Internet of Agricultural Things (IoAT)-Based Smart Irrigation and Fertigation Management for Sustainable Agriculture: A Critical Review and Synthesis

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ABSTRACT
Global agriculture is facing a major challenge: irrigation already accounts for the major share of freshwater withdrawal around the world, but it is characterized by inefficient water and fertilizer use, which contributes to depletion of the resources and deterioration of soil and water quality. The Internet of Agricultural Things (IoAT), which is the agricultural branch of the Internet of Things that consists of soil and nature sensor systems, wireless communication, edge computing, cloud computing and AI systems, has appeared as the key concept in solving this problem based on smart irrigation and mechanization of feeding. The article reviews the existing research focusing on smart irrigation and mechanization of feeding based on the IoAT concept. All research results analyzed show that moisture, electrics and pH sensor systems in conjunction with automatics of valves and fertilizer injecting devices allow to apply water and fertilizers directly on the basis of current requirements and not in compliance with a schedule. The results show that WUE of [amount] and NUE of [amount] are achieved at various configurations based on multiple use of fertigation and irrigation methods that provide [amount] improvement in yield. Wireless sensor LoRaWAN and similar low-power, wide-area network types of technology combined with edge devices powered by solar energy have been chosen as preferred means of communication for deployment of IoAT on-field as they provide optimal balance between long-distance communication, energy efficiency and price. AI-based support, usually using some machine learning models for prediction or classification purposes turns multi-sensor observations into specific plans for irrigation and fertilization applications, often showing high accuracy above 90% in controlled conditions. The review also summarizes existing problems, including high cost of sensors and other devices, requirement of constant calibration and maintenance for EC/pH/nutrient sensors, problems with interoperability of devices of different manufacturers, as well as inconsistent information on operational characteristics of the systems like the response time and energy consumption. Thus, it concludes that implementation of IoAT based solutions in irrigation and fertilizing processes is a good scientifically-sound way towards sustainable water and nutrients use.

Keywords: Precision water management; Wireless Sensor Networks; Automated Nutrient delivery; Edge-cloud computing; AI-based models; Precision management; Sustainable use of resources; Variable rate application

1. Introduction
Agriculture is responsible for approximately 70% of the world's freshwater use, and irrigation efficiency of the flood- and surface-irrigated areas of agriculture is still well below the desired level. The gap between these two variables gets bigger as the climate changes and cities and industries compete for greater shares of water resources (FAO, 2023) [20]. The same problem applies for fertilizer management because the same time-based fertilization process does not match the real needs of the crop. As a result, some plants either lack nutrients or suffer due to overuse of fertilizers leading to environmental pollution (Xing and Wang, 2024) [10].

Precision irrigation technology suggests that farmers need to apply water according to specific needs of crops and soil in real time instead of following fixed schedules. The effectiveness of precision irrigation process in terms of water efficiency and yield has been proven numerous times (Bwambale *et al*., 2022) [9] (Sachin *et al*., 2023) [11].

Smart irrigation technologies based on IoAT principles usually include real-time soil moisture monitoring, weather-based scheduling algorithms, and automated valve control, which means that they are able to provide variable-rate application of water according to current soil conditions and expected environmental conditions (Ayaz *et al*., 2019) [2] (Hamami and Nassereddine, 2020) [3]. Automated fertigation follows the same principle as far as nutrient management is concerned. In particular, electrical conductivity (EC) and pH sensors used in fertigation systems help to monitor both nutrient content in water used for irrigation and nutrients in the root zone soil (Barkunan *et al*., 2019) [8] (Bwambale *et al*., 2022) [9]. Automated fertigation systems use fertigation units that act according to pre-determined or machine learning-based nutrient delivery schedules for supplying water-soluble fertilizers through an irrigation system depending on the actual crop requirements (Barkunan *et al*., 2019) [8] (Xing and Wang, 2024) [10].

Decision support systems are based on artificial intelligence and machine learning technologies that enable turning data from multiple sensors in IoAT systems into actionable commands for irrigation and fertigation. Various applications exist for this technology including evapotranspiration forecasting, soil moisture prediction, and classification of the nutrient status of soil. The commonly used algorithms for the operations of irrigation and fertigation systems include random forest, support vector regression, and neural networks (Hamami and Nassereddine, 2020) [3] (Bwambale *et al*., 2022) [9].

The current interest in remote sensing and its application in precision farming has grown recently, among other things, which allows ground-based IoAT sensor networks to provide uniform and timely information needed to inform decision-making in terms of variable-rate management. This process employs UAVs and satellites for vegetation indices, models that take into account nitrogen status incorporating the stage of crop growth, and approaches of integrating remote sensing and crop models which have been applied in other domains of precision farming, but this aspect has not been substantially covered in the literature and has received little attention among the studies concentrated on the application of ground-based IoAT solutions (Zha *et al*., 2020) [24] (Wan *et al*., 2020) [25] (Huang *et al*., 2016) [28]. Sustainable resource management that includes the objectives of saving water and promoting resource efficiency is stated as the main aim of the majority of studies on IoAT irrigation and fertigation (Hamami and Nassereddine, 2020) [3] (Nasirahmadi and Hensel, 2022) [5] (Morchid *et al*., 2024) [22].

The present-day academic publications are divided, even though substantial studies are published in this regard, as many articles on sensor network and communication technology studies, AI-enabled irrigation scheduling studies, and fertigation-centric nutrient management studies are published and reviewed separately, while very few materials provide the integrated article on the entire system chain of IoAT which includes soil sensing, environmental sensing and communication, edge-cloud computing, AI-based support for decision making, and automatic irrigation-fertigation (Mowla *et al*., 2023) [1] (Hamami and Nassereddine, 2020) [3]. The measurement of the system-level performance metrics is less consistent than the measurement of the farming results and yields (Kalyani and Collier, 2021) [4] (Bwambale *et al*., 2022) [9].

This study fills that void by amalgamating peer-reviewed data on IoAT technology for efficient irrigation and fertilization management in agriculture. Its main aims are to (i) define the theoretical principles for establishing an integrated IoAT system that covers sensing of soil parameters and environmental conditions, wireless communications, computing on the edge and in the cloud, and AI-supported decision-making; (ii) analyze the data on the performance of smart irrigation technologies, including water efficiency and irrigation optimization; (iii) summarize the findings on the efficiency of automated fertilization technologies in terms of nutrients use efficiency and crop yield; and (iv) identify gaps in knowledge and areas for improvement of the IoAT irrigation and fertilizing technologies from its research phase to operation in practice.

2. Conceptual Architecture of the IoAT Framework

An IoAT-based smart irrigation and fertigation system is conventionally organized into four functional layers: a field sensing layer, a communication layer, a computing and analytics layer, and an actuation layer that executes irrigation and fertigation commands (Mowla *et al*., 2023) [1] (Kalyani and Collier, 2021) [4]. The field sensing layer comprises soil moisture, soil temperature, soil EC, and soil pH sensors, typically deployed at multiple depths and field locations, together with an automated weather station recording air temperature, relative humidity, solar radiation, rainfall, and wind speed, and water flow sensors monitoring irrigation volume delivered (Mowla *et al*., 2023) [1] (Hamami and Nassereddine, 2020) [3].

The communication layer transmits field sensor data to edge and cloud computing resources, most commonly using low-power wide-area network protocols such as LoRaWAN, which offer a favorable balance of transmission range, energy consumption, and cost for the distributed, often rural deployment contexts typical of agricultural fields (Pagano *et al*., 2023) [21]. Mesh or star network topologies are both reported in the literature, with topology selection generally driven by field size, terrain, and the number and spatial distribution of sensor nodes (Hamami and Nassereddine, 2020) [3] (Pagano *et al*., 2023) [21].

The computing and analytics layer comprises a solar-powered edge computing gateway, which performs initial data cleaning, filtering, and local decision logic for time-critical functions, and a cloud platform, which hosts historical data archives, longer-horizon AI-based predictive models, and the farmer-facing mobile dashboard (Kalyani and Collier, 2021) [4] (Zamora-Izquierdo *et al*., 2019) [6]. This tiered edge-cloud architecture mirrors the broader cloud-fog-edge computing paradigm increasingly standard across smart agriculture applications, balancing the low-latency requirements of automated control against the computational demands of model-based prediction (Kalyani and Collier, 2021) [4].

The actuation layer executes the system's core function: automated irrigation valves deliver variable-rate water application based on real-time soil moisture status and weather-informed scheduling, while a fertigation control unit, comprising a fertilizer injection mechanism and EC/pH monitoring, delivers variable-rate nutrient application synchronized with irrigation events (Barkunan *et al*., 2019) [8] (Xing and Wang, 2024) [10]. A representative synthesis of IoAT platform components reported across the reviewed smart irrigation and fertigation literature is presented in Table 1, and a synthesis of reported irrigation and fertigation experimental design elements described in the literature is presented in Table 2.

Table 1: Representative IoAT System Components Reported in Smart Irrigation and Fertigation Literature

Component	Typical Reported Specification / Approach	Representative Sources
Soil moisture / temperature sensors	Capacitive/resistive probes; multi-depth deployment	[1, 3]
Soil EC / pH sensors	Electrochemical / conductivity-based probes for root-zone nutrient status	[10, 13]
Weather station	Air temperature, humidity, solar radiation, rainfall, wind speed	[1, 3]
Water flow / consumption sensors	Inline flow meters for irrigation volume monitoring	[1, 3]
Fertigation control unit	Venturi injector / dosing pump with EC-pH-linked regulation	[10]
Communication network	LoRaWAN low-power wide-area network; star/mesh topology	[21, 27]
Edge gateway	Solar-powered local preprocessing and time-critical control logic	[4, 6]
Cloud platform	Historical data storage, AI model hosting, dashboard delivery	[4, 6]

Table 2: Experimental Design Elements Commonly Reported in IoAT Smart Irrigation and Fertigation Studies

Design Element	Typical Reported Approach	Representative Sources
Irrigation treatments	Sensor-guided variable-rate vs. calendar-based conventional scheduling	[9, 16]
Fertigation treatments	EC/pH-regulated variable-rate vs. fixed-concentration conventional fertigation	[10, 29]
Nutrient scheduling basis	Growth-stage-informed nitrogen/nutrient demand curves	[19, 23]
Observation intervals	Continuous/near-continuous sensor logging; periodic manual validation	[1, 3]
Comparative evaluation	Sensor-guided system vs. conventional flood/calendar-based practice	[9, 11]

3. Smart Irrigation Systems: Sensing, Scheduling, and Control

Real-time soil moisture monitoring is the foundational input for smart irrigation scheduling, with capacitive and resistive soil moisture probes the most commonly reported sensor types owing to their relatively low cost and established reliability across diverse soil textures (Mowla *et al*., 2023) [1] (Hamami and Nassereddine, 2020) [3]. Weather-based irrigation scheduling combines soil moisture data with reference evapotranspiration estimates derived from weather station observations, allowing the system to anticipate crop water demand rather than respond only to already-depleted soil moisture, a distinction increasingly recognized as important for both water conservation and avoidance of water stress-induced yield loss (Bwambale *et al*., 2022) [9] (Verdouw *et al*., 2021) [16].

Automated irrigation control, executed through solenoid valves or similar actuators linked to the edge gateway, translates scheduling decisions into field-level water delivery, with variable-rate irrigation capability, applying different water volumes to different zones of a field based on spatially resolved soil moisture or crop status data, increasingly reported as a key differentiator between basic automated irrigation and genuinely precision-oriented systems (Hamami and Nassereddine, 2020) [3] (Bwambale *et al*., 2022) [9]. Barkunan *et al*. [8] describe an automatic drip irrigation system for paddy cultivation employing smart sensor feedback to regulate water delivery with improved precision relative to manually scheduled irrigation, illustrating the applicability of sensor-guided automated control even in flood-adapted cropping systems.

Sensor-based precision irrigation management has been repeatedly associated with substantial water-use efficiency gains in the peer-reviewed literature. Sachin *et al*. [11] report that sensor-guided irrigation management, employing tools such as SPAD meters, NDVI-based sensors, infrared thermometers, and soil moisture meters, improved water productivity and physiological performance in soybean under a system of crop intensification, with sprinkler-based sensor-guided irrigation associated with water-use efficiency gains of approximately 20-30% and water savings of approximately 30-45% relative to conventional practice in the broader literature they synthesize. Water consumption monitoring, typically via inline flow sensors, provides the closed-loop feedback necessary to verify that scheduled irrigation volumes are actually delivered, supporting both system diagnostics and downstream water-use efficiency calculation (Mowla *et al*., 2023) [1] (Hamami and Nassereddine, 2020) [3].

4. Smart Fertigation Systems: Nutrient Sensing and Automated Delivery

Automated fertigation integrates nutrient delivery directly into the irrigation event, dissolving water-soluble fertilizers and injecting them into the irrigation stream via venturi injectors or dosing pumps under sensor and controller regulation (Xing and Wang, 2024) [10]. EC monitoring provides a rapid, indirect proxy for the total dissolved nutrient concentration of the irrigation solution or root-zone soil solution, while pH monitoring ensures nutrient solubility and availability remain within the range appropriate for target crop uptake; both parameters are continuously monitored and used to trigger automated adjustment of fertilizer concentration or injection rate (Xing and Wang, 2024) [10] (Singh and Singh, 2026) [29].

Soil EC sensing for fertigation management requires care in interpretation, since EC values are influenced not only by nutrient concentration but also by soil water content, organic matter, and soil texture, meaning EC-based nutrient inference benefits from calibration against local soil conditions rather than universal thresholds (Sudduth *et al*., 2001) [13]. Direct ion-specific and electrochemical soil nutrient sensors offer more specific nutrient information than EC alone but remain comparatively less mature and more costly for continuous field deployment, a limitation noted consistently across the precision fertigation literature (Sachin *et al*., 2023) [11] (Sudduth *et al*., 2001) [13].

Reported gains from precision fertigation are substantial and consistent across multiple independent reviews. Singh and Singh [29] report that IoT-based sensor-guided fertigation approaches can improve water-use efficiency by approximately 61-64.1% and increase crop yield by approximately 12-35%, that time-domain reflectometry-based irrigation approaches can increase water-use efficiency by approximately 40-56%, and that GreenSeeker-based nutrient sensing can enhance nutrient-use efficiency by approximately 20-45%; drip fertigation specifically was associated with water-use efficiency gains of approximately 9-70% and nutrient-use efficiency gains of approximately 16.5-29% across the studies they synthesize, alongside measurable improvements in soil enzyme activity relevant to long-term soil health. Nutrient scheduling in the reviewed literature increasingly incorporates crop growth-stage information, recognizing that nutrient demand, particularly for nitrogen, varies substantially across phenological stages, a principle well established in rice nitrogen management research and increasingly transferred into automated fertigation logic for other crops (Chivenge *et al*., 2021) [19] (Yao *et al*., 2012) [23]. Textural and spectral biomass estimation approaches developed for UAV-based precision agriculture applications further illustrate a complementary remote sensing pathway that could, in principle, be fused with ground-based IoAT nutrient sensing to refine fertigation timing, though this integration is not yet widely implemented in operational IoAT fertigation systems (Tsouros *et al*., 2019) [18] (Zheng *et al*., 2019) [26].

Table 3: AI and Communication Technologies Reported Across the IoAT Smart Irrigation and Fertigation Literature

Technology Category	Representative Approach	Representative Sources
Machine learning for scheduling	Random forest, SVR, and neural network-based evapotranspiration/moisture prediction	[3, 17]
Nutrient status classification	EC/pH-based classification models for fertigation triggering	[10, 29]
Wireless communication protocol	LoRaWAN low-power wide-area network	[21, 27]
Edge-cloud computing	Tiered architecture for latency-sensitive control and longer-horizon analytics	[4, 6]
Digital twin-adjacent approaches	Continuous field-model synchronization for irrigation/fertigation decision support	[14, 16]

5. Data Acquisition, System Performance, and AI-Based Decision Support

Beyond soil and nutrient sensing, comprehensive IoAT deployments integrate air temperature, relative humidity, solar radiation, rainfall, and wind speed data from automated weather stations, providing the environmental context required for evapotranspiration-based scheduling and for distinguishing genuine crop water stress from transient environmental fluctuation (Mowla *et al*., 2023) [1] (Hamami and Nassereddine, 2020) [3]. Crop growth observations, whether from manual scouting or, increasingly, integrated low-cost imaging sensors, provide an agronomic validation layer against which sensor-derived irrigation and fertigation recommendations can be periodically checked (Bwambale *et al*., 2022) [9].

System performance evaluation in the IoAT literature spans both agronomic and engineering metrics. Agronomic metrics, water-use efficiency, nutrient-use efficiency, irrigation efficiency, and fertigation efficiency, are reported with reasonable consistency, generally calculated as the ratio of yield or biomass output to water or nutrient input (Sachin *et al*., 2023) [11] (Singh and Singh, 2026) [29]. Engineering metrics, sensor accuracy, system response time, decision-support accuracy, and energy consumption, are reported considerably less consistently, representing a persistent gap between agronomic outcome reporting and system-level engineering validation across the reviewed studies (Mowla *et al*., 2023) [1] (Kalyani and Collier, 2021) [4].

AI-based decision support in IoAT systems most commonly applies machine learning regression for evapotranspiration and soil moisture prediction and classification algorithms for nutrient status categorization, with random forest, support vector machine, and neural network architectures among the most frequently reported approaches, mirroring patterns observed in the broader precision agriculture and digital twin literature (Hamami and Nassereddine, 2020) [3] (Awais *et al*., 2025) [15] (Breiman, 2001) [17]. Edge computing architectures are consistently associated with reduced decision latency relative to cloud-only processing, an important consideration for automated control functions where delayed response can translate directly into over- or under-irrigation events (Kalyani and Collier, 2021) [4] (Zamora-Izquierdo *et al*., 2019) [6]. A synthesis of reported IoAT system performance metrics is presented in Table 4, reported growth and productivity outcomes under IoAT-managed irrigation and fertigation are summarized in Table 5, and a comparative synthesis of international IoAT case studies is presented in Table 6.

Table 4: Reported Performance Outcomes of IoAT-Based Smart Irrigation and Fertigation Systems

Performance Indicator	Reported Approach	Reported Outcome
Water Use Efficiency (WUE)	IoT-based sensor-guided fertigation	Improved by approximately 61-64.1% [29]
Water Use Efficiency (WUE)	TDR-based irrigation approach	Improved by approximately 40-56% [29]
Water Use Efficiency (WUE)	Drip fertigation	Improved by approximately 9-70% [29]
Nutrient Use Efficiency (NUE)	GreenSeeker-based nutrient sensing	Enhanced by approximately 20-45% [29]
Nutrient Use Efficiency (NUE)	Drip fertigation	Improved by approximately 16.5-29% [29]
Crop yield	Precision fertigation (general)	Increased by approximately 12-35% [29]
Water Use Efficiency / water savings	Sensor-guided sprinkler irrigation	WUE gain ~20-30%; water savings ~30-45% [11]

Table 5: Crop Growth and Productivity Considerations Reported Under Sensor-Guided Irrigation and Fertigation Management

Parameter	Reported Sensing / Assessment Approach	Representative Sources
Physiological performance	SPAD, NDVI, infrared thermometry, soil moisture sensing	[11]
Water productivity	Yield-to-water-applied ratio under sensor-guided vs. conventional management	[11, 16]
Soil enzyme activity (soil health)	Catalase, urease, phosphatase activity under precision fertigation	[29]
Nitrogen use efficiency and yield (rice)	N source type and rate under sensor-informed management	[12, 19]
Growth-stage-specific nutrient demand	Canopy sensor-based nitrogen status monitoring	[19, 23]

Table 6: Comparative Summary of International Studies on IoAT-Based Smart Irrigation and Fertigation Systems

Crop / System	Sensor & Communication Technologies	Key Finding	Source
Paddy rice	Smart sensor-based automatic drip irrigation	Improved irrigation precision and water application control	Barkunan *et al.* [8]
Multi-crop (Brazil/Europe pilots)	IoT-based smart water management platform (SWAMP)	Demonstrated scalable, replicable IoT precision irrigation architecture	Kamienski *et al.* [7]
Soybean (system of crop intensification)	Sensor-guided precision nutrient and irrigation management	Improved physiological performance, water productivity, and yield	Sachin *et al.* [11]
General precision fertigation (multi-crop synthesis)	IoT sensors, TDR, GreenSeeker, drip fertigation	WUE gains of 9-70%; NUE gains of 16.5-45%; yield gains of 12-35%	Singh & Singh [29]
Multi-crop precision agriculture (systematic review)	Digital twins integrating IoT + UAV + ML across 167 studies	Synthesized framework for DT design and integration in smart farming	Awais *et al.* [15]
General smart farming IoT platform	Edge + cloud computing architecture	Demonstrated low-latency, high-reliability architecture for real-time monitoring and control	Zamora-Izquierdo *et al.* [6]

6. Conceptual, Architectural, and Comparative Illustrations

Figure 1 presents the conceptual workflow of the IoAT-based smart irrigation and fertigation framework, synthesizing field sensing, wireless communication, edge-cloud computing, AI-based decision support, and automated control, as described across the reviewed literature. Figure 2 provides an engineering illustration of the IoAT system architecture as deployed in an agricultural field. Figure 3 synthesizes reported water-use efficiency, nutrient-use efficiency, and yield gains across the reviewed IoAT irrigation and fertigation studies. Figure 4 provides an illustrative GIS-based spatial-variability schematic consistent with the visualization approaches described in the literature. Figure 5 presents the IoAT decision-support framework linking real-time sensing and AI-based analytics to specific irrigation and fertigation recommendations.

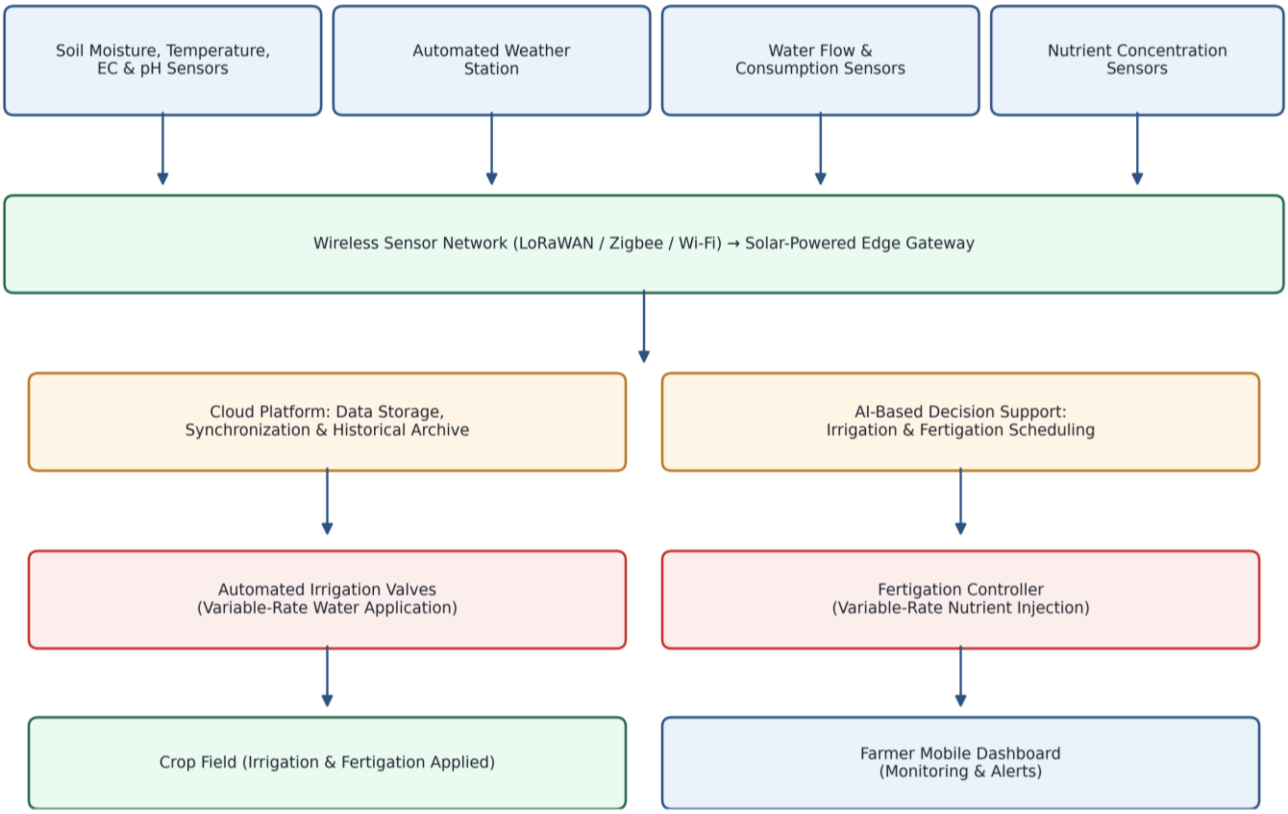

Fig 1: Conceptual workflow of the IoAT-based smart irrigation and fertigation management framework, synthesized from the reviewed literature.

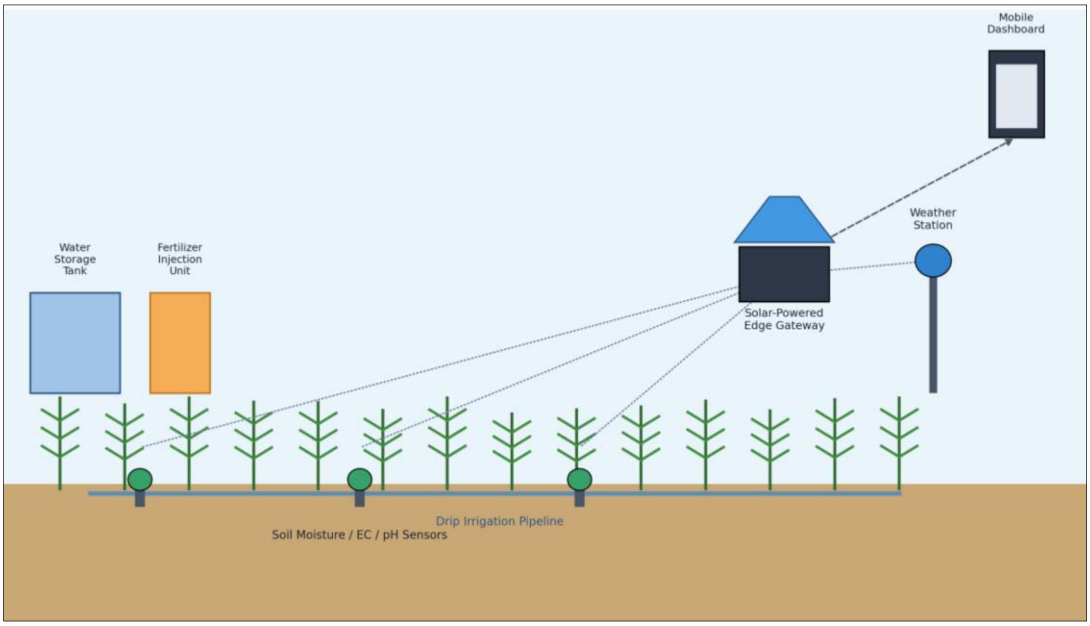

Fig 2: Engineering illustration of the IoAT system architecture deployed in an agricultural field.

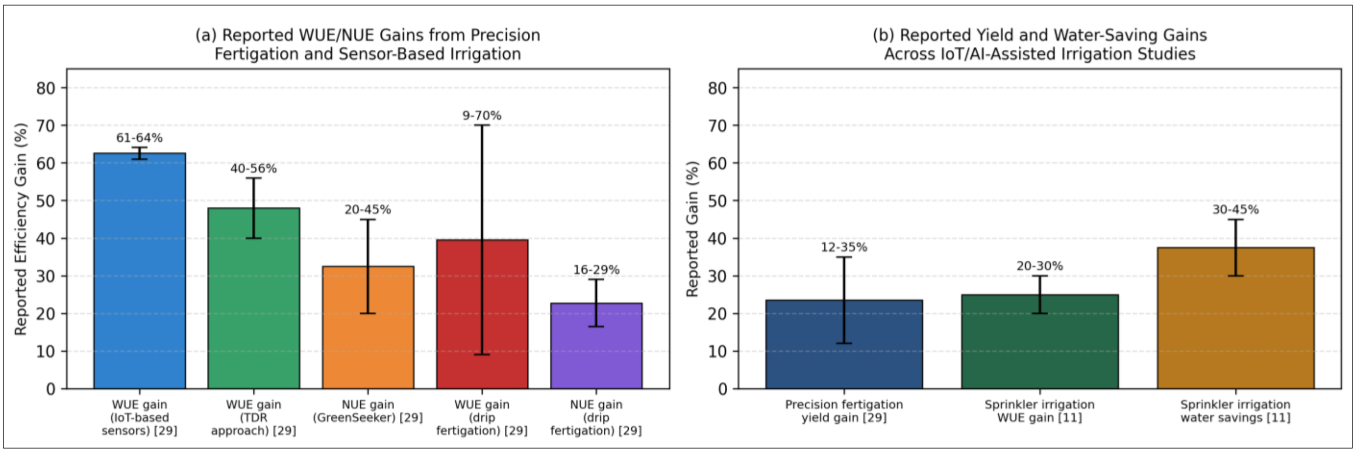

Fig 3: Literature-synthesized water-use efficiency, nutrient-use efficiency, and yield gains reported for IoAT-based smart irrigation and fertigation systems, drawn from the studies summarized in Table 4 and Table 6.

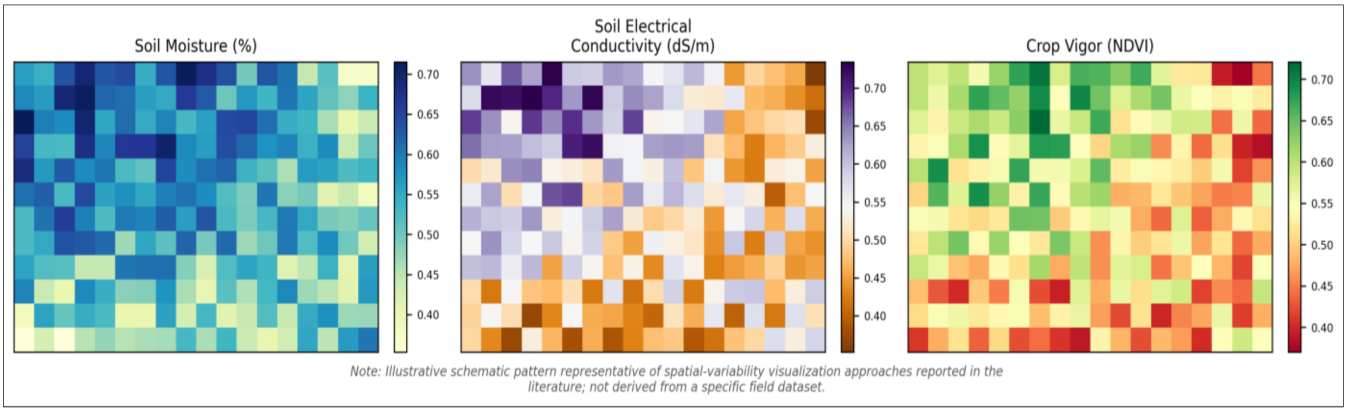

Fig 4: Illustrative GIS-based spatial-variability schematic for soil moisture, electrical conductivity, and crop vigor integrated with IoAT field data (not derived from a specific field dataset).

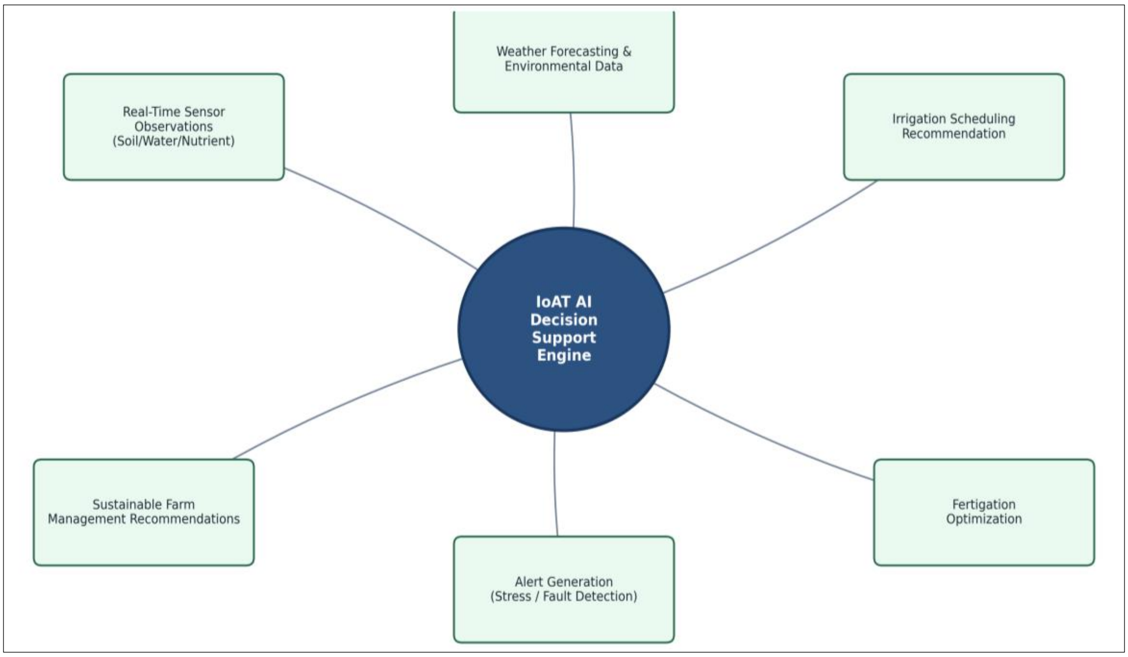

Fig 5: IoAT decision-support framework integrating real-time sensing, weather forecasting, and AI-based analytics for irrigation and fertigation management.

7. Discussion

The reviewed literature converges on strong, consistent evidence that IoAT-based smart irrigation and fertigation improves water-use efficiency, nutrient-use efficiency, and, in most reported cases, crop yield relative to conventional, uniformly scheduled management (Barkunan *et al*., 2019) [8] (Bwambale *et al*., 2022) [9] (Sachin *et al*., 2023) [11] (Singh and Singh, 2026) [29]. This evidence base spans multiple independent reviews, sensor deployment studies, and crop-specific field validations, lending reasonable confidence to the general conclusion that sensor-guided, automated water and nutrient delivery outperforms calendar-based conventional practice across a wide range of cropping systems and environments (Hamami and Nassereddine, 2020) [3] (Bwambale *et al*., 2022) [9] (Verdouw *et al*., 2021) [16].

At the same time, the magnitude of reported gains varies considerably across studies, from single-digit to double-digit percentage improvements in some contexts to gains exceeding 60% in others, a range that likely reflects genuine heterogeneity in baseline conventional practice efficiency rather than inconsistency in IoAT system performance itself: sites with already-efficient conventional irrigation show smaller relative gains from IoAT adoption than sites transitioning from highly inefficient flood irrigation (Bwambale *et al*., 2022) [9] (Singh and Singh, 2026) [29]. This pattern has an important practical implication for adoption planning: the water and nutrient savings achievable through IoAT adoption at a specific site depend substantially on that site's baseline practice, and prospective adopters should calibrate expectations accordingly rather than assuming reported literature maxima will be universally achieved.

Communication infrastructure and computing architecture choices are increasingly well standardized in the literature, with LoRaWAN-based wireless sensor networks and tiered edge-cloud computing now representing something close to a de facto consensus architecture for field-scale IoAT deployment (Kalyani and Collier, 2021) [4] (Pagano *et al*., 2023) [21]. This convergence is a positive sign for interoperability and long-term technology maturation, though the literature also notes that cross-vendor interoperability and data-format standardization remain incomplete, a challenge also documented in the broader agricultural digital twin and smart farming literature (Mowla *et al*., 2023) [1] (Kalyani and Collier, 2021) [4].

Sensor cost and maintenance present a more persistent barrier than communication architecture. Soil moisture sensors are comparatively affordable and robust, but EC, pH, and direct nutrient sensors are more expensive, require more frequent calibration, and are more sensitive to fouling and drift under field conditions, particularly in fertigation contexts where sensors are directly exposed to concentrated nutrient solutions (Sachin *et al*., 2023) [11] (Sudduth *et al*., 2001) [13]. This cost and maintenance asymmetry likely explains why smart irrigation, built primarily on moisture and weather sensing, is more widely deployed in the literature and in commercial practice than fully automated smart fertigation, which depends on the less mature EC/pH/nutrient sensing layer (Xing and Wang, 2024) [10] (Sudduth *et al*., 2001) [13].

Comparison with international case studies (Table 6) indicates that IoAT architectural principles, tiered sensing, wireless communication, edge-cloud computing, and AI-based decision support, generalize across crop systems and geographic contexts, from paddy rice cultivation to diversified row-crop and horticultural systems, even as sensor configurations and fertigation-specific requirements vary by crop (Kamienski *et al*., 2019) [7] (Barkunan *et al*., 2019) [8] (FAO, 2023) [20]. This generalizability supports the broader case for continued IoAT investment as a cross-cutting precision agriculture infrastructure rather than a narrowly crop-specific technology.

Future research priorities emerging from this synthesis include: more consistent reporting of engineering performance metrics, sensor accuracy, system response time, and energy consumption, alongside agronomic outcome metrics; standardized, multi-site field validation that explicitly reports baseline conventional-practice efficiency to contextualize reported IoAT gains; continued development of lower-cost, more robust EC/pH/nutrient sensing technologies to close the maturity gap between smart irrigation and smart fertigation; and expanded economic feasibility analysis addressing smallholder-accessible deployment models, given that current evidence is concentrated in research-station and larger commercial contexts.

8. Conclusion

This article provides an overview of the literature on smart irrigation and fertigation management through IoAT systems. The literature provides overwhelming evidence for large gains in water-use efficiency (9-70% depending on their initial practices and settings), nutrient-use efficiency (16.5%-45%) and yield (12-35%) achieved with sensor-automated irrigation systems. The literature confirms the successful application of wirelessly-operated sensor networks based on LoRaWAN technology and tiered edge-cloud computing architecture, as well as the growing use of AI in managing the streams of data from multiple sensors for generating accurate irrigation and fertigation commands.

Though relevant evidence has been collected, researchers are to find ways to improve the reporting of the system engineering performance results along with agronomic outcomes of businesses in question, and to develop more affordable and reliable nutrient-sensing technologies in order to catch up with smart irrigation technologies. Farmers can also be provided with evidence on the water- and nutrient-efficiency importance.

This approach is heavily reliant on established conventional practices, coupled with the current cost structures that seem to favor adoption in situations requiring higher-value realization or larger-scale production. The investment of policymakers and agricultural extension services in sensor and communication infrastructure, farmer training as well as furthering costs of EC/pH/nutrient sensing technology greatly improves access to IoAT supporting the general objective of water/nutrient-efficient environmentally-sound agriculture at the large scale.

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