An Intelligent Irrigation Decision Support System using IoT and Weather Data

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***Abstract*—Efficient irrigation is a critical challenge in agriculture, particularly in regions like Bangladesh, where over 70% of cultivated land depends on supplemental watering. Conventional irrigation practices often rely on fixed schedules or manual monitoring, resulting in under-irrigation or over-irrigation, leading to water wastage, reduced crop yield, and increased operational costs. This paper presents an intelligent irrigation decision support system that integrates Internet of Things (IoT) sensors, environmental parameters, and real-time weather forecasts to optimize irrigation scheduling. The proposed system employs IoT-based sensors to continuously monitor soil moisture, temperature, and humidity, transmitting the data via an ESP32 microcontroller to a cloud platform. Additional contextual information, including soil type, crop type, rainfall predictions, reference evapotranspiration (ET_0), and crop-specific parameters, is incorporated into a formula-driven algorithm to determine the optimal irrigation volume and timing. The computed decisions are either executed automatically through actuators, such as solenoid valves or motor pumps, or presented as actionable recommendations via a mobile dashboard, enabling real-time adaptive irrigation management. The system aims to improve water-use efficiency, enhance crop productivity, and support sustainable farming practices. The results demonstrate the potential of integrating IoT and weather-informed decision-making to enable precise, data-driven irrigation for diverse agricultural environments.**

***Keywords*—Smart irrigation, IoT, Sensors, ESP32, MQTT, HTTP Cloud, Mobile Application Soil moisture, Weather forecast, Evapotranspiration**

I. Introduction

Agriculture remains a cornerstone of global economies, particularly in developing countries, serving as the primary livelihood for over 2.5 billion people and significantly contributing to employment, food security, and rural development [1]. In Bangladesh, the sector employs roughly 40% of the workforce and contributes about 13% of the national GDP, with more than 70% of cultivated land relying on supplemental irrigation [2]. Despite this dependence, traditional irrigation practices are often inefficient, leading to water wastage, nutrient loss, and reduced crop yields. Over-irrigation can cause waterlogging, nutrient leaching, and increased greenhouse gas emissions, while under-irrigation results in crop stress, lower yields, and greater vulnerability to pests and diseases [3]. These challenges underscore the need for intelligent, data-driven irrigation systems that optimize water usage while enhancing agricultural productivity.

Traditional irrigation decisions often rely on farmers' intuition, experience, or fixed schedules rather than data-driven insights, leading to inefficient and untimely water application [4]. In many regions, real-time soil moisture and local weather data remain unavailable or underutilized, limiting accurate assessment of crop water needs. Manual monitoring is labour-intensive and prone to human error, making it unsuitable for large or diverse farms [5], [6]. As a result, irrigation inefficiencies of 30–40% are common, with many farmers over-applying water by more than 50% [5]. Such imbalances contribute to major agronomic losses, including yield reductions from waterlogging, which alone can reduce output by about one-third [7]. These challenges highlight the need for precise, sensor-assisted, and data-driven irrigation systems.

Recent advances in IoT, sensor networks, and automated irrigation technologies have enabled real-time monitoring of soil moisture, temperature, and humidity, often combined with rule-based or machine learning models for irrigation scheduling [8]–[10]. These approaches have demonstrated water savings of 30–50% and improved crop productivity in controlled environments [11], [12]. Other studies have explored neural networks and fuzzy logic for automated pump control using environmental parameters [13], [14]. However, most existing systems rely heavily on dense sensor deployments and frequent soil property testing, which are costly, impractical, and difficult to scale across diverse farms. Additionally, many approaches depend solely on instantaneous or historical sensor data, lack real-time weather forecasting inputs, and are validated only on small-scale or region-specific setups [10], [15]. These limitations underscore the need for more scalable, predictive, and adaptable intelligent irrigation frameworks.

This work presents intelligent irrigation decision support system that leverages IoT sensor data and weather forecasts to determine irrigation needs using formula-based algorithms.

The contributions of this article has been summarised as follows:

- Eliminates the need for extensive soil testing and crop tetsing while maintaining irrigation accuracy.
- Integrates real-time weather forecasts to dynamically adjust irrigation schedules, increasing irrigation efficiency.
- Provides a scalable, practical, and lightweight system suitable for diverse field conditions.

Field sensors measure soil moisture, temperature, and humidity, transmitting data via an ESP32 gateway to a cloud backend. The server combines these readings with crop and soil type, and computes optimal irrigation volume and timing using agronomic parameters from predefined tables. Decisions are sent to actuators for automatic irrigation and to a mobile dashboard for monitoring, enhancing water efficiency and supporting sustainable crop management.

The remainder of this paper is organized as follows. Section II reviews related works on IoT-based irrigation and data-driven water management. Section III presents the methodology of the proposed system, including system architecture and communication flow. Section IV discusses the results of the proposed approach based on a benchmark dataset. Section V outlines limitations and future work, and Section VI concludes the paper.

II. Related Work

IoT-based irrigation systems have emerged as efficient solutions for optimizing agricultural water use. By continuously monitoring environmental parameters such as soil moisture, temperature, and humidity, these systems enable precise irrigation, reduce water wastage, and support crop health. Unlike traditional fixed-schedule irrigation, which often leads to over- or under-watering, IoT-enabled decision support systems (DSS) adapt irrigation dynamically based on field conditions, soil characteristics, and crop requirements [16], [17]. Such systems have shown potential to improve water efficiency and crop productivity across various agricultural settings [18], [19].

Key contributions in IoT-based irrigation research include:

- Weather Integration: Incorporating weather forecasts allows systems to anticipate irrigation needs, reducing water usage and operational costs [20], [21]. Accurate predictions require proper data acquisition and continuous model calibration [22].
- Machine Learning Integration: Several DSS frameworks, including IrrigaSys and CropWat-IoT, combine IoT data with machine learning (ML) to automatically determine optimal irrigation schedules [23], [24]. Regression models and neural networks forecast soil moisture and recommend precise irrigation based on real-time environmental and weather data [25], [26]. These approaches have shown notable improvements in yield prediction and water conservation over traditional rule-based strategies [27].
- Communication Protocols: Robust communication is critical for IoT irrigation systems. Technologies like LoRaWAN, Wi-Fi, and NB-IoT transmit sensor data between field devices, gateways, and cloud servers [28]. LoRaWAN provides long-range, low-power communication for remote areas, while Wi-Fi and NB-IoT offer high-bandwidth transfer in stable networks [29]. Typical architectures integrate sensors, microcontrollers, communication modules, cloud DSS, and actuators controlling irrigation valves [30].

Despite these advancements, current systems face limitations:

- Forecast uncertainty can lead to incorrect irrigation timing [20], [22].
- Low-cost soil sensors are prone to drift, requiring frequent calibration [24].
- Connectivity and power issues in remote farmlands may affect real-time data transmission [28].
- High costs and technical complexity limit scalability and adoption among smallholder farmers [19].
- Security and privacy remain concerns due to potential unauthorized access or data breaches [25], [29].

Table I presents a gap analysis of selected works from 2012 to 2023, summarizing problem statements, contributions, limitations, and proposed enhancements. While many studies address specific aspects such as energy efficiency or yield improvement, few offer a holistic approach combining scalability, cost-effectiveness, energy efficiency, and secure real-time decision-making. The proposed system aims to bridge these gaps by integrating real-time IoT data, weather forecasts, and a formula-based algorithmic framework into a practical and scalable irrigation decision support system.

III. Methodology

This section presents the design and implementation of the proposed intelligent irrigation decision support system. The overall architecture integrates IoT-based sensing, cloud-based data processing, and algorithmic decision-making to achieve efficient irrigation scheduling. Each component of the system is described in detail, including data acquisition, decision algorithm, and actuation mechanisms that collectively enable real-time, automated, and adaptive irrigation control.

A. System Architecture and Overview

The proposed intelligent irrigation decision support system integrates IoT sensors, environmental monitoring, and weather-based analytics to enable adaptive irrigation management. The system consists of soil moisture, temperature, and humidity sensors, an ESP32 microcontroller, a cloud platform, a formula-based decision algorithm, actuators (solenoid valves or motor pumps), and a mobile dashboard. Sensor data are transmitted via the ESP32 to the cloud, where they are combined with soil type, crop type, and weather forecasts, including rainfall predictions and reference evapotranspiration (ET_0). The algorithm computes the optimal irrigation

TABLE I: Gap Analysis of Related Works

Ref.	Problem Statement	Contribution	Limitations	Proposed Work
[16]	Limited IoT solutions for real-time monitoring.	Automated water distribution for conservation.	No weather prediction integration.	Advanced weather algorithms with IoT.
[17]	Lack of IoT-weather data integration.	Weather forecasting with IoT for irrigation.	Insufficient historical data use.	Hybrid system with historical and real-time data.
[18]	Adapting IoT to large-scale diverse fields.	Scalable IoT for large farms.	Scalability issues.	Flexible system for varying farm sizes.
[19]	Manual control inefficiencies.	Smart devices for automatic control.	High initial cost.	Affordable system for small-scale farmers.
[20]	Limited smart irrigation in rural areas.	IoT-based decision support systems.	Poor connectivity in rural areas.	Reliable communication protocols for remote areas.
[21]	Scaling IoT across diverse farm types.	Flexible IoT system for various farms.	Diverse crop challenges.	Adaptive system for multiple crops.
[22]	Lack of comprehensive decision support.	DSS combining weather and IoT data.	Weather forecasting accuracy issues.	Enhanced weather prediction models.
[23]	High energy consumption.	Energy-efficient IoT irrigation systems.	Increased energy for large-scale use.	Energy-efficient solutions.
[24]	Limited economic consideration.	Cost-effective smart irrigation models.	No cost-benefit analysis.	ROI models for economic sustainability.
[25]	Lack of comprehensive decision models.	Smart decision models using IoT.	Limited flexibility.	Comprehensive decision support models.
[26]	Inadequate real-time predictive integration.	AI and ML for irrigation decisions.	Limited ML integration.	Enhanced ML for improved accuracy.
[27]	No unified irrigation scheduling system.	Hybrid systems integrating multiple data.	Data integration challenges.	Integrated IoT, AI, and weather system.
[28]	Need for low-cost systems.	Affordable IoT for smallholders.	Single model limitations.	Low-cost scalable sensor systems.
[29]	Limited automated weather-based irrigation.	Real-time adaptive systems.	Sensor reliability issues.	Real-time adaptive control systems.
[30]	Poor scalability to large fields.	Adaptive systems for various crops.	High maintenance costs.	Energy-efficient cost-effective solutions.

volume and timing, which is executed automatically by actuators or presented to the farmer through the dashboard for real-time monitoring. This architecture supports responsive, environment-aware irrigation while providing a scalable framework for precision agriculture. The system workflow is illustrated in Fig. 2.

B. Data Acquisition

The proposed system integrates heterogeneous data sources to ensure accurate and context-aware irrigation decisions. Real-time environmental data, including soil moisture, temperature, and humidity, are collected through IoT-based sensors strategically placed across the cultivation area. Moisture sensors are embedded at the root-zone depth to capture effective soil-water availability, while temperature and humidity sensors are positioned above ground to monitor microclimatic variations. For large fields, sensors are deployed at intervals ensuring representative spatial coverage, minimizing redundancy while maintaining precision. The ESP32 microcontroller aggregates sensor readings at regular intervals—typically every 5 to 10 minutes—and transmits them to the cloud via Wi-Fi using lightweight communication protocols such as MQTT. Complementary inputs, including crop type and soil type, are provided by the user through a mobile or web interface. Additionally, weather forecasts and reference evapotranspiration (ET_0) values are retrieved from external APIs, while agronomic constants such as field capacity, wilting point, root-zone depth, and crop coefficient (K_c) are obtained from standard agricultural datasets. All sensor modules undergo calibration to ensure measurement accuracy, and data consistency is periodically validated. This integrated data acquisition framework provides a reliable foundation for the subsequent decision-making process, detailed in the following subsection on data processing and irrigation algorithm design.

C. Data Preprocessing

The collected data from sensors and external APIs underwent systematic preprocessing to ensure consistency and reliability before being used for irrigation decision-making. This step was essential to remove noise, handle missing values, and align measurements from multiple data sources into a unified analytical framework.

Occasional transmission losses and noisy sensor readings were mitigated using linear interpolation and median filtering techniques. Sensor outputs were standardized to maintain uniform measurement units across datasets. The soil moisture sensor provided volumetric water content (VWC) in percentage, while temperature and humidity were obtained in degrees Celsius and relative percentage, respectively. Rainfall and reference evapotranspiration (ET_0) data, retrieved from the weather API, were expressed in millimeters per day. When used in the soil water balance equations, volumetric soil moisture was converted to equivalent water depth (mm) using the effective root-zone depth and field capacity parameters. All datasets were synchronized to a common daily time interval, ensuring temporal alignment between sensor, weather, and agronomic parameters. The cleaned and integrated data were subsequently stored in a cloud database, forming the basis for irrigation scheduling and soil moisture prediction models.

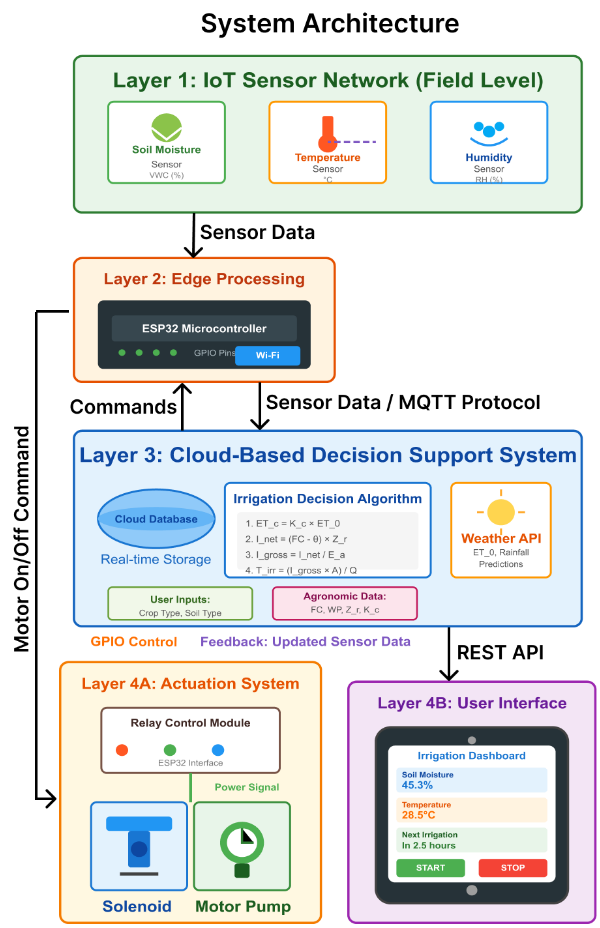

Fig. 1: Overall architecture of the IoT-based Smart Irrigation System.

D. Irrigation Decision Algorithm

The irrigation decision algorithm combined current soil water status with short-term weather forecasts to determine whether and how much water to apply. The principal quantities used were the total available water (TAW), current depletion (D), the readily available water threshold (RAW), and the forecasted net water requirement (NetNeed). These were computed as follows:

$$\mathrm{TAW} = (\theta_{\mathrm{fc}} - \theta_{\mathrm{wp}})\, z_r \times 1000 \tag{1}$$

where θ_{fc} and θ_{wp} are field capacity and wilting point ($\mathrm{m}^3/\mathrm{m}^3$), z_r is root-zone depth (m), and the factor 1000 converts metres to mm.

Current depletion was defined as

$$D = (\theta_{\mathrm{fc}} - \theta_{\mathrm{current}})\, z_r \times 1000, \tag{2}$$

which represents the depth (mm) by which the root zone is below field capacity.

The management threshold RAW was obtained by

$$\mathrm{RAW} = p \cdot \mathrm{TAW}, \tag{3}$$

where p is the allowable depletion fraction (dimensionless). The short-term forecasted requirement was expressed as

$$\mathrm{NetNeed} = ET_c - P_{\mathrm{eff}}, \tag{4}$$

with ET_c the crop evapotranspiration (mm) and P_{eff} effective rainfall (mm) over the chosen horizon.

Decision logic was implemented as a rule-based policy:

$$\begin{cases} \text{Irrigate now,} & \text{if } D > \mathrm{RAW}, \\ \text{Schedule irrigation,} & \text{if } D \le \mathrm{RAW} \\ \quad \text{and NetNeed} > 0 & \\ \quad \text{and } D \text{ is approaching RAW,} & \\ \text{Do not irrigate,} & \text{otherwise.} \end{cases}$$

When irrigation was required, the refill depth (net) and gross depth (accounting for application efficiency E_a) were computed as

$$I_{\mathrm{refill,mm}} = D, \qquad I_{\mathrm{gross,mm}} = \frac{I_{\mathrm{refill,mm}}}{E_a}. \tag{5}$$

The gross depth was converted to volume for an area A (m^2) by

$$\mathrm{Liters} = I_{\mathrm{gross,mm}} \times A, \qquad \mathrm{m}^3 = \frac{I_{\mathrm{gross,mm}}}{1000} \times A. \tag{6}$$

Finally, actuator runtime was derived from pump flow Q_{lpm} (L/min):

$$t_{\mathrm{min}} = \frac{\mathrm{Liters}_{\mathrm{required}}}{Q_{\mathrm{lpm}}}, \qquad t_{\mathrm{sec}} = 60\, t_{\mathrm{min}}. \tag{7}$$

Each equation was interpreted in the control loop: the rule-based decision determined whether to irrigate; refill/gross calculations provided the required depth and volume; and runtime calculation produced an actuator command. In operation, flowmeter feedback and post-irrigation soil moisture checks closed the loop to prevent overapplication. Detailed parameter choices and software implementation are provided in the following subsections.

E. Communication Flow

The communication and actuation layer served as the operational bridge between the sensing network, cloud-based intelligence, and the physical irrigation infrastructure. Sensor data, including soil moisture, temperature, and humidity readings, were transmitted from the field to the cloud using the ESP32 microcontroller over a Wi-Fi network. Data packets were structured with timestamps and transmitted through a lightweight protocol MQTT, to ensure reliability and synchronization. Upon arrival at the cloud, the server processed the incoming data and executed the irrigation decision algorithm, which determined the optimal irrigation schedule and volume. The resulting control command was then transmitted back to the ESP32, which interfaced with field actuators.

The actuation system consisted of solenoid valves or motor pumps, driven by relay modules connected to the ESP32's GPIO pins. Based on the computed decision, these actuators either initiated automatic irrigation or allowed manual intervention through a farmer-accessible mobile dashboard. The dashboard displayed real-time environmental conditions, system status, and irrigation recommendations. A feedback mechanism verified irrigation completion by updating the soil moisture readings after each event. This closed-loop communication and control framework ensured reliable, data-driven irrigation operations. The next section presents the implementation and experimental results of the proposed system.

F. Performance Evaluation

The performance of the proposed irrigation decision algorithm was evaluated using a dataset collected from Kaggle. Since the algorithm operates based on deterministic formulae rather than a trained model, evaluation was performed on the entire dataset without any data splitting. For the classification task of determining whether irrigation is required, standard metrics including accuracy, precision, recall, and F1-score were computed to quantify the system's ability to correctly identify both irrigation and non-irrigation cases. For the regression task of estimating irrigation volume, performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), providing insight into the algorithm's precision and reliability in predicting the required water volume. These evaluation metrics collectively demonstrate the effectiveness of the equation-based method in generating reliable irrigation decisions and estimating irrigation requirements across diverse soil and climatic conditions.

IV. Results & Discussions

To evaluate the performance of the proposed intelligent irrigation decision support system, experiments were conducted using a comprehensive dataset collected from Kaggle, representing diverse environmental, soil, and crop conditions for a one-acre agricultural field. The dataset consisted of 10,000 samples, each containing measurements of soil moisture, temperature, humidity, reference evapotranspiration (ET_0), crop coefficient (K_c), effective rainfall, field capacity, wilting point, root-zone depth, and other agronomic parameters relevant to irrigation decision-making. Both categorical inputs, such as crop type and soil type, and continuous environmental variables were included to capture realistic field variability.

The proposed rule-based irrigation algorithm was applied to the entire dataset, generating two outputs for each sample: a binary irrigation decision (irrigate or not) and the corresponding irrigation volume in cubic meters for the field. Performance evaluation focused on the accuracy of the irrigation decision and the precision of predicted irrigation amounts. The experiments were designed to examine the system's response under varying soil-water conditions, weather patterns, and crop stages, thereby providing a comprehensive assessment of its capability to support data-driven irrigation scheduling.

The first stage of performance evaluation focused on the binary irrigation decision, which determines whether irrigation is required under given environmental and soil conditions. The decision model was tested on the full dataset, and its performance was assessed using standard classification metrics such as accuracy, precision, recall, and F1-score. The obtained results are summarized in Table II.

TABLE II: Classification Performance Metrics for Irrigation Decision

Metric	Value
Accuracy	0.816
Precision	0.863
Recall	0.793
F1-score	0.827

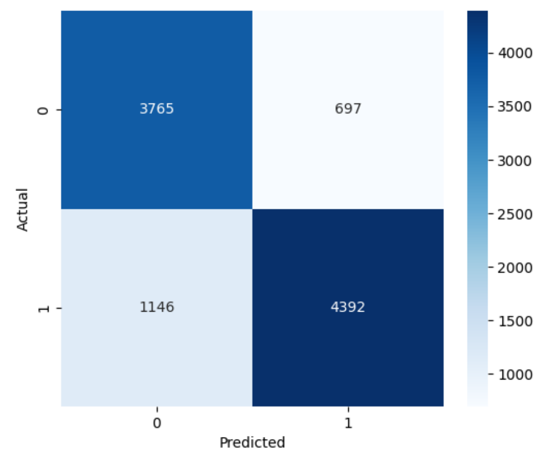

Fig. 2: Confusion matrix showing the performance of the irrigation decision model.

The confusion matrix provides a detailed breakdown of the model's performance in distinguishing between irrigation and non-irrigation conditions. Most samples were correctly classified, with 3,765 true negatives (non-irrigation) and 4,392 true positives (irrigation required). Meanwhile, 697 false positives and 1,146 false negatives were recorded. The relatively low number of false positives indicates that the system seldom triggers irrigation unnecessarily, which is important for conserving water and preventing over-irrigation. However, the false negatives—cases where irrigation was actually required but not triggered—suggest that some under-irrigation scenarios may occur. These can be reduced in future iterations through further model optimization or by including additional input features such as soil nutrient content or real-time weather parameters.

The classification metrics further reinforce the effectiveness of the model. With an accuracy of 81.6%, a precision of 86.3%, a recall of 79.3%, and an F1-score of 0.827, the model demonstrates strong predictive reliability. The high precision value indicates that when the model recommends irrigation, it is correct in most cases, thereby minimizing water waste. Similarly, the recall score shows that a majority of irrigation-required cases are successfully detected. The balanced F1-score highlights that the system effectively maintains equilibrium between these two aspects. Overall, these results confirm that the classification model offers robust and efficient decision-making capability, suitable for supporting intelligent irrigation systems that aim to optimize water use without compromising crop health.

To further evaluate the classification model's reliability, a class-wise comparison between the actual and predicted irrigation decisions was conducted. Fig. 3 illustrates the comparison in the form of a bar chart, showing the total number of samples belonging to each class ("Irrigation Not Required" and "Irrigation Required") against the corresponding predicted values.

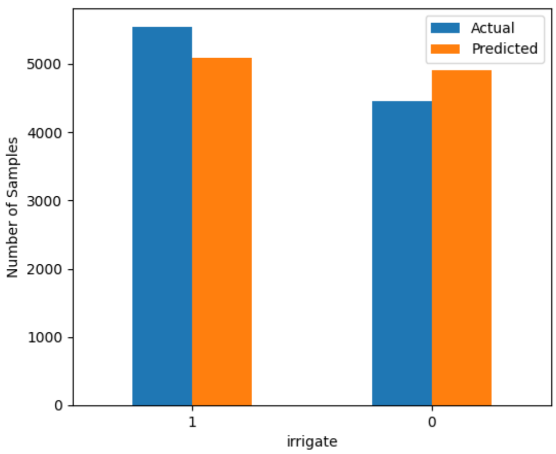

Fig. 3: Comparison between actual and predicted instances for each irrigation class.

From the confusion matrix, it is seen, the system correctly classified most irrigation and non-irrigation cases, with only minor misclassifications. The bar chart of actual versus predicted values shows a strong alignment between the two classes, indicating balanced performance without bias toward over- or under-irrigation. This consistency confirms the model's robustness and reliability in making irrigation decisions under varying soil and climatic conditions.

Following the classification evaluation, the system's performance in estimating irrigation volumes was analyzed to assess its practical utility in water management. The regression evaluation was conducted using standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2-score. The results are summarized in Table III, indicating that the algorithm provides reasonably accurate volume estimates for the 1-acre field scenario.

TABLE III: Regression Metrics for Predicted Irrigation Volume

Metric	Value (m^3)
RMSE	151.121
MAE	64.851
R^2	0.679

Figure 4 shows a scatter plot of predicted versus actual irrigation volumes. Most data points are closely aligned along the diagonal, indicating that the predicted volumes are generally consistent with actual requirements. Deviations occur near the zero axes, reflecting instances where the algorithm predicted no irrigation despite actual need, or vice versa. These deviations correspond to the misclassifications observed in the earlier classification analysis.

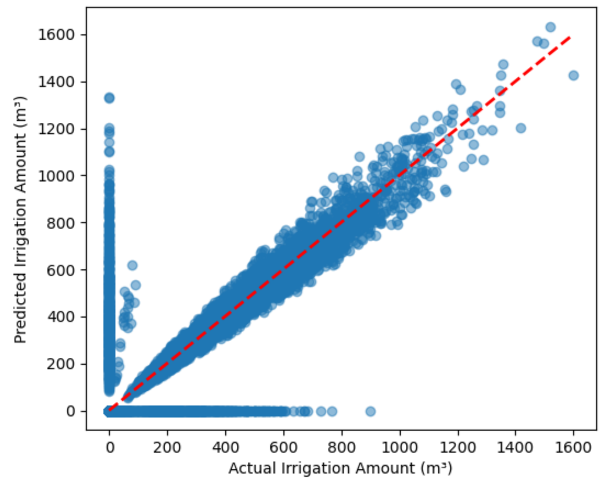

Fig. 4: Scatter plot of predicted versus actual irrigation volume.

The residuals, shown in Figure 5, are centered around zero and follow an approximately normal distribution, indicating minimal systematic error. This alignment demonstrates that the equation-based irrigation algorithm accurately estimates irrigation volumes across the dataset, reflecting its capability to produce reliable and consistent results under varying soil moisture and climatic conditions.

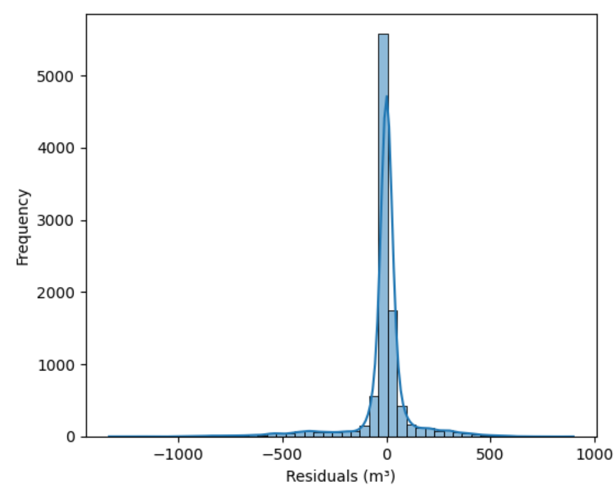

Fig. 5: Residual plot of predicted versus actual irrigation volume.

Figure 6 illustrates the relationship between soil moisture and residuals of the predicted irrigation volume. It can be observed that for soil moisture values above 35%, the residuals are minimal, indicating precise predictions in well-watered conditions. Below 35%, residuals are distributed fairly evenly on both sides of zero, with slightly higher dispersion on the negative side, but no evident correlation is present. This suggests that the algorithm maintains consistent performance across a wide range of soil moisture levels, without systematic under- or over-prediction.

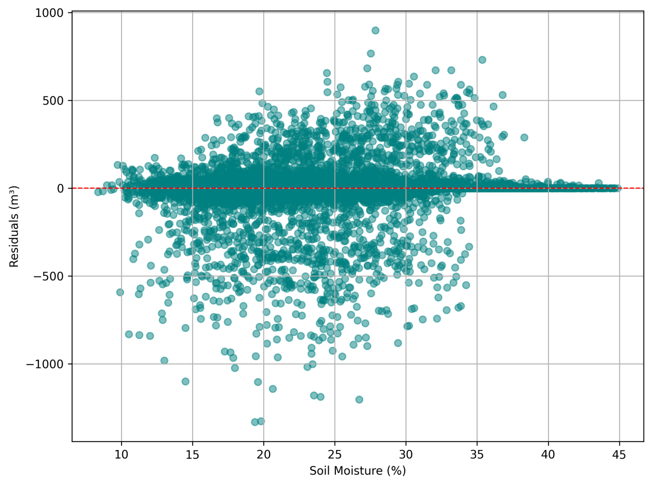

Fig. 6: Soil moisture (%) versus residuals of predicted irrigation volume.

Overall, the combined analysis of classification and regression results demonstrates that the equation-based irrigation decision algorithm effectively identifies irrigation needs and estimates water volumes with reasonable accuracy. The methodology provides a reliable tool for data-driven irrigation scheduling, supporting water-efficient and crop-sensitive management practices.

V. Limitations and Future Work

Despite demonstrating promising results, the proposed equation-based irrigation decision support system has certain limitations. First, practical implementation in real agricultural fields was not performed; the system was tested using a publicly available Kaggle dataset rather than data collected directly from IoT sensors. Second, while some input features were supposed to be obtained from pre-defined tables according to our methodology, testing data were solely collected from the Kaggle dataset, which may introduce variability and affect system accuracy in real case. Additionally, the current study considered a limited variety of crops and soil types, and real-world heterogeneity may pose further challenges.

Future work will focus on addressing these limitations. Practical deployment of the system on agricultural fields will be undertaken to evaluate real-time performance and reliability. The system will be extended to support multiple crops and heterogeneous soil conditions, and integration with additional sensor modalities will be explored to enhance decision-making. Moreover, real-time edge-based processing and automated actuation can be incorporated to further improve responsiveness and robustness.

VI. Conclusion

This paper presented an intelligent irrigation decision support system that integrates soil moisture, meteorological data, and crop information to provide accurate irrigation scheduling recommendations. By employing an equation-based approach rather than a machine learning framework, the proposed method offers transparency, simplicity, and interpretability in determining irrigation requirements. The system was evaluated using a Kaggle dataset, where performance metrics indicated strong consistency between predicted and actual irrigation needs. Analysis of residuals further demonstrated the robustness of the proposed model, with minimal bias and no evident correlation with soil moisture levels, confirming its reliability across varying environmental conditions. Although the system achieved satisfactory accuracy, certain limitations were identified. The dataset used for evaluation was collected from online sources rather than physical sensors, and real-world data acquisition may introduce additional noise and variability. Future work will focus on implementing the system in a real agricultural environment using sensor-based data collection to validate its practical applicability and enhance its accuracy through adaptive calibration and real-time data integration.

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