# A Conceptual Framework for Agricultural Water Management Through Smart Irrigation

# Abdelouahed Tricha, Laila Moussaid, Najat Abdeljebbar

National High School for Electricity and Mechanics (ENSEM), Hassan II University of Casablanca, Casablanca, Morocco

Abstract—The demand for freshwater resources has risen significantly due to population growth and increasing drought conditions in agricultural regions worldwide. Irrigated agriculture consumes a substantial amount of water, often leading to wastage due to inefficient irrigation practices. Recent breakthroughs in emerging technologies, including machine learning, the Internet of Things, wireless communication, and advanced monitoring systems, have facilitated the development of smart irrigation solutions that optimize water usage, enhance efficiency, and reduce operational costs. This paper explores the critical parameters and monitoring strategies for smart irrigation systems, emphasizing soil and water management. It also presents a conceptual framework for implementing sustainable irrigation practices aimed at optimizing water use, improving crop productivity, and ensuring cost-effective management across different agricultural settings.

#### Keywords—Agriculture; irrigation system; water management; Internet of Things; sustainability

#### I. INTRODUCTION

The growing global population demands a continuous supply of high-quality food, placing increasing pressure on agriculture to boost productivity [1]. Achieving this goal requires effective water management, as irrigation plays a critical role in crop yield. However, managing complex agricultural ecosystems demands constant monitoring and control of multiple factors, such as soil moisture, weather conditions, and crop health. To address these challenges, information and communication technologies (ICT) offer valuable solutions by enabling the efficient collection, transmission, and analysis of diverse datasets. ICT facilitates decision-making and policy development for agricultural planning and improves water management through remote monitoring and control of irrigation systems. With real-time feedback, farmers can optimize irrigation schedules, reducing water waste and enhancing crop performance. Additionally, ICT promotes the integration and interoperability of different irrigation technologies, including soil moisture sensors, water balance models, plant signals, remote sensing tools, and GPS mapping, leading to more sustainable and efficient farming practices.

Irrigation is one of the most vital services in the agricultural industry, particularly in regions with low rainfall. Meeting the water demands of crops is crucial for crop quality and production. However, inadequate irrigation can lead to a decrease in crop quality and production [1], [2]. Diverse methods and technologies are used to effectively manage water resources to address this issue. These include water balance, plant signals, or soil moisture sensors, which can be technically backed by cloud computing and the Internet of Things (IoT). IoT uses low-power network connectivity to link physical items to the internet. One application of IoT for irrigation scheduling includes wireless sensor networks (WSN), which connect soil moisture sensors to the web [3], [4], [5], [6], [7]. This allows farmers to remotely monitor and control their irrigation systems, leading to more efficient water usage and potentially higher crop yields. Additionally, the data collected from these sensors can be analyzed to provide insights into soil health and crop growth patterns, aiding in decision-making for future planting seasons.

This paper contributes to the field of smart irrigation by addressing critical gaps in the literature and proposing a systematic approach to enhance water management and sustainability in agriculture. By focusing on both the technical and practical challenges, the paper offers an integrated framework for developing more efficient irrigation systems. The paper is structured as follows: Section I introduces the importance of irrigation and water management in agriculture, while Section II presents a comprehensive survey of the literature on current smart irrigation technologies. In Section III, we explore critical parameters for smart irrigation systems, including soil and water management. Section IV reviews monitoring strategies, focusing on soil-based and weather-based approaches. In Section V, we propose a conceptual framework for implementing a smart irrigation system, including system architecture and workflow. Finally, Section VI concludes the paper by summarizing the key insights and potential directions for future research.

# II. RELATED WORKS

In recent years, diverse technologies such as the IoT, machine learning (ML), and big data have significantly impacted irrigation practices. This section delves into various studies and works that involve the application of these emerging technologies in irrigation system management and control. The focus is on the primary technologies and methods used in smart irrigation systems: IoT, data-driven approaches, and advanced technologies. Each subsection summarizes key findings, advantages, and drawbacks of existing studies, while identifying research gaps and opportunities for future work.

#### A. Internet of Things

The IoT is a network of physical objects connected to the internet, capable of communication, data collection, and data exchange. IoT has been widely applied in irrigation, enabling remote monitoring and control of systems, and the collection and analysis of diverse datasets related to soil, weather, and crop conditions.

Several studies have explored IoT-based irrigation systems for precision agriculture using various techniques and platforms. One such system developed an IoT-based irrigation system via the ARETHOU5A platform, incorporating wireless sensor nodes powered by a rectenna, which recovers radio frequency energy to power the nodes [8]. Another notable work proposed a highly accurate irrigation system utilizing IoT, fuzzy logic, and GSM [9]. This system employs a fuzzy logic controller to compute input variables such as humidity, temperature, and soil moisture to generate motor status, and includes an automatic shut-off mechanism during precipitation to conserve resources. Additionally, an intelligent multi-agent IoT precision irrigation strategy has been presented, leveraging technologies like the MQTT protocol and IoT for real-time monitoring and analysis of crop water requirements [10].

While these studies highlight the potential of IoT to enhance smart irrigation systems, they also underscore several challenges. Data quality and security of IoT devices and networks are major concerns. IoT devices, often exposed to harsh environmental conditions, can face reliability and accuracy issues. Furthermore, these devices and networks are vulnerable to cyberattacks, potentially compromising the integrity and availability of irrigation systems. Ensuring the robustness and resilience of IoT devices and implementing stringent data quality and security measures is crucial. Another challenge is the scalability and interoperability of IoT-based systems. Integrating and coordinating a growing number and diversity of IoT devices and platforms can be difficult, necessitating the development and adoption of common standards, protocols, and architectures to ensure seamless integration.

# B. Data-Driven Approaches

Data-driven approaches utilize data to generate insights, predictions, or decisions, playing a significant role in optimizing irrigation systems by analyzing water usage based on various data sources and techniques. For instance, integrating Geographic Information System (GIS) technology with irrigation systems has improved water use efficiency [11]. A system leveraging cloud-based near real-time data storage and processing enables the adaptation of the Penman-Monteith evapotranspiration coefficient to local weather conditions, incorporating data collection and soil moisture measurement capabilities. Another study focused on optimizing water usage in an IoT system by moving data computation to the edge, allowing for real-time data processing and quick decisionmaking despite limited internet connectivity [12]. This system estimates water requirements by calculating evapotranspiration potential and employs AI algorithms for detecting plant diseases and pests. Furthermore, a non-contact vision system using a standard video camera and a neural network has been proposed to predict the irrigation needs of loamy soils based on soil color differences [13].

These studies illustrate the benefits of data-driven approaches in optimizing water usage and improving crop yield. However, challenges such as data availability and accessibility persist. Large and diverse data sets are essential for accurate results, but data may be scarce due to a lack of sources, collection devices, or sharing platforms. Incomplete, inconsistent, or noisy data can further affect result quality. Ensuring data availability, accessibility, and implementing proper data cleaning, preprocessing, and validation techniques is vital. Additionally, the complexity and interpretability of datadriven methods can pose difficulties, especially for non-experts. Simplifying and explaining these methods and results, along with providing user-friendly interfaces and feedback mechanisms, is crucial.

### C. Advanced Technologies

Advanced technologies offer innovative solutions for enhancing smart irrigation systems, providing automation, intelligence, and security. An automatic irrigation system measuring soil humidity and temperature with sensors was designed to prevent irrigation when humidity is high, conserving water resources, and to permit irrigation when humidity is low [14]. This system employs the Decision Tree algorithm to predict and analyze data. Additionally, WSN have been leveraged to build comprehensive irrigation systems, covering different farm regions with various sensor modules transmitting data to a shared server [15]. ML algorithms support crop and weather-based irrigation model predictions. Addressing security concerns, lightweight cryptography techniques in IoT, such as the Expeditious Cipher (X-cipher) for secure channels in the MQTT protocol, have been proposed to protect data integrity and confidentiality [16].

While these studies highlight the benefits of advanced technologies in irrigation, challenges such as cost, maintenance, compatibility, and integration remain. Advanced technologies can be expensive and complex to acquire, install, and operate, especially for small-scale farmers. Frequent maintenance and updates increase operational costs. Ensuring the affordability, simplicity, and providing adequate training and support for users is essential. Additionally, integrating advanced technologies with existing systems and practices can be difficult, necessitating efforts to ensure compatibility and seamless integration.

#### III. CRITICAL PARAMETERS FOR SMART IRRIGATION

Several parameters are used to assess the efficacy of the smart irrigation system. Both soil and water management are incorporated into an intelligent irrigation system. Soil management incorporates numerous parameters, including soil moisture, temperature, conditions, salinity, and so on. Water management parameters consist of dewpoint temperature, evapotranspiration, air temperature, atmospheric temperature, and relative humidity. In addition to these variables, the smart irrigation system must take forecast accuracy, data transmission rate, and actual usage into account [17].

### A. Soil Management

Historically, soil supervision was once among the most difficult agricultural tasks for both businesses and cultivators. Several environmental issues that affect agricultural performance are revealed by soil analysis. If these types of obstacles are precisely characterized, agricultural models and methods can be easily understood. Soil management involves various parameters, such as soil moisture, soil temperature, soil conditions, soil salinity, and so on.

Soil moisture is one of the most important parameters for irrigation scheduling, as it indicates the water content and availability in the soil. Soil temperature is another parameter that affects the crop growth and development, as it influences the germination, root growth, nutrient uptake, and microbial activity. Soil conditions refer to the physical, chemical, and biological properties of the soil, such as texture, structure, pH, organic matter, nutrients, and microorganisms. They affect the water retention, infiltration, drainage, and availability in the soil, as well as the crop health and quality. Soil salinity is the concentration of soluble salts in the soil, which can affect the osmotic potential, water uptake, and nutrient availability for the crops. Soil salinity can be caused by natural factors, such as weathering, evaporation, or seawater intrusion, or by human factors, such as irrigation, fertilization, or drainage. Moisture sensors can measure these parameters using different methods, such as capacitance, resistance, or gravimetric for the moisture, thermistors or thermocouples for the temperature, electrodes or spectrometers for soil conditions, and conductivity, reflectance, or fluorescence for soil salinity. These sensors can be integrated with IoT systems to transmit the soil parameters data to a cloud server, where it can be processed and analyzed to determine the optimal irrigation status, to support fertilization and irrigation decisions, and to prevent the effects of soil salinity on the crops. The results of a soil analysis survey are used to enhance crop production and provide producers with fertilization options [18]. Overfertilization and crop degradation can be avoided when using IoT techniques for identifying dirty soil.

Soil management preserves and improves productivity. It boosts agricultural productivity and quality, lowers input costs, and reduces pollution. For the crop to grow quickly and efficiently, the topsoil must be in good condition before planting. Even if each farm and crop have its own soil requirements, organic fertilization, soil testing, right tillage, chemical soil protection, etc. can encourage healthy soil biology [19].

#### B. Water Management

Determining the proper amount of water needed in greenhouses is a challenging task. Several IoT strategies are used to place and control smart sensors to prevent water waste. Greenhouses achieve water storage by using an automated drip irrigation system that is controlled by a soil moisture threshold. Utilizing various types of sensors, IoT technology can aid in water management by preventing water loss. The quantity of water in the tank is monitored by sensors, and the data is stored in the cloud via a mobile app, so farmers can track the water level with their smartphones. Using this method, the engine will run autonomously. The engine will automatically start if the water level declines below a predetermined level, and if the water level rises above a predetermined level, the engine will automatically shut off. IoT-powered intelligent irrigation systems can help farmers conserve water and improve crop quality by watering crops at the optimal time. Intelligent irrigation systems deploy temperature and soil sensors on farms, and these sensors transmit field data to producers via a gateway. Controllers for weather-based precision agriculture monitor and adjust irrigation schedules based on local weather data [19], [20], [21].

In addition to IoT, numerous other technologies can be used to manage irrigation water and to estimate the quantity of irrigation water required by adjusting the evapotranspiration coefficient calculated using the Penman-Monteith method [22].

#### IV. IRRIGATION MONITORING STRATEGIES

Constructing an effective irrigation management system that increases food production while minimizing water loss necessitates a dependable monitoring system for the various variables influencing plant growth and development. To collect data that precisely reflects the current soil, plant, and weather conditions of plant irrigation zones, the IoT and WSN technologies are both used for monitoring in the field of precision irrigation [23], [24].

When developing a real-time monitoring system, sensors must be integrated with the IoT Framework or a wireless sensor communication network. Because of their capabilities for sensing, processing, and transmission, wireless networks are vital for real-time monitoring in smart irrigation. Geography or climate may affect monitoring in intelligent irrigation.

# A. Soil-Based Monitoring

One of the most important factors in the growth of plants is soil moisture. Comprehensive geographical and temporal monitoring of the soil moisture content is required to ensure effective irrigation scheduling. Additionally, it is crucial to monitor soil moisture in the plant roots because it sheds light on moisture dynamics and the relationship between irrigation water volume and plant water uptake. There are various indirect techniques for determining soil moisture levels, including electromagnetism, thermal conductivity, neutron counting, water potential, electrical resistance, and direct measurements of soil moisture (gravimetric sample) [25].

Real-time soil moisture monitoring using sensors is a practical and accurate method for measuring moisture fluxes [26]. This approach involves accurately correlating the volumetric water content of the soil with the capacity of the inserted sensor probes. A highly accurate method for soil moisture measurement uses time-domain reflectometry (TDR) sensors [27], which consist of two parallel rods inserted into the soil at a depth corresponding to the target moisture level. In another example, the IoT soil moisture surveillance solution proposed by [28] leveraged wireless networks, specifically GSM and infrared communication, to provide automatic irrigation and conserve water. The system used a capacitancebased soil moisture sensor with two electrodes to measure soil resistance, which was then processed by a PIC 16F877A microcontroller. Based on the detected soil moisture level, the microcontroller activated or deactivated the water pump through a relay driver.

# B. Weather-Based Monitoring

Real-time estimation of baseline evapotranspiration using observed meteorological variables as an indicator of water loss from the plant and soil environment is becoming increasingly popular in weather-based monitoring. Solar radiation, ambient temperature, and wind velocity are the primary determinants of the rate of water loss. These parameters can be determined using a weather station [23].

The FAO Penman-Monteith equation [29], provides a robust method for estimating daily or hourly evapotranspiration values from standard meteorological data, including atmospheric temperature, solar radiation, relative humidity, and wind speed. This method is widely recognized as a reliable approach for calculating reference evapotranspiration ( $ET_0$ ), which serves as the baseline for determining the water needs of crops. The equation is expressed as in Eq. (1):

$$ET_0 = \frac{0.408\Delta(R_N - G) + \gamma \frac{900}{T + 273}\mu_2(u_s - u_a)}{\Delta + \gamma(1 + 0.34\mu_2)}$$
(1)

Where ET<sub>0</sub> is the reference evapotranspiration (mm/day),  $R_N$  is the net radiation at the crop surface (MJ/m<sup>2</sup>/day), G is the soil heat flux density (MJ/m<sup>2</sup>/day), T is the mean daily air temperature (°C),  $\mu_2$  is the wind speed at 2 meters (m/s),  $u_s$  is the saturation vapor pressure deficit (kPa),  $u_a$  is the actual vapor pressure (kPa),  $\Delta$  is the slope of the vapor pressure curve (kPa/°C),  $\gamma$  is the psychrometric constant (kPa/°C).

The daily crop evapotranspiration (ETc) is then calculated using Eq. (2):

$$ET_{C} = k_{C} * ET_{0}$$
(2)

Hence:  $ET_C$  is the evapotranspiration of plants (mm / Day).  $K_C$  is the crop coefficient and  $ET_0$  is the evapotranspiration reference (mm / Day).

This method allows for the precise calculation of water requirements tailored to specific crops, ensuring that irrigation is applied in accordance with actual crop water demand. Weather-based monitoring systems often rely on WSN to monitor environmental conditions accurately. These systems have been widely implemented as an efficient method for interconnecting numerous sensors over large agricultural areas. Closed-loop, real-time monitoring, and analysis of sensor data activate control devices based on a predetermined threshold value [30], [31].

These strategies are visually summarized in Fig. 1, highlighting the key parameters for both soil-based and weather-based monitoring approaches.

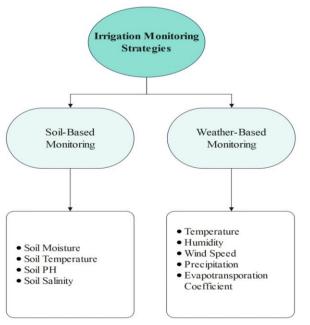


Fig. 1. Irrigation monitoring strategies adopted from study [25].

#### V. PROPOSED FRAMEWORK FOR A COMPREHENSIVE SMART IRRIGATION SYSTEM

# A. System Overview

The proposed smart irrigation system is a sophisticated framework engineered to optimize water resource management in agricultural settings. It integrates advanced sensing technologies, data analytics, and automated control mechanisms to ensure precise, efficient, and sustainable irrigation practices. The system's core functionalities include real-time data acquisition, processing, analysis, and intelligent decisionmaking that leads to highly accurate control of irrigation processes. As illustrated in Fig. 2, the system's architecture comprises multiple interconnected components, each playing a pivotal role in the overall management process. The system operates hierarchically, with data flowing from field-level sensors to the cloud, where comprehensive analysis and remote monitoring are conducted.

# B. Fundamental Layers of the System

The proposed smart irrigation system is structured into distinct components that work collaboratively to ensure efficient and precise water management. These components are organized into layers, each with a specific function, enhancing the system's scalability, reliability, and ease of operation. Fig. 3 provides an overview of these layers.

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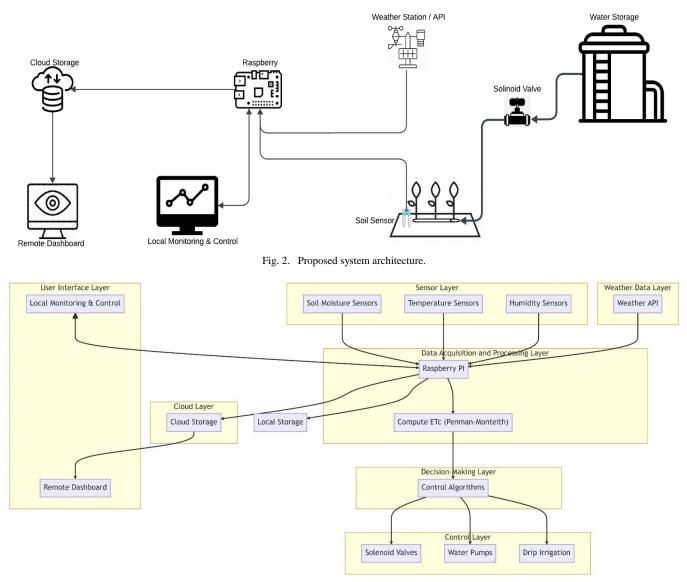


Fig. 3. Layers of the proposed system.

1) Sensor layer: The sensor layer forms the foundational tier of the system, designed to capture essential agroclimatic data from the field. This layer includes soil moisture sensors placed at various depths, allowing for accurate real-time monitoring of soil water content. These sensors provide critical insights into the hydration status of the soil, which directly informs irrigation decisions.

In addition to soil moisture sensors, the system integrates weather data either through meteorological stations or APIs, collecting parameters like temperature, humidity, solar radiation, wind speed, and precipitation. By combining soil and environmental data, the system accurately assesses water stress in crops, enabling precise irrigation scheduling. This data also plays a significant role in calculating the  $ET_0$  using the Penman-Monteith Eq. (1), crucial for determining the crops' water needs. 2) Data acquisition and processing layer: This layer is responsible for collecting, transmitting, and preparing the data for further analysis. Sensor readings are transmitted to the control unit via efficient wireless communication protocols like LoRaWAN or Zigbee, ensuring low power consumption and minimal data loss. Once received, raw data undergoes preprocessing (cleaning, calibration, and normalization) to ensure accuracy and comparability. This process transforms the data into actionable insights, such as identifying soil moisture trends and temperature fluctuations.

Processed data is stored locally for real-time decisionmaking and periodically synchronized with the cloud for longterm analysis and backup. This dual-storage approach ensures the system operates efficiently while enabling remote access to historical data for improved decision-making. 3) Decision making layer: The decision-making layer is essential to the smart irrigation system, responsible for analyzing data from various sensors to generate precise irrigation schedules. It extracts insights on soil moisture, weather conditions, and crop development, enabling informed water management decisions based on real-time environmental factors. A critical function is calculating  $ET_C$  based on  $ET_0$  (1) and applying crop coefficients  $K_C$  (2).

This layer generates irrigation schedules that optimize water usage by considering soil moisture, weather forecasts, and irrigation efficiency. Optimization algorithms or rule-based approaches ensure efficient irrigation timing. Additionally, ML models enhance decision-making by learning from historical data, improving predictions of crop water requirements and refining irrigation strategies over time, akin to methods used in precipitation prediction in Casablanca, Morocco [32].

4) Control layer: The control layer manages the execution of irrigation commands. It coordinates devices such as valves, pumps, and sprinklers, ensuring that water is delivered according to the schedules generated by the decision-making layer. The system continuously monitors environmental conditions and adjusts irrigation in real time. For instance, in case of unexpected rainfall, the control layer can halt irrigation to prevent overwatering.

Furthermore, this layer handles error detection and power management, optimizing energy use by aligning irrigation activities with off-peak hours, which reduces operational costs. By efficiently managing water and energy resources, the control layer supports sustainable irrigation practices.

5) Cloud layer: The cloud layer in the proposed smart irrigation system is primarily used for data storage and remote visualization through a centralized dashboard. It stores processed data, including sensor readings and irrigation schedules, ensuring secure, long-term access for analysis and system optimization. This approach is particularly suited for regions with poor or intermittent internet connectivity, as the system can function locally and synchronize data with the cloud when the connection is available, maintaining continuous operation without relying on constant internet access.

In addition to storage, the cloud layer provides real-time data visualization via a web-based dashboard. This allows farmers and administrators to remotely monitor critical metrics such as soil moisture levels, irrigation schedules, and overall system performance, even in areas where reliable connectivity is limited.

6) User interface layer: The user interface layer facilitates human-computer interaction for system monitoring, control, and data visualization. It comprises two primary components:

• Local User Interface: A user-friendly interface accessible through a local device (e.g., tablet, computer) allows farmers to monitor real-time sensor data, control

irrigation schedules, and make necessary adjustments directly within the system. This local interface provides full control over the irrigation process, enabling immediate responses to changing conditions in the field.

• Cloud-Based User Interface: A web-based interface provides remote access for data visualization and performance monitoring. Through this interface, farmers and system administrators can visualize real-time and historical data, review system performance metrics, and analyze trends.

# C. System Functionality and Workflow

The proposed smart irrigation system operates through a sequential process involving data acquisition, processing, analysis, decision-making, control, and user interaction. Fig. 4 illustrates the flowchart of this process.

- Data Acquisition: The system gathers environmental data, including soil moisture, temperature, humidity, and solar radiation, from sensors strategically placed throughout the agricultural field and weather station. This data is essential for understanding field conditions and informing irrigation decisions.
- Data Transmission: Collected data is transmitted to the central control unit via wireless communication protocols, ensuring reliable and efficient data transfer.
- Data Preprocessing: Raw sensor data undergoes cleaning, normalization, and feature extraction to prepare it for analysis and decision-making. Data cleaning identifies and removes outliers, missing values, or inconsistencies. Normalization scales data to a common range, facilitating comparison and analysis.
- ETc Calculation: Crop water requirements are estimated using the Penman-Monteith method as shown in Eq. (1) and Eq. (2).
- Irrigation Scheduling: Optimal irrigation schedules are generated based on ETc, soil moisture data, and weather conditions. Optimization algorithms or rule-based approaches are employed to determine the most efficient irrigation strategies.
- Irrigation Control: Irrigation devices are activated and deactivated according to the generated schedules. Real-time adjustments can be made based on sensor data and weather conditions.
- Data Analysis and Monitoring: Collected data and system performance metrics are analyzed to evaluate irrigation efficiency, crop water use, and equipment status. Regular monitoring and analysis enable continuous improvement and optimization of the system.
- User Interaction: Farmers and system administrators can interact with the system through local and cloud-based interfaces to monitor performance, adjust parameters, and access historical data.

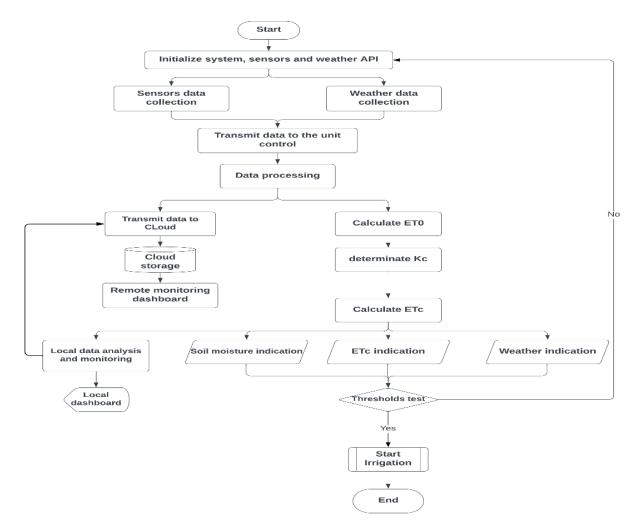


Fig. 4. Workflow of the proposed approach.

# VI. CONCLUSION

The integration of advanced technologies into irrigation systems plays a pivotal role in delivering efficient and sustainable solutions for modern agriculture. Our proposed smart irrigation system, leveraging IoT technology, sensor networks, and intelligent algorithms, addresses the pressing challenges of water conservation while enhancing crop productivity. At its foundation, the sensor layer provides crucial real-time data on soil moisture and environmental conditions, feeding into advanced data processing and decision-making layers. By correlating soil moisture levels with meteorological data and calculating reference evapotranspiration, the system achieves a nuanced understanding of crop water requirements, enabling precise irrigation management that minimizes water waste while maximizing yield and crop quality.

While our approach shows great promise, further research and field testing are necessary to validate its effectiveness across various crop types and climatic conditions. Future work should focus on refining the system's predictive capabilities, incorporating ML algorithms, and exploring the integration of additional data sources. As we continue to refine and expand this system, we move closer to realizing the vision of precision agriculture, where resource use is optimized, environmental impact is minimized, and crop yields are maximized. Our proposed smart irrigation system represents a significant step forward in the pursuit of sustainable and efficient agricultural water management, offering a practical solution to the global challenge of water scarcity in agriculture.

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