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Review Article

IoT-enabled LoRaWAN gateway for monitoring and predicting spatial environmental parameters in smart greenhouses: A review

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ABSTRACT

The integration of the Internet of Things (IoT) with Long Range Wide Area Network (LoRaWAN) technology has revolutionized precision agriculture, particularly in smart greenhouse environments. This review explores the role of IoT-enabled LoRaWAN gateways in monitoring and predicting spatial environmental parameters, which are crucial for optimizing crop growth, reducing resource consumption, and enhancing productivity. LoRaWAN ensures seamless communication between data management platforms and sensor networks by minimizing packet loss and enhancing network reliability through the use of adaptive data rate (ADR) and Just-In-Time (JIT) scheduling. An IoT-based automated irrigation system utilizing LoRaWAN communication demonstrated up to a 34% improvement in water use efficiency by enabling precise soil moisture monitoring and data-driven irrigation scheduling. Blockchain-based systems and AES-128 encryption strengthen security by guaranteeing distributed access and thereby guarding against cyberattacks. Key challenges such as network scalability, data security, interoperability, and energy efficiency are also analyzed. By synthesizing recent advancements and emerging trends, this review highlights the potential of IoT-enabled LoRaWAN gateways in transforming greenhouse agriculture and provides insights into future research directions.

KEYWORDS : Smart greenhouse, LoRaWAN, Wireless sensor networks, Edge computing, Spatial monitoring

Introduction

The rapid advancement of technology has significantly transformed agricultural practices, enabling a shift from traditional farming to precision agriculture. Smart agriculture leverages advanced sensors, automation, and data analytics to optimize resource utilization, improve crop yields, and enhance sustainability. Among the various applications of smart agriculture, greenhouse farming has gained prominence due to its ability to provide controlled environmental conditions for crops, ensuring year-round production and reduced dependency on climatic variations (Lee et al., 2023). However, effective greenhouse management requires continuous monitoring and control of critical environmental parameters such as temperature, humidity, light intensity, soil moisture, and CO_2 levels (Bersani et al., 2022).

The integration of the Internet of Things (IoT) in precision agriculture has revolutionized data collection, analysis, and decision-making processes. IoT-based solutions facilitate real-time monitoring and automation, thereby reducing labor costs and improving overall efficiency (Ali et al., 2024). Wireless communication technologies play a crucial role in transmitting data from distributed sensor nodes to centralized systems, where advanced analytics can be performed. The selection of an

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appropriate wireless communication protocol is essential to ensure seamless connectivity, low power consumption, and long-range data transmission, particularly in large-scale greenhouse environments (Ahmed et al., 2024). Among these advancements, LoRaWAN has emerged as a promising spatial environmental monitoring and prediction solution in smart greenhouses (Sharma and Shivandu, 2024). LoRaWAN gateway technology facilitates real-time data collection and transmission over long distances while maintaining low power consumption, making it an ideal choice for remote and large-scale agricultural applications (Aldhaheri et al., 2024). In a smart greenhouse environment, LoRaWAN-based IoT networks enable the efficient transmission of environmental data such as temperature, humidity, light intensity, soil moisture, and carbon dioxide levels from distributed sensor nodes to a central gateway, which subsequently relays this information to a cloud-based server (Mowla et al., 2023). The collected data is then processed and visualized through an intuitive user interface, allowing real-time monitoring, spatial analysis, and predictive decision-making. Spatial monitoring of key environmental parameters provides growers with granular insights into microclimatic variations within different greenhouse zones, enabling targeted interventions that optimize growing conditions and enhance crop yield and quality (Hosny et al., 2024).

Temperature, humidity, light intensity, soil moisture, and carbon dioxide were among the most critical environmental factors influencing crop growth, transpiration, and disease control. Each crop exhibits specific temperature requirements throughout its growth stages; cool-season crops such as lettuce and spinach thrive at 15°C to 20°C, whereas warm-season crops like tomatoes and peppers prefer 25°C to 30°C (Singh 2018; Chaudhary et al., 2022). The humidity levels significantly impact plant physiology, with leafy greens thriving at 70% to 80% humidity, while fruit crops perform best at 60% to 70% humidity to minimize fungal risks (Ferrante and Mariani, 2018). To address challenges in environmental sensing within greenhouses, researchers have increasingly explored the integration of IoT with long-range communication technologies such as LoRaWAN. This combination enables real-time, scalable monitoring solutions that enhance precision agriculture practices in smart greenhouse environments (Shamshiri et al., 2021). The physical performance of LoRaWAN technology ensures stable communication and network reliability, which is essential for large-scale environmental monitoring in greenhouses. The study showed that LoRaWAN networks maintain an SNR (Signal-to-Noise Ratio) above 11.875 dB within a range of 50 to 100 meters, ensuring robust connectivity and minimal data loss (Kufakunesu et al., 2024). The distance extends beyond 500 meters, the SNR declines below 4.3 dB, resulting in connectivity issues, increased error rates, and reduced system reliability (Ketshabetswe et al., 2019). To mitigate these limitations, strategic solutions such as optimized antenna placement, signal repeaters, and adaptive network configurations must be implemented to sustain uninterrupted data transmission and ensure the reliability of predictive greenhouse monitoring systems.

The adoption of LoRaWAN-enabled IoT systems in smart agriculture has demonstrated significant advantages, including long-range communication, low power consumption, cost-effectiveness, and scalability. Research has proven the effectiveness of LoRaWAN in applications such as remote soil moisture monitoring, automated irrigation control, and livestock tracking, making it a versatile solution for various smart farming operations (Alumfareh et al., 2024). Looking ahead, future advancements in machine learning, advanced analytics, and automation are expected to further enhance predictive capabilities, enabling real-time decision-making and adaptive environmental management (Sun and Scanlon, 2019). As global food security challenges continue to grow, integrating LoRaWAN technology with AI-driven predictive modeling and automation will play a pivotal role in ensuring sustainable agricultural practices, optimized resource utilization, and climate-resilient farming systems (Shahab et al., 2024).

Despite the growing adoption of LoRaWAN-enabled IoT solutions in smart agriculture, challenges such as data reliability, network scalability, interoperability, and energy efficiency remain key concerns. While various studies have explored LoRaWAN applications in precision farming, a focused review of its role in monitoring and predicting spatial environmental parameters in smart greenhouses is lacking. Given the increasing demand for automation and data-driven decision-making in controlled agricultural environments, there is a critical need to synthesize existing research, identify current limitations, and highlight future directions. This review aims to bridge this gap by providing a comprehensive analysis of IoT-enabled LoRaWAN gateway deployment in smart greenhouses. The objective of this review was to explore the deployment of IoT-enabled LoRaWAN gateways for monitoring and predicting spatial environmental parameters in smart greenhouses. It provides a comprehensive analysis of the architecture, communication protocols, sensor integration, and data processing methodologies employed in these systems.

IoT and LoRaWAN applications in smart greenhouses

Smart agriculture is revolutionizing traditional farming methods by integrating advanced technologies such as the IoT and LoRaWAN. These technologies facilitate precision farming, enabling real-time data collection, analysis, and automation. Among the most transformative applications of IoT and LoRaWAN is their role in smart greenhouses, where they enhance crop growth, optimize resource usage, and improve overall productivity (Mowla et al., 2023; Kim et al., 2023). Smart greenhouse uses IoT and LoRaWAN technologies to efficiently and cheaply monitor spatial environmental parameters at scale, energy. IoT sensor networks enable precision and climate-adaptive farming by collecting real environmental data (Selvam, 2023). LoRaWAN sensor nodes typically consume 7.66 μA up 34mA in sleep mode, depending on the device and configuration, and are priced below $10 per unit, making them highly suitable for long-term, low-maintenance deployment in greenhouse environments where energy efficiency and cost-effectiveness are critical (López-Ortiz et al., 2020) Recent studies suggest that LoRaWAN-enabled smart agriculture systems outperform conventional monitoring methods. The packet delivery rate at 700 meters was 40.9%, this performance significantly surpassed that of conventional Wi-Fi systems operating under the same greenhouse interference conditions. These findings underscore LoRaWAN superior robustness and suitability for long-range, low-power communication in complex greenhouse environments (Singh et al., 2020).

Alongside environmental monitoring, IoT-LoRaWAN infrastructures enhanced by predictive analytics and AI have significantly advanced decision-making in agriculture. Kontogiannis et al. (2024) developed a deep learning-based LoRaWAN system to predict vineyard diseases and detect early fungal infections, achieving an accuracy of above 90% for relative humidity and temperature between 12°C and 26°C. The model achieved high accuracy due to the stable microclimate of the greenhouse, LoRaWAN significantly contributed by enabling continuous, real-time data transmission. This connectivity is vital for supporting predictive analytics and responsive control systems in smart greenhouse applications (Valente et al., 2023). Recent advances in edge computing and federated learning have improved the real-time processing capabilities of

LoRaWAN-enabled agricultural systems, reducing reliance on cloud infrastructure and enhancing data security (Ray and Skala, 2022). Recent studies have introduced LoRaWAN-specific enhancements such as the use of directional antennas, Adaptive Data Rate (ADR) optimization, and elevated gateway placement, which collectively reduced packet loss by up to 35% in greenhouses affected by structural interference. These modifications improve communication reliability in complex indoor agricultural settings (Frausto-Vicencio et al., 2021). Fig. 1 shows an IoT and LoRaWAN-based smart farm monitoring greenhouse system. The system automates environmental monitoring with a microprocessor, power supply, sensors, and actuators.

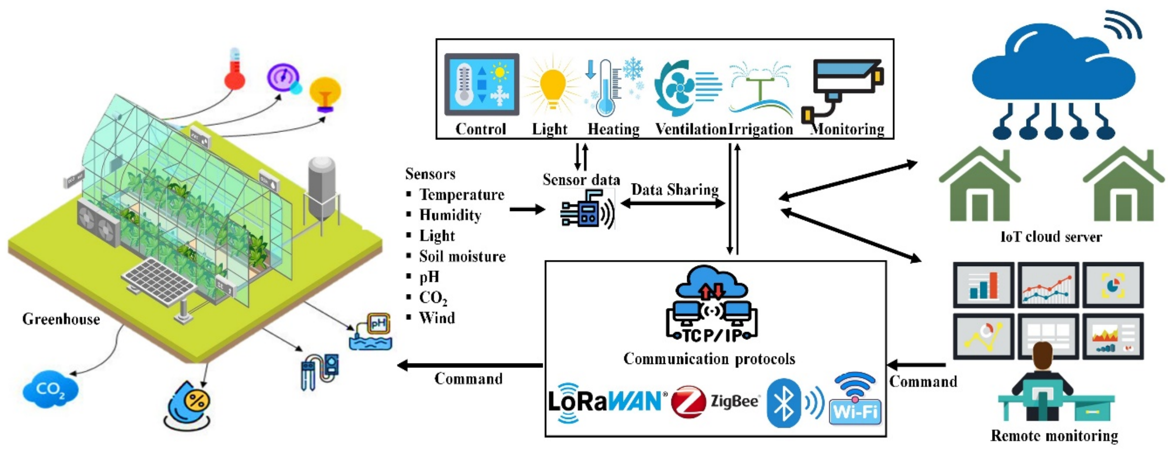

Fig. 1. An IoT and LoRaWAN-based smart greenhouse monitoring and control system.

LoRaWAN technology for smart greenhouse management

LoRaWAN technology in a smart greenhouse enables efficient, long-range, low-power communication between several sensor nodes and a cloud-based monitoring system. The ability to preserve signal integrity over extended distances with minimum power and data loss makes it an ideal solution for large-scale environmental monitoring and predictive analytics in controlled agricultural environments (Aldhaheri et al., 2024). The implementation of Adaptive Data Rate (ADR) and error-checking protocols ensures the LoRaWAN gateways can reliably transmit data over 15 kilometers with a packet loss rate of less than 0.1% in rural and semi-urban applications (Kufakunesu et al., 2020; Tamang et al., 2022). The integration of Ethernet and cellular connectivity boosts network uptime to 99.9%, making greenhouse environmental monitoring systems more reliable (Bolla et al., 2011). The architecture of the LoRaWAN gateway facilitates seamless interaction between sensor nodes and centralized data management platforms by employing Chirp Spread Spectrum (CSS) modulation within sub-GHz ISM bands. LoRaWAN ensures high inference immunity and energy-efficient transmission, making it well-suited for greenhouse applications.

ADR algorithms modify transmission parameters based on environmental and network conditions to enhance network performance (Abdallah et al., 2024). The large-scale agricultural installations, ADR-based optimization reduced packet loss by 28% and increased network performance by 35% (Gkotsiopoulos et al., 2021). Fig. 2 illustrates the comparison of

LoRaWAN communication classes for Class A, which is ideal for low-power battery-operated sensors with high latency and limited downlink availability. Class C offers real-time control with frequent downlink access but consumes the most power, while Class B provides a balanced trade-off between power consumption and responsiveness (Cheong et al., 2017).

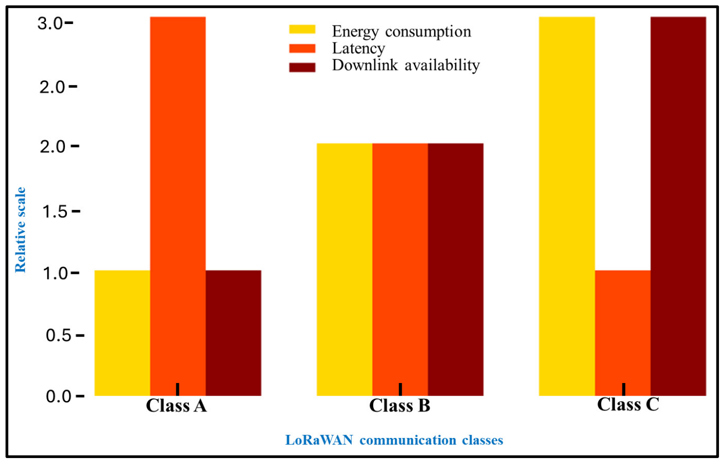

Fig. 2. Comparison of LoRaWAN communication classes for IoT-based smart greenhouse monitoring.

The physical procedure sub-layer of the LoRaWAN gateway operates through a Finite State Machine (FSM) model, ensuring efficient channel access, message scheduling, and error management. The structured approach reduces packet collisions and enhances throughput, especially in crowded sensor setups where gateway congestion could be an issue (Park and Kim, 2021). Field tests have shown that FSM-based scheduling enhances channel efficiency by 22% and decreases retransmission rates by 19% compared to conventional time-division methods (Sachtleben and Peleska, 2022). Just-In-Time (JIT) scheduling for enhanced packet forwarding efficiency, a dual buffer-queue system, utilizing JIT scheduling principles, is implemented to enhance packet forwarding efficiency. The experimental findings indicate that JIT scheduling effectively minimizes thread blocking and decreases packet latency by as much as 30%, facilitating uninterrupted data transmission, especially in Class C device operations that necessitate continuous downlink communication (Wang and Fan, 2020). Long-term evaluation demonstrates an 18% reduction in packet queuing delays, thereby greatly improving the reliability of real-time data in environmental monitoring applications (Lazarescu, 2013). Table 1 shows the impact of JIT scheduling on network performance in greenhouse monitoring applications.

LoRaWAN end-node communication achieves an optimal balance between transmission range and energy efficiency. Field studies indicate that battery-operated end nodes can function for over 10 years, benefiting from ADR optimization and low-power listening modes (Mehic et al., 2022). Class A devices further enhance climate control actuation by automatically adjusting greenhouse conditions in response to environmental fluctuations. LoRaWAN-based climate monitoring systems have been shown to improve crop yields by up to 20%, attributed to precise microclimate management (Et-taibi et al., 2024). Security and data integrity in LoRaWAN networks LoRaWAN operates through three distinct communication classes (A, B, and C), each designed to optimize energy consumption, communication delay, and data security. Fig. 3 shows LoRaWAN security architecture for end-node communication. Secure wireless transmission is achieved through AES-128 encryption, ensuring data integrity and protection against unauthorized access (Thaenkaew et al., 2023).

Table 1. JIT scheduling impact on network performance in greenhouse monitoring applications.

Performance metric	JIT scheduling impact	Formula	Application scenario	Reference
Channel efficiency (CE)	Enhance channel efficiency	$CE = \frac{\text{Successful transmissions}}{\text{Total transmissions}} \times 100\%$	Greenhouse sensor congestion management	Săcăleanu et al. (2024)
Retransmission rate (RR)	Decreases retransmission rate	$RR = \frac{\text{Retransmissions}}{\text{Total transmissions}} \times 100\%$	Mitigating message collisions in high-density networks	Larsson et al. (2016)
Packet latency (PL) reduction	Reduces packet latency	$PL = T_b - T_a$ T_b= Packet latency before JIT scheduling, and T_a= Packet latency after JIT scheduling	Optimizing downlink communications for Class C devices	Flach et al. (2013)
Packet queuing delay (QD) reduction	Reduces queuing delays	T_{qb} = Queue delay before JIT scheduling, T_{qa} = Queue delay after JIT scheduling	Long-term performance enhancement	Xue et al. (2024)
Reliability (R) improvement in real-time data	Improves real-time data reliability	$RR = \frac{\text{Valid data packets}}{\text{Total data packets}} \times 100\%$	Reliable environmental monitoring data transmission	Liu et al. (2019)

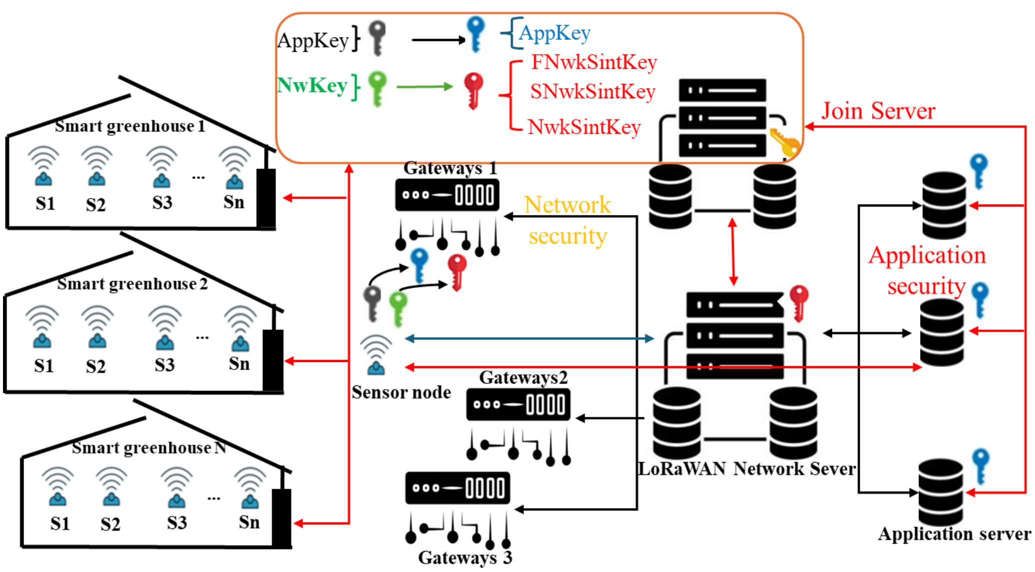

Fig. 3. LoRaWAN security architecture for end-node communication.

Smart greenhouse control and environmental monitoring using IoT technology for optimal crop productivity, plant health, and disease prevention, it is essential to maintain the greenhouse temperature and humidity at ideal levels. Environmental parameters such as temperature, humidity, CO_2 concentration, and soil moisture must be continuously monitored to prevent yield losses due to insect infestations, mildew infections, and unfavorable growing conditions (Ali et al., 2024). IoT-enabled sensor networks provide real-time environmental data, empowering growers to make informed decisions regarding greenhouse climate control. Energy efficiency for smart greenhouse automation systems leveraging LoRaWAN for ventilation and heating optimization can achieve energy savings of up to 26% (Rayhana et al., 2020). Enhancing water use efficiency through automated irrigation technologies integrated with LoRaWAN-enabled IoT systems has proven effective in optimizing irrigation scheduling and reducing water waste (Glória et al., 2020) and disease prevention such as machine learning-based predictive analytics can detect early-stage fungal infections with 87% accuracy, mitigating crop loss risks (Zhao et al., 2024). LoRaWAN connectivity enables continuous environmental monitoring, ensuring real-time modifications to climate control settings that enhance crop growth, reduce resource waste, and improve overall agricultural efficiency compared to conventional manual monitoring techniques (Ahmed et al., 2024). A typical LoRaWAN-based deployment in greenhouses involves placing sensor nodes at both canopy and root zones, spaced approximately 10–20 meters apart to ensure optimal coverage. Gateways are commonly installed at heights of 2.5 meters or more to maintain line-of-sight and reduce interference from metallic greenhouse structures (Singh et al., 2020). Future advancements in AI-driven analytics, blockchain-based data security, and integrated automation will further enhance LoRaWAN's role in predictive greenhouse management, fostering sustainable smart farming practices and improving food security worldwide (Lim et al., 2023). Fig. 4 represents an IoT-based smart agriculture monitoring system, structured into four layers: perception layer, network layer, middleware layer, and application layer. Each layer plays a distinct role in data acquisition, transmission, processing, and visualization.

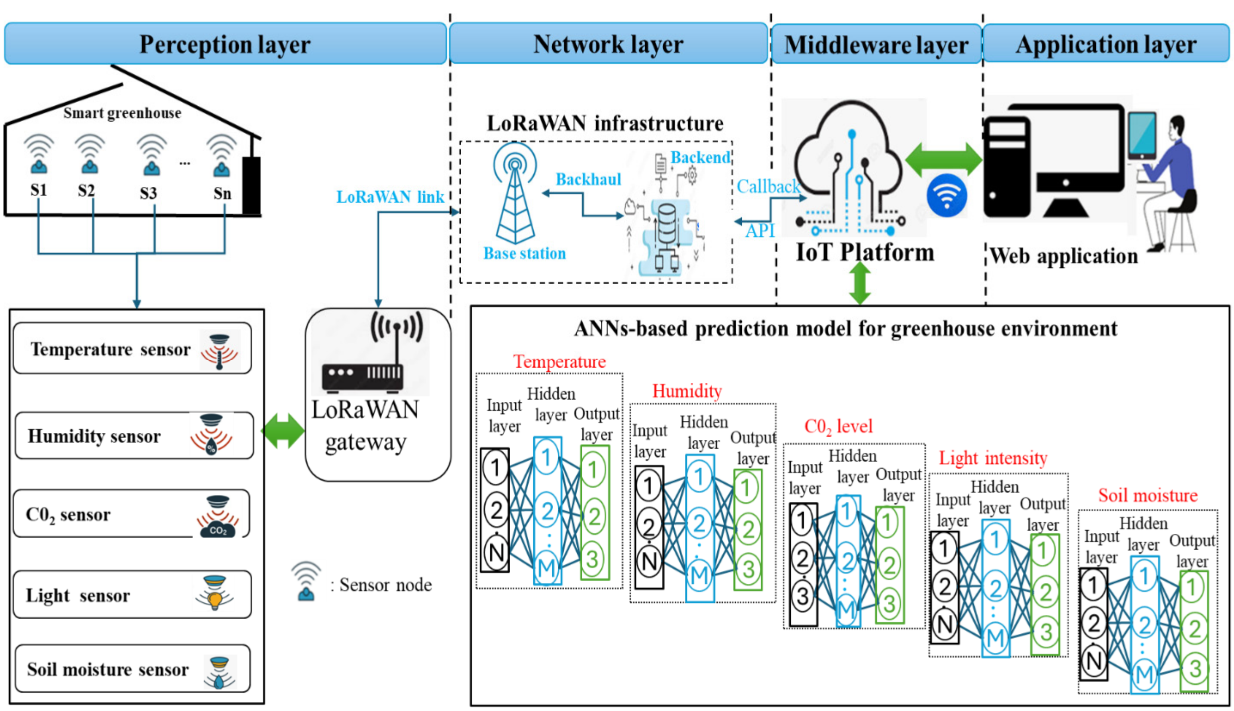

Fig. 4. IoT-based spatial monitoring and environment prediction system for smart greenhouses.

Spatial environmental monitoring in smart greenhouses

Spatial variability refers to the differences in environmental and soil conditions that occur naturally or due to external influences in a greenhouse (Iqbal et al., 2023). Uneven light distribution, temperature fluctuations, soil nutrient imbalances, and inconsistent humidity levels can negatively impact plant growth, leading to suboptimal yields and quality variations (Iqbal et al., 2023; Reza et al., 2023). Addressing these disparities is crucial for maintaining uniform growth conditions, ensuring that each plant receives the optimal resources required for its development. Spatial environmental monitoring in smart greenhouses collects and analyzes data like temperature, humidity, CO_2 concentrations, light intensity, and soil moisture sensors across many locations (Ahmed et al., 2019). Spatial monitoring utilizes dispersed sensor networks to collect real-time environmental variability data, enabling adaptive management of plant growth, resource usage, and production, unlike single-point greenhouse monitoring methods (Bersani et al., 2022). In greenhouse environments, variations in temperature and humidity often caused by inconsistent airflow, structural shading, or equipment heat can influence transpiration, photosynthesis, and nutrient uptake, thereby complicating precise climate control (Costantino et al., 2021). Temperature variations over 2°C among greenhouse zones can diminish crop uniformity by 12% (Ahmed et al., 2019). Localized CO_2 variations might lower carbon absorption rates, lowering yield potential (Parry et al., 2011). Recent Studies show that producers need real-time geographical monitoring for temperature adjustment to manage climatic variations proactively (Parra-López et al., 2024). Site-specific temperature management increased greenhouse crop output by 18% and reduced energy usage by 25%, regardless of spatial environmental monitoring (Nadal et al., 2017). Resource loss has increased by 30% due to regional water and nutrient application unpredictability (Mueller et al., 2012). Despite these obstacles, spatial environmental monitoring has several benefits. Precision agriculture greenhouse operations can benefit from data-driven, site-specific treatments (Getahun et al., 2024). Climate modeling suggests that automated control systems for spatial environmental monitoring reduce plant stress and increase production (Manfreda et al., 2018). Precision irrigation and fertilization using spatial data analysis have reduced water and fertilizer use by 35% while preserving crop quality (Ahmed et al., 2023). Automation reduces plant stress and boosts output (Chauhdary et al., 2024). Precision irrigation and fertilization using spatial data analysis can save 35% while preserving production quality (Lu et al., 2022). Table 2 illustrates the comprehensive summary of sensor types, measurement ranges, accuracy levels, and spatial monitoring applications for environmental parameter assessment.

Table 2. Environmental sensors for spatial monitoring in smart greenhouse.

Type	Name	Range	Accuracy	Application	References
Temperature sensors	Thermocouple sensor	-200°C to 1300°C	±0.5°C to ±2.0°C	Spatial temperature distribution	Zhao et al. (2021)
	RTD sensor	-200°C to 850°C	±0.1°C to ±0.5°C	Precise localized temperature data	Ruan et al. (2023)
	Thermistor sensor	-50°C to 150°C	±0.2°C to ±1.0°C	Fine-scale monitoring	Navarro-Serrano et al. (2019)
	Silicon sensor	-55°C to 150°C	±0.5°C	Temperature mapping	Sadiqbatcha et al. (2022)

Table 2. Environmental sensors for spatial monitoring in smart greenhouse. (Continued)

Type	Name	Range	Accuracy	Application	References
Humidity sensors	Capacitive sensor	0% to 100% RH	±2% to ±5% RH	Wide-area assessment	Renzone et al. (2022)
	Resistive sensor	10% to 95% RH	±3% to ±7% RH	Localized humidity variations	Ismail et al. (2016)
	Thermal sensor	0% to 100% RH	±2% to ±5% RH	Spatial distribution of humidity	Kowli et al. (2023)
CO_2 sensors	Optical-based sensor	0 to 5000 ppm	±50 ppm or ±3%	CO_2 concentration mapping	Buckley et al. (2020)
	Electrochemical sensor	0 to 10000 ppm	±50–100 ppm	Spot measurements in the greenhouse	Bassous et al. (2024)
	Metal oxide-based sensor	400 to 5000 ppm	±100–200 ppm	General air quality monitoring	Zhang et al. (2022)
Light sensors	Photo active radiation sensor	400 to 700 nm	±5% to ±10%	Light intensity variation mapping	Zeng et al. (2019)
	Photo diode sensor	320 to 1100 nm	±2% to ±5%	Point-based light level detection	Honkavaara et al. (2016)
	Photo transistor sensor	400 to 700 nm	±5% to ±10%	Small-scale light monitoring	Tang et al. (2024)
	Pyranometer sensor	300 to 2800 nm	±3% to ±5%	Greenhouse-wide light distribution	da Rocha et al. (2021)
	Light-dependent resistor sensor	400 to 700 nm	±10%	Simple brightness level mapping	Al-Haija and Samad (2020)
Soil moisture sensors	Tensiometer sensor	0 to -100 kPa	±1% to ±5%	Point-based soil moisture levels	Bierer and Tang (2024)
	Granular matrix sensor (GMS)	0 to -200 kPa	±2% to ±5%	Distributed soil moisture tracking	Gorthi et al. (2020)
	TDR sensor	0% to 100% VWC	±1% to ±3%	High-resolution soil mapping	Bicamumakuba et al. (2024)
	Capacitive sensor	5% to 50% VWC	±3% to ±7%	Large-scale soil moisture assessment	Adla et al. (2020)

Environmental monitoring serves as a smart greenhouse with IoT-enabled real-time data collecting, analysis, and control. To monitor local greenhouse conditions, IoT sensor networks use ecological sensors like temperature, humidity, CO_2, light intensity, and soil moisture sensors (Hosny et al., 2024). The claim was that by 20–30% suitable sensor placement including height and inter-sensor spacing improves data dependability and predictive modelingfor or real-time environmental data collecting. LoRaWAN facilitates continuous, long-range data acquisition, which is fundamental for training and operating AI-based predictive models in greenhouse environments. Recent studies have demonstrated that LoRa-integrated deep learning systems can achieve over 94% accuracy in forecasting microclimatic conditions and plant diseases, underscoring the synergy between reliable data transmission and advanced analytics (Ihoume et al., 2023). Fig. 5 displays the LoRaWAN mesh network topology (Cotrim and Kleinschmidt, 2020). Smart greenhouse sensor networks would benefit from LoRaWAN low-power, long-range wireless communication, which uses 50% less power than Wi-Fi and Zigbee (Arshad et al., 2022). LoRaWAN-based monitoring systems effectively transmit data. Conventional wireless methods exhibited 40% poorer network stability and data accuracy than LoRaWAN-enabled greenhouses (Citoni, 2022). Edge computing improves system responsiveness by lowering cloud dependency and latency, therefore lessening their influence. While keeping extremely accurate greenhouse environmental parameter prediction compared to cloud-based processing, edge computing reduces data transmission costs (Hamdan et al., 2020). Blockchain-based data security guards greenhouse monitoring data from cyberattacks and illegal access evaluated LoRaWAN and 5G hybrid communication systems for data transmission efficiency enhanced sensor calibration and produced machine-learning-driven anomaly detection methods (Garcia and Patel, 2017).

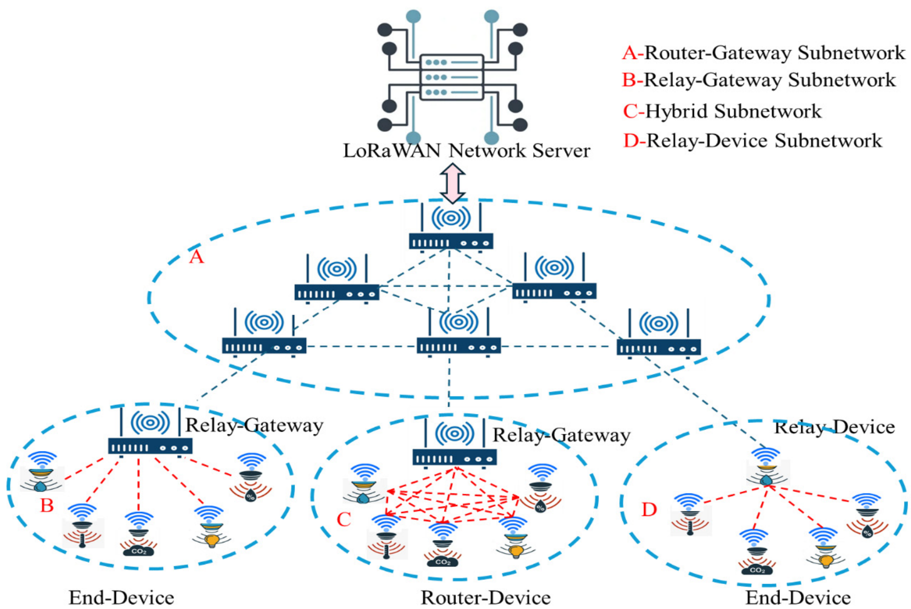

Fig. 5. LoRaWAN mesh network topology for real-time environmental data collection.

Environmental prediction models for smart greenhouses control

Environmental prediction models for smart greenhouses control are essential for enhancing climate regulation, energy efficiency, and plant growth management. These models are categorized into two primary types: those based on energy and mass equations, and those based on inputs, outputs, and optimization methods (Chen et al., 2022). Artificial intelligence (AI) and machine learning (ML) have led smart greenhouses to increasingly depend on AI-driven environmental prediction models to improve precision agriculture (Hoseinzadeh and Garcia, 2024). Microclimate prediction models employ machine learning algorithms, such as regression analysis, artificial neural networks, and time-series forecasting, to anticipate variations in environmental concentration (Han et al., 2024). The forecasts provide immediate environmental modifications, enhancing cultivation conditions while reducing resource utilization. The illustrated formula 1 and 2 shows the energy balance equation for greenhouse temperature prediction and AI-based disease prediction using logistic regression for the environmental prediction models for smart greenhouses control (Lee et al., 2024).

$$C_p m \frac{dT}{dt} = Q_{in} - Q_{out} + Q_{gen} \tag{1}$$

$$P\left(y = \frac{1}{x}\right) = \frac{1}{1 + e^{(\omega_1 x_{1+\omega_2} x_{2+} \ldots\ldots + \omega_n x_n + b)}} \tag{2}$$

Where, C_p represents the specific heat capacity of air, m is the mass of air inside the greenhouse, dT/dt is the rate of temperature change, Q_{in} is the incoming heat energy from solar radiation and artificial heating, Q_{out} is the outgoing heat loss due to ventilation, conduction, and radiation and Q_{gen} in the internally generated heat from plant respiration and heating systems while P(y=1/x) is the probability of disease occurrence, ω_i is the model weights and bi s the bias term.

Recent studies have shown that integrating data-driven decision support systems (DSS) into smart greenhouse control frameworks enhances climate management strategies, reducing energy consumption by up to 25% (Ukoba et al., 2024). Fig. 6 illustrates microclimate prediction, energy optimization, and plant growth management using computational models. The models are classified into energy/mass equation-based models and data-driven AI/optimization models for analysis to enhance smart greenhouse control.

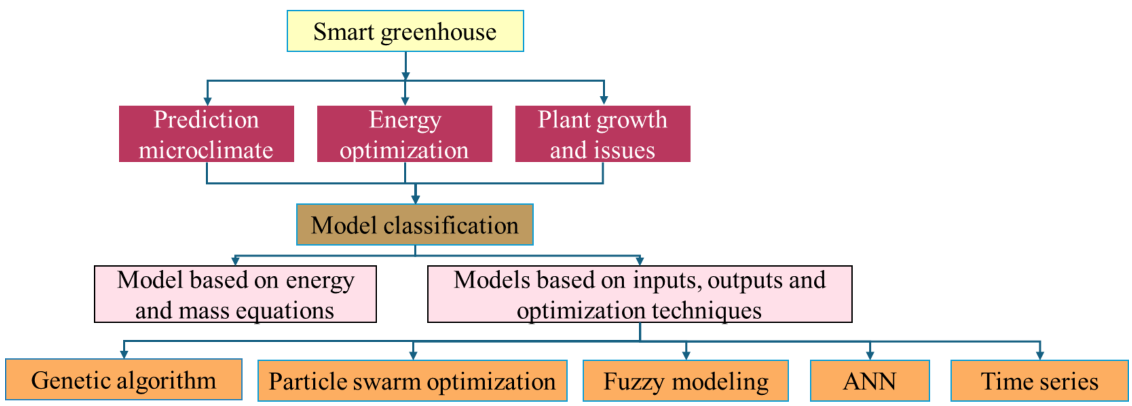

Fig. 6. The environmental prediction model framework for smart greenhouses.

Energy optimization models improve efficiency with AI-based methods including genetic algorithms, PSO, and fuzzy modeling. Research shows that AI-driven temperature control systems increase crop uniformity and output by 18% while reducing energy use (Habeeb et al., 2023). The AI-enhanced irrigation and fertilization models reduced water and fertilizer utilization by 35% without affecting crop quality and monitoring plant health and identifying risks, plant growth, and issue detection models use AI-driven disease prediction and optimization (Wei et al., 2024). A logistic regression model can be used for AI-based disease detection: where are environmental and physiological variables, model weights, bias term, and sigmoid activation function. AI-based disease detection systems can detect early-stage fungal infections with 87% accuracy, reducing crop losses (Fatima, 2025). Predictive AI-based environmental regulation boosts crop output by 20%, demonstrating AI importance in sustainable greenhouse management (Kale, 2024). The models show that artificial neural networks, genetic algorithms, fuzzy modeling, and time-series forecasting are increasingly used to optimize greenhouse conditions. Future research should improve real-time processing using edge computing and integrate blockchain technology for safe data management to make AI-powered greenhouse management resilient and efficient.

Security and privacy considerations in IoT and LoRaWAN communication

Effective communication in smart greenhouses utilizing LoRaWAN technology requires a focus on security and privacy, given the sensitivity of environmental data and the potential security threats to agricultural IoT networks (Garcia and Patel, 2017). Key management issues, device authentication, and repeat assaults all depend on improved security mechanisms. You et al. (2018) pointed out that LoRaWAN networks were vulnerable to unwanted access due to static session keys, emphasizing the need for dynamic authentication and key rotations. The controlled penetration test of a smart agricultural LoRaWAN system revealed that ABP devices exhibited a higher vulnerability to packet injection attacks compared to Over-The-Air-Activation (OTAA) devices. The use of blockchain-based authentication decreases illegal access attempts from 14 per hour to just two when paired with ECC-based encryption, thereby enhancing network resilience (Kuntke et al., 2022).

Packet transmission frequency and network traffic analysis allow attackers to determine geographical patterns and activity levels, compromising privacy. In a large-scale privacy investigation of LoRaWAN installations in smart agricultural systems. Asteriou et al. (2024) discovered that nodes broadcasting at fixed intervals without adaptive scheduling were more vulnerable to pattern recognition attacks. Field testing reveals that improved LoRaWAN protocol with pseudonymized device addresses reduces packet correlation by 40%. Privacy-preserving federated learning models reduce data transport issues, while dynamic key management frameworks and AI prevent intrusion. Future advancements in blockchain-based security, AI-driven threat detection, post-quantum cryptography, and zero-trust architecture will further strengthen IoT and LoRaWAN networks against evolving cyber threats. As precision agriculture increasingly relies on IoT, prioritizing security and privacy measures will be crucial to ensuring reliable and resilient smart greenhouse operations.

Challenges and future directions

Despite the significant advancements in IoT-enabled LoRaWAN gateways for smart greenhouse monitoring, several challenges remain that must be addressed to maximize their efficiency, scalability, and reliability. As the number of sensor nodes increases, LoRaWAN networks face congestion, packet collisions, and reduced data transmission efficiency. Interoperability between different IoT platforms, sensor types, and communication protocols remains a key challenge, requiring standardized frameworks and seamless integration strategies. Although LoRaWAN offers long-range communication, its data transmission is susceptible to packet loss, signal attenuation, and interference, particularly in dense sensor environments. Just-In-Time (JIT) scheduling and Adaptive Data Rate (ADR) mechanisms need further optimization to reduce latency and improve real-time decision-making.

Many greenhouse sensors and gateways rely on battery power, requiring energy-efficient designs for prolonged operation. While LoRaWAN enables low-power communication, optimizing duty cycles and integrating renewable energy sources (e.g., solar energy) is crucial for sustainable deployment. LoRaWAN's security framework employs AES-128 encryption for secure end-to-end communication, but vulnerabilities still exist, such as unauthorized access, jamming attacks, and data spoofing. Blockchain-based security solutions and advanced encryption techniques can further enhance data integrity and privacy. Greenhouses experience fluctuating environmental conditions, including temperature extremes, humidity variations, and electromagnetic interference. Ensuring the robustness of LoRaWAN-enabled IoT hardware and maintaining stable network performance under diverse climatic conditions is a challenge that requires further research.

AI-powered predictive models can enhance the accuracy of spatial environmental monitoring, enabling automated decision-making for climate control and irrigation management. Future studies should focus on real-time AI processing through edge computing to reduce cloud dependency and improve response times. Combining LoRaWAN with other wireless communication technologies such as 5G, LPWAN, and satellite communication can provide more reliable, scalable, and high-speed data transmission for large-scale smart greenhouse applications. Edge computing reduces latency and enhances system responsiveness by processing environmental data locally before transmitting it to the cloud. Future research should explore efficient edge-computing architectures and their integration with LoRaWAN for smart greenhouse monitoring.

To improve energy sustainability, smart greenhouses should integrate renewable energy sources such as solar panels and energy-harvesting techniques to power IoT sensor nodes and gateways efficiently. Implementing blockchain technology can enhance data security, provide transparent record-keeping, and protect against cyber threats in LoRaWAN-enabled greenhouse monitoring systems. Future studies should examine the feasibility of blockchain-based smart contracts for automated greenhouse management. Enhancing the accuracy and reliability of environmental monitoring requires multi-sensor fusion techniques that combine data from different types of sensors. Machine learning algorithms can be used to calibrate sensors dynamically and improve data consistency.

By addressing these challenges and exploring future research directions, LoRaWAN-enabled IoT solutions can revolutionize smart greenhouse management, improving sustainability, efficiency, and food security.

Conclusions

The integration of IoT-enabled LoRaWAN gateways in smart greenhouses has revolutionized spatial environmental monitoring, enabling real-time data collection, predictive analytics, and automated climate control. This review has highlighted the key advantages of LoRaWAN technology, including its long-range communication capabilities, low power consumption, and cost-effectiveness for large-scale greenhouse applications. LoRaWAN networks facilitate the seamless transmission of crucial environmental parameters such as temperature, humidity, soil moisture, CO_2 concentration, and light intensity, providing growers with actionable insights to optimize crop yield and resource utilization. The deployment of machine learning models further enhances predictive decision-making, enabling proactive interventions to maintain optimal growing conditions.

However, challenges such as network scalability, data reliability, security vulnerabilities, and energy management must be addressed to maximize the effectiveness of LoRaWAN-based monitoring systems. Future advancements in AI-driven analytics, edge computing, blockchain security, and hybrid communication networks will play a crucial role in overcoming these limitations and enhancing the robustness of smart greenhouse technologies.

As global food security challenges intensify, the continued development of IoT-based smart farming solutions will be essential for sustainable agriculture. By integrating LoRaWAN with AI, automation, and secure data management systems, greenhouse operations can achieve higher efficiency, reduce environmental impact, and improve crop quality. Ongoing research and innovation in this field will ensure that smart greenhouses remain at the forefront of precision agriculture, contributing to a more resilient and productive agricultural ecosystem.

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Conflict of Interest

All authors declare there is no conflict of interest.

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