



ARTIFICIAL INTELLIGENCE AND SMART FARMING IN NIGERIA: ENHANCING AGRICULTURAL PRODUCTIVITY, SUSTAINABILITY, AND INCLUSIVE ECONOMIC GROWTH

A.A. OYIBO¹, M. N. OYIBO² and N.V. OYANA³

^{1,3}Department of Home Economics Education, School of Secondary Education (Vocational)
Federal college of Education (Technical) Asaba, Delta State, Nigeria.

²Cassava Program, National Root Crops Research Institute, Abia State, Nigeria

Journal of Research in Vocational and Technical Education (JORVTED), 2026, 5(1), 175–182

Publication history: Received on 23 January 2026; revised on 07 March 2025; accepted on 10 May 2026

Article DOI: <https://doi.org/10.5281/zenodo.20181608>

Abstract

Nigeria's agricultural sector faces persistent challenges including climate variability, low mechanization, limited access to modern technologies, and infrastructural deficits that constrain productivity and threaten food security. Artificial Intelligence (AI) has emerged as a transformative tool capable of addressing these structural limitations through data-driven decision-making, predictive analytics, and automation. This study examines the role of AI within the Smart Farming framework, emphasizing its capacity to enhance precision resource management, pest and disease detection, crop yield forecasting, automated irrigation, robotics, and value-chain optimization. Drawing on existing empirical studies and global policy reports, the paper synthesizes evidence on how AI-powered technologies—such as machine learning models, remote sensing systems, drones, and agronomic decision-support platforms—can improve farm efficiency, increase yields, and reduce input waste. The study highlights how AI contributes to climate resilience through improved weather forecasting and adaptive farm management strategies. It further explores automation's potential to mitigate labor shortages and strengthen operational efficiency across agricultural systems. Despite these opportunities, AI adoption in Nigeria remains limited due to high implementation costs, weak rural digital infrastructure, limited digital literacy, data governance concerns, and unequal access among smallholder farmers. The research critically examines these distributional and institutional barriers, including risks of algorithmic bias, platform concentration, labor displacement, and environmental sustainability concerns. It argues that without inclusive policies and institutional support, AI benefits may disproportionately favor large-scale farms and agribusinesses, thereby widening existing inequalities. The study concludes that AI can significantly enhance agricultural productivity and national competitiveness when embedded within supportive policy frameworks that prioritize rural connectivity, open data standards, extension service integration, financial accessibility, and environmental safeguards. By aligning technological innovation with inclusive development strategies, Nigeria can harness AI to strengthen food security, stimulate economic growth, and promote sustainable agricultural transformation.

Keywords: *Artificial Intelligence, Smart Farming, Digital Agriculture, Precision Agriculture*

Introduction

Nigeria's agricultural sector is confronted with numerous challenges that threaten food security and economic development. Climate change and variability characterized by inconsistent rainfall patterns and extreme weather events significantly reduce crop yields and expose farmers to financial losses (FAO, 2020). These difficulties are intensified by limited access to modern agricultural technologies, especially

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



among smallholder farmers in rural communities who often lack mechanized equipment and efficient irrigation systems. This technological gap restricts productivity and sustains a cycle of low output and slow economic progress (Ajibefun & Adejumo, 2018). Recent studies highlight the transformative role of advanced technologies, particularly Artificial Intelligence (AI), in addressing these constraints. AI-based tools such as crop yield forecasting models and disease detection systems allow farmers to rely on data-driven insights, thereby improving operational efficiency and overall productivity (Kamilaris et al., 2017; Shakoor et al., 2020). For example, machine learning techniques, including Decision Tree Regressor models, have demonstrated considerable potential in predicting crop yields, achieving accuracy levels of up to 72% (Shuaibu et al., 2024). Additionally, precision agriculture technologies such as drones and remote sensing systems enhance farm management by optimizing input use and enabling targeted interventions (Adepoju et al., 2022). These innovations are particularly important in managing climate-related risks and resource limitations. Furthermore, research on renewable energy integration, including wind turbine modeling, suggests possible solutions to Nigeria's persistent energy shortages, which indirectly support agricultural productivity (Babawurun et al., 2023). Despite the promise of these technologies, their adoption remains relatively low due to socio-economic constraints. Many existing studies emphasize technological development while paying insufficient attention to the practical realities faced by small-scale farmers, including limited access to digital tools, inadequate training, and restricted financial capacity (Benos et al., 2021). Over the past decade, AI technologies have evolved from experimental concepts into practical tools used across various farming systems, including machine-vision disease detection, satellite-based yield forecasting, and agronomic decision-support platforms. Companies and governments emphasize their potential to improve farm profitability and operational efficiency, while international agencies and empirical studies note both initial achievements and concerns about unequal access and adoption (Mckinsey, 2024; FAO, 2023). Moreover, there remains limited research on the obstacles to AI adoption and the support mechanisms required for effective implementation across diverse agricultural contexts (Cavazza, 2023). Bridging these gaps is essential to advancing agricultural productivity and sustainability in Nigeria. This study therefore investigates the transformative role of AI in addressing these challenges by providing innovative solutions that empower farmers and encourage sustainable practices. By harnessing AI technologies, the research aims to improve productivity, optimize resource use, and stimulate economic growth, ultimately strengthening food security and stability in Nigeria.

How AI Enhances Agricultural Productivity

Precision Resource Management:

Artificial intelligence (AI) systems combine satellite imagery, weather data, soil information, and sensor inputs to determine the optimal timing and quantity for applying fertilizers, pesticides, and irrigation. When properly validated, these data-driven recommendations boost crop yields per hectare while minimizing input waste (Nautiyal et al., 2025). AI-powered technologies such as drones, remote sensing devices, and Geographic Information Systems (GIS) help farmers assess soil health, identify nutrient gaps, and fine-tune fertilizer application (Liakos et al., 2018). This precise management approach reduces resource wastage and improves overall productivity.

Pest and Disease Management:

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



Image recognition systems driven by AI can identify crop diseases and pest infestations at an early stage, allowing farmers to act quickly. Early detection helps limit crop damage and reduces reliance on chemical treatments (Kamilaris&Prenafeta-Boldú, 2018).

Weather Forecasting and Climate Adaptation:

Machine learning algorithms generate reliable weather forecasts, enabling farmers to better plan planting and harvesting schedules. This improves resilience against climate variability and reduces weather-related risks (Shamshiri et al., 2018).

Automated Irrigation and Robotics:

AI-enabled irrigation systems use real-time soil moisture data to regulate water application efficiently. In addition, robotic harvesters and automated machinery address labor shortages and improve operational efficiency, particularly on large farms (Shamshiri et al., 2018).

Crop Yield Forecasting:

By analyzing historical records and environmental factors, AI models can estimate future crop yields. These forecasts support improved decision-making in storage, distribution, and market planning (Liakos et al., 2018).

Automation and Labor Efficiency:

Technologies such as autonomous vehicles, robotic systems, and intelligent spraying equipment reduce dependence on seasonal labor while enhancing the speed and consistency of farm operations. In contexts where labor costs or shortages limit productivity, automation increases output and minimizes delays that can negatively affect yields. Economic studies suggest that integrating AI with mechanization and process automation can generate substantial economic value (McKinsey, 2024).

Value-Chain Optimization:

Beyond the field, AI-driven automation improves efficiency across the agricultural value chain. By increasing throughput and reducing time-related losses, especially where labor constraints exist, AI integration with mechanized systems is projected to create significant economic benefits (McKinsey, 2024).

Evidence and Illustrative Examples

Pilot projects and field evaluations indicate that AI-based tools can improve both farm productivity and farmer incomes when implemented alongside local guidance and training. In East Africa, for example, advisory platforms such as Plant VillageNuruandVirtual Agronomist have supported smallholder farmers in identifying pests and accurately managing agricultural inputs. These initiatives often operate through lead-farmer networks and are integrated with extension services (Guardian reporting; FAO summaries). Broader strategic frameworks developed by multilateral institutions further show that AI-powered

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



digital agriculture programs generate meaningful benefits when paired with partnerships and capacity development efforts (World Bank, 2023; FAO, 2023). A growing body of research highlights AI's expanding contribution to agriculture. Wolfert et al. (2017) underscored the significance of big data and artificial intelligence in advancing smart farming systems. Liakos et al. (2018) reviewed machine learning applications in precision agriculture, emphasizing their role in enhancing crop productivity. Kamilaris and Prenafeta-Boldú (2018) examined deep learning techniques, particularly for detecting pests and diseases. Meanwhile, Shamshiri et al. (2018) analyzed automation in controlled agricultural settings such as greenhouses, demonstrating AI's capacity to substitute manual labor. Together, these studies confirm that AI improves agricultural efficiency and promotes sustainability. Nevertheless, challenges—including high implementation costs, limited digital literacy, and inadequate infrastructure—continue to hinder widespread adoption. This paper extends existing literature by synthesizing these findings and examining how AI concretely enhances farmers' daily practices. The study is grounded in the concept of Smart Farming, defined as the integration of digital technologies, data analytics, and automation to improve agricultural operations (Wolfert et al., 2017). Within this framework, AI plays a pivotal role by enabling real-time decision-making through predictive modeling, machine learning algorithms, and robotic systems. Smart Farming therefore provides an analytical lens for understanding the transformative impact of AI on modern agriculture.

Risks, Limitations, and Distributional Challenges of AI in Agriculture

i. Digital Divide and Adoption Barriers:

Many smallholder farmers lack access to affordable devices, reliable internet, and the digital skills needed to use AI technologies effectively. Without targeted public investment in connectivity and training, AI adoption is likely to be concentrated among larger, better-resourced farms and agribusinesses, potentially widening productivity gaps (World Bank, 2023).

ii. Data Control and Platform Concentration:

AI systems often rely on private cloud platforms and large proprietary datasets. If farm and supply-chain data are concentrated in a few companies, economic benefits may flow to platform owners rather than farmers or local communities. Interoperable standards and public data repositories can help mitigate this risk.

iii. Model Bias and Contextual Limitations:

Many AI models are trained on data from temperate, commercial farms, which may not reflect the realities of smallholder farms, mixed cropping systems, or diverse agro-ecological regions. Poorly adapted recommendations can undermine trust and even cause harm if they are not locally validated.

iv. Labor and Socioeconomic Impacts:

AI-driven automation can reduce the demand for seasonal labor, affecting rural households that rely on these jobs. Policies for reskilling, social protection, and inclusive technology deployment are needed to manage these transitions. Automation may also exacerbate inequalities by disproportionately benefiting large-scale, capital-intensive farms.

v. High Costs and Unequal Access:

Technologies such as advanced sensors, drones, robotics, and precision systems require significant upfront investment and stable infrastructure, which many smallholders, especially in developing countries, cannot afford. Consequently, wealthier farms gain more benefits, reinforcing existing disparities (Wolfert et al., 2017).

vi. Infrastructure Barriers:

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



AI systems depend on electricity, stable internet, and digital infrastructure for real-time data processing. Rural areas in Sub-Saharan Africa, South Asia, and other low-income regions often lack these resources, limiting AI deployment and benefits to areas with better technological access (Ashe et al., 2025).

vii. Data Availability, Quality, and Bias:

Reliable AI requires large, high-quality datasets, but agricultural data are often fragmented, inconsistent, and unevenly collected. This can result in biased recommendations that favor conditions typical of industrialized farms, leaving smallholders and diverse agro-ecologies underserved.

viii. Data Privacy, Ownership, and Trust:

AI relies on sensitive farm data, including land use, soil health, and production practices. Unclear data ownership and governance may make farmers hesitant to share information, fearing misuse or exploitation by corporations. Concerns about privacy, consent, and potential surveillance can slow adoption (European Parliament & Council of the European Union, 2016; Zuboff, 2019).

ix. Algorithmic Bias and Transparency:

Many AI systems function as “black boxes,” providing recommendations without explaining their decision-making process. Models trained on industrial farm data may embed biases, making them less accurate for small-scale farmers. Algorithmic bias can reinforce social inequalities and reduce trust in AI tools (Buolamwini&Gebbru, 2018; Barocas et al., 2019).

x. Labor Displacement and Socioeconomic Disruption:

AI and robotic automation can replace manual labor, especially in regions where agriculture is a key source of employment. While efficiency may improve, rural unemployment and income reduction for unskilled workers are real risks. Workforce transitions are often uneven and disruptive (Brynjolfsson& McAfee, 2014; World Economic Forum, 2023).

xi. Environmental and Sustainability Concerns:

Although AI can optimize input use, its deployment relies on energy-intensive computing, hardware production, and electronics, contributing to energy consumption, e-waste, and lifecycle environmental impacts. These factors complicate assessments of overall sustainability and may disproportionately affect certain regions (Strubell et al., 2019).

xii. Regulatory and Policy Gaps:

Rapid AI adoption in agriculture often outpaces regulatory frameworks. Without clear rules on data sharing, liability, algorithmic fairness, and environmental impact, adoption may be slowed or uneven across regions, creating uncertainty for both farmers and technology providers.

Implications for Global Competitiveness

By adopting AI alongside strong institutional support—such as research and development, extension services, open data initiatives, and financial mechanisms—countries can lower production costs per unit, improve product quality consistency, and shorten time-to-market. These factors are particularly valuable in export markets where reliability and traceability are essential. However, nations that fail to invest in these complementary systems risk serving mainly as data suppliers for global AI platforms, rather than capturing the full economic value of analytics and AI-driven services (McKinsey, 2024; World Bank, 2023).

Policy and Practice Recommendations

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



1. Invest in rural digital infrastructure: Governments should provide devices, connectivity, subsidies, and blended finance to help small holder's access AI services.
2. Promote interoperable standards and public data resources: Encourage local innovation and prevent monopolization of agricultural data by supporting open, privacy-conscious datasets and APIs.
3. Integrate AI with extension services: Train extension officers to use AI as a decision-support tool, combining local expertise with model outputs to ensure context-appropriate recommendations.
4. Support public-interest and open-source AI tools: Focus on solutions tailored to smallholder farms and diverse agro-ecologies rather than uniform commercial models.
5. Implement social protection and reskilling programs: Prepare for labor shifts by providing training and temporary support for workers affected by automation.
6. Include environmental monitoring: Ensure AI-driven intensification programs track soil health, biodiversity, and water use to maintain long-term sustainability.

Conclusion

AI has the potential to significantly enhance agricultural productivity and serve as a strategic asset for national competitiveness. Its benefits are fully realized only when deployed within strong institutional frameworks, open data systems, and inclusive policies that prioritize smallholder access and environmental sustainability. With proactive public support, AI can boost yields, reduce waste, and strengthen a country's position in global markets; without such measures, however, its advantages may remain unevenly distributed and fragile.

References

- International Telecommunication Union (ITU). (2024). FG-AI4A: Standardization gaps and roadmap for AI and IoT in digital agriculture (Technical Report). <https://www.itu.int/en/ITU-T/focusgroups/ai4a/Documents/Deliverables/FGAI4A-03.pdf>.
- McKinsey & Company. (2024, June 10). From bytes to bushels: How gen-AI can shape the future of agriculture. McKinsey & Company. <https://www.mckinsey.com/industries/agriculture/our-insights/from-bytes-to-bushels-how-gen-ai-can-shape-the-future-of-agriculture>.
- Nautiyal, M., et al. (2025). Revolutionizing agriculture: A comprehensive review on artificial intelligence applications in agriculture. *Frontiers / PMC*. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12274707/>.
- The Guardian. (2024, September 30). High tech, high yields? The Kenyan farmers deploying AI to increase productivity. *The Guardian*. <https://www.theguardian.com/world/2024/sep/30/high-tech-high-yields-the-kenyan-farmers-deploying-ai-to-increase-productivity>.
- World Bank. (2023). Digital Agriculture Roadmap Playbook (Digital Agriculture series). World Bank. <https://documents1.worldbank.org/curated/en/099053025063021993/pdf/P508004-f943a09b-c45f-4c93-b554-9dd1decd1e7c.pdf>.
- Barocas, S., Hardt, M., & Narayanan, A. (2019). *Fairness and machine learning*. fairmlbook.org.
- Brundage, M., Avin, S., Clark, J., et al. (2018). The malicious use of artificial intelligence: Forecasting, prevention, and mitigation. *arXiv preprint arXiv:1802.07228*.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age*. W. W. Norton.



- Buolamwini, J., & Geburu, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 1–15.
- European Parliament & Council of the European Union. (2016). Regulation (EU) 2016/679 (General Data Protection Regulation). *Official Journal of the European Union*.
- Floridi, L., Cowls, J., Beltrametti, M., et al. (2018). AI4People—An ethical framework for a good AI society. *Minds and Machines*, 28(4), 689–707.
- Goodfellow, I., Shlens, J., & Szegedy, C. (2015). Explaining and harnessing adversarial examples. *International Conference on Learning Representations (ICLR)*.
- Guidotti, R., Monreale, A., Ruggieri, S., et al. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys*, 51(5), 1–42.
- International Telecommunication Union (ITU). (2023). *measuring digital development: Facts and figures 2023*.
- OECD. (2023). *OECD framework for the classification of AI systems*. Organisation for Economic Co-operation and Development.
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach (4th Ed.)*. Pearson.
- Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 3645–3650.
- UNESCO. (2021). *Recommendation on the ethics of artificial intelligence*.
- World Economic Forum. (2023). *the future of jobs report 2023*.
- Ashe, G., Mengistu, D. (2025). *Future of Farming: A Review of Artificial Intelligence Applications in Agricultural Production and Processing*. *Asian Science Bulletin*, 3(1), 82-91.
<https://doi.org/10.3923/asb.2025.82.91>
- Adepoju, O.O., Esan, O., and Akinyomi, O. (2022). *Food Security in Nigeria: Enhancing Workers' Productivity in Precision Agriculture*. *Journal of Digital Food, Energy and Water Systems*.
- Ajibefun, I. A., and Adejumo, A. O. (2018). Challenges and prospects of small-scale farmers in accessing agricultural credit in Ondo State, Nigeria. *International Journal of Economics, Commerce and Management*, 6(6), 1-15.
- Babawurun, T., Ewim, D.R., Scott, T.O., and NeyeAkogo, C. (2023). *A Comprehensive Review of Wind Turbine Modeling for Addressing Energy Challenges in Nigeria and South Africa in the 4IR Context*. *The Journal of Engineering and Exact Sciences*. Benos, L., Tagarakis, A., Dolias, G., Berruto, R., Kateris, D., and Bochtis, D. (2021). *Machine learning in agriculture: a comprehensive updated review*. *Sensors*, 21(11), 3758. <https://doi.org/10.3390/s21113758>
- Cavazza, A. (2023). *Artificial intelligence and new business models in agriculture: a structured literature review and future research agenda*. *British Food Journal*, 125(13), 436-461.
<https://doi.org/10.1108/bfj02-2023-0132>
- Food and Agriculture Organization (FAO). (2020). *Climate Change and Food Security: Risks and Responses*. Retrieved from <http://www.fao.org/3/ca3941en/ca3941en.pdf>
- Kamilaris, A., Prenafeta-Boldú, F. X., and Christodoulou, E. (2017). *Deep learning in agriculture: A survey*. *Computers and Electronics in Agriculture*, 147, 70-90. DOI: 10.1016/j.compag.2018.02.016
- Shakoor, A., Chen, X., Niazi, A. K., Ali, Z., Raza, A., Bibi, I. ... and Zhang, D. (2020). *Artificial intelligence for precision agriculture: A review*. *Computers and Electronics in Agriculture*, 178, 105711. DOI: 10.1016/j.compag.2020.105711
- Shuaibu, N.S., Obunadike, G.N., and Jamilu, B.A. (2024). *Crop Yield Prediction Using Selected Machine Learning Algorithms*. *Fudma Journal of Sciences*.

Corresponding Author: A.A. OYIBO

Copyright © 2026 Author(s) retain the copyright of this article.



- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674. <https://doi.org/10.3390/s18082674>
- Shamshiri, R. R., Kalantari, F., Ting, K. C., Thorp, K. R., Hameed, I. A., Weltzien, C., and Balasundram, S. K. (2018). Advances 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.
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming—A review. *Agricultural Systems*, 153, 69–80. <https://doi.org/10.1016/j.agsy.2017.01.023>