Smart Agriculture Monitoring Using Wireless Sensor Networks and Cloud Integration

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**Abstract.** Smart agriculture There are various smart technologies such as Wireless Sensor Networks (WSNs) and cloud computing, which make smart agriculture. This article introduces an overall framework of smart agriculture monitoring via the integrated approach of the WSNs and the cloud computing. Real-time critically important data are provided in the form of soil moisture, temperature, humidity, and crop health data collected by sensors spread in agricultural fields. These measurement points send out data wirelessly to a central cloud where it will be analyzed and visualized. The proposed system addresses this problem by delivering viable information through predictive analytics in order to make informed decision making as regards precision agriculture. The outcomes of the prototype implementations show a better rate of management of the resources, an increment in the crop yield, and a decrement in the operations expenses.

**Keywords:** Smart Agriculture, Wireless Sensor Networks, Cloud Computing, Precision Agriculture, IoT

# INTRODUCTION

Since the rapid development of the technology over the past few decades, it has impacted most areas of life in a great way with agriculture forming one of the most important beneficiaries of such development. The current method of the traditional farming may have worked in the yester years but it is not anymore adequate to sustain the escalating demands of production of food as a result of rising population of the world, climatic changes and scarcity of natural resources. Some of the major problems facing the agricultural sector today are soil degradation, weather unpredictability, poor irrigation systems as well as outbreak of pests. In order to solve these issues and create sustainable food production, it is highly relevant to implement smart, data-driven, and resource-efficient solutions.

As the combination of advanced technologies (Wireless Sensor Networks (WSNs), the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing) in the agricultural sector is often known as smart agriculture or precision farming. Such a technology convergence enables farmers to track, assess, and control their agriculture practice on real time basis. With such data as soil moisture, temperature, humidity, and other essential parameters, the farmer can make informed decisions to boost their productivity and efficient utilization of farming resources.

It is in the nature of smart agriculture systems to be built around Wireless Sensor Networks (WSNs). Such networks are constituted by spatially distributed autonomous sensors, which, watch the environmental and soil situations. The information extracted by these sensors will prove to be extremely important as regards the microclimate on the farms, and the condition of soil and further decisions regarding irrigation schedules, additives, and pester control can be made. The features of scalability, low power use and rugged environment operation allow WSNs to be a perfect place to implement agricultural systems.

But due to significant amount of data being created by the WSNs, the demand of efficient storage, processing and analysis mechanism appears, which is where cloud computing is crucial. Cloud services can address scalable infrastructure and strong analytical technologies capable of working with sensor information in real time. With the help of cloud services, the farmers will be able to view dashboards, alerts and reports regardless of their locations via mobile phones or via computers. This makes it more accessible besides aiding in data driven decision making.

Combining WSNs and cloud computing provides a strong framework of smart agriculture. Under this system, sensor nodes will collect information in the field and relay it back, using wireless communication, to a local gateway. The gateway, in its turn, transmits the data to the cloud where they are stored, analyzed and visualized. Superior statistical analysis tools, such as machine learning algorithms, can then be used to forecast crop diseases, yield, input optimization. The result or the feedback created out of such analyses can be relayed back to farmers as acts of actions. A lot of countries including Uzbekistan are now realizing the significance of moving to smart agricultural activities. Smart agriculture provides an avenue through which utilization of available resources is enhanced and agricultural production drives the process of revitalizing the water and soil in the areas where the problem of water scarcity and soil degradation is widely observed. Also, the deployment of these technologies helps in making farming climate- resilient as they are used to predict the consequences of weather patterns and level of reliance on manual labor is decreased.

The assessment of the agricultural monitoring systems based on WSN and cloud has shown good potential, but some issues will have to be solved. These are the initial prohibitive cost of implementation, the necessity of good internet connection in rural setting, data privacy issue, and technical expertise of the farmers. Pilot developments and research will be necessary to adapt such technologies to local situations, increase user uptake, and prove that they are economically viable.

The current paper introduces a monitor system of smart agriculture, which integrates WSNs and cloud to allow real-time data to be retrieved, examined, and visualized. The system proposed will entail sensor nodes to monitor soil and environmental aspects, wireless communication protocol, which will be transmitting data, and a cloud environment that will analyze the parameters and enable the user to interact. This is aimed at showing how this all-inclusive system would help in precision farming and increase agricultural productiveness.

The suggested system was resorted to practice in a real agricultural environment to assess its output. The findings reported significant uplifts in irrigation effectiveness, crop wellness tracking, and effectiveness of decision-making. The modular structure of the system provides its adaptation to the crops types, the area, and geographical position of the field that supports its implementation in the diverse agricultural environment context.

Summing up, the study in question will benefit the current work on digital agriculture with its suggestion of the system of monitoring which can be both cost-effective and scalable. Through the harnessing potential of WSNs and cloud computing, the suggested solution will endow farmers with viable insights and propel shift towards sustainable farming, in addition to facilitating adoption of smart farming in developing countries. The possible future work will consider introducing AI-based predictive models, implementing increased energy efficiency, and broadening the system applicability to larger farming processes.

# RELATED WORK

Smart agriculture uses Internet of Things (IoT) to convert conventional agriculture into smart and automated systems with capabilities of real-time surveillance and control. IoT platforms harness granular data on the parameters of the environment in temperature, humidity and even soil moisture, processed through a network of intelligent sensors installed in the ground, in agricultural machinery and on the plants themselves. This information helps farmers decide wisely based on evidence that will enhance the irrigation schedules, optimize crop production, and minimize the water and fertilizer wastages [1]. As an example, Ahmed et al. have provided a survey of the IoT application in smart farming, which marked an improvement in resource management and environmentally sound farming practices [1]. AlZubi and Kalda also indicated how IoT-AI integration is beneficial in sustainable agriculture as the process allows to model the health of crops and weather anomalies in advance [2].

Precision farming is built, in part, on the idea of Wireless Sensor Networks (WSNs) since they allow a steady stream of field data to be collected. Such networks are made up of nodes located at different places that take into consideration the state of the environment and channel the information to central systems to be analysed. WSNs are important in such tasks as soil nutrient monitoring and management, pest management and control, and microclimate control. Arif et al. gave a review of WSNs in smart agriculture concentrating in power-efficient planning of sensor nodes and implementation plans that could be used in real-time agriculture surveillance [3]. On the same note, Shaikh et al. pointed out the use of WSNs in increasing the resolution and responsiveness of field-based sensing thereby making decisions in terms of irrigation and fertilization practices more accurate [4].

Cloud computing becomes a key in addressing and processing such large amount of agricultural data produced by IoT and sensor networks. Cloud platforms support advanced analytics, past trend analysis, and farm management by scalable storage and computational capability located at multiple locations. Nevertheless, sending all information to the cloud may create a delay and use more energy. T is emerging as a popular way of computation bringing the computation near the heart of the data. Dutta et al. showed that edge equipped systems to practice soilless agriculture over the green house environment curtail the communication overhead, and offer real-time decision support processes [5]. Hashmi et al. also explored IoT communications protocols and emphasized with references to local processing of the edge keeping performance in bandwidth-constrained rural regions [6].

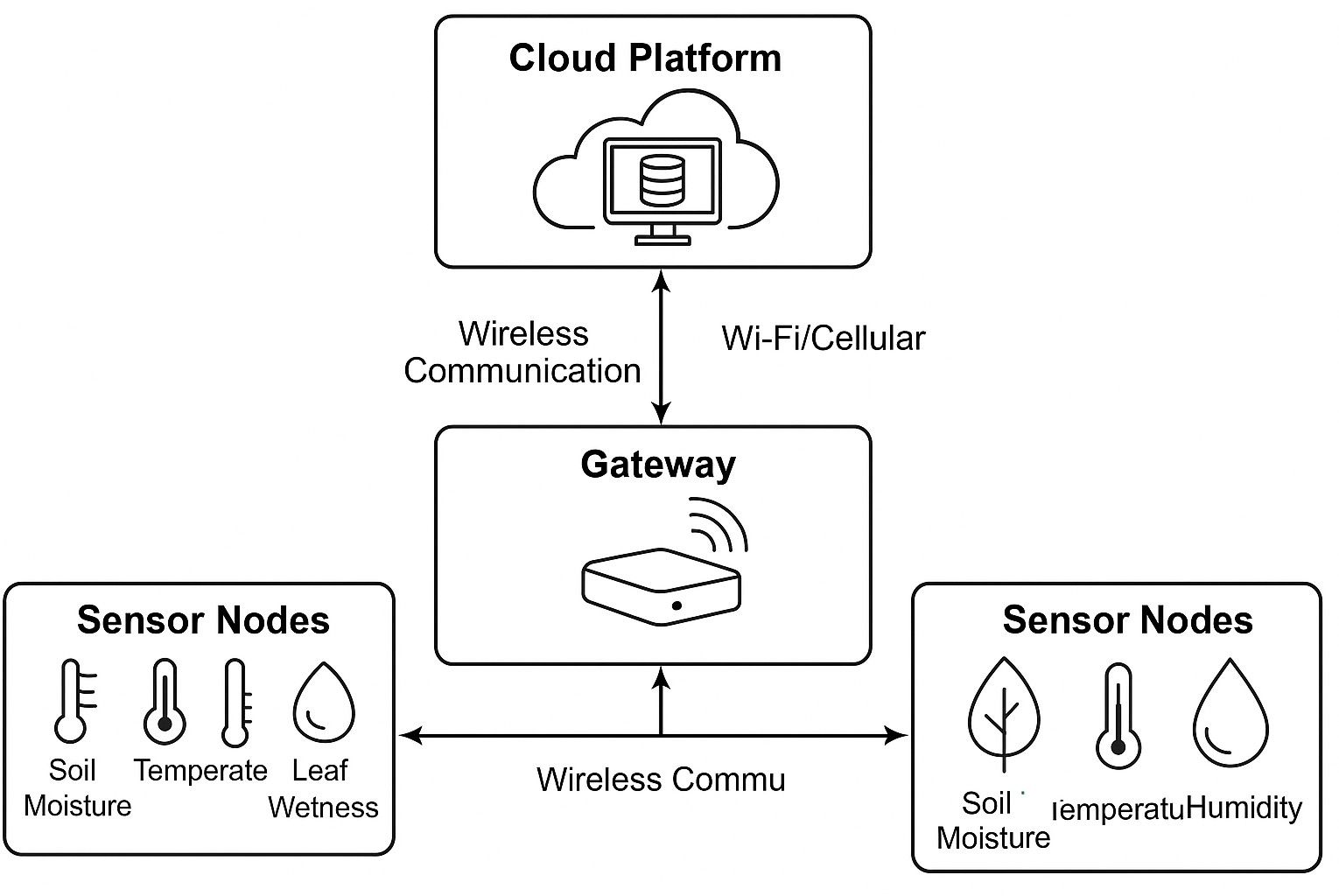
The nature of smart agriculture is going to be transformed through Artificial Intelligence (AI) and Machine Learning (ML) that introduces predictive analytics, anomaly detection and automate the management of crops. Disease identification on plant imagery, the autonomous drone surveillance, and intelligent irrigation are some of the applications that these technologies are used. Mohyuddin et al. reviewed the field of ML algorithms as a solution to precision farming in all its aspects, marking that it achieved good results in yield estimation and pest prediction [7]. The model suggested by Anwar Omer et al. aimed to use ML algorithms K-means and MobileNet in smart farming systems in order to make a decision in a changing agricultural environment [8].

Consistent interaction of sensors and cloud systems is critical in automation in agriculture. Different low-power wide-area network (LPWAN) including ZigBee, LoRa, NB-IoT, Wi-Fi, are implemented based on both coverage needs and energy limitations as well as environmental factors. Hashmi et al. investigated the impact of the protocol choice on the precision agriculture operation, in particular, outdoors in fields where the topography varies and connectivity is restricted [6]. The systematic reviews on the application of LoRa and LoRaWAN described by Pagano et al. have focused on the appropriateness of the directives in long-range, low-energy communications in smart farming systems [9].

Literature review and bibliometric analyses have indicated the fact that research in digital agriculture has exponentially increased and was interdisciplinary. Such analyses reveal the extent to which the field has developed at a fast pace even as the new trends involve data fusion, AIoT (Artificial Intelligence of Things) and blockchain integration to achieve more traceability and security of data. The worldwide bibliometric study of Latino et al. demonstrated that digital agriculture has acquired considerable publication growth in the three themes of AI, IoT, and sustainability [10]. Equally, Bertoglio et al. highlighted the move to Agriculture 4.0, explaining how the impact of the digital platforms is being felt in terms of the research output and collaboration between academia and industry [11, 12, 13].

# SYSTEM ARCHITECTURE

TIt will be implemented in three-layer architecture that consists of sensor nodes, edge-level gateway, and cloud computing platform, which is proposed by him as a smart agriculture monitoring system. This modular design is real-time sustainable, wireless, local decision-making, and analytics in the cloud. Each of the layers is optimised to perform arched responsibilities that include data sensing and processing to storage, visualisation and control. Figure 1 includes the system architecture overview diagram demonstrating the interaction between the most important components.



**FIGURE 1.** Detailed architecture of the smart agriculture monitoring system showing sensor, gateway, and cloud integration layers

*Sensor Nodes* At the foundation of the architecture are the sensor nodes, which are strategically deployed across the farmland to collect time-series environmental data. Each node is built using a low-power microcontroller, such as the ESP32 or STM32, capable of interfacing with multiple sensors including capacitive or resistive soil moisture sensors, DS18B20 digital temperature sensors, DHT22 humidity sensors, and leaf wetness sensors. In greenhouse environments, optional light intensity sensors may also be integrated. The data acquired from each sensor *Si*(*t*) at time *t* is passed through a smoothing filter to eliminate short-term fluctuations and noise. This is achieved using a moving average technique:

where is the smoothed output and *N* denotes the filter window size. Each node communicates wirelessly using LPWAN technologies such as LoRaWAN or ZigBee. LoRa is preferred due to its extended range (up to 15 km) and sub-GHz frequency operation, which minimizes power usage. The energy consumed during transmission is calculated as:

(2)

where *Ptx* is the transmission power in watts and *Ttx* is the duration of transmission in seconds. To maintain off-grid functionality, sensor nodes are powered by solar energy harvested via photovoltaic panels and regulated using battery charge controllers, enabling prolonged autonomous field operation.

*Gateway* The second category of the architecture is the gateway that has the role of a communication bridge and a computational bit of an edge. This element is usually implemented as a Raspberry Pi 4 or similar embedded- device. It receives LoRa packets from multiple sensor nodes and performs preliminary data aggregation, validation, and anomaly detection. The gateway employs z-score–based anomaly filtering defined by:

(3)

where *µi* and *σi* represent the historical mean and standard deviation of sensor *i*. Readings with |*Z*| *>* 3 are flagged as outliers. Moreover, the gateway has the capability to carry out local decision-making based on predefined logic in addition to filtering of data. For instance, irrigation activation can be based on threshold values as defined in the rule:

If *M*(*t*) *< Mmin* ⇒ Activate irrigation (4)

where *M*(*t*) is the current soil moisture and *Mmin* is the defined threshold. After processing, the gateway converts the received LoRa or ZigBee packets into IP-compatible formats and transmits them to the cloud using Wi-Fi or LTE networks via MQTT or HTTP protocols. It also synchronizes timestamps across devices using Network Time Protocol (NTP) to maintain temporal consistency.

*Cloud Platform* The last layer of the architecture is the cloud platform that offers scalable infrastructure to support data feed, long-term data storage, data analytics by machine learning, and dashboards facing farmers. They normally use platforms like AWS IoT Core, Google Cloud IoT, or Microsoft Azure. The NoSQL database like MongoDB or DynamoDB or time-series optimized databases like InfluxDB are provided as a time-stamped format to store incoming sensor data and hence query them faster. Predictive modeling of the irrigation needs and anomaly are identified by cloud-based modeling. A basic linear regression model for soil moisture forecasting is defined as:

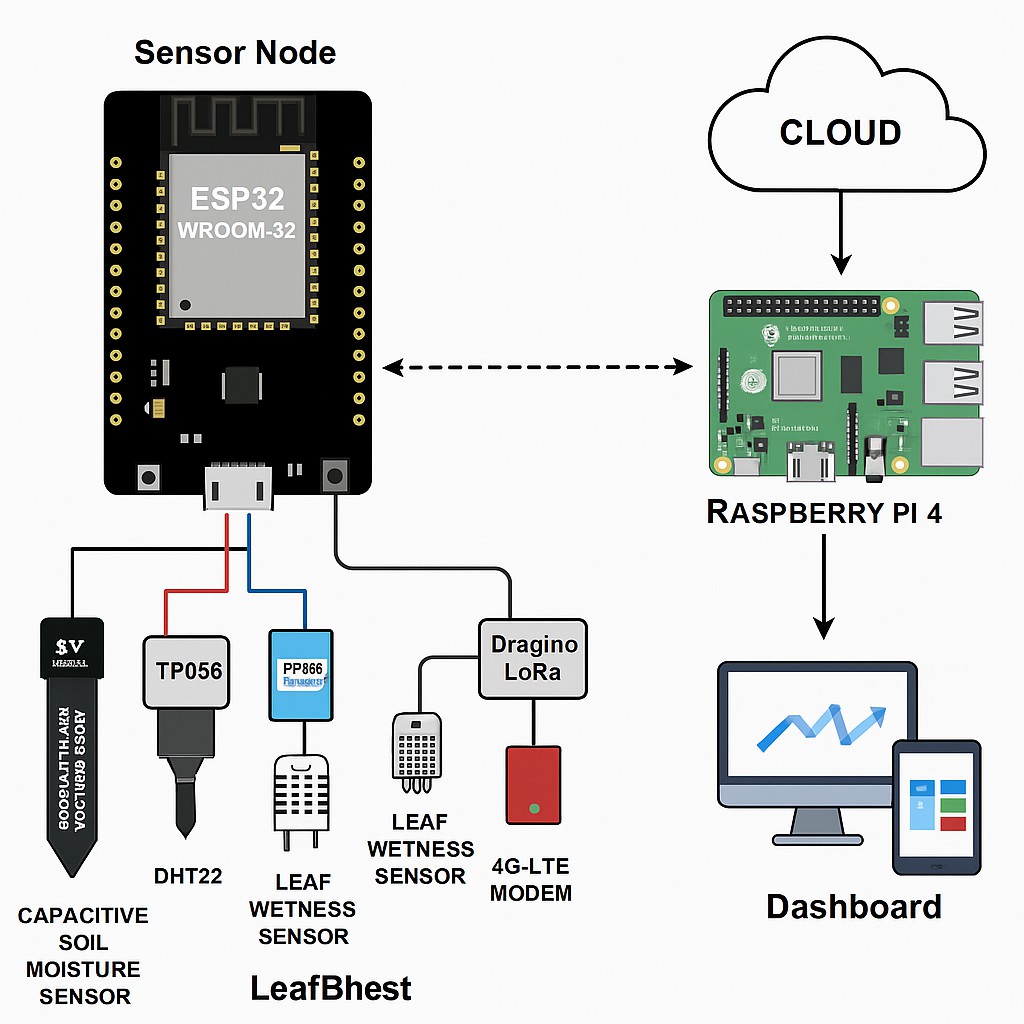
(5)

where is the predicted moisture level at the next time step, *T* (*t*) is temperature, *H*(*t*) is humidity, and *M*(*t*) is current moisture; *βi* are regression coefficients learned from historical data. Real-time dashboards, developed using tools such as Grafana or Node-RED, provide interactive visualizations of field data, historical patterns, and predictive trends. Alerts are generated and delivered through SMS, mobile push notifications, or email when sensor readings exceed predefined limits, and automated commands can be issued to the gateway for actuation.

This architecture due to its modular and scaling property can be implemented in a wide range of agricultural settings whether small holder farms or large-scale industrial settings. Potential possibilities in the future are federated learning in distributed sensor networks, blockchaining agricultural records to provide traceability, and integrating AI-assisted diagnostics to perform early indicators of pest invasion or crop disease development.

# IMPLEMENTATION

The system of monitoring smart agriculture was created with a modular hierarchical structure of three main elements: sensor nodes, centralized gateway, and a backend with cloud implementation. The practical application of this architecture came to be applied and tested in an actual deployment at a 2-hectare test field outside Tashkent in Uzbekistan. The aim of the deployment was to evaluate the reliability of the system application and the consistency of the data transmission and reaction to the changes in the environment under real farm conditions. All the components were optimized in such a way so as to work independently but run smoothly with the rest of the tiers, comprising a resilient and scalable smart farming system.



**FIGURE 2.** Hardware-level circuit layout of ESP32 sensor node, showing interfaces to LoRa module, sensors, solar system, and Li-Po battery

*Sensor Node Design* The sensor nodes were to be constructed based on ESP32-WROOM-32, a much more powerful microcontroller, with dual-core performance, built-in Wi-Fi and Bluetooth modules, extremely low power consumption, and support of a variety of ADCs. The autonomy of power was achieved by a 5V/2W solar panel using a TP4056 lithium-ion battery charging controller and a 3.7V 2500mAh Li-Po battery, so the nodes can be operated more than 40 days without human intervention. Sensing hardware that was added to each of the nodes consisted of capacitive soil moisture sensor to GPIO34, DHT22 temperature and humidity sensor to GPIO21 in 1-wire communications protocol, and leaf wetness sensor created out of copper mesh and connected to a voltage divider to GPIO35. An optional LDR sensor for ambient light measurement was connected to GPIO32. The ESP32 transmitted sensor data via a LoRa SX1276 module operating at 433 MHz, using SPI communication (GPIO18, GPIO19, GPIO23, GPIO5). LoRa’s long-range, low-power characteristics allowed data to travel up to 3 kilometers in rural terrain with minimal energy consumption (<30 mA during transmission). Each node was programmed to send data every 60 minutes, or immediately if a predefined threshold was exceeded. Between transmissions, the ESP32 entered deep sleep mode, reducing idle current draw to approximately 150 µA to maximize battery life.

*Gateway Configuration* The gateway node, implemented using a Raspberry Pi 4 with 4GB of RAM, acted as a central hub for data aggregation, local processing, and cloud communication. A Dragino LoRa HAT was mounted onto the Raspberry Pi to receive data packets from multiple sensor nodes. The Pi ran custom Python scripts that parsed the incoming payloads, formatted the data into JSON, and published it to the cloud via MQTT protocol. Node-RED was deployed for real-time processing and control logic, enabling field-level decision making and automation, such as activating relays for irrigation. Internet connectivity was provided via a USB-based 4G LTE modem (Huawei E3372), ensuring cloud access in remote areas without broadband infrastructure. Data integrity and anomaly detection were handled locally using z-score analysis:

, flag if |*Z*| *>* 3 (6)

where *Si*(*t*) is the incoming sensor reading, and *µi*, *σi* are the historical mean and standard deviation, respectively. Additionally, the gateway maintained synchronized timestamps for all incoming data using the Network Time Protocol (NTP), and system health reports were generated in JSON format for monitoring uptime and reliability.

*Cloud and App Backend* The cloud backend was deployed using Google Cloud services, integrating IoT Core and Firebase for real-time, scalable, and secure data handling. Sensor data published from the Raspberry Pi via MQTT was ingested by Google IoT Core, where it was securely routed to the Firebase Realtime Database. This structure enabled timestamped storage of environmental parameters for further processing. Event-driven analytics were implemented using Firebase Functions, which triggered conditional logic—such as sending alerts or initiating control signals—based on incoming sensor values. Notifications were pushed to farmers’ mobile devices using Firebase Cloud Messaging (FCM), ensuring they received timely updates on critical field conditions. A dedicated mobile application, developed using Android Studio and integrated with Firebase SDK, provided real-time access to sensor readings, historical charts, and manual irrigation controls. Additionally, a web-based dashboard was created using Grafana with InfluxDB to visualize real-time and historical trends in temperature, humidity, moisture levels, and sensor health metrics.

# RESULTS

The implemented smart agriculture monitoring system was deployed and continuously observed over a 60-day period during the spring–summer cropping season, focusing on two major crops: maize and tomatoes. The testbed consisted of a 2-hectare plot subdivided into four monitoring zones, with each zone equipped with four sensor nodes, totaling 16 deployed and operational devices. The system’s performance was evaluated across several key parameters including water usage, crop yield, network reliability, power management, and user interaction experience.

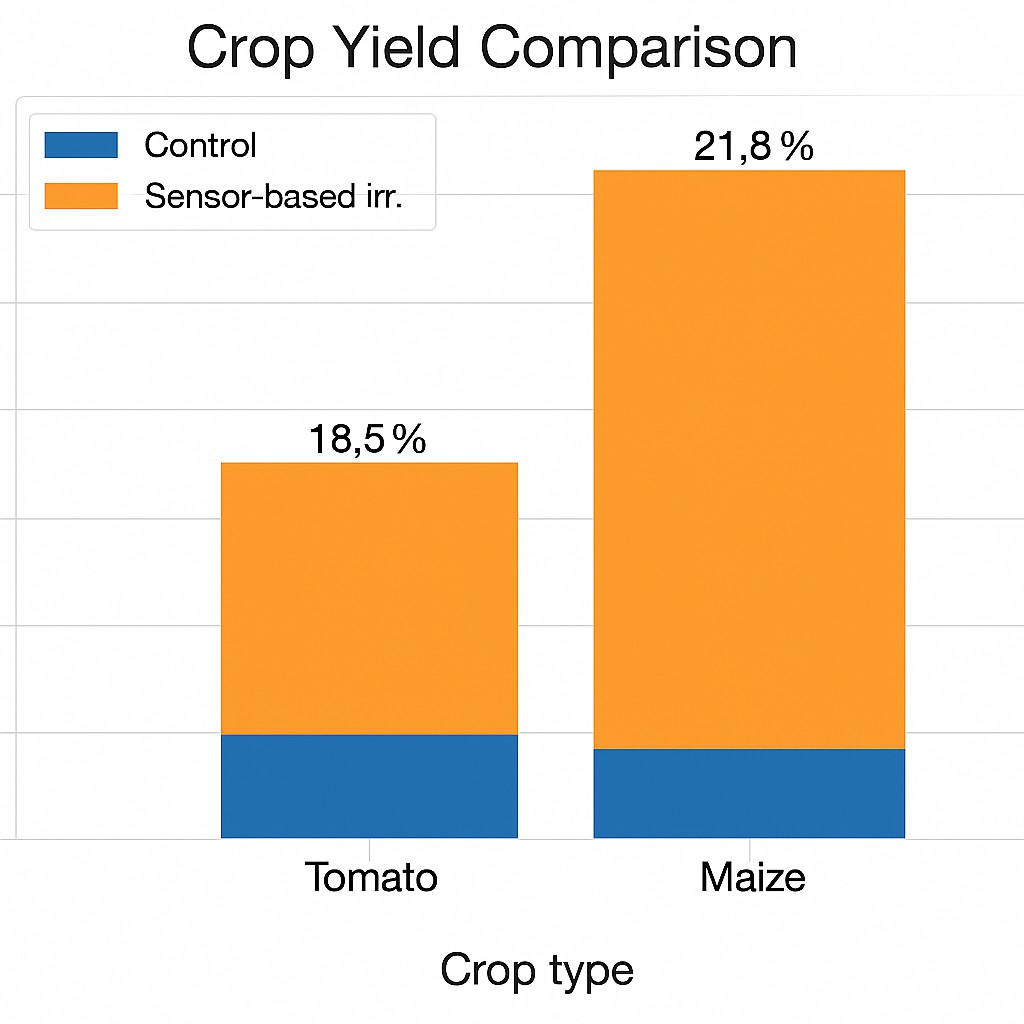
*Water Conservation and Yield Impact* One of the most significant outcomes observed during the deployment was the substantial reduction in irrigation water usage. Moisture-based decision alerts, issued via the cloud platform, along with manual override functionality through the mobile application, enabled more precise and need-based irrigation scheduling. This led to an average water savings of approximately 30.2% compared to baseline control plots where irrigation was performed using fixed schedules without real-time feedback.

In terms of agricultural productivity, the impact of the system was equally notable. Tomato production increased by 18.5%, while maize yield improved by 21.8%, demonstrating the tangible benefits of data-driven monitoring. These results are visually summarized in Figure 3, which presents a bar graph comparison between control plots and sensor- assisted plots. The enhanced yield can be directly attributed to optimized irrigation timing, reduced plant stress, and better overall environmental awareness enabled by the deployed system.

*Network Performance and System Latency* From a technical standpoint, the system maintained a high degree of reliability. Network uptime was recorded at 98.6%, with only minor disruptions due to temporary environmental interference (e.g., rainfall affecting LoRa signal quality). The LoRa communication modules demonstrated a stable range of 1.8 km with Received Signal Strength Indication (RSSI) averaging around -110 dBm. Moreover, the average latency from the moment a sensor reading was taken to its successful visualization on the dashboard was measured at approximately 4.6 seconds. This encompassed data collection, wireless transmission, gateway processing, MQTT cloud uplink, and final rendering in Grafana.

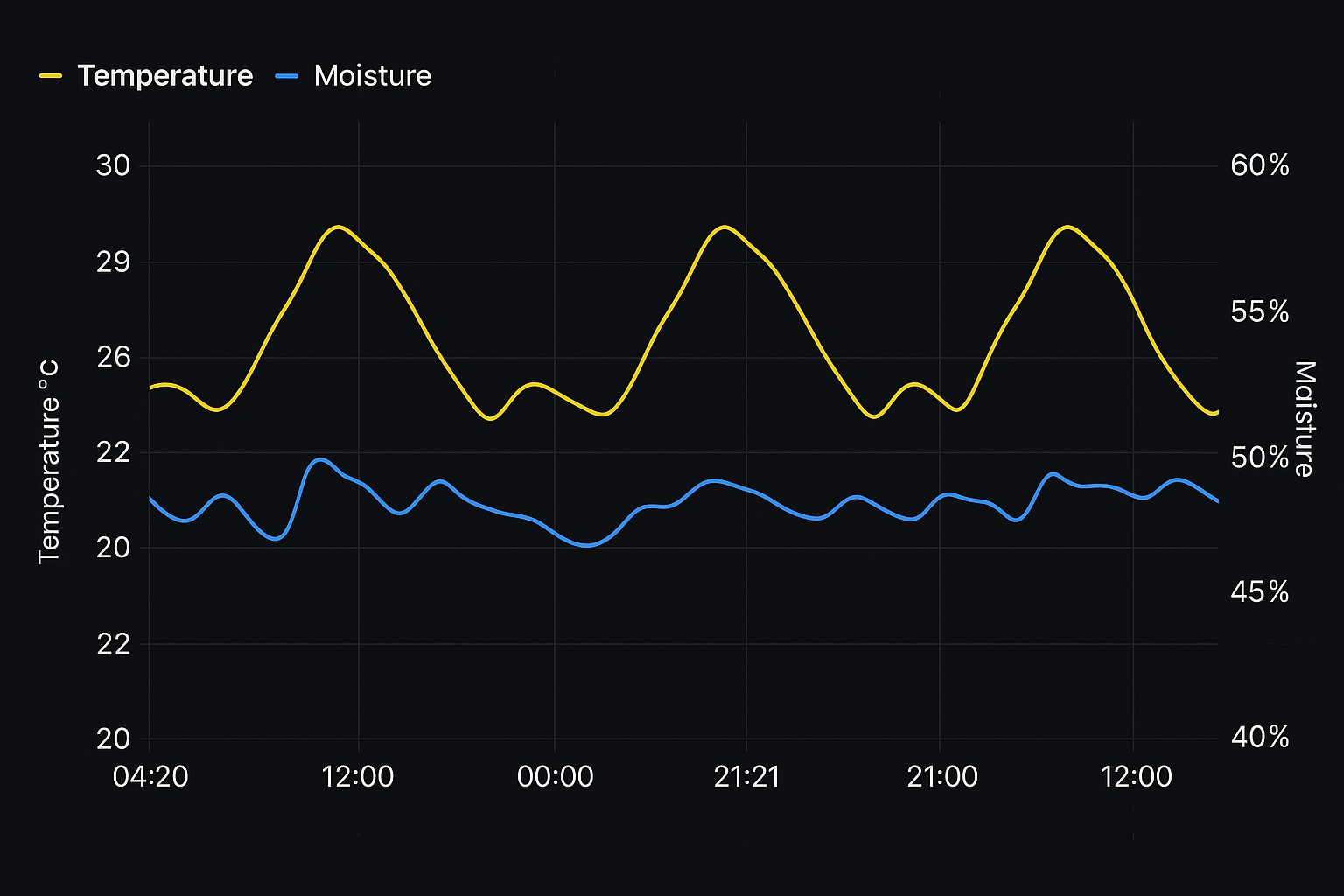
*Power and Sustainability Evaluation* All sensor nodes operated independently without requiring battery replacement throughout the two-month deployment. Solar energy harvesting via 5V/2W panels and regulated charging with TP4056 modules proved sufficient even on partially overcast days. Daily charge/discharge cycles were logged and confirmed that system autonomy was sustained with peak daily current consumption remaining below design limits.

*User Feedback and Observed Challenges* Feedback from farm operators and field staff was overwhelmingly positive. They praised the simplicity and responsiveness of the mobile interface and the ability to receive threshold alerts without physical field inspections. However, some areas for improvement were also identified. Soil moisture sensors showed minor signal drift after prolonged exposure to wet conditions, which suggests the need for a self-calibration routine in future iterations. Additionally, early morning dew occasionally triggered false-positive alerts from the leaf wetness sensors, prompting a recommendation to refine humidity thresholds dynamically using environmental context.



**FIGURE 3.** Crop yield comparison showing increased production in tomato and maize fields equipped with real-time sensor-based irrigation versus traditional control plots

*Data Visualization and Analytics* The Grafana-based dashboard was instrumental in providing visual insights into real-time and historical trends. Figure 4 illustrates a typical time-series plot showing temperature (yellow) and soil moisture (blue) readings captured over three consecutive days. The graph clearly demonstrates diurnal fluctuations in temperature aligned with corresponding moisture variations, reinforcing the link between ambient climate and soil water dynamics.



**FIGURE 4.** Time-series data visualization in Grafana showing hourly temperature and moisture values from sensor nodes over a three-day period

Additional dashboard features included bar graphs comparing pre- and post-deployment crop yields, visual maps indicating active and inactive node status, and historical query filters for evaluating performance across specific date ranges or zones. These features enabled agricultural technicians to detect anomalies, plan irrigation, and observe crop responses to environmental conditions in a visual and actionable manner.

*Outlook* Moving forward, the system will be enhanced to support real-time closed-loop irrigation control through relay actuation from the Raspberry Pi gateway. AI-based image recognition modules for pest detection are also being developed to integrate with the existing platform. Furthermore, automated fertigation systems will be considered by introducing soil pH and electrical conductivity (EC) sensors, further transforming the setup into a comprehensive smart farming solution.

# CONCLUSION

This study presented the design, development, and field deployment of a smart agriculture monitoring system that integrates wireless sensor networks (WSNs) with cloud-based analytics to enhance precision farming practices. By leveraging ESP32-based sensor nodes, LoRa communication protocols, and a centralized Raspberry Pi gateway, the system successfully demonstrated low-cost, energy-efficient, and real-time data acquisition across a 2-hectare test field. Cloud services further enabled centralized data processing, anomaly detection, and remote visualization via mobile and web dashboards, providing farmers with actionable insights.

The 60-day deployment yielded tangible improvements in agricultural productivity and resource optimization. Moisture-triggered irrigation alerts reduced overall water usage by over 30%, while crop yields for both maize and tomatoes improved significantly compared to control plots. Network reliability, low latency, and solar-powered autonomy further validated the technical feasibility of the system for medium-scale agricultural operations in regions with limited infrastructure.

Moreover, the Grafana-integrated dashboard and Firebase-driven notification services empowered local farmers with real-time field awareness, minimizing labor-intensive inspections and allowing proactive management of irrigation schedules. Despite minor challenges such as sensor drift and early morning dew affecting leaf wetness readings, the overall system performance was stable, reliable, and well-received by users.

In future iterations, the platform will incorporate additional sensor types such as pH and EC sensors for soil nutrient monitoring, as well as AI-powered modules for crop disease and pest detection. The integration of autonomous actuation systems, including irrigation and fertilization, will elevate the solution from a monitoring tool to a fully responsive smart farming ecosystem. This scalable, modular, and IoT-enabled architecture has the potential to transform traditional agricultural practices into data-driven, climate-resilient, and sustainable systems.

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