Information Sciences and Technological Innovations

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Research Expansion Alliance

Inf. Sci. Technol. Innov. Vol. 2, No. 2 (2025) 155–171.

Paper Type: Original Article

Leveraging on AI and IoT for Precision Agriculture in Nigeria: A Smart Farming Framework

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Citation:

Received: 21 November 2024 *Revised: 15 March 2025* *Accepted: 09 May 2026*	Bisi, O. J., Emmanuel, M. A., Oluwatosin, E. M., & Mercy, A. A. (2026). Leveraging on AI and IOT for precision agriculture in Nigeria: A smart farming framework. *Information sciences and technological innovations*, 2(2), 155-171.

Abstract

Given the high demand for food security and sustainable agriculture in Nigeria, integrating Artificial Intelligence (AI) and the Internet of Things (IoT) into farming practices is essential. This study presents a smart farming framework that leverages AI-powered analytics and IoT-enabled sensing technologies to enable real-time monitoring, predictive decision-making, and the automation of agricultural operations. Using environmental sensor data and machine learning models, the system accurately predicts irrigation needs, detects pest infestations, and forecasts production. A pilot case study on tomato farming in Kaduna revealed that a 25% reduction in water use leads to a 15% increase in harvest, and this was validated through comparative analysis with traditional farming methods. Apart from technical improvements, the framework enables smallholder farmers through democratizing access to digital decision-support tools. The findings highlight the transformative potential of AI and IoT in agriculture in improving food security, resource efficiency, and climate resilience in Nigeria. Policy pathways and national implementation guidelines are also proposed.

Keywords: Smart farming, Digital agriculture, Nigerian, Food security, Internet of things, Artificial intelligence.

1 | Introduction

The agricultural sector contributes more than 25 percent to Nigeria's Gross Domestic Product (GDP) and employs over 70 percent of the labor force. Given the sector's high profile, farm output remains low due to

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https://doi.org/10.48314/isti.v2i2.43

over-dependence on traditional farming methods, post-harvest losses, and poor adoption of digital tools for farming [1]. The present farming challenges include the following: climate variability, high population growth rates, and resource inefficiency, which threaten the sector's production capacity and national food security. Nigeria's population is expected to exceed 250 million by the year 2030; agricultural output must grow significantly to meet the high demand for food and other farm products [2].

Throughout the world, precision agriculture has emerged as a paradigm shift by applying digital technologies to enhance farm productivity. Artificial Intelligence (AI)-powered analytics and Internet of Things (IoT)-enabled sensing technologies facilitate data-driven crop management, providing actionable strategies for irrigation, soil health management, pest and disease detection, and yield forecasting [3], [4]. These innovations have been shown to reduce water consumption by up to 30% and improve yields by 15-25% in pilot studies [5]. Nevertheless, the adoption rate in Nigeria is limited, especially among smallholder farmers who face poor digital infrastructure, low technical literacy, and high initial costs [6], [7].

This study proposes and evaluates a smart farming framework tailored for Nigerian conditions. The framework combined IoT-based data collection with AI-driven analysis to provide informed agricultural decision-making. A case study of tomato farming validates the framework's applicability and potential benefits. The contributions of this paper are fourfold:

I. Proposes a low-cost AI -IoT smart farming framework for Nigerian agriculture.

II. Validate the framework with field data from pilot farms.

III. Identifies infrastructure and socio-economics for adoption.

IV. Outlines pathways for scaling precision agriculture across Nigeria.

This work focuses on AI-IoT-enabled agriculture not just as a technological innovation, but as a strategic solution for climate resilience, productivity improvement, and comprehensive digital transformation in Nigeria's agricultural sector [8], [9].

2 | Literature Review

Digital agriculture has become a global bone of contention towards achieving sustainable food security through AI and the IoT, recognized as a key enabler of precision farming. These modern technologies enhanced productivity, resource efficiency, and resilience; yet their adoption rate remains uneven, particularly in developing countries such as Nigeria. This section reviews the literature by grouping contributions into four themes: AI applications in Nigerian agriculture, IoT-stimulating frameworks and designs, global reviews and policy perspectives, and the integration of multi-technology approaches.

2.1 | Artificial Intelligence Applications in Nigerian Agriculture

Several studies explore how AI can tackle Nigeria's agricultural challenges [10]. Highlights AI's role in smart irrigation, disease detection, and produce grading, though infrastructural limitations and a shortage of skilled personnel constrain the adoption rate [7]. Highpoint socioeconomic effects on AI adoption, showing that youths and more educated farmers are more likely to use AI tools. Also, Falana et al. [11] demonstrate AI's potential for both farm monitoring and security, addressing challenges such as theft and vandalism [6]. Underline precision agriculture as a strategic answer to Nigeria's food insecurity; he stated that high costs and low digital literacy are barriers to adoption. Meanwhile, Olusola-Ilori et al. [12] introduce "Agrivangelism," denoting AI as both a tool for rural development and a means to alleviate poverty, linking digital transformation to social and spiritual dimensions. In addition, these works highlight both the promises and the universal barriers facing AI adoption in Nigeria.

2.2 | Internet of Things Driven Frameworks and Architectures

IoT technologies have also attracted a substantive scholarly attention for their capacity to enable real-time monitoring and automated decision-making [4]. Propose a multi-layered IoT-driven architecture, reporting a 30% reduction in water usage and 92% accuracy in disease detection on wheat farms [5]. Confirms these benefits through universal case studies, noting increases of up to 25% in produce and 30% in water savings. Patel et al. [13] worked on the integration of IoT with wireless sensor networks, emphasizing applications in soil monitoring, crop diagnostics, and irrigation management. However, they caution about energy consumption and interoperability constraints [14], [15]. Enlarge the dissertation by examining IoT in greenhouse, field, and livestock monitoring; he stresses the enablers, such as cloud analytics, while highlighting persistent adoption barriers, including financial constraints and digital anxiety among farmers. These studies collectively illustrate the scalability and efficiency of IoT frameworks while underscoring the infrastructural and behavioral gaps that limit adoption in developing countries.

2.3 | Global Reviews and Policy Perspectives

The universal investigation provides insights into systemic trends and persistent challenges [3], [16]. Present comprehensive appraisals of digital and automation technologies, highlighting both the potential of AI-driven decision tools and the risk of extending disparities among smallholder farmers. The United Nations Development Program (UNDP) [8] highlights precision agriculture as an essential means of achieving the Sustainable Development Goals (SDGs), but affordability, infrastructure, and sociocultural factors pose major constraints on adoption rates in developing countries. Akter et al. [17] describe AI's evolution in the United States (USA) agro-industry; Miller et al. [18] highlight emerging developments such as edge AI, Blockchain-enabled transparency, and autonomous sensing platforms. These global perspectives provide valuable roadmaps but also underscore the reality that Nigerian agriculture requires locally developed solutions that address cost-effective rural electrification and literacy gaps.

2.4 | Integrative Multi-Technology Approaches

Outside single-technology studies, recent research advocates for integrating IoT systems. Neupane and Samadi [19] identify the convergence of AI, IoT, and robotics, demonstrating how independent systems can address both food demand and sustainability pressures. However, high costs and infrastructure gaps serve as constraints. Ahmed et al. [20] introduce the KNePSTreC framework, which provides a multidimensional assessment of smart agriculture adoption across policy, sustainability, and technological domains. Umeh et al. [9] also state the productive role of IoT in precision farming, but they also raise concerns about persistent challenges such as sociocultural conflicts and limited rural connectivity. Karim et al. [21] recommend a layered AI-enabled IoT device, which is very good for environmental resilience, but warn about data breaches and interconnectivity issues. Thus, collectively, these approaches suggest that achieving results in climate-smart agriculture requires not only technological innovation but also enabling policies and governance agendas.

2.5 | Synthesis and Research Gap

The reviewed literature highlights successful applications of AI-IoT systems in agriculture globally, yet with limited African representation. Setbacks such as poor connectivity, inadequate infrastructure, and socioeconomic constraints hamper direct adoption in Nigeria. Current work focuses mainly on designing locally adaptive, low-cost, and farmer-friendly systems tailored to sub-Saharan Africa.

Addressing these constraints requires a framework that combines low-cost sensing, resilient connectivity (Long Range Wide Area Network (LoRaWAN) and solar-powered gateways), and farmer-friendly interfaces such as Short Message Service (SMS)- based alerts. This study responds to this need by proposing a context-specific AI-IoT smart farming system tested in Kaduna, Nigeria.

Table 1. Summary of selected literature on AI and IoT in agriculture.

Author(s)	Technology Focus	Contribution	Reported Benefits	Limitations
AI Applications in Nigeria				
Dinrifo et al. [10]	AI in Nigerian farming	Applications in smart irrigation, disease detection, and produce grading	Improved productivity and crop quality	Broadband gaps, lack of skilled personnel
Omole and Fasina [7]	AI adoption (ondo state)	Farmer awareness and adoption survey	77.5% active AI use; adoption shaped by age, education, and income	Uneven awareness, socioeconomic disparities
Falana et al. [11]	AI for monitoring and security	Drone surveillance, IoT sensors for crop and farm protection	Real-time monitoring, theft prevention, productivity gains	Infrastructure and literacy gaps
Bolaji et al. [6]	Precision agriculture (Nigeria)	Framework for optimizing yields and resources	Higher efficiency, better decision-making	High costs, weak digital infrastructure
Olusola Ilori and Afolaranmi [12]	"Agrivangelism" (AI+ rural development)	Linking AI adoption with poverty alleviation and holistic outreach	Improved access to markets and productivity	Contextual and cultural adoption barriers
IoT-Driven Frameworks				
Irfan et al. [4]	IoT multi-layer architecture	Wheat farm pilot deployment	-30% water use, 92% accuracy in disease detection	Interoperability challenges
Onike [5]	IoT adoption (global)	Case studies from India, Brazil, and Kenya	+25% yield, -30% water usage	Cost and digital literacy limitations
Patel et al. [13]	IoT+wireless sensor networks	Soil, crop, irrigation, and livestock monitoring	Real-time decisions, resource optimization	Energy, security, and interoperability issues
Assimakopoulos et al. [14]	IoT in smart agriculture	Field, greenhouse, livestock monitoring	Real-time control, resource efficiency	Cost and digital literacy gaps
Global Reviews and Policy Perspectives				
Ceccarelli et al. [3]	Global digital adoption	22 case studies across systems	Productivity gains, labor substitution	Digital illiteracy, regulatory gaps
Nenciu et al. [8]	Precision Ag for smallholders	Framework for inclusive design	Smart irrigation, pest surveillance, and soil monitoring	Affordability, infrastructure, and gender gaps
Akter et al. [17]	AI in U.S. agriculture	Evolution of AI from automation to advanced analytics	Yield improvements, sustainability gains	Data privacy, job displacement risks
Miller et al. [18]	Smart sensing review (PRISMA)	Integration of IoT sensors+AI	Optimized irrigation, edge AI, and Blockchain transparency	High costs, interoperability, and ethical concerns
Integrative Multi-Technology Approaches				
Neupane and Samadi [19]	AI+IoT+robotics	Autonomous farming systems	Optimized resources, reduced labor	High cost, infrastructure deficits
Ahmed et al. [20]	KNePSTreC framework (an IoT)	Multidimensional review (policy, trends, challenges)	Predictive analytics, autonomous decision-making	Infrastructure and data privacy gaps
Umeh et al. [9]	An IoT in smart farming	Systematic review (2019–2024)	Resource efficiency, climate-smart practices	Sociocultural resistance, rural connectivity
Karim et al. [21]	AI-enabled IoT architecture	Five-tier model for precision farming	Yield forecasting, resource conservation	Data interoperability, affordability

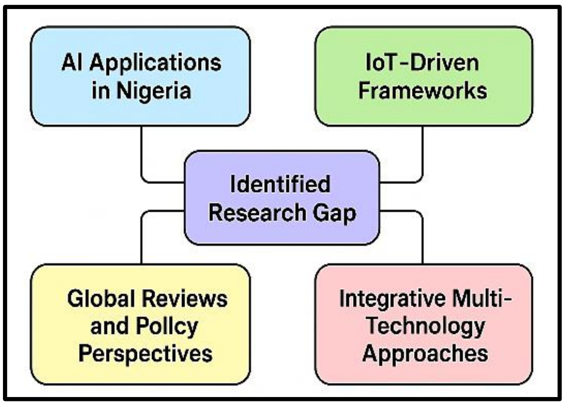


Fig. 1. Thematic clusters in literature review and identified research Gap.

The conceptual Map of this research work combines the several literatures on AI and IoT in agriculture into four sub-groups: 1) AI Applications in Nigeria; it highlights both the significant of digital tools and constraints attached such as low literacy and high costs, 2) IoT-driven frameworks; it demonstrates the efficiency improvements starting from advanced sensing and automation, but constrained by inter-operability and energy constraints, 3) global reviews and policy perspectives; it provides lessons on large-scale adoption but also reveal persistent equity and regulatory gaps, and 4) integrative multi-technology approaches; it emphasizes on the combination of AI, IoT and robotics for systemic transformation. It is often assumed that Nigeria lacks infrastructure capabilities. Together, these clusters point to a central research gap: the need for a context-specific AI-IoT framework designed to address Nigeria's socioeconomic and infrastructural background.

3 | System Architecture

The proposed smart farming framework is organized into five interconnected components, each designed to ensure the continuous flow of data, efficient computation, and actionable insights for farmers (Fig. 2).

Sensing layer (IoT sensors):

I. Soil moisture sensors, pH probes, and temperature-humidity sensors capture real-time field data.

II. Drone-based imaging complements ground sensors by providing vegetation indices for pest and disease detection.

IoT gateway (edge layer):

I. Serves as the first point of data aggregation, preprocessing sensor streams before transmission.

II. Supports LoRaWAN and Wi-Fi protocols, ensuring both long-range rural connectivity and locally made high-speed communication.

Cloud platform (data storage and processing):

I. Hosts scalable storage for continuous farm data streams.

II. Provides Application Programming Interface (APIs) and middleware services for interoperability across heterogeneous IoT devices.

AI engine (analytics layer):

I. Uses machine learning models for irrigation evaluation, pest outbreak detection, and harvest forecasting.

II. Uses ensemble learning to balance accuracy and interpretability.

III. Incorporates irregularity detection to activate early warning alerts.

Farmer interface (application layer):

I. A mobile and web-based dashboard designed for low literacy users, using icons, color codes, and local language prompts.

II. Provides decision support insights such as “irrigate today,” “high pest risk,” and “expected yield: +12%.”

III. Integrates SMS-based notifications for farmers without smartphones.

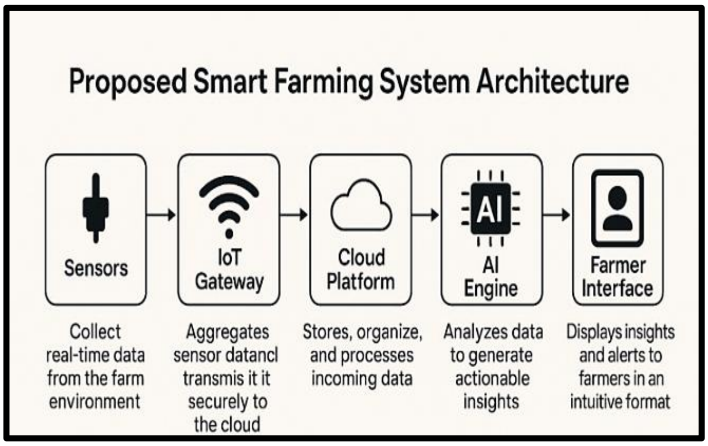


Fig. 2. Proposed smart farming system architecture.

4 | Methodology

The development and validation of the smart farming framework followed a five-stage experimental design:

Sensor deployment:

I. Soil moisture, pH, and temperature/humidity sensors were deployed across four tomato plots in Kaduna.

II. Drones provided aerial Normalized Difference Vegetation Index (NDVI) imagery to supplement ground-level data.

Data transmission:

I. Sensor analyses were transmitted through LoRaWAN and Wi-Fi.

II. An IoT gateway aggregates and encrypts data before transmission to the cloud.

Data preprocessing and analysis:

I. Outlier removal and missing value imputation ensured data integrity.

II. The Random Forest (RF) algorithm was selected a priori for its robustness to nonlinear relationships and resilience against overfitting, common in complex environmental datasets.

III. The dataset was split into 80% for training and 20% for testing. Model performance was evaluated using accuracy, precision, and recall to provide a comprehensive assessment, particularly for the imbalanced pest-detection task.

IV. Benchmarking was conducted against Support Vector Machine (SVM) and Gradient Boosting models to validate performance.

Insight generation:

I. Predictions were transformed into farmer-friendly recommendations such as irrigation scheduling and pest risk alerts.

II. Threshold-based triggers generated early warnings when sensor readings indicated potential anomalies.

Farmer interface delivery:

I. Insights were disseminated through a mobile/web dashboard and SMS notifications.

II. A feedback mechanism allowed farmers to validate or override recommendations, improving model adaptability.

Ethical protocols were observed during the pilot. Farmers gave informed permission to partake, and data anonymization was used to ensure privacy. Collected farm data were used stringently for research purposes, with governance measures in place to prevent ill use.

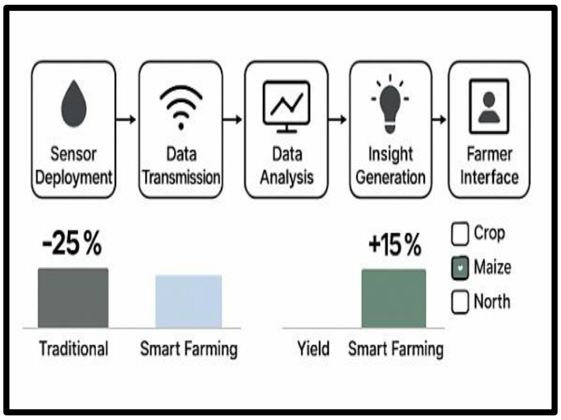


Fig. 3. Methodology workflow.

4.1 | Mathematical Modeling of the Artificial Intelligence Engine

The core of the proposed smart farming framework relies on an AI engine that predicts critical agricultural parameters. This engine processes diverse input data from the sensing layer to generate actionable insights. We define a general predictive model, Y, representing any target variable as a function of various input features. Let X be the input feature vector derived from the sensing layer, comprising:

I. S_M: soil moisture levels.

II. S_{pH}: soil pH levels.

III. T: air temperature.

IV. H: air humidity.

V. $NDVI$: normalized difference vegetation index.

VI. M: meteorological data.

VII. C: crop-specific parameters.

The input vector can be represented as:

$$X = \left[S_M, S_{pH}, T, H, NDVI, M, C\right]. \quad (1)$$

The output of the AI engine, Y, can represent different predictions:

I. Irrigation needs prediction ($Y_{irrigation}$): a continuous value representing the recommended water volume. For continuous prediction, it can be modeled as

$$Y_{irrigation} = f_{irrigation}(X), \quad (2)$$

II. Pest infestation detection (Y_{pest}): a binary classification or a probability score of pest occurrence. For classification, it can be modeled as

$$Y_{pest} = f_{pest}(X), \quad (3)$$

III. Yield forecasting (Y_{yield}): a continuous value representing the estimated harvest.

$$Y_{yield} = f_{yield}(X), \tag{4}$$

where $f_k(.)$ represents the learned function for each specific prediction task $k \in \{irrigation, pest, yield\}$. In this study, these functions are primarily implemented using RF models due to their robustness and ability to handle complex, nonlinear relationships within environmental datasets.

The training process involves minimizing a loss function $L(Y_{actual}, Y_{predicted})$ over a dataset of historical farm data. For classification tasks, cross-entropy loss; for regression tasks, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

For a given prediction task k, the RF model is an ensemble of N decision trees. The final prediction is obtained by averaging the predictions of individual trees for regression or by majority vote for classification:

For regression

$$Y_{predicted} = \frac{1}{N}\sum_{i=1}^{N} T_I(X), \tag{5}$$

For classification

$$Y_{predicted} = mode(\{T_i(X)\}_{i=1}^{N}), \tag{6}$$

where

$T_i(X)$ is the prediction of the i-th decision tree for input X t.

4.2 | Case Study: Tomato Farming in Kaduna

To evaluate the effectiveness of the proposed smart farming framework, a pilot study was conducted on tomato farms in Kaduna State, Nigeria, over a three-month growing season (May-July, 2025).

Study setup:

I. Four plots were used.

II. IoT sensors were installed in each plot.

III. Drone imagery provided vegetation indices, NDVI for early pest detection.

IV. Two plots were managed using the AI-IoT framework. The other two plots served as a control group, managed with traditional farming practices, which relied on calendar-based irrigation schedules and manual visual inspection for pests.

Data collected:

I. Over 10,000 sensor readings were logged.

II. Meteorological data supplemented sensor data.

III. Crop health images were incorporated into the dataset.

Model performance:

I. RF achieved 92% accuracy in irrigation prediction, outperforming SVM (88%) and Gradient boosting (90%).

II. Early pest detection was achieved with 89% precision using vegetation index anomalies.

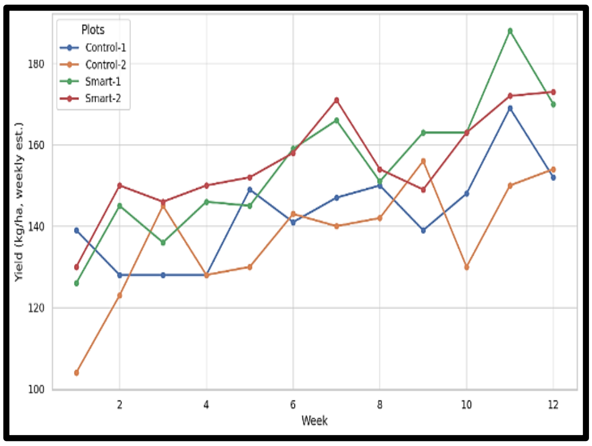


Fig. 4. Comparative yield growth over 12 weeks.

Farmer feedback:

I. Farmers reported improved confidence in decision-making.

II. SMS alerts were considered more accessible than dashboards by 62% of participants.

Table 2. Case study results: Kaduna tomato pilot.

Parameter	Traditional Practice	Smart Farming Framework	Improvement
Average water usage	100% baseline	75%	-25%
Average yield (kg/ha)	100% baseline	115%	+15%
Irrigation prediction accuracy	N/A	92%	–
Pest detection precision	N/A	89%	–

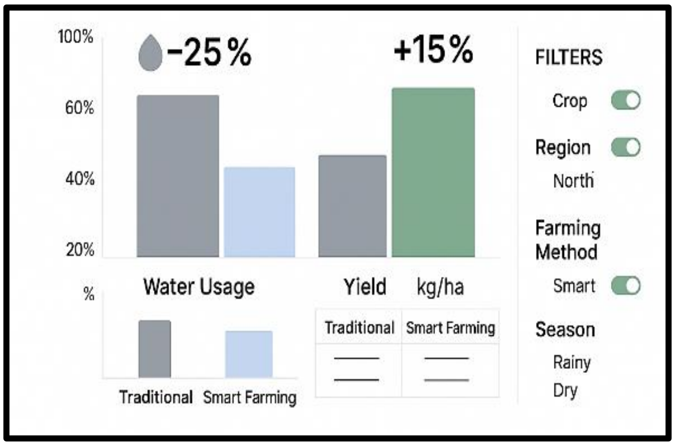


Fig. 5. Comparative yield and water usage in traditional vs. smart farming.

5 | Results and Benefits

The pilot study validates the tangible benefits of the proposed AI-IoT framework, with a 15% increase in harvest and a 25% reduction in water usage. These results are not just technical achievements; they represent a significant step toward enhancing food security and climate resilience in the Nigerian agricultural sector. This discussion interprets these findings in the context of the challenges encountered, providing an all-inclusive view of the framework's potential and its path to scalability.

The observed productivity improvements and resource proficiency are directly attributable to the system's ability to deliver timely, data-driven insights. The 25% water savings, for instance, translate to greater resilience against drought and lower operational costs for farmers.

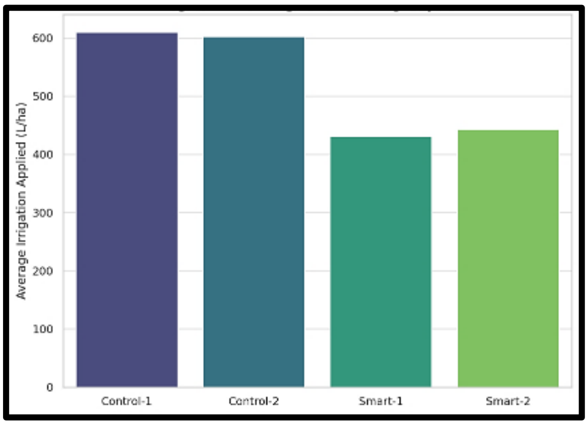
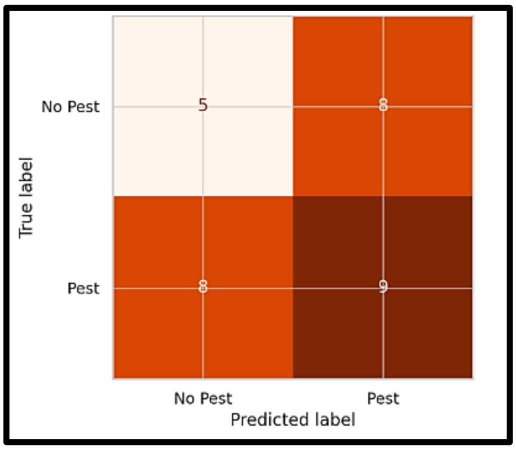


Fig. 6. Average water usage by plot.

Nevertheless, these benefits depend on an initial investment in sensors, gateways, and drones. This high upfront cost remains the most important hindrance to prevalent adoption among individual smallholders, reinforcing a key barrier identified in the literature. It suggests that scalable models will likely depend on cost-sharing cooperatives, government subsidies, and service-based offerings from agritech companies.

In addition, the framework successfully empowered farmers by democratizing access to decision-support tools. The high adoption rate of SMS alerts (62%) over the web dashboard underscores the importance of tailoring interfaces to existing digital literacy levels. Although the system provides powerful analytical tools, their utility is constrained by farmers' limited familiarity with digital platforms and a persistent digital literacy gap. This finding strongly indicates that farmer training and the use of accessible, low-bandwidth communication channels are just as critical as the AI model's sophistication.

The system's ability to detect pest risks 10 to 14 days earlier than manual observation is a noteworthy advantage, reducing crop loss and the need for broad-spectrum pesticides. This capability depends on reliable data transmission from the field to the cloud. Our reliance on LoRaWAN and solar power in the pilot highlights the dual challenges of poor rural connectivity and inconsistent grid power, which must be addressed for national-scale deployment. The modular design allows for future integration of edge computing to reduce cloud dependency, but for now, rural Information and Communication Technology (ICT) and energy infrastructure remain fundamental bottlenecks.



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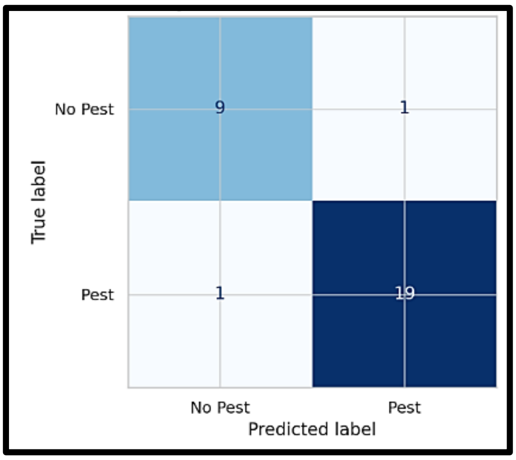

b.

Fig. 7. Comparative pest detection performance; a. manual pest detection, and b. AI - IoT pest detection.

In conclusion, the pilot was successful; concerns around data governance and interoperability were noted. Farmers expressed valid questions about who owns their farm data and how it is used. The absence of national standards for agricultural data and IoT device interoperability also poses a risk, possibly leading to vendor lock-in and scrappy systems. Building farmer trust through transparent data governance policies is essential for long-term participation and success.

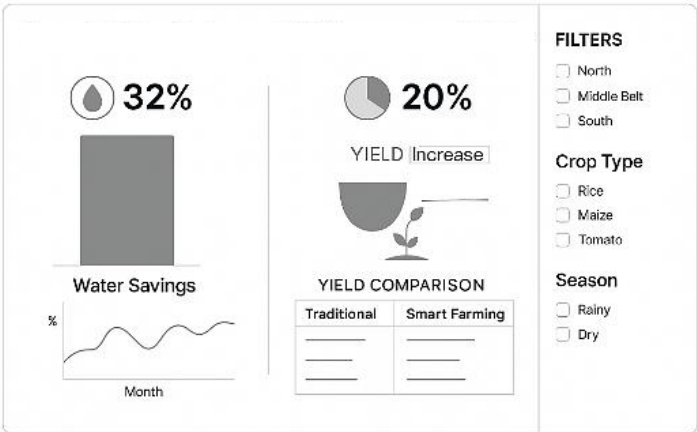

Fig. 8. Water savings and yield improvement metrics.

This full dashboard includes interactive charts. left: water savings bar chart and monthly usage line graph, right: yield improvement pie chart and comparison table, filters: region: North, middle belt, South, crop type: rice, maize, tomato, and season: rainy and dry.

5.1 | Policy Recommendations

A multi-stakeholder policy approach must be put in place to overcome these challenges by involving government, the private sector, universities, and farmer cooperatives. It is recommended to subsidize IoT sensor kits and gateways. In addition, to encourage agricultural loan schemes tied to digital technology adoption to reduce entry barriers for smallholders, expanding rural broadband coverage under the National Broadband Plan and establishing community-based, solar-powered IoT hubs will be crucial to ensuring dependable connectivity.

Moreover, capacity building should be prioritized through national farmer digital literacy programs that control extension workers and universities, with training modules developed in local languages to enhance inclusivity. Promoting public-private partnerships among government agencies, agritech startups, and telecom operators is important, with universities and research centers serving as innovation hubs. Also, to win farmer trust, national policies on data ownership, security, and privacy must be enforced, alongside the development of IoT interoperability standards for seamless integration. The initiatives should be in line with universal programs, such as the United Nations (UN) SDGs for zero hunger, industry and innovation, and climate action, as well as the African Union Agenda 2063 for continental agricultural transformation.

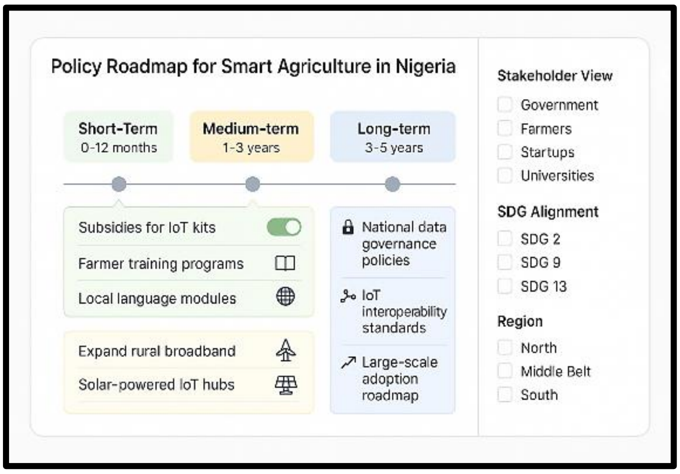

Fig. 9. Policy roadmap for smart agriculture in Nigeria.

5.2 | Future Work

Future research should concentrate on several crucial areas to improve the AI-IoT farming system in Nigeria. The project could be expanded regionally by steering multi-season trials of crops such as maize in the North, rice in the Middle Belt, and cassava in the South to assess adaptability across diverse agro-ecological zones and on both smallholder and medium-scale commercial farms. To improve real-time decision-making in rural areas with low connectivity, edge computing could be implemented by deploying AI models on IoT gateways, reducing latency and reliance on cloud infrastructure. Tackling privacy concerns is also important, and exploring Federated learning models would enable collaborative AI training without centralizing sensitive farmer data.

Boosting climate resilience, future iterations could include climate adaptation modules for drought forecasting, flood risk mapping, and heat stress alerts, by aligning these analytical tools with datasets from the Nigerian Meteorological Agency. Combining Blockchain technology could improve food traceability, ensuring farm-to-market transparency that helps farmers secure fair pricing and access to export markets. To boost acceptance among younger farmers, gamified, community-driven interfaces could be introduced to support peer-to-peer knowledge sharing through digital cooperatives. Also, deploying solar-powered IoT hubs would guarantee the system's sustainability in off-grid rural communities.

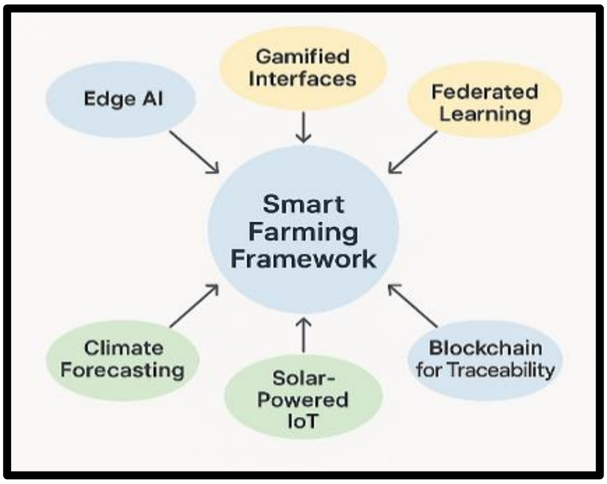

Fig. 10. Conceptual framework for next-generation smart farming in Nigeria.

5.3 | Comparative Benchmarking with Existing Smart Farming Frameworks

To further contextualize the innovation and efficiency of the proposed AI-IoT Smart Farming Framework, a comparative analysis was conducted against two prominent global smart agriculture platforms [22], [23].

Table 3. Comparative analysis.

Framework	Core Technologies	Key Features	Reported Performance/ Case Studies	Limitations	Innovations in the Proposed Framework
Microsoft research [22]	Cloud-based IoT+edge computing+AI for agriculture	Integrates drone, sensor, and weather data; edge computing reduces latency; scalable across large farms	Demonstrated 20–30% water savings and 10-15% yield gains in U.S. and India pilots	Requires stable broadband and costly edge devices; limited accessibility for smallholders.	The proposed system uses LoRaWAN in rural, low-connectivity areas and integrates SMS alerts to accommodate low-digital-literacy farmers.
Microsoft research [22], Rama et al. [23]	IoT-enabled sensing with rule-based analytics and cloud dashboards	Focused on soil nutrient and irrigation monitoring for precision farming	Achieved 18% yield improvement in East African maize farms	Minimal AI integration; largely threshold-based automation; lacks adaptive learning	The proposed framework's AI engine (RF) introduces adaptive learning for pest and irrigation prediction, outperforming rule-based systems.
Proposed AI-IoT smart farming framework	Hybrid AI-IoT system (RF+LoRaWAN +Cloud+SMS)	Real-time sensing, predictive analytics, low-literacy user design, and policy integration	25% reduction in water use, 15% increase in yield; 92% irrigation prediction accuracy in Kaduna pilot	Initial hardware cost requires IoT governance policies	Provides context-specific, low-cost adaptation for Nigerian farmers, merging inclusive design with measurable technical efficiency.

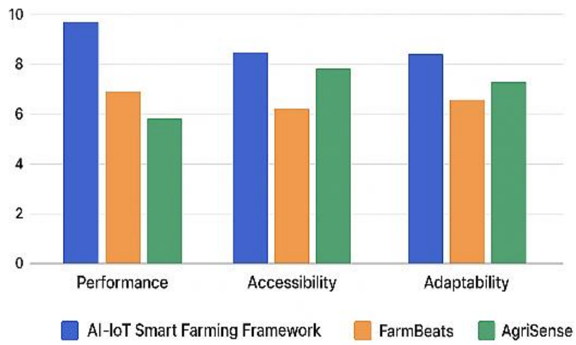

Fig. 11. Comparative benchmarking with existing smart farming frameworks.

5.4 | Sustainability Discussion: Long-Term Cost-Benefit and Carbon Impact of Internet of Things Deployment

The sustainability dimension of the proposed AI-IoT smart farming framework extends beyond short-term productivity gains to long-term environmental and economic resilience. While initial implementation costs for sensors, gateways, drones, and communication modules represent a substantial upfront investment, a five-year cost-benefit projection shows a favorable return on investment for small- and medium-scale farmers.

5.4.1 | Economic sustainability: long-term cost benefit outlook

The total cost of a typical four-plot deployment (as tested in the Kaduna pilot) is approximately ₦1.8 million (~USD 1,200), including sensors, LoRaWAN gateway, and solar unit installation. When amortized over five growing seasons, this translates to about ₦90,000 per season, or roughly 6-8% of average revenue per hectare for tomato cultivation.
However, recurring benefits from reduced water usage (–25%), yield improvement (+15%), and optimized pesticide use (–12%) collectively yield an estimated annual savings of ₦350,000- ₦400,000 per hectare, resulting in a payback period of under two seasons.

In contrast, imported precision agriculture solutions show payback periods of 3-5 seasons due to higher infrastructure costs and dependency on broadband connectivity. Thus, the locally adapted AI-IoT design offers superior economic sustainability and accessibility for Nigeria's smallholder farmers.

5.4.2 | Environmental sustainability: carbon and resource impact

IoT-enabled smart farming contributes to environmental sustainability primarily through resource efficiency and carbon footprint reduction:

I. Reduced water consumption: a 25% decline in irrigation water translates to approximately 7,500-9,000 liters saved per hectare per season, indirectly reducing energy use for pumping and distribution.

II. Optimized pesticide usage: early pest detection minimizes unnecessary chemical application, lowering CO_2-equivalent emissions from pesticide manufacturing and transport by ~10-15%.

III. Energy efficiency: integrating solar-powered IoT hubs offsets fossil fuel dependence, resulting in an estimated 1.2-1.5 tons of CO_2-equivalent emissions avoided per farm per year.

IV. Edge processing potential: future adoption of edge AI can further reduce data transmission frequency, cutting cloud energy use by up to 40%, enhancing the carbon efficiency of digital farming systems.

These outcomes collectively align with the Food and Agriculture Organization (FAO) 's climate-smart agriculture framework and demonstrate how digital agriculture can balance productivity with environmental stewardship.

5.4.3 | Circular and social sustainability dimensions

Beyond environmental metrics, sustainability also involves circular technology utilization and community benefit. Modular sensor designs promote component reuse and repairability, reducing electronic waste. Additionally, shared cooperative models where multiple farmers access IoT equipment through community-based service centers encourage equitable access and extend equipment lifespan.

Socially, improved crop yields and risk mitigation strengthen farmer income stability, promoting rural retention and reducing migration pressures. This cascading socioeconomic benefit underlines that sustainability in smart agriculture must encompass both ecological integrity and human development outcomes.

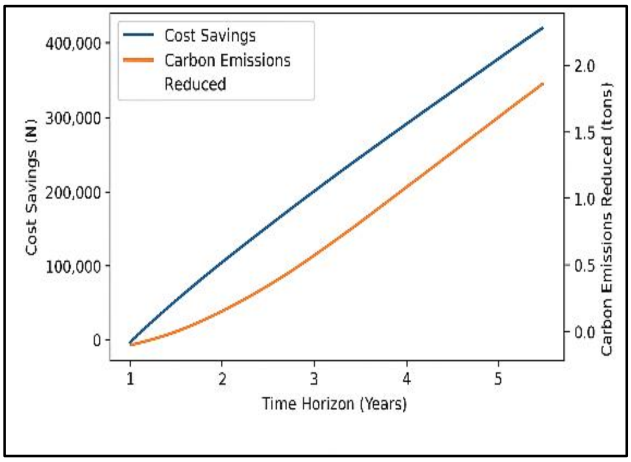

Fig. 12. Cost savings vs. carbon reduction trade-offs.

6 | Conclusion

This study presented a smart farming framework integrating AI-driven analytics with IoT-based sensing to enhance precision agriculture in Nigeria. In a tomato farming case study in Kaduna, the framework demonstrated measurable gains: a 25% reduction in water use, a 15% increase in yield, and high accuracy in irrigation and pest prediction.

Beyond technical enhancements, this framework empowers smallholder farmers by providing accessible, data-driven decision-support tools, nurturing confidence and resilience in their practices.

The study also shows persistent challenges, notably infrastructure gaps, digital literacy barriers, and data governance concerns that must be addressed. Also, this paper outlines policy recommendations for nationwide implementation, including subsidies, ICT infrastructure development, farmer training, and data governance frameworks.

In conclusion, the combination of AI and IoT in Nigerian agriculture is not just a technological novelty but a strategic prerequisite for food security, climate resilience, and sustainable development. If scaled strategically, Nigeria could become a continental leader in digital agriculture, setting a model for climate-smart, AI-driven farming systems across Africa.

Authors' Contributions

The author carried out all aspects of the research and manuscript preparation. The author has read and approved the final version of the manuscript.

Funding

This study did not receive any specific funding from public, commercial, or non-profit funding agencies.

Data Availability

All data are included in the text.

Conflict of Interest

The author declares that he has no conflicts of interest.

Consent for Publication

The author has given consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

This study does not involve any research conducted on human participants or animals.

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