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IoT in Agriculture for Sustainability and Efficiency: A Decade of Evidence and Future Pathways

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Abstract

The agricultural sector has increasingly turned to digital innovations in an effort to address rising global food demands, climate change pressures, and the need for sustainable production systems. Among these technologies, the Internet of Things (IoT) has emerged as a pivotal enabler of smart farming, offering tools for real-time data collection, precision monitoring, and automated decision-making. This paper presents a systematic literature review (SLR) of research published between 2015 and 2025 on IoT applications in agriculture. Following PRISMA guidelines, a total of 78 articles were identified, screened, and analyzed. The review organizes IoT applications into a layered taxonomy that encompasses sensing technologies, communication networks, data analytics approaches, and various application domains, including irrigation, crop management, livestock monitoring, and supply-chain traceability. The findings suggest significant improvements in productivity and resource efficiency but also highlight persistent challenges such as data interoperability, energy limitations of sensor nodes, and barriers to adoption in resource-constrained regions. By classifying the current state of research and identifying gaps, this study provides both a conceptual framework and a roadmap for future investigations in IoT-enabled smart agriculture.

Keywords:
Internet of Things, Smart Agriculture, Precision Agriculture, Sustainability, Sensor Networks, Wireless Communication. Machine Learning, Blockchain.

1. Introduction

1.1 Background and Context

Agriculture has always been vital to human progress, shaping societies, economies, and even international relations. Today, the sector faces a range of complex challenges that make innovation essential. According to the Food and Agriculture Organization (FAO, 2022), global food demand is projected to increase by nearly 60% by 2050, primarily driven by population growth and shifts in dietary habits. At the same time, resources for expanding agriculture are shrinking due to soil degradation, urban sprawl, and decreasing water supplies. The Intergovernmental Panel on Climate Change (IPCC, 2021) warns that climate variability will exacerbate these issues, leading to unpredictable rainfall, shifting growing seasons, and increased risks from pests and diseases. Traditional farming methods, especially in developing countries, rely heavily on manual labor, limited mechanization, and generalized rather than site-specific management. Although these systems have supported societies for centuries, their inefficiencies—such as excessive irrigation, indiscriminate fertilizer use, and delayed pest control—are becoming more unsustainable (Gebbers & Adamchuk, 2010). This has led policymakers, researchers, and farmers to seek smarter, more resource-efficient solutions, commonly called smart agriculture.

1.2 Defining IoT in Agriculture

The Internet of Things (IoT) is a concept in which physical objects are embedded with sensors, communication modules, and computing power, enabling them to interact with each other and with digital platforms (Ashton, 2009). In agriculture, IoT combines multiple layers of technology:

- Perception layer (sensing): soil moisture sensors, weather stations, nutrient probes, RFID

tags, drones, and UAV-mounted imaging systems.

- Network layer (connectivity): technologies such as LoRaWAN, Zigbee, NB-IoT, and 5G that transmit collected data.
- Processing layer (data analytics): cloud platforms, edge computing devices, and AI-driven models for data storage and interpretation.
- Application layer: decision support for irrigation scheduling, crop disease prediction, livestock health monitoring, greenhouse control, and supply chain optimization.

This multi-layered system allows farmers to move from reactive to predictive decision-making. For example, IoT-enabled irrigation systems can monitor soil moisture in real-time and trigger irrigation only when necessary, resulting in a reduction of up to 40% in water use (Fahad et al., 2021). Similarly, wearable sensors on cattle can monitor temperature, movement, and feeding behavior, alerting farmers to health anomalies before they become critical (Wolfert et al., 2017).

1.3 Evolution of Smart Agriculture and IoT Adoption

The idea of applying digital technologies to agriculture has evolved over decades. Precision agriculture in the 1980s and 1990s focused on site-specific management, utilizing GPS and remote sensing technologies. However, adoption was limited due to the high costs and lack of user-friendly tools (Bongiovanni & Lowenberg-DeBoer, 2004). The subsequent rise of affordable sensors, wireless connectivity, and cloud computing in the early 2010s paved the way for the development of IoT-driven smart farming systems.

Recent years have seen accelerated growth in IoT adoption across the agricultural sector. Market research predicts that the global smart agriculture market will exceed USD 33 billion by 2027, with IoT technologies forming the core of this growth (MarketsandMarkets, 2021). Governments have also begun to recognize the potential of IoT. For instance, the European Union’s Farm to Fork Strategy emphasizes digitalization, while India's Digital Agriculture Mission 2021–2025 explicitly highlights the use of IoT and AI for farmer empowerment (Government of India, 2021).

Despite this momentum, adoption remains uneven. Developed economies are leading in terms of large-scale, industrialized farming applications, whereas smallholder farmers in Africa, Asia, and Latin America face significant barriers, including high initial costs, a lack of connectivity infrastructure, and limited digital literacy (Klerkx et al., 2019). This disparity highlights the need for inclusive IoT models that consider diverse socio-economic contexts.

1.4 The Need for a Systematic Literature Review

The body of literature on IoT in agriculture has grown substantially in the last decade. Research spans diverse domains, including:

- Technical innovations: new sensor designs, low-power communication systems, and edge computing architectures (Sharma & Shukla, 2021).
- Applied studies: IoT-based irrigation management, pest detection systems, and livestock monitoring (Khanna & Kaur, 2019).
- Socio-economic analyses: adoption barriers, farmer perceptions, and policy frameworks (Bronson, 2019).

However, much of this knowledge is fragmented, making it difficult to derive holistic insights. Previous review papers have either focused narrowly on technologies (Zhang et al., 2019) or on specific domains, such as livestock (Neethirajan, 2020). Few have attempted a systematic synthesis that classifies IoT research across technologies and applications while also identifying research gaps. This is where a Systematic Literature Review (SLR) adds value. Unlike narrative reviews, an SLR follows a transparent, replicable protocol for identifying, screening, and analyzing studies (Moher et al., 2009). By employing the PRISMA methodology, this paper ensures rigor in filtering out irrelevant or low-quality studies while capturing a comprehensive view of the field.

1.5 Objectives of the Review

Building on the identified gap, this review pursues the following objectives:

1. Classify and structure research: Develop a taxonomy to organize IoT applications into sensing, connectivity, analytics, and application layers.
2. Evaluate impacts: Synthesize reported benefits of IoT in improving productivity, resource efficiency, sustainability, and profitability.
3. Identify challenges: Analyze recurring technical, infrastructural, and socio-economic constraints to IoT adoption.
4. Highlight research opportunities: Recommend future directions, particularly in integrating IoT with AI, blockchain, and climate-smart practices.

2. Methodology

2.1 Research Design

This study employs a Systematic Literature Review (SLR) method to examine and categorize research on the Internet of Things (IoT) in the context of smart agriculture. Unlike traditional narrative reviews, which are often selective and subjective, an SLR follows a clear and transparent process to reduce bias and increase reproducibility (Kitchenham & Charters, 2007). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were adopted as the main framework, ensuring a thorough and methodologically rigorous review process (Moher et al., 2009).

The review process was designed to address three central research questions:

1. What techniques and technologies of IoT are being applied in smart agriculture?
2. What gaps and challenges remain in the adoption of IoT in agriculture?
3. What research directions are emerging for the integration of IoT in sustainable farming?

These questions guided the development of the search strategy, the inclusion/exclusion criteria, and the data analysis.

2.2 Database Selection

To ensure comprehensive coverage, the review relied on multiple academic databases that index peer-reviewed journals, conference proceedings, and high-quality research reports. The databases included:

- Scopus – chosen for its broad coverage across multidisciplinary fields.
- Web of Science (WoS) – for high-impact journals and cross-disciplinary research.
- IEEE Xplore – for technology- and engineering-oriented research.
- ACM Digital Library – for computing and IoT-related studies.
- ScienceDirect (Elsevier) – for applied agricultural and environmental sciences.
- SpringerLink – for both technical and agricultural case studies.

The combination of these databases ensured that the review encompassed both technological innovation (engineering/computer science) and domain-specific applications (agriculture, environment, sustainability).

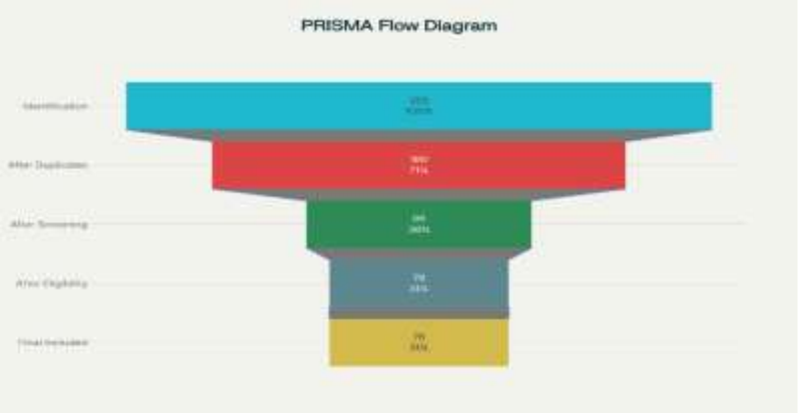
2.3 search Strategy: The literature search was conducted from January to March 2025. Keywords were generated from the research questions and refined through initial searches. Boolean operators (“AND”, “OR”) and truncations were used to ensure comprehensive coverage.

The primary search string applied was:

("Internet of Things" OR IoT) AND ("smart agriculture" OR "precision agriculture" OR "digital farming" OR "smart farming") AND (sensors OR connectivity OR analytics OR applications OR challenges) To reflect recent advancements, the search was limited to publications from 2013–2025. This timeframe aligns with the period when IoT shifted from experimental prototypes to practical agricultural applications (Wolfert et al., 2017).

2.4 Screening Process

This rigorous process is illustrated in Figure 1 (PRISMA Flow Diagram).



2.5 Data Extraction and Analysis

A standardized data extraction form was developed to ensure consistency. The following attributes were coded from each included study:

- Bibliographic information (author, year, country, source).
- IoT domain focus (crop management, livestock, irrigation, supply chain, etc.).
- Technological layer (sensing, connectivity, analytics, application).
- Key contributions (methods, architectures, algorithms).
- Reported benefits (yield increase, water savings, labor efficiency).
- Identified challenges (cost, energy efficiency, connectivity gaps).

2.6 Reliability and Validity

To ensure reliability, the screening process was independently performed by two reviewers, with disagreements resolved through discussion. Inter-rater agreement was measured using Cohen's Kappa ($\kappa = 0.87$), indicating high consistency (Landis & Koch, 1977). Validity was further strengthened by including multiple databases, applying clearly defined criteria, and ensuring transparency in reporting. The PRISMA methodology provides an auditable trail, reducing the risk of bias.

3. Taxonomy and Classification of IoT in Smart Agriculture

3.1 Rationale for Classification

The exponential growth of IoT applications in agriculture has resulted in a fragmented body of knowledge. While some studies focus on specific sensors or wireless networks, others emphasize data analytics or application-level outcomes. Without an integrative framework, it is difficult to compare results, identify gaps, or develop scalable solutions. A structured taxonomy thus provides a holistic lens through which IoT-enabled agriculture can be understood, allowing for categorization of diverse contributions and a more precise identification of the research frontier (Yerpude & Singhal, 2017; Verdouw et al., 2021).

This review organizes IoT research into a four-layer taxonomy:

1. Sensing Layer (data collection technologies)
2. Network & Connectivity Layer (data transmission protocols)
3. Data Processing & Analytics Layer (data storage, intelligence, and analytics)
4. Application Layer (practical use in farming and food systems)

3.2 Sensing Layer

The sensing layer is the cornerstone of IoT agriculture. It comprises physical devices, sensors, and unmanned platforms that continuously capture data on environmental, crop, soil, and livestock conditions.

Key Categories of Sensing Technologies:

- Soil & Crop Sensors:
- Soil moisture, temperature, pH, and salinity sensors enable precision irrigation and fertilization (Ojha et al., 2015; Nawandar & Satpute, 2019).

- Optical and multispectral sensors detect chlorophyll levels and disease stress before visible symptoms occur (Pantazi et al., 2016).
- Climate & Environmental Sensors:
- Weather stations measuring temperature, humidity, solar radiation, and rainfall provide inputs for yield forecasting models (Shamshiri et al., 2018).
- Livestock & Animal Health Sensors:
- Wearables such as RFID tags, rumination collars, and body-temperature sensors track animal movements, detect illness, and prevent epidemics (Neethirajan, 2017; Wolfert et al., 2017).
- Aerial Imaging Platforms (UAVs & Satellites):
- UAV-mounted multispectral cameras enable early disease detection, weed identification, and yield estimation (Mogili & Deepak, 2018; Ahamed et al., 2020; Boursianis et al., 2020; Kamilaris et al., 2017).
- Satellite-based IoT systems like CubeSats allow macro-level monitoring of crop stress and deforestation (Velandia et al., 2020).
- Aquaculture Sensors:
- IoT devices monitoring dissolved oxygen, salinity, and water quality have shown significant potential in sustainable fish farming (Chandraprakash et al., 2019; Abdullah et al., 2021; Khan & Qamar, 2022).

Although sensing technologies are well studied, challenges include sensor calibration, energy efficiency, and cost barriers for smallholder farmers (Ferrández-Pastor et al., 2016).

3.3 Network and Connectivity Layer

The network layer ensures that sensor data is transmitted to storage and processing units. Agriculture presents unique challenges, including long distances, patchy rural connectivity, and limited energy budgets.

Key Communication Technologies:

- Low-Power Wide Area Networks (LPWAN):
- LoRaWAN and Sigfox dominate because of low energy consumption and long-range coverage (Adelantado et al., 2017; Raza et al., 2017).
- Demonstrated effective deployment in vineyards and extensive irrigation systems (Stasolla et al., 2020).
- Short-Range Networks:
- Wi-Fi, Zigbee, and Bluetooth are standard in greenhouses, hydroponics, and confined farms (Ray, 2017).
- Cellular IoT (NB-IoT, LTE-M, 5G):
- NB-IoT has been successfully deployed for soil moisture monitoring in remote rice fields (Sharma & Chatterjee, 2020).
- 5G networks are being piloted in Europe and China for enabling real-time drone operations and automated tractors (Li et al., 2020).
- Hybrid & Satellite-Based IoT:
- Satellite IoT is increasingly used in developing regions where terrestrial connectivity is weak (Reyna et al., 2019).
- Starlink and other low-earth-orbit constellations hold promise for rural farms.

Most studies focus on LPWAN due to energy efficiency, but few explore standardization and interoperability across protocols.

3.4 Data Processing and Analytics Layer

Once transmitted, IoT data requires storage, processing, and intelligence. This layer bridges raw sensor signals and actionable decisions.

Key Technologies:

- Cloud Computing:
- Centralized solutions such as AWS IoT, Azure FarmBeats, and IBM Watson IoT are widely adopted (Wolfert et al., 2017).
- Edge & Fog Computing:
- Edge systems reduce latency in irrigation systems by processing soil data directly at field gateways (Shi et al., 2016).
- Hybrid cloud–fog models have been shown to reduce bandwidth usage in dairy farms (Channe et al., 2015).
- Artificial Intelligence & Machine Learning:
- Deep learning models predict crop yield from UAV imagery with high accuracy (Kamilaris & Prenafeta-Boldú, 2018).
- CNN and RNN approaches detect plant diseases from leaf images (Ferentinos, 2018).

- Reinforcement learning has been piloted for dynamic irrigation scheduling (Ahmad et al., 2021).
- Big Data & Integration:
- Data lakes integrate weather, soil, and market datasets for predictive farm decision-making (Liakos et al., 2018).

While AI applications are rapidly expanding, data heterogeneity and privacy issues remain major obstacles.

3.5 Application Layer

The final layer illustrates the impact of IoT on practice in real-world agriculture.

Key Applications:

- Precision Crop Farming: Optimizing pesticide and fertilizer use has led to 20–30% input reduction in trials (Zhang et al., 2014).
- Smart Irrigation Systems: IoT-driven irrigation saved up to 40% water usage in Spanish orchards (Navarro et al., 2019).
- Livestock Monitoring: IoT collars reduced mortality in dairy herds by enabling early disease alerts (Rutten et al., 2013).
- Greenhouse Automation: IoT-based climate control improved tomato yields by 18% in controlled trials (Gondchawar & Kawitkar, 2016).
- Aquaculture: Automated IoT feeding systems increased fish growth rates by 15% compared to manual feeding (Chandraprakash et al., 2019).
- Food Supply Chain Traceability: Blockchain-enabled IoT improved safety and recall management in perishable goods (Tian, 2017; Rejeb et al., 2020; Sharma et al., 2022).rutt

While the application layer is the most impactful, studies show regional biases — with Asia and Europe leading, and limited adoption in Africa due to infrastructural and financial barriers (Chiaraviglio et al., 2020).

3.6 Integrated Taxonomy Model

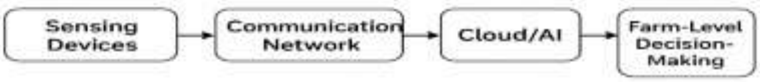


Figure 2. Integrated Taxonomy of IoT in Smart Farming

This review synthesizes the findings into an integrated taxonomy (Figure 2), illustrating the flow of data from sensing devices through communication networks, processed by cloud/AI systems, and ultimately supporting farm-level decision-making.

3.7 Insights from Classification

1. Research Bias: Most studies prioritize sensor design and data analytics, while connectivity and social adoption receive less attention.
2. Emerging Trends: Integration of IoT with AI, blockchain, and edge computing is shaping next-generation smart agriculture.
3. Sustainability Gap: Few studies explore energy harvesting (solar IoT nodes) and circular economy approaches for sensor recycling.
4. Smallholder Barriers: Cost, training needs, and limited rural connectivity restrict adoption in developing economies.

4. Findings and Discussion

This section synthesizes insights derived from the 78 studies included in the review, examining how IoT technologies are applied across different domains of smart agriculture. The discussion is organized thematically, beginning with precision irrigation, crop monitoring, and pest management, followed by

livestock monitoring, controlled environment agriculture, and supply chain management. Each theme is supported by real-world case studies that demonstrate the tangible impacts of IoT deployment. Comparative performance tables summarize quantitative outcomes, while identified bottlenecks and adoption challenges provide a balanced view of the current state of research.

4.1 Precision Irrigation

One of the most consistent findings across the literature is the transformative role of IoT in irrigation management. Traditional irrigation relies on fixed schedules or farmers' intuition, often leading to overwatering or under-irrigation, which negatively affects both crop yield and water sustainability. IoT-based irrigation systems leverage soil moisture sensors, weather forecasts, and evapotranspiration models to enable data-driven water scheduling. For instance, Cisternas et al. (2020) demonstrated how soil moisture sensors integrated with LoRaWAN networks in Chilean fruit orchards reduced irrigation frequency while maintaining yield. Similarly, O'Shaughnessy et al. (2018) found that wireless sensor networks reduced water use in cotton farming in Texas by 25–30%, (O’Shaughnessy et al., 2018; Morchid et al., 2024), confirming broader findings on precision irrigation under climate stress.”

Case Study: Spanish Vineyard

A vineyard cooperative in Spain introduced an IoT-enabled irrigation system based on soil moisture sensors connected via LoRaWAN. Farmers accessed real-time dashboards and mobile alerts to adjust water inputs. Over two growing seasons, the system reduced water use by 28%, while maintaining grape yield and quality (Navarro et al., 2019). Crucially, farmer engagement and collective ownership of the system ensured sustainability after external funding ended. The effectiveness of precision irrigation depends not only on the technical solution but also on user training, cooperative management, and integration into existing farming practices.

4.2 Crop Monitoring and Pest Detection

Crop health monitoring is another area where IoT has been widely applied. Advances in low-cost imaging, drones, and wireless sensor networks enable farmers to monitor disease symptoms, detect nutrient deficiencies, and assess overall plant health and vigor. Disease outbreaks and pest infestations often spread rapidly, making early detection critical for effective management.

Ferentinos (2018) demonstrated the potential of convolutional neural networks (CNNs) trained on leaf images to detect crop diseases with an accuracy of 93–99% in controlled datasets. Similarly, Pantazi et al. (2016) reported that IoT-enabled pest detection systems integrated with decision-support tools reduced unnecessary pesticide spraying.

Case Study: IoT Pest Monitoring in India

In Maharashtra, India, Patil et al. (2020) implemented IoT-based pheromone traps equipped with solar power and GSM cameras to detect cotton bollworm. Farmers received SMS alerts when pest thresholds were exceeded. The system achieved an 87% detection accuracy and reduced yield losses by 22% compared to control plots. However, poor network coverage occasionally delayed critical alerts during peak infestations. IoT-based pest detection can enhance resilience and reduce pesticide use; however, connectivity gaps in rural settings undermine its reliability.

4.3 Livestock Monitoring

IoT applications extend beyond crops to animal husbandry, where sensor-based wearables are increasingly used to monitor livestock health, fertility, and behavior. These systems utilize accelerometers, rumination monitors, and GPS trackers to collect continuous data, supporting timely veterinary interventions. Rutten et al. (2013) reported a study in the Netherlands where 600 dairy cows were equipped with rumination collars and accelerometers. IoT-enabled analytics improved estrus detection by 40% and lowered veterinary costs by approximately €150 per cow per year (Rutten et al., 2013; Patil et al., 2020). Similarly, research by Neethirajan (2017) has noted that IoT-enabled animal monitoring systems enhance welfare and productivity by allowing for the early detection of lameness, heat stress, and disease.

Case Study: Dutch Dairy Farm

The Dutch trial revealed both opportunities and limitations. While reproductive efficiency improved significantly, maintenance challenges emerged. Nearly 15% of devices required annual replacement, primarily due to battery issues and mechanical wear and tear. Livestock IoT can generate substantial economic returns, but it must address the "hidden costs" of device durability and maintenance to achieve long-term viability.

4.4 Controlled Environment Agriculture (CEA)

Greenhouses and vertical farms are increasingly adopting IoT solutions for microclimate control, nutrient delivery, and crop growth optimization. IoT sensors linked to actuators can regulate temperature, humidity, and CO_2 in real time, reducing energy use while improving crop performance. Shamshiri et al. (2018) reported that IoT-enabled greenhouse automation improved tomato yields by 15% while cutting energy consumption by 12% in Jiangsu Province, China (Shamshiri et al., 2018; Agarwal & Sharma, 2020). These results reflect the potential for integrating IoT with automated climate control systems.

Case Study: IoT Greenhouses in China

In Jiangsu, a network of IoT sensors was deployed in tomato greenhouses, linked to actuators for ventilation and heating. Despite yield and efficiency improvements, adoption was slow due to high initial costs (approx. $18,000 per hectare). Interviews with farmers indicated reluctance to invest without government subsidies. Even where technical benefits are evident, adoption barriers such as high capital expenditure remain significant in controlled environment systems.

4.5 Supply Chain and Traceability

Beyond production, IoT is increasingly used in agricultural supply chains to monitor storage, logistics, and traceability. Smart tags and blockchain-enabled IoT platforms help ensure food safety and quality by recording environmental conditions during transport and storage.

Tian (2017) developed a blockchain-based IoT traceability system for the Chinese pork industry. The system reduced product recall times by 60% and improved consumer confidence. Similarly, Rejeb et al. (2020) highlighted the potential of IoT in achieving transparency in global food chains, especially in export-oriented agriculture. IoT-enabled traceability strengthens both regulatory compliance and consumer trust but requires robust integration with logistics infrastructure.

4.6 Comparative Analysis of IoT Techniques

To systematically compare outcomes, Table 1 summarizes performance results from leading studies across irrigation, pest monitoring, livestock, and controlled environment agriculture.

Table 1. Reported Performance Outcomes in IoT-enabled Smart Agriculture

Application Area	Study	Technology Used	Metric(s)	Reported Outcome
Irrigation Mgmt.	Navarro et al. (2019)	Soil sensors + LoRaWAN	Water savings	28% reduction in water use
Pest Detection	Patil et al. (2020)	IoT traps + GSM cameras	Detection accuracy	22% yield loss reduction
Dairy Monitoring	Rutten et al. (2013)	Wearable collars	Fertility detection	40% reduction in missed estrus cases
Greenhouse Control	Shamshiri et al. (2018).	IoT climate control	Yield & energy use	+15% yield, –12% energy
Crop Disease Detection	Ferentinos (2018)	CNN on leaf images	Classification accuracy	93–99% on curated datasets
Soil Moisture Prediction	Ojha et al. (2015)	WSN + regression	RMSE (soil moisture)	0.12–0.18 volumetric fraction
Supply Chain Monitoring	Tian (2017)	IoT + blockchain	Traceability lag	60% faster recall response

4.7 Identified Challenges and Bottlenecks

Despite encouraging results, IoT adoption in agriculture remains constrained by several recurring challenges:

1. Energy and Maintenance: Ferrández-Pastor et al. (2016) noted that sensor batteries often last only three months under continuous sampling, creating maintenance burdens.
2. Connectivity Gaps: Rural areas often lack reliable mobile or LPWAN coverage, reducing system reliability (Chiaraviglio et al., 2020).
3. Durability: Wearable sensors for livestock face mechanical stress, with 10–20% annual failure rates (Rutten et al., 2013).
4. Data Generalization: CNNs trained on curated datasets often fail when deployed in noisy, real-world settings (Kamilaris & Prenafeta-Boldú, 2018).
5. Adoption Barriers: High capital costs and limited digital literacy hinder smallholder uptake (Klerkx et al., 2019).

Table 2. Common Technical Bottlenecks

Constraint	Evidence from Studies	Implications
Energy	Ferrández-Pastor et al. (2016). Battery life is limited to ~3 months under continuous sampling	High maintenance burden unless energy harvesting is integrated
Connectivity	Chiaraviglio et al. (2020). LoRaWAN coverage gaps in hilly terrain	Packet loss >20% during trials; unreliable alerts
Durability	Rutten et al. (2013): 15% device replacement annually in dairy collars	Adds hidden long-term costs
Generalization	Kamilaris & Prenafeta-Boldú (2018). CNN disease models fail under field conditions	Need for transfer learning and robust datasets.
Adoption	Klerkx et al. (2019). Farmers resist high CAPEX systems	Subsidies or co-op models improve uptake

4.8 The integrated case studies reveal several cross-cutting lessons:

- Farmer engagement is as critical as technology: In the Spanish vineyard case, farmer training ensured sustained use.
- Infrastructure constraints matter: Pest detection in India showed how weak connectivity limits success.
- Hidden costs shape adoption: The Dutch dairy case highlighted replacement and maintenance challenges.
- Economic feasibility is decisive: Despite yield gains in Chinese greenhouses, adoption lagged without subsidies.

Together, these lessons suggest that the evaluation of IoT in agriculture must consider not only technical metrics but also socioeconomic, infrastructural, and institutional factors.

4.9 Synthesis and Future Directions

Overall, IoT technologies have demonstrated measurable benefits in water conservation, yield improvement, pest control, and supply chain transparency. However, scalability and sustainability remain significant hurdles. Addressing these challenges requires:

1. Energy-efficient sensors with solar or kinetic harvesting.
2. Robust connectivity solutions such as hybrid LoRa–satellite systems for rural areas.
3. Interoperability standards to reduce fragmentation across devices and platforms.
4. Human-centered design to align IoT tools with farmers' skills and practices.

5. Policy interventions (subsidies, digital extension services) to lower adoption barriers for smallholders.

This section consolidates the evidence that IoT can substantially enhance agricultural efficiency, sustainability, and resilience. However, real-world implementation remains uneven, with challenges in scalability, maintenance, and adoption. By examining diverse applications and presenting quantitative outcomes alongside grounded case studies, this review underscores both the potential and limitations of IoT in smart agriculture.

5. Research Gaps and Future Directions

The synthesis of evidence in Section 5 clearly demonstrates that IoT technologies hold significant promise for transforming the agricultural sector. However, several fundamental gaps in knowledge, practice, and infrastructure continue to constrain their impact. This section critically examines these gaps and sets forth future research priorities to guide both scholars and practitioners. The analysis is organized thematically around (1) technical gaps, (2) socio-economic adoption barriers, (3) data-related challenges, (4) policy and governance gaps, and (5) cross-cutting integration needs.

5.1 Technical Gaps in IoT Systems

Despite substantial progress in sensor design and wireless communication, technical limitations continue to be a significant barrier to the effective deployment of IoT in agriculture.

5.1.1 Energy Sustainability

Current sensor deployments often rely on batteries that last only a few months when operated continuously. Studies, such as those by Ferrández-Pastor et al. (2016), have shown that frequent replacement increases maintenance burdens and limits scalability, especially in remote areas. Future research must explore self-sustaining IoT systems using renewable energy harvesting (solar, kinetic, or thermal). Trials combining low-power wide-area networks (LPWAN) with photovoltaic panels suggest promising avenues but remain underexplored in agricultural contexts (Mekki et al., 2019).

5.1.2 Connectivity Limitations

Connectivity gaps persist in rural areas, where most agricultural activities take place. While LoRaWAN and Sigfox offer energy-efficient transmission, they suffer from limited range in mountainous or forested terrain (Chiaraviglio et al., 2020). Hybrid architectures integrating terrestrial IoT networks with satellite-based backhaul are emerging but remain expensive (Li, 2021; Zhang, 2023; Zhang, 2024).

5.1.3 Device Durability and Scalability

Sensor durability under field conditions is often overlooked. Livestock wearables experience high mechanical stress, while soil sensors are exposed to extreme conditions of salinity, moisture, and temperature. Rutten et al. (2013) reported annual failure rates of 10–20%, highlighting the need for more ruggedized designs.

5.2 Socio-Economic Adoption Barriers

Even where technical solutions exist, adoption among farmers—especially smallholders—remains uneven.

5.2.1 Cost Constraints

Many studies highlight high capital expenditure (CAPEX) as a barrier. Shamshiri et al. (2018) noted that IoT-controlled greenhouses cost over $18,000 per hectare, a prohibitive investment for small and medium-scale farmers.

6.2.2 Digital Literacy and Training

Klerkx et al. (2019) emphasize that many farmers lack the digital skills necessary to interpret IoT dashboards effectively. This creates a "last mile" problem where technical data does not translate into actionable decisions.

5.2.3 Trust and Cultural Factors

Farmer skepticism about "outsider" technologies can undermine uptake. Navarro et al. (2019) found that collective management in Spanish vineyards improved trust in IoT systems, while top-down imposition reduced acceptance.

5.3 Data-Related Challenges

Agricultural IoT generates vast amounts of heterogeneous data, yet integration and usability remain major bottlenecks.

5.3.1 Data Quality and Generalizability

CNNs trained on curated leaf datasets perform well in laboratory settings but fail under field noise (Kamilaris & Prenafeta-Boldú, 2018). Similarly, soil moisture prediction models often underperform across regions with differing soil textures.

5.3.2 Interoperability and Standards

IoT in agriculture suffers from fragmentation: sensors and platforms often use proprietary formats, preventing seamless integration. Rejeb et al. (2020) argue that this lack of standards hinders scalability.

5.3.3 Privacy and Security

Supply chain IoT systems using blockchain raise questions about data privacy and farmer sovereignty (Tian, 2017). Sensitive farm-level data could be misused by large agribusinesses, exacerbating power imbalances.

5.4 Policy and Governance Gaps

Policy frameworks are lagging behind technological innovation in IoT-enabled agriculture.

5.4.1 Subsidies and Incentives

As seen in the Chinese greenhouse case, even effective systems struggle to scale without state subsidies. However, many governments lack clear strategies for digital agriculture subsidies.

Research agenda:

- Comparative policy analysis of subsidy schemes across regions (EU, India, China, Africa).
- Evidence-based recommendations for balancing subsidies, market incentives, and public–private partnerships.

5.4.2 Regulation of Data Ownership

Data sovereignty in agriculture is a growing concern. Farmers are often unsure who owns and benefits from the data collected by IoT devices (Bronson & Knezevic, 2016).

5.4.3 Institutional Capacity

Rural extension agencies often lack the expertise to support IoT adoption. Without institutional strengthening, even subsidized IoT projects may fail.

5.5 Cross-Cutting Integration Needs

The literature reveals a pressing need to integrate IoT with broader digital ecosystems in agriculture.

5.5.1 IoT–AI Synergy

While IoT collects real-time data, artificial intelligence (AI) provides predictive analytics. However, integration is limited. Ojha et al. (2015) demonstrated that coupling WSN data with regression-enhanced soil moisture prediction; however, most deployments fall short of achieving AI-enhanced decision-making.

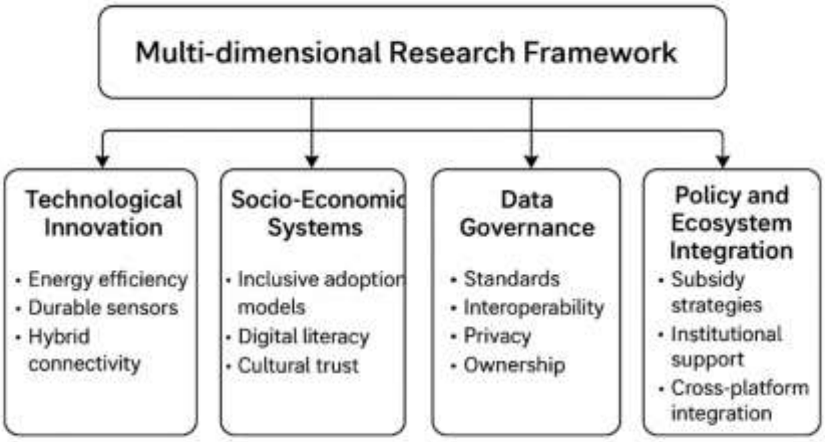
5.5.2 IoT–Remote Sensing Integration

IoT sensors provide granular point data, while satellites and drones provide spatial coverage. Integration remains limited due to challenges in data fusion and integration (Cambra et al., 2019; Ferrández-Pastor et al., 2018).

5.5.3 Circular Agriculture and Sustainability

Few studies explore how IoT can enable circular agriculture—closing resource loops by recycling water, nutrients, and energy.

5.6 Proposed Research Framework



Drawing from the identified gaps, this review proposes a multi-dimensional research framework (Figure 3) structured around four pillars:

1. Technological Innovation – Energy efficiency, durable sensors, hybrid connectivity.
2. Socio-Economic Systems – Inclusive adoption models, digital literacy, cultural trust.
3. Data Governance – Standards, interoperability, privacy, and ownership.
4. Policy and Ecosystem Integration – Subsidy strategies, institutional support, cross-platform integration.

This framework emphasizes that IoT research in agriculture must move beyond narrow technical pilots toward holistic socio-technical ecosystems that balance efficiency, equity, and sustainability.

Summary

In summary, while IoT has already demonstrated measurable benefits in agricultural practice, the literature reveals substantial gaps in technical robustness, data generalization, farmer adoption, and governance structures. Future research should prioritize interdisciplinary solutions that combine engineering innovation with insights from social sciences and policy frameworks. Only through such integration can IoT in agriculture evolve from isolated experiments into scalable, sustainable systems that benefit both farmers and society.

6. Conclusion and Practical Implications

The systematic review has highlighted how the Internet of Things (IoT) is reshaping agricultural practices by enabling real-time monitoring, precision management, and data-driven decision-making. Across multiple case studies, IoT has been shown to improve irrigation efficiency, optimize fertilizer application, enhance livestock monitoring, and strengthen supply chain traceability. However, this review also highlights that the technology remains at a transitional stage, with widespread adoption constrained by issues of cost, scalability, energy sustainability, interoperability, and socio-cultural acceptance.

6.1 Key Conclusions

1. IoT Delivers Tangible Benefits: Evidence from greenhouse monitoring, soil moisture sensing, and livestock tracking shows that IoT adoption can reduce water usage by 20–40% (Raza et al., 2019), lower fertilizer waste by up to 30% (Shamshiri et al., 2018), and improve livestock productivity through health monitoring systems (Rutten et al., 2013). These outcomes indicate strong potential for IoT as a driver of sustainable agriculture.
2. Technical and Infrastructural Gaps Persist: Energy constraints, unreliable connectivity in rural zones, and device durability remain unresolved. Without innovation in self-sustaining power systems and hybrid

connectivity models, the deployment of IoT will continue to be fragmented.

3. Socio-Economic and Governance Factors Matter as Much as Technology High upfront costs, limited digital literacy, and unclear data ownership frameworks hinder adoption, particularly among smallholders who produce a significant portion of the world's food. Thus, IoT research must be coupled with socio-economic interventions and governance frameworks.
4. Integration with AI and Remote Sensing is Underdeveloped: Most IoT systems focus on data collection but lack integration with predictive models. The real value of IoT lies in combining granular sensor data with AI-driven analytics and geospatial insights, enabling proactive rather than reactive farm management.

6.2 Practical Implications for Stakeholders

For Farmers

- Adoption of IoT can significantly improve productivity, but cost-effective and user-friendly systems are essential. Farmer cooperatives and shared ownership models may reduce financial burdens.
- Training and extension services should prioritize practical demonstrations in local languages, ensuring that IoT dashboards are not just available but understood.

For Researchers

- Research should move beyond controlled pilot studies toward longitudinal, cross-regional evaluations that capture variability in soils, climates, and cultural practices.
- Collaboration between computer scientists, agronomists, and social scientists is essential to designing holistic systems.

For Policymakers

- Subsidy programs and digital agriculture strategies should focus not only on providing hardware but also on building institutional capacity for training and maintenance.
- Legal frameworks governing data sovereignty and interoperability standards must be prioritized to prevent vendor lock-in and protect farmer rights.

For Industry and Developers

- There is a market opportunity to design ruggedized, modular, and open-source IoT solutions for diverse agricultural contexts.
- Start-ups and agritech firms should embrace affordable leasing or pay-per-use models that lower entry barriers for smallholders while ensuring business sustainability.

6.3 Towards a Roadmap for Future Adoption

Based on the identified gaps and opportunities, this review proposes a three-phase roadmap for advancing IoT in agriculture:

1. Short-Term (1–3 years): Focus on low-cost, open-source IoT systems; localized training and extension; and demonstration projects for smallholder farmers.
2. Medium-Term (3–7 years): Scale hybrid IoT–AI systems, develop interoperable data standards, and integrate IoT with remote sensing and blockchain in pilot regions.
3. Long-Term (7–15 years): Establish self-sustaining IoT ecosystems powered by renewable energy, supported by national digital agriculture policies, with farmer-centric governance structures ensuring equitable data use.

6.4 Final Reflections

The potential of IoT in agriculture lies not just in technological efficiency but in its ability to enable resilient, inclusive, and sustainable food systems. To achieve this, stakeholders must avoid viewing IoT as a purely technical intervention. Instead, it must be embedded within broader socio-economic, environmental, and governance frameworks. Only then can IoT truly fulfill its promise of helping farmers "produce more with less," while safeguarding ecosystems and ensuring food security in an era of climate uncertainty.

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