A Crop-Intelligence Driven IoT Framework for Precision Irrigation: Review, Gaps, and Future Design Directions

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Abstract
The rapid expansion of IoT-enabled irrigation technologies has significantly improved on-farm monitoring; however, most existing systems remain limited to threshold-based or descriptive control and lack crop-intelligent, analytically grounded decision-making capabilities. This paper presents a structured review of IoT-based precision irrigation systems, AI-driven decision-support approaches, and their associated limitations, highlighting critical gaps related to intelligence, data integration, decision architecture, scalability, affordability, and long-term validation. Building on these gaps, the study proposes a novel conceptual IoT framework for precision irrigation that integrates soil moisture sensing, climatic and evapotranspiration analytics, and crop growth-stage intelligence within a hybrid rule-based and AI-driven decision architecture. The framework is designed to enable adaptive, explainable, and rational irrigation decisions while remaining practical for real-world deployment, particularly in developing and smallholder-dominated agricultural contexts. Through logical and conceptual validation, the proposed design demonstrates clear advantages over moisture-only systems in terms of water-use efficiency, energy conservation, and yield reliability. The study contributes a scientifically grounded and deployment-oriented perspective to smart irrigation research, offering a strategic pathway toward sustainable agricultural water management.

Keywords: Smart irrigation; Internet of Things (IoT); Precision agriculture; Artificial intelligence; Decision support systems; Crop water management; Sustainable agriculture

Introduction

Globally, the agricultural water demand takes the most significant portion of freshwater abstraction, as population increase, dietary changes, and irrigated land expansion lead to water use in agriculture [1]. Nonetheless, the industry is experiencing a long-term dilemma of excessive and inadequate irrigation. Excessive irrigation causes waterlogging, salinization, nutrient loss, and decreasing water productivity, and inadequate irrigation limits crop growth, lowers yields, and raises the risk of production [2], [3]. Climate change further increases these inefficiencies by changing the precipitation patterns, increasing droughts and floods, and increasing evapotranspiration, thus increasing uncertainty in water availability and crop water demand [4] . Here, there is a great need to improve the efficiency of irrigation and sustainability of resource use to satisfy the increasing food demand and protect the limited freshwater ecosystems. More focused on water management, better scheduling, and intelligent irrigation technologies are becoming seen as the key to higher water productivity, climate resilience, and sustainable agricultural intensification. In turn, the discussion of the complex issues of inappropriate irrigation management and climate strain highlights the necessity of effective and sustainable strategies of agricultural water utilization.

The adoption of the Internet of Things (IoT) in agriculture has fundamentally transformed the manner in which water is monitored, managed and utilized in crop production systems. The IoT technologies, which include sensor networks, wireless communications, cloud platforms, and analytical intelligence, can be used to monitor the critical field parameters of soil moisture, temperature, humidity, and crop conditions in real-time and make informed irrigation decisions based on the data instead of intuition or routine practice [5]. This technological potential has been accompanied by the wider advent of digital farming and smart agriculture paradigms, in which large-scale analytics of big data, cyber-physical systems, and artificial intelligence all make agriculture no longer a resource-based sector but an information-based one [6], [7]. Digital agriculture views the farm as a system that is interdependent where real-time sensing, connectivity, and computational intelligence help optimize inputs, increase productivity, and environmental stewardship. Among the most significant changes in this digital transition is the area of irrigation. In the past, irrigation was greatly dependent on manual decision-making, fixed schedules and uniform application of water which in most cases led to inefficiency and wastage of resources. These traditional methods have been overtaken by automated and semi-automated irrigation systems that can supply water with great accuracy in respect to crop water needs both in time and space [8], [9].

Precision irrigation is a modern IoT-based system that incorporates wireless sensor networks, automated control units, and decision-support algorithms to optimize water delivery, minimize human intervention, and increase system responsiveness to climatic and field variability [10]. As a result, the IoT-based irrigation systems are a highly important technological development that does not only enhance the efficiency of irrigation but also promotes the sustainability agenda by conserving water, stabilizing crop production, and enhancing resilience to environmental risks.

Although the IoT technologies in the agricultural sector have become widely disseminated, the majority of the currently existing IoT-enabled irrigation systems are largely monitoring-oriented, i.e., they are oriented towards sensing and reporting environmental and soil parameters, but do not allow making truly intelligent and decision-driven irrigation management. Existing systems tend to focus on data collection, especially the soil moisture, temperature, and humidity, but offer little analytical insight on adaptive irrigation decisions [10], [11]. Also, a significant percentage of these solutions are based on basic soil-moisture thresholding methods, where irrigation is activated when moisture drops below a pre-established point. Despite decreasing human intervention and enhancing fundamental efficiency, threshold-based control usually does not consider the heterogeneity of the spatial-temporal fields, does not respond to weather changes, and does not consider the dynamics of plant water needs [8], [12]. As a result, these systems are prone to either early irrigation or late watering and hence, compromise the possible benefits of precision irrigation. More importantly, integration of crop intelligence into existing IoT irrigation systems is very minimal. Crop-growth stages, evapotranspiration dynamics, and agronomic models [3] that could be necessary to determine water demand accurately in relation to crop phenology and environmental variability are often omitted in most systems [3]. Researchers are increasingly stating that until crop physiology, growth-stage sensitivity, and predictive modelling are integrated into IoT designs, precision irrigation will not be able to advance beyond automation to real optimization [6]. Thus, the major research issue is not only to sense the state of water but to develop towards smart, crop-sensitive, and context-responsive irrigation systems that will assist in the process of managing sustainable and resilient agricultural water.

Considering the shortcomings of current monitoring-based IoT irrigation systems, there is an urgent need to create decision-aware irrigation systems that transcend the scope of data collection to responsive, analytically oriented, and agronomically relevant water management. Researchers always note that the next generation of irrigation technology should be informed not only by technological interconnection but also by intelligent design that could respond dynamically to environmental, crop, and climatic cues to aid in making the best decisions [6], [9]. The key elements of such intelligence are incorporation of stage-specific water requirements of crops, as the water demand fluctuates greatly among phenological stages, and when the crop development is ignored, there is either excess supply or dire stress at critical developmental stages like flowering or fruiting [13], [14]. In conjunction with phenological intelligence, there is an attractive necessity to add weather and evapotranspiration analytics to irrigation systems. Meteorologically-assisted evapotranspiration-based estimation has proven to be a scientifically sound method of estimating the correct irrigation demand especially in the face of growing climatic variability [2], [15]. Besides, precision irrigation should become more dependent on adaptive decision-support systems capable of automatically changing the schedule, volumes, and frequency of irrigation based on changing field conditions, as opposed to traditional threshold-based triggers. This adaptive potential is critical in terms of ensuring resilience to uncertainty caused by climate, water allocation optimization, and improvement of productivity and sustainability outcomes. Hence, the motivation behind this study is the promotion of the IoT-based irrigation beyond mere automation to a comprehensive, crop-aware, climate-responsive, and decision-intelligent irrigation framework with the potential to facilitate sustainable water management in agriculture in the modern age.

2. Objectives and Contributions

The present study is positioned to advance the discourse on IoT-enabled precision irrigation by systematically addressing the limitations of existing approaches and steering the research focus toward decision-intelligent, crop-aware water management. Specifically, the key objectives and contributions of this study are as follows:

- To provide a comprehensive and structured review of IoT-based precision irrigation research, synthesizing technological developments, application architectures, control strategies, and agronomic integration in existing studies.
- To critically identify the major research gaps in prevailing IoT irrigation solutions, particularly the dominance of monitoring-centric designs, limited decision intelligence, inadequate integration of crop-growth dynamics, and insufficient incorporation of climate-responsive analytics.
- To propose a conceptual crop-intelligent IoT framework that embeds growth-stage awareness, evapotranspiration analysis, and adaptive decision-support intelligence to enable more precise, context-aware, and sustainable irrigation management.

- To outline future research directions, highlighting methodological, technological, and implementation pathways necessary to transition IoT irrigation systems from automated control toward truly intelligent, resilient, and sustainability-oriented agricultural water management.

3. Related Work

IoT in Agriculture: A Short introduction.

The development of the Internet of Things (IoT) in agriculture has gone beyond the initial conceptualizations of the connection of smart objects in the late 1990s and early 2000s to fully-fledged, data-driven agricultural systems that combine sensing, communications, and analytics features [6], [16]. The main technological enablers of this change are advanced soil moisture, crop health, and environmental sensor systems; low-power wide-area networks (LPWAN) like LoRaWAN and NB-IoT to support long-range, energy-efficient data communications; and cloud computing services to support large-scale data storage, processing, and real-time decision support [17]. All of these infrastructures allow precision irrigation, resource optimization, yield prediction, and more intelligent farm management. The use of IoT-based smart agriculture has gained momentum globally due to the necessity to enhance productivity, resilience, and sustainability, but it is still unevenly distributed, with the most developed economies showing higher integration rates than developing regions, where limitations in the form of infrastructure, affordability, digital literacy, and institutional support are still present [7]. However, new data reveal that there is an increasing adoption in the developing economies especially in Asia and Africa which is facilitated by the falling cost of technology, increasing rural connectivity, and policy-specific measures to boost digital agriculture [18].

Precision Irrigation Systems based on IoT.

Soil-Moisture Based Irrigation Systems.

Much of the body of IoT-enabled irrigation studies has been on soil-moisture-based control structures whereby sensors are used to measure volumetric water content or soil matric potential and initiate irrigation when specified thresholds are violated. The systems mainly record subsurface dynamics of moisture without considering wider climatic or crop-physiological conditions, thereby providing only a partial description of the plant water requirements [8], [10]. The majority of the implementations use threshold-based or rule-based logic due to simplicity, low-computational needs, and cost-effectiveness, which renders them appealing to smallholder settings. Nevertheless, these methods are not always adaptive and can be poorly functioning in the conditions of a fast-changing environment, soil heterogeneity and seasonal variations. Most automation is generally easy to perform with remote control of valves and pumps, but without predictive intelligence, optimization is limited to simple water-saving results.

Systems Based on Weather and Evapotranspiration.

To supplement soil-based systems, many IoT systems use weather-based and evapotranspiration (ET)-based scheduling to more holistically estimate crop water demand. These methods use meteorological parameters like temperature, humidity, solar radiation, wind speed, and rainfall to calculate ET, thus making irrigation supply more in line with atmospheric demand and physiological processes of crops [13]. On-farm weather stations, satellite information, and environmental sensing are integrated to increase temporal responsiveness and spatial relevance. It is indicated that the ET-based scheduling can lead to more precise irrigation, less unjustified applications, and better yield-water productivity relationships, especially in climates with high seasonal and diurnal variability [19]. However, the use of precise weather information and high-quality calibration is a very important operational need.

Hybrid IoT Irrigation Solutions.

Recent trends indicate a shift towards hybrid IoT irrigation architectures that combine several data streams soil moisture, weather, ET, crop parameters and in some cases remote sensing inputs to support context-based, adaptive decision-making. These systems will address the weaknesses of single-parameter designs by integrating heterogeneous information through state-of-the-art analytics, optimization models and more and more machine learning and artificial intelligence systems. The hybrid strategies have been shown to be more accurate in irrigation scheduling, more resilient to uncertain climatic conditions and more subject to real-time optimization. Similar initiatives focus on deploying intelligence into edge devices to allow decentralized decision-control and minimize reliance on constant cloud connectivity. Despite this promise, there are still issues with complexity of systems, costs, scalability, and applicability to agricultural environments that are resource constrained, particularly in developing economies.

Smart Irrigation and AI and Decision Support.

Artificial intelligence (AI) has enabled the capabilities of IoT-based agriculture in terms of analytical and decision-making processes beyond rule-based automation through the integration of artificial intelligence (AI). The use of machine learning-based models (artificial neural networks, support vector machines, decision trees, and ensemble models) has become a common practice to model non-linear relationships between soil moisture, weather variables, crop characteristics, and irrigation outcomes. These methods can be used to estimate crop water needs, identify anomalies and control adaptively in a heterogeneous field.

Based on this principle, predictive irrigation studies focus on forecasting the dynamics of soil moisture, evapotranspiration, and irrigation demand using past and real-time information, thus enabling proactive and not reactive water management. Empirical literature records an increase in water-use efficiency and yield stability when predictive models are incorporated into decision-support systems. However, a lot of the current work is still at an experimental or pilot level, and early trial systems are often conducted in controlled settings or on a small scale, which does not allow generalization and scalability [20], [21]. The problem of data availability, model transferability, interpretability, as well as integration with farmer decision-making processes, still limits the extensive application of AI-based irrigation solutions.

Limitations of Existing Approaches: A Thematic Synthesis.

Although the use of IoT- and AI-based irrigation has made significant progress, current solutions have a number of interconnected limitations that limit their usefulness and general use. Technologically, most systems are based on the single-parameter sensing, intermittent connectivity, and energy-consuming architectures, which result in data gaps, reliability problems, and low resilience to field variability [19]. Limitations associated with decisions are also eminent since a significant percentage of deployed systems are threshold-based or black-box predictive, with limited flexibility, visibility and situational awareness to dynamic agro-climatic situations [20], [21].

Scalability is another important issue, especially in agricultural systems dominated by smallholders, where pilot-scale applications do not necessarily scale to large-scale or multi-crop applications because of dependency on infrastructure and the complexity of maintenance [6]. The affordability factor also acts as an obstacle to diffusion in developing economies because the initial cost of sensors, communication modules, and cloud services is not affordable to farmers with limited resources [18]. Finally, farmer usability remains an underaddressed dimension; many systems inadequately incorporate local knowledge, linguistic accessibility, and intuitive interfaces, resulting in low trust, limited engagement, and suboptimal utilization of decision-support outputs [7]. Collectively, these limitations underscore the need for irrigation solutions that are not only technologically advanced but also interpretable, scalable, affordable, and aligned with farmer-centric decision contexts.

The reviewed literature suggests remarkable technological progress in IoT- and AI-enabled irrigation systems; however, significant conceptual and implementation gaps persist. In particular, limitations related to adaptive decision-making, scalability, affordability, and farmer-centric usability indicate that existing approaches remain insufficient to fully address the complex and dynamic nature of agricultural water management. These unresolved gaps provide a clear rationale for the development of more integrated, intelligent, and context-aware smart irrigation frameworks in subsequent research.

4. Research scope & problem statement.

Existing IoT-based irrigation systems are largely monitoring focused and mostly limited to rule-based or descriptive control logic and have minimal analytical and crop-intelligent decision support. Their inability to provide adaptive and accurate irrigation results is limited by the lack of incorporated attention to soil conditions, climatic dynamics, and growth and water needs of crops. Hence, a conceptual IoT-based irrigation architecture that would effectively combine soil, weather, and crop intelligence into an analytically based decision model is clearly needed to enhance rational, adaptive, and efficient irrigation management.

5. Suggested conceptual framework.

Conceptual Foundation and Design Philosophy.

The framework proposed is based on the well-known agricultural water science, especially the concepts of crop water requirement, evapotranspiration (ET), and irrigation scheduling of specific growth stages, which guarantees agronomic validity, but not the ad hoc automation. It is consistent with modern IoT computing developments through exploiting low-power sensing, dependable communication, and hybrid intelligence to go beyond monitoring to decision-centric control. Notably, the design philosophy focuses on practical deployability, i.e., focusing on modularity, low computational overhead, intermittent connectivity tolerance, and cost-consciousness, which can be implemented on-farm, including resource-constrained rural environments.

System Architecture Overview.

Macro-wise, the system operates in a closed-loop manner: multi-source field data are sensed, transported by robust networks, processed with a hybrid intelligence engine that incorporates crop and climate knowledge, translated into transparent irrigation decisions, and implemented with automated actuators, and users are continuously fed with feedback via an intuitive interface.

Layered Architecture

Sensing Layer

The layer records the real-time field conditions with the main input of soil moisture sensors, which are supplemented by temperature and humidity sensors to describe the microclimate. The optional inputs (rainfall sensors, NDVI, or other vegetation indices) may be included to provide more information on crop conditions and understanding of spatial variability.

Communication Layer

The transmission of the data is supported by the flexibility in communication options such as the use of LPWAN technologies (e.g. LoRa), GSM, or WiFi, which are chosen depending on the size of farms, the availability of connectivity, and the power limitations. LPWAN-based options are more reliable and energy-efficient in wide-area rural applications, whereas GSM/WiFi can be integrated with existing infrastructure.

The processing and intelligence layer.

This is the core layer that incorporates a hybrid decision engine based on rule-based logic with AI-driven analytics. The agronomic knowledge (soil-specific thresholds, safety constraints) is coded into rule-based components, whereas the non-linear interaction between soil moisture, weather variables, ET estimates, and crop development stages is learnt by AI models. A crop intelligence module explicitly makes a correlation between phenological stages and a dynamic, stage-sensitive water demand, which makes the decisions regarding irrigation stage-sensitive instead of being constant. Weather and ET analytics also put decisions into context, considering atmospheric demand and short-term climatic variability.

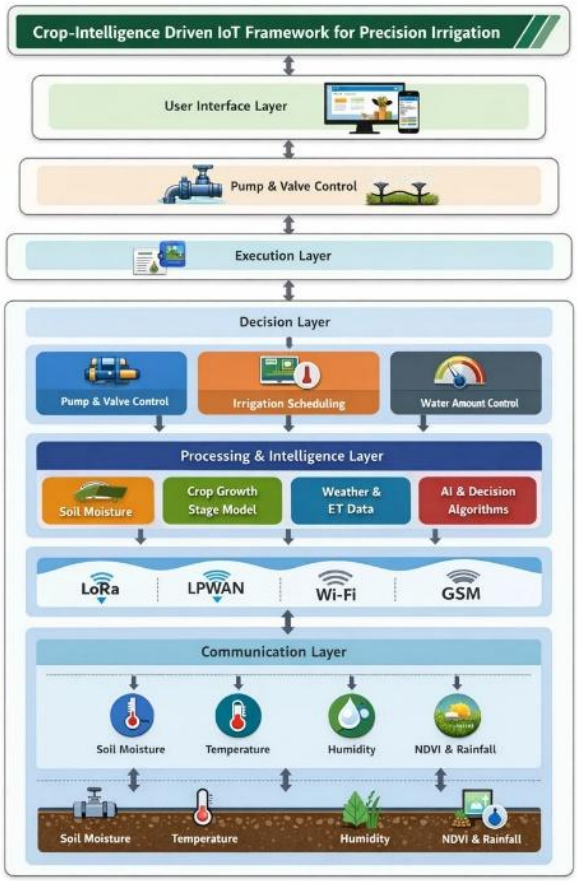


Fig.1 Conceptual Framework

Decision Layer

The decision layer transforms intelligence into practical results to provide answers to three important questions: When to irrigate, how much water to apply, and why the decision is agronomically sound. This layer converts the predictions and the rules into rational and explainable irrigation recommendations, minimizing uncertainty and guesswork.

Execution Layer

The automated operation of pumps and valves is used to make decisions that have been validated, allowing water to be delivered accurately with little human involvement, and still allowing the possibility of a manual override in the case of safety and trust.

User Interface Layer

A mobile app or web-based dashboard serves a farmer with the simplified, interpretable status, advice, and logs of the execution in the system. It is focused on usability, local relevance, and transparency to increase farmer confidence, adoption, and continued engagement.

Working Logic Flow

The operational logic employs the continuous monitoring of the soil and climatic parameters and then transmits the data to the processing unit. The intelligence layer analyses crop stage, ET demand and environmental conditions based on hybrid

analytics, produces irrigation decisions with clear justification, executes control actions and recycles results into the system to learn and be cognizant to the user.

Conceptual Advantages

The suggested structure allows quantifying water savings based on the demand-driven implementation, increases energy efficiency by preventing the unnecessary pumping, and makes the yield more reliable by matching irrigation with crop physiology and climate dynamics. With scientific reasoning entrenched in an automated control, the system substitutes the intuitive-driven irrigation with analytically-based and adaptive decision-making.

6. Conceptual and outcomes to be expected

Compared advantage over current systems.

Theoretically, the given framework has a transparent benefit over moisture-only irrigation models that are limited to one-parameter control. Whereas traditional systems react to soil moisture levels, the proposed architecture introduces crop growth phases, weather interactions and ET analytics into a hybrid intelligence processor. This allows anticipatory and contextual irrigation decisions in place of fixed responses. The combination of agronomic knowledge based on rules with AI-facilitated learning further increases the rationality of decisions, their interpretability, and flexibility, making the framework analytically superior to descriptive or monitoring-focused models that are common in the literature.

Practical Deployment Advantages.

In deployment terms, the framework is especially applicable to the developing-region agriculture, where the smallholder dominance, resource scarcity and climatic uncertainty are the norm. The layered pipeline design is modular, enabling farmers to start with simple sensing and gradually add intelligence features. Loosely coupled communication, a minimalist form of automation, and user-friendly interfaces reduce barriers to entry, and the ability to scale via flexible network options and cloud-edge interoperability. All these characteristics make it more feasible, adoptable and sustainable in the real-world rural environment.

Weaknesses of the Proposed Concept.

Though the framework has some conceptual strengths, it has its limitations. Its success is determined by the reliability of the sensors, quality of data and correct characterisation of crop-stage, which may not be universal. AI elements need adequate historical data to calibrate, which may be a constraint to its performance in a data sparse setting with early deployment. In addition, although the sensors are affordable, the cumulative cost of sensors, maintenance, and connection could also remain a problem to the marginal farmers without institutional backing. These shortcomings show that the framework should be implemented gradually, customized to the situation, and empirically validated in the future to prove its practical impact.

In sum, the suggested framework can be discussed as a logical, theoretically-based improvement of the existing systems, considering the practical limitations that shape the future research and field-based performance.

7. Conclusion

This paper provided a methodical survey of the development of IoT-based precision irrigation, which includes soil-moisture-based, weather- and evapotranspiration-driven, and AI-assisted decision-support systems. The review indicated that there was significant technological advancement, but it also indicated that there were still significant constraints associated with intelligence, integration, decision architecture, scalability, affordability, and empirical validation. All these gaps gave emphasis to the insufficiency of most monitoring-focused and threshold based irrigation solutions in dealing with the dynamic and multifaceted nature of agricultural water management.

The study, in turn, suggested a rational, layered conceptual framework, which combines soil, climatic, and crop intelligence as a hybrid rule-based and AI-driven decision architecture. The framework provides explicit integration of crop growth phases, weather analytics, and explainable decision logic, which moves irrigation management from reactive control to adaptive and scientifically-based decisions.

As a strategy, the given framework is important to the increase of water-use efficiency, energy saving, and balance of crop production, especially in agriculture systems that are challenged by water stress and resource scarcity. It provides a channel of moving away the intuition-based irrigation practices into data-based, sustainable water management. In general, the framework has great potential to develop further in the future and implement and deploy, and is a significant leap towards the realization of resilient and sustainable agricultural production amidst increasing climatic and resource pressures.

8. Future Work

The integration with AI and Digital Twins is available

The proposed framework can be expanded in future studies by adding AI-based digital twins of fields and crops, which will allow simulating the interaction of soil, plants, and the atmosphere in real-time. These virtual imitations could be used to aid the analysis of scenarios, stress forecasting, and adaptive optimization of the irrigation practices within different climatic and management environment.

Smart Irrigation Cybersecurity and Data Integrity.

With more and more irrigation systems becoming

interconnected, cybersecurity and data integrity become a major concern. Studies should be conducted to come up with lightweight security measures, secure communication, and trusted mechanisms that safeguard sensor data, decision making logic, and actuation instructions without incurring too much computational and energy expensive costs.

Interaction with Satellites and UAVs.

The combination of ground sensing, which is supported by IoT and satellite imaging and UAV-collected data has high prospects with respect to spatially explicit irrigation management. Future designs can use vegetation indices, canopy temperature and soil moisture maps to provide field-scale intelligence and resolve within-field heterogeneity.

Economical viability and Policy Support.

Future research is advised to evaluate the economic feasibility of smart irrigation systems based on cost-benefit analyses, modes of adoption, and funding. Research policy questions can be addressed using policy research on subsidies, digital agriculture initiatives, and institutional support mechanisms needed to speed up adoption by small and marginal farmers.

Experimentation and Long-Term validation requirements.

Lastly, to demonstrate system robustness, learning stability and long-term benefits, long-term, multi-season field experiments in diverse agro-climatic settings are necessary. This type of empirical research would build the evidence base, test design assumptions, and facilitate the shift to scaled and field tested irrigation solutions.

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