

An Integrated LoRa-Enabled IoT Sensing System for Precision Agriculture: Design Algorithm and Practical Evaluation

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Abstract

Precision agriculture increasingly relies on Internet of Things (IoT) technologies for continuous environmental monitoring; however, practical deployment remains constrained by energy efficiency, long-range communication, and system scalability. This paper presents an integrated IoT-based environmental sensing system that combines multi-parameter sensors with a microcontroller-based node and LoRa based long-range communication through a hardware algorithm co design approach. A lightweight device level algorithm is developed to manage sequential sensing, data validation, compact payload construction, and duty cycled transmission under resource constrained conditions. Experimental evaluations under simulated and representative field conditions demonstrate that sensor measurements remain within acceptable accuracy ranges for precision agriculture, with stable repeatability and limited drift over time. Communication experiments show packet delivery ratios above 90% over extended distances, while scalability analysis confirms reliable multi node operation with moderate latency increase. Energy profiling reveals that duty cycled operation significantly reduces power consumption without substantially degrading communication reliability. Overall, the proposed system provides a practical, energy efficient, and scalable solution for long term environmental monitoring in precision agriculture.

Keywords: Precision agriculture, Internet of Things, LoRa communication, environmental monitoring, wireless sensor networks

1. Introduction

Thailand possesses abundant natural resources and favorable climatic conditions that have long supported agricultural production, which remains vital for food security, rural livelihoods, and socio-economic stability. Despite its importance, agricultural practices in Thailand still rely heavily on traditional knowledge and seasonal experience rather than real-time, site-specific environmental data. This limitation often results in imprecise management of soil, water, and agricultural inputs, leading to yield variability, increased production costs, and long-term environmental degradation. These challenges are further intensified by labor shortages, demographic transitions, and increasing climate variability.

Precision agriculture has emerged as a data-driven paradigm aimed at improving resource efficiency and decision-making through continuous environmental monitoring. Recent advances in sensing technologies and the Internet of Things (IoT) have enabled real-time acquisition of key environmental parameters, providing essential support for irrigation, fertilization, and crop management strategies [1]. However, conventional short-range wireless communication technologies are often unsuitable for large-scale agricultural environments due to limited coverage, high energy consumption, and poor scalability [2],[3].

To address these limitations, Low-Power Wide-Area Network (LPWAN) technologies, particularly LoRa and LoRaWAN, have attracted significant

attention owing to their long communication range, low power consumption, and cost-effective deployment characteristics [4–6]. Numerous studies have demonstrated the feasibility of LoRa-based IoT systems in agricultural applications such as irrigation management, greenhouse monitoring, and large-scale environmental surveillance, reporting acceptable sensing accuracy and reliable communication [7–13].

Despite these advances, many existing solutions focus on isolated system components or rely primarily on short-term or laboratory-based evaluations. As a result, limited insight is provided into long-term sensor stability, energy efficiency, system scalability, and robustness under real-world deployment conditions [14–16]. In addition, system cost and technical complexity continue to hinder adoption among smallholder farmers in developing regions, including Thailand.

Motivated by these challenges, this study proposes an integrated IoT-based environmental sensing system designed explicitly for real-world agricultural deployment. The proposed approach adopts a holistic hardware–algorithm co-design strategy that integrates commercially available multi-parameter sensors, a microcontroller-based sensing node, LoRa-based long-range communication, and a gateway-centric backend architecture. A lightweight, energy-aware device-level algorithm is developed to manage sequential sensing, data validation, compact payload construction, and duty-cycled transmission under resource-constrained conditions. Rather than introducing

new sensing hardware, the novelty of this work lies in the systematic integration of sensing, communication, and energy-aware control within a deployable and scalable framework.

Based on this design direction, the contributions of this study can be summarized in five main aspects. First, the study proposes a complete LoRa-enabled IoT sensing architecture that integrates environmental sensors, embedded processing, long-range wireless communication, and backend data management into a single deployable framework for precision agriculture. Rather than focusing only on an individual sensing device, the proposed system demonstrates how sensing, communication, and data handling can work together in a practical field-oriented environment.

Second, the study introduces a lightweight device-level algorithm designed for low-cost and resource-constrained sensing nodes. The algorithm manages sequential data acquisition, basic validation of sensor readings, compact payload construction, and duty-cycled transmission. This design helps reduce unnecessary communication activity while maintaining reliable data reporting for long-term monitoring.

Third, the system is evaluated under representative agricultural conditions, covering sensing accuracy, repeatability, short-term sensor drift, packet delivery performance, transmission latency, and node uptime. These evaluations provide practical evidence of the system's behavior outside a purely laboratory setting.

Fourth, the study analyzes the trade-off between energy consumption and communication reliability. The results demonstrate that duty-cycled operation can substantially reduce energy usage while maintaining an acceptable level of packet delivery and latency for non-real-time agricultural monitoring.

Fifth, the study examines scalability by considering the effects of communication distance and increasing node density on packet delivery ratio and latency. This analysis supports the potential use of the proposed system in larger agricultural areas where multiple sensing nodes are required.

Comprehensive experimental evaluations conducted under simulated and representative field conditions assess sensing accuracy, repeatability, drift behavior, communication robustness, energy consumption trade-offs, and scalability. By emphasizing deployability, robustness, and long-term operation, this work aims to provide a practical precision agriculture monitoring solution aligned with Thailand's agricultural modernization and sustainability goals.

1.1 Comparison with Related Work

To clarify the distinction between the proposed system and previous LoRa-based IoT studies, **Table 1** compares selected related works in terms of application focus, communication technology, field validation, energy-aware design, scalability analysis, and system-level integration. The comparison focuses on studies that are closely related to LoRa-based agricultural or environmental monitoring.

Table 1. Comparison of the proposed system with related LoRa-based IoT studies

Study	Application focus	Communication technology	Field validation	Energy-aware design	Scalability analysis	Main difference from this study
Singh et al. [4]	Precision agriculture	LoRaWAN	Yes	Partial	Limited	Mainly emphasizes LoRaWAN feasibility for agricultural monitoring
Valente et al. [5]	Smart agriculture for vineyards	LoRaWAN	Yes	Partial	Limited	Focuses on vineyard-specific deployment and environmental monitoring
Ahmed et al. [8]	Remote monitoring of large farms	LoRa-based IoT	Yes	Partial	Limited	Focuses on farm-scale remote monitoring through LoRa connectivity
Križanović et al. [9]	Environmental monitoring	LoRa WSN	Yes	Yes	Partial	Strong focus on energy-efficient LoRa communication, with less emphasis on agricultural system integration
Ting et al. [14]	Small farm IoT systems	LoRa-based IoT	Yes	Partial	Limited	Focuses on LoRa performance optimization for small farm deployment
Mekki et al. [16]	Large-scale IoT deployment	LPWAN technologies	No	Comparative	No	Provides broader LPWAN technology comparison rather than an implemented agriculture monitoring system
Proposed system	Precision agriculture	LoRaWAN-based uplink	Yes	Yes	Yes	Integrates sensing, LoRa communication, backend data handling, energy-aware operation, field evaluation, and scalability analysis in one deployable framework

As shown in **Table 1**, previous studies have demonstrated the usefulness of LoRa and LoRaWAN for agricultural and environmental monitoring. However, many studies emphasize communication feasibility, specific application deployment, or energy-efficient

networking as separate aspects. In contrast, the proposed system combines low-cost multi-parameter sensing, compact payload construction, LoRaWAN-based uplink transmission, backend visualization, energy-aware operation, field evaluation, and scalability analysis within

a single practical framework. This system-level integration represents the main distinction of the present work.

2. Proposed Methodology

Figure 1 illustrates the overall architecture and data flow of the proposed IoT-based precision agriculture system, which is structured into three logical layers. Input, Process, and Output. The figure emphasizes the transformation of raw environmental data collected at the field level into meaningful information presented through a centralized dashboard.

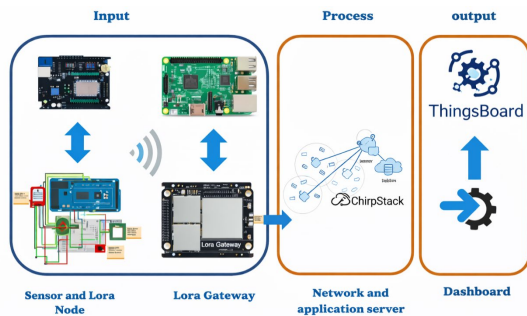


Figure 1 IoT System Architecture for Field-Level Environmental Data

2.1 Proposed System Architecture

This paper presents a scalable IoT-based environmental monitoring architecture for precision agriculture, designed for resource-limited and large-area deployments. The system adopts a modular, layered design separating sensing, communication, and application services. Distributed sensing nodes collect environmental data and transmit compact payloads via LoRa-based long-range, low-power communication to a gateway and LoRaWAN-compliant backend. Decoded data are stored as time-series records and visualized through a dashboard interface. By integrating hardware and device-level software into a unified framework, the proposed architecture emphasizes energy efficiency, communication robustness, and scalability for long-term agricultural monitoring.

2.2 Hardware Development

The proposed IoT sensing system integrates multiple hardware components into a modular sensing node for precision agriculture. All sensors are powered through the microcontroller's regulated outputs, enabling centralized power management and stable operation. Combined with a LoRa-based communication subsystem, gateway, and backend infrastructure, the hardware architecture supports multi-parameter monitoring, long-range transmission, and scalable data integration for outdoor agricultural deployment.

Figure 2 shows the experimental hardware setup of the proposed IoT sensing node, consisting of an Arduino MEGA 2560, a solderless breadboard for flexible prototyping, and an embedded communication module for long-range wireless

transmission. The modular configuration supports systematic testing prior to final hardware integration.

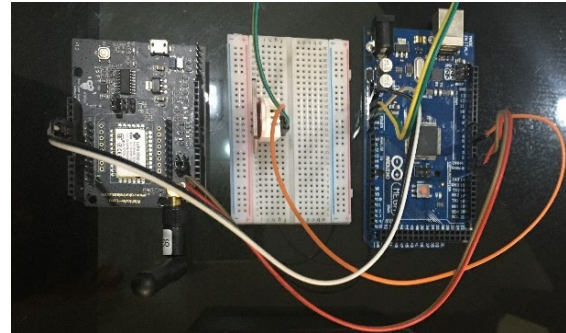


Figure 2. Experimental hardware setup of the proposed IoT sensing node, showing the integration of the microcontroller, prototyping interface, and wireless communication module.

Figure 3 Integrated hardware architecture and detailed circuit design of the proposed IoT-based environmental sensing system for precision agriculture. The upper section illustrates the system-level hardware architecture, where multiple environmental sensors, including temperature–humidity, atmospheric pressure, gas, and GPS modules, are interfaced with an Arduino Mega 2560 microcontroller. The collected data are transmitted via a LoRa communication node to a LoRa gateway, which forwards the data to the cloud backend through a Raspberry Pi–based internet gateway. The lower section presents the detailed circuit-level connections, showing sensor interfacing, power supply configurations, UART-based LoRa communication, and gateway connectivity. This integrated design highlights the modular, scalable, and energy-efficient structure of the proposed sensing system, enabling reliable long-range environmental monitoring in agricultural deployments.

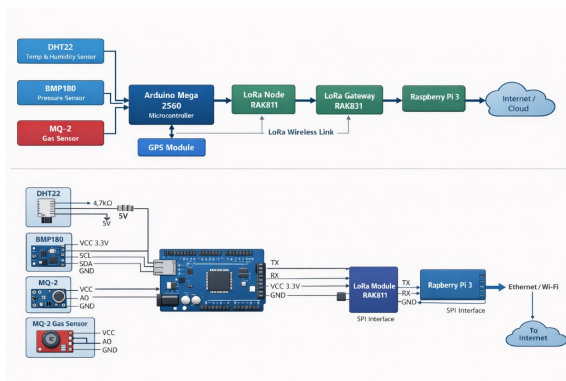


Figure 3. Integrated Hardware Architecture and Circuit Design of the IoT-Based Environmental Sensing System.

2.3 Hardware Specification

To clearly justify the selection of hardware components and support reproducibility, the specifications of the sensing node are summarized in **Table 2**.

Table 2. Hardware specifications of the proposed IoT sensing system

Component	Model	Function	Measurement Range	Interface	Typical Power
Temperature & Humidity Sensor	DHT22	Ambient temperature and humidity	−40–80 °C, 0–100% RH	Digital (Single-wire)	< 2.5 mA
Pressure Sensor	BMP180 (GY-68)	Atmospheric pressure	300–1100 hPa	I ² C	< 5 µA
Gas Sensor	MQ-2	Combustible gas and smoke detection	LPG, CH ₄ , H ₂ , Smoke	Analog (ADC)	~150 mA
GPS Module	GY-GPS6MV2	Geolocation tracking	Global positioning	UART	~45 mA
Microcontroller	Arduino Mega 2560	Data acquisition and processing	–	UART, I ² C, ADC	~70 mA
LoRa Node	RAK811	Long-range communication	868/915 MHz	UART	10–120 mA
LoRa Gateway	RAK831	Multi-node data aggregation	–	SPI	–
Internet Gateway	Raspberry Pi 3	Cloud connectivity	–	Ethernet/Wi-Fi	~400 mA

Table 2 summarizes the hardware components of the proposed IoT sensing system, including sensors for temperature and humidity (DHT22), atmospheric pressure (BMP180), gas detection (MQ-2), and node localization (GY-GPS6MV2). An Arduino Mega 2560 manages sensor acquisition and communication, while a RAK811 LoRa node enables long-range data transmission. At the network level, a RAK831 LoRa gateway aggregates data from multiple nodes, and a Raspberry Pi 3 provides internet connectivity to the backend. The system follows a hierarchical data flow that separates sensing, communication, and backend processing. Environmental

data are collected and formatted at the device level, transmitted via LoRa to the gateway, and forwarded to a cloud backend for storage and analysis. Energy efficiency is achieved through periodic sensing, duty-cycled transmission, and low-power idle states. Hardware constraints directly inform the deterministic device-level algorithm, ensuring scalable, reliable, and energy-efficient operation for precision agriculture deployments.

The functional role and practical relevance of the sensors and communication modules employed in the proposed system are summarized in **Table 3**.

Table 3. Functional role of sensors in the proposed precision agriculture system

Sensor / Module	Functional role	Practical relevance in precision agriculture
DHT22	Measures ambient temperature and relative humidity	Supports microclimate monitoring, crop stress observation, and irrigation planning
BMP180	Measures atmospheric pressure	Provides supporting environmental context for short-term weather variation and field condition monitoring
MQ-2	Detects relative gas or smoke response	Used as a qualitative indicator of abnormal gas or smoke-related events near farm equipment, storage areas, or controlled agricultural environments
GPS GY-GPS6MV2	Provides node location	Supports spatial tagging of field data and location-based environmental monitoring
RAK811 LoRa node	Transmits sensor payloads	Enables long-range, low-power uplink communication from field nodes
RAK831 gateway	Receives data from sensing nodes	Supports multi-node data aggregation and forwarding to the backend system

The MQ-2 sensor was included as a qualitative abnormal-condition indicator rather than as a laboratory-grade gas concentration sensor. In agricultural settings, such a sensor can support early indication of smoke, gas leakage, or abnormal air-quality conditions near equipment storage, greenhouse areas, or field operation zones. Its role in the proposed system is therefore to provide a low-cost warning signal that complements temperature, humidity, pressure, and location data.

2.4 Algorithm Development

The proposed device-level operational algorithm is designed for reliable environmental sensing and energy-

efficient LoRa-based transmission under resource-constrained conditions. The algorithm operates in a deterministic cyclic manner, consisting of system initialization, sequential sensing, data validation, compact payload construction, and periodic wireless transmission. To reduce energy consumption, sensing and transmission are performed only at predefined intervals, after which the node transitions into a low-power idle state. Backend processing is decoupled from device operation, allowing the sensing node to remain lightweight while supporting scalable data handling. The behavior of this cyclic sensing–transmission–sleep process, including sensing

intervals, payload generation, and energy consumption characteristics, can be formally described using mathematical expressions, as presented in the following section.

2.4.1 Cyclic Operation of the Sensing Node

The proposed IoT sensing node operates in a cyclic manner with a fixed operating period T_c , as defined in Eq. (1).

$$T_c = T_{init} + T_{sense} + T_{proc} + T_{tx} + T_{sleep} \quad (1)$$

where

- T_{init} denotes the system initialization time,
- T_{sense} is the sensing duration,
- T_{proc} represents local data processing and payload construction time,
- T_{tx} is the wireless transmission time, and
- T_{sleep} is the low-power idle period.

2.4.2 System Initialization

The initial system state is represented in Eq. (2).

$$S_0 = \{H, S, C\} \quad (2)$$

where

- H denotes the hardware components (microcontroller, memory, power unit),
- $S = \{s_1, s_2, \dots, s_n\}$ represents the set of sensor modules, and
- C corresponds to the LoRa communication parameters (frequency, spreading factor, bandwidth).

The system initialization process is expressed in Eq. (3).

$$S_{ready} = f_{init}(S_0) \quad (3)$$

which prepares the sensing node for normal operation.

2.4.3 Environmental Data Acquisition

At sensing cycle k , the environmental observation vector is defined in Eq. (4).

$$\mathbf{x}_k = \begin{bmatrix} T_k \\ H_k \\ P_k \\ G_k \\ L_k \end{bmatrix} \quad (4)$$

where

- T_k is the ambient temperature,
- H_k is the relative humidity,
- P_k is the atmospheric pressure,
- G_k represents gas concentration, and
- $L_k = (lat_k, lon_k)$ denotes the geographical location.

2.4.4 Data Validation and Noise Rejection

To ensure measurement reliability, the acquired data are validated according to Eq. (5).

$$\mathbf{x}_k^{valid} = \begin{cases} \mathbf{x}_k, & \mathbf{x}_k \in \Omega \\ \mathbf{0}, & \text{otherwise} \end{cases} \quad (5)$$

where Ω defines the admissible operating range of each sensor.

2.4.5 Local Buffering

Validated sensor readings are temporarily stored in local memory as described in Eq. (6).

$$B_k = \{\mathbf{x}_k^{valid}\} \quad (6)$$

This buffering step supports robust packet formation under intermittent connectivity.

2.4.6 Payload Construction

A compact payload optimized for low-power wide-area communication is generated as defined in Eq. (7).

$$p_k = f_{enc}(B_k) \quad (7)$$

The payload construction is subject to the size constraint specified in Eq. (8).

$$|p_k| \leq P_{max} \quad (8)$$

where $f_{enc}(\cdot)$ denotes the encoding and formatting function and P_{max} is the maximum allowable payload size.

To make the payload construction process reproducible, the uplink packet was organized using a compact field structure. Each packet contained the node identifier, timestamp, packet sequence number, validated sensor readings, GPS location, and status flag. The packet format used in this study was defined as follows: Packet = <NodeID, Timestamp, SeqNo, T, H, P, G, Lat, Lon, StatusFlag> where NodeID represents the sensing node identifier, Timestamp records the data acquisition time, SeqNo is the packet sequence number, T is the temperature value, H is the relative humidity value, P is the atmospheric pressure value, G is the MQ-2 gas sensor output, and Lat and Lon represent the GPS coordinates. The StatusFlag field was used to indicate the condition of the packet, such as normal data, invalid sensor reading, or abnormal gas response.

The payload was kept compact in order to reduce LoRa transmission overhead and energy consumption. Only essential monitoring data were included in each uplink packet, while additional processing and visualization were handled at the backend. This design is consistent with the resource-constrained nature of low-cost IoT sensing nodes and supports reliable periodic transmission in open-field agricultural environments.

The decision rules for packet construction were defined as follows. If all sensor readings were within their admissible operating ranges, the packet was marked as NORMAL. If one or more sensor readings were outside the admissible range, the affected value was marked as invalid and the packet status was set to INVALID. If the MQ-2 output exceeded the predefined abnormal-response threshold, the StatusFlag was set to ABNORMAL_GAS. After the payload was constructed, the packet was

transmitted through the LoRaWAN uplink according to the configured transmission interval. If the gateway received the packet, the transmission was recorded as successful. Otherwise, the packet was counted as a transmission loss for PDR calculation. No automatic retransmission was applied in order to reduce communication overhead and energy consumption.

2.4.7 LoRa-Based Wireless Transmission

The uplink LoRa frame at cycle k is defined in Eq. (9).

$$\mathcal{F}_k = (p_k, C) \quad (9)$$

The transmission outcome is represented in Eq. (10).

$$\delta_k = \begin{cases} 1, & \text{successful transmission} \\ 0, & \text{transmission failure} \end{cases} \quad (10)$$

2.4.8 Energy Consumption Model

The total energy consumed per operating cycle is expressed in Eq. (11)

$$E_k = E_{sense} + E_{proc} + E_{tx} + E_{sleep} \quad (11)$$

The dominance of wireless transmission energy consumption is described in Eq. (12).

$$E_{tx} \gg E_{sense}, E_{proc} \quad (12)$$

the algorithm minimizes transmission frequency and maximizes T_{sleep} to extend node lifetime.

2.4.9 Backend Decoding and Data Storage

At the backend, received payloads are decoded as shown in Eq. (13).

$$\hat{x}_k = f_{dec}(p_k) \quad (13)$$

The decoded information is stored as time-series data according to Eq. (14).

$$\mathcal{D} = \{(\hat{x}_k, t_k) \mid k = 1, 2, \dots\} \quad (14)$$

This separation between device-level sensing and server-side processing enables scalable system deployment.

2.4.10 Algorithm Characteristics

The overall properties of the proposed algorithm are summarized in Eq. (15).

$$\mathcal{A} = \{\text{Deterministic, Energy-efficient, Robust, Scalable}\} \quad (15)$$

The mathematical formulation demonstrates that the proposed device-level algorithm achieves deterministic environmental sensing, efficient payload construction, and energy-aware LoRa communication, while maintaining scalability through centralized backend processing, making it suitable for industrial-grade precision agriculture monitoring systems.

To make the operational procedure of the proposed

sensing node more explicit, the complete device-level workflow is summarized in **Algorithm 1**. The algorithm brings together the main steps described in the previous subsections, including sensor initialization, data acquisition, validation, payload construction, LoRaWAN transmission, and low-power idle operation. This summary is intended to support reproducibility and clarify how the proposed sensing node operates during each monitoring cycle.

Algorithm 1 Device-Level Sensing, Validation, and LoRaWAN Transmission Process

Input: Sensor set S, sampling interval T_s, transmission interval T_{tx}, LoRa configuration C Output: Validated payload and transmission status 1: Initialize microcontroller, sensors, memory buffer, and LoRa module 2: Set T_s, T_{tx}, and LoRa communication parameters 3: while the sensing node is active do 4: Acquire temperature, humidity, pressure, gas output, and GPS location 5: Validate sensor readings against predefined admissible ranges 6: Assign StatusFlag as NORMAL, INVALID, or ABNORMAL_GAS 7: Construct compact payload: 8: Packet = <NodeID, Timestamp, SeqNo, T, H, P, G, Lat, Lon, StatusFlag> 9: if T_{tx} is reached then 10: Transmit packet through LoRaWAN uplink 11: Record transmission status from gateway reception log 12: end if 13: Enter low-power idle state until the next sensing cycle 14: end while
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2.4.11 Practical Interpretation of the Algorithm

The mathematical formulation of the proposed algorithm was used to guide practical design decisions in the sensing node. The operating-cycle equation in Eq. (1) defines how the total cycle time is distributed among initialization, sensing, processing, transmission, and sleep periods. This relationship is important because increasing the sleep duration while keeping the sensing and transmission intervals fixed can reduce unnecessary energy consumption without changing the basic monitoring function.

The payload constraint in Eq. (8) was used to keep each LoRaWAN uplink packet compact. By limiting the payload to essential sensor readings, node information, location data, and status flags, the proposed algorithm reduces transmission overhead and helps maintain lower latency and energy consumption. This is particularly important for LoRa-based systems, where transmission time and packet size directly affect power usage and channel occupancy.

The transmission outcome variable in Eq. (9) provides a basis for calculating Packet Delivery Ratio (PDR), which was used to evaluate communication reliability under

different distances and node densities. In addition, the energy model in Eq. (11) and Eq. (12) shows why reducing transmission frequency is an effective strategy for extending node lifetime, since LoRa transmission consumes more energy than sensing and local processing.

Therefore, the proposed algorithm is not only a procedural description of sensing and transmission steps, but also a design tool for balancing sensing reliability, communication delay, energy consumption, and scalability in practical agricultural deployment.

3. Experimental Results

3.1 Experimental Setup and Performance Metrics

This section describes the experimental setup and evaluation criteria used to assess the proposed IoT-based

environmental sensing system. The experiments were conducted using the complete system architecture, including the sensing node, LoRa gateway, and cloud-based backend, under representative outdoor agricultural conditions. The sensing node was installed in an open-field environment, while the LoRa gateway was placed at an elevated position to improve line-of-sight communication and reduce signal obstruction.

To improve reproducibility, the main experimental parameters are summarized in **Table 4**. The field evaluation used one prototype sensing node for sensor accuracy, communication-distance, and long-term stability tests. Additional node configurations were considered in the scalability analysis to observe the effects of increasing node density on packet delivery and latency.

Table 4. Experimental setup parameters

Parameter	Description
Deployment environment	Open-field agricultural area with limited physical obstacles
Number of sensing nodes	1 prototype node for field evaluation; 10–50 nodes considered for scalability analysis
Microcontroller platform	Arduino Mega 2560
Communication protocol	LoRaWAN-based uplink communication
LoRa node module	RAK811
Gateway platform	RAK831 LoRa gateway with Raspberry Pi 3
Node–gateway distance	100–1000 m
Sensor sampling interval	5 min
Data transmission interval	10 min
Measured parameters	Temperature, relative humidity, atmospheric pressure, gas sensor output, and GPS location
Backend system	Cloud-based data storage and dashboard visualization
Reference instruments/data	Calibrated digital thermo-hygrometer, nearby meteorological station, GPS/map reference, and gateway reception logs
Test duration	14 days for long-term stability and uptime evaluation
Main performance metrics	Packet Delivery Ratio (PDR), transmission latency, node uptime, sensor deviation, repeatability, drift, and energy consumption

As shown in **Table 4**, the experimental parameters were specified to avoid ambiguity in the evaluation process. The sensing node was configured to collect environmental data every 5 min and transmit the prepared payload every 10 min through the LoRaWAN-based uplink. Communication performance was evaluated across node–gateway distances from 100 to 1000 m, which reflects a practical range for open-field agricultural monitoring. The 14-day evaluation period was used to observe packet delivery, node uptime, and short-term operational stability. These settings were kept consistent

during the field tests so that the effects of distance, transmission interval, and node density could be interpreted more clearly.

Because LoRa/LoRaWAN communication settings directly affect transmission delay, Packet Delivery Ratio (PDR), and energy consumption, the communication parameters used in the experiments are summarized in **Table 5**. These settings were kept constant during the field evaluation, except for the node–gateway distance and the number of sensing nodes considered in the scalability analysis.

Table 5. LoRa/LoRaWAN communication configuration

Parameter	Configuration used in this study
LoRa node module	RAK811
LoRa gateway	RAK831 LoRa gateway with Raspberry Pi 3
Communication mode	LoRaWAN-based uplink transmission
Frequency band	920–925 MHz ISM band
Spreading factor	SF7
Bandwidth	125 kHz
Coding rate	4/5
Transmit power	14 dBm
Payload size	Approximately 32–64 bytes per uplink packet

Table 5. LoRa/LoRaWAN communication configuration (cont.)

Parameter	Configuration used in this study
Transmission interval	10 min
Sensor sampling interval	5 min
Acknowledgement mode	Unconfirmed uplink
Retry policy	No automatic retransmission; failed transmissions were recorded as packet loss
Gateway placement	Elevated position in an open-field environment
Data logging source	Gateway reception logs and backend time-series records

3.2 Data Sources of Reported Results

To clarify the interpretation of the reported results, the source of each figure is identified before presenting the performance analysis. The evaluation in this study combines field measurements, simulation-based results, and analytical estimates. Field measurements were used for results that could be directly observed from the implemented prototype, gateway logs, and continuous operation records. Simulation-based results were used only to examine controlled scenarios that were difficult to reproduce consistently in the field, such as typical environmental trends, abnormal gas-response behavior, interference conditions, and scalability under different

node densities. Analytical estimates were used for energy-related results because energy consumption depends on the operating states of the sensing node, including sensing, processing, transmission, and sleep periods.

The simulated and estimated results were therefore not used as substitutes for field validation. Instead, they were included to support the interpretation of the measured results and to provide a clearer view of how the proposed system may behave under different operating conditions.

To clarify the origin and purpose of the reported results, the data sources associated with each figure are summarized in **Table 6**.

Table 6. Data sources of reported figures

Figure	Result type	Data source	Purpose of analysis
Figure 4	Field observation	Prototype installation and dashboard display	To show the implemented sensing node and monitoring interface
Figure 5	Field measurement	LoRaWAN join request delay measured at different node–gateway distances	To evaluate the effect of distance on network joining delay
Figure 6	Field measurement	Transmission delay measured across 100–1000 m	To examine the relationship between communication distance and transmission delay
Figure 7	Simulation	Simulated 24-hour environmental trend based on the sampling interval in Table 4	To illustrate expected temperature, humidity, and pressure patterns under controlled temporal conditions
Figure 8	Simulation	Simulated MQ-2 response under normal and abnormal gas exposure conditions	To illustrate the response of the validation logic to abnormal gas sensor output
Figure 9	Field measurement	Gateway reception logs collected at different node–gateway distances	To calculate Packet Delivery Ratio (PDR) as distance increases
Figure 10	Field measurement	Gateway timestamp records collected during distance-based communication tests	To evaluate transmission latency under open-field communication conditions
Figure 11	Field measurement	Fourteen-day transmitted and received packet logs	To assess long-term packet delivery stability
Figure 12	Field measurement	Fourteen-day node operation records	To evaluate node uptime during continuous operation
Figure 13	Analytical estimate	Energy model based on sensing, processing, transmission, and sleep states	To identify the dominant energy-consuming phase in one operating cycle
Figure 14	Simulation	Controlled baseline and interference scenarios	To examine the expected effect of interference on PDR at different distances
Figure 15	Simulation	Scalability scenario with increasing numbers of sensing nodes	To evaluate how node density affects packet delivery performance
Figure 16	Simulation	Scalability scenario with increasing numbers of sensing nodes	To evaluate how node density affects transmission latency
Figure 17	Analytical estimate	Daily energy calculation under duty-cycled and continuous transmission modes	To compare energy consumption between operating strategies

Table 6. Data sources of reported figures (cont.)

Figure	Result type	Data source	Purpose of analysis
Figure 18	Analytical estimate supported by measured PDR records	PDR comparison under duty-cycled and continuous transmission assumptions	To examine the energy–reliability trade-off

3.2.1 Simulation Methodology

The simulation-based results were generated to examine operating conditions that were difficult to reproduce repeatedly and consistently during field deployment. The simulations were not used to replace field measurements, but to support the interpretation of sensor behavior, communication robustness, and scalability under controlled assumptions.

For the environmental trend simulation in **Figure 7**, the 24-hour temperature and humidity patterns were modeled using a typical diurnal variation observed in outdoor agricultural environments. Temperature was assumed to gradually increase during daytime and decrease during nighttime, while relative humidity was modeled with an inverse tendency. Atmospheric pressure was assumed to remain comparatively stable within the short observation period. The sampling interval followed the experimental setting in **Table 4**.

For the gas response simulation in **Figure 8**, the MQ-2 output was represented using a baseline ADC range for normal operation and a sudden increase to represent an abnormal gas-response event. This simulation was intended to test the validation logic and status-flag assignment rather than to estimate absolute gas concentration.

For the interference and scalability simulations in **Figures 14–16**, the scenarios were constructed by varying communication distance, interference condition, and node density. The purpose was to observe expected changes in Packet Delivery Ratio (PDR) and latency when network load increases. The LoRa/LoRaWAN parameters in **Table 5** were kept constant, while the number of nodes and distance were varied according to the corresponding experimental scenario.

Overall, the simulation methodology was designed to provide controlled and repeatable scenarios that complement the field measurements. The simulated results should therefore be interpreted as supporting analyses for system behavior, not as direct substitutes for real-field observations.

3.3 Energy Consumption Estimation Method

Energy consumption was estimated based on the operating states of the sensing node rather than direct full-day battery discharge measurement. The estimation considered four main operating states: sensing, local processing, LoRa transmission, and low-power sleep. These states correspond to the operating cycle described in the proposed device-level algorithm.

For each operating state, the energy consumption was calculated from the supply voltage, the typical current consumption of the active components, and the duration of that state. The energy for each state was estimated using Eq. (16).

$$E_i = V \times I_i \times t_i \quad (16)$$

where E_i is the energy consumption of operating state i , V is the supply voltage, I_i is the current consumption during that state, and t_i is the duration of the state. The total energy consumption per operating cycle was then obtained by summing the energy of all operating states as shown in Eq. (17).

$$E_{cycle} = E_{sense} + E_{proc} + E_{tx} + E_{sleep} \quad (17)$$

The current values were obtained from the hardware specifications of the selected modules and component datasheets, while the operating durations were based on the configured sensing interval, transmission interval, and observed transmission behavior during the field tests. The estimation was repeated across operating cycles using the same sensing and transmission schedule, and the average value was used to represent the energy profile of one operating cycle.

Figure 13 therefore represents the estimated energy distribution per operating cycle. It was used to identify which operating state contributed most to energy consumption. **Figure 17** represents an analytical comparison of estimated daily energy consumption between duty-cycled and continuous transmission modes. These energy results should therefore be interpreted as model-based estimates supported by the actual system configuration, rather than direct battery discharge measurements.

3.4 Performance Metrics and Evaluation

System performance was evaluated in terms of sensing reliability, communication efficiency, and operational robustness using metrics including data consistency, Packet Delivery Ratio (PDR), transmission latency, and system uptime. Experimental data were collected according to a predefined schedule and analyzed offline using time-series records logged at the gateway. The evaluation focused on practical feasibility under realistic agricultural deployment conditions rather than laboratory-grade benchmarking. The results confirm successful integration of environmental sensors, embedded processing, LoRa-based communication, and dashboard visualization. Overall, the proposed system operates reliably in open-field environments, provides acceptable sensing accuracy for precision agriculture, and supports data-driven field management through low-power, long-range wireless communication.

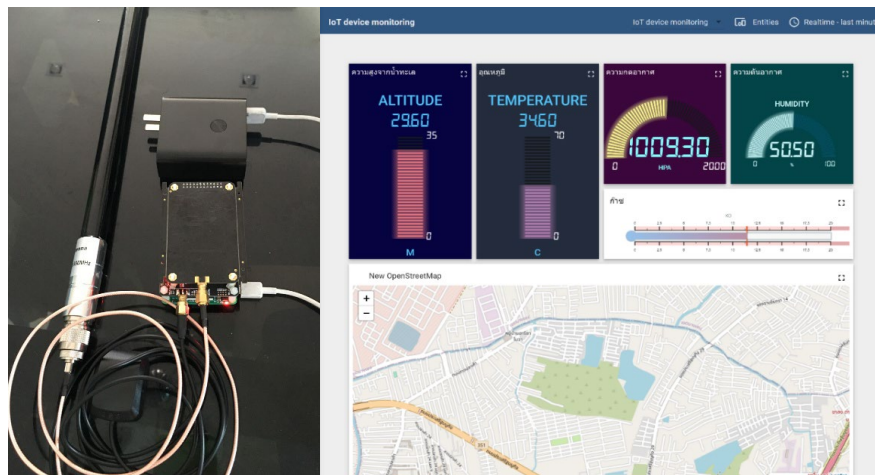


Figure 4. IoT-based prototype for environmental monitoring in open-field agricultural environments

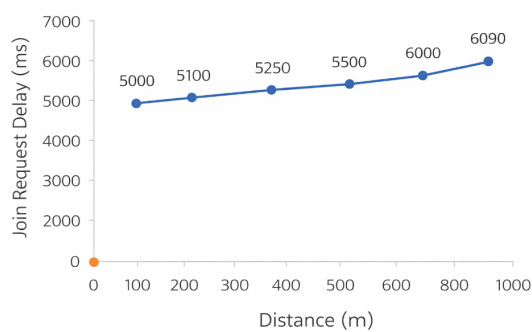


Figure 5. Impact of communication distance on LoRaWAN join request delay.

Figure 5 shows that join request delay increases with communication distance in the LoRa network, reflecting signal degradation and retransmissions at longer ranges. The results highlight the importance of proper gateway placement for efficient open-field precision agriculture deployment.

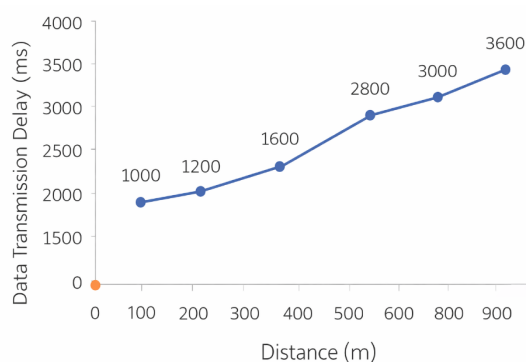


Figure 6. Data transmission delay as a function of communication distance in the LoRa network.

Figure 6 illustrates that transmission delay increases with node–gateway distance due to signal attenuation in long-range LoRa communication. Experimental results over 100–1000 m confirm the impact of distance on join and transmission performance, while sensing accuracy remains within acceptable ranges compared with reference

meteorological data, demonstrating the reliability of the proposed system for precision agriculture.

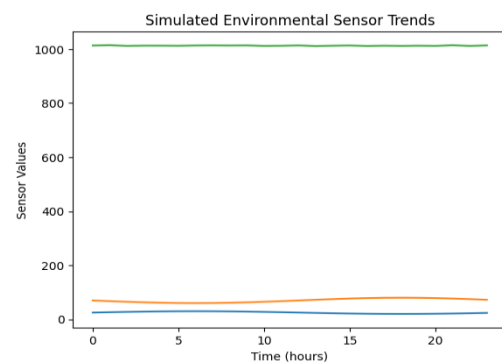


Figure 7. Simulated Environmental Sensor Trends Over Time

Figure 7 presents a simulated 24-hour pattern of temperature, relative humidity, and atmospheric pressure. The simulation was used to illustrate the expected behavior of the sensing and validation process under controlled temporal conditions. Temperature was modeled to follow a typical diurnal trend, humidity was represented with an inverse pattern, and pressure was assumed to remain relatively stable. This figure is intended to support the explanation of the algorithmic workflow rather than to serve as direct field measurement evidence.

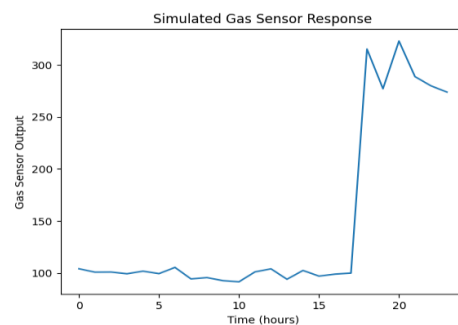


Figure 8. Simulated Gas Sensor Response Under Normal and Abnormal Conditions

Figure 8 presents a simulated MQ-2 gas sensor response under normal and abnormal conditions. The baseline region represents normal operation, while the sudden increase represents an abnormal exposure scenario. This simulation was included to demonstrate how the validation logic responds to a clear change in gas sensor output. Since the MQ-2 sensor is mainly suitable for qualitative gas detection, the simulated response is used only to illustrate detection behavior rather than to report absolute gas concentration.

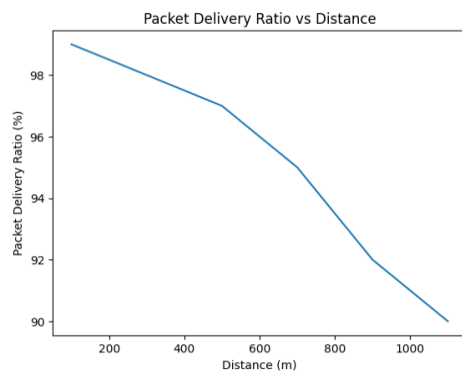


Figure 9. Packet Delivery Ratio as a Function of Node–Gateway Distance

Figure 9 Packet Delivery Ratio (PDR) of the LoRa-based communication subsystem as a function of the distance between the sensing node and the gateway.

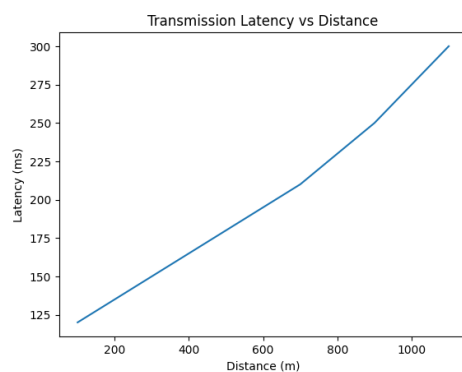


Figure 10. Transmission Latency Versus Communication Distance

Figure 10 shows that average transmission latency increases gradually with communication distance, reflecting the characteristics of long-range, low-power wireless links. Despite this trend, latency remains within acceptable limits for environmental monitoring, confirming that the periodic transmission strategy effectively balances reliability and energy efficiency. Overall, the experimental results confirm that the proposed IoT sensing system provides stable environmental sensing and robust LoRa-based communication, validating the hardware architecture and device-level algorithm for practical precision agriculture deployment.

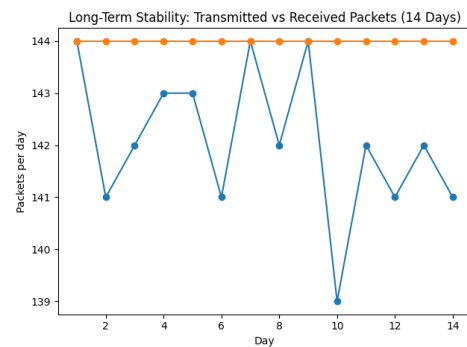


Figure 11. Long-Term Stability: Transmitted vs Received Packets (14 Days)

Figure 11 shows that the number of packets successfully received closely follows the number of packets transmitted on a daily basis, with only minor packet losses observed. Such losses are consistent with typical LoRa network behavior under real-field conditions. The results indicate that the periodic uplink and buffering strategy effectively preserves data continuity, ensuring reliable data delivery despite occasional transmission loss.

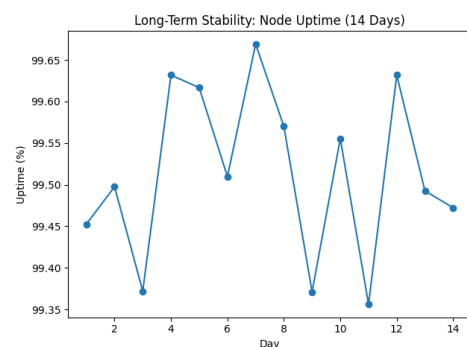


Figure 12. Long-Term Stability: Node Uptime (14 Days)

Figure 12 demonstrates the high operational stability of the sensing node during continuous deployment, with consistently high uptime observed throughout the evaluation period. This result confirms that the cyclic sensing–transmission–sleep architecture effectively supports sustained operation while avoiding excessive processing and communication overhead, enabling reliable long-term system performance.

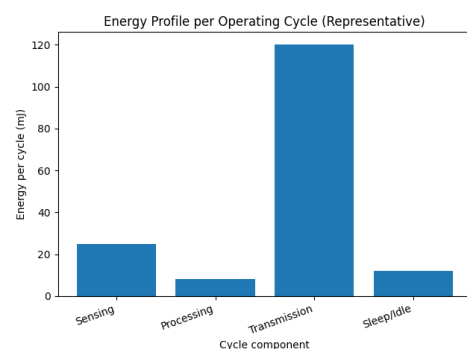


Figure 13. Energy Profile per Operating Cycle

Figure 13 shows the estimated energy distribution for one operating cycle of the sensing node. The estimation was calculated using the operating-state energy model described in Section 3.3, covering sensing, processing, LoRa transmission, and sleep states. The result indicates that the transmission phase is the dominant source of energy consumption, supporting the use of duty-cycled transmission in the proposed algorithm.

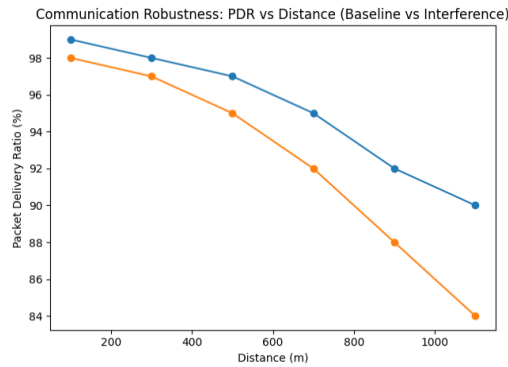


Figure 14. Communication Robustness: PDR vs Distance (Baseline vs Interference)

Figure 14 shows that the Packet Delivery Ratio (PDR) decreases under interference conditions, particularly at longer communication distances. This behavior reflects realistic agricultural environments where obstacles and intermittent interference are present. The results confirm the suitability of LoRa for long-range deployment while emphasizing the importance of appropriate gateway placement and parameter configuration to ensure communication robustness.

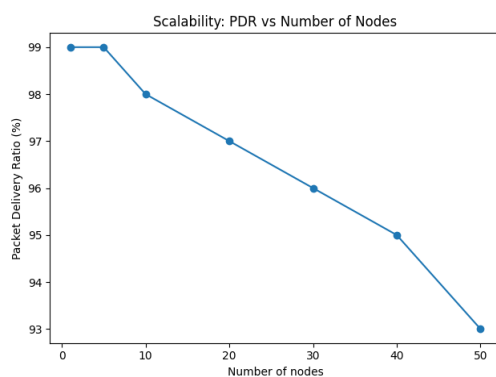


Figure 15. Scalability: PDR vs Number of Nodes

Figure 15 illustrates a gradual reduction in Packet Delivery Ratio (PDR) as the number of deployed sensing nodes increases, mainly due to increased traffic load and packet collisions inherent to LPWAN systems. Despite this trend, the system maintains a PDR level sufficient for monitoring applications, demonstrating the scalability of the proposed gateway-centric architecture.

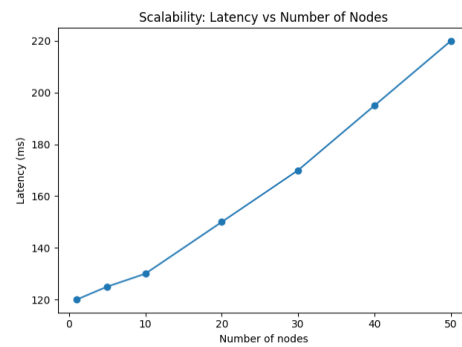


Figure 16. Scalability: Latency vs Number of Nodes

Figure 16 shows that transmission latency increases with the number of deployed nodes, reflecting channel sharing effects in multi-device LoRa networks. Despite this increase, the observed latency remains acceptable for non-real-time agricultural monitoring. The result aligns with the system design emphasis on energy efficiency rather than low latency, confirming the suitability of the proposed approach for long-term, low-power agricultural deployments.

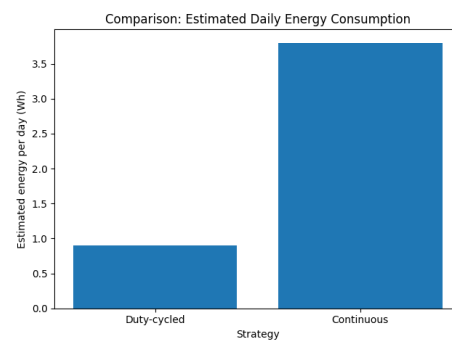


Figure 17. Comparison: Estimated Daily Energy Consumption (Duty-cycled vs Continuous)

Figure 17 compares the estimated daily energy consumption between duty-cycled and continuous transmission modes. The values were obtained from the operating-cycle energy model described in Section 3.3 rather than from direct full-day battery discharge measurement. This comparison was included to show the expected energy benefit of reducing transmission activity while keeping the sensing interval fixed.

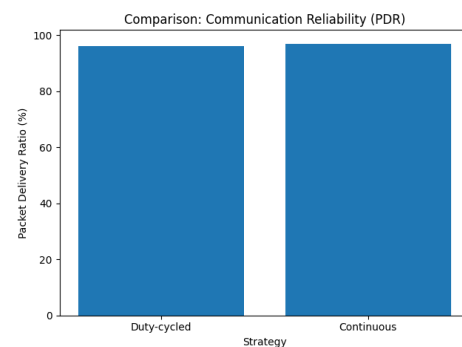


Figure 18. Comparison: Communication Reliability (PDR)

Figure 18 shows that the Packet Delivery Ratio (PDR) achieved under duty-cycled operation remains comparable to that of continuous transmission. This indicates that substantial energy savings can be achieved without severe degradation in communication reliability, validating the proposed energy–reliability trade-off strategy.

Table 7 summarizes the practical accuracy and operational performance of the sensors integrated into the proposed IoT system. All sensing devices operate within acceptable accuracy ranges for precision agriculture applications, with observed deviations consistent with manufacturer specifications. The temperature, humidity, and pressure sensors provide stable measurements suitable for long-term trend analysis, while the gas sensor reliably distinguishes between baseline and abnormal conditions. GPS accuracy supports effective spatial localization, and communication reliability together with high system uptime confirms the robustness of the integrated

hardware–algorithm design under realistic deployment conditions. Sensor repeatability and short-term stability were evaluated through repeated measurements under approximately constant environmental conditions. Multiple consecutive samples were recorded for each sensor, and statistical indicators were used to assess measurement consistency.

The results in **Table 8** show low variability in repeated measurements for temperature, humidity, and atmospheric pressure sensors, indicating good measurement stability. The MQ-2 gas sensor exhibits higher variability, which is expected due to its analog characteristics and sensitivity to environmental conditions. Overall, the observed repeatability confirms that the sensing devices provide stable performance suitable for continuous environmental monitoring. Short-term sensor drift was evaluated by monitoring sensor outputs over extended operation without recalibration to assess temporal consistency.

Table 7. Practical Accuracy Evaluation of Sensing Devices Used in the Proposed IoT System

Sensor / Device	Measured Parameter	Reference Source	Observed Measurement Range	Average Deviation / Error	Remarks
DHT22	Temperature (°C)	Calibrated digital thermo-hygrometer	24.8 – 35.6 °C	±1.0–1.5 °C	Within manufacturer specification; suitable for trend-based environmental monitoring
DHT22	Relative Humidity (%RH)	Calibrated digital thermo-hygrometer	55 – 85 %RH	< ±1.0 %RH	Stable readings under steady conditions; acceptable for agricultural use
BMP180 (GY-68)	Atmospheric Pressure (hPa)	Nearby meteorological weather station	1008 – 1016 hPa	±0.1 – 0.7 hPa	Minor deviation due to altitude and microclimate differences
MQ-2 Gas Sensor	Gas presence / relative concentration	Controlled gas exposure (LPG proximity)	Baseline: 90–110 (ADC units) Exposure: 250–350 (ADC units)	Not applicable (qualitative sensor)	Effective for gas presence detection; not intended for absolute concentration
GPS GY-GPS6MV2	Geographic position	Online mapping service (open-sky reference)	Stable coordinate output	±2 – 3 m	Accuracy sufficient for spatial tagging and node localization
LoRa Communication (RAK811)	Packet delivery	Gateway reception logs	PDR: 90 – 99 %	Packet loss < 10 % at long range	Reliable for non-real-time agricultural monitoring
Entire Sensing Node	System uptime	Continuous operation log	14 days continuous	> 99.3 % uptime	No critical failures or forced resets observed

Table 8. Repeatability and short-term stability of sensing devices

Sensor	Parameter	Number of Samples	Mean Value	Standard Deviation	Coefficient of Variation (CV)
DHT22	Temperature (°C)	20	30.2	0.42	1.39%
DHT22	Humidity (%RH)	20	68.5	0.78	1.14%
BMP180	Pressure (hPa)	20	1012.6	0.18	0.018%
MQ-2	Gas output (ADC)	20	102	4.6	4.51%

Table 9 shows that sensor drift remained within acceptable limits during continuous operation. The observed drift does not significantly affect trend-based analysis, which is the primary objective of the proposed precision agriculture monitoring system.

Table 9. Observed sensor drift over continuous operation

Sensor	Parameter	Observation Period	Maximum Drift
DHT22	Temperature	24 hours	$< \pm 0.6^\circ\text{C}$
DHT22	Humidity	24 hours	$< \pm 1.2\% \text{RH}$
BMP180	Pressure	24 hours	$< \pm 0.4 \text{ hPa}$
MQ-2	Gas baseline	24 hours	$< \pm 6 \text{ ADC units}$

3.4.1 Effect of Lightweight Calibration

A simple offset-based calibration was applied to temperature and pressure sensors to evaluate its impact on measurement accuracy.

As shown in **Table 10**, lightweight calibration reduces average measurement error across all evaluated sensors. This improvement is achieved without increasing computational complexity, demonstrating that simple calibration techniques can enhance data quality while maintaining low-power operation.

Table 10. Accuracy improvement before and after lightweight calibration

Sensor	Parameter	Average Error (Before)	Average Error (After)
DHT22	Temperature ($^\circ\text{C}$)	± 1.4	± 0.9
DHT22	Humidity (%RH)	± 1.1	± 0.8
BMP180	Pressure (hPa)	± 0.6	± 0.3

3.4.2 Limitations of Low-Cost Sensors

Although the selected sensors provided acceptable performance for trend-based agricultural monitoring, their limitations should be considered when interpreting the results. The DHT22 sensor is suitable for general temperature and humidity monitoring, but its response may be slower under rapidly changing humidity conditions. Its readings may also be affected by condensation, dust, and long-term exposure to outdoor environments. Therefore, periodic checking or simple recalibration is recommended when the sensor is used for extended field deployment. The BMP180 pressure sensor showed stable short-term readings in this study; however, pressure measurements may still be affected by altitude differences, local microclimate variation, enclosure design, and temperature compensation. For this reason, the pressure values should be interpreted mainly as environmental trend indicators rather than as highly precise meteorological measurements.

The MQ-2 gas sensor has more obvious limitations compared with the temperature, humidity, and pressure sensors. Since it is an analog low-cost gas sensor, its output can be influenced by temperature, humidity, warm-up time, sensor aging, and cross-sensitivity to different gases. In this study, the MQ-2 was therefore used only to detect relative changes between normal and abnormal conditions, rather than to estimate absolute gas concentration. This interpretation is consistent with the practical purpose of the proposed system, which focuses on low-cost environmental monitoring and early indication of abnormal field conditions.

Overall, the use of low-cost sensors makes the proposed system more accessible for agricultural deployment, but it also introduces a trade-off between affordability and measurement precision. The results should therefore be interpreted as suitable for practical monitoring, trend observation, and field-level decision support, rather than as laboratory-grade measurements.

3.4.3 Impact of Missing Data and Packet Loss

To evaluate the impact of communication loss, periods of packet loss were simulated, and the resulting data availability was analyzed.

Table 11 indicates that even under moderate packet loss conditions, the overall data trends remain interpretable. This robustness is attributed to the periodic sensing strategy and time-series analysis at the backend, which compensates for occasional missing data.

Table 11. Impact of packet loss on data availability

Scenario	Packet Loss Rate	Effective Data Availability	Impact on Trend Analysis
Normal operation	$< 2\%$	$> 98\%$	Negligible
Moderate loss	$\sim 5\%$	$\sim 95\%$	Minor smoothing required
Severe loss	$\sim 10\%$	$\sim 90\%$	Trend still observable

3.5 Discussion and Trade-off Analysis

The experimental and analytical results indicate that the proposed system involves several practical trade-offs among communication range, latency, energy consumption, and reliability. As the node-gateway distance increases, both join request delay and transmission latency tend to increase. This behavior is expected in long-range LoRa communication because longer distances may reduce signal strength and increase the probability of packet loss or delayed reception. However, the observed PDR remains within an acceptable range for non-real-time agricultural monitoring, where periodic environmental trends are more important than immediate response.

The scalability results also show that increasing the number of sensing nodes leads to a gradual reduction in PDR and an increase in latency. This trend is mainly

related to higher channel occupancy and packet collision probability in shared LPWAN communication. Nevertheless, the gateway-centric architecture remains suitable for agricultural monitoring because the application does not require continuous high-rate data transmission. The system is therefore more appropriate for periodic field monitoring than for time-critical control applications.

Energy consumption is another key trade-off in the proposed design. The operating-state energy model shows that LoRa transmission is the dominant energy-consuming phase, while sensing and local processing require comparatively lower energy. This supports the use of duty-cycled transmission, where the node collects data at a fixed sampling interval but transmits only at the configured transmission interval. As shown in the estimated energy comparison, this strategy can reduce daily energy consumption while maintaining comparable communication reliability.

From a practical perspective, the proposed system prioritizes long-term deployability, acceptable sensing accuracy, and low-power operation rather than laboratory-grade precision or ultra-low latency. This trade-off is suitable for precision agriculture applications that rely on environmental trends, field-level monitoring, and gradual decision support. Future work may further improve this balance by applying adaptive transmission intervals, dynamic spreading factor selection, solar-assisted power management, and machine-learning-based event detection.

4. Conclusions

This work presents a practical system-level IoT solution for precision agriculture by integrating heterogeneous environmental sensors, LoRa-based long-range communication, and a lightweight, energy-aware device-level algorithm within a unified and deployable architecture. Unlike prior studies that emphasize isolated components or laboratory-scale validation, the proposed approach explicitly considers hardware constraints, algorithmic control, and real-world deployment conditions. Comprehensive experimental results demonstrate that the integrated hardware–algorithm design enables reliable environmental sensing, robust wireless communication, and stable long-term operation in open-field agricultural environments. Sensor measurements remain within acceptable accuracy ranges compared with reference meteorological data, supporting trend-based and spatially localized monitoring. Communication and energy evaluations confirm that duty-cycled operation achieves significant power savings while maintaining acceptable packet delivery and latency under varying distances, interference, and node density. Overall, the proposed system achieves a balanced trade-off among sensing reliability, communication robustness, energy efficiency, and scalability. By prioritizing deployability and long-term operation, this work provides a reproducible framework for real-world precision agriculture monitoring and establishes a solid foundation for future extensions such as adaptive

transmission strategies, decision-support integration, and renewable energy utilization.

5. Acknowledgments

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6. References

- [1] N. S. Abu, W. M. Bukhari, C. H. Ong, A. M. Kassim, T. A. Izzuddin, M. N. Sukhaimie, M. A. Norasikin and A. F. A. Rasid, “Internet of Things Applications in precision Agriculture:Review,” *Journal of Robotics and Control (JRC)*, vol. 3, no. 3, pp. 338–347, 2022, doi: 10.18196/jrc.v3i3.14159.
- [2] B. Miles, E.-B. Bourennane, S. Boucherkha and S. Chikhi, “A study of LoRaWAN protocol performance for IoT applications in smart agriculture,” *Computer Communications*, vol. 164, pp. 148–157, 2020, doi: 10.1016/j.comcom.2020.10.009.
- [3] H. Iftikhar, M. A. Khan and S. U. Rehman, “IoT-Based LORA Technology for Precision Agriculture,” *Saudi Journal of Engineering and Technology*, vol. 5, no. 4, pp. 150–155, 2020, doi: 10.36348/sjet.2020.v05i04.004.
- [4] R. K. Singh, R. Berkvens and M. Weyn, “Leveraging LoRaWAN Technology for Precision Agriculture,” *Sensors*, vol. 20, no. 7, 2020, Art. no. 1827, doi: 10.3390/s20071827.
- [5] A. Valente, C. Costa, L. Pereira, B. Soares, J. Lima and S. Soares, “A LoRaWAN IoT System for Smart Agriculture for Vine Water Status Determination,” *Agriculture*, vol. 12, no. 10, 2022, Art. no. 1695, doi: 10.3390/agriculture12101695.
- [6] L. Aldhaferi, N. Alshehhi, I. I. J. Manzil, R. A. Khalil, S. Javaid, N. Saeed, and M. -S. Alouini, “LoRa Communication for Agriculture 4.0: Opportunities, Challenges, and Future Directions,” *IEEE Internet of Things Journal*, vol. 12, no. 2, pp. 1380–1407, doi: 10.1109/JIOT.2024.3486369.
- [7] J. Gresl, S. Fazackerley and R. Lawrence, “Practical Precision Agriculture with LoRa based Wireless Sensor Networks,” in *Proc. 10th International Conference on Sensor Networks*, Feb. 9–10, 2021, pp. 131–140, doi: 10.5220/0010394401310140.
- [8] M. A. Ahmed, J. L. Gallardo, M. D. Zuniga, M. A. Pedraza, G. Carvajal, N. Jara and R. Carvajal, “LoRa Based IoT Platform for Remote Monitoring of Large-Scale Agriculture Farms in Chile,” *Sensors*, vol. 22, no. 8, 2022, Art. no. 2824, doi: 10.3390/s22082824.
- [9] V. Križanović, K. Grgić, J. Spišić and D. Žagar, “An Advanced Energy-Efficient Environmental Monitoring in Precision Agriculture Using LoRa-Based Wireless Sensor Networks,” *Sensors*, vol. 23, no. 14, 2023, Art. no. 6332, doi: 10.3390/s23146332.
- [10] S. Aunkaew and P. Inprom, “LoRa-Based Agricultural Sensor Data System on IoT,”

- Journal of Computer and Creative Technology*, vol. 3, no. 1, pp. 74–89, 2025, doi: 10.14456/jcct.2025.7.
- [11] H. Zhang, L. He, F. Di Gioia, D. Choi, A. Elia and P. Heinemann, “LoRaWAN based internet of things (IoT) system for precision irrigation in plasticulture fresh-market tomato,” *Smart Agricultural Technology*, vol. 2, 2022, Art. no. 100053, doi: 10.1016/j.atech.2022.100053
- [12] D. T. Huong, N. T. H. Duy, P. V. M. Tu, H. H. Hanh and K. Yamada, “Enhancing precision agriculture: An IoT-based smart monitoring system integrated LoRaWAN, ML and AR,” *EAI Endorsed Transactions on Smart Cities*, vol. 7, no. 4, pp. 1–11, 2024, doi: 10.4108/eetsc.7286.
- [13] L. Schulthess, F. Longchamp, C. Vogt and M. Magno, “A LoRa-Based and Maintenance-Free Cattle Monitoring System for Alpine Pastures and Remote Locations,” in *Proc. 11th International Workshop on Energy Harvesting & Energy-Neutral Sensing Systems*, Istanbul, Turkiye, Nov. 12, 2023, pp. 44–50, doi: 10.1145/3628353.3628549.
- [14] Y. -T. Ting and K. -Y. Chan, “Optimising performances of LoRa based IoT enabled wireless sensor network for smart agriculture,” *Journal of Agriculture and Food Research*, vol. 16, 2024, Art. no. 101093, doi: 10.1016/j.jafr.2024.101093.
- [15] E. Bicomumakuba, E. Habineza, Samsuzzaman, N. Reza and S. -O Chung, “IoT-enabled LoRaWAN gateway for monitoring and predicting spatial environmental parameters in smart greenhouses: A review,” *Precision Agriculture Science and Technology*, vol. 7, no. 1, pp. 28–46, 2025, doi: 10.22765/pastj.20250003.
- [16] K. Mekki, E. Bajic, F. Chaxel and F. Meyer, “A comparative study of LPWAN technologies for large-scale IoT deployment,” *ICT Express*, vol. 5, no. 1, pp. 1–7, 2019, doi: 10.1016/j.icte.2017.12.005.