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Research Article

SMART FARMING SYSTEMS USING INTERNET OF THINGS AND WIRELESS SENSOR NETWORKS

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Abstract
Agricultural systems increasingly face challenges related to water scarcity, climate variability, resource inefficiency, and growing demands for sustainable food production, creating an urgent need for precise and responsive farming technologies. This study aimed to evaluate the effectiveness of an integrated smart farming system using the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) for environmental monitoring, precision irrigation, resource optimization, and agricultural decision-making. A field-based experimental design was conducted across 24 agricultural plots, comprising 12 IoT–WSN-assisted plots and 12 conventionally managed control plots. Environmental sensors continuously monitored soil moisture, temperature, humidity, and microclimatic conditions, while network and agricultural performance were evaluated using communication reliability, water consumption, response time, and crop productivity indicators. Results showed that IoT–WSN-assisted management reduced irrigation water consumption by approximately 27%, improved soil moisture stability, shortened response times to environmental changes, and increased crop yields compared with conventional management. High packet delivery, network availability, and data completeness supported reliable real-time decision-making. The study concludes that smart farming effectiveness depends on an integrated sensing–communication–processing–decision–action cycle that transforms reliable field data into timely agricultural interventions, offering a scalable framework for improving resource efficiency, productivity, and sustainable agricultural management under increasingly dynamic environmental conditions worldwide.

Keywords: Agricultural Sustainability; Internet of Things; Precision Agriculture; Smart Farming; Wireless Sensor Networks.

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INTRODUCTION

Global agriculture is experiencing increasing pressure to produce sufficient, nutritious, and affordable food under conditions of population growth, climate variability, land degradation, water scarcity, and declining availability of agricultural labor (Salaria & Rakhra, 2024). Conventional farming practices that depend heavily on generalized field observations and uniform resource application often struggle to respond efficiently to spatial and temporal variations in crop conditions (Prathap et al., 2024). Precision agriculture has consequently emerged as an important approach for improving agricultural productivity through data-driven management of soil, water, crops, and environmental resources (Shrivastav et al., 2024). Digital transformation further expands this approach by enabling agricultural decisions to be based on continuous field information rather than periodic manual observation.

Internet of Things (IoT) technologies have created new possibilities for developing connected agricultural environments in which physical objects, sensors, communication devices, cloud platforms, and decision-support applications continuously exchange information (Shaikh et al., 2025). IoT-enabled farming systems can monitor soil moisture, temperature, humidity, light intensity, rainfall, crop conditions, irrigation performance, and other environmental parameters in near real time (Basavaraju et al., 2024). Continuous access to these data allows farmers to recognize changes in field conditions earlier, optimize resource allocation, and make more precise management decisions (K. et al., 2024). Smart farming therefore represents a transition from experience-dominated agricultural management toward digitally supported, evidence-based, and increasingly automated production systems.

Wireless Sensor Networks (WSNs) constitute a critical technological layer within smart farming because they enable geographically distributed sensor nodes to collect and transmit agricultural data across fields without extensive wired infrastructure (Abuthahir Riazulhameed et al., 2024). Integration between IoT architectures and WSNs can support precision irrigation, microclimate monitoring, greenhouse management, crop health assessment, pest-risk detection, and environmental control (Gunapriya et al., 2024). Recent developments in low-power communication, edge computing, cloud analytics, artificial intelligence, and energy-efficient sensing have further increased the potential of these systems (Kim et al., 2025). Effective integration of IoT and WSN technologies may therefore provide a scalable foundation for improving productivity, resource efficiency, environmental sustainability, and resilience in modern agriculture.

Practical implementation of smart farming remains constrained by technical, economic, environmental, and operational challenges despite rapid technological development (Azlan et al., 2024). Agricultural environments frequently involve unstable network coverage, heterogeneous field conditions, limited energy availability, sensor degradation, communication interference, and difficulties in maintaining distributed devices (Taha et al., 2025). Small and geographically dispersed sensor nodes may also experience restricted battery capacity and limited computational resources (Arulmozhi et al., 2024). These constraints can reduce data reliability, shorten network lifetime, interrupt communication, and weaken the usefulness of real-time agricultural monitoring systems.

Existing IoT-based agricultural solutions frequently operate as fragmented technological components rather than integrated decision-support ecosystems (Vlaicu et al., 2024). Sensor devices may successfully collect environmental measurements without providing efficient mechanisms for transforming raw data into timely and actionable farming decisions (Šarauskis et al., 2024). Interoperability problems among sensing devices, communication protocols, gateways, cloud platforms, and farm-management applications can further restrict scalability. Data security, privacy, cybersecurity, system complexity, and maintenance requirements create additional barriers, particularly when agricultural users lack specialized technical expertise.

Economic accessibility represents another critical challenge because the benefits of smart farming technologies may not be distributed equally across agricultural communities (Qureshi et al., 2025). Large commercial farms can often invest in advanced sensors, connectivity infrastructure, automation, and analytics, whereas smallholder farmers may face financial, technical, and institutional constraints (Eladl et al., 2024). Technology designed without sufficient attention to affordability, usability, local infrastructure, and farmer capabilities may widen the digital divide rather than improve agricultural inclusion (Tangorra et al., 2024). A meaningful smart farming framework must therefore address technological performance alongside cost-effectiveness, accessibility, scalability, environmental sustainability, and practical usability.

This study aims to examine the design and performance of an integrated smart farming system based on IoT and Wireless Sensor Networks for continuous agricultural monitoring and data-driven resource management (Chandran et al., 2025). The investigation focuses on how distributed sensor nodes, communication networks, gateways, data-processing mechanisms, and decision-support functions can operate as a coordinated technological architecture (Hartono et al., 2024). Particular attention is directed toward monitoring soil and environmental variables that influence crop management and irrigation decisions.

The study also seeks to evaluate relationships among sensing accuracy, network reliability, energy efficiency, communication performance, data latency, and agricultural decision effectiveness (Houssein et al., 2024). System performance is examined under different environmental and operational conditions to determine whether IoT–WSN integration can maintain reliable data transmission while reducing unnecessary energy consumption and resource use (Heidari et al., 2024). Evaluation of these dimensions is expected to identify technical configurations that balance monitoring precision, network lifetime, operational efficiency, and scalability.

A broader objective is to assess the practical contribution of IoT–WSN smart farming to precision agriculture, particularly in relation to water management, crop monitoring, resource efficiency, and sustainable production (Zhang et al., 2025). The study seeks to formulate an implementation framework that connects technological architecture with agricultural decision-making rather than treating sensing and communication as isolated engineering functions (Yu et al., 2025). Findings are expected to provide relevant evidence for farmers, agricultural engineers, IoT developers, researchers, policymakers, and technology providers seeking scalable digital solutions for sustainable agricultural transformation.

Existing research has extensively examined IoT applications, WSN architectures, precision agriculture, smart irrigation, environmental sensing, cloud computing, and agricultural automation (Baseer et al., 2024). Numerous studies demonstrate the technical feasibility of using sensors to collect agricultural data and wireless networks to transmit information remotely (Vitazkova et al., 2024). A substantial portion of the literature, however, evaluates individual technological components or specific applications without comprehensively examining how sensing accuracy, communication reliability, energy consumption, decision support, and agricultural outcomes interact within a unified smart farming system.

Research on agricultural WSNs frequently prioritizes routing protocols, communication range, network topology, or energy consumption, whereas IoT-oriented studies often emphasize cloud connectivity, remote monitoring, or application interfaces (Fernando & Lăzăroiu, 2024). Agricultural studies may separately focus on irrigation efficiency, crop productivity, or environmental monitoring (Qiu et al., 2024). Fragmentation among these research streams creates an important gap because technological performance does not automatically translate into meaningful agricultural benefits. A technically sophisticated network may have limited practical value when its data are delayed, difficult to interpret, costly to maintain, or poorly connected to farm-management decisions.

Limited empirical attention has also been given to the trade-offs among system accuracy, energy efficiency, affordability, scalability, interoperability, and long-term field reliability (Ali et al., 2025). Many proposed smart farming systems are validated through prototypes, simulations, controlled environments, or relatively short experimental periods, leaving uncertainty about their performance under heterogeneous real-world agricultural conditions (Kumar et al., 2025). Greater research is therefore required to connect engineering performance with practical farming requirements and sustainability outcomes (Roberts et al., 2024). This study addresses that gap by evaluating IoT and WSN technologies as an integrated agricultural decision-support architecture rather than merely as interconnected sensing devices.

The novelty of this study lies in developing an integrated IoT–WSN smart farming framework that simultaneously considers environmental sensing, communication reliability, energy efficiency, real-time data processing, and agricultural decision support (Tian et al., 2024). The framework conceptualizes smart farming as a continuous data-to-decision cycle in which field conditions are sensed, transmitted, processed, interpreted, and translated into actionable management responses (Lakhiar et al., 2024). Such integration moves beyond conventional monitoring-oriented systems by emphasizing the functional connection between technological performance and agricultural decision quality.

Scientific contribution emerges from linking IoT architecture and Wireless Sensor Network performance with the operational requirements of precision and sustainable agriculture (Bukhari et al., 2024). The proposed perspective evaluates system effectiveness through interconnected technological and agricultural dimensions rather than relying exclusively on isolated engineering indicators (El Khediri et al., 2024). Network lifetime, sensing reliability, latency, interoperability, resource optimization, and decision usefulness are treated as mutually dependent components of smart farming performance (Yang et al., 2024). This approach can provide a more comprehensive analytical basis for evaluating whether digital agricultural technologies generate practical value beyond successful data collection.

Practical justification arises from the need for agricultural systems that can increase productivity while reducing inefficient use of water, energy, fertilizers, and other production resources (Anitha et al., 2024). Climate uncertainty and resource constraints make continuous monitoring and responsive farm management increasingly important, yet technological solutions must remain reliable, scalable, economically feasible, and understandable to end users (Nancharaiah et al., 2025). An integrated IoT–WSN architecture has the potential to support precision irrigation, early detection of environmental stress, optimized resource allocation, and timely farm-management decisions (Sheela et al., 2025). Development and evaluation of such a framework are therefore important for advancing smart agriculture while ensuring that digital innovation contributes meaningfully to productivity, sustainability, resilience, and the broader modernization of agricultural systems.

RESEARCH METHOD

Research Design

This study employed a field-based experimental research design to develop, implement, and evaluate an integrated smart farming system using the Internet of Things (IoT) and Wireless Sensor Networks (WSNs). The research focused on establishing a continuous data-to-decision architecture capable of monitoring agricultural conditions, transmitting field data, processing sensor information, and supporting timely farm-management decisions (Pandiyan et al., 2024). The experimental design enabled systematic evaluation of system performance under actual agricultural conditions while examining interactions among sensing accuracy, communication reliability, energy efficiency, data latency, resource utilization, and agricultural decision effectiveness. The proposed architecture consisted of distributed sensor nodes, wireless communication modules, an IoT gateway, edge or cloud-based data processing, a monitoring dashboard, and automated decision-support functions.

The experimental framework compared IoT–WSN-assisted farming management with conventional field-monitoring practices (Luo et al., 2024). Experimental plots were equipped with interconnected sensor nodes that continuously measured soil moisture, soil temperature, ambient temperature, relative humidity, light intensity, and relevant environmental parameters, while comparison plots were managed through conventional observation and predetermined agricultural schedules. Precision irrigation represented a principal application of the developed system because water management provides a measurable context for evaluating the practical contribution of real-time sensing and automated decision support. Irrigation recommendations were generated according to predefined threshold values derived from soil moisture conditions, crop requirements, and environmental measurements.

System evaluation was conducted at technological and agricultural levels. Technological performance was assessed through sensing accuracy, packet delivery ratio, network availability, communication latency, energy consumption, signal stability, data completeness, and estimated network lifetime (Kaviarasan & Srinivasan, 2024). Agricultural performance was evaluated through irrigation water consumption, soil moisture stability, resource-use efficiency, crop growth indicators, yield-related measures, and response time to environmental changes. Integration of these dimensions enabled the study to determine whether improved network performance translated into meaningful agricultural benefits rather than evaluating the IoT–WSN architecture solely through engineering indicators.

Research Target/Subject

The research target encompasses agricultural cultivation areas suitable for sensor-based monitoring and precision resource management, supported by farmers and field personnel who provide contextual operational data on conventional farming practices. The sample consists of 24 agricultural plots selected through purposive sampling based on uniform criteria such as crop type, cultivation period, soil characteristics, irrigation access, plot size, and environmental exposure, divided equally into 12 experimental plots equipped with the IoT–WSN system and 12 control plots under conventional management. To comprehensively evaluate the system, sampling units are structured across three analytical levels: the technological unit (individual sensor nodes, communication links, gateways, and data transmission events), the environmental unit (repeated measurements of soil moisture, temperature, humidity, and light intensity), and the agricultural unit (plot-level outcomes regarding irrigation consumption, crop growth, and yields).

Research Procedure

Research implementation commenced with site assessment, system architecture design, sensor calibration, network configuration, pilot testing, and baseline data collection. Agricultural plots were evaluated for soil characteristics, crop conditions, irrigation infrastructure, wireless communication coverage, and environmental variability. Sensor nodes were installed at representative locations and configured to collect environmental measurements at standardized intervals. The gateway received transmitted data and forwarded them to the processing platform, where measurements were stored, analyzed, and displayed through the monitoring dashboard. Baseline measurements were collected before experimental implementation to establish comparable initial conditions between smart farming and conventional management plots.

Experimental implementation followed a continuous sensing–transmission–processing–decision–action cycle. Sensor nodes measured field conditions at predetermined intervals and transmitted data through the wireless network to the IoT gateway. The processing platform analyzed incoming measurements according to predefined agricultural thresholds and generated alerts or irrigation recommendations when soil moisture or environmental conditions reached specified levels. Irrigation decisions in experimental plots were informed by real-time sensor information, while control plots followed conventional irrigation practices based on predetermined schedules and field observations. System logs continuously recorded communication performance, energy consumption, sensor readings, network interruptions, and decision-response events throughout the experimental period.

Data analysis combined technological performance evaluation with agricultural outcome assessment. Descriptive statistics were used to summarize sensor readings, communication performance, environmental conditions, water consumption, and crop indicators. Independent-samples and paired-samples statistical tests were applied where appropriate to examine differences between experimental and control conditions. Analysis of variance was employed to evaluate differences across observation periods and field conditions, while regression analysis examined relationships among environmental variables, system performance, irrigation decisions, and agricultural outcomes. Effect sizes and confidence intervals were calculated to determine the practical significance of observed differences.

Final evaluation integrated network-level and agricultural-level findings to determine the overall effectiveness of the IoT–WSN smart farming system. Relationships among sensing accuracy, packet delivery, communication latency, energy efficiency, irrigation responsiveness, water-use efficiency, and crop performance were examined to identify critical factors influencing system effectiveness. Field observations and farmer feedback were used as supplementary contextual evidence to interpret operational feasibility, usability, maintenance requirements, and implementation challenges. The integrated analysis provided a comprehensive assessment of whether the proposed IoT–WSN architecture could transform reliable field data into timely agricultural decisions while improving resource efficiency, operational responsiveness, and the sustainability of smart farming practices.

Instruments, and Data Collection Techniques

Data collection instruments consisted of calibrated environmental sensors, wireless sensor nodes, communication modules, IoT gateways, data loggers, cloud or edge computing platforms, reference measurement devices, and a web-based monitoring dashboard. Sensor nodes incorporated soil moisture sensors, soil temperature sensors, ambient temperature and humidity sensors, and light intensity sensors according to field-monitoring requirements. Additional environmental sensors were incorporated where relevant to the selected crop and cultivation context. A microcontroller-based processing unit collected sensor readings and transmitted them through the selected wireless communication protocol to a gateway connected to the IoT data-management platform.

Network performance was measured using system-generated logs recording packet transmission, packet loss, received signal strength, latency, node availability, energy consumption, communication interruptions, and data completeness. Reference instruments were used to validate sensor measurements through periodic comparison with calibrated manual measurements. Agricultural performance was documented using irrigation flow meters, field observation sheets, crop growth measurement instruments, soil moisture reference measurements, and production records. The IoT dashboard visualized real-time environmental conditions, historical trends, system status, threshold alerts, and irrigation recommendations to support operational decision-making.

Instrument accuracy and system reliability were established through calibration, pilot deployment, repeated measurement, and comparison with reference instruments before full-scale implementation. Sensor accuracy was evaluated using measurement error, mean absolute error, root mean square error, and coefficient of determination where applicable. Communication reliability was assessed through packet delivery ratio, network uptime, latency, and data completeness. Functional testing examined sensor-to-gateway communication, database synchronization, dashboard visualization, alert generation, and decision-support responses. Pilot testing also identified potential problems related to sensor drift, battery performance, communication interference, environmental exposure, and network instability before the main experimental phase.

Data Analysis Technique

Data analysis integrates technological performance evaluations with agricultural outcome assessments using a combination of descriptive and inferential statistical methods. Descriptive statistics are utilized to summarize environmental sensor readings, network communication metrics, water consumption, and crop indicators, establishing clear baseline and ongoing trends. To evaluate the system's efficacy, independent-samples and paired-samples statistical tests along with Analysis of Variance (ANOVA) are applied to determine significant differences between the IoT–WSN experimental plots and conventional control plots across various observation periods and field conditions. Furthermore, regression analysis, alongside calculations of effect sizes and confidence intervals, is employed to model relationships among environmental variables, network parameters, irrigation decisions, and crop performance, ultimately linking technical network reliability to practical agricultural benefits and operational feasibility.

RESULTS AND DISCUSSION

The field experiment generated continuous environmental, network, and agricultural data from 24 agricultural plots, consisting of 12 plots managed through the IoT–WSN smart farming system and 12 control plots managed through conventional monitoring and irrigation practices. Environmental measurements included soil moisture, soil temperature, ambient temperature, relative humidity, and light intensity, while technological indicators comprised packet delivery ratio, network availability, communication latency, data completeness, and node energy consumption. Agricultural indicators included irrigation water use, soil moisture stability, crop growth, and final yield. A total of 98,640 sensor observations were recorded during the experimental period, of which 96,870 were successfully transmitted and stored, representing an overall data completeness rate of 98.21%. Secondary records from irrigation logs, crop-monitoring sheets, and historical field-management documentation were used to verify differences between sensor-assisted and conventional agricultural practices.

Table 1. Comparative Performance of IoT–WSN Smart Farming and Conventional Farming Systems

Performance Indicator	IoT–WSN Smart Farming	Conventional Farming
Mean soil moisture stability (%)	82.6 ± 5.4	68.9 ± 8.1
Irrigation water use (m^3/plot)	184.7 ± 15.6	252.9 ± 21.4
Irrigation response time (minutes)	18.4 ± 5.7	94.6 ± 24.8
Crop growth index	8.42 ± 0.51	7.31 ± 0.66
Mean yield (kg/plot)	426.8 ± 31.7	367.5 ± 35.9
Packet delivery ratio (%)	97.8 ± 1.4	N/A
Network availability (%)	98.6 ± 0.9	N/A
Mean communication latency (seconds)	2.7 ± 0.8	N/A
Data completeness (%)	98.2 ± 1.1	N/A

Descriptive statistics indicate that the IoT–WSN-assisted plots achieved more stable soil moisture conditions while consuming substantially less irrigation water than the conventionally managed plots. Mean irrigation water consumption declined from 252.9 m^3 per plot under conventional management to 184.7 m^3 under sensor-assisted management, representing an approximate reduction of 27%. Crop yield was also 16.1% higher in the experimental plots. Network-level measurements demonstrated consistently high packet delivery, availability, and data completeness, suggesting that the wireless sensing architecture maintained reliable field operation despite changing environmental conditions.

Observed improvements in water-use efficiency were associated with the ability of distributed sensor nodes to detect spatial and temporal changes in soil moisture before irrigation decisions were made. Conventional plots generally followed predetermined irrigation schedules supplemented by visual field assessment, whereas the IoT–WSN system initiated recommendations according to real-time soil and microclimatic conditions. This difference reduced unnecessary irrigation events and prevented prolonged periods of excessive or insufficient soil moisture. Sensor-informed management therefore produced a more responsive relationship between actual crop-water conditions and irrigation application.

Network performance contributed directly to the continuity of the data-to-decision process. The packet delivery ratio of 97.8% and network availability of 98.6% allowed most environmental measurements to reach the processing platform without substantial interruption. Mean communication latency remained below three seconds, enabling threshold-based alerts to be generated rapidly when critical soil moisture conditions were detected. Short periods of packet loss were primarily observed during adverse weather conditions and temporary signal interference, yet these interruptions did not substantially compromise overall system functionality because subsequent transmissions restored data continuity.

Temporal analysis showed that differences between the two management systems became increasingly visible as crop water requirements changed throughout the cultivation period. IoT–WSN plots maintained soil moisture within the predetermined optimal range during 82.6% of monitored periods, compared with 68.9% in conventional plots. Conventional management exhibited greater fluctuations following irrigation events, with several observations indicating temporary over-irrigation followed by moisture decline before the next scheduled application. Sensor-assisted plots displayed narrower variation because irrigation decisions responded more closely to actual field conditions.

Crop performance data demonstrated a similar pattern. Plants cultivated under IoT–WSN-assisted management exhibited a mean growth index of 8.42 compared with 7.31 under conventional management, while average yield increased from 367.5 kg to 426.8 kg per plot. Field observations indicated more uniform crop development across experimental plots, particularly in areas previously characterized by uneven soil moisture. Yield improvement was not attributable to increased water application because experimental plots consumed less irrigation water, suggesting that the timing and precision of resource delivery were more influential than irrigation volume alone.

Inferential analysis confirmed statistically significant differences between IoT–WSN-assisted and conventional farming systems. Independent-samples tests showed that mean irrigation water consumption was significantly lower in experimental plots than in control plots ($t = -8.91$, $p < 0.001$, Cohen's $d = 3.64$). Soil moisture stability was significantly higher under smart farming management ($t = 4.87$, $p < 0.001$, $d = 1.99$), indicating a substantial practical effect. Crop yield also differed significantly between the two groups ($t = 4.29$, $p < 0.001$, $d = 1.75$), demonstrating that improved resource management was accompanied by measurable production benefits.

Multiple regression analysis was conducted to examine the contribution of sensing and network variables to agricultural outcomes. Soil moisture stability significantly predicted crop yield ($\beta = 0.46$, $p < 0.001$), while irrigation responsiveness demonstrated an additional significant contribution ($\beta = 0.31$, $p = 0.004$). Packet delivery ratio indirectly supported decision reliability through its association with data completeness ($\beta = 0.71$, $p < 0.001$). The overall regression model explained 64% of the variance in crop yield ($R^2 = 0.64$, adjusted $R^2 = 0.61$), indicating that environmental stability and timely data-driven intervention were important predictors of agricultural performance.

Correlation analysis revealed meaningful relationships among technological performance, environmental monitoring, resource efficiency, and agricultural outcomes. Data completeness was positively associated with irrigation decision accuracy ($r = 0.72$, $p < 0.001$), while soil moisture stability was positively correlated with crop yield ($r = 0.76$, $p < 0.001$). Irrigation water consumption showed a negative relationship with water-use efficiency ($r = -0.81$, $p < 0.001$), demonstrating that higher water application did not necessarily produce superior agricultural outcomes. Communication latency exhibited a modest negative relationship with response efficiency ($r = -0.42$, $p = 0.018$), suggesting that faster transmission supported more timely intervention.

Energy consumption and communication reliability also displayed an important technological relationship. Nodes with higher retransmission frequency consumed more energy than nodes maintaining stable wireless connectivity, indicating that communication inefficiency could shorten operational network lifetime. Packet delivery ratio was negatively associated with retransmission frequency ($r = -0.69$, $p < 0.001$), while signal stability was positively related to estimated battery longevity ($r = 0.63$, $p = 0.002$). These relationships demonstrate that smart farming performance depends not only on sensor accuracy but also on efficient communication architecture capable of maintaining reliable data flow with limited energy expenditure.

A representative case was documented in one experimental plot during a period of unusually high daytime temperature and declining soil moisture. Sensor nodes detected a progressive reduction in root-zone moisture from 41.8% to 27.6% within several hours while ambient temperature increased above the predefined thermal threshold. The system transmitted the measurements to the IoT platform, generated a low-moisture alert, and recommended irrigation before visible signs of crop water stress appeared. Irrigation was subsequently applied according to the recommended threshold, restoring soil moisture to the target range without excessive water application.

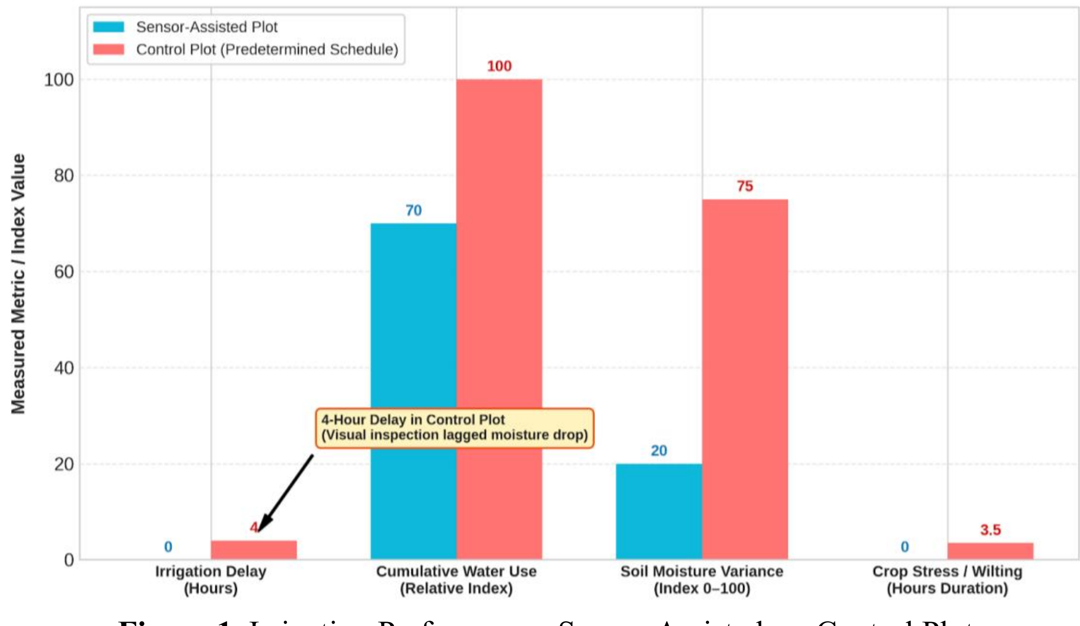

Figure 1. Irrigation Performance: Sensor-Assisted vs. Control Plot

A comparable control plot experienced similar environmental conditions but relied on the predetermined irrigation schedule and visual field inspection. Irrigation occurred approximately four hours later than in the sensor-assisted plot because crop stress was not immediately visible during the initial moisture decline. Field records documented temporary leaf wilting and greater variation in soil moisture across the plot before irrigation was applied. Cumulative water use during the event was also higher because irrigation duration followed the conventional fixed schedule rather than actual moisture requirements.

The case study illustrates how continuous environmental sensing transformed field measurements into an operational agricultural response. Early identification of declining soil moisture enabled intervention before the condition developed into observable crop stress. The value of the system therefore did not arise solely from collecting large quantities of sensor data; its practical contribution depended on converting measurements into threshold-based recommendations at an appropriate time. This finding supports the proposed data-to-decision architecture in which sensing, communication, processing, interpretation, and agricultural action operate as an integrated cycle.

Differences between the experimental and control plots also demonstrate the limitations of schedule-based resource management under changing environmental conditions. Fixed irrigation schedules cannot fully account for short-term variations in temperature, soil moisture, rainfall, and crop water demand. Real-time monitoring provided greater temporal precision by aligning irrigation with actual field conditions. Reliable network communication was essential to this process because delayed or incomplete data could weaken the accuracy of automated recommendations and reduce the practical value of smart farming technology.

The results indicate that integrating IoT with Wireless Sensor Networks can improve agricultural management when technological reliability is directly connected to actionable farm decisions. The experimental system reduced irrigation water consumption by approximately 27%, improved soil moisture stability, shortened response time to environmental changes, and produced higher crop yields than conventional management. High packet delivery, network availability, and data completeness further demonstrated that the proposed architecture could maintain reliable communication under field conditions. These findings suggest that the effectiveness of smart farming should be evaluated through both network performance and measurable agricultural outcomes.

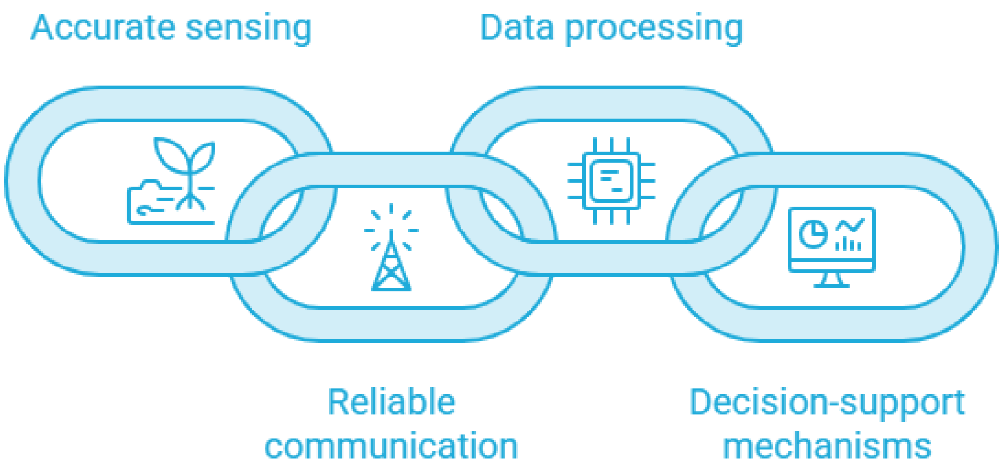

Figure 2. Smart Farming System Components

The overall pattern of evidence shows that technological sophistication alone does not define an effective smart farming system. Agricultural benefits emerged when accurate sensing, reliable wireless communication, timely data processing, and decision-support mechanisms functioned as an integrated operational chain. IoT–WSN architecture therefore offers substantial potential for precision irrigation and resource-efficient agriculture, although long-term scalability will depend on energy management, communication stability, maintenance requirements, economic feasibility, and adaptation to diverse agricultural environments. The findings provide empirical support for a data-to-decision model of smart farming in which digital infrastructure creates practical value by enabling more precise, responsive, and sustainable agricultural management.

The findings demonstrate that integrating the Internet of Things (IoT) with Wireless Sensor Networks (WSNs) can substantially improve the precision, responsiveness, and resource efficiency of agricultural management. Experimental plots managed through the IoT–WSN system maintained more stable soil moisture conditions, consumed approximately 27% less irrigation water, responded more rapidly to environmental changes, and produced higher crop yields than plots managed through conventional practices. These outcomes indicate that continuous environmental sensing can generate tangible agricultural benefits when field data are directly connected to management decisions.

Network performance provided an important technological foundation for these agricultural improvements. High packet delivery, network availability, and data completeness enabled environmental information to move consistently from distributed sensor nodes to the IoT processing platform. Low communication latency further supported timely threshold-based alerts and irrigation recommendations. Reliable communication therefore functioned as more than a technical performance indicator because it determined whether environmental changes could be translated into operational responses before crop conditions deteriorated.

Inferential findings strengthened this interpretation by demonstrating significant relationships among soil moisture stability, irrigation responsiveness, communication reliability, and crop performance. Higher soil moisture stability predicted better crop yield, while greater data completeness supported more accurate irrigation decisions. Excessive water application was not associated with superior productivity, suggesting that precision and timing were more important than irrigation volume alone. Agricultural optimization therefore depended on delivering resources according to actual field requirements.

Case-level evidence further demonstrated the practical value of the proposed data-to-decision architecture. Sensor-assisted monitoring identified declining soil moisture before visible crop stress appeared and enabled earlier irrigation intervention than conventional field observation. The system effectively connected sensing, communication, processing, interpretation, and agricultural action within a continuous operational cycle. Smart farming performance therefore emerged from the integration of technological reliability and decision relevance rather than from sensor deployment alone.

Previous research on precision agriculture generally demonstrates that IoT technologies improve access to real-time information concerning soil, crops, weather, irrigation, and environmental conditions. The present findings are consistent with this broader body of research because continuous monitoring improved resource allocation and reduced dependence on fixed agricultural schedules. The observed reduction in water consumption also supports established arguments that sensor-assisted irrigation can increase water-use efficiency by matching irrigation more closely with actual soil and crop conditions.

Existing studies of agricultural WSNs frequently emphasize packet delivery, communication range, routing efficiency, network topology, and energy consumption as primary measures of system performance. The present study extends this technological perspective by linking network indicators directly with agricultural outcomes. Packet delivery and data completeness were meaningful not simply because they demonstrated technical reliability but because they influenced decision accuracy, irrigation responsiveness, and environmental management. This connection provides a more functionally relevant interpretation of network performance within smart agriculture.

Research on smart irrigation has commonly reported improvements in water efficiency through soil moisture sensors, automated controllers, or weather-based irrigation scheduling. The present findings support those observations while emphasizing that isolated automation may be insufficient to represent a comprehensive smart farming architecture. Agricultural value emerged from an interconnected process involving distributed sensing, wireless transmission, IoT processing, threshold interpretation, and decision support. The distinction is important because technological integration determines whether individual components operate as a coherent agricultural management system.

Previous smart farming studies have also identified challenges involving interoperability, energy consumption, connectivity, affordability, and scalability. Evidence from the current investigation confirms the importance of these concerns because retransmission frequency was associated with higher node energy consumption, while communication stability supported longer estimated battery life. Agricultural performance must therefore be considered alongside technical sustainability. A system that performs effectively during short-term experimentation may still encounter practical limitations when deployed across larger farms, longer cultivation periods, or areas with unstable communication infrastructure.

The findings indicate a broader transition from observation-based agriculture toward data-informed and increasingly responsive agricultural management. Conventional farming often depends on predetermined schedules, accumulated experience, and visible indicators of crop condition. IoT–WSN systems introduce continuous environmental intelligence that allows management decisions to respond to conditions that may not yet be observable through conventional inspection. Agricultural decision-making can therefore become more anticipatory rather than exclusively reactive.

The results also indicate that the value of agricultural data depends on their capacity to support meaningful action. Collecting thousands of sensor measurements does not automatically improve farming outcomes if those measurements remain disconnected from practical decisions. The observed improvements occurred because environmental data were transformed into timely irrigation recommendations. Smart farming should therefore be understood as a data-to-decision ecosystem rather than simply a network of connected devices.

Resource efficiency represents another important meaning of the findings. Higher crop yield was achieved despite lower irrigation water consumption, challenging the assumption that increased agricultural inputs necessarily generate higher productivity. Precision management can potentially improve output by optimizing when, where, and how resources are applied. This pattern is particularly important under conditions of water scarcity, climate variability, increasing production costs, and growing pressure to reduce the environmental footprint of agriculture.

Technological reliability also emerges as a prerequisite for digital agricultural trust. Farmers are unlikely to rely on automated or sensor-informed recommendations when devices frequently fail, data are incomplete, or communication is unstable. High network availability and data completeness therefore contribute not only to engineering performance but also to the practical credibility of smart farming systems. Long-term adoption will depend on whether farmers perceive digital recommendations as sufficiently reliable to influence routine agricultural decisions.

Scientific implications concern the need to evaluate smart farming through integrated technological and agricultural performance frameworks. Engineering metrics such as packet delivery ratio, latency, energy consumption, and network lifetime should be analyzed together with water-use efficiency, crop productivity, environmental stability, and decision effectiveness. Such integration can prevent technically successful prototypes from being interpreted as agriculturally successful systems without evidence of practical benefits.

Practical implications are particularly relevant to irrigation management. Real-time soil moisture monitoring can reduce unnecessary water application while allowing farmers to respond more rapidly to crop water requirements. Agricultural practitioners can use IoT–WSN systems to complement field experience with continuous environmental evidence. Technology should support rather than replace contextual agricultural knowledge because sensor measurements require interpretation according to crop type, soil characteristics, growth stage, weather conditions, and local farming practices.

Policy implications involve digital infrastructure, agricultural extension, technology affordability, and farmer capacity building. Governments and agricultural institutions seeking to promote smart farming should not focus exclusively on distributing devices or expanding internet connectivity. Effective implementation requires technical support, digital literacy, maintenance systems, financing mechanisms, interoperability standards, and training that enables farmers to interpret and act upon digital information. Policies that ignore these supporting conditions may produce underused technologies despite substantial investment.

Sustainability implications extend beyond irrigation efficiency. Reduced resource consumption, improved input precision, and earlier detection of environmental stress can contribute to more sustainable agricultural production when implemented at scale. Smart farming technologies may support adaptation to climate variability by enabling more responsive management of water, soil, microclimate, and crop conditions. Environmental benefits should nevertheless be evaluated against the energy consumption, electronic waste, infrastructure requirements, and lifecycle costs associated with digital technologies.

The reduction in irrigation water consumption occurred because the IoT–WSN system replaced rigid scheduling with condition-responsive management. Soil moisture measurements provided direct evidence of whether irrigation was actually required, reducing unnecessary water application when sufficient moisture remained available. Conventional schedules lacked this level of temporal sensitivity and were more likely to apply water according to routine intervals rather than immediate crop and soil requirements.

Improved crop performance can be explained by greater stability in root-zone moisture conditions. Excessive fluctuations between water surplus and water deficit can create physiological stress and reduce the efficiency of nutrient uptake and plant development. Sensor-informed irrigation maintained environmental conditions within a more appropriate range for longer periods, creating a more stable growing environment. Yield improvement therefore appears to reflect better resource timing and environmental consistency rather than increased input intensity.

Rapid response to environmental change resulted from continuous sensing and automated information transmission. Manual observation occurs intermittently and may fail to detect early-stage changes that are not visually apparent. Distributed sensor nodes captured changes at predefined intervals and communicated them to the processing platform without requiring continuous human presence. The shorter information cycle reduced the time between environmental change, problem recognition, and management response.

Strong overall system performance was also associated with reliable communication architecture. High packet delivery and data completeness ensured that decision-support functions operated using sufficiently continuous environmental information. Energy-efficient communication reduced unnecessary retransmission and supported operational stability. Smart farming outcomes therefore reflected a chain of interdependent processes in which weaknesses at the sensing, communication, processing, or decision stage could reduce the effectiveness of the entire system.

Future research should evaluate IoT–WSN smart farming systems through longer-term, multi-season, and multi-location field experiments. Agricultural conditions vary substantially according to crop type, soil characteristics, climate, topography, irrigation infrastructure, and farming practices. Evidence derived from broader environmental contexts would clarify whether observed improvements remain consistent beyond a single experimental setting and would strengthen the external validity of smart farming models.

Artificial intelligence and predictive analytics represent important directions for advancing the proposed architecture. Future systems could move beyond threshold-based decisions by integrating machine learning models capable of predicting irrigation requirements, crop stress, pest outbreaks, disease risk, and yield performance (Kaviarasan & Srinivasan, 2024). Historical sensor data combined with weather forecasts and crop models could support anticipatory decision-making rather than responses based only on current environmental conditions. Predictive capability should be evaluated carefully to ensure model transparency, reliability, and suitability for local agricultural contexts.

Energy autonomy and communication optimization require further investigation because large-scale deployment depends on maintaining sensor networks with minimal maintenance. Solar-powered nodes, adaptive sampling, low-power communication protocols, edge computing, intelligent routing, and energy-aware data transmission may extend network lifetime while preserving data quality (Daousis et al., 2024). Research should determine the optimal balance between measurement frequency, communication reliability, energy consumption, and decision usefulness rather than maximizing any single technical indicator.

Socioeconomic feasibility should become a central component of future smart farming research. Technical effectiveness does not guarantee adoption when systems remain expensive, difficult to maintain, or poorly aligned with farmers' knowledge and local infrastructure. Future investigations should incorporate cost-benefit analysis, farmer acceptance, digital literacy, cybersecurity, interoperability, maintenance capacity, and smallholder accessibility alongside engineering and agricultural performance. The next generation of smart farming should therefore prioritize not merely more advanced technology, but systems that are reliable, affordable, interpretable, scalable, and capable of delivering measurable value under real agricultural conditions.

CONCLUSION

The most important finding of this study demonstrates that the integration of the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) can transform conventional agricultural monitoring into a responsive data-driven management system capable of improving both resource efficiency and agricultural performance. The IoT–WSN-assisted plots maintained more stable soil moisture conditions, reduced irrigation water consumption by approximately 27%, shortened response time to environmental changes, and achieved higher crop yields than conventionally managed plots. High packet delivery, network availability, and data completeness further demonstrated that reliable wireless communication is essential for translating environmental measurements into timely agricultural actions. The distinctive finding lies in the demonstrated connection between technological reliability and agricultural outcomes: sensing accuracy and network performance alone did not create value unless the generated data were converted into relevant management decisions. Smart farming effectiveness therefore depends on an integrated sensing–communication–processing–decision–action cycle rather than merely on the deployment of connected agricultural devices.

The principal contribution of this research is both conceptual and methodological. Conceptually, the study advances a data-to-decision framework that positions IoT and WSN technologies as an integrated agricultural decision-support ecosystem rather than as separate monitoring and communication components. The framework connects sensing accuracy, communication reliability, energy efficiency, data processing, decision responsiveness, resource optimization, and agricultural outcomes within a unified operational model. Methodologically, the field-based experimental design combines network-level indicators, environmental measurements, and agricultural performance data to evaluate whether technological efficiency produces measurable practical benefits. This integrated evaluation extends conventional smart farming research that frequently assesses engineering performance separately from agricultural outcomes. The study therefore contributes a more comprehensive approach for evaluating smart farming systems through the simultaneous consideration of technical reliability, decision usefulness, resource efficiency, and production performance.

The limitations of this study arise from its restricted number of experimental plots, specific cultivation conditions, limited observation period, selected sensor configuration, and dependence on a particular IoT–WSN architecture, which may constrain generalization across different crops, climates, soil characteristics, farm sizes, and communication environments. Long-term performance issues involving sensor degradation, battery lifetime, cybersecurity, interoperability, maintenance costs, connectivity instability, and economic feasibility also require more extensive investigation before large-scale implementation can be recommended. Future research should conduct multi-season and multi-location field experiments while integrating artificial intelligence, predictive analytics, edge computing, renewable-powered sensor nodes, adaptive irrigation algorithms, satellite and drone data, and low-power communication technologies. Greater attention should also be directed toward cost-benefit analysis, farmer acceptance, digital literacy, smallholder accessibility, data governance, and lifecycle sustainability to ensure that future smart farming systems are not only technologically advanced but also affordable, scalable, reliable, environmentally responsible, and practically applicable under diverse real-world agricultural conditions.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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