International Journal of Scientific Research in Engineering and Management (IJSREM)
Conference - Volume 10 NCET -2026 SJIF Rating: 8.659 ISSN: 2582-3930

Internet of Things (IOT) in Smart Agriculture: Transforming Traditional Farming through Intelligent, Sustainable, and Data-Driven Technologies

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***Abstract*—Agriculture must produce more food while responding to climate variability, water constraints, labor shortages, and pressure on natural resources. This paper examines how the Internet of Things (IoT) can support this transition through connected sensing, communication, analytics, and automated actuation. A structured literature synthesis is used to clas-sify IoT-enabled agricultural applications, identify technologies across the farm data cycle, and compare their contributions and implementation barriers. The analysis shows that IoT is particularly valuable for precision irrigation, environmental and crop monitoring, greenhouse automation, livestock management, and data-driven decision support. Integration with edge/cloud computing, artificial intelligence, machine learning, and remote sensing can extend these capabilities from monitoring to prediction and autonomous control. The paper proposes a layered smart-agriculture framework and discusses practical challenges involving connectivity, cost, interoperability, security, sensor reliability, and farmer skills. The study concludes that context-aware, scalable, and affordable IoT architectures can improve resource efficiency, resilience, and sustainable farm management.**

***Index Terms*—Internet of Things (IoT), smart agriculture, precision agriculture, agricultural sensors, smart irrigation, crop monitoring, edge computing, sustainable farming, data analytics.**

I. Introduction

Agriculture is central to food security, rural livelihoods, and sustainable economic development. At the same time, agricultural systems are exposed to climate variability, water scarcity, soil degradation, pest and disease pressure, rising input costs, and shortages of skilled labor. The Food and Agriculture Organization (FAO) identifies science, technology, and innovation as important enablers for making agrifood systems more efficient, inclusive, resilient, and sustainable [11]. Water management is especially important because agriculture remains the largest user of freshwater withdrawals globally, while climate change is increasing uncertainty in water availability and crop water demand [12]. These pressures create a need for farming approaches that can measure field conditions continuously and support timely decisions.

The Internet of Things (IoT) provides a technological foundation for such approaches. In general, IoT connects physical objects equipped with sensors, communication capabilities, processing resources, and actuators so that data can be collected and exchanged across networks [1]. In agriculture, this concept enables physical conditions in soil, crops, greenhouses, irrigation systems, weather stations, machinery, and livestock to become observable and actionable. Instead of relying only on periodic manual inspection, farmers can obtain near-real-time information and use it to decide when, where, and how much water, fertilizer, energy, or labor is required.

Smart agriculture is therefore not simply the installation of sensors. It is a cyber-physical management approach in which sensing, connectivity, data processing, decision support, and actuation form a continuous loop. Previous studies have identi-fied IoT applications in monitoring, irrigation, agrochemical management, disease management, harvesting, supply chains, and other agricultural practices [8]. IoT-based systems can also be integrated with cloud computing, artificial intelligence (AI), machine learning (ML), unmanned aerial vehicles (UAVs), and remote sensing to convert raw observations into predictions and recommendations.

Despite these opportunities, adoption is uneven. Rural connectivity may be unreliable, devices can be costly to deploy and maintain, sensors require calibration, and heterogeneous platforms may not interoperate. Data ownership, privacy, cybersecurity, and technical skills also influence adoption. These issues are particularly important for small and marginal farmers, for whom a technically sophisticated solution may be impractical if it has high recurring costs or requires specialist support.

This paper investigates the role of IoT in smart agriculture through a structured review and technology-oriented synthesis. The main contributions are: (1) a layered framework linking sensing to intelligent decision-making and actuation; (2) a classification of major agricultural applications and their expected benefits; (3) a qualitative comparison of enabling technologies and operational requirements; and (4) an analysis of challenges and future research directions for scalable and sustainable deployment.

II. Related Work and Literature Review

The IoT paradigm has evolved through the convergence of identification, sensing, wireless communication, embedded processing, and distributed intelligence [1]. Its agricultural application has developed from isolated sensor deployments to-ward integrated cyber-physical systems. Ray reviewed IoT tech-nologies, practices, and future directions for smart agriculture

and emphasized sensing, communication, processing, and application layers as important components of agricultural IoT architectures [2]. Tzounis *et al.* examined recent advances and future challenges and highlighted the importance of reliable communication, interoperability, and system integration [3].

Elijah *et al.* analyzed IoT and data analytics in agriculture and described benefits including improved monitoring, resource management, and decision-making, while identifying challenges related to data, communication, and implementation [4]. Ayaz *et al.* presented a broad review of IoT-based smart agriculture and described applications involving field monitoring, irrigation, greenhouse management, livestock, and agricultural automation [5]. A systematic review by Walter *et al.* applied PRISMA-based methods to examine IoT solutions for smart farming, reflecting the growing research interest in connected agricultural systems [6].

Water management is one of the strongest application areas. Garcia *et al.* reviewed IoT-based smart irrigation systems and discussed sensors, communication technologies, and control approaches used in precision irrigation [7]. More recent systematic analysis has also reported increasing research activity in IoT-enabled irrigation and a trend toward low-power and scalable communication technologies for real-time data acquisition [10].

The value of IoT increases when sensor data are combined with analytical infrastructures. Wolfert *et al.* described smart farming as a data-intensive development in which IoT and cloud computing can support predictive insights, real-time operational decisions, and new data-driven processes across the food chain [9]. Friha *et al.* further classified agricultural IoT applications into areas such as smart monitoring, water management, agro-chemical applications, disease management, smart harvesting, supply chain management, and smart agricultural practices [8]. The literature indicates that the research field has moved beyond the question of whether IoT can be used in agriculture toward questions of scalability, affordability, interoperability, security, and measurable farm-level value. A recurring gap is the need for architectures that connect technical components with farmer-centered decision workflows. This paper addresses that gap by synthesizing the components into an end-to-end framework rather than treating individual sensor applications as isolated solutions.

III. Proposed IoT-Enabled Smart Agriculture Framework

The proposed framework follows a layered architecture designed to convert physical farm observations into actionable decisions. It is intended as a conceptual reference model that can be adapted to open-field farming, horticulture, protected cultivation, and livestock systems. Fig. 1 shows the principal layers.

A. Sensing Layer

The sensing layer provides the primary connection between the physical farm and the digital system. Soil-moisture, soil-temperature, air-temperature, relative-humidity, light-intensity, rainfall, leaf-wetness, water-level, and electrical-conductivity sensors can be selected according to the crop and management objective. Livestock systems can use wearable or environmental sensors to monitor location and selected health-related indicators. Sensor selection should be driven by agronomic relevance, measurement accuracy, environmental durability, energy consumption, and maintenance requirements rather than by the number of parameters collected.

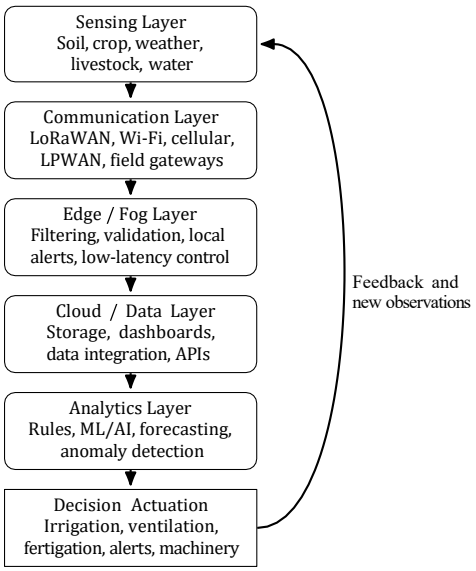


Fig. 1. Conceptual layered architecture for IoT-enabled smart agriculture.

B. Communication Layer

The communication layer transfers observations from field devices to gateways, edge nodes, or cloud services. Short-range technologies such as Wi-Fi and Bluetooth can be suitable for controlled environments, whereas low-power wide-area approaches and cellular connectivity can support larger or geographically distributed fields. The appropriate choice depends on field size, terrain, energy availability, required data rate, latency, and network coverage. Communication redundancy can be valuable where temporary network loss would otherwise interrupt critical operations.

C. Edge, Cloud, and Data Layer

Edge or fog processing reduces the need to transmit every raw measurement and can provide immediate responses for time-sensitive actions. Examples include detecting a sudden fall in soil moisture or triggering a greenhouse ventilation rule. Cloud services can provide scalable storage, historical analysis, dashboards, remote access, and integration with external weather or market information. A practical architecture should therefore use edge computing for local resilience and cloud computing for long-term analysis and coordination.

D. Analytics and Decision Layer

The analytics layer transforms observations into information. Simple threshold rules remain useful for transparent actions,

TABLE I
MAJOR IOT APPLICATIONS AND EXPECTED CONTRIBUTIONS

Application	IoT Components	Expected Contribution
Precision irrigation	Soil-moisture sensors, weather data, valves, pump control	Water-use efficiency; timely irrigation
Crop monitoring	Environmental sensors, cameras, UAV/remote sensing	Early stress detection; field visibility
Greenhouse automation	Temperature, humidity, light, CO_2 sensors; actuators	Stable microclimate; automated control
Livestock monitoring	Wearable/location sensors, gateways	Continuous observation; faster alerts
Pest/disease support	Cameras, leaf-wetness sensors, analytics	Early identification; targeted intervention
Machinery monitoring	GPS, vibration, fuel and operational sensors	Utilization; maintenance planning

while statistical models and ML can identify trends, anomalies, and relationships among environmental variables. For exam-ple, irrigation decisions can combine soil moisture, weather conditions, crop stage, and recent irrigation history rather than relying on a single sensor threshold. AI should be treated as a decision-support component whose predictions are validated against agronomic knowledge and local conditions.

E. Actuation and Feedback

The final layer converts decisions into actions. Actuators can operate pumps, valves, fans, greenhouse shades, lighting systems, fertigation equipment, or selected machinery. Alerts can also be sent to farmers through mobile or web interfaces when manual intervention is required. The feedback loop is essential: after an action is taken, new sensor observations should be used to determine whether the desired condition has been achieved. This closes the monitoring-control cycle and distinguishes smart agriculture from passive data collection.

IV. MAJOR APPLICATIONS OF IOT IN SMART AGRICULTURE

IoT applications can be grouped according to the agricultural process they improve. Table I summarizes representative applications and expected contributions.

A. Precision Irrigation

Irrigation is an especially important use case because water availability directly affects crop productivity and sustainability. Sensor-based irrigation can replace fixed schedules with condition-based decisions. A basic control rule can be represented as

$$I(t) = \begin{cases} 1, & M(t) < M_{min} \\ 0, & M(t) \geq M_{min}, \end{cases} \quad (1)$$

where $M(t)$ is measured soil moisture and M_{min} is a crop-and soil-specific lower threshold. More advanced systems can include rainfall forecasts, evapotranspiration estimates, crop growth stage, and water availability. IoT-based irrigation reviews show that sensor selection and communication design are central to reliable precision irrigation [7], [10].

B. Crop and Environmental Monitoring

Continuous monitoring can reveal microclimatic and soil variability that may be hidden by occasional manual measurements. Temperature, humidity, rainfall, soil moisture, leaf wetness, and light data can be combined to identify conditions associated with crop stress. Camera systems and UAVs can add visual information for crop growth assessment and spatial mapping. The result is a shift from reactive inspection to more timely field management.

C. Greenhouse and Controlled-Environment Agriculture

In greenhouses, environmental variables can change rapidly and can be controlled more directly than in open fields. IoT systems can integrate sensors with fans, vents, irrigation, shading, and lighting. A rule-based controller can maintain conditions within a desired range, while predictive models can anticipate changes. The key benefit is the coordination of multiple variables rather than isolated control of individual devices.

D. Livestock and Farm Asset Monitoring

IoT can extend beyond crop production to livestock and agricultural machinery. Location and environmental sensors can support monitoring of animal movement and farm conditions, while equipment sensors can assist maintenance and utilization planning. These applications can reduce the need for continuous manual inspection and generate records that support operational decisions.

V. RESEARCH METHODOLOGY

This study adopts a structured literature-synthesis methodology rather than reporting a field experiment. The objective is to consolidate evidence on IoT architectures, applications, enabling technologies, benefits, and barriers and to use that evidence to develop a practical conceptual framework. The review focuses on peer-reviewed studies and authoritative agricultural sources covering IoT, smart farming, precision irrigation, data analytics, and digital agriculture [4]–[6], [8].

The analysis was organized into four stages. First, the litera-ture was classified by application domain, including monitoring, irrigation, greenhouse management, livestock, disease/pest support, and machinery. Second, enabling technologies were mapped across sensing, connectivity, edge/cloud computing, analytics, and actuation. Third, benefits and implementation barriers were extracted and grouped into operational, technical, economic, and organizational categories. Fourth, the findings were synthesized into the layered framework presented in Fig. 1.

This approach provides traceability between the literature and the proposed model without claiming experimental performance that has not been measured in a field deployment.

For qualitative comparison, each technology component was assessed against four practical criteria: data timeliness, scalability, automation potential, and deployment complexity. The resulting interpretation is shown in Table II. The assessment is directional rather than a statistical benchmark; it is intended to guide architecture selection and future experimental evaluation.

TABLE II
QUALITATIVE ASSESSMENT OF IOT COMPONENTS

Component	Timeliness	Scale	Automation	Complexity
Local sensors	High	Medium	Medium	Low
LPWAN/field gateway	Medium–High	High	Medium	Medium
Edge computing	Very high	Medium–High	High	Medium
Cloud platform	Medium	Very high	High	Medium
AI/ML analytics	Medium	High	Very high	High
Actuation system	Very high	Medium	Very high	Medium–High

VI. RESULTS AND DISCUSSION

The literature synthesis produces five principal findings. First, IoT creates the greatest value when sensing is connected to a decision or control action. A sensor that only displays measurements has limited operational impact compared with a system that interprets those measurements and recommends or performs an appropriate action. Second, irrigation and environmental monitoring are mature application areas because the variables can be measured frequently and connected directly to controllable resources such as pumps and valves [7]. Third, the integration of IoT with cloud, edge, AI, and remote sensing expands the system from descriptive monitoring toward predictive and prescriptive management [8], [9].

Fourth, the analysis shows that no single communication or computing technology is optimal for every farm. Field conditions, energy supply, connectivity, crop type, farm size, and required latency determine the appropriate architecture. A hybrid design that combines local processing with cloud services can provide a practical balance between responsiveness and scalability. Fifth, adoption is strongly influenced by nontechnical factors. Cost, maintenance, digital skills, data governance, and the ability to demonstrate measurable value are as important as sensor accuracy.

The proposed framework also highlights the importance of feedback. Traditional digital monitoring often stops at data visualization. A smart agriculture system should instead establish a closed loop: *sense, communicate, analyze, decide, act, and verify*. This design principle can reduce unnecessary resource use while allowing farmers to intervene when automated decisions are uncertain. It also provides a foundation for future AI models because historical sensor and action data can be used to improve prediction and calibration.

From a sustainability perspective, IoT can support the principle of producing more with fewer inputs by improving the timing and spatial targeting of agricultural interventions. FAO emphasizes the importance of digital innovation, efficient resource use, resilience, and evidence-based decision-making in agrifood transformation [11], [12]. However, sustainability should not be assumed simply because a system is digital. Devices consume energy and materials, sensors require replace-ment, communication infrastructure has environmental costs, and poorly designed automation can create new inefficiencies. Therefore, life-cycle considerations should be incorporated into future smart-farming evaluations.

sectionImplementation Considerations and Evaluation Met-rics
A practical smart-agriculture deployment should begin with the agricultural decision rather than the technology. The first step is to identify a measurable problem, such as excessive irrigation, delayed detection of crop stress, unstable greenhouse conditions, or inefficient machinery use. The second step is to identify the minimum set of variables required to support that decision. This avoids unnecessary sensing and reduces hardware, communication, and storage costs. The third step is to select sensors, connectivity, processing, and actuation according to field conditions. Finally, the system should be piloted, calibrated, evaluated with farmers, and expanded only after reliability and value have been demonstrated.

A useful implementation workflow is therefore: *problem definition → sensing design → connectivity selection → edge/cloud integration → analytics → decision rule → actuation → validation*. This workflow is consistent with the broader smart-farming concept in which information and communication technologies participate in a cyber-physical farm-management cycle [9]. It also helps prevent a common weakness in IoT projects: collecting large quantities of data without a clearly defined operational purpose.

Data quality should be treated as a first-class requirement. A measurement x_t can be checked using range, rate-of-change, and consistency rules before it enters the analytical pipeline. For example,

$$Q(x_t) = R(x_t) \wedge C(x_t, x_{t-1}) \wedge S(x_t), \tag{2}$$

where R represents an acceptable physical range, C represents temporal consistency, and S represents sensor-status validation. Measurements that fail validation can be flagged, replaced using an appropriate estimation method, or withheld from automated control. This is important because an incorrect sensor value can cause an automated system to make an incorrect agricultural intervention.

System evaluation should also use multiple dimensions rather than a single accuracy value. Table III presents a proposed evaluation matrix for future field studies. Technical metrics measure whether the system works as intended, agricultural metrics measure whether the intervention benefits the farm, and adoption metrics measure whether farmers can use and maintain the system. Such multidimensional evaluation is particularly important because a technically accurate system may still be unsuitable if its cost, maintenance burden, or interface prevents adoption.

For precision irrigation, for instance, water productivity can be represented as

$$WP = \frac{Y}{W}, \tag{3}$$

where Y is marketable crop yield and W is the volume of irrigation water applied. Comparing WP between a conventional control strategy and an IoT-assisted strategy under similar agronomic conditions would provide stronger evidence than reporting sensor accuracy alone. Similar experimental designs

TABLE III
PROPOSED EVALUATION METRICS FOR FIELD VALIDATION

Dimension	Representative Metric	Purpose
Technical	Packet delivery, latency, sensor uptime	Assess communication and reliability
Data quality	Missing data, anomaly rate, calibration error	Assess trustworthiness of observations
Agricultural	Yield, water productivity, input use	Measure farm-level outcomes
Economic	Installation cost, operating cost, payback	Assess financial feasibility
Energy	Battery life, energy per observation	Assess field sustainability
Usability	Task completion, training time, user feedback	Assess farmer acceptance
Environmental	Water use, chemical use, emissions indicators	Assess sustainability impacts

can be used to assess labor savings, energy use, crop quality, and intervention frequency.

Security should be incorporated throughout the deployment lifecycle. Devices should have unique identities, communication should be protected using appropriate encryption, access permissions should follow least-privilege principles, and firmware should be updated through controlled mechanisms. Edge gateways can provide an additional security boundary between constrained sensors and external networks. For cloud platforms, authentication, authorization, logging, backup, and data-retention policies should be defined before deployment. These measures become increasingly important when agricultural systems control pumps, valves, ventilation, or other physical equipment.

The architecture can also be designed for graceful degrada-tion. If the cloud service becomes unavailable, the edge gateway should retain recent measurements and continue essential local rules. If a sensor fails, the system should detect the failure and notify the farmer rather than silently producing a false measurement. If connectivity is lost, buffered data can be synchronized after service restoration. These resilience mechanisms are particularly relevant in rural settings where network conditions may vary.

From a deployment perspective, modularity is preferable to a monolithic design. A farm should be able to begin with one application, such as soil-moisture monitoring, and later add weather sensing, crop imaging, automated irrigation, or predictive analytics. Open APIs and standardized data formats can make this incremental approach more feasible. It also reduces the risk that a farmer becomes locked into a single vendor or technology platform. The literature on smart farming emphasizes the importance of data infrastructures, governance, and standards as the agricultural IoT ecosystem expands [9].

VII. CHALLENGES AND LIMITATIONS

Despite its potential, IoT-based smart agriculture faces several barriers.

Connectivity and infrastructure: Rural farms may have weak or intermittent connectivity. Systems should support buffering, local control, and store-and-forward communication so that temporary network failures do not stop critical operations.

Cost and affordability: Hardware, gateways, cloud services, installation, calibration, and maintenance create both initial and recurring costs. Affordable modular systems are important for smallholders.

Sensor reliability: Sensors are exposed to moisture, dust, heat, chemicals, and mechanical stress. Calibration, redundancy, fault detection, and preventive maintenance are necessary to preserve data quality.

Interoperability: Agricultural IoT environments often contain devices from different manufacturers. Open interfaces, common data models, and standardized protocols can reduce vendor lock-in and facilitate integration.

Security and privacy: Connected devices increase the attack surface of agricultural systems. Secure authentication, encrypted communication, access control, software updates, and device lifecycle management should be considered from the design stage.

Data governance and ownership: Farmers and organizations need clarity about who owns sensor data, who can access it, how long it is stored, and whether it can be shared with third parties. Governance becomes increasingly important as cloud and AI services are introduced [9].

Technical skills and adoption: Farmers may require training to interpret dashboards and respond to alerts. User interfaces should present actionable information rather than overwhelming users with raw measurements. Local agricultural knowledge should remain part of the decision process.

A limitation of this study is that the proposed framework and qualitative assessment have not yet been validated through a controlled field deployment. Therefore, the paper does not claim specific percentage improvements in yield, water savings, or cost. Such metrics should be established through crop-specific experiments under defined climatic, soil, and management conditions.

VIII. FUTURE RESEARCH DIRECTIONS

Future research should move from isolated prototypes toward interoperable, farmer-centered platforms. First, low-power and energy-aware sensor networks should be investigated for remote farms. Energy harvesting and long-life battery technologies may reduce maintenance requirements. Second, edge AI can be explored for local disease, anomaly, and irrigation decisions when connectivity is limited. Third, digital twins and predictive models can combine historical observations, weather forecasts, crop growth stages, and farm actions to support scenario-based decision-making.

Another important direction is trustworthy data management. Secure device identity, encrypted communication, access control, and auditable data sharing can improve confidence in connected agricultural systems. Interoperability should be addressed through open APIs and common data models so that farmers can combine sensors, gateways, analytics tools, and machinery from different vendors.

Finally, future evaluations should include not only technical accuracy but also total cost of ownership, water productivity, energy consumption, farmer usability, environmental impact, and long-term reliability. Participatory research involving farmers, agronomists, engineers, and technology providers can help ensure that systems solve real agricultural problems rather than simply demonstrating new technology.

IX. Conclusion

IoT provides an important technological pathway for trans-forming conventional agriculture into a more intelligent, con-nected, and data-driven system. By linking sensors, communica-tion networks, edge/cloud computing, analytics, and actuators, IoT can enable continuous monitoring and timely intervention across irrigation, crop management, greenhouse operations, livestock, and farm machinery. The literature reviewed in this study indicates that the strongest value arises when sensing is integrated with decision support and closed-loop control rather than used only for visualization.

The proposed layered framework provides a practical way to organize these capabilities while accommodating different farm sizes and connectivity conditions. At the same time, successful adoption depends on affordability, reliability, interoperability, cybersecurity, data governance, and farmer skills. IoT should therefore be implemented as part of a broader socio-technical agricultural strategy. Future field validation should quantify its effects on yield, water productivity, input use, labor, energy, and farm economics. With context-aware design and responsible integration with AI, cloud/edge computing, remote sensing, and automation, IoT-enabled smart agriculture can contribute to more resilient, efficient, and sustainable food-production systems.

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