE 2: WEATHER DATA IN PRECISION AGRICULTURE

S/N	Weather Element	Data Collected	Tool to Use/Source	Application	Author source
1	Temperature	Daily/hourly (from soil/air)	IOT weather stations, Thermocouples	Forecasting planting dates, timing for irrigation, diseases and risk etc	[15, 3]
2	Solar radiation	Solar irradiance, photosynthetic periods, and timing	Satellite imaging, pyranometers	To determine crop growth models, optimize photosynthesis	[18]
3	Precipitation	Amount of rainfall/frequency/duration	Rain Guage	To predict water stress and schedule irrigation	[17]
4	Humidity	Dew point, relative humidity	IoT climate station, Hygrometer	To predict diseases/water stress	[19]
5	Wind speed/direction	Wind direction and speed	Anemometers	Liquid nutrient/pesticide spray optimization	[20a]
6	Evaporation	Crop cover estimate	Multiple weather inputs used	Water conservation, irrigation scheduling	[21]
7	Soil Moisture	Water content/ volume, tension	Tensionmeters, Soil probes	Drought response modelling, irrigation scheduling	[22].

V. OPTIMIZING FOOD SYSTEMS TO PREVENT WASTE

One of the biggest obstacles to attaining food security is pre- and post-harvest losses, including food waste, even after processing. Not less than 1.3 billion tons of food are annually lost or wasted. This is approximately one-third of the food produced worldwide that is lost or wasted, according to the [23]. By enhancing supply chain management, smart agriculture tackles this problem. [16] opined that to guarantee food reaching markets and consumers in the best possible condition, AI algorithms may be deployed to optimize the timing of harvest, storage conditions, and transportation logistics. [15] identified remote sensing, Yield prediction using AI, precision irrigation etc, as intervention means from the production stage to harvesting that will greatly reduce losses.

Better still, block and cold chain technology are other elements of smart agriculture that provide transparency and traceability throughout the food supply chain with adequate and improved packaging. By doing this, inefficiencies are decreased, spoilage is avoided, and stakeholder accountability is guaranteed [25,26]. Additionally, AI-powered digital marketplaces can connect smallholder farmers with customers or retailers directly, cutting down on layers of middlemen and minimizing food loss. Processing and manufacturing efficiency by adopting waste recycling into animal feed is expected to significantly reduce waste and promote circular economy [27].

VI. ENCOURAGING ACCESS AND INCLUSIVE GROWTH

Another essential component of food security is having physical and financial access to food. By giving them access to resources and knowledge that increase output and revenue, smart agriculture can empower smallholder farmers, who make up a sizable share of the global agricultural workforce. AI-enabled mobile apps can provide farmers with localized guidance on crop management, weather predictions, and pest control based on their unique location and crop type [28].

Farmers' resilience and financial capacity to invest in improved inputs and technologies are further enhanced by digital financial services, such as mobile banking and agricultural insurance. Smart agriculture also helps to lower economic inequality and rural poverty, these are two issues that are closely related to food insecurity [29].

VII. CHALLENGES TO ALL-INCLUSIVE AI EMPOWERMENT

The shift to smart agriculture is fraught with challenges, despite its long-standing benefits. Widespread awareness and adoption are severely hampered by the high upfront financial and gadget investment, low levels of digital literacy, and inadequate infrastructure (to power and synergize the process), especially in developing nations are all areas demanding critical attention in AI-driven Agricultural productivity. If underprivileged communities do not have access to these technologies, there is therefore the digital divide that will widen the gap in acceptance and adoption [1].

To gain users' trust, issues with cybersecurity, ownership, and data privacy must also be resolved.

Governments and international organizations must develop inclusive policies, provide capacity-building programs, and incentivize research and development to ensure that the benefits of smart agriculture are equitably distributed. For the pro-poor smallholder farmers, who are the foundation of the world's food production, public-private partnerships, policy support, and capacity-building programs are crucial in order to gain and secure their attention in espousing and the deployment of AI.

VIII. Conclusion

Precision agriculture stands out as a crucial pillar in the quest for a fair and food-secure future as international efforts come together to achieve the United Nations Sustainable Development Goal 2 (zero Hunger). The future of AI and data-driven Agriculture is promoted by the integration of AI across agricultural operations, despite the overwhelming challenges which include inadequate digital infrastructure, digital divide, ethical issues, lack of and inadequate capacity building, unavailable data etc. Albeit the Future of AI with the emerging cutting-edge computing, swarm robotics, and blockchain integration, artificial intelligence in agriculture is expected to secure global food demands. The relationship between AI in smart agriculture and food security is multifaceted as it requires a multidisciplinary approach in developing requisite AI tools for respective agricultural operations. Enhancing productivity through AI promotes building resilience, reducing food waste, improving access to food and agricultural services through digital marketing etc. In order to enable wide acceptance and adoption of AI in smart farming technologies, especially by smallholder farmers who are financially impoverished, supportive policies, targeted investments, capacity building and public-private partnerships must be embraced, implemented and promoted. Gains in Precision agriculture is being transformed and implemented by AI, which increases agricultural resilience, sustainability, and efficiency. To fully utilize AI in agriculture, it will be essential to guarantee fair access and address ethical issues.

References

1. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90.
2. **Adebiyi, M. O., Ogundokun, R. O., & Abokhai, A. A. (2020). Machine learning–based predictive farmland optimization and crop monitoring system. scientifica, 2020(1), 9428281.**
3. Zhang, C., & Kovacs, J. M. (2019). The application of small unmanned aerial systems for precision agriculture: A review. Precision Agriculture, 13, 693–712.
4. Ramesh, A., et al. (2020). AI and nutrient optimization in precision farming. Agronomy, 10(11), 1676.
5. FAO. (2017). The Future of Food and Agriculture – Trends and Challenges. Rome: Food and Agriculture Organization of the United Nations.
6. **Aremu, C., Ojuederie, O., Olayanju, A., Modupe, A., Kayode, O., Erere, A., ... & Adebayo, S. (2021). Agricultural Productivity: A Key Component of Inclusive Growth Towards Food Security. Food Security and Safety: African Perspectives, 195-216.**
7. Jones, H. G., et al. (2021). Smart irrigation management using AI. Irrigation Science, 39(2), 179–192.
8. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318.
9. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
10. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.
11. Zhang, Y., et al. (2020). Autonomous farming: Challenges and opportunities. Journal of Field Robotics, 37(8), 1223–1242.
12. Chlingaryan, A., et al. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture. Computers and Electronics in Agriculture, 151, 61–69.
13. **Raphael, O. D., Aniobi, M. M., & Aremu, C. O. 2022. The use of rice husk as soilless medium to grow capsicum Chinense: Effect of biochar and irrigation. In IOP Conference Series: Earth and Environmental Science (Vol. 1054, No. 1, p. 012001). IOP Publishing.**
14. Slaughter, D. C., et al. (2008). Autonomous robotic weed control systems: A review. Computers and Electronics in Agriculture, 61(1), 63–78.
15. Jeong, J. H., et al. (2016). Random forest-based crop yield prediction model using remote sensing data. KSCE Journal of Civil Engineering, 20(1), 143–150.
16. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming – A review. Agricultural Systems, 153, 69–80.
17. Patel, N., Shah, K., & Bhargava, A. (2021). Smart weather sensing systems for precision farming. Sensors and Actuators A: Physical, 330, 112854.
18. Wang, X., Liu, B., & Zhang, Y. (2020). Solar radiation modeling in crop growth prediction using remote sensing and AI. Remote Sensing, 12(17), 2812.
19. Jones, H. G., Serraj, R., & Tardieu, F. (2019). Using humidity sensors in plant science and precision agriculture. Agricultural Water Management, 217, 265–276.

20. Khosla, R., Ingram, L., & Reich, R. M. (2022). Wind modeling for pesticide applications in precision agriculture. Precision Agriculture, 23, 847–860.

21. Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper 56.

22. Ojha, T., Misra, S., & Raghuwanshi, N. S. (2021). Wireless sensor networks for precision agriculture: Soil moisture monitoring. Computers and Electronics in Agriculture, 157, 110–126.

23. FAO. (2011). Global food losses and food waste – Extent, causes and prevention. Rome: Food and Agriculture Organization of the United Nations.

24. De Gorter, H., Drabik, D., & Just, D. R. (2018). The economics of food loss in the produce industry: A theory of optimal food waste. American Journal of Agricultural Economics, 100(1), 48–64. https://doi.org/10.1093/ajae/aax036.

25. Reynolds, C., Mirosa, M., & Clothier, B. (2016). Food and Energy Security, 5(3), 1–22. https://doi.org/10.1002/fes3.109.

26. Kitinoja, L. (2013). Innovative small-scale postharvest technologies for reducing losses in horticultural crops. Journal of Horticulture and Forestry, 5(3), 29–37.

27. Alexander, P., Brown, C., Arneth, A., Finnigan, J., Moran, D., & Rounsevell, M. D. A. (2017). Could consumption of insects, cultured meat or imitation meat reduce global agricultural land use? Global Food Security, 15, 22–32. https://doi.org/10.1016/j.gfs.2017.04.001

28. Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. Information, 10(11), 349.

29. Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. Frontiers in Plant Science, 10, 621.

30. Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2018). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23–37.