# An Intelligent Irrigation Decision Support System using IoT and Weather Data

*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 system integrates IoT sensing, cloud processing, and a rule-based irrigation algorithm to enable adaptive and automated irrigation scheduling.

### A. System Architecture and Overview

The proposed intelligent irrigation decision support system collects soil moisture, temperature, and humidity data from field sensors, which are transmitted to the cloud server via an ESP32 microcontroller gateway. The backend web server retrieves additional inputs from predefined tables such as field capacity, wilting point, root-zone depth, and crop coefficient ($K_c$) based on user-given soil type and crop type input. Live weather data such as rainfall predictions and reference evapotranspiration ($ET_0$) are also collected from weather APIs. Using formula-based calculations, the server determines optimal irrigation timing and volume. The decision is then sent to the ESP32 microcontroller to control the pump actuator via a relay, and simultaneously displayed on the mobile dashboard for farmer guidance and real-time monitoring. The system workflow is illustrated in Fig. 1.

### B. Data Acquisition

The system integrates heterogeneous data for accurate, context-aware irrigation. Soil moisture, temperature, and humidity sensors are strategically placed across the field, with moisture sensors at root-zone depth and temperature/humidity sensors above ground. The ESP32 microcontroller aggregates readings every 5–10 minutes and transmits them via MQTT to the cloud. Complementary inputs, including crop type, soil type, weather forecasts, and $ET_0$ values, are combined with agronomic constants (field capacity, wilting point, root-zone depth, $K_c$) from standard datasets. Sensors are calibrated and validated to ensure data reliability for irrigation decisions.

### C. Data Preprocessing

Sensor and API data were preprocessed to ensure consistency and reliability for irrigation decisions. Noise and missing values were addressed using linear interpolation and median

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. |

filtering. Measurements were standardized across datasets, with soil moisture in volumetric water content (%), temperature in °C, humidity in %, and rainfall/$ET_0$ in mm/day. Soil moisture was converted to water depth using root-zone depth and field capacity. All data were synchronized to a daily interval and stored in the cloud, providing a unified and reliable basis for irrigation scheduling.

### D. Irrigation Decision Algorithm

The irrigation algorithm evaluates soil water status and short-term weather conditions to determine irrigation need and volume. Total available water (TAW), depletion ($D$), readily available water (RAW), and forecasted net requirement (NetNeed) are computed as:

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

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

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

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

Decision rules are defined as:

$$\begin{cases} \text{Irrigate}, & D > \mathrm{RAW}, \\ \text{Schedule irrigation}, & D \leq \mathrm{RAW} \text{ and } \mathrm{NetNeed} > 0, \\ \text{Do not irrigate}, & \text{otherwise}. \end{cases}$$

When irrigation is required, refill and gross depths are calculated as:

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

Volume for an area $A$ ($\mathrm{m}^2$) is:

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

Actuator runtime based on pump flow rate $Q_{\mathrm{lpm}}$ is:

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

These computations guide both automatic actuation and dashboard recommendations.

### E. Communication Flow

The communication and actuation layer connected sensors, cloud processing, and irrigation infrastructure. Sensor data—soil moisture, temperature, and humidity—were sent via ESP32 over Wi-Fi using MQTT protocol. The cloud server processed the data with the irrigation algorithm to compute optimal irrigation schedules and volumes. Commands were sent back to the ESP32, which controlled solenoid valves or motor pumps via relays. A mobile dashboard provided real-time monitoring, recommendations, and manual override, while post-irrigation feedback updated soil moisture, ensuring a reliable closed-loop, data-driven irrigation system.

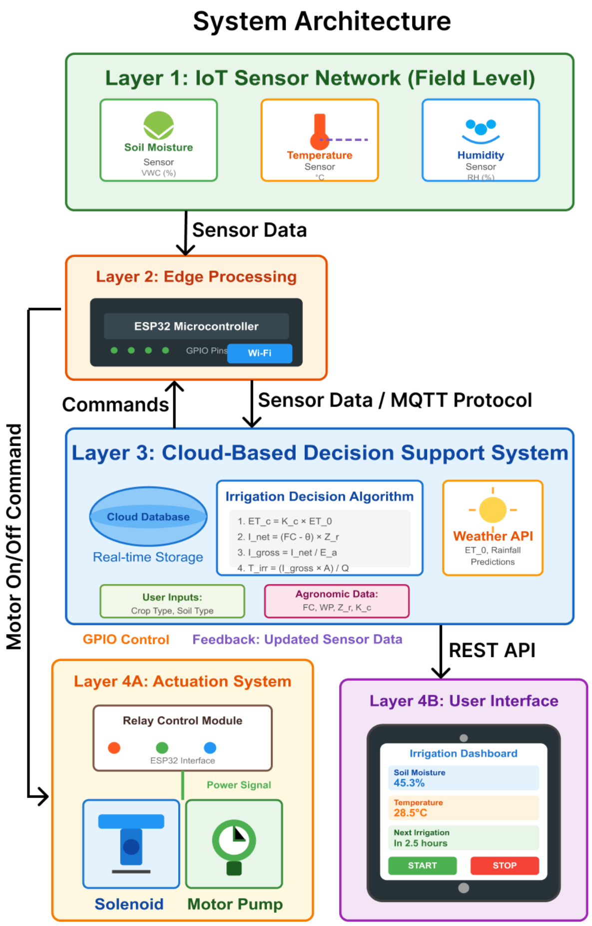


Fig. 1: Overall architecture of the IoT-based Smart Irrigation System.

### *F. Performance Evaluation*

The proposed irrigation decision algorithm was evaluated using a Kaggle dataset. As a formula-based deterministic method, the entire dataset was used without splitting. For irrigation requirement classification, accuracy, precision, recall, and F1-score quantified the system's ability to identify irrigation and non-irrigation cases. For irrigation volume estimation, RMSE, MAE, and $R^2$ measured prediction precision and reliability. These metrics collectively demonstrate the algorithm's effectiveness in producing accurate irrigation decisions and estimating water requirements across diverse soil and climatic conditions.

## IV. Results & Discussions

To evaluate the proposed irrigation decision support system, experiments used a Kaggle dataset of 10,000 samples representing diverse soil, crop, and environmental conditions for a one-acre field. Each sample included soil moisture, temperature, humidity, reference evapotranspiration ($ET_0$), crop coefficient ($K_c$), effective rainfall, field capacity, wilting point, root-zone depth, and categorical attributes such as soil and crop types. This dataset provided a broad and realistic testbed to assess the rule-based algorithm's decisions under varied agronomic scenarios.

The algorithm produced two outputs per sample: a binary irrigation decision and an estimated irrigation volume ($m^3$). Performance was measured using standard classification metrics (accuracy, precision, recall, F1-score) for the decision task, and RMSE, MAE, and $R^2$ for volume estimation. Results below summarize the system's practical effectiveness.

The classification evaluation (Table II) reports Accuracy = 0.816, Precision = 0.863, Recall = 0.793, and F1-score = 0.827. The confusion matrix in Fig. 2 shows 4,392 true positives and 3,765 true negatives, with 697 false positives and 1,146 false negatives. The low false-positive rate indicates the system seldom recommends unnecessary irrigation, supporting water conservation. The false-negative rate is higher, indicating some missed irrigation events; these cases could be mitigated by incorporating additional contextual inputs (e.g., nutrient status or higher-frequency weather updates) or adjusting threshold parameters. Overall, the classification results demonstrate robust decision-making suitable for operational deployment.

TABLE II: Classification Performance Metrics for Irrigation Decision

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

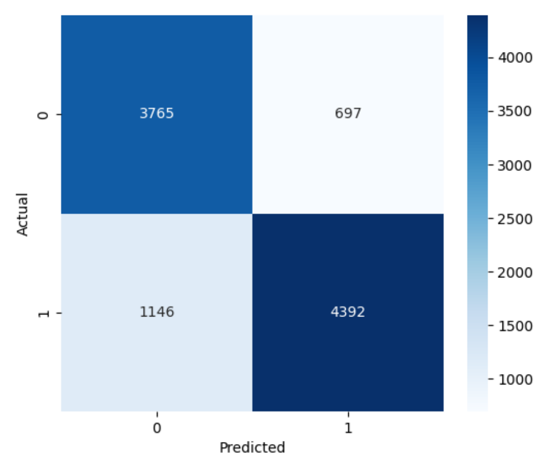


Fig. 2: Confusion matrix showing the performance of the irrigation decision model.

Class-wise counts (Fig. 3) confirm balanced performance with no pronounced bias toward either class. Predicted and actual distributions align closely, supporting the system's generalizability across different sample conditions.

For irrigation volume estimation, regression metrics in Table III show RMSE = 151.121 $m^3$, MAE = 64.851 $m^3$, and $R^2$ = 0.679. These values indicate acceptable agreement between predicted and actual volumes for field-scale planning, with $R^2$

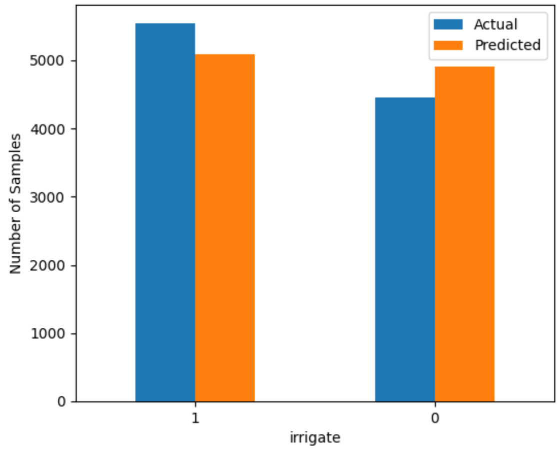


Fig. 3: Comparison between actual and predicted instances for each irrigation class.

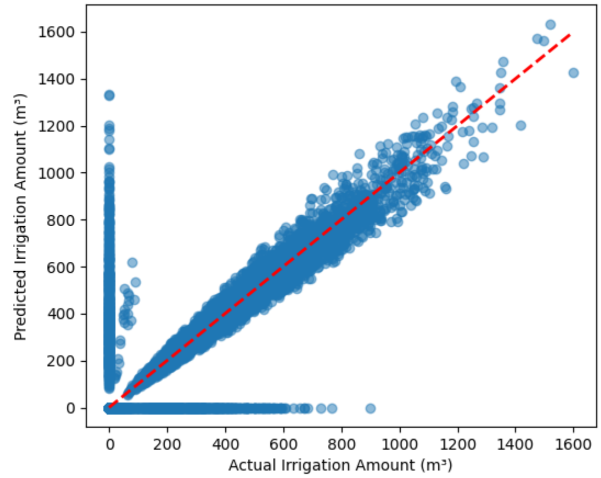


Fig. 4: Scatter plot of predicted versus actual irrigation volume.

suggesting that the formula-based model explains a substantial portion of variance in the dataset.

TABLE III: Regression Metrics for Predicted Irrigation Volume

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

The scatter plot in Fig. 4 shows most predictions near the diagonal, indicating good concordance; deviations near zero correspond to the misclassified samples identified earlier. Residuals (Fig. 5) are centered around zero and approximately symmetric, indicating no strong systematic bias in volume estimates. The soil moisture versus residuals plot (Fig. 6) reveals minimal residuals for moisture above 35%, with slightly greater dispersion at lower moisture levels; however, no clear linear dependence is observed.

In summary, the rule-based irrigation algorithm reliably identifies irrigation needs and estimates water volumes for one-acre fields. Classification results (F1-score 0.827) show strong decision-making while reducing unnecessary irrigation, supporting water conservation. Regression analysis ($R^2$ = 0.679) indicates predicted volumes closely match actual requirements, enabling practical irrigation planning. Remaining limitations—mainly false negatives and higher variance at low soil moisture—suggest future improvements, such as adding contextual inputs, refining decision thresholds, or using higher-resolution weather data.

## V. Limitations and Future Work

Despite promising results, the proposed equation-based irrigation decision support system has some limitations. First, it was not implemented in real agricultural fields and was tested only using a publicly available Kaggle dataset rather than data from IoT sensors. Second, although some input features should come from pre-defined tables, the testing relied solely on the

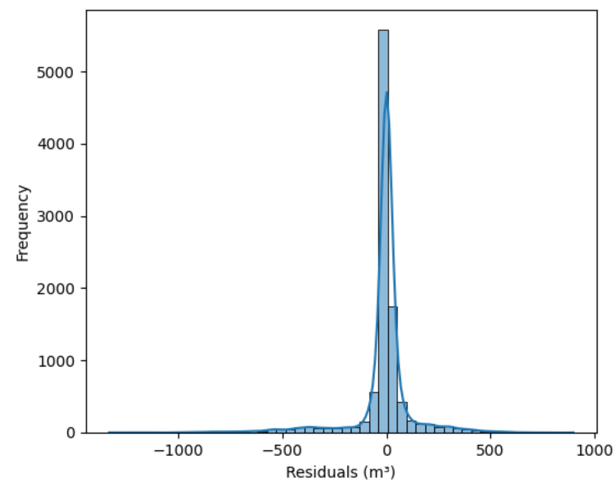


Fig. 5: Residual plot of predicted versus actual irrigation volume.

Kaggle dataset, which may affect accuracy. Additionally, only a limited range of crops and soil types were considered, and real-world heterogeneity could present further challenges.

Future work will address these limitations by deploying the system in actual fields to evaluate real-time performance and reliability. Extensions will include support for multiple crops and diverse soil conditions, integration of additional sensor modalities, and potential incorporation of real-time edge-based processing to 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

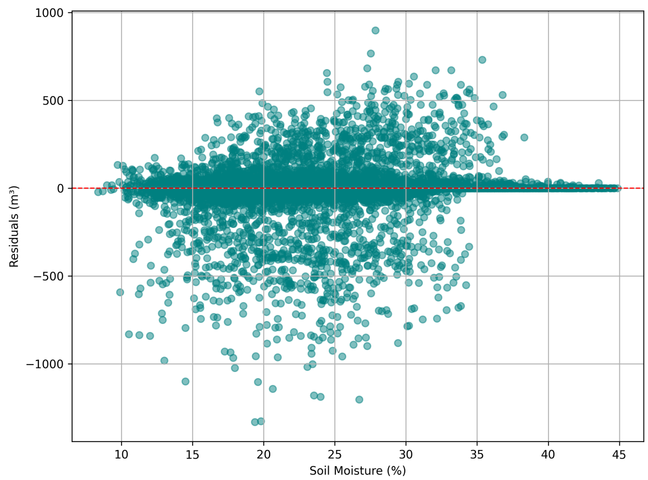


Fig. 6: Soil moisture (%) versus residuals of predicted irrigation volume.

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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