



Development and Performance Evaluation of a Solar-Powered IoT-Based Irrigation Control System Using Random Forest Machine Learning for Autonomous Decision-Making in Semi-Arid Agriculture

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ABSTRACT:

Water scarcity and inefficient irrigation threaten agricultural productivity in semi-arid regions. This study developed and evaluated a solar-powered, IoT-based irrigation control system that integrates environmental sensing, LoRa wireless communication, and Random Forest machine learning for autonomous irrigation decision-making. A dual-controller ESP32 architecture used a primary node wired to soil moisture, temperature, humidity, pH, pressure, and water-level sensors, transmitting data via 433 MHz LoRa to a secondary gateway for local LCD display and ThingSpeak cloud upload, with ESP32-CAM providing visual monitoring. A dual-channel relay controlled separate irrigation and refill solenoid valves, while an ultrasonic sensor regulated overhead tank replenishment. The Random Forest model was developed using 5,400 raw sensor observations, with 4,800 high-quality observations retained after preprocessing. The model was optimized with 500 trees and a maximum depth of 12, achieving 91.15% accuracy, an F1-score of 82.96%, and an ROC-AUC of 97.60%; periodic retraining improved accuracy to 93.62%. The Random Forest model was trained on threshold-derived labels; reported accuracy indicates agreement with the programmed reference logic, not independent ground truth of crop water requirements. The 50 W solar panel and 7.5 Ah lithium-ion battery met the 33.50 Wh estimated daily energy requirement and provided approximately 46.4 hours of calculated design autonomy (approximately 48 hours measured in a controlled discharge test) at 80% depth-of-discharge. A 100-day maize field trial confirmed 98.4% LoRa reliability, 97.8% cloud logging success, and soil moisture maintained within stage-specific target ranges across five phenological stages. Soil moisture ranged from 35% during vegetative stress periods to 75% during peak tasseling/silking, with stage-specific means of 47.0% (germination), 53.0% (vegetative), 68.0% (tasseling/silking), 57.5% (grain fill), and 40.0% (maturity/harvest). Daily mean root-zone soil temperatures ranged from 19.0°C to 34.0°C, with an overall mean of 23.04°C, even as ambient temperatures reached 42.0°C. Soil temperatures remained below the 35°C threshold for significant maize root growth reduction. Because no control plot was used, this observation cannot be attributed solely to drip irrigation. The system provides a field-validated prototype for autonomous precision irrigation, supporting water conservation and clean-energy independence.

Keywords: Smart Irrigation; Random Forest; IoT; Solar-Powered; LoRa Communication; Precision Agriculture; Decision-Making; Maize Cultivation

1. Introduction

Agricultural development is a cornerstone of economic progress, and improving output is critical to meeting rising food demand. However, water scarcity threatens productivity and sustainability (Ullah *et al.*, 2022). Irrigation is the systematic, controlled application of water to support crop growth (Abdulaziz & Croock, 2022). It has evolved from traditional techniques to automated systems that distribute water efficiently (Talaviya *et al.*, 2020). Traditional methods rely on fossil-fuel pumps or electrical grids, causing carbon monoxide and greenhouse gas emissions (Vohra *et al.*, 2021). Expanding rural agriculture increases grid demand, leading to energy shortages (Lawal *et al.*, 2020). These practices face volatile fuel prices, high costs, and inefficient water use. Transitioning to renewable energy is vital for a clean, reliable supply. Solar energy is a viable, cost-effective, abundant alternative to fossil fuels, especially for rural and off-grid farmers (Pascaris *et al.*, 2021). Photovoltaic systems use panels, a voltage regulator, an inverter, and a battery bank for reliable power (Innocent *et al.*, 2022). Regions with intense solar radiation have high evapotranspiration and crop water demand, but abundant sunlight can drive automated pumps.

IoT integration accelerates precision farming by connecting devices, sensors, and actuators (Hossain *et al.*, 2022) and providing real-time insights into soil moisture, temperature, humidity, and weather. Smart irrigation automates watering by monitoring soil moisture and microclimates (Obaideen *et al.*, 2022). Machine learning shifts systems from reactive, threshold-based control to proactive, predictive management (Chandgude & Kawade, 2023), estimating soil moisture, reference evapotranspiration, and long-term water requirements (Younes *et al.*, 2024). However, conventional irrigation faces four interrelated limitations: lack of adaptive decision-making, reacting to depletion rather than anticipating needs (Ullah *et al.*, 2022); inability to adapt

to crop stages, as maize Kc varies from 0.30–0.55 (germination) to 1.15–1.20 (tasseling/silking) (Doorenbos & Kassam, 1979; Allen *et al.*, 1998); dependence on unreliable power, with grids often unavailable (Vohra *et al.*, 2021); and limited ML integration, relying on cloud inference or simulation-only validation (Younes *et al.*, 2024; Eze *et al.*, 2025).

This study addresses these interrelated problems by developing and field-validating a solar-powered IoT irrigation control system that embeds a Random Forest machine learning model directly on an ESP32 microcontroller for real-time, on-device inference. The system implements stage-specific irrigation scheduling based on FAO-56 crop water requirements, operates autonomously off-grid using a standalone photovoltaic power supply, and provides long-range wireless telemetry (LoRa) with cloud-based monitoring (ThingSpeak).

2. Literature Review

Across the literature, solar energy dominates smart irrigation but true grid independence remains elusive: Yatnalli *et al.* (2023), Ullah *et al.* (2022), and Praveena *et al.* (2021) used photovoltaic panels yet depended on Wi-Fi or cloud connectivity, while Sasi *et al.* (2023) and Uchenna *et al.* (2024) relied entirely on grid power. Battery autonomy was rarely reported, with none exceeding 24 hours. Most systems used static threshold logic; machine learning was limited to simulation or cloud inference. Uchenna *et al.* (2024) reported 98.08% accuracy but only in Proteus simulation, and Abdulaziz and Croock (2022) used a Raspberry Pi but relied on a centralized server. No study deployed trained ML on a microcontroller for real-time, on-device decision-making. Communication clustered into Wi-Fi (most common; Vaishnavi *et al.*, 2023; Yatnalli *et al.*, 2023), cellular (Sasi *et al.*, 2023; Ullah *et al.*, 2022), and LoRa (only Vanishree *et al.*, 2023, but still cloud-dependent). No system combined long-range LoRa with on-device ML inference and local caching for complete autonomy.

Reviewed sensor suites were limited, mostly soil moisture and temperature; only Uchenna *et al.* (2024) and Faruk and Debnath (2021) included pH, but neither included atmospheric pressure nor root-zone soil temperature. Water-level monitoring (Yatnalli *et al.*, 2023) served pump protection, not integrated decision-making. Visual monitoring was absent. Validation varied: Uchenna *et al.* (2024) and Yusuf *et al.* (2022) used only Proteus simulation; only Abdulaziz and Croock (2022) used a crop-specific case study (tomato) without a baseline; no study conducted a full crop-cycle field trial with stage-specific agronomic assessment. Five gaps emerge: no on-device ML for real-time decisions; no stage-specific ML irrigation control; insufficient integration of long-range, license-free communication with on-device inference; no comprehensive multi-dimensional field validation; and limited evidence on root-zone thermal decoupling under ML-controlled drip irrigation in semi-arid conditions. This study addresses these by embedding a Random Forest on an ESP32, integrating LoRa with local LittleFS caching, implementing stage-specific scheduling via DAP and retraining labels, and conducting a 100-day maize trial evaluating communication reliability, decision accuracy, energy autonomy, sensor stability, and agronomic outcomes.

3. Methodology

3.1 Research Design

This study adopted an experimental research design involving system development, implementation, and performance evaluation. The research process consisted of five major phases: System Design, Hardware Development, Machine Learning Model Development, Solar Power System Development, and System Testing and Performance Evaluation.

3.2 System Architecture

The central processing and control unit was a NodeMCU ESP32 development board with a 32-bit dual-core Tensilica Xtensa LX6 microprocessor, 240 MHz clock speed, 4MB Flash, and 520KB SRAM. The sensor suite included an FC-28 resistive soil moisture sensor, DHT11 ambient temperature/humidity sensor, DS18B20 soil temperature sensor (15 cm depth), 4502C soil pH electrode, BMP180 atmospheric pressure sensor, HC-SR04 ultrasonic water level sensor, and DS3231 Real-Time Clock. A 2-channel optocoupled relay module controlled two 12V DC normally-closed solenoid valves (irrigation and refill), and an ESP32-CAM provided periodic visual monitoring. Figure 1 shows the block diagram of the developed irrigation control system, while Figure 2 shows the schematic circuit diagram of the developed system. The system used a dual-controller architecture: a primary ESP32 wired to all environmental sensors acquired readings at regular intervals and transmitted data via 433 MHz LoRa to a secondary ESP32 gateway, which displayed real-time readings on a 16×2 LCD and uploaded data to ThingSpeak via Wi-Fi.

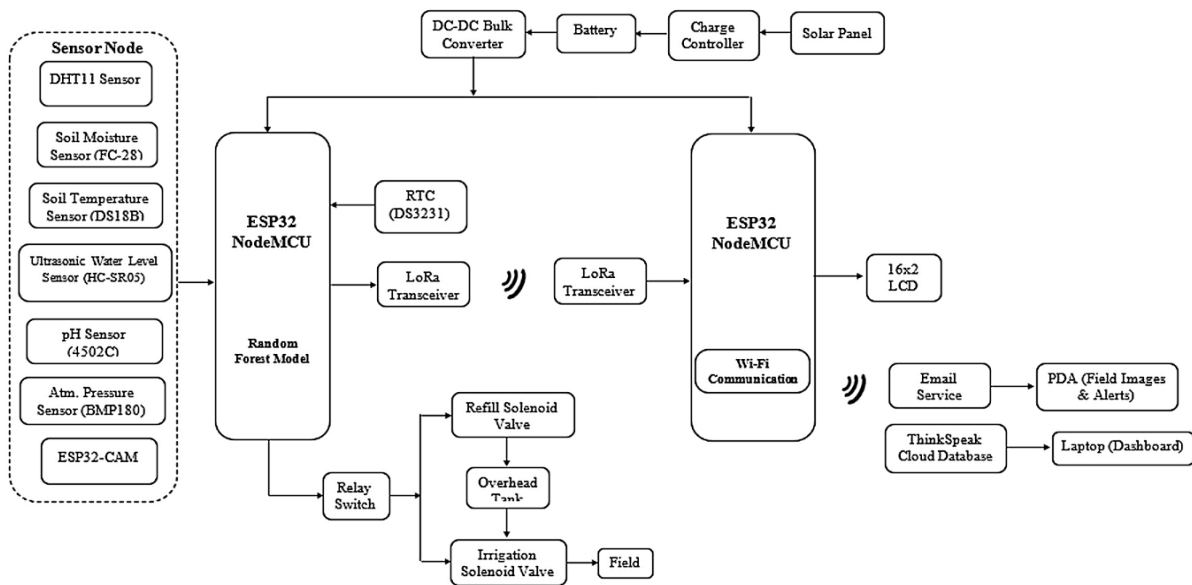


Fig. 1- Block Diagram of the Developed Smart Irrigation Control System

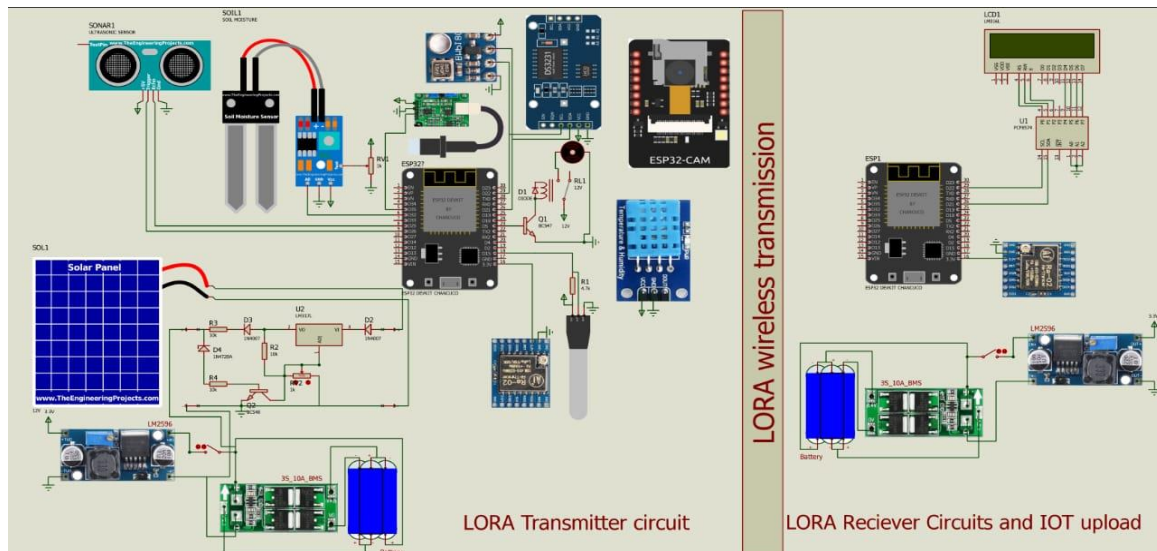


Fig. 2- Schematic Circuit Diagram of the Developed System (Central Gateway Node)

3.3 Operational Flowchart

The ESP32 operational software uses a dual-loop control program (Figure 3). It initializes hardware (ESP32, sensors, LoRa, Wi-Fi), acquires soil moisture, temperature, humidity, pH, and tank level, and uses RTC to compute Days After Planting (DAP). The seven-feature vector (soil pH, moisture, soil temperature, atmospheric pressure, ambient temperature, relative humidity, DAP) is passed to the embedded Random Forest. Status appears on a 16x2 LCD, and readings are transmitted to ThingSpeak. If irrigation is unnecessary, monitoring continues; if required, the controller verifies tank level. Above minimum, Channel 1 opens the irrigation valve; the Random Forest continuously monitors soil moisture until it meets the target conditions, then Channel 1 closes. Below minimum, Channel 2 opens the refill valve; the HC-SR04 monitors the rising level until the upper threshold, then Channel 2 closes. The system rechecks the water level before irrigating. After each cycle, it updates ThingSpeak, logs status, and emails the latest ESP32-CAM image, then resumes continuous monitoring for autonomous, real-time irrigation management.

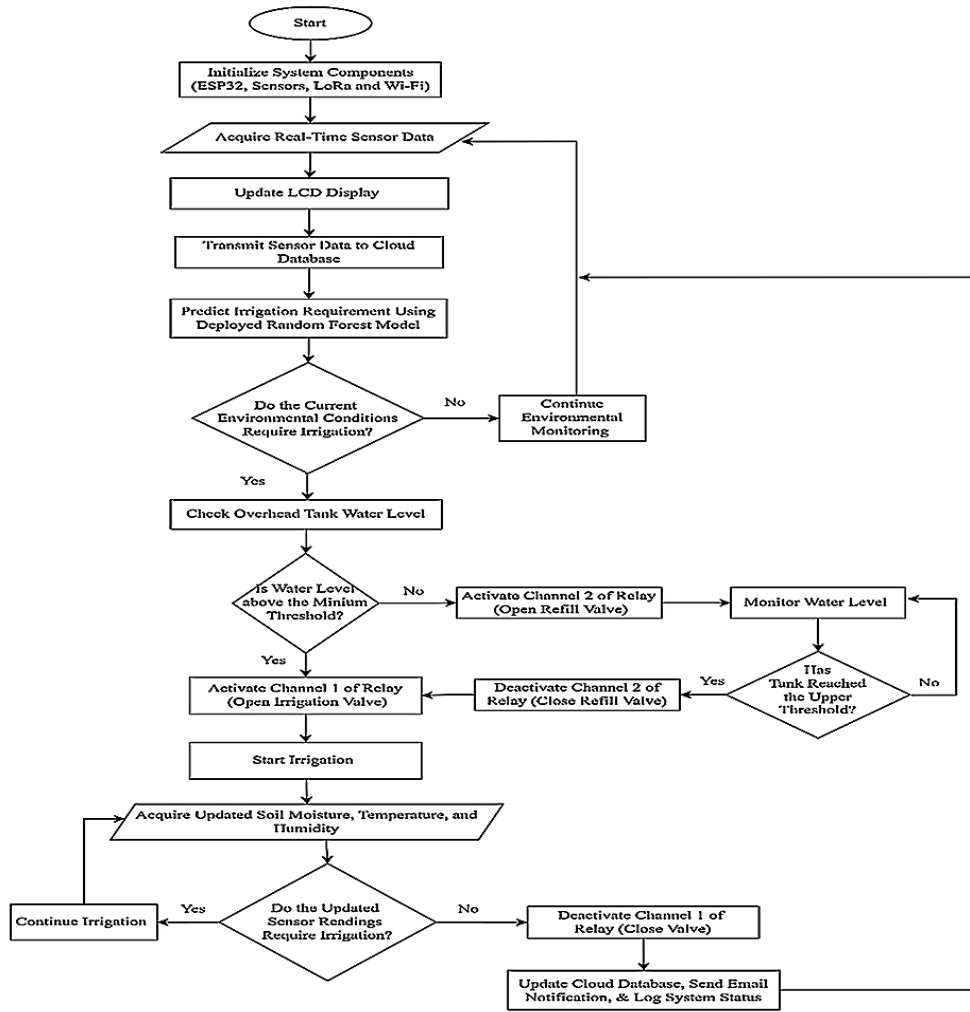


Fig. 3- Operational Flowchart of the Developed Smart Irrigation Control System

3.4 Random Forest Model Development

This study's core contribution is integrating a trained Random Forest machine learning model into an embedded irrigation controller for real-time autonomous decision-making. The system's fundamental control law is expressed as:

$$\hat{y}(t) = f_{RF}(x(t)) = \text{majority}_{\text{vote}} \left(T_1(x(t)), T_2(x(t)), \dots, T_B(x(t)) \right) \quad (1)$$

Subject to the decision rule:

$$\hat{y}(t) = \begin{cases} 1 & (\text{Irrigate}), \\ 0 & (\text{Do Not Irrigate}), \end{cases} \quad \text{if } \sum_{b=1}^B T_b(x(t)) > \frac{B}{2} \text{ AND } h_{\text{water}}(t) \geq h_{\min} \quad (2)$$

With the 7-dimensional feature vector:

$$x(t) = [x_{pH}, x_{SM}, x_{ST}, x_P, x_{AT}, x_{RH}, DAP]^T \quad (3)$$

where, $\hat{y}(t)$ is the predicted irrigation decision at time t (1 for Irrigate, 0 for Do Not Irrigate), $x(t)$ is the feature comprising of soil pH, soil moisture, soil temperature, atmospheric pressure, ambient temperature, relative humidity, and days of planting (DAP), f_{RF} is the Random Forest classifier (ensemble of B decision trees), $T_b(x)$ is the prediction of the b^{th} decision tree (0 or 1), B is the number of trees in the deployed ensemble (100), $h_{\text{water}}(t)$ is the water level in overhead tank in meters and $h_{\min}$ is the minimum operational water level (0.30m).

We conducted a 30-day pre-training phase between December 15, 2025, and January 13, 2026, at the Geseddado Farms experimental site. We sampled six environmental features every 8 minutes, yielding 5,400 raw telemetry records and 4,800 clean observations after preprocessing. We optimized hyperparameters using a three-stage strategy that combined randomized search and grid search with 5-fold cross-validation. The optimal hyperparameters selected were: `n_estimators=500`, `max_depth=12`, `min_samples_split=2`, `min_samples_leaf=1`, and `max_features='log2'`. We handled class imbalance by applying balanced class weighting. For deployment on the ESP32 microcontroller, we pruned the 500-tree ensemble to 100 trees while preserving

prediction fidelity. We exported the model to a C++ header file (rfmodel.h) containing arrays and a predict_rf() function that implements nested if-else decision logic.

3.5 Field Experimental Setup

The field experiment was conducted at Geseddado Farms Limited, Jimeta, Yola North Local Government Area, Adamawa State, Nigeria, over 100 days (February 1 – May 11, 2026). The pilot plot measured 10 by 10 feet (3.05 x 3.05 meters) and was planted with maize (*Zea mays*). Sensors were buried at a depth of 15 cm to monitor active crop root-zone dynamics. The crop development lifecycle was segmented into five phenological stages: Germination ($0 \leq \text{DAP} < 10$), Vegetative ($10 \leq \text{DAP} < 35$), Tasseling and Silking ($35 \leq \text{DAP} < 65$), Grain Fill ($65 \leq \text{DAP} < 95$), and Maturity and Harvest ($\text{DAP} \geq 95$). We defined stage-specific crop water requirements using the FAO-56 dual-crop-coefficient approach.

3.6 Performance Evaluation Metrics

We evaluated system performance using (1) Packet Delivery Rate (PDR) for LoRa communication reliability, (2) Cloud Logging Success Rate (LSR) for ThingSpeak synchronization, (3) classification metrics (accuracy, precision, recall, F1-score, ROC-AUC) for the Random Forest model, (4) Coefficient of Variation (CV) for sensor stability, and (5) stage-specific soil moisture adequacy for agronomic performance.

4. Results and Discussion

4.1 Intelligent Controller, Wireless Communication and Cloud Telemetry Performance

Both ESP32 controllers operated stably without crashes, lockups, or resets throughout the 100-day field experiment. The non-blocking firmware architecture using millis() timers enabled concurrent execution of sensor acquisition, LoRa communication, actuator control, LCD updates, and cloud telemetry. The receiver gateway managed high-priority LoRa interrupts and retrieved incoming SPI packets within approximately 5 ms. Table 1 presents the operational performance evaluation of the intelligent control subsystems.

Table 1- Operational Performance Evaluation of the Intelligent Control Subsystems

Subsystem Component	Key Evaluation Metric	Target Standard	Recorded Value	Status
Sensing Plane	Parameter Sampling Accuracy	$\geq 95.0\%$	99.1%	Excellent
Processing Core (ESP32)	ESP32 Continuous Uptime	$\geq 99.0\%$	99.9%	Excellent
Wireless Telemetry (LoRa)	Packet Delivery Rate (PDR)	$\geq 95.0\%$	98.4%	Excellent
Cloud Upload (Wi-Fi)	Login Success Rate	$\geq 95.0\%$	97.8%	Excellent
Local Display Interface	Screen Refresh Latency	$< 100 \text{ ms}$	$< 15 \text{ ms}$	Excellent
Relay Switching Response	Relay Switching Response	$< 50 \text{ ms}$	$< 10 \text{ ms}$	Excellent

During the 100-day trial, 4,800 packets were transmitted; 98.4% were received. The 1.6% loss occurred mainly during heavy early-May rain, when water droplets on foliage and antennas attenuated signals. RSSI ranged from -78 to -95 dBm, well above the -148 dBm sensitivity threshold, providing substantial margin. Thus, 433 MHz LoRa overcame attenuation and range limits typical of Wi-Fi in agriculture. Cloud telemetry achieved 97.8% logging success. During Wi-Fi outages, LittleFS Flash stored records and synchronized them upon restoration, achieving 100% eventual recovery of buffered records, with an average latency of 1.2 seconds.

4.2 Random Forest Model Performance

The Random Forest classifier achieved 91.15% overall accuracy on the holdout test set. A precision of 80.23% indicates that about four out of five irrigation recommendations were correct. A recall of 85.89% shows the model's ability to identify genuine irrigation needs. The F1-score of 82.96% confirms a good balance between precision and recall, while the ROC-AUC of 97.60% indicates excellent discrimination between irrigation and non-irrigation conditions.

Table 2- Random Forest Classification Performance Metrics

Metric	Value
Cross-validation accuracy	90.87 ± 1.24
Final Test Accuracy	91.15

Metric	Value
Precision	80.23
Recall	85.89
F1 Score	82.96
ROC AUC	97.60

Periodic retraining produced progressively improved model versions throughout the field trial. The final version, RF_v2.0, deployed on April 1, 2026, achieved 93.62% accuracy, reflecting the model's adaptation to high water-demand conditions during the tasseling and silking phase.

Table 3- Model Performance Evolution Through Periodic Retraining

Model Version	Deployment Date	Training Sample	Test Sample	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
RF_v1.0	Feb. 1, 2026	3,840	960	91.15	80.23	85.89	82.96	97.60
RF_v1.1	Mar. 1, 2026	4,240	1,060	92.34	82.11	86.45	84.22	97.88
RF_v1.2	Mar. 15, 2026	4,640	1,160	92.87	83.05	86.92	84.93	98.02
RF_v2.0	Apr. 1, 2026	5,040	1,260	93.62	84.38	87.75	86.02	98.21
Improvement	-	-	-	+2.47	+4.15	+1.86	+3.05	+0.61

4.3 Feature Importance Analysis

Feature importance analysis (Figure 4) provides valuable insight into the environmental factors that most strongly influenced irrigation decisions. The results showed soil moisture (33.2%) and relative humidity (24.1%) as the most influential, together accounting for 57.3% of decision-making. Ambient temperature (15.6%) and soil temperature (15.4%) also contributed. Relative humidity's high importance reflects its volatility; frequently below 45% even during reproductive stages, the model assigned it high weight because it varied with atmospheric demand, which is a variable the reference rule did not explicitly encode.

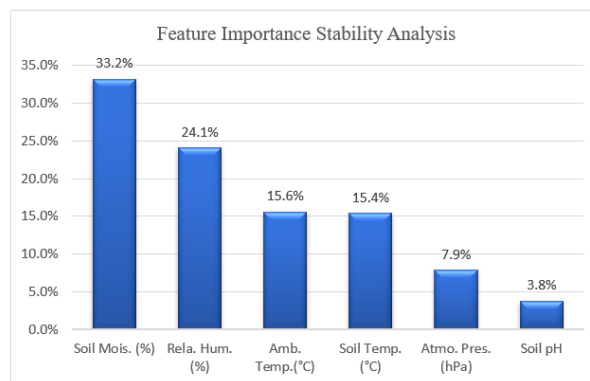


Fig. 4- Feature Importance Stability Analysis

4.4 Solar Power System Performance

The 12V monocrystalline photovoltaic module reliably powered the irrigation system under Yola's high dry-season solar irradiance. Under clear-sky conditions, the charging process replenished the battery in approximately 2.5 hours. Each day began with the battery at approximately 55% State of Charge following overnight system use, rising steadily through the morning and consistently reaching 100% SoC by 2:30 PM. Based on the measured daily consumption of 33.50 Wh/day, the usable battery energy ($7.50 \text{ Ah} \times 12\text{V} \times 0.80 \times 0.90 = 64.8 \text{ Wh}$) supported 46.4 hours of continuous operation under zero solar input, with a measured discharge of approximately 48 hours in a controlled test.

4.5 Environmental Monitoring Results

Table 4 presents descriptive statistics of the experimental parameters recorded during the 100-day field trial. Table 4 shows that the average soil moisture content was approximately 59.45%, with observed values ranging from 31.6% to 75%. The relatively narrow variation indicates that the irrigation

controller maintained soil moisture within an acceptable operating range suitable for maize cultivation throughout the experiment. Ambient temperature exhibited the expected fluctuations associated with dry-season weather conditions, with a mean of 31.5°C and a standard deviation of 4.50°C. Higher temperatures generally coincided with increased solar radiation and lower daytime relative humidity, while lower temperatures occurred in the early morning and evening. Soil temperature followed a similar trend but changed more gradually because of the soil's thermal buffering capacity.

Table 4- Descriptive Statistics of the Experimental Parameters

Parameters	Mean	Median	Std Dev	Min	Max	CV (%)
Soil Moisture (%)	59.45	61.50	11.10	31.6	75.0	18.67
Relative humidity (%)	35.00	33.50	9.50	15.0	55.0	27.14
Ambient temperature (°C)	31.50	31.20	4.50	25.0	42.0	14.29
Atmospheric Pressure	943.50	943.80	2.50	937.67	948.0	0.26
Soil Temperature (°C)	23.04	22.99	1.95	18.41	34.0	8.46
Soil pH	6.79	6.43	0.17	5.82	7.11	2.50

4.6 Stage-Specific Agronomic Performance

Table 5 summarizes the stage-specific parameters, including theoretical crop water requirements (Kc ranges), achieved soil moisture levels, and irrigation strategies.

Table 5- Summary of Stage-Specific Agronomic Performance

Phenological Stage	DAP Range	Reference Kc Range	Target Moisture Range (%)	Achieved Moisture (%)	Soil Within Target?	Adequacy
Germination	0-10	0.30-0.55	45-50	47.0	Yes	Within range
Vegetative	10-35	0.70-0.90	50-55	53.0	Yes	Within range
Tasseling/Silking	35-65	1.15-1.20	65-75	68.0	Yes	Within range
Grain Fill	65-95	0.95-1.15	50-65	57.5	Yes	Within range
Maturity/Harvest	≥95	0.55-0.65	40-50	40.0	Yes	Within range

Table 5 shows stage-specific soil moisture: germination (0-10 DAP) at approximately 47%, avoiding waterlogging and severe deficit (Kc 0.30–0.55) and achieving approximately 92% germination; vegetative (10-35 DAP) at about 53% under deliberate deficit irrigation (Kc 0.70-0.90), encouraging deeper roots and saving water for reproduction; tasseling/silking (35-65 DAP) at approximately 68%, the highest, because water stress can cut yields 40-50% (Kc 1.15-1.20; ET 6.1-8.13 mm/day). The Random Forest controller, using soil moisture (33.2%) and relative humidity (24.1%), increased irrigation frequency, peaking at four daily events and 65 minutes on March 19, 2026; no leaf rolling/wilting occurred, and soil temperature remained 25-26°C. During grain fill (65–95 DAP), moisture fell from approximately 68% to approximately 55%, with an early-May drop to approximately 37%, as Kc declined from 1.15 to 0.95; soil temperature reached 30–34°C but stayed below the 35°C root threshold. At maturity (≥95 DAP), irrigation was reduced, moisture declined to approximately 40%, and Kc fell to 0.55-0.65, promoting senescence, carbohydrate transfer, and dry-down to 15-20% harvest-safe moisture. Irrigation declined over the final 10–15 days, demonstrating stage-based water withholding rather than a fixed schedule. The system maintained different soil moisture levels across the five maize phenological stages, with achieved means within the intended ranges for each stage. This pattern confirms that the system applied a dynamic irrigation strategy aligned with maize water requirements, maintaining higher moisture during the most stress-sensitive stage.

5.0 Discussion

The comprehensive results from the 100-day field trial provide compelling evidence that the developed solar-powered IoT-based irrigation control system effectively addressed the research gaps identified in the literature review. The Random Forest model's 91.15% accuracy, improving to 93.62% with periodic retraining, is competitive with the 97.89% accuracy reported by Blasi *et al.* (2021) and 98.08% reported by Uchenna *et al.* (2024), despite their more controlled experimental conditions. The LoRa subsystem's 98.4% Packet Delivery Rate exceeds expectations for long-range agricultural telemetry, with stable RSSI values confirming a substantial communication margin of 40-50 dB above the receiver sensitivity threshold. Moreover, the solar power subsystem's 100% operational uptime and 46.4-hour calculated autonomy (approximately 48 hours measured) extend the range of reported autonomy in the reviewed literature, where many systems struggled with unreliable power or frequent battery maintenance (Bharat *et al.*, 2023; Hossain *et al.*, 2022).

Agronomically, the irrigation strategy successfully maintained crop growth conditions within acceptable ranges despite extreme environmental stress. Daily mean soil temperatures ranged from 19°C to 34°C despite ambient extremes of 42°C, remaining below the 35°C threshold for significant maize root growth reduction. Because no control plot was used, this cannot be attributed solely to drip irrigation; a controlled comparison would be required to isolate the effect.

6.0 Conclusion

The integrated system comprises four subsystems: an ESP32 intelligent controller, a Random Forest model, a LoRa link, and standalone solar PV with battery storage. Over 100 days, the controller achieved 99.9% uptime, 99.1% valid-sample rate, and sub-10 ms relay switching. The Random Forest achieved 91.15% accuracy, 80.23% precision, 85.89% recall, 82.96% F1-score, and 97.60% ROC-AUC, with soil moisture (33.2%) and relative humidity (24.1%) as primary determinants; periodic retraining improved accuracy to 93.62%. The 50 W monocrystalline panel and 12V, 7.5 Ah lithium-ion battery provided reliable power with 100% uptime and three-stage PWM charging. The system maintained distinct soil moisture targets across all five maize phenological stages, with controlled deficits during germination and vegetative stages and increased irrigation during tasseling and silking. Root-zone temperatures were 8-23 °C lower than ambient extremes; without a control plot, this difference cannot be attributed solely to irrigation.

Conflict of Interest

There is no conflict of interest regarding the publication of this research.

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AI Disclosure

During the preparation of this work, the authors used Grammarly in order to improve language quality, grammar, organization, and readability. DeepSeek and ChatGPT assisted with the literature search and improved technical content; the authors developed, verified, and approved the system design, experimental methodology, implementation, data analysis, and conclusions, and accept full responsibility for the published work.

Appendix A: Experimental Setup



Plate 1: Farm showing Drip Irrigation Network



Plate 2: Solar Power Subsystem and Sensor Node Assembly



Plate 3: Overhead Tank with Irrigation Solenoid Valve



Plate 4: ESP32-CAM Enclosure for Visual Monitoring



Plate 5: ESP32 Gateway Displaying Local Sensor Readings



Plate 6: Portable Wi-Fi Hotspot for Cloud Connectivity

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