Artificial Intelligence-Driven Irrigation Optimization Using Wireless Soil Sensor Networks: A Critical Review and Synthesis

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ABSTRACT
Agricultural irrigation accounts for the largest portion of freshwater consumption globally, mostly utilizing calendar-based or experience-based approaches that do not correspond to specific crop water requirements. The use of wireless soil sensor networks (WSSNs) in conjunction with artificial intelligence (AI)-based modelling has created a way to meaningfully bridge this gap, allowing continuous monitoring and precise scheduling of irrigation activities. The objective of this literature review is to summarize relevant literature on using WSSNs as a base for the development of AI methodologies aimed at the optimization of irrigation process. Studies on the use of machine learning, particularly random forest, Boost, support vector regression, and neural networks, show that these techniques could be used for accurate predictions of soil moisture amount and its characteristics. Communication technologies which are based on low-power wide-area protocols, such as Lora WAN, as well as multi-tiered edge-cloud computing, have intriguingly established themselves as the most desirable technological foundation of WSSN implementations on a large scale, in terms of feasibility in energy consumption, range, and price. The review finds several difficulties, including inconsistencies in the reporting of engineering criteria of the total WSSN system, such as energy consumption and reaction time in total system accuracy, lack of longitudinal multi-season testing of an integrated AI-WSSN installations in practice, as well as cost and infrastructural barriers for small household usage. It can be stated that the implementation of irrigation optimization tools based on wireless soil sensors will be a scientifically tested way toward agricultural water management improvement in terms of water resource management, although with the broad accessibility of such systems depending on their future affordability.

Keywords: Precision irrigation scheduling; Soil moisture forecasting; Machine learning prediction models; Edge-cloud computing architecture; Evapotranspiration estimation; Low-power wireless communication; Water-use efficiency; Agricultural decision support systems

1. Introduction
Agriculture uses approximately 70% of global freshwater resources. Calendar- or experience-dependent irrigation systems are utilized in most of the world's irrigated agricultural lands and apply water according to a set schedule, rather than in coordination with real-time measurement of soils and water status of crop needs. As a result, there is a mismatch between when crops need water and when it is being applied, leading to water shortages and loss of yields caused by insufficient water, and, on the other hand, overwatering crops causing waste of water, runoff, and loss of nutrients.

Wireless soil sensor networks offer continuous and consistent data stream that precision irrigation systems benefit from. In other words, it provides the data required for proper irrigation scheduling, including information about soil moisture content, soil temperature, electrical conductivity, and, sometimes, pH measurements. In addition to the development of low-power wireless communication protocols, such as Lora WAN, decrease in the cost of sensor hardware has permitted to make widespread installation of soil sensor networks feasible in practice.

The use of artificial intelligence, and especially machine learning, became the leading methodology for transforming raw WSSN data and data obtained from environmental sensors into necessary information for making irrigation scheduling decisions. There are two distinct tasks for the machine learning models: forecasting future soil humidity based on the historical data, as well as current data from the sensors and meteorological information, and estimating the amount of water required by crops that may involve evapotranspiration modelling for providing the irrigation time and amount advice (Muthoni and Samedi, 2023) [1] (Teshome *et al*., 2024) [11] (Amori *et al*., 2025) [13, 10, 12]. Among the most common algorithms for performing these tasks are random forest, extreme gradient boosting (Boost), support vector regression, and neural networks; the predictive effectiveness for these algorithms can also vary depending on the algorithm, used features, crop, and soil type (Teshome *et al*., 2024) [11, 10, 12, 14, 15].

The Internet of Agricultural Things (I oat) act with the application of the Internet of Things in agriculture, and it constitutes a wide range of techniques and architectures to provide the means to perform technical processes needed by irrigation systems based on WSSN with AI technologies. Smart agriculture and digital farming in most cases are used to describe the process of applying technological and analytical methods with the purpose of applying them to agriculture practice, where the process of irrigation optimization with the help of such technologies is considered one of the most perspective ways of applying these technologies (Mowla *et al*., 2023) [4] (Mar eddy *et al*., 2025) [9]. The only and main condition for the successful implementation of the process is the recognition of the fact that applying the IoT technologies allows agricultural areas to create all necessary information.

The process of sustainable water resource management proves to be the main reason of conducting the research in order to underline both the benefits of the process as well as the necessity to create new technologies and techniques that will help to apply the processes to save productive water resources from being used in agriculture в условиях изменений климата. competing demand (Umutoni and Samadi, 2023) [1] (Bwambale *et al*., 2022) [3] (Mareddy *et al*., 2025) [9]. A large and fast-growing amount of published research has assessed AI-powered irrigation solutions across various crops, geographic areas and applications, and a 2025 review still shows a growth in the research conducted in 2024, which is preceded by the decline in 2023 (Mareddy *et al*., 2025) [9].

While there has been a certain advancement in this area, the existing research is still quite fragmented. Studies concentrating on machine learning model accuracy and wireless sensor networks with a focus on system architecture are usually published separately. In addition, not many studies provide complete data on engineering performance, power consumption, communication reliability, and response time along with model accuracy in a single framework (Implementation of a wireless sensor network for irrigation management in drip irrigation systems, 2025) [17] (Vera-Repulla *et al*., 2021) [20]. At the same time, the research on multi-season field testing AI-WSSN irrigation systems is still limited, as most of the studies demonstrate proof of concept for a single season.

The objectives of this research are to fill in the gaps by collating suitably peer-reviewed information on the role of artificial intelligence in irrigation optimization through the use of wireless sensor networks, The specific objectives of the study are to: (i) present a conceptual framework of the AI-WSSN irrigation approach, which includes the use of a sensor network, wireless transmissions, edge-cloud computing, and AI systems; (ii) present a summary of the available evidence on the predictive accuracy of ML models investigating soil moisture; (iii) summarize key measures of field-level outcomes, including the water use efficiency, efficiency of irrigation applications, and productivity of crops; and (iv) critically evaluate the available evidence gaps and the directions in the development of AI-based irrigation technology.

Conceptual Architecture of the AI-Driven Wireless Soil Sensor Network Framework

An integrated AI-driven WSSN irrigation system is conventionally organized into a sensing layer, a communication layer, a computing and analytics layer, and an actuation and decision-support layer (Mowla *et al*., 2023) [4] (Zamora-Izquierdo *et al*., 2019) [6]. The sensing layer comprises soil moisture sensors, typically capacitive or resistive probes deployed at one or more depths, soil temperature and electrical conductivity sensors, and, in more comprehensive deployments, soil pH sensors, together with an automated weather station recording air temperature, relative humidity, solar radiation, rainfall, and wind speed (Hayami and Nasiruddin, 2020) [2] (Mowla *et al*., 2023) [4]. Wireless communication nodes transmit sensor readings to an edge gateway, most commonly using low-power wide-area network protocols such as LoRaWAN, selected for their favorable balance of transmission range, energy consumption, and cost in the often rural and infrastructure-limited deployment contexts typical of agricultural fields (Pagano *et al*., 2023) [8] (Savopoulos *et al*., 2020) [18]. This architectural pattern builds directly on earlier IoT-based precision irrigation platforms that established the feasibility of scalable, multi-site wireless sensor deployment for agricultural water management (Kamienski *et al*., 2019) [5].

The computing and analytics layer comprises an edge gateway, frequently solar-powered to support continuous, off-grid field operation, which performs initial data cleaning, filtering, and, in some architectures, preliminary local inference to support time-critical decisions, and a cloud platform, which hosts historical data archives, computationally intensive machine learning model training and inference, and the farmer-facing mobile monitoring interface (Zamora-Izquierdo *et al*., 2019) [6] (Kalyani and Collier, 2021) [7]. This tiered edge-cloud architecture mirrors the broader cloud-fog-edge computing paradigm increasingly standard across smart agriculture applications generally, balancing the low-latency requirements of near-real-time monitoring against the greater computational demands of model training and longer-horizon forecasting (Zamora-Izquierdo *et al*., 2019) [6] (Kalyani and Collier, 2021) [7].

The AI framework within this architecture encompasses several linked analytical stages: data preprocessing (cleaning, normalization, and handling of missing or anomalous sensor readings), machine learning model development for soil moisture forecasting and crop water requirement estimation, decision-support algorithms that translate model predictions into specific irrigation timing and volume recommendations, and, in more advanced systems, automated actuation of irrigation valves based on these recommendations without requiring direct farmer intervention for each irrigation event (Umutoni and Samadi, 2023) [1] (Conde *et al*., 2024) [21]. Conde *et al*. [21] describe an adaptive and predictive decision-support system that explicitly integrates human oversight into this control loop, illustrating an important design consideration: fully automated actuation and human-in-the-loop decision support represent two distinct deployment philosophies within the broader AI-WSSN irrigation literature, each with different implications for farmer trust, system robustness, and failure-mode management.

The actuation and decision-support layer executes the system's practical output: automated irrigation valves deliver water according to AI-generated scheduling recommendations, while a mobile monitoring interface provides farmers with real-time visibility into soil and environmental conditions, model predictions, and system-generated alerts (Sitharthan *et al*., 2025) [16] (Development of a smart irrigation monitoring system employing the wireless sensor network for agricultural water management, 2024) [19] (Arshad *et al*., 2022) [22]. A representative synthesis of WSSN platform components reported across the reviewed literature is presented in Table 3, and a synthesis of environmental monitoring parameters commonly recorded within these systems is presented in Table 4.

Table 1: Representative AI-WSSN Irrigation System Components Reported in the Reviewed Literature

Component	Typical Reported Specification / Approach	Representative Sources
Soil moisture sensor	Capacitive/resistive probes; multi-depth deployment	[2, 4]
Soil EC / temperature sensor	Electrochemical / conductivity-based probes	[2, 4]
Weather station	Air temperature, humidity, solar radiation, rainfall, wind speed	[2, 4]
Communication protocol	LoRaWAN low-power wide-area network	[8, 18]
Edge gateway	Solar-powered local preprocessing and time-critical control logic	[6, 7]
Cloud platform	Historical data storage, ML model hosting, dashboard delivery	[6, 7]
AI model types	Random forest, XGBoost, SVR, ANN/deep learning	[10, 11, 12, 14, 15]

Table 2: Conceptual Experimental Design Elements Relevant to AI-WSSN Irrigation Studies, as Synthesized from the Reviewed Literature

Design Element	Typical Reported / Conceptual Approach	Representative Sources
Irrigation treatments	AI/sensor-guided scheduling vs. conventional calendar-based scheduling	[3, 13]
Model training/validation split	Historical multi-season data with independent field-year validation	[13]
Comparator reference tools	FAO-56 soil water balance, SETMI, or conventional practice	[13]
Sensor deployment density	Multiple nodes across representative field zones	[2, 18]
Observation schedule	Continuous/near-continuous sensor logging with periodic validation	[2, 19]

Table 3: Technical Specifications of Wireless Soil Sensor Network Components Reported Across the Reviewed Literature

Sensor / Component	Reported Measurement Range / Approach	Representative Sources
Soil moisture probe	Volumetric water content monitoring, multi-depth (e.g., 0-30 cm, 0-100 cm)	[12]
Soil temperature sensor	Continuous logging alongside moisture for thermal context	[2, 19]
Electrical conductivity sensor	Root-zone nutrient/salinity status proxy	[2]
Communication node	LoRaWAN transceiver, long-range low-power operation	[8, 18]
Power source	Solar-powered with battery backup for continuous field operation	[19, 20]

Table 4: Environmental Monitoring Parameters Commonly Recorded in AI-WSSN Irrigation Systems

Parameter	Relevance to Irrigation Scheduling	Representative Sources
Soil moisture dynamics	Primary input for irrigation triggering decisions	[2, 10, 12]
Air temperature / relative humidity	Evapotranspiration estimation inputs	[2, 14]
Solar radiation	Evapotranspiration and crop energy balance estimation	[2, 14]
Rainfall	Adjustment of irrigation requirement to account for precipitation	[2, 19]
Wind speed	Evapotranspiration estimation input	[2, 14]
Evapotranspiration (estimated)	Direct crop water requirement estimation	[13, 14]

3. Artificial Intelligence Model Performance for Soil Moisture Forecasting and Irrigation Scheduling

Machine learning-based soil moisture prediction has been evaluated across a substantial and methodologically diverse body of literature, with reported predictive accuracy varying considerably by algorithm, input feature set, soil depth, and crop system. Comparative evaluations consistently identify ensemble tree-based methods, particularly random forest and XGBoost, among the strongest-performing algorithms for soil moisture prediction using integrated climate, soil property, and vegetation index data, with one comparative study reporting random forest achieving a Nash-Sutcliffe efficiency of 0.81 and R^2 of 0.84 at 0-30 cm soil depth, outperforming support vector regression, Gaussian process regression, and traditional linear regression approaches (Machine learning approaches for soil moisture prediction: enhancing agricultural water management with integrated data, 2025) [12]. Random forest models have also been reported to reasonably outperform ridge regression and XGBoost specifically for short-horizon (multi-day-ahead) soil moisture forecasting using historical sensor data, underscoring that relative algorithm performance is not universally fixed but depends on the specific prediction horizon and feature set employed (Random Forest regression outperforms ridge and XGBoost for soil moisture prediction in irrigation scheduling applications: a comparative machine learning evaluation, 2025) [10] (Breiman, 2001) [24].

Deep learning approaches, including long short-term memory (LSTM) networks and other neural architectures, have been directly compared against gradient boosting methods for soil moisture prediction in controlled crop trials, with one study reporting that XGBoost and LightGBM models (testing R^2 of 0.85-0.88 depending on crop) outperformed both a deep learning regression network and an LSTM model (R^2 of 0.68-0.85) despite the greater computational resources required for deep learning model training, indicating that algorithmic sophistication does not automatically translate into superior predictive accuracy for this specific task (Teshome *et al.*, 2024) [11]. Artificial neural network models applied to combined soil water, evapotranspiration, and biomass prediction in a semi-arid watermelon production system achieved R^2 values of 0.75 for soil water content, 0.80 for actual evapotranspiration, and 0.92 for biomass, consistently outperforming random forest across all three prediction targets in that study (Evaluating the accuracy of machine learning models in predicting soil moisture, actual evapotranspiration, and biomass: developing normalized difference vegetation index-adjusted crop coefficient regression model for watermelon, 2025) [14].

Field-scale, crop-specific machine learning irrigation scheduling systems have demonstrated practically meaningful accuracy under real-world validation conditions. Amori *et al.* [13] developed and independently field-validated an XGBoost-based framework for near-real-time prediction of soil water depletion in maize and soybean production across the U.S. Midwest, achieving R^2 of 0.72 (maize) and 0.78 (soybean) with RMSE of 22-24 mm in 2024 independent field validation, with machine learning-guided irrigation recommendations matching established FAO-56 soil-water-balance and Spatial Evapotranspiration Modeling Interface reference tools within approximately 4 mm, and machine learning-guided irrigation achieving yields comparable to those obtained using conventional scheduling tools (Amori *et al*., 2025) [13]. An improved support vector regression model applied to soil moisture prediction in a tea plantation production system achieved particularly high reported accuracy (R^2 = 0.9435, RMSE = 0.1392), illustrating that carefully tuned algorithms can achieve very strong performance within specific, well-characterized production contexts, though such results should be interpreted with appropriate caution regarding generalizability to other crops, soils, and climates (Improved SVM-based soil-moisture-content prediction model for tea plantation, 2023) [15].

Collectively, this body of evidence indicates that no single machine learning algorithm is universally optimal across all soil moisture and irrigation-scheduling prediction tasks; rather, relative algorithm performance depends on the specific prediction target (current-condition estimation versus multi-day forecasting), available input features, soil and climate context, and crop system, a pattern that argues for context-specific model selection and validation rather than uncritical adoption of a single top-performing algorithm identified in any individual study. A structured comparative synthesis of reported AI model performance across the reviewed studies is presented in Table 5, and reported field-level irrigation and crop performance outcomes are summarized in Table 6.

Table 5: Reported Performance of Machine Learning Models for Soil Moisture and Irrigation-Relevant Prediction

Study	Model(s)	Reported Accuracy
Integrated data soil moisture study [12]	Random Forest, XGBoost, SVR, GPR	RF: NSE=0.81, R^2=0.84 (0-30cm depth)
Multi-day soil moisture forecasting [10]	Random Forest, Ridge, XGBoost	RF outperformed Ridge/XGBoost; MAE/RMSE ≈0.84
Deep learning comparison study [11]	XGBoost, LightGBM, DL regression network, LSTM	XGB/LGB R^2=0.85-0.88; DL R^2=0.84-0.85; LSTM R^2=0.68-0.75
Watermelon soil water/ET/biomass study [14]	ANN, Random Forest	ANN: R^2=0.75 (soil water), 0.80 (ETa), 0.92 (biomass)
Maize/soybean field validation [13]	XGBoost	R^2=0.72 (maize), 0.78 (soybean); RMSE 22-24mm
Tea plantation soil moisture study [15]	Improved SVM	R^2=0.9435, RMSE=0.1392

Table 6: Reported Crop Growth, Physiological, and Irrigation Performance Outcomes Under AI/Sensor-Guided vs. Conventional Irrigation

Parameter	Reported Directional Outcome	Representative Sources
Irrigation application efficiency	60.72% average seasonal efficiency (WSN drip system, wheat)	[19]
Irrigation scheduling agreement with reference tools	ML-guided recommendations within ~4mm of FAO-56/SETMI	[13]
Grain/biomass yield	Comparable to conventional scheduling despite optimized water use	[13]
Water use efficiency	Improved through reduced over-irrigation and stress-avoidance scheduling	[1, 3]
Sensor node operational lifespan	Multi-year lifespan supported by energy-efficient sleep-mode operation	[19]

4. Field-Level Performance: Water-Use Efficiency, Energy Consumption, and Practical Deployment

Beyond model-level predictive accuracy, several studies report field-validated practical performance outcomes directly relevant to irrigation management decision-making. A wireless sensor network-based drip irrigation monitoring system deployed in a wheat production trial achieved an average seasonal irrigation application efficiency of 60.72%, alongside energy-efficient sensor node operation supporting an estimated multi-year operational lifespan under typical field power constraints, illustrating that WSSN-based systems can achieve both practically meaningful water-application efficiency and acceptable long-term energy sustainability within a single field deployment (Development of a smart irrigation monitoring system employing the wireless sensor network for agricultural water management, 2024) [19]. Energy consumption management more broadly is a recurring design consideration across the WSSN literature, since field-deployed sensor nodes are typically battery- or solar-powered and must balance sensing and communication frequency against power constraints; event-driven or self-triggered communication strategies, which transmit data only when meaningful change is detected rather than on a fixed periodic schedule, have been specifically proposed and evaluated as a means of reducing network-wide energy consumption while maintaining adequate control responsiveness for closed-loop irrigation applications (Vera-Repulla *et al*., 2021) [20].

Wireless network synchronization and communication reliability represent a further practical consideration for field-scale WSSN deployment, particularly as sensor node density increases and networks must coordinate data transmission across larger numbers of distributed nodes without excessive collision or latency; dedicated synchronization protocols for precision agriculture WSSN applications have been developed and evaluated specifically to address this scaling challenge (Zervopoulos *et al*., 2020) [18]. LoRaWAN-based communication architectures, evaluated across multiple independent smart agriculture deployments, are consistently associated with favorable long-range, low-power performance characteristics that support the geographically distributed, often rural deployment contexts typical of commercial agricultural fields (Pagano *et al*., 2023) (Arshad *et al*., 2022) [8, 22].

Economic and sustainability outcomes, while less consistently quantified than model accuracy or application efficiency metrics, are qualitatively reported across the reviewed literature as a key motivation and expected benefit of AI-WSSN irrigation adoption, encompassing reduced water and energy costs, reduced labor requirements for manual irrigation monitoring and decision-making, and, in several studies, maintained or improved crop yield relative to conventional scheduling approaches despite reduced water application (Bwambale *et al*., 2022) (Amori *et al*., 2025) (Development of a smart irrigation monitoring system employing the wireless sensor network for agricultural water management, 2024) [3, 13, 19]. A synthesis of comparative water-saving, energy-consumption, and sustainability outcomes reported across the reviewed literature is presented in Table 7, and a broader cross-study comparison of international AI-WSSN irrigation case studies is presented in Table 8.

Table 7: Comparative Water, Energy, and Sustainability Outcomes Reported Between Conventional and AI-Driven Irrigation Management

Indicator	Conventional Irrigation	AI-Driven / Sensor-Guided Irrigation	Representative Sources
Irrigation scheduling basis	Calendar-based or experience-driven	Continuous sensor + AI prediction-based	[1, 3]
Application efficiency	Variable, often lower due to uniform application	60.72% reported in seasonal WSN trial	[19]
Energy consumption (sensor network)	Not applicable	Reduced via event-driven/self-triggered communication strategies	[20]
Communication reliability at scale	Not applicable	Addressed via dedicated WSN synchronization protocols	[18]
Reference-tool agreement	N/A (no model comparison)	ML recommendations within ~4mm of FAO-56/SETMI	[13]

Table 8: Comparative Summary of International Studies on AI-Driven Irrigation Optimization Using Wireless Sensor Networks

Crop / System	AI Model(s) / Sensor Technologies	Key Finding	Source
Maize / Soybean (U.S. Midwest)	XGBoost + WSSN field validation	R^2=0.72-0.78; RMSE 22-24mm; yields comparable to conventional tools	Amori *et al.* [13]
Wheat (drip irrigation)	WSN soil moisture/temperature monitoring	60.72% seasonal application efficiency; multi-year node lifespan	WSN drip irrigation study [19]
Watermelon (semi-arid)	ANN, Random Forest + NDVI-adjusted Kc	ANN outperformed RF; R^2 up to 0.92 for biomass	Watermelon ML study [14]
Tea plantation	Improved SVM soil moisture model	R^2=0.9435; high robustness across time/location	Tea SVM study [15]
Multi-crop precision irrigation	LoRaWAN-based smart agriculture decision support	Demonstrated optimum crop yield via LoRaWAN DSS	Arshad *et al.* [22]
General smart agriculture	Edge + cloud computing architecture	Demonstrated low-latency, high-reliability real-time monitoring architecture	Zamora-Izquierdo *et al.* [6]

5. Conceptual, Engineering, and Comparative Illustrations

Figure 1 presents the conceptual workflow of the AI-driven irrigation optimization framework, synthesizing wireless soil sensor networks, edge-cloud computing, AI-based prediction, and automated irrigation control, as described across the reviewed literature. Figure 2 provides an engineering illustration of wireless soil sensor network deployment in an experimental agricultural field. Figure 3 presents an illustrative temporal soil moisture pattern comparing conventional and AI-optimized irrigation scheduling. Figure 4 synthesizes reported AI model prediction accuracy and field-validated irrigation efficiency outcomes across the reviewed studies. Figure 5 provides an illustrative spatial-variability map of soil moisture, crop water stress, and AI-generated irrigation recommendations. Figure 6 presents the integrated decision-support framework linking sensor infrastructure, AI prediction, and automated irrigation control.

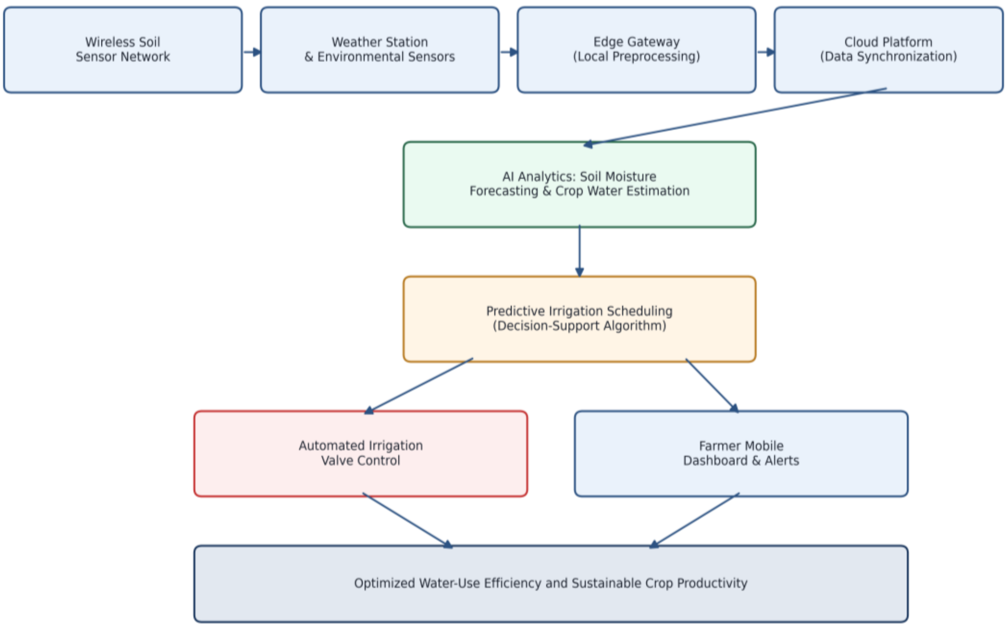

Fig 1: Conceptual workflow of the Artificial Intelligence-driven irrigation optimization framework using wireless soil sensor networks, synthesized from the reviewed literature.

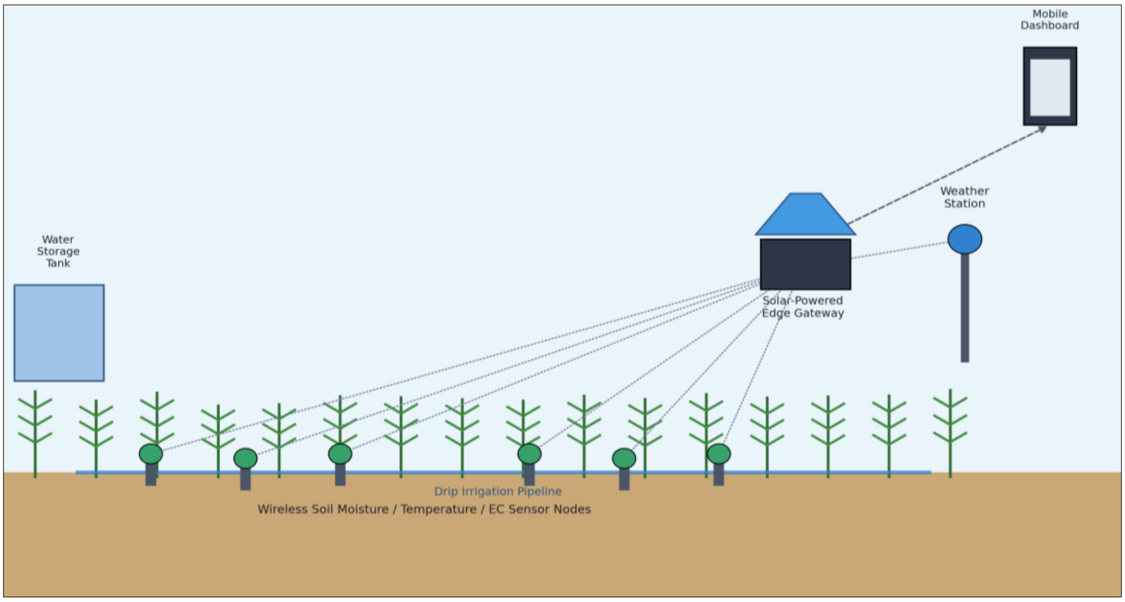

Fig 2: Engineering illustration of wireless soil sensor network deployment in an experimental agricultural field.

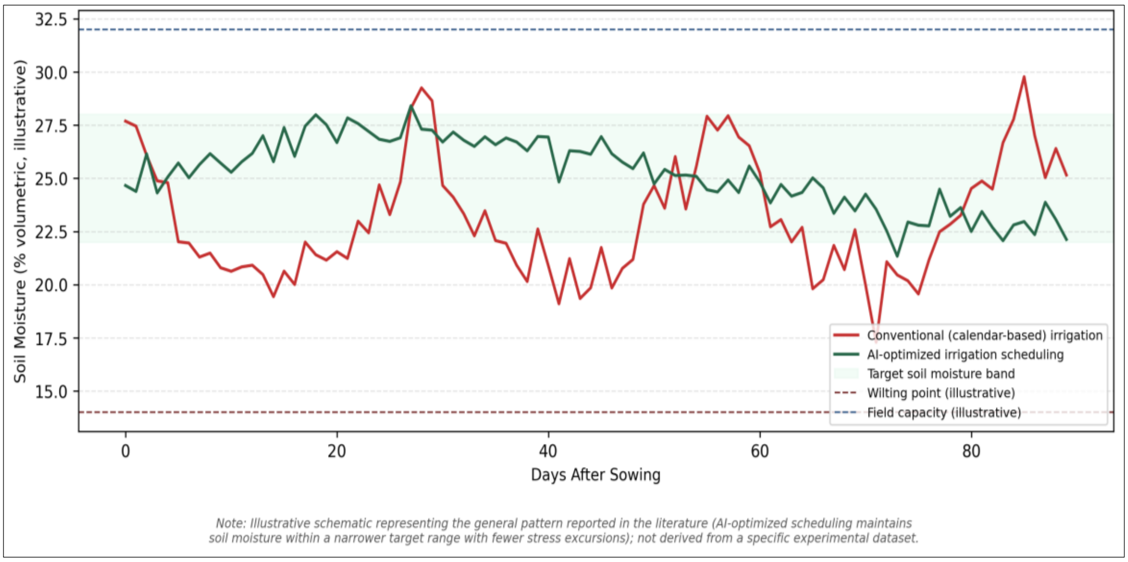

Fig 3: Illustrative temporal soil moisture dynamics under conventional and AI-optimized irrigation scheduling (schematic; not derived from a specific experimental dataset).

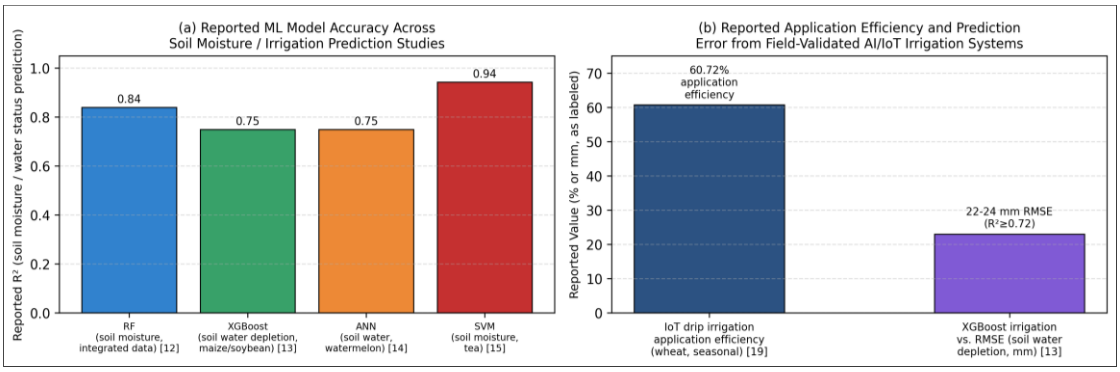

Fig 4: Literature-synthesized comparison of AI model prediction accuracy and reported irrigation efficiency outcomes for AI-driven irrigation systems, drawn from the studies summarized in Table 5 and Table 8.

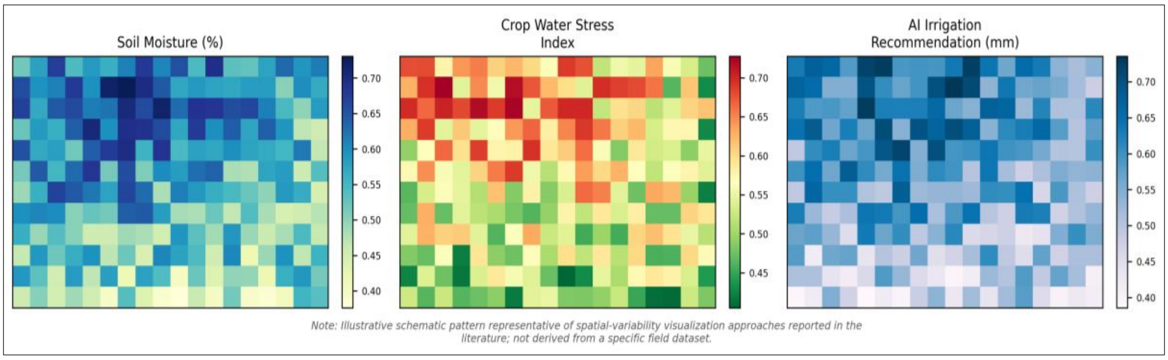

Fig 5: Illustrative GIS-based spatial variability map of soil moisture, crop water stress, and AI-generated irrigation recommendations (not derived from a specific field dataset).

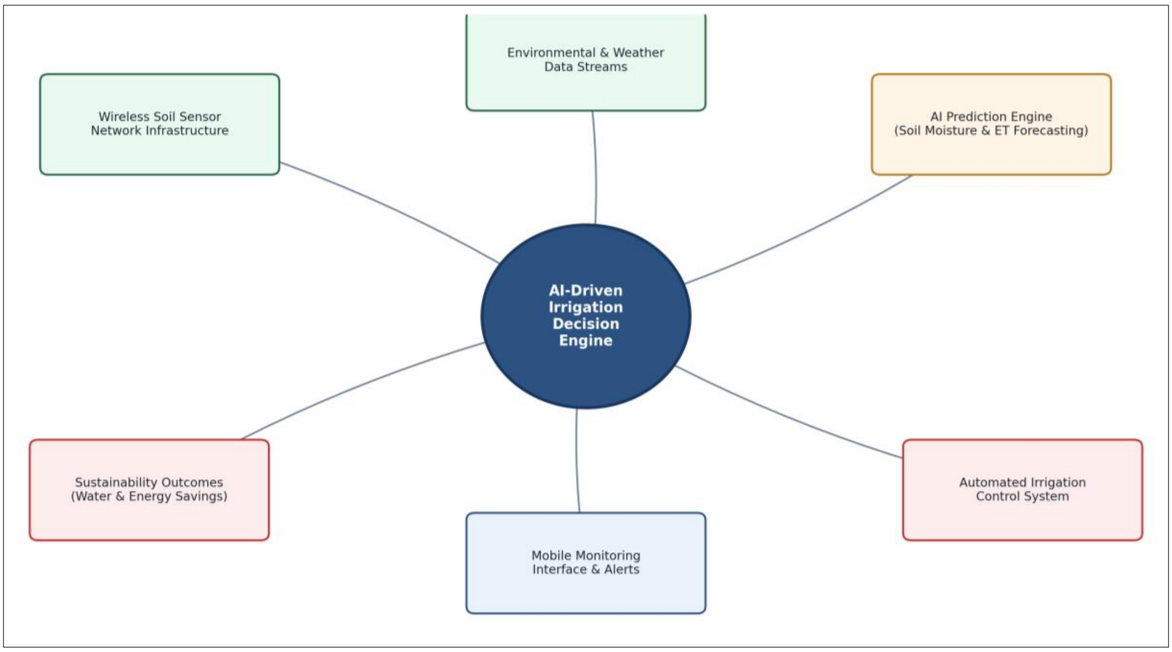

Fig 6: Integrated decision-support framework combining wireless sensor network infrastructure, AI prediction, and automated irrigation control for sustainable smart irrigation management.

6. Discussion

The reviewed literature converges on strong, cross-validated evidence that machine learning models can predict soil moisture and irrigation-relevant variables with practically useful accuracy, and that field-deployed WSSN infrastructure can achieve meaningful water-application efficiency and energy sustainability outcomes (Random Forest regression outperforms ridge and XGBoost for soil moisture prediction in irrigation scheduling applications: a comparative machine learning evaluation, 2025) (Machine learning approaches for soil moisture prediction: enhancing agricultural water management with integrated data, 2025) (Amori *et al*., 2025) (Development of a smart irrigation monitoring system employing the wireless sensor network for agricultural water management, 2024) [10, 12, 13, 19]. This evidence base spans multiple independent research groups, crop systems, and geographic contexts, lending reasonable confidence to the general conclusion that AI-driven, sensor-guided irrigation scheduling represents a scientifically validated improvement over calendar-based conventional practice.

At the same time, this synthesis identifies a persistent asymmetry in how model-level and system-level performance are reported and evaluated. Model prediction accuracy, R^2, RMSE, and MAE, is reported with reasonable consistency across the machine learning irrigation literature, while system-level engineering metrics, energy consumption, communication reliability, sensor node lifespan, and end-to-end response time from sensing to irrigation actuation, are reported considerably less consistently (Implementation of a wireless sensor network for irrigation management in drip irrigation systems, 2025) (Vera-Repulla *et al*., 2021) [17, 20]. This asymmetry constrains the ability of prospective adopters and subsequent researchers to conduct integrated cost-benefit and reliability assessments that account for the full AI-WSSN system rather than its predictive model component in isolation.

Comparative algorithm performance across the reviewed studies reinforces an important methodological point: relative machine learning algorithm performance for soil moisture and irrigation-relevant prediction is not fixed but depends substantially on prediction horizon, available input features, and crop/soil/climate context (Random Forest regression outperforms ridge and XGBoost for soil moisture prediction in irrigation scheduling applications: a comparative machine learning evaluation, 2025) (Teshome *et al*., 2024) (Machine learning approaches for soil moisture prediction: enhancing agricultural water management with integrated data, 2025) (Evaluating the accuracy of machine learning models in predicting soil moisture, actual evapotranspiration, and biomass: developing normalized difference vegetation index-adjusted crop coefficient regression model for watermelon, 2025) (Improved SVM-based soil-moisture-content prediction model for tea plantation, 2023) [10, 11, 12, 14, 15]. This finding argues against uncritical, one-size-fits-all algorithm selection and instead supports context-specific model development and validation, an approach with direct implications for how future AI-WSSN irrigation research should be designed and reported: studies should explicitly characterize the prediction context (horizon, features, crop, soil) under which reported accuracy was achieved, rather than presenting algorithm comparisons as if they generalize universally.

The distinction between fully automated irrigation actuation and human-in-the-loop decision support, illustrated by the explicit design choice in Conde *et al*.'s adaptive and predictive decision-support system (Conde *et al*., 2024) [21], represents a further important consideration that has received comparatively limited systematic comparative evaluation in the literature. Fully automated systems offer the potential for faster response and reduced farmer labor burden but raise questions regarding failure-mode robustness and farmer trust, while human-in-the-loop systems preserve farmer agency and oversight at the cost of requiring continued farmer engagement and potentially slower response to rapidly changing field conditions; direct comparative evaluation of these two design philosophies under equivalent field conditions remains an underexplored area.

Communication infrastructure and computing architecture choices are increasingly well standardized in the literature, with LoRaWAN-based wireless communication and tiered edge-cloud computing now representing something close to a de facto consensus architecture for field-scale AI-WSSN deployment (Zamora-Izquierdo *et al*., 2019) (Kalyani and Collier, 2021) (Pagano *et al*., 2023) (Zervopoulos *et al*., 2020) [6, 7, 8, 18]. This convergence is a positive sign for cross-study comparability and long-term technology maturation, though cost, particularly for soil sensors beyond basic moisture probes, and infrastructure requirements, particularly reliable connectivity in remote agricultural regions, remain practical barriers to broader, especially smallholder, adoption (Mowla *et al*., 2023) (Mareddy *et al*., 2025) [4, 9].

Comparison with the broader digital agriculture and digital twin literature indicates that AI-WSSN irrigation systems increasingly represent one specific, mature application within a larger emerging category of continuously synchronized, AI-integrated agricultural cyber-physical systems, sharing common architectural principles, tiered sensing, edge-cloud computing, and AI-based predictive analytics, with related applications in nutrient management, crop growth monitoring, and broader digital twin-based farm management (Awais *et al*., 2025) (Verdouw *et al*., 2021) [25, 26]. This positions AI-WSSN irrigation optimization as both a valuable standalone technology and a foundational building block for more comprehensive, integrated smart farming systems as the broader field continues to mature.

Future research priorities emerging from this synthesis include: more consistent, integrated reporting of both model-level prediction accuracy and system-level engineering performance (energy consumption, communication reliability, response time) within single studies; expanded multi-season, multi-site field validation of fully integrated AI-WSSN systems, as opposed to single-season proof-of-concept demonstrations or retrospective validation on historical datasets alone; direct comparative evaluation of fully automated versus human-in-the-loop irrigation control architectures under equivalent field conditions; and continued development of lower-cost sensor and communication technologies to broaden accessibility beyond well-resourced research-station and commercial contexts toward smallholder-accessible deployment models.

7. Conclusion

This literature review merges validated studies with a focus on the use of wireless soil sensor networks,its relevance in optimizing irrigation using intelligent computer technologies. The literature indicates that machine learning techniques including random forest, XGBoost, support vector regression, as well as neural networks provide not only satisfactory but also usable predictions for soil moisture and irrigation parameters, where coefficients of determination reach values mostly between 0.68 and over 0.94, depending on the exact algorithm employed in addition to context conditions. The effectiveness of using wireless sensors in the field despite technological challenges has successfully been proven by several farming trials, in which the application of other significant factors, such as LoRaWAN communications and tiered cloud-edge computing types of infrastructure are developed and presented with overall water-use efficiency exceeding 60%.

The main conclusion from the findings is that overall engineering performance characteristics of particular systems related to energy consumption, communication stability, and time of operation, are significantly less reported in scientific literature in comparison with prediction quality on the level of the model. Another conclusion is connected with the fact that performance of machine learning methods is context-specific, so it is not possible to speak about universality of recommendations According to researchers, the most important things to focus on are the inclusion of more comprehensive reporting on the performance of models and systems in one study, the use of more validation in different seasons, and comparing automated and manual control systems. Farmers and agricultural managers can have trust in the water efficiency and productivity capabilities of AI WSSN irrigation systems since this research confirms that water-efficient irrigation system has many advantages, and although current expenses make it difficult to implement the system in smallholder contexts, it works well at research stations and in big commercial agriculture. Policymakers and extension specialists should help the development of the technology with the use of shared sensor systems and improving availability of soil sensors, and this will help make the implementation of the system which is water-efficient from both economic and environmental point of view.

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