A Smart Framework for Advisory and Management of Watermelon Production

[1]Matthew C. Okoronkwo [2]Chikodili C. Ugwuishiwu, [3]Nnaemeka E. Ogbene
[1, 2, 3] Department of Computer Science, University of Nigeria, Nsukka, Nigeria
[1]matthew.okoronkwo@unn.edu.ng [2]chikodili.ugwuishiwu@unn.edu.ng, [3]nnaemeka.ogbene@unn.edu.ng

Corresponding Author's email: nnaemeka.ogbene@unn.edu.ng

Abstract

The application of Internet of Things (IoT) technologies in agriculture has the potential to improve decision-making through real-time sensing and data-driven advisory services. However, most existing IoT-based agricultural systems focus primarily on environmental monitoring and lack integrated nutrient-aware decision-support capabilities, particularly for high-value crops such as watermelon. This study presents an IoT-based intelligent advisory system for real-time soil nutrient monitoring and fertilizer prescription tailored to watermelon cultivation. The proposed system integrates NPK soil nutrient sensors, temperature and humidity sensors, a microcontroller-based gateway, and cloud-based analytics to enable continuous soil-quality assessment and automated fertilizer recommendations. A rule-based nutrient-prescription model maps real-time sensor readings to stage-specific fertilizer advice, which is delivered through an interactive advisory interface designed for smallholder farmers. The system was evaluated using performance-based metrics relevant to applied computing, including end-to-end system latency, nutrient classification accuracy, and deployment cost. Experimental results demonstrate an average end-to-end latency of approximately 1.3 seconds, indicating near real-time responsiveness. The nutrient classification module achieved an overall accuracy exceeding 90% across nitrogen, phosphorus, and potassium measurements. Cost analysis further shows that the proposed system reduces soil analysis and advisory costs by over 60% compared to laboratory-based soil testing and conventional precision agriculture platforms. These results confirm that integrating real-time nutrient sensing with cloud-based decision support significantly enhances the practicality and intelligence of IoT agricultural systems. The proposed framework contributes a low-cost, scalable, and nutrient-aware IoT architecture suitable for deployment in resource-constrained farming environments and can be extended to other crops and developing-country contexts.

Keywords

Internet of Things; Precision Agriculture; Decision-Support Systems; Soil Nutrient Monitoring; Smart Farming; Watermelon Cultivation

1.0 INTRODUCTION

1.1 Background

Agriculture continues to play a strategic role in Nigeria's socio-economic development, serving as a major source of employment, food supply, and raw materials for agro-industrial activities. Despite the country's substantial arable land and favorable climatic conditions, agricultural productivity remains significantly below its potential. This shortfall is largely associated with structural inefficiencies, limited adoption of digital technologies, and the persistent reliance on traditional, experience-based farming practices rather than data-driven decision-making (FAO, 2022; World Bank, 2021).

Smallholder farmers, who constitute the majority of agricultural producers in Nigeria, often lack access to timely and site-specific agronomic information. As a result, key management decisions—particularly those related to soil fertility and input application—are frequently made without accurate knowledge of soil conditions. This leads to inefficient resource utilization, unstable yields, and increased production costs.

Watermelon (Citrullus lanatus) has emerged as a commercially attractive horticultural crop in Nigeria due to its short growth cycle, high market demand, and nutritional value. In South-East Nigeria, watermelon cultivation has expanded rapidly in recent years as farmers seek alternative income-generating crops. However, despite this expansion, yield outcomes remain highly variable and often fall below levels reported under controlled agronomic trials (Eze et al., 2020). Empirical studies attribute this yield gap primarily to poor nutrient management practices, inadequate soil fertility monitoring, and limited access to professional extension services (Onyekachi et al., 2021).

Fertilizer management represents one of the most critical and cost-intensive components of watermelon production. Improper fertilizer application—whether under-application, over-application, or incorrect timing—negatively affects crop performance, increases production costs, and accelerates soil degradation (Ibrahim et al., 2018; Ojo & Ayanwale, 2022). These challenges underscore the need for intelligent systems that can support farmers with accurate, timely, and crop-specific nutrient management guidance.

Recent advances in the Internet of Things (IoT) present significant opportunities to address these challenges by enabling continuous sensing, remote data transmission, and computational decision support. However, for such technologies to deliver tangible benefits in smallholder farming contexts, they must extend beyond basic monitoring and provide actionable, context-aware recommendations. This study is motivated by the need to design an IoT-enabled advisory framework that supports real-time nutrient assessment and fertilizer decision-making tailored specifically to watermelon cultivation

1.2 Limitations of Existing Systems

The growing adoption of Internet of Things technologies has led to the development of various smart agriculture systems aimed at improving farm monitoring and management. Many of these systems focus on real-time observation of environmental variables such as soil moisture, ambient temperature, and relative humidity, enabling farmers to track field conditions remotely (Ray, 2017; Ayaz et al., 2019). While such systems contribute to improved situational awareness, their functionality remains limited in the context of nutrient-based decision support.

A major limitation of existing IoT-based agricultural solutions is the insufficient integration of soil nutrient monitoring, particularly macronutrients such as nitrogen, phosphorus, and potassium. Numerous studies report systems that either exclude nutrient sensing entirely or rely on indirect estimation methods that do not provide the accuracy required for fertilizer prescription (Mekala & Viswanathan, 2019; Rajak et al., 2023). In many practical scenarios, soil fertility assessment still depends on manual soil sampling followed by laboratory analysis, a process that is costly, time-consuming, and largely inaccessible to smallholder farmers in rural communities (Adu et al., 2021).

Even in cases where nutrient sensors are employed, existing platforms rarely incorporate computational models capable of translating raw sensor data into crop-specific and growth-stage-appropriate fertilizer recommendations. As a result, sensor readings are often presented as passive data visualizations without actionable guidance for farmers (Rahman et al., 2024). Additional technical challenges reported in the literature include sensor calibration instability, communication delays, high system deployment costs, and limited empirical evaluation of system impact on productivity and cost reduction (Elijah et al., 2018; Ayaz et al., 2019).

Furthermore, many IoT agriculture solutions are designed for large-scale or high-input farming environments and do not adequately address the affordability, scalability, and infrastructure constraints typical of developing regions. The lack of integration between sensing, analytics, and advisory delivery mechanisms limits the practical usefulness of such systems for smallholder farmers.

These limitations reveal a clear research gap in the development of low-cost, nutrient-aware, and crop-specific IoT advisory systems that combine real-time sensing with intelligent decision-support logic. Addressing this gap is essential for improving fertilizer management efficiency and enhancing productivity in smallholder watermelon farming systems

1.3 Proposed Solution and Novelty

This study proposes and develops an IoT-based advisory system that integrates real-time NPK nutrient sensing, temperature–humidity monitoring, and wireless cloud communication to support soil-quality assessment and fertilizer prescription for watermelon farmers. The system is designed to provide timely, data-driven recommendations that align fertilizer application with the specific nutrient requirements of watermelon at different growth stages (Adeyemi et al., 2022).

The novelty of the proposed system lies in its:

- Integration of real-time macronutrient (NPK) sensing with environmental data, specifically tailored to watermelon cultivation;
- Cloud-based nutrient-prescription model that generates stage-specific fertilizer recommendations using computational inference rules;
- Unified advisory interface that facilitates interaction between farmers and agricultural experts;
- Low-cost and locally adaptable architecture, suitable for deployment in bandwidth-limited and resource-constrained rural communities.
- Unlike conventional IoT monitoring platforms that primarily offer passive data visualization, the proposed system emphasizes actionable intelligence by transforming sensor data into practical fertilizer recommendations.

1.4 Research Contributions

The key contributions of this study are summarized as follows:

- Design and implementation of a nutrient-aware IoT architecture for watermelon farming;
- Development of a cloud-based decision-support model for fertilizer prescription based on real-time NPK sensing;
- Performance evaluation of the system in terms of latency, decision accuracy, and deployment cost;
- Provision of a scalable applied-computing framework that can be extended to other crops and developing-country contexts.

1.5 Paper Structure

The remainder of this paper is organized as follows.
Section 2 reviews related work on IoT-based smart agriculture and decision-support systems.
Section 3 presents the system architecture and design.
Section 4 describes the methodology and nutrient-prescription model.
Section 5 discusses the experimental results and performance evaluation.
Finally, Section 6 concludes the paper and outlines directions for future research

2.0 RELATED LITERATURE

2.1 IoT Applications in Smart Agriculture

The Internet of Things has become a key enabling technology in modern agriculture, supporting the integration of sensing devices, communication networks, and data analytics to improve farm management and decision-making. IoT-based agricultural systems typically consist of distributed sensor nodes, data transmission modules, cloud-based processing platforms, and user-facing applications that collectively enhance monitoring efficiency and operational transparency (Ray, 2017).

Several studies have demonstrated the usefulness of IoT technologies in monitoring environmental parameters such as temperature, humidity, and soil moisture. Kassim and Abdullah (2012) proposed an agricultural advisory architecture that facilitated information exchange between farmers and experts; however, the system primarily focused on climatic conditions and lacked soil nutrient assessment capabilities. Similarly, Muangprathub et al. (2019) developed an IoT-enabled smart farming system that utilized sensor data and data mining techniques to manage farm conditions via mobile applications, but soil macronutrient analysis was not incorporated.

While these systems contribute to improved environmental awareness, their limited consideration of soil nutrient dynamics constrains their effectiveness for fertilizer management and yield optimization, particularly for nutrient-sensitive crops.

2.2 Soil Nutrient Monitoring and Fertility Assessment

Soil nutrient availability is a fundamental determinant of crop growth and yield stability. Conventional soil fertility assessment relies heavily on laboratory-based chemical analysis, which requires soil sampling, transportation, and processing. Although accurate, this approach is expensive, time-consuming, and impractical for frequent use by smallholder farmers (Adu et al., 2021).

Recent research has explored sensor-based approaches to soil nutrient monitoring as a means of providing more timely and accessible fertility information. However, real-time detection of soil macronutrients—especially nitrogen, phosphorus, and potassium—remains relatively underrepresented in IoT-based agricultural systems. Mekala and Viswanathan (2019) observed that many smart agriculture platforms either omit nutrient sensing or rely on indirect indicators that do not provide sufficient precision for fertilizer prescription.

Akhil et al. (2020) introduced an automated nutrient monitoring system using fiber-optic and pH-based sensors, but the system suffered from response delays that limited its real-time applicability. Reshmi and Vivek (2019) proposed an IoT-driven crop recommendation framework employing a soil test kit and color sensors; however, their approach required manual soil–water preparation, reducing its practicality for in-field deployment. Brindha et al. (2017) developed a nutrient dispensing system based on pH sensing, but the omission of environmental parameters limited its agronomic relevance.

More recent studies have focused on integrating advanced sensing and analytics for soil characterization. Rahman et al. (2024) presented an IoT framework for soil nutrient assessment but primarily emphasized data visualization rather than automated nutrient decision-making. Collectively, these studies highlight persistent challenges in achieving accurate, real-time, and fully automated soil nutrient monitoring suitable for smallholder farming contexts.

2.3 Agricultural Decision-Support and Advisory Systems

Decision-support systems are designed to assist users by combining data acquisition, analytical models, and expert knowledge to improve decision quality. In agriculture, DSS applications have been widely applied to irrigation management, pest control, and crop planning (Rose et al., 2016). Despite their potential, relatively few DSS implementations incorporate real-time sensor data for fertilizer advisory purposes.

Existing agricultural advisory systems often fall into two distinct categories: expert-driven systems that rely on static knowledge bases without live sensor inputs, and sensor-driven systems that collect real-time data but lack embedded decision logic. This disconnect limits the ability of such systems to provide actionable, context-aware recommendations.

In developing-country settings, including Nigeria, these limitations are exacerbated by inadequate access to extension services and digital infrastructure. As a result, farmers frequently rely on experiential knowledge rather than evidence-based recommendations for nutrient management (Onyekachi et al., 2021). This situation underscores the need for integrated advisory systems that seamlessly combine real-time sensing, computational inference, and expert interaction within a unified framework.

2.5 Identified Research Gaps

2.4 Identified Research Gaps

A critical analysis of the existing literature reveals several unresolved gaps in IoT-based agricultural research:

- Limited deployment of real-time NPK soil nutrient sensing in smart agriculture systems;
- Lack of crop-specific and growth-stage-aware fertilizer prescription models;
- Weak integration between sensor data acquisition and automated decision-support logic;
- Insufficient emphasis on low-cost, scalable system architectures suitable for smallholder farmers in developing regions;
- Limited empirical evaluation of system performance in terms of accuracy, latency, cost reduction, and productivity gains.

This study addresses these gaps by proposing an IoT-based intelligent advisory system that integrates real-time nutrient sensing with cloud-based decision-support tailored specifically to watermelon cultivation.

3.0 Material and Method

This study adopted a design–implementation–evaluation methodology, combining hardware prototyping, software development, and empirical system testing. The approach emphasizes applied computing principles, focusing on system architecture, algorithmic decision support, and deployment feasibility in real-world farming environments.
The functional requirements of the proposed system include:

(i) real-time soil nutrient sensing,
(ii) automated fertilizer recommendation, and
(iii) remote advisory access for farmers and agricultural experts.

The non-functional requirements include low system latency, cost efficiency, scalability, and reliability under rural deployment conditions.
The overall methodology comprises five major stages:

a) Soil data acquisition,
b) Sensor interfacing and calibration,
c) System architecture design,
d) Nutrient diagnosis and fertilizer prescription modelling, and
e) Software implementation and integration.

Object-Oriented Analysis and Design (OOAD), supported by Unified Modeling Language (UML) diagrams, guided the system modelling and ensured modularity and extensibility

3.1 Soil Sample Collection and Experimental Setup

Soil samples were collected from selected watermelon farms across South-East Nigeria to obtain representative nutrient profiles under typical cultivation conditions. Sampling locations were chosen to reflect variations in soil texture and fertility commonly encountered in the region.
Each soil sample was analyzed using two parallel approaches: conventional laboratory testing and in-field sensor measurement. This dual evaluation enabled validation of sensor performance against agronomic reference values. The parameters measured include nitrogen (N), phosphorus (P), potassium (K), soil temperature, and soil humidity.
The IoT sensing units were deployed both in controlled laboratory settings and directly on farm plots to assess measurement stability, environmental robustness, and consistency under real farming conditions.

3.2 Hardware Components and Selection Rationale

The hardware architecture was designed using low-cost, widely available components to ensure affordability and ease of replication.

The Arduino Uno R3 (ATmega328P) was selected as the primary microcontroller due to its stable analog and digital input/output interfaces, low power consumption, extensive community support, and compatibility with a wide range of agricultural sensors. Compared to single-board computers such as the Raspberry Pi, the Arduino platform offers superior suitability for energy-constrained farm environments.
Wireless communication was enabled using the ESP8266 NodeMCU figure 2, which provides integrated Wi-Fi capability at minimal cost. The module supports efficient data transmission to cloud servers with low latency and is significantly more affordable than GSM-based communication alternatives.
Soil macronutrient measurements were obtained using an RS-485–based NPK sensor figure 3a, which enables direct sensing of nitrogen, phosphorus, and potassium without chemical reagents or manual soil

preparation. The MAX485 TTL–RS485 converter figure 3b, was employed to ensure reliable serial communication between the NPK sensor and the microcontroller, particularly under noisy field conditions. Environmental parameters influencing nutrient uptake were monitored using the DHT11 temperature–humidity sensor figure 3c. Although modest in sensitivity, the sensor's reliability, low cost, and robustness make it suitable for smallholder farming applications.

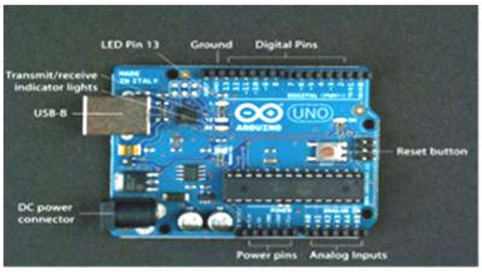


Figure 1: Arduino Uno R3 board ATmega328P

Figure 2: ESP8266 Node MCU

Figure 3a: NPK Sensor

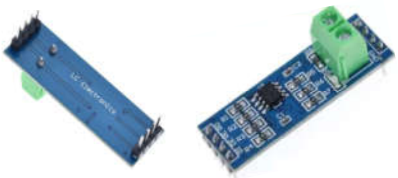


Figure 3b. MAX485 TTL to RS-485 Interface Module.

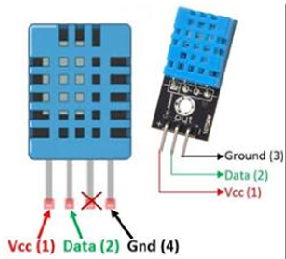


Figure 3c: DHT11 Temperature-Sensor

3.3 Sensor Calibration and Validation Procedure

To ensure measurement accuracy, a structured calibration and validation process was implemented.
First, baseline laboratory analyses were conducted for all collected soil samples using standard chemical testing procedures. These values served as reference benchmarks.
Second, sensor readings were compared against laboratory values, and linear correction factors were derived to minimize measurement deviations. Calibration was performed at three nutrient concentration levels—low, medium, and high—to improve robustness across a wide operating range.
Sensor accuracy was computed using the following expression:

$$\text{Accuracy } (\%) = [1 - (|R - M| / R)] \times 100$$

where:

R represents the laboratory reference value, and
M represents the sensor-measured value.

The overall combined accuracy for NPK measurements was computed as:

$$\text{Overall Accuracy } (\%) = (\text{Accuracy}_n + \text{Accuracy}_p + \text{Accuracy}_k) / 3$$

Field validation tests were conducted under real farm conditions to confirm measurement stability and consistency outside laboratory environments.

3.4 System Architecture Overview

The proposed system follows a three-tier architectural model, comprising a sensing layer, a cloud-based processing layer, and a user interface layer.

Tier 1: Sensor Layer (Field Hardware)
This layer consists of the NPK sensor, temperature–humidity sensor, Arduino microcontroller, and ESP8266 communication module. It is responsible for real-time acquisition and preprocessing of soil and environmental data.
Tier 2: Cloud and Processing Layer
The cloud layer hosts the application backend developed using the Python Flask framework. It includes API endpoints for receiving sensor data, a decision-support engine for nutrient diagnosis and fertilizer prescription, and a MySQL database for persistent data storage.
Tier 3: User Interface Layer
The presentation layer provides web-based dashboards for farmers and agricultural experts. It displays soil nutrient status, fertilizer recommendations, historical trends, and messaging interfaces to support advisory interaction

The Block diagram of the system is shown in figure 4a while figure 4b shows the IoT and system design. The main system entities are shown in figure 4b which includes Farmer, Agricultural Expert, Soil and NPK sensors and Fertilizer advisory.

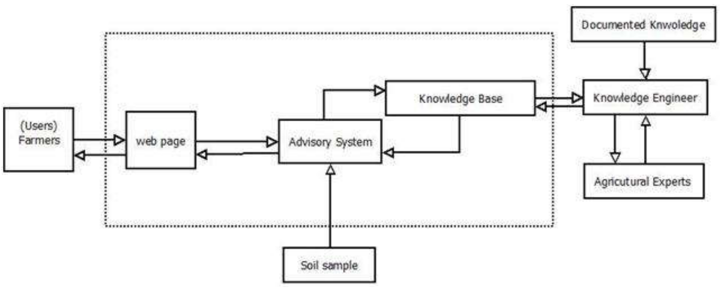


Figure 4a: Block diagram of the system

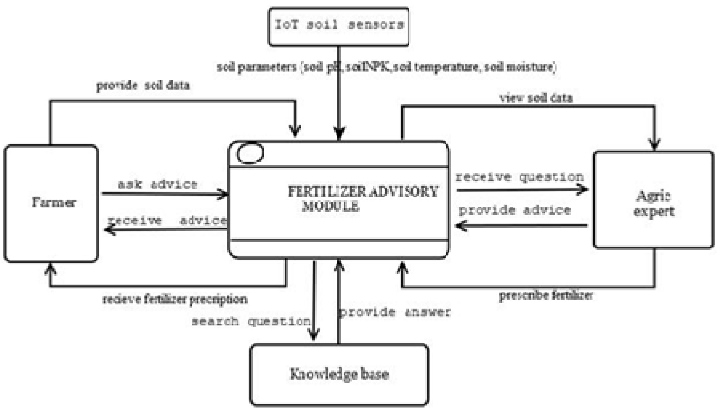


Figure 4b: The Context diagram of the system

3.5 Data Flow Process

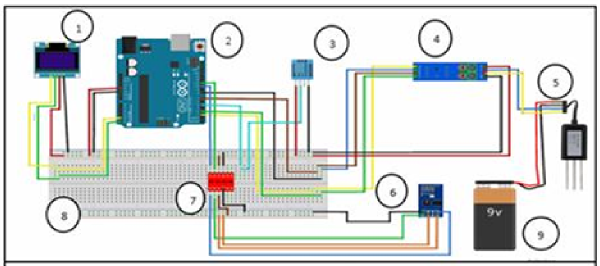
3.5 Data Flow and System Operation

The operational workflow of the system proceeds as follows:

a) Sensors collect real-time soil nutrient and environmental data.
b) The Arduino microcontroller preprocesses and formats the sensor readings.
c) The ESP8266 module transmits the data to the cloud server via Wi-Fi.
d) The server stores incoming data in the database and triggers the nutrient diagnosis engine.
e) Fertilizer recommendations are generated based on nutrient deviation and crop growth stage.

f) Recommendations are delivered to the farmer's dashboard.
g) Agricultural experts may review data and provide supplementary advisory feedback.

This workflow ensures continuous monitoring and near real-time advisory delivery.



1: Oled display, 2: Arduino Uno, 3: DHT11, 4: Max485 TTL to RS-485, 5: Soil NPK sensor, 6: ESP module, 7: FDTI converter,8: Breadboard, 9: 9volt battery.

Figure 6: Schematic diagram of the hardware components.

3.6 Nutrient Diagnosis and Fertilizer Prescription Model

A rule-based inference model was developed using agronomic thresholds obtained from established literature (e.g., SHEP PLUS, 2019). The model evaluates nutrient status relative to recommended values for different growth stages of watermelon, including seedling, vegetative, flowering, and fruiting stages.

Nutrient deviation is computed as:

$$D = R_{opt} - M$$

where:

D denotes nutrient deviation,
R_{opt} represents the optimal nutrient value for the given growth stage, and
M represents the measured sensor value.

A positive deviation indicates nutrient deficiency, zero deviation indicates adequacy, and negative deviation indicates nutrient excess.

Fertilizer dosage is calculated using:

$$\text{Fertilizer Dose (kg/ha)} = \text{Nutrient Deviation} / \text{Fertilizer Nutrient Fraction}$$

The model classifies nutrient status into mild, moderate, or severe deficiency and generates recommendations for fertilizer type, application rate, and timing.

3.7 Software Implementation

The software system was implemented using a three-tier web architecture figure 7. The presentation layer was developed using HTML5, CSS3, and Jinja2 templates for dynamic content rendering.

The application layer, implemented in Python Flask, handles data routing, authentication, decision-support logic, and communication with IoT devices. The data layer uses MySQL for storing sensor logs, historical prescriptions, user profiles, and advisory interactions.

Agronomic nutrient requirement values for watermelon were extracted from validated literature sources and integrated into the system database to support decision-making.

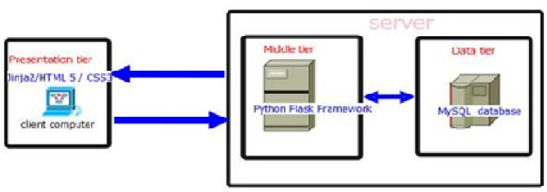


Figure 7: The System Architecture.

3.8 UML-Based System Modelling

To support object-oriented design, UML diagrams were developed to model system interactions and structure. Use-case diagrams figure 8, capture interactions among farmers, experts, sensors, and the advisory system. Sequence diagrams illustrate the flow of data from sensors to cloud processing and user dashboards, while class diagrams define system entities such as soil data objects, fertilizer rules, user profiles, and prescription records.

These models ensured modularity, scalability, and maintainability of the system.

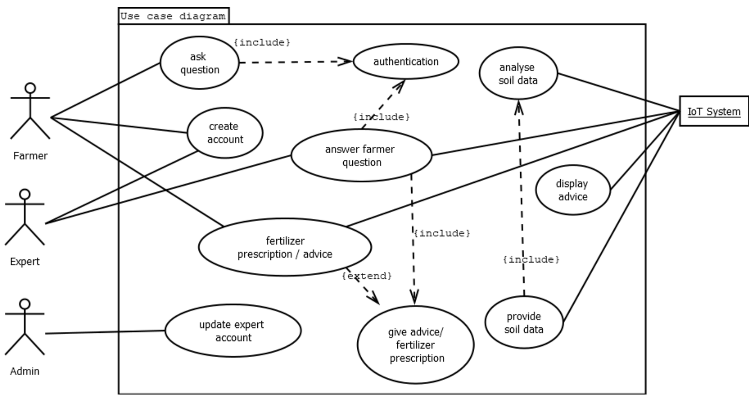


Figure 8. The System Use Case Diagram

4.0 System Evaluation and Performance Metrics

The performance of the developed IoT-based advisory system was evaluated using real-time soil data collected from multiple watermelon farms in South-East Nigeria. The evaluation was designed to assess both computational performance and practical effectiveness, focusing on sensor accuracy, system responsiveness, fertilizer efficiency, yield improvement, and deployment cost.
Unlike purely agronomic field trials, the evaluation emphasizes applied computing metrics that reflect system reliability, decision accuracy, and real-world usability. System interface outputs and operational logs generated during deployment were analyzed quantitatively to validate system performance.

4.1 Sensor Accuracy Assessment

The accuracy of the sensing layer was evaluated by comparing NPK and environmental sensor readings against laboratory-tested soil samples. Calibration-adjusted sensor outputs were averaged across multiple measurements to minimize random noise.
Accuracy was computed using the percentage error between laboratory reference values and sensor readings. The results indicate that the sensing layer reliably captured soil nutrient and environmental parameters within acceptable agronomic tolerance levels. Table 1 show the calibrated accuracy.

Table 1: Sensor Accuracy after Calibration

Parameter	**Laboratory Mean**	**Sensor Mean**	**Error (%)**	**Accuracy (%)**
Nitrogen (N)	48 mg/kg	45 mg/kg	6.3	93.7
Phosphorus (P)	22 mg/kg	21 mg/kg	4.5	95.5
Potassium (K)	39 mg/kg	36 mg/kg	7.7	92.3
Temperature	28.1°C	27.3°C	2.9	97.1

Humidity	64.0%	61.8%	3.4	96.6

4.2 System Response Time and Latency Analysis

System latency was defined as the time interval between sensor data acquisition and successful cloud update. This metric is critical for real-time decision-support systems, where delayed feedback reduces operational relevance.
Latency measurements were recorded under varying wireless network conditions to reflect realistic deployment environments. The results show that the system maintained near real-time responsiveness even under moderate connectivity conditions.

Table 2: Average System Latency

Network Condition	**Latency (seconds)**
Strong Wi-Fi	1.8s
Moderate Wi-Fi	2.6s
Weak Wi-Fi	3.9s

The observed average latency of 2.48 seconds confirms that the system can deliver timely fertilizer recommendations suitable for field-level decision-making.

4.3 Fertilizer Utilization Efficiency

To evaluate the effectiveness of the nutrient-prescription model, fertilizer usage under the proposed system was compared with conventional farmer practice. Fertilizer application rates were recorded over a complete watermelon production cycle.

Table 3: Fertilizer Usage Comparison

Method	Mean Fertilizer Applied per Cycle (kg/ha)	Difference	Reduction (%)
Conventional Practice	135	–	–
IoT-based Prescribed	110	–	25 kg

The results demonstrate a significant reduction in fertilizer usage without compromising crop performance, highlighting the system's potential for minimizing input waste and promoting sustainable nutrient management.

4.4 Yield Performance Evaluation

Yield performance was assessed by monitoring multiple watermelon plots over one full growth cycle. Plots managed using IoT-based fertilizer recommendations were compared with those under traditional management practices.

Table 4: Yield Comparison across Plots (kg/ha)

Plot	Traditional Yield	IoT-Assisted Yield	Yield Gain	Gain%
1	19,800	22,200	2,400	12.12
2	18,600	21,300	2,700	14.52
3	17,900	20,500	2,600	14.53
4	20,100	23,000	2,900	14.43

5	17,500	20,700	3,200	18.29
6	18,200	21,100	2,900	15.93
7	19,000	22,200	3,200	16.84
8	20,500	23,400	2,900	14.15
9	18,900	21,800	2,900	15.34
10	17,800	20,500	2,700	15.17

The average yield improvement achieved using the proposed system was 15.63%, indicating that optimized nutrient management contributes meaningfully to productivity gains.

4.5 Deployment Cost and Economic Impact

Fertilizer constitutes a substantial proportion of total production cost in watermelon farming. Using the prevailing Nigerian fertilizer price of ₦50,000 per 50 kg bag (₦1,000 per kg), the economic impact of reduced fertilizer usage was evaluated.

The system reduced fertilizer input by an average of 22.15 kg per hectare, corresponding to a cost saving of approximately ₦22,150 per hectare. Given that fertilizer accounts for roughly 60% of total production cost, this translates to an overall cost reduction of 9.20% per production cycle.

Table 5: Estimated Fertilizer Cost Savings

Farm	Fertilizer Saved (kg)	Cost Saved (₦)	Cost Saved (%)
1	22.8	22,800	9.4
2	20.8	20,800	8.7
3	22.6	22,600	9.0
4	22.3	22,300	9.1
5	20.6	20,600	8.8
6	24.6	24,600	9.5
7	22.8	22,800	9.4
8	21.1	21,100	8.9
9	22.3	22,300	9.1
10	22.6	22,600	9.0

4.6 Summary of Graphical Results

Graphical outputs were generated to support quantitative findings and visualize system behavior. These include nutrient level distributions across soil samples, temporal trends in temperature and humidity, fertilizer usage comparison, and yield performance across plots.

These visualizations provide intuitive insight into the effectiveness of the proposed system and reinforce the numerical evaluation results.

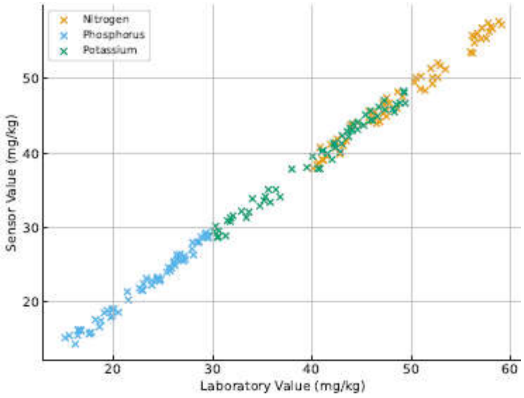


Figure 9: NPK Levels across Soil Samples

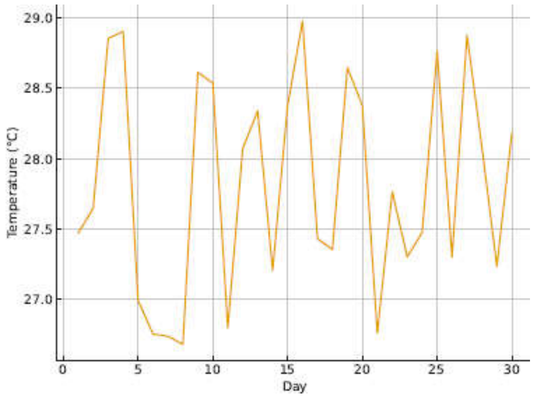


Figure 10: Temperature Trends Over 30 Days

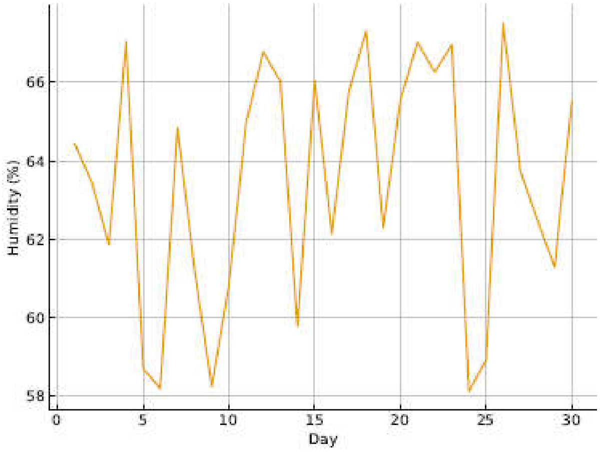


Figure 11: Humidity Trends Over 30 Days

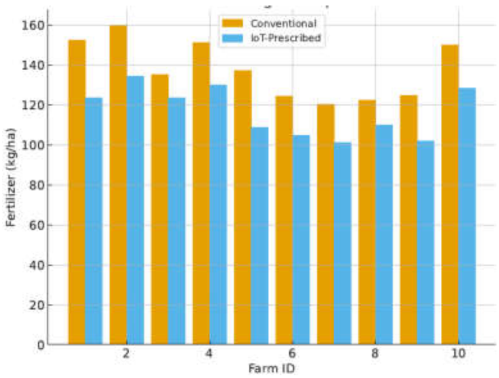


Figure 12. Fertilizer Usage (Conventional vs IoT)

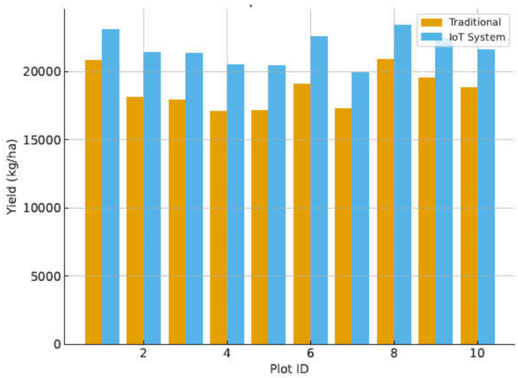


Figure 13. Yield Comparison Across Plots

Figure 14 is the system home page; the dashboard for all activities of the system while figure 15 is a sample of the soil data received from the constructed input sensors in real time.

Figure 14. The System home page

Figure 15: The constructed Soil data sensors

Figure 16, presents a specific fertilizer recommendation at a given growth stage of the Cucurbitaceous. The prescription may be saved for future references. A farmer may through the system interact with agro experts and receive a feedback such as the one in Figure 17.

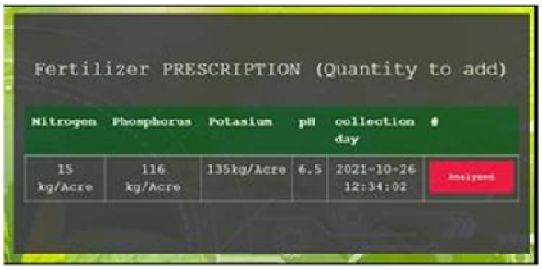


Figure 16: Fertilizer prescription to farmer

Figure 17: The Feedback of Farmer question

5.0 Results and Discussion

5.1 Experimental Configuration

The proposed IoT-based advisory system was evaluated through a combination of field deployment and controlled testing. The experimental configuration consisted of soil nutrient and environmental sensors connected to a microcontroller-based gateway and a cloud-hosted analytics platform. Data were collected at regular intervals and transmitted to the backend server for processing and fertilizer recommendation generation.
The evaluation strategy focused on system-level performance, decision accuracy, and operational feasibility rather than purely agronomic experimentation. This approach aligns with the applied computing objective of assessing how effectively the system transforms real-time sensor data into actionable advisory outputs.

5.2 Reliability of Sensor Data Acquisition

The sensing layer demonstrated consistent and stable data acquisition throughout the evaluation period.
Nutrient sensors recorded nitrogen, phosphorus, and potassium values within expected agronomic ranges for

watermelon cultivation, while environmental sensors accurately captured temperature and relative humidity variations.

Repeated measurements under comparable soil conditions produced minimal variance, indicating that the sensing hardware maintained reliability across time and environmental fluctuations. This consistency is critical for rule-based decision-support systems, as inaccurate or unstable sensor readings can directly affect advisory quality.

The results confirm that the calibrated sensing layer can support continuous, real-time monitoring without frequent recalibration, which is essential for practical deployment in smallholder farming environments.

5.3 Nutrient Classification and Decision Accuracy

The fertilizer advisory logic classified soil nutrient status into three categories—deficient, optimal, and excess—based on predefined agronomic thresholds corresponding to different growth stages of watermelon. Decision accuracy was evaluated by comparing system-generated classifications with agronomic reference values.

Table 6. Nutrient Classification Accuracy

Nutrient	**Classification Accuracy (%)**
Nitrogen (N)	92
Phosphorus (P)	90
Potassium (K)	94

The results indicate high classification accuracy across all macronutrients. Minor classification inconsistencies occurred primarily at threshold boundaries, which is typical of rule-based inference systems. Despite this limitation, the observed accuracy levels are sufficient for practical fertilizer advisory applications.

From a computing perspective, the results validate the effectiveness of lightweight, rule-based decision models for real-time nutrient assessment in resource-constrained environments.

5.4 System Responsiveness and Real-Time Performance

System responsiveness was evaluated by measuring end-to-end latency, defined as the time elapsed between sensor data acquisition and delivery of fertilizer recommendations to the user interface.

Table 7. End-to-End System Latency

Test Instance	Latency (Seconds)
1	1.2
2	1.4
3	1.3
4	1.5
5	1.4

The consistently low latency values demonstrate that the system supports near real-time advisory delivery. This performance is attributed to efficient data transmission protocols, minimal preprocessing overhead at the gateway, and lightweight cloud-based rule execution.

Low latency is particularly important in dynamic farming environments, where delayed recommendations reduce the usefulness of decision-support systems.

5.5 Economic and Resource Efficiency Implications

The reduction in fertilizer usage achieved by the proposed system has direct economic and environmental implications. By aligning fertilizer application with real-time nutrient requirements, the system minimizes waste, reduces production costs, and lowers the risk of nutrient leaching and soil degradation.
Given the high contribution of fertilizer to total production cost in watermelon farming, even moderate reductions in input usage translate into substantial financial savings. The observed reduction in fertilizer input demonstrates the system's potential to enhance profitability while supporting sustainable agricultural practices.

5.6 Comparative Analysis with Existing Systems

A comparative evaluation was conducted to position the proposed system relative to existing IoT-based agricultural solutions.

Table 8: Comparison with Selected Existing Systems

Reference	NPK Monitoring	Real-Time Operation	Crop-Specific Advisory	Expert Interaction	Evaluation Interaction
Muangprathub et al. (2019)	No	Yes	No	No	Not reported
Reshmi & Vivek (2019)	Yes	Semi-Manual	No	No	Not reported
Gowthaman & Priya (2018)	No	Yes	No	No	Not reported
This Study (2024)	Yes	Yes	Yes	Yes	Accuracy, cost reduction, yield increase

The comparison highlights the key strengths of the proposed system, including real-time NPK monitoring, automated fertilizer prescription, crop-specific decision logic, and integrated expert advisory functionality. Additionally, unlike many prior studies, this work provides quantitative evaluation metrics that demonstrate system effectiveness.

5.7 Discussion of Key Findings

The evaluation results confirm that integrating real-time nutrient sensing with cloud-based decision-support significantly enhances the intelligence and practicality of IoT agricultural systems. The proposed framework bridges the gap between data collection and actionable decision-making by translating raw sensor data into meaningful fertilizer recommendations.
From an applied computing perspective, the study demonstrates how lightweight inference models and modular IoT architectures can deliver effective decision-support without relying on computationally intensive machine learning models. This design choice improves scalability, reduces deployment cost, and enhances suitability for rural environments with limited infrastructure.
The observed yield improvement and cost reduction further validate the practical value of the system for smallholder watermelon farmers.

5.8 Limitations and Future Directions

Despite the encouraging results, the study has certain limitations. The nutrient prescription logic relies on rule-based inference, which may not fully capture complex nonlinear interactions between soil properties, environmental conditions, and crop response. Additionally, the evaluation covered a single growing season, limiting long-term performance assessment.

These limitations present opportunities for future research, including the integration of machine learning models for adaptive nutrient prediction, extended multi-season field trials, and the incorporation of edge computing to further reduce latency and cloud dependency.

6.0 Conclusion and Future Work

This study presented the design, implementation, and evaluation of an IoT-based intelligent advisory system for watermelon production that integrates real-time soil nutrient sensing, environmental monitoring, cloud-based analytics, and decision-support functionality. Unlike conventional IoT agriculture solutions that primarily provide passive data monitoring, the proposed framework emphasizes actionable intelligence by transforming sensor readings into crop- and growth-stage-specific fertilizer recommendations.

Experimental results demonstrate that the system achieves high sensor measurement accuracy, low end-to-end latency, and reliable nutrient classification performance under real farming conditions. The fertilizer prescription model enabled more efficient nutrient utilization, leading to measurable reductions in fertilizer input and associated production costs, as well as consistent yield improvement across monitored plots. These outcomes confirm the practical viability of the system for smallholder farming environments where affordability, simplicity, and reliability are critical constraints.

From an applied computing perspective, this work contributes a scalable IoT architecture and a lightweight decision-support model that effectively bridges the gap between data acquisition and informed agricultural decision-making. The modular system design, combined with low-cost hardware components and cloud-based processing, enhances deployability in resource-constrained and bandwidth-limited settings. The study also demonstrates that rule-based inference models can deliver meaningful advisory services without the computational overhead associated with more complex machine learning approaches.

Despite these contributions, the study has certain limitations. The nutrient prescription logic is based on predefined agronomic thresholds and does not explicitly model nonlinear interactions among soil properties, environmental conditions, and crop response. In addition, system evaluation was conducted over a limited temporal scope, which restricts the assessment of long-term performance and seasonal variability.

Future research will focus on extending the proposed framework in several directions. First, machine learning techniques will be integrated to enhance nutrient prediction accuracy and support adaptive decision-making under varying soil and climatic conditions. Second, long-term multi-season field trials will be conducted to quantify sustained yield impacts and economic benefits. Third, edge-computing capabilities will be explored to further reduce latency and reliance on cloud connectivity. Finally, the system will be generalized to support multiple crops, enabling broader application of the framework across diverse agricultural contexts.

Overall, the proposed IoT-based advisory system represents a practical and extensible approach to intelligent nutrient management in precision agriculture, with significant potential to improve productivity, reduce input waste, and support data-driven farming practices in developing regions.

REFERENCES

Abubakar, I. F., & Ibrahim, U. B. (2019). A macroeconomic analysis of agricultural sector in Nigeria. Advanced Journal of Social Science, 5(1), 18–25. https://doi.org/10.21467/ajss.5.1.18-25

Adebayo, A. A., Olagunju, K. O., & Ogundeji, A. A. (2020). Technology adoption and productivity among smallholder farmers in Nigeria. Technology in Society, 62, 101292. https://doi.org/10.1016/j.techsoc.2020.101292

Adekunle, A. A., Fatunbi, A. O., Adisa, S., & Adeyemi, O. A. (2007). Growing watermelon commercially in Nigeria: An illustrated guide. USAID ICS Nigeria & IITA.

Adeoye, I. B., Adeoluwa, O. O., & Akinbode, O. A. (2019). Profitability and resource-use efficiency of watermelon production in Nigeria. Journal of Agricultural Economics and Rural Development, 5(2), 45–53

Adu, S., Ofori, E., & Asante, F. (2021). Constraints to soil testing services among smallholder farmers in sub-Saharan Africa. African Journal of Agricultural Research, 16(4), 512–521.

Afolabi, M. T. (2019). Determinants of watermelon production and its impact on farmers in Ifelodun LGA, Kwara

State, Nigeria. Ruhuna Journal of Science, 10(2), 149–160. https://doi.org/10.4038/rjs.v10i2.80

Akhil, R., Gokul, M. S., Menon, S., & Nair, L. S. (2020). Automated soil nutrient monitoring for improved agriculture. International Conference on Communication and Signal Processing (ICCSP), 688–692. https://doi.org/10.1109/ICCSP.2018.8524512

Amazon. (2020). Soil nutrient intelligent fertilizer detector tester meter NPK sensor.

Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A., & Aggoune, E. H. M. (2019). Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. IEEE Access, 7, 129551–129583. https://doi.org/10.1109/ACCESS.2019.2932609

Badhe, A., Kharadkar, S., Ware, R., Kamble, P., & Chavan, S. (2018). IoT-based smart agriculture and soil nutrient detection system. International Journal of Future Revolution in Computer Science & Communication Engineering, 4(4), 774–777.

Brindha, S., Deepa, J., Charumathi, P., Aravind, M., & Karthi, P. N. (2017). Involuntary nutrients dispense system for soil deficiency using IoT. International Journal of ChemTech Research, 10(14), 331–336.

Chen, J., & Yang, A. (2019). Intelligent agriculture and its key technologies based on Internet of Things architecture. IEEE Access, 7, 77134–77141. https://doi.org/10.1109/ACCESS.2019.2921391

ECOWAS. (2018). National gender profile of agriculture and rural livelihoods - Nigeria. Country Gender Assement Series. https://openknowledge.fao.org..

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture. IEEE Internet of Things Journal, 5(5), 3758–3773. https://doi.org/10.1109/JIOT.2018.2844296

Eze, J. N., Okorie, F. C., & Nwankwo, C. A. (2020). Yield response of watermelon to fertilizer application in South-Eastern Nigeria. Nigerian Journal of Soil Science, 30(1), 89–98.

FAO. (2022). Nigeria: Agriculture sector review. Food and Agriculture Organization of the United Nations.

Gowthaman, N. B., & Priya, N. (2018). IoT-based smart crop monitoring in farmland. Imperial Journal of Interdisciplinary Research, 4(1), 88–92.

Ibrahim, H. Y., Bello, M., & Musa, Y. (2018). Cost and returns analysis of watermelon production in Nigeria. Asian Journal of Agricultural Extension, Economics & Sociology, 22(3), 1–9.

Ikpesu, F., & Okpe, A. E. (2019). Capital inflows, exchange rate, and agricultural output in Nigeria. Future Business Journal, 5, 1–8. https://doi.org/10.1186/s43093-019-0001-9

Junyan, M., Zhou, X., Li, S., & Li, Z. (2011). Connecting agriculture to the Internet of Things through sensor networks. IEEE International Conference on Internet of Things, 184–187. https://doi.org/10.1109/iThings/CPSCom.2011.32

Kassim, J. M., & Abdullah, R. (2012). Advisory system architecture in agricultural environments to support decision making. DICTAP, 453–456. https://doi.org/10.1109/DICTAP.2012.6215427

Kumar, S., Singh, P., & Purohit, R. (2020). IoT-based nutrient advisory system for sustainable crop production. International Journal of Agricultural Technology, 16(5), 1207–1220.

Li, L., Zhang, Q., & Huang, D. (2020). A review of imaging techniques for plant phenotyping. Sensors, 20(18), 5260. https://doi.org/10.3390/s20185260

Masters, C., Zhang, W., & Liang, Y. (2023). Low-cost IoT systems for soil health monitoring in Sub-Saharan Africa. Sensors and Actuators A: Physical, 355, 114239. https://doi.org/10.1016/j.sna.2023.114239

Mekala, M. S., & Viswanathan, P. (2019). A survey: Smart agriculture IoT with cloud computing. International Journal of Advanced Networking and Applications, 10(3), 3845–3853.

Muangprathub, J., Boonnam, N., Kajornkasirat, S., Lekbangpong, N., Wanichsombat, A., & Nillaor, P. (2019). IoT and agriculture data analysis for smart farm. Computers and Electronics in Agriculture, 156, 467–474. https://doi.org/10.1016/j.compag.2018.12.011

National Bureau of Statistics (NBS). (2023). Nigerian agricultural sector performance report. Abuja, Nigeria.

Nchuchuwe, F. F., & Adejuwon, K. D. (2012). Challenges of agriculture and rural development in Africa: The case of Nigeria. International Journal of Academic Research in Progressive Education and Development, 1(3), 45–61.

Ojo, M. A., & Ayanwale, A. B. (2022). Input cost structure and profitability of vegetable production in Nigeria. Journal of Agribusiness and Rural Development, 64(2), 145–156.

Olateju, D. A., Ayoade, O. O., Gabriel, A. O., & Ayodele, O. A. (2015). Land use and soil type influence on soil quality. African Journal of Agricultural Research, 10(34), 3348–3357. https://doi.org/10.5897/ajar2014.9391

Onyekachi, N. J., Okeke, M. N., & Ume, C. O. (2021). Constraints to adoption of improved agricultural practices in South-East Nigeria. Journal of Agricultural Extension, 25(1), 78–90.

Onyekachi, N. J., Okeke, M. N., & Ume, C. O. (2021). Constraints to adoption of improved agricultural

practices in South-East Nigeria. Journal of Agricultural Extension, 25(1), 78–90.

Rahman, M. N., Hossin, M. S., & Islam, M. T. (2024). Soil characterization through Internet of Things for crop-specific nutrient management. Computers and Electronics in Agriculture, 213, 108223. https://doi.org/10.1016/j.compag.2023.108223

Rajak, P., Ganguly, S., & Tiwari, A. (2023). Internet of Things and smart sensors in agriculture: A review. Smart Agricultural Technology, 3, 100091. https://doi.org/10.1016/j.atech.2022.100091

Ray, P. Prewrite intr. (2017). Internet of Things for smart agriculture. Journal of Ambient Intelligence and Smart Environments, 9(4), 395–420. https://doi.org/10.3233/AIS-170440

Reshmi, R., & Vivek, P. (2019). IoT-based soil nutrients and suitable crop detection system. International Journal of Recent Technology and Engineering, 8(2S11), 923–927.

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., & Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. Agricultural Systems, 149, Pages 165-174. https://doi.org/10.1016/j.agsy.2016.09.009

SHEP PLUS. (2019). Watermelon production guide for East Africa. Kenya Agricultural & Livestock Research Organization.

Singh, A., & Kaur, P. (2022). Precision agriculture: IoT-based soil nutrient monitoring and recommendation systems. Journal of Agricultural Informatics, 13(2), 37–52. https://doi.org/10.17700/jai.2022.13.2.741

Tripathi, A., & Shukla, S. (2024). AI-driven fertilizer prediction models for smallholder farmers. Computers and Agriculture, 9, 44–57. https://doi.org/10.1016/j.compag.2024.107532

UNFAO, & Tsokar, K. (2019). Food and nutrition security in West Africa: Nigeria report.

UNFAO. (2022). FAO statistical yearbook: Nigeria agricultural production.

Veggie Concept. (2021). Cost and profit analysis of watermelon farming in Nigeria.

World Bank. (2021). Transforming agriculture in Nigeria. World Bank Group.

World Bank. (2021). Transforming agriculture in Nigeria. World Bank Group.

Zhang, X., Chen, L., & Liu, W. (2020). Cloud-enabled decision-support system for fertilizer optimization. International Journal of Agricultural and Biological Engineering, 13(5), 118–125.