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Artificial Intelligence of Things (AIoT) for Precision Irrigation: A Comprehensive Review of Applications, Challenges, and Future Directions

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Abstract

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has given rise to the Artificial Intelligence of Things (AIoT), a paradigm that is fundamentally reshaping agricultural water management. This review synthesises current AIoT applications in precision irrigation, examining how sensor networks, edge and cloud computing infrastructures, and machine learning algorithms are being deployed to optimise water utilisation in agricultural systems. Through a systematic examination of recent literature, it analyses the technological enablers, implementation architectures, machine learning models, and decision-support frameworks that constitute modern AIoT irrigation systems. The evidence indicates that AIoT-driven systems can substantially reduce water consumption while simultaneously improving crop yields through real-time soil moisture monitoring, predictive analytics, and autonomous irrigation scheduling. Machine learning models—including Random Forest, Support Vector Machines, Artificial Neural Networks, and Long Short-Term Memory networks—have demonstrated considerable efficacy in modelling the complex, non-linear relationships among soil properties, climatic variables, and crop characteristics that underpin accurate irrigation forecasting. Deep learning approaches, particularly Convolutional Neural Networks and hybrid architectures, have achieved high precision in predicting evapotranspiration and soil moisture dynamics. Reinforcement learning is emerging as a promising approach for autonomous irrigation optimisation, wherein an AI agent develops optimal irrigation strategies through iterative environmental interaction. However, these advances are accompanied by substantial implementation challenges, including prohibitive upfront costs, inadequate rural connectivity, inconsistent sensor reliability, cybersecurity vulnerabilities, and limited scalability for smallholder farming systems. This review argues that AIoT can support climate-smart, sustainable agriculture by transforming raw data into actionable decisions that enhance resilience, food security, and environmental outcomes, provided that persistent technical, economic, and institutional barriers are systematically addressed.

Keywords: *Artificial Intelligence of Things, precision irrigation, smart agriculture, machine learning, Internet of Things, water use efficiency, sustainable agriculture.*

1. Introduction

1.1 Background and Rationale

Global agriculture faces two pressures at once: increasing food production to meet the demands of a growing population while simultaneously reducing water consumption and adapting to a changing climate. Agriculture currently accounts for approximately 70% of global freshwater withdrawals [1]; however, substantial proportions of this water are lost to evaporation, runoff, and deep percolation due to inherently inefficient irrigation practices. Water scarcity is intensifying, with nearly four billion people experiencing severe water scarcity for at least one month annually [2]. The United Nations projects that the global population will approach 10 billion by 2050, necessitating a substantial increase in food production over current levels [3]. This demographic pressure elevates water management from a secondary consideration to a central challenge, at a time when arable land availability is contracting rather than expanding.

Irrigated agriculture already contributes a disproportionate share of global food output relative to the land area it occupies. Consequently, even modest efficiency improvements in irrigated systems translate into considerable absolute water savings. This is precisely the gap that AIoT-based precision irrigation is positioned to address: rather than treating water as a fixed input applied according to predetermined schedules, AIoT systems conceptualise water as a resource metered against continuously measured crop requirements. The remainder of this review critically examines the extent to which the underlying technologies have progressed and evaluates where the evidence for real-world impact is robust or remains insufficient.

Traditional irrigation approaches—reliant on fixed schedules, manual field inspections, and farmer intuition—struggle to accommodate the complexity inherent in modern agricultural water management [4]. These approaches

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were developed during an era when water was comparatively abundant and labour represented the primary constraint; they are ill-suited to a period in which water availability is the binding constraint and computational resources are inexpensive. The Intergovernmental Panel on Climate Change (IPCC) has warned that climate variability and extreme weather events will exacerbate water scarcity, threatening agricultural productivity in vulnerable regions [5]. Rainfall patterns, against which irrigation calendars were originally calibrated, are shifting; static schedules are consequently becoming less reliable, even in regions where they once performed adequately. Intelligent irrigation systems have emerged as a practical response to this combination of water scarcity and food security pressures [6], substituting continuous measurement and adaptive decision-making for the fixed assumptions upon which traditional scheduling depends.

Intelligent irrigation encompasses a spectrum of technologies, ranging from simple threshold-triggered controllers at one end to fully autonomous, learning-based systems at the other—the latter being the primary focus of this review. This distinction is critical because the evidence discussed subsequently applies unevenly across this spectrum; treating all forms of intelligent irrigation as equivalent risks overstating the maturity of the field.

The Internet of Things (IoT) and Artificial Intelligence (AI) have converged into what is now termed the Artificial Intelligence of Things (AIoT), representing a significant advancement in precision agriculture. IoT deploys interconnected sensor networks that collect real-time data on soil conditions, weather patterns, and crop health; AI transforms that data into actionable decisions [7]. Together, these technologies enable agricultural systems to operate with enhanced autonomy and situational awareness, fundamentally transforming water management practices in the field [8]. The value proposition is not merely additive: a sensor network without an analytic layer still requires human interpretation, while an AI model without adequate sensing lacks reliable data for reasoning. AIoT is valuable precisely because it closes the loop end-to-end—from measurement to decision to actuation—without requiring human intervention at every step. However, this closed-loop operation introduces its own dependencies, as the final irrigation decision is only as reliable as the weakest layer in the chain—whether that be a poorly calibrated sensor, an intermittent network connection, or a model trained on conditions that do not match the deployment site.

1.2 The Evolution from IoT to AIoT in Agriculture

The transition from IoT-based monitoring to AIoT-driven agriculture represents a qualitative leap in precision farming capability, not merely an incremental enhancement. Early IoT systems in agriculture predominantly collected data and supported remote monitoring, which, while useful, still required human interpretation of the numerical data and subsequent decision-making [8]. In practice, the value of an IoT deployment was constrained by the availability and expertise of the individual interpreting the dashboard. A farmer or extension worker without the time or training to analyse soil moisture trends against weather forecasts derived comparatively little benefit from the sensor data, however accurate the readings might have been. This observation is worth emphasising because it explains why simply deploying additional sensors on a farm does not automatically improve water-use outcomes. The bottleneck was frequently the decision layer rather than the measurement layer.

With AIoT, connected systems can now analyse data, identify patterns, and make autonomous decisions [8]. These systems integrate sensing, connectivity, edge intelligence, data pipelines, and decision-support tools to manage agriculture in real time. In practice, this integration has resulted in improved resource allocation and enhanced climate resilience, as systems can anticipate and recover from environmental perturbations more rapidly [8]. The shift is as much organisational as technical. Whereas IoT monitoring assumed a human decision-maker at the centre of the loop, AIoT assumes that the default decision-maker is a model, with the human retained primarily for oversight, exception handling, and calibration. This reallocation of responsibility enables AIoT systems to scale to farm sizes and staffing levels where continuous manual interpretation of sensor data was never realistic. This is arguably more significant for adoption than any single algorithmic improvement.

For irrigation specifically, AIoT has shifted water management from reactive to predictive. Fixed timers and farmer intuition are giving way to systems that continuously integrate soil moisture, meteorological data, crop phenological stage, and evapotranspiration rates to determine optimal irrigation timing and volume [6]. These systems can now irrigate fields autonomously, adjusting to real-time soil and weather conditions without manual intervention [6]. In practice, the reactive-to-predictive shift means irrigation timing moves from being anchored to a calendar or a single moisture threshold to being anchored to a forecast of future plant water demand—which, in principle, enables water application slightly ahead of stress rather than after it has already begun to affect the crop. Whether this advantage consistently holds under field conditions, rather than only in controlled trials, remains an open question, as predictive accuracy that appears robust on held-out historical data does not always transfer cleanly to live field conditions with drifting sensors and unmodelled local variability.

1.3 Scope and Objectives of the Review

This review critically examines AIoT applications in precision irrigation, focusing on smart irrigation systems, machine learning models, implementation architectures, challenges, and future directions. Specifically, it aims to:

i. Synthesise the current state of AIoT technologies for precision irrigation;
ii. Examine the machine learning and artificial intelligence models employed in irrigation scheduling and water management;
iii. Analyse the architecture and components of AIoT-based irrigation systems;
iv. Identify the benefits and challenges of AIoT irrigation systems;
v. Explore the transition from IoT to AIoT across agricultural contexts; and
vi. Propose future research directions and technological advances.

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 protocol [9]. The literature search encompassed Scopus, Web of Science, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and ScienceDirect databases using search terms including "AIoT irrigation," "smart irrigation," "precision agriculture," "machine learning irrigation," and "IoT water management." A total of 130 articles were identified as relevant and examined in detail. Hammouch *et al.* [9] found that 41.8% of the studies they reviewed focused on IoT sensor field measurements, 37% on remote sensing, and 21.1% on AI methods—a distribution suggesting that empirical, field-validated AI-driven scheduling still constitutes a minority of the published evidence base relative to descriptive sensor deployments.

2. Artificial Intelligence of Things Architecture for Precision Irrigation

2.1 Overview of AIoT System Architecture

An AIoT-based precision irrigation system is constructed from several interoperable layers that collectively enable intelligent water management: sensing technologies, connectivity, edge intelligence, data processing, and decision-support mechanisms, based on the architectures described in the literature [6], [8]. Figure 1 summarises this layered structure and the flow of data from field-level sensing through to the actuation of irrigation equipment. This representation is a useful simplification; however, real deployments rarely implement every layer in the idealised form described in the literature. Many smallholder systems collapse the edge and application layers into a single low-power controller, while larger commercial deployments may bypass local edge processing entirely in favour of continuous cloud connectivity. The five layers described below are best interpreted as a reference model against which to compare specific implementations, rather than as a description of any single deployed system.

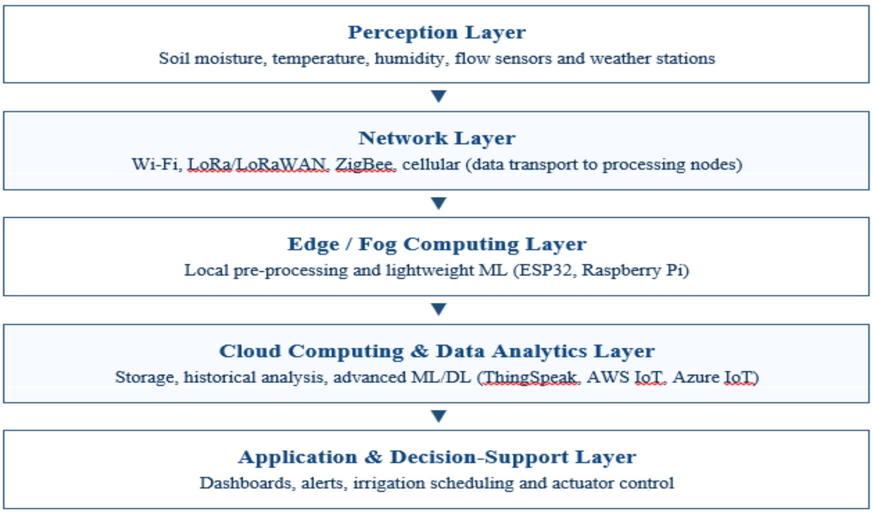

Figure 1: Layered architecture of a typical AIoT-based precision irrigation system, showing the flow of data from field sensing through to irrigation decision-making and control

2.1.1 Perception Layer

The perception layer comprises the physical sensors and actuators deployed in the field—soil moisture sensors, temperature and humidity sensors, flow sensors, and weather stations [7]. Capacitive soil moisture sensors are commonly employed due to their low cost, minimal maintenance requirements, and compatibility with microcontrollers [10]. Flow sensors monitor irrigation application rates and cumulative water consumption [11].

2.1.2 Network Layer

The network layer carries data from field sensors to processing nodes and the cloud. Protocol selection involves trade-offs among data rate, transmission range, power consumption, and reliability, all of which affect system reliability and scalability [12]. Wi-Fi provides high bandwidth and direct internet access; LoRa and LoRaWAN trade bandwidth for extended range and low power consumption, making them more suitable for remote field deployments [6].

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2.1.3 Edge and Fog Computing Layer

The edge and fog computing layer processes and analyses data in proximity to its generation point [8]. ESP32 microcontrollers and Raspberry Pi boards can execute lightweight machine learning models locally, reducing latency, bandwidth utilisation, and cloud dependency [8]. Field validation supports this approach: a study of an edge-AI system for cocoa production in rural Colombia, employing DHT11 sensors with a Raspberry Pi 4 and a multilayer perceptron model on Arduino Uno, reduced water consumption by 25% while maintaining soil moisture within agronomic thresholds of 70–85%, with the neural network achieving 82% classification accuracy in predicting irrigation states [13]. This result supports the contention that edge-based AIoT architectures can function effectively in infrastructure-limited tropical settings.

2.1.4 Cloud Computing and Data Analytics Layer

The cloud computing and data analytics layer provides storage, analytical capabilities, and infrastructure for more complex AI models [9]. Platforms such as ThingSpeak, AWS IoT, and Azure IoT support remote monitoring, visualisation, historical analysis, and advanced machine learning [12].

2.1.5 Application and Decision-Support Layer

The application and decision-support layer translates analytical outputs into actionable formats such as dashboards, alerts, and irrigation equipment controls [10]. This layer can either recommend irrigation decisions to farmers or directly actuate solenoid valves [6]. The five layers interact sequentially, but data and control signals also flow in the reverse direction, as decisions made at the application layer typically need to be logged back into the cloud analytics layer to refine future predictions. This closed-loop characteristic distinguishes AIoT architectures from earlier telemetry-only IoT deployments, where data flowed upward for human review without a corresponding downward channel for automated control. It is also where most of the system's fragility concentrates: a failure at any point along the loop—a depleted sensor battery, a dropped LoRa packet, a cloud outage—can silently degrade the final irrigation decision without producing a failure that a farmer would readily detect in the field.

2.2 Sensing Technologies for Data Acquisition

Soil moisture sensors constitute the backbone of AIoT irrigation systems, providing real-time measurements of water availability in the root zone [11]. Capacitive sensors, which measure the soil's dielectric permittivity, are widely used for the reasons noted above: low cost, low maintenance, and ease of microcontroller integration [14]. Combining sensors for multiple parameters generally improves irrigation decision quality [15]. Soil moisture alone is rarely sufficient for accurate scheduling, as the same volumetric water content reading can indicate very different levels of plant-available water depending on soil texture, organic matter content, and root depth. This is one reason the literature increasingly favours multi-sensor fusion over single-parameter thresholds, pairing moisture readings with temperature, humidity, and, where feasible, canopy or leaf-level indicators of plant water status.

Colizzi *et al.* [10] reviewed AI and IoT applications for water conservation in agriculture, covering sensors for data acquisition, network protocols and architectures, and AI models for decision-making. They identified three principal benefits of smart irrigation: water conservation, enhanced productivity through fertigation that activates only when required, and improved efficiency from remote control and precise sensors. Their review also notes that sensor placement and density are critical because soil moisture varies spatially even within a single field; a single sensor is often unrepresentative of the entire irrigated zone. Addressing this properly typically requires deploying multiple, geostatistically placed sensors per management zone, or supplementing point sensors with remote-sensing-derived moisture proxies—both of which increase the cost and complexity of the perception layer beyond what simplified systems can accommodate.

2.3 Microcontroller and Communication Platforms

The ESP32 has become a popular microcontroller for AIoT irrigation due to its integrated Wi-Fi and Bluetooth capabilities, low power consumption, and sufficient processing power for sensor interfacing and control logic [8]. Its deep-sleep modes facilitate operation in solar-powered configurations where power conservation is critical [8]. This power profile is more significant than it might initially appear, as field controllers are frequently located at distances from mains electricity that make battery or solar power the only realistic option. A controller that cannot sustain operation through intermittent solar charging during cloudy periods will simply go offline precisely when adaptive scheduling would be most valuable—during unsettled weather. Energy-aware scheduling combined with optimised communication protocols has been shown to meaningfully improve sustainability: an ESP32-based smart irrigation system reduced water consumption by 47% while increasing yield by 43% [16].

Protocol selection is a significant consideration. Bwambale *et al.* [6], in their review of smart irrigation monitoring and control strategies, emphasised the importance of selecting protocols appropriate to the agricultural

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context, as range, data rate, power consumption, reliability, and cost all factor into the decision. Li *et al.* [11], reviewing sensor-network irrigation systems using IoT and remote sensing, identified interoperability and standardisation as recurring challenges. This is not purely academic: sensors, gateways, and analytics platforms from different vendors often cannot be combined without custom integration work, which increases deployment costs and discourages the modular, incremental upgrading that would otherwise allow a farm to add capability over time rather than commit to a single vendor's ecosystem from the outset.

2.4 Cloud Platforms and Data Management

Cloud platforms handle remote monitoring, storage, and analytics for AIoT irrigation systems, supporting visualisation, historical analysis, and decision-support algorithms [12]. Omar *et al.* [12] also flagged that dataset availability is critical for replicating irrigation experiments and building upon prior research. Hammouch *et al.* [9], in their systematic review and meta-analysis, found that 41.8% of studies relied on field measurements from IoT sensors—a data-management approach that enhances reproducibility and validation. This reproducibility point warrants emphasis, as it represents one of the clearer, more actionable gaps in the reviewed literature: many of the machine learning and deep learning models used for irrigation prediction are trained and validated on proprietary, unpublished datasets collected at single sites, making it difficult for independent researchers to confirm reported accuracy figures or compare models fairly. Cloud platforms that support standardised data logging and open dataset publication, rather than only proprietary dashboards, would directly address this limitation, and a small but growing number of the studies reviewed here advocate for precisely such a shift.

3. Machine Learning and AI Models for Predictive Irrigation

3.1 Overview of ML Models in Irrigation Management

Machine learning and AI are now central to predictive irrigation scheduling, facilitating the optimisation of water use from real-time and historical data [17]—one specific application of a broader shift toward adaptive, self-learning approaches to farm operations generally [18]. Models integrate weather data, soil moisture readings, evapotranspiration rates, crop species characteristics, and growth stage information to determine optimal irrigation timing and volume [4]. Pairing AIoT with predictive models enables automated, data-driven irrigation [10]. Random Forest, Support Vector Machines, Artificial Neural Networks, and LSTM networks are the models most commonly employed to capture the non-linear relationships inherent in agricultural data [7], continuously processing sensor data to either recommend action or control irrigation equipment directly [19].

Bayar *et al.* [7] found that AI models combining real-time sensor data with environmental variables can support site-specific irrigation decisions, reducing both over- and under-irrigation. Table 1 synthesises the reported empirical outcomes from several of these studies, enabling the comparative strengths of different model families, and the conditions under which each was evaluated, to be viewed collectively rather than distributed throughout the narrative. As the table demonstrates, the strongest and most consistently reported empirical finding across the literature is that hybrid or ensemble approaches tend to outperform any single algorithm. This pattern recurs with sufficient consistency across independently conducted reviews to count as one of the more robust findings in the field, even though the individual studies vary considerably in crop type, climate, and evaluation methodology.

Table 1: Summary of reported empirical outcomes from selected studies reviewed in this article

Study	Focus of the Work	Reported Empirical Outcome / Key Finding
[10]	AI and IoT for water-saving irrigation (systematic review)	Identifies water conservation, fertigation-driven productivity gains, and remote-control efficiency as the three recurring benefits reported across the reviewed field deployments.
[6]	Smart irrigation monitoring and control strategies	Field-level syntheses show meaningful reductions in applied water when autonomous, sensor-driven scheduling replaces fixed-interval irrigation; multi-sensor integration is identified as key to reliable autonomous operation.
[9]	Systematic review and meta-analysis of intelligent irrigation systems	Meta-analysis of the reviewed literature found 41.8% of studies relied on IoT sensor field measurements, 37% on remote sensing, and 21.1% on AI-based methods, indicating sensor-driven approaches still dominate empirical deployments.
[4]	AI-driven irrigation systems (systematic review and meta-analytical insights)	Meta-analytical synthesis reports that ML-based scheduling consistently produced measurable water savings alongside yield gains relative to conventional, non-AI scheduling across the pooled studies.
[17]	Machine learning applications for precision agriculture (broad	Comparative analysis across studies shows hybrid and ensemble ML models (e.g., Random Forest/Gradient

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Study	Focus of the Work	Reported Empirical Outcome / Key Finding
	review: soil parameter, yield, and disease/weed prediction)	Boosting combinations) consistently outperform single-model approaches across precision-agriculture prediction tasks generally, of which irrigation-relevant soil-moisture prediction is one example.
[19]	Evaluation of ML approaches for precision farming	Cross-study evaluation finds decision-tree-based ensembles (Random Forest, XGBoost) generally achieving lower prediction error than simple regression baselines for soil-moisture and scheduling tasks.
[11]	Sensor-network irrigation systems using IoT and remote sensing	Reviewed deployments repeatedly report interoperability and sensor calibration drift as the technical faults most responsible for degraded field performance.
[21]	Fourth industrial revolution technologies in smart irrigation (sub-Saharan Africa)	Assessment of implemented pilots across the region found adoption consistently constrained by high upfront cost and weak institutional support rather than by the underlying technology's technical performance.
[13]	Edge-AI irrigation for cocoa production, rural Colombia	Field validation over nine weeks: neural network model achieved 82% classification accuracy; system reduced water consumption by 25% while maintaining soil moisture within 70–85% threshold; average daily energy consumption 204 Wh powered entirely by solar PV.
[16]	IoT-driven smart irrigation for sustainable agriculture	ESP32-based system achieved 47% water consumption reduction and 43% yield increase; maintained optimum soil moisture threshold of 26% with wood vinegar dilution; reported lowest disease severity index at 7.78%.

3.2 Machine Learning for Soil Moisture Prediction and Irrigation Scheduling

Automated irrigation scheduling represents one of AIoT's more clearly demonstrated successes. Systems combining ML, AI, and IoT sensors to make real-time irrigation decisions have become prevalent in recent years [15], continuously processing sensor data on soil moisture, temperature, and weather to determine irrigation timing [14]. Predictive scheduling forecasts future irrigation requirements instead of merely reacting to current conditions [4], identifying patterns that are not readily apparent from direct observation. Oğuztürk [4] found that ML-based scheduling produced meaningful water savings and yield gains compared with traditional methods, and [17] and [19] corroborate this finding in their respective reviews of ML applications for precision agriculture—helping to confirm that the effect is not an artefact of any single study's methodology. In one recent empirical study, a hybrid LSTM approach for irrigation scheduling in maize fields in Bursa, Turkey, achieved R^2 values ranging from 0.8163 to 0.9181, demonstrating the effectiveness of deep learning for precise agricultural irrigation when supported by simulation models to address data limitations [20].

Several ML approaches recur for soil moisture prediction, and it is worth being explicit about how they differ, as the choice of model is not interchangeable in practice:

i. Regression Models: Linear and polynomial regression predicting soil moisture from meteorological data [19]. These are computationally inexpensive and easy to interpret, which suits low-power edge deployment, but they generally struggle with the non-linear interactions among soil, crop, and weather variables that irrigation-relevant prediction typically involves.

ii. Decision Tree-Based Models: Random Forest, Gradient Boosting Machines, and XGBoost tend to outperform simpler models [17], largely because ensembles of trees can represent threshold effects and interactions—how soil texture modifies the relationship between rainfall and infiltration, for example—that a single linear model cannot capture. A scalable ML framework for adaptive irrigation management in the U.S. Midwest demonstrated that ensemble methods including Random Forest, Extreme Gradient Boosting, and LightGBM handle overfitting and the complexity of agricultural datasets effectively [22].

iii. Neural Network Models: ANNs and Deep Neural Networks are adept at capturing the complex relationships among soil, climate, and irrigation variables [7], but require larger training datasets and more computational resources than tree-based methods—a genuine constraint for smallholder deployments with limited historical data.

iv. Hybrid Models: Combining several ML techniques generally outperforms any single model [9], though this entails greater model complexity, more tuning effort, and a higher risk of overfitting to the specific site conditions on which the hybrid was trained.

Jaiswal *et al.* [14] reviewed smart drip irrigation systems (architectures, ML models, emerging trends) and found ML playing a growing role throughout. Mohyuddin *et al.* [19] separately reviewed ML approaches for precision farming, evaluating techniques specifically for irrigation scheduling. Reading these two reviews together exposes a tension that neither study fully acknowledges on its own: different studies use different evaluation metrics, different train-test splits, and different local climate and soil conditions. A model reported as "best performing" in one review is not necessarily the model that would perform best on a different farm. This presents a genuine limitation of the current evidence base rather than a settled conclusion. It is also one reason standardised benchmarking across studies would merit prioritisation in future work.

3.3 Deep Learning-Based Crop Water Requirement Forecasting

Deep learning models forecast crop water requirements by modelling the interactions among soil, plant, and climate variables [15]. CNNs, LSTMs, and hybrid models predict evapotranspiration, soil moisture, and irrigation needs with notable precision, and pairing them with AIoT supports real-time scheduling with efficient water use [7], [8]. Deep learning, a subset of ML, is reshaping crop growth monitoring, yield prediction, and early disease detection in agriculture more broadly [23], and has proven especially useful for the narrower problem of estimating crop water stress and evapotranspiration, where older, purely empirical methods fall short [17]. The advantage over classical evapotranspiration formulas stems largely from data availability. Deep learning models can incorporate far more input variables, including remote-sensing imagery and high-frequency sensor streams, than the handful of parameters around which classical empirical equations were constructed, enabling them to capture site-specific effects that a generic formula necessarily averages away. Several specific applications illustrate where this is being deployed:

i. Evapotranspiration Prediction: Deep learning outperforms traditional empirical methods in this domain [19]. Bayar *et al.* [7] reported that hybrid CNN-LSTM architectures, in particular, have demonstrated high precision in predicting evapotranspiration and soil moisture dynamics.

ii. Soil Moisture Forecasting: LSTM networks handle temporal dependencies effectively [7]. A hybrid LSTM approach for maize irrigation in Turkey reported R^2 values ranging from 0.8163 to 0.9181 for soil moisture content prediction across different phases of the growing season [20].

iii. Crop Water Stress Detection: CNN models employing thermal or multispectral imagery can detect stress at early stages [9].

iv. Yield Prediction: Models integrating soil, climate, and irrigation data predict yield under different irrigation scenarios [4]. One IoT-driven smart irrigation system reported a 43% yield increase alongside a 47% reduction in water consumption [16].

Singh *et al.* [15] reviewed recent advances in intelligent controllers for smart irrigation, focusing on AI's role in optimising water application, and [23] covered automation in agriculture using AI more broadly, including irrigation optimisation. A caveat running through this body of work, and one that is not always foregrounded, is that most reported deep learning accuracy figures originate from a small number of well-instrumented experimental sites rather than broad, multi-site field trials. This matters because deep learning models are known to generalise poorly outside the conditions on which they were trained—a CNN that detects water stress accurately for the crop variety, canopy structure, and camera setup employed in one study is not guaranteed to perform as well elsewhere without retraining or, at minimum, careful validation.

3.4 Reinforcement Learning for Autonomous Irrigation Optimization

Reinforcement learning (RL) offers a distinct approach wherein an agent learns irrigation strategies through environmental interaction rather than being provided with predetermined rules [10]. Given soil moisture data, crop stress indicators, and weather variables, RL algorithms such as Deep Q-Networks and Proximal Policy Optimisation adjust irrigation timing and volume when integrated with IoT sensing [8]. In practice, the model attempts different irrigation strategies, receives feedback based on plant growth, yield, and water use, and gradually converges on improved policies [7]. RL algorithms enable an agent to recognise the state of the environment and develop a policy around a specific objective, which suits dynamic agricultural conditions well [7].

RL offers several clear advantages for irrigation:

i. Adaptive Learning: The system continuously learns as conditions change

ii. Multi-Objective Optimization: It can balance multiple objectives simultaneously

iii. Unsupervised Operation: It can function without constant human input in complex settings

iv. Transfer Learning: Policies learned in one field can be transferred to similar environments

However, deploying RL for irrigation presents challenges, including the need for extensive simulation environments, difficulties in defining appropriate reward functions, and substantial computational costs [14]. This deserves closer scrutiny than it typically receives, as it may represent the single greatest obstacle to practical RL adoption. Training an RL agent typically requires thousands of trial-and-error irrigation episodes to converge on an effective policy, and executing that many episodes directly on a live crop is neither practical nor advisable—a poorly performing early-stage policy could damage the crop or waste substantial water volumes before the agent learns anything useful. The conventional response in the literature is to train agents in simulation first and transfer the learned policy to the field; however, simulators are themselves simplifications of real soil-plant-atmosphere dynamics, so the reliability of the final field policy depends heavily on how faithfully the simulator captures the specific conditions of the deployment site. Reward function design compounds this challenge: an agent rewarded purely for water savings may under-irrigate at the expense of yield unless the reward function is carefully balanced against crop-health indicators—precisely the multi-objective optimisation problem RL is intended to solve, but only if it is specified correctly from the outset.

3.5 Hybrid AI Approaches for Irrigation Optimization

Combining ML and DL techniques, sometimes termed hybrid AI, has become a common approach to irrigation optimisation, as it enables researchers to leverage the strengths of different models while mitigating their weaknesses. Oğuztürk [4] found hybrid approaches increasingly prevalent in irrigation and water management research generally. Sharma *et al.* [17], reviewing ML applications for precision agriculture, emphasised the extent to which hybrid models improve prediction accuracy. Colizzi *et al.* [10] reached a similar conclusion in their review of AI and IoT for water conservation: combining IoT and AI tends to produce better water conservation outcomes than either approach alone. Taken together with the pattern already visible in Table 1, this convergence across independently authored reviews represents one of the more defensible generalisations this review can draw—regardless of the specific crop, climate, or sensor configuration, combining complementary model types consistently outperforms relying on a single technique, even if the specific hybrid architecture that performs best varies from one study to the next.

4. Applications of AIoT in Precision Irrigation

4.1 Real-Time Soil Moisture Monitoring and Control

Real-time soil moisture monitoring constitutes the foundation upon which all other AIoT irrigation capabilities are built. IoT sensors measure volumetric water content at multiple depths, providing a detailed picture of moisture dynamics [11], and this data feeds into edge devices or the cloud for analysis [7]. Once AI is layered on top of moisture monitoring, irrigation ceases to be purely threshold-based and becomes predictive. Models can interpret historical moisture data, weather forecasts, and crop characteristics to anticipate moisture deficits and schedule irrigation proactively [15], helping to avoid both water stress and over-irrigation [6].

Hammouch *et al.* [9] found that 41.8% of intelligent irrigation studies centred on IoT sensor field measurements, and [15] emphasised the importance of real-time monitoring for effective water management. Real-time monitoring and predictive scheduling are not the same capability, even though they are often discussed together: a system can report soil moisture in real time while still scheduling irrigation on a fixed calendar, and a predictive model is only as reliable as the real-time data feeding it. The empirical benefit attributed to AIoT irrigation in the literature almost always depends on both capabilities being present together—a distinction worth keeping in mind when weighing how much of the reported water savings derive from sensing accuracy versus the scheduling algorithm itself.

4.2 Predictive Irrigation Scheduling

Predictive scheduling forecasts irrigation requirements in advance rather than reacting to current conditions [4], identifying patterns that plain observation would miss and improving water efficiency, yield, and sustainability as a result [17]. The principal benefits reported in the literature include:

i. Proactive Water Management: Irrigation occurs before crop water stress develops
ii. Optimized Water Use: Water is applied only when necessary
iii. Integration with Weather Forecasts: Forecast rainfall can delay scheduled irrigation
iv. Adaptive Scheduling: Schedules shift as weather and crop conditions change

Colizzi *et al.* [10], reviewing smart irrigation and fertigation, identified the same benefits noted earlier: water conservation, fertigation-driven productivity, and remote-control efficiency. One limitation cuts across most of these reported benefits and warrants direct acknowledgment: the studies establishing them are drawn overwhelmingly from research-station and pilot-scale trials, not from ordinary commercial farms without dedicated technical support. Predictive scheduling that performs well under close researcher supervision, with sensors regularly checked and recalibrated, does not automatically demonstrate that the same benefits would hold once a system is handed to a farmer with no specialist training and left to run unattended for a full growing season. This is not a reason to dismiss the reported benefits, but it is a reason to treat the magnitude of water and yield gains reported in the wider literature as an upper bound on what typical field deployment is likely to achieve.

Promising evidence from commercial-scale applications is beginning to emerge, however. The European Innovation Partnership's IRRISMA Operational Group in Greece developed a smart water management system combining precision irrigation technology with tailored advice for cotton cultivation. The system achieved a 5% yield improvement and 7–10% water use reduction compared to conventional plots, while maintaining or

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improving crop quality and protecting groundwater resources [24]—one of the few documented examples of AIoT-style irrigation benefits at a commercially relevant scale.

4.3 Autonomous Irrigation Systems

If predictive scheduling represents AIoT learning to anticipate a field's water needs, full autonomy represents the point at which that anticipation is permitted to act independently. The distinction matters practically as well as conceptually: a predictive system can still leave the final decision to a human, using its forecast as a recommendation, while an autonomous system closes the loop completely, allowing sensor readings, model output, and valve actuation to operate as one uninterrupted sequence without human verification at each step [7], [8]. In the systems reviewed here, this typically means the same soil-moisture, weather, and crop-stage inputs already discussed feed continuously into a controller that adjusts valves in real time, maintaining soil moisture within a target range rather than reacting only once a threshold has been crossed—intended to reduce water consumption while increasing yield as the underlying model accumulates more field data over successive seasons [4] [15].

Bwambale *et al.* [6], in their review of smart irrigation monitoring and control strategies, traced much of the reported success of these autonomous systems to a single design choice: integrating multiple sensor types rather than relying on any one signal alone. A controller reasoning only from soil moisture cannot distinguish a genuinely dry field from a sensor that has drifted out of calibration, whereas a controller that cross-checks soil readings against recent rainfall, ambient temperature, and crop growth stage has some basis for detecting such an inconsistency before it results in an erroneous irrigation decision. This is a useful finding, but it also points to the central weakness of full autonomy as currently practised: removing the human from the loop does not eliminate the possibility of failure, it merely changes what failure looks like. A conventional threshold-based controller that malfunctions tends to fail conspicuously—running continuously or not at all—in a manner that a farmer walking the field would notice within a day or two. A fully autonomous, model-driven controller can fail more quietly, continuing to irrigate on the strength of a prediction that appears internally consistent but is erroneous, for long enough that the effect on the crop, rather than the malfunction itself, becomes the first visible symptom. Strikingly few of the studies surveyed here specify what fail-safe behaviour their autonomous systems actually implement, whether that is a simple sanity-check threshold or an automatic reversion to manual scheduling. This appears less like an oversight in any one paper and more like a shared gap in how the field currently designs and reports these systems—one that building explicit fail-safe logic into autonomous controllers, and reporting on it as routinely as accuracy metrics are reported now, would help address.

4.4 Integration with Fertigation in AIoT Systems

Once an AIoT system already possesses the sensing and actuation infrastructure to control irrigation autonomously, extending that same control loop to fertigation—delivering dissolved nutrients through the irrigation water itself—is a comparatively modest technical step with a disproportionately large agronomic payoff. Colizzi *et al.* [10], in their systematic review of AI and IoT for water conservation, found that pairing drip irrigation with AIoT-controlled fertigation allows nutrient delivery to track crop demand far more closely than a fixed fertiliser schedule can, placing nutrients directly at the root zone and reducing losses to leaching and volatilisation that occur when fertiliser is applied broadly and expected to reach the roots eventually. The benefits [10] report for this combination echo those established for irrigation alone: measurable water conservation, targeted productivity gains from fertigation activating only when the crop requires it rather than on a calendar, and the general efficiency advantage of remote, sensor-driven control over manual application [9].

Del-Coco *et al.* [25] offer a useful complement, though from a narrower perspective: their review catalogues the traditional machine learning and deep learning architectures used specifically to convert sensor and weather data into irrigation scheduling decisions, without extending that treatment to nutrient management. Read alongside [10], the two reviews suggest a field that is somewhat uneven in how far it has developed: the modelling techniques for determining optimal irrigation timing and volume are comparatively mature and well catalogued, while the parallel problem of modelling nutrient uptake and translating it into a fertigation decision has received considerably less dedicated methodological attention. The likely reason is not that fertigation is less important, but that it is more challenging to model effectively: predicting how much nitrogen or potassium a crop actually requires at a given growth stage requires soil chemistry data that most current AIoT irrigation deployments were never designed to collect, as their sensor suites were configured around moisture and weather variables rather than nutrient status. Coupling fertigation to an existing irrigation control loop is, in practice, an easier hardware problem than a modelling one: adding a nutrient-dosing actuator to a system that already has automated valve control costs comparatively little, but making that actuator's decisions genuinely intelligent, rather than merely following the same schedule irrigation already follows, would require a class of soil-chemistry sensing and modelling that the reviewed literature has not yet developed to the same standard as its irrigation-scheduling counterpart.

5. Benefits and Challenges of AIoT Irrigation Systems

5.1 Water Conservation and Efficiency Gains

AIoT irrigation has demonstrated measurable water savings. Systems that irrigate fields autonomously based on soil moisture and weather data have shown meaningful reductions in water use in field trials, which matters both for water scarcity and for sustainable agriculture more broadly [6]. Colizzi *et al.* [10] again identify the same benefits (conservation, targeted fertigation productivity, remote-control efficiency), and [4] confirmed that AI-driven systems can produce substantial water savings without sacrificing crop productivity. As Table 1 shows, [9] corroborates this independently, which is reassuring—though it is worth repeating a caveat that applies across most of the benefits discussed here: the reported magnitude of these savings derives disproportionately from controlled or research-supported trials, and this review found comparatively few large-sample, multi-season studies quantifying water savings under ordinary commercial farm management.

Nevertheless, a growing body of empirical evidence from diverse geographic contexts supports the water-saving potential of AIoT irrigation. In Colombia, an edge-AI irrigation system for cocoa production reduced water consumption by 25% while maintaining soil moisture within optimal agronomic thresholds [13]. In Greece, the IRRISMA smart water management system achieved 7–10% water savings alongside a 5% yield improvement in commercial cotton production [24]. Perhaps most strikingly, an IoT-driven smart irrigation system for sustainable agriculture reported a 47% reduction in water consumption while achieving a 43% increase in yield [16]. What would most effectively address the evidence gap is more large-sample, multi-season studies quantifying water savings under ordinary commercial farm management, rather than additional small-scale trials confirming the same general direction of effect.

5.2 Yield Improvement and Crop Quality Enhancement

AIoT irrigation is also associated with improved crop yield and quality. Colizzi *et al.* [10] found smart irrigation improving both productivity and quality [7]. Improved crop outcomes represent a major driver of AIoT adoption: precision farming, implemented with appropriate methods, genuinely helps farmers increase production [23], whether through remote sensing, drone technology, GPS-guided equipment, or IoT devices [17]. It is worth being precise about the mechanism here, as it is not simply that more water produces more yield—irrigation science has long established that over-irrigation can depress yield just as under-irrigation can, through waterlogging, nutrient leaching, and increased disease pressure in saturated soils. The yield gains attributed to AIoT irrigation in the reviewed literature are better understood as arising from precision—applying water closer to the crop's actual optimal water requirement rather than either excess or deficit—than from simply increasing the total volume of water applied. This distinction matters for how the benefit is communicated to prospective adopters, as it implies AIoT irrigation can improve yield even where water is not scarce, as long as existing manual scheduling was previously over- or under-applying water relative to the crop's true requirement.

5.3 Economic Considerations of AIoT Adoption

Economically, IoT systems can reduce labour costs and increase revenue [8], but infrastructure and maintenance costs remain a significant barrier in low-resource settings. Solar power supports sustainability, though scaling requires policy support [12]. Smallholder farmers tend to face high upfront costs, limited digital literacy, and insufficient institutional backing [14]. Data privacy is also a concern, as IoT systems transmit farm-level data to the cloud. None of these challenges can be resolved without government policy, farmer training, and cheaper, more scalable IoT models [14].

Wanyama *et al.* [21], reviewing fourth industrial revolution technologies in smart irrigation across sub-Saharan Africa, made the same point: economic and technical barriers must be addressed for wider adoption. Their assessment, summarised in Table 1, is instructive in a more granular reading: it found that adoption in the pilots examined was constrained primarily by cost and institutional support rather than by any shortfall in the underlying technology's technical performance. This is a meaningful distinction for policy purposes, as it suggests continued algorithmic improvement, while valuable, is not the binding constraint on adoption in the contexts where AIoT irrigation is arguably needed most. Financing mechanisms, extension services, and after-sales technical support are likely to matter at least as much as further gains in prediction accuracy.

5.4 Technical Challenges and Barriers

Set against the benefits described above, the reviewed literature is fairly consistent regarding where AIoT irrigation still falls short in practice, and several of these limitations are supported by more than general impression. Cost is the most frequently quantified: [12], in their systematic review of IoT- and AI-based irrigation systems, found that sensor procurement, connectivity infrastructure, and the computing resources required to run AI models impose a genuine financial barrier to adoption—one that falls hardest on precisely the smaller operations that might benefit most from water savings. Connectivity is the second recurring constraint, and it is geographically uneven: [6] documented how unreliable rural internet access limits which communication protocols are even viable in a given deployment, often forcing a trade-off toward lower-bandwidth, longer-range options that constrain how much data a system can transmit in real time.

Sensor reliability may be the most consequential of these challenges because, unlike cost or connectivity, it degrades a system's output without announcing itself. Li *et al.* [11], reviewing sensor-network-based irrigation systems, found inconsistent field calibration recurring across the deployments they examined. The mechanism warrants explanation: a miscalibrated soil-moisture sensor does not merely produce one erroneous reading; it silently corrupts the training data on which downstream machine learning models rely, propagating that error into every irrigation decision the model subsequently makes. Because calibration drift accumulates gradually rather than failing catastrophically, it is also more difficult for a farmer or technician to detect through routine observation, and the literature offers comparatively little concrete guidance on how frequently field sensors should be recalibrated or replaced under realistic operating conditions. Cybersecurity is a related but distinct concern: [12] flagged that routing farm-level operational data to cloud platforms for processing creates genuine exposure, as that data, once off the farm, is only as secure as the platform handling it—a risk that grows as more of an operation's day-to-day decisions come to depend on that data flowing correctly.

Scalability completes this set of challenges, and it is as much a design bias as a technical limitation: [14], in their review of smart drip irrigation systems, observed that most published AIoT architectures are built and validated with large, well-resourced commercial farms in mind, leaving an open question about how well the same architectures would transfer to the smaller, more resource-constrained operations that dominate agriculture in much of the world. These five challenges do not operate independently: a farm that cannot afford reliable connectivity is also less likely to afford the frequent sensor recalibration that would offset poor calibration, and a system designed around a large-farm budget is, almost by definition, one that has not been tested against the constraints a smallholder actually faces. Addressing any one of them in isolation is unlikely to advance adoption very far without the others being addressed alongside it.

5.5 Socio-Economic and Ethical Concerns

Adoption is not solely a technical problem; it is also a socio-economic and ethical one [8]. The same barriers recur: high upfront costs, limited digital literacy, weak institutional support [14], plus data privacy concerns as farm-level data moves to the cloud. Government policy, training programmes, and lower-cost IoT models are what close this gap in practice [12]. Scaling smart irrigation further will depend on policy support, investment, and the rate of technology diffusion [21]. These farm-level technology solutions are not a substitute for the broader institutional water-governance frameworks many countries already rely on; Integrated Water Resources Management (IWRM) strategies, for instance, address water allocation, policy coordination, and cross-sectoral institutional support at a scale AIoT deployments cannot reach on their own, and the two are best understood as complementary rather than competing [26]. Governments, academia, industry, and international organisations working together appears to be the realistic path to realising AIoT's impact on irrigation sustainability and food security.

There is also a distributional dimension here that the reviewed literature touches on but does not fully develop: because AIoT adoption currently correlates strongly with farm size and access to capital, the technology risks widening rather than narrowing the productivity gap between large commercial operations and smallholder farms, at least in the near term, unless the cost and complexity barriers identified above are deliberately addressed through policy. Data ownership is a related and increasingly relevant concern: as farm-level operational data accumulates on third-party cloud platforms, questions regarding who has the right to access, aggregate, or resell that data, and what happens to a farmer's historical operating data if a platform provider ceases operation, are not yet well settled in the agricultural context, even though comparable questions have been debated at length in other IoT domains. This review treats both as legitimate ethical dimensions of AIoT adoption that deserve more direct attention than they have received to date.

6. Future Directions and Research Opportunities in AIoT

6.1 Advancements in 5G and Edge Computing

5G could unlock genuine opportunities for AIoT in agriculture: high bandwidth, low latency, and support for numerous connected devices simultaneously, which matters for large-scale IoT deployments requiring real-time data processing [8], particularly for applications such as autonomous irrigation control that necessitate rapid decision-making [8]. Edge computing is the complementary component, processing data in proximity to its generation point [27], which offers several advantages:

i. Reduced Latency: Local processing supports real-time decisions
ii. Bandwidth Optimization: Only relevant data is transmitted to the cloud
iii. Improved Privacy: Sensitive data can remain local
iv. Enhanced Reliability: Systems continue functioning even offline

5G and edge computing address somewhat different weaknesses identified elsewhere in this review: 5G primarily targets network-layer connectivity limitations, while edge computing addresses both connectivity and the offline-reliability and data-privacy concerns associated with routing sensitive farm data to distant servers. In rural agricultural contexts specifically, 5G rollout is likely to lag behind urban and peri-urban areas for some years given the infrastructure investment involved, which means edge computing, precisely because it reduces dependence on continuous high-bandwidth connectivity, may in practice be the more immediately relevant of the two for smallholder AIoT adoption, even though 5G tends to receive more attention in the literature. The evidence from Colombia supports this: an edge-AI system powered entirely by a standalone solar photovoltaic unit operated at an average daily consumption of 204 Wh, demonstrating that edge-based architectures can function reliably in infrastructure-limited settings [13].

6.2 Sensor Miniaturisation and Energy Efficiency

Sensor technology continues to become smaller and more energy-efficient, which matters for long-term field deployment [11]. Smaller sensors cost less, are easier to deploy, and can monitor a wider range of parameters [7]. Energy efficiency matters most in remote areas with limited power access. Solar power and energy-harvesting technologies can reduce operating costs and improve sustainability in such contexts [8]. Miniaturisation has a secondary benefit worth noting: as unit cost decreases, it becomes economically feasible to deploy a denser network of sensors per field, directly addressing the spatial under-sampling that several of the reviewed studies identify as a source of scheduling error, without requiring any change to the underlying prediction algorithms.

6.3 Integration with Renewable Energy

Pairing AIoT irrigation with renewable energy, primarily solar, offers clear sustainability benefits [12]. Solar-powered AIoT systems can operate off-grid, which suits remote agricultural areas well [8]. Solar adoption represents a straightforward sustainability improvement [8], and there is scope for future research to combine AI-driven energy management with irrigation scheduling to optimise water and energy use together [14]—for instance, timing energy-intensive pumping to coincide with periods of peak solar generation rather than scheduling pumping and power generation independently. There is already empirical support for this: the edge-AI irrigation system for cocoa production in Colombia operated at an average daily consumption of 204 Wh, powered entirely by a standalone solar photovoltaic unit, demonstrating that renewable-energy-powered AIoT systems can function effectively in tropical, infrastructure-limited settings [13].

6.4 Scalable Low-Cost AIoT Models

Cheaper, more scalable AIoT models matter most for smallholder farmers [12]. Several priorities recur in the research:

i. Standardized Platforms: Modular, interoperable AIoT components
ii. Open-Source Solutions: Open hardware and software to reduce costs.
iii. Pay-as-You-Go Models: Flexible pricing for smallholder adoption
iv. Collaborative Networks: Shared infrastructure across communities
v. Capacity Building: Training to develop technical skills and digital literacy

Jaiswal *et al.* [14], in their review of smart drip irrigation systems, made the case for developing scalable, cost-effective solutions specifically for smallholder farmers. Read together, these five priorities amount to an argument that the primary obstacle to wider AIoT adoption is no longer primarily algorithmic—the modelling techniques surveyed earlier in this review are already capable of producing useful irrigation guidance. The obstacle is largely cost structure, interoperability, and institutional support—a different category of research problem than the one that has historically received the most attention in the computer-science-oriented literature on this topic. This review sees this reorientation, from optimising model accuracy toward optimising deployability and affordability, as the most consequential shift on which the future-directions literature is currently converging.

7. Conclusion

The Artificial Intelligence of Things—the convergence of IoT and AI—has emerged as a practically useful approach to agricultural water management. This review has examined its applications, challenges, and future directions in precision irrigation, synthesising recent literature into a more structured picture of where the field currently stands. The evidence points to concrete benefits: water conservation, improved yields, and more efficient resource utilisation. Autonomous systems can now irrigate fields based on soil moisture and weather data without manual scheduling. Random Forest, SVM, ANN, and LSTM models handle the non-linear relationships among soil, climate, and crop variables sufficiently well to make irrigation forecasting noticeably more accurate, and deep learning approaches predict evapotranspiration and soil moisture dynamics with notable precision. The transition from IoT monitoring to AIoT-driven agriculture has enabled connected systems to operate with enhanced autonomy and situational awareness, supporting precision farming, improved resource allocation, and greater climate resilience as farms become better able to absorb and recover from environmental perturbations.

The challenges are equally significant: high setup costs, patchy rural connectivity, inconsistent sensor reliability, cybersecurity risk, and limited scalability for smallholders. Several of these compound one another rather than operating independently, as this review has argued throughout: sensor unreliability degrades the training data on which predictive models depend, weak connectivity undermines the closed-loop architecture on which autonomous control relies, and high upfront costs concentrate adoption among precisely the large commercial farms that need the technology's efficiency gains the least. Data privacy and the digital divide are ethical concerns that require attention alongside the technical ones, and this review has also identified fail-safe design and data ownership as gaps that the current literature does not yet address in sufficient depth. Nevertheless, 5G, edge computing, sensor miniaturisation, and renewable energy integration all point toward pathways for scaling AIoT further. Where this field progresses next depends on developing cheaper, more scalable solutions that actually fit different agricultural contexts, and on policy and institutional support: adoption incentives, infrastructure, and capacity building.

Governments, academia, industry, and international organisations will need to collaborate for AIoT to meaningfully improve irrigation sustainability and food security. AIoT will not solve water scarcity, food security, or climate resilience on its own, but it provides agriculture with a workable means of transforming data into better decisions. What happens next depends on continued research, innovation, and collaboration, and, based on the evidence surveyed here, on whether that effort is directed as much toward affordability, standardisation, and field-scale validation as it has historically been directed toward incremental gains in model accuracy.

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