

IoT-Driven Smart Farming for Sustainable Agriculture: A Systematic Review of Technologies, Challenges, and Socio-Economic Implications

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Abstract

Sustainability concerns and the pressure to use agricultural resources more efficiently have pushed modern farming toward IoT-enabled smart systems. Conventional cultivation, which still depends largely on manual inspection and uniform field treatment, often results in wasted water, mistimed irrigation, and slow reaction to environmental change. This review examines the IoT-driven smart farming literature across four interconnected dimensions: smart farming architectures, AI-assisted agricultural models, wireless communication frameworks, and the socio-economic sustainability of these systems. A PRISMA-inspired selection procedure was applied to articles drawn from IEEE Xplore, ScienceDirect, Springer, MDPI, and other indexed databases. The review synthesises recent advances in smart farming architectures, communication standards, precision irrigation, AI-enabled applications, and edge-assisted monitoring. Although IoT-based agriculture offers clear gains in environmental observation, irrigation control, and resource efficiency, persistent issues—infrastructure dependency, weak rural connectivity, high deployment cost, energy constraints, computational demands, and limited fit with rural realities—continue to limit large-scale adoption. The analysis surfaces important research gaps in scalability, long-term field deployment, socio-economic integration, and end-user usability, and indicates that future research should target low-cost, scalable, energy-aware architectures that can be realistically sustained in everyday agricultural settings.

Keywords: IoT, Smart Farming, Precision Agriculture, Sustainable Farming, Sensor Networks, Smart Irrigation, AI, Edge Computing, Agricultural Monitoring, AIoT, Rural Sustainability.

Introduction

Traditional cultivation methods alone no longer answer the demands placed on farming today. Across many regions, particularly in developing economies, day-to-day operations still rely on direct field observation, seasonal habit, and experience-based judgement. These methods have carried agriculture for generations, yet they sit awkwardly against an environment that is becoming progressively more uncertain and more sensitive to resource use [1], [5]. Irregular rainfall, shrinking water reserves, rising input costs, and environmental variability weigh most heavily on small and marginal cultivators, who typically work with minimal technological support for irrigation, crop health, and environmental observation [6], [22]. Under these conditions, even modest delays in irrigation scheduling can translate into meaningful losses in productivity and economic stability.

Over the past decade, Internet of Things (IoT)-based smart farming has become one of the most actively investigated branches of precision agriculture [10], [19]. The term refers broadly to interconnected sensors, communication links, processing units, and monitoring platforms that observe agricultural conditions continuously and in real time. Recent work demonstrates that such systems sharpen environmental monitoring, irrigation control, crop observation, and overall resource efficiency through automated data acquisition [2], [11]: parameters that once depended on occasional manual checks—soil moisture, humidity, temperature, pH—can now be tracked dynamically, supporting a shift from uniform practice toward condition-based management.

Smart farming is not defined by sensing alone. Artificial intelligence, machine learning, cloud computing, edge computing, and wireless sensor networks are increasingly woven into agricultural systems to sharpen analytical capability and responsiveness [7], [20]. AI-assisted models now appear in research on crop disease prediction, irrigation forecasting, yield estimation, and environmental analysis, while edge-enabled architectures mitigate communication latency by processing data near the field itself [4], [8]. Sustainability sits at the heart of this agenda: IoT-driven precision agriculture is frequently positioned as a route toward more careful water use, lower energy waste, and long-term ecological balance [4], [14].

Rapid technological progress notwithstanding, large-scale deployment remains difficult. Much published work centres on sophisticated architectures developed in controlled or infrastructure-rich environments [12], [13], leaning on stable internet, cloud processing, costly sensors, or continuous technical upkeep—conditions not always met in real rural settings. Systems that perform well in pilot conditions often struggle in long-term deployment because of maintenance burden, communication instability, power management issues, or user unfamiliarity [5], [22]. Adoption turns on more than technical efficiency; it depends equally on affordability, ease of use, digital literacy, and farmer trust.

Although the literature now spans communication architectures, precision irrigation, AI-driven applications, edge computing, and sustainability-oriented design [3], [16], [16], most existing reviews summarise technical advances rather than drawing implementation constraints, socio-economic effects, and rural adaptability into a single analytical frame. The present review accordingly offers a systematic, critical analysis of IoT-driven smart farming with deliberate emphasis on sustainability, deployment barriers, and socio-economic relevance, paying particular attention to small and marginal farming communities—the segment in greatest need of low-cost, scalable, practically adaptable solutions.

Review Methodology

The rapid expansion of IoT-enabled agriculture research has produced a large and uneven body of literature. A systematic review methodology was therefore adopted, following established principles [15] and proceeding through database identification, keyword searching, screening, duplicate removal, inclusion and exclusion filtering, and comparative assessment within a PRISMA-inspired structure.

- **Database Selection**

Publications were drawn from internationally recognised databases: IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, MDPI Open Access Journals, Wiley Online Library, Google Scholar, and Scopus-indexed repositories, which collectively index a substantial body of peer-reviewed research on IoT systems, sensor networks, precision agriculture, and AI-assisted farming [1], [19]. Non-indexed or unverified outlets were excluded.

- **Search Strategy**

Keyword combinations covered both technological and socio-economic facets, including "IoT in Agriculture," "Smart Farming," "Precision Agriculture," "Smart Irrigation Systems," "Wireless Sensor Networks in Agriculture," "AI in Smart Farming," "Edge Computing Agriculture," and "Sustainable Agriculture IoT," refined with Boolean operators (e.g., IoT AND Smart Agriculture). The search concentrated on 2019–2024, retaining older publications only where they offered foundational grounding [4], [19], [24].

- **Inclusion Criteria**

A study was retained if it discussed IoT-based smart farming or agricultural monitoring; addressed precision agriculture, smart irrigation, wireless sensor networks, AI-assisted agriculture, or edge computing; was peer-reviewed, published in English between 2019 and 2024; and contained practical

applications, comparative analysis, or discussion of sustainability and socio-economic aspects of adoption. Additional weight was given to low-cost, scalable, implementation-oriented systems.

- **Exclusion Criteria**

Excluded categories comprised publications unrelated to agriculture; exclusively industrial IoT research; non-peer-reviewed and commercial material; duplicates; studies lacking methodological detail; predatory-journal publications; purely theoretical models; and reviews with heavy thematic overlap.

- **PRISMA-Based Literature Selection Flow**

Identified records were screened for duplicates, assessed via title and abstract analysis against the review themes, and then judged at full text on implementation relevance, methodological clarity, publication quality, and alignment with the review objectives. The final set consisted primarily of peer-reviewed studies addressing IoT architectures, precision irrigation, wireless sensor networks, AI-assisted farming, edge computing, sustainable agriculture, and adoption challenges. The workflow is summarised in Fig. 1.

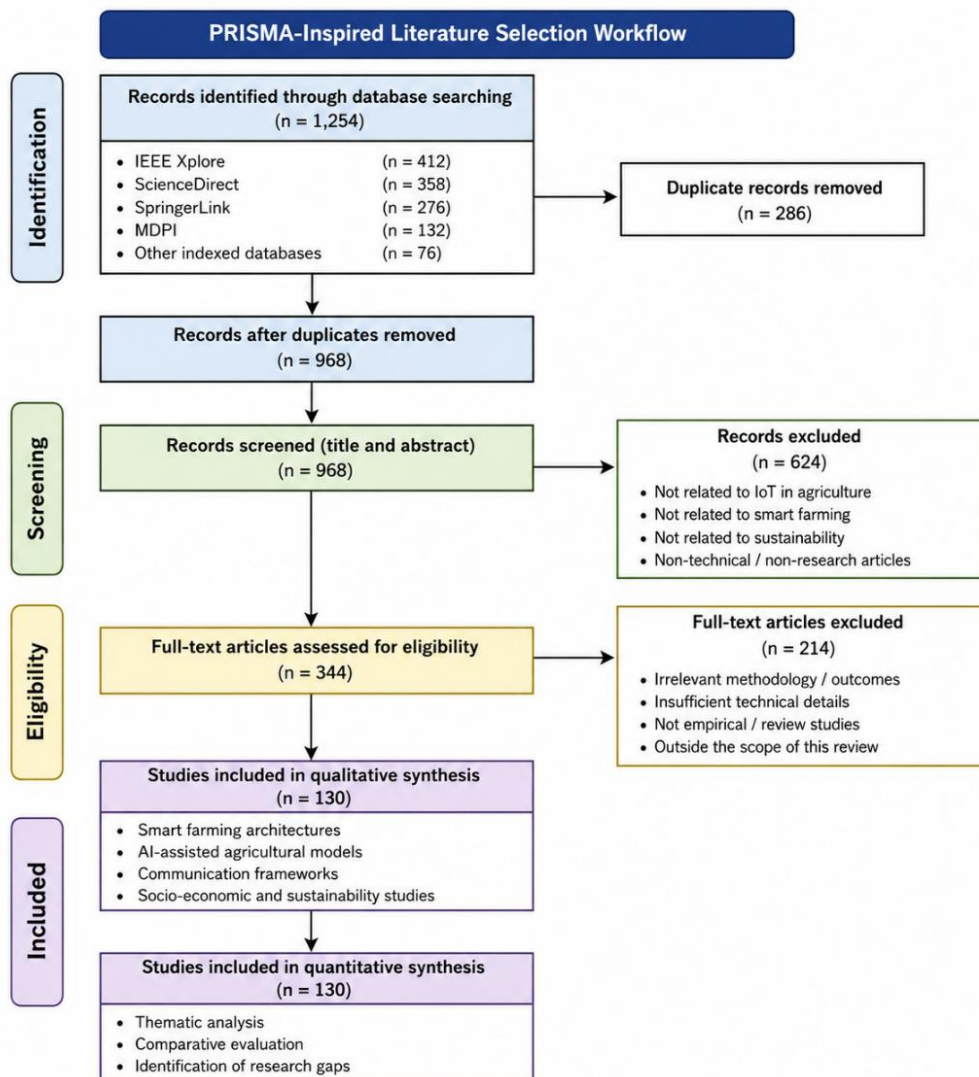


Fig. 1: PRISMA-inspired literature selection workflow

IoT in Smart Agriculture

IoT in agriculture denotes a coordinated set of connected sensors, communication links, embedded units, and monitoring platforms that exchange field information in real time. Soil moisture, humidity, temperature, pH, and broader environmental conditions are tracked continuously [10], [13], with growing adoption across irrigation management, greenhouse control, crop analysis, livestock observation, and environmental sensing [2], [22]. The literature consistently links such monitoring with a shift from fixed-schedule operations toward condition-based practice [1], [6], [17]: IoT-enabled irrigation, for example, replaces preset timing with continuous sensing and automated control, with reported gains in water-use efficiency [2], [11].

A further trend is the rise of low-cost sensing: where earlier precision farming was associated with expensive infrastructure suited to large commercial operations, recent designs lean toward affordable, scalable architectures essential in developing agricultural economies [12], [14]. Wireless sensor networks play a central role, with distributed nodes monitoring multiple field locations simultaneously [13]. Among communication options—Wi-Fi, ZigBee, GSM, LoRaWAN, and NB-IoT [9], [14], [25]—LoRaWAN attracts particular attention for its long range and low energy draw in rural settings, though connectivity stability remains a persistent obstacle in remote regions [5], [22].

Beyond monitoring, IoT-enabled agriculture is moving toward intelligent decision support. AI-assisted frameworks appear in studies on disease detection, predictive irrigation, environmental forecasting, and crop analysis [3], [7], [20]. Cloud computing has long served as the default processing platform, supporting centralised storage and large-scale analysis [4], [19], [21], but cloud-centric architectures introduce communication delays and infrastructure issues in rural settings [8], [14]. Edge-assisted designs that process sensor data closer to the field have therefore moved into the foreground: Issa et al. [8] observe that they improve responsiveness by lowering dependence on continuous internet communication—a benefit most visible in automated irrigation control, where even short delays compromise efficiency.

Recurring limitations nonetheless come through clearly. Infrastructure dependency tops the list [5], [12]: many frameworks assume stable internet, uninterrupted power, and continuous maintenance. Operational complexity follows, since smaller communities struggle with calibration and day-to-day usability—adoption rests more on affordability, digital familiarity, and simplicity than on technical capability [5], [22]. Data security is also gaining attention as farming becomes more deeply wired into wireless and cloud-assisted monitoring [18], [25]. A conceptual architecture is shown in Fig. 2.

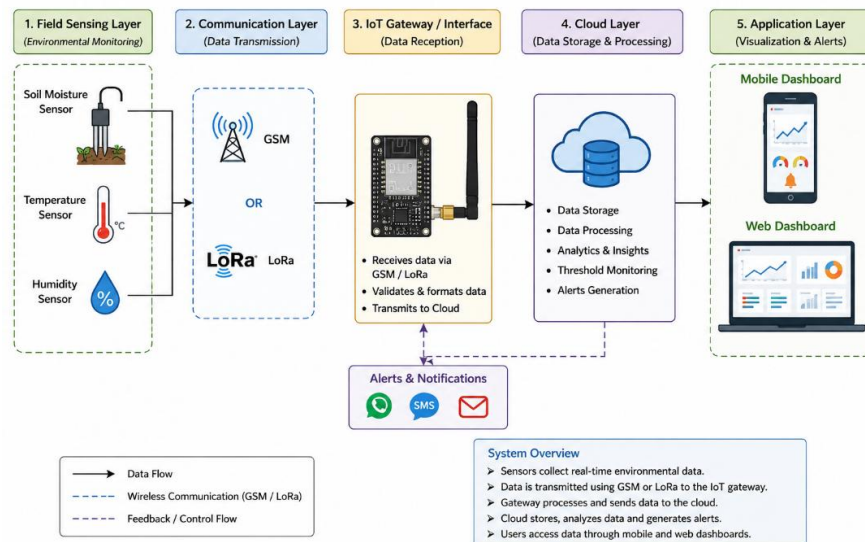


Fig. 2. Conceptual IoT-driven smart farming architecture.

Fig. 2: Conceptual IoT-driven Smart Farming Architecture

Precision Agriculture Systems

Precision agriculture directly targets productivity through accurate monitoring and controlled use of inputs. Traditional methods apply irrigation, fertiliser, and pesticide uniformly, yet fields rarely behave uniformly: soil character, moisture, nutrients, and environmental exposure vary across sections of land [4], [19], so generalised practice produces inefficient resource use and inconsistent performance. Precision farming instead monitors field-level variation continuously and supports condition-based, location-specific decisions [24], [25]—a transition sharply accelerated by IoT, which gives cultivators near-immediate visibility into changing conditions while reducing wastage [1], [2], [11].

Among the applications, smart irrigation has drawn the most sustained attention, since water management remains one of the most pressing concerns in global agricultural sustainability. In many regions irrigation still follows fixed timing rather than measured soil state [6], [22], with over- or under-irrigation as common consequences. IoT-assisted precision irrigation addresses this through soil moisture sensors that measure water availability dynamically, and comparative studies indicate meaningful gains in water-use efficiency when automation is paired with real-time monitoring [2], [6], [11], [17]. Wireless sensor networks form a further pillar [13], while LoRaWAN-based architectures combine long range with low power demand [14], though connectivity reliability remains a serious concern at rural scale [5], [12].

Cloud-assisted precision agriculture underpins centralised storage and remote monitoring through mobile dashboards [4], [19], but heavy cloud reliance introduces delays where connectivity is inconsistent [8], [14]. Recent studies therefore look toward edge-assisted precision agriculture, processing selected data closer to the field [4], [7], and toward AI for predictive irrigation: such systems mine historical environmental data, weather records, and sensor streams to anticipate irrigation needs [3], [20].

Implementation hurdles nonetheless persist. Cost recurs most frequently [5], [12], [22]: advanced architectures involve expensive sensors, proprietary software, and complex infrastructure. Maintenance sustainability follows closely—agricultural environments expose devices to moisture, dust, temperature swings, and physical disturbance [23], so prototypes that perform well over short tests often falter in extended use. Finally, farmer acceptance depends on operational simplicity, affordability, and trust in the system's recommendations [5]. Future precision agriculture should therefore focus not only on automation capability but on scalable, economically feasible deployment in real agricultural environments.

AI and Edge Computing IN Smart Farming

The integration of AI and edge computing marks a departure from purely monitoring-based farming toward intelligent, predictive management: the data collected by early IoT systems is increasingly recognised as a foundation for forecasting, automation, and decision-making [7], [19]. AI in agriculture covers machine-learning algorithms, predictive analytics, and automated reasoning, with growing interest in crop disease detection, irrigation prediction, yield estimation, and decision support [3], [7], [20].

Crop disease detection is among the most discussed applications: where traditional identification relies on visual inspection, with symptoms often noticeable only after significant damage, AI-assisted image processing attempts earlier detection, and deep learning and CNN-based models feature prominently in disease and leaf-abnormality classification [16], [16], [20]. Irrigation prediction is the second major site: AI models combine sensor streams with weather and historical patterns to estimate future requirements, reducing unnecessary irrigation [3], [7], [22]. Machine learning is also being tested in yield prediction and crop recommendation [4], [14].

AI-assisted agricultural systems nonetheless confront practical limits. Data dependency is the most frequently flagged: machine-learning algorithms require large, reliable training datasets [7], [16], yet sensor failures, communication interruptions, and environmental disturbance often produce incomplete field records, so models that excel in the laboratory encounter difficulty in deployment. Computational complexity is closely related—advanced models demand substantial processing and storage [4], [20], which smaller communities cannot readily sustain [5], [12].

Cloud computing initially became the default route for agricultural data handling [4], [19], but rural regions contend with unstable internet and bandwidth limits, and continuous transmission to distant servers adds overhead and delay [8], [14]. Edge computing—processing data closer to its source—has therefore moved to the centre of modern design, improving responsiveness, reducing communication dependency, and improving energy efficiency for power-constrained sensor nodes [4], [7], [8], [13]. Hybrid cloud–edge

architectures attract growing interest [3], [16], though integrating multiple technologies can raise complexity and maintenance burden in resource-constrained settings [5], [22].

Finally, AI-driven agriculture is better positioned as decision support than as a replacement for farmer experience: agricultural environments carry seasonal uncertainty and localised conditions not fully captured by computational models [5], [14]. The next generation of frameworks should focus on scalable, practically adaptable AI-assisted systems that operate effectively under real farming conditions.

Socio-Economic Implications of Smart Farming

While smart farming systems are routinely judged on sensing accuracy, communication performance, and automation capability, their long-term success turns on how well they fit the economic conditions and social structures of farming communities [5], [22]—particularly in developing regions where small and marginal farmers constitute a major share of the workforce. Technological advance alone does not guarantee agricultural transformation [1], [14]: adoption turns on affordability, operational simplicity, perceived usefulness, and long-term sustainability.

Improved resource management is the most frequently cited benefit: sensor-assisted irrigation and monitoring cut unnecessary water consumption [2], [6], [11], translating directly into reduced operational cost in water-stressed regions, while real-time monitoring supports quicker response to environmental stress [1], [22]. Labour optimisation is a further dimension—remote observation via mobile interfaces reduces constant physical inspection [10], [19] and lowers repetitive manual effort [3], [7]. Yet in many rural communities farming supports local employment, and rapid automation that ignores these structures raises concerns about displacement and uneven technological access [5], [14].

Affordability remains one of the most significant barriers: many architectures involve expensive sensors, proprietary software, subscription-based cloud services, and complex infrastructure [12], [22], and farmers respond more readily to low-cost technologies with immediate usefulness and manageable maintenance demands [5], [12]. Digital literacy is the next major concern—many systems implicitly assume comfort with mobile applications, dashboards, and sensor calibration [5], [17], while in practice usability often shapes adoption more strongly than technical capability. Infrastructure constraints—unreliable internet, unstable electricity, scarce technical support—weigh similarly on implementation sustainability [8], [14], partly explaining the attention now given to edge-assisted architectures and low-power communication [4], [7].

Trust also matters: when digital recommendations clash with years of cultivation experience, farmers hesitate to defer to the technology [5], [22]; supportive tools are far more likely to be adopted than rigid replacements for judgement. Government programmes shape the picture too [14], [19], though hardware deployment without training tends to produce low utilisation. Smart farming is thus no universal solution [5], [12]: long-term transformation depends equally on affordability, digital accessibility, infrastructure reliability, farmer trust, and practical adaptability.

Comparative Analysis of Existing Smart Farming Studies

The reviewed studies set out to improve efficiency through technological integration yet differ considerably in implementation approach, scalability, and practical applicability [15], [18]. A first cluster focuses on IoT-assisted irrigation: Dhanaraju et al. [1], García et al. [6], and Bashir et al. [11] examine sensor-based architectures that optimise water use through continuous soil moisture monitoring, reporting efficiency gains while assuming stable communication infrastructure. Wireless sensor network research foregrounds distributed environmental monitoring as the backbone of precision agriculture [13], though it also documents recurring challenges around power management, communication reliability, and outdoor maintenance. Communication studies [9], [14], [25] compare Wi-Fi, ZigBee, GSM, LoRaWAN, and NB-IoT; LoRaWAN stands out for range and energy efficiency, but latency, reliability, and infrastructure dependency register as major concerns at scale.

AI-assisted smart farming forms a third direction: Senoo et al. [3], Muhammed et al. [7], and Kamilaris and Prenafeta-Boldú [20] demonstrate strong analytical potential, yet their frameworks lean on large datasets, cloud infrastructure, and significant computation, limiting suitability for smaller communities [5], [12]. Edge computing reduces communication dependency [4], [8], though literature on large-scale deployment remains thin. Socio-economic sustainability receives uneven treatment: affordability, digital literacy, and operational simplicity strongly influence adoption [5], [12], [22], yet many advanced frameworks optimise primarily for technical performance, and most studies address individual components rather than integrated sustainability frameworks. The comparative observations are summarised in Table 1.

Table 1: Comparative Analysis of Existing Smart Farming Studies

Ref.	Study Focus	Technologies Used	Major Contribution	Identified Limitation
[1]	Smart farming framework	IoT sensors, cloud	Sustainable agricultural monitoring	Infrastructure dependency
[2]	Smart irrigation	Soil moisture sensors, IoT	Water optimisation	Limited scalability discussion
[3]	AI precision agriculture	AI, IoT, ML	Predictive farming analysis	Computational complexity
[5]	Smart farming adoption	IoT systems	Rural sustainability analysis	Limited technical implementation
[6]	IoT irrigation systems	Sensors, wireless networks	Real-time irrigation monitoring	Connectivity dependency
[7]	AIoT agriculture	AI, edge, IoT	Intelligent agricultural systems	High computational requirements
[8]	Digital agriculture	AI, robotics, edge computing	Real-time agricultural processing	Practical deployment limitations
[11]	Precision irrigation	IoT sensors, automation	Improved irrigation efficiency	Sensor maintenance issues
[12]	Low-cost IoT farming	IoT devices	Affordable agricultural framework	Limited field-scale validation
[13]	WSN agriculture	Wireless sensor networks	Distributed field monitoring	Energy management concerns
[14]	Sustainable IoT agriculture	LoRaWAN, IoT	Rural communication support	Infrastructure variability
[20]	Deep learning agriculture	Deep learning, AI	Crop disease analysis	Data dependency
[22]	Smart agriculture systems	IoT, precision farming	Sustainable resource management	Cost and adoption challenges
[4]	Big data smart farming	Cloud, edge computing	Agricultural analytics	Large-scale deployment complexity

The comparison underscores substantial headway in sensing, irrigation automation, AI-assisted analysis, and communication frameworks, set against recurring obstacles: infrastructure dependency, communication reliability, energy management, affordability, computational complexity, and farmer adaptability appear again and again [5], [12], [22]. Practical deployment is far less explored than prototype-level implementation—many studies report successful outcomes under controlled conditions but spend little time on long-term operational sustainability. The pull toward scalable, low-cost, farmer-oriented systems suited to resource-constrained rural environments is therefore growing [5], [14].

Research Gaps in IoT-Driven Smart Farming

Close inspection of the literature surfaces a set of unresolved limitations that constrain practical applicability, particularly for small and marginal farming communities. The most visible is the mismatch between technological sophistication and real-world fit: many architectures perform well in controlled environments yet offer limited evidence of long-term deployment under practical rural conditions [5], [12], with baked-in assumptions—stable internet, uninterrupted electricity, continuous maintenance—that frequently fail to hold. Infrastructure dependency is thus the headline unresolved issue: cloud-assisted systems support centralised monitoring and analytics [4], [19], but heavy reliance on continuous communication erodes reliability where infrastructure is inconsistent, and while edge computing offers a counterweight [7], [8], large-scale edge deployment literature remains thin.

Affordability constitutes a second major gap: much research centres on technically advanced configurations whose cost is impractical for small farming communities [3], [5], [20], [22], and while low-cost architectures appear [12], comprehensive frameworks combining affordability, scalability, and intelligent monitoring remain underdeveloped. Relatedly, farmer usability is comparatively unexamined—adoption depends on whether cultivators can operate, maintain, and trust systems [5], [14], yet few

frameworks build usability in from the outset. Communication reliability registers as another gap: comparative evaluations rest primarily on technical grounds [9], [13], [25], with less attention to how environmental exposure, terrain, and seasonal conditions influence stability during deployment. Energy management is similarly under-addressed, with comprehensive energy-aware frameworks remaining limited [13], [14], [23].

Structural gaps compound these issues. Research remains fragmented across individual components—irrigation automation, AI prediction, communication optimisation, environmental sensing [2], [3], [11]—with few integrated frameworks combining IoT monitoring, AI analytics, edge computing, affordability, and socio-economic sustainability in one architecture. Detailed analysis of adoption behaviour and rural implementation barriers is often thin [5], [22]; long-term deployment validation is sparse, with many evaluations based on short experiments or simulation rather than prolonged exposure to dust, rainfall, and sensor degradation [12], [14]; data dependency and computational complexity persist in AI-assisted research [7], [20]; and limited standardisation makes comparative assessment difficult [15], [18]. The major gaps are summarised in Table 2.

Table 2: Major Research Gaps Identified in Existing Smart Farming Literature

Research Area	Identified Gap
IoT architecture	Excessive infrastructure dependency
Smart irrigation	Limited scalability validation
Wireless communication	Rural connectivity instability
AI-assisted farming	High computational requirements
Edge computing	Limited real-world deployment studies
WSN systems	Energy management challenges
Sustainability research	Insufficient socio-economic integration
Farmer adoption	Limited usability-focused design
Smart agriculture frameworks	Fragmented implementation approaches
Long-term deployment	Lack of prolonged field validation
Low-cost farming systems	Limited scalable architectures
Agricultural data processing	Standardisation challenges

Taken together, the gaps suggest that future research should move beyond isolated technological optimisation toward integrated, scalable, practically adaptable frameworks that balance technological intelligence with affordability, operational simplicity, communication reliability, and socio-economic accessibility simultaneously.

Future Directions in IoT-Driven Smart Farming

Future research is likely to focus on systems that remain scalable, affordable, sustainable, and adaptable under real farming conditions. A first priority is low-cost, resource-efficient architectures balancing monitoring accuracy with affordability, since economic constraints currently limit adoption among small communities [5], [12]. Edge-assisted systems will become increasingly significant—the trajectory in the literature [4], [7] suggests hybrid cloud–edge architectures in which critical decisions are handled locally while long-term analytics remain cloud-supported [8], [14]. AI is expected to take on a larger role, with the next research wave targeting lightweight models capable of running effectively on low-power embedded devices rather than depending on large datasets and heavy computation [3], [5], [16], [20].

Multimodal sensing represents a further direction: most current frameworks track a limited parameter set [2], [11], while future systems are likely to combine nutrient analysis, crop imaging, pest monitoring, and soil health assessment within unified platforms. Communication technologies will evolve toward adaptive frameworks that dynamically select pathways according to environmental conditions and network stability [9], [25], and energy-efficient monitoring will integrate low-power sensing, energy-aware protocols, and renewable-energy-assisted frameworks such as solar-powered sensor networks [13], [23].

Beyond technology, several studies argue for integrated agricultural ecosystems combining IoT monitoring, AI analytics, edge processing, and socio-economic adaptability within unified architectures [5], [22]. Socio-economic sustainability is expected to move to the centre of research, with user-centred design minimising complexity, paired with farmer education and participatory development, since adoption barriers often stem from unfamiliarity rather than resistance [5], [14], [17]. Emerging directions also include

blockchain and agricultural cybersecurity [18], [25]; climate-resilient agriculture incorporating prediction and adaptation mechanisms [14], [22]; and autonomous and robotic agriculture spanning drone-assisted observation and robotic monitoring [8], [20]. Above all, field-level validation, prolonged deployment analysis, and scalable implementation strategies—rather than limited prototype demonstrations—should be central [12], [14].

Conclusion

This review has examined IoT-driven smart farming in sustainable agricultural development, spanning wireless sensor networks, precision irrigation, artificial intelligence, cloud computing, and edge-assisted monitoring. Smart agriculture has moved beyond basic sensing toward intelligent, data-assisted ecosystems that improve monitoring accuracy, irrigation responsiveness, and resource utilisation [1], [19]. Sensor-assisted irrigation demonstrably cuts water waste [2], [11]; wireless sensor networks combined with LoRaWAN, ZigBee, GSM, and NB-IoT have widened the reach of distributed monitoring [9], [13], [25]; and AI-assisted systems for disease prediction and irrigation forecasting [3], [7], [20], complemented by edge architectures [4], [8], mark a clear trajectory toward predictive farming ecosystems.

At the same time, the comparative analysis reveals persistent implementation limits: infrastructure dependency, communication instability, energy management, affordability, and computational complexity recur across the literature [5], [12], [22], and many systems that perform well in controlled conditions offer limited evidence of long-term rural sustainability. Socio-economic sustainability remains insufficiently integrated—farmer usability, digital literacy, operational simplicity, and long-term adaptability are addressed only partially [5], [14]—and the field remains fragmented across isolated domains, with integrated frameworks and long-term field validation comparatively rare.

Future research should therefore prioritise low-cost architectures, energy-efficient communication, edge-assisted processing, and practically adaptable AI models suited to resource-constrained rural conditions, treating usability, sustainability, and farmer accessibility as seriously as technological sophistication. The literature points firmly to the substantial potential of IoT-driven smart farming for sustainable agriculture; long-term success, however, will hinge on developing scalable, affordable, socio-economically sustainable agricultural ecosystems that function effectively beyond controlled research environments and deliver meaningful, inclusive agricultural transformation.

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