Smart Irrigation Systems Using Wireless Sensor Networks and Machine Learning for Water Use Efficiency

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***Abstract**: This study presents the design, implementation, and evaluation of a Smart Irrigation System (SIS) that integrates Wireless Sensor Networks (WSNs) with Machine Learning (ML) to optimize water use efficiency in agriculture. Conducted over two crop seasons in a semi-arid region of Maharashtra, India, the research employed real-time environmental data from a multi-sensor WSN—including soil moisture, temperature, humidity, light intensity, and rainfall—captured every 30 minutes. A Random Forest Regression model was trained to forecast short-term soil moisture levels and guide dynamic irrigation scheduling. The system achieved a high predictive accuracy (R^2 = 0.912) with minimal error (RMSE = 1.83%), demonstrating the reliability of data-driven irrigation control. The SIS reduced average daily water usage by 28.7%, improved grain yield by 10.8%, and enhanced water productivity by over 50%, compared to traditional irrigation methods. Additionally, energy consumption related to pump usage was lowered by 28.4%, affirming the system's efficiency in both water and energy domains. Operational metrics indicated system robustness with 97.4% sensor uptime and minimal data packet loss. This research addresses a critical literature gap by validating a full-cycle, field-based SIS under real-world conditions, and offers a scalable, cost-effective model for sustainable agriculture. The findings have significant implications for smallholder farming, climate resilience, and digital agriculture policy.*

Keywords**: **Smart irrigation, wireless sensor networks, machine learning, water use efficiency, predictive agriculture, energy conservation

1. Introduction

Water scarcity remains a pressing challenge for global agriculture, especially in arid and semi-arid regions where irrigation consumes over 70% of freshwater resources globally (Mekonnen et al., 2019). Traditional irrigation methods often result in water wastage due to manual scheduling and uniform application irrespective of crop or soil condition. Precision irrigation, enhanced through digital technologies, presents a promising alternative. Specifically, Smart Irrigation Systems (SIS) incorporating Wireless Sensor Networks (WSNs) and Machine Learning (ML) have emerged as transformative tools for optimizing irrigation by enabling real-time monitoring, data analytics, and automated decision-making (Goap et al., 2018).

WSNs collect field-level data including soil moisture, humidity, temperature, and weather forecasts, while ML algorithms interpret these datasets to make predictive or prescriptive decisions about irrigation scheduling. This combination is reshaping the landscape of agricultural water management. Recent studies have demonstrated water savings between 20% and 40% using SIS compared to manual or timer-based irrigation (Ndunagu et al., 2022). Furthermore, when implemented at scale, such technologies not only improve water use efficiency (WUE) but also enhance crop yield, reduce labor input, and optimize energy consumption through intelligent pump scheduling (Sami et al., 2022).The integration of IoT-based sensors with ML models has shown substantial promise in making agriculture data-driven and environmentally sustainable. Tace et al. (2022) proposed an intelligent irrigation model using ML and IoT components that dynamically adjusts water supply based on soil and climatic variations. Meanwhile, Kirtana et al. (2018) incorporated Zigbee-based sensor networks for reliable communication in field deployments. These innovations signify a paradigm shift in irrigation technology from static control systems to dynamic, data-responsive frameworks that react to micro-level environmental changes.

Although the growing body of literature showcases various attempts to build and deploy SIS, significant limitations persist. Most research efforts remain confined to controlled environments such as greenhouses or small-scale test beds, limiting real-world applicability and scalability. Many models are trained on limited datasets, lacking multi-seasonal or multi-regional diversity. For instance, Janani and Jebakumar (2019) focused on ML algorithms to optimize irrigation, but their implementation lacked spatial scalability and real-time adaptability.Moreover, current literature often addresses WSN and ML components in isolation rather than as an integrated, cohesive system. Raghuvanshi et al. (2022) discussed WSN deployment for smart farming but focused primarily on risk mitigation and intrusion detection. Similarly, Singh et al. (2019) emphasized soil moisture prediction using ML but did not account for network reliability or energy efficiency of the sensors. This fragmented approach undermines the holistic potential of smart irrigation systems.

Another gap lies in the lack of comparative, longitudinal field studies that assess not only the water efficiency but also energy usage, system robustness, and maintenance feasibility over time. The robustness of ML models under fluctuating environmental conditions and real-world network disruptions remains underexplored. These gaps emphasize the need for an integrated, field-level validation of smart irrigation systems incorporating both WSN and ML in resource-constrained agricultural settings.Despite technological advances in smart agriculture, there exists a tangible void in the development and empirical validation of integrated SIS that are both scalable and adaptable to diverse field conditions. Most existing systems either emphasize sensor deployment without predictive intelligence or apply ML models without real-time sensor integration. This paper addresses this deficiency by developing and validating a fully integrated Smart Irrigation System leveraging WSNs and ML for optimized water use efficiency under semi-arid conditions.

The overarching aim of this research is to design, implement, and validate a Smart Irrigation System that utilizes a hybrid of WSN and ML to enhance irrigation efficiency in real-time farming environments. The specific objectives are:

1. To deploy a real-time, multi-sensor WSN architecture for soil and environmental data collection.
2. To train and validate supervised ML algorithms (such as Random Forest and Artificial Neural Networks) on sensor and weather data to forecast irrigation needs accurately.
3. To assess the system’s impact on water consumption, crop yield, and energy usage compared to traditional methods.

4. To analyze the robustness and scalability of the system across variable environmental and operational conditions.

The potential contributions of this study are multifaceted. From an academic perspective, it bridges the gap between WSN deployment and ML application in smart irrigation by offering a unified, empirically validated framework. From a technological standpoint, it proposes a cost-effective, scalable model that could be adapted by smallholder farmers with limited technical expertise or infrastructure.In practical terms, the outcomes of this study can inform policy and practice in sustainable water resource management, contributing to environmental conservation and agricultural productivity. The integration of predictive analytics with IoT infrastructures supports proactive irrigation strategies, minimizing resource waste and environmental impact. Finally, the research aligns with broader global objectives such as the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation), by fostering innovations that enhance food security and water sustainability.

2. Literature Review

2.1. Review of Scholarly Works

This section organizes and critically analyzes prior studies on smart irrigation systems, structured thematically to align with our research objectives: (i) integration of machine learning with sensor-based irrigation systems, (ii) energy-efficient wireless sensor networks (WSNs) for real-time monitoring, (iii) predictive water demand modeling, and (iv) system-level deployment and decision support in agricultural environments.

Theme 1: Machine Learning Integration with Sensor-Based Irrigation

Several studies explored how ML algorithms enhance sensor-based irrigation through real-time prediction and automation. Mekonnen et al. (2019) investigated the application of supervised learning models in wireless sensor networks for precision agriculture. They used soil moisture and temperature sensors connected to WSNs and applied regression algorithms to forecast irrigation needs. Their findings showed up to 35% improvement in water efficiency, highlighting ML's role in refining irrigation scheduling.

Sami et al. (2022) proposed a deep learning-based sensor model integrated with WSN for field deployment across multiple regions in Sindh, Pakistan. Their model included convolutional neural networks (CNNs) trained on sensor datasets to autonomously identify optimal irrigation cycles. The results achieved over 91% prediction accuracy for soil moisture levels, demonstrating the feasibility of AI-driven irrigation under diverse climatic conditions.

Tace et al. (2022) implemented an intelligent irrigation model using supervised ML algorithms like decision trees and support vector machines (SVM), combined with environmental sensors. Their approach successfully reduced water usage by 28.6%, validating ML’s potential to dynamically adapt to real-time soil and weather conditions.

Theme 2: Design and Optimization of Wireless Sensor Networks for Irrigation

The second group of studies focused on the structure and sustainability of sensor networks essential for field deployment. Ndunagu et al. (2022) designed a wireless sensor network for a smart irrigation system in sub-Saharan conditions using Arduino-based microcontrollers and LoRa technology. They used Microsoft Excel and Jupyter Notebook to process over 5,700 sensor readings, achieving consistent reliability and minimal data packet loss during peak humidity cycles.

Ding and Du (2024) emphasized the importance of system autonomy in WSNs through the use of deep reinforcement learning. Their study optimized irrigation scheduling and network communication frequency based on environmental context, achieving a 20.2% extension in node battery life and a 14.9% increase in irrigation precision. This contribution directly aligns with our study's goal to validate system robustness over extended agricultural seasons.

González-Briones (2018) also addressed the energy-efficiency aspect, proposing a hybrid WSN-ML framework combining unsupervised and supervised learning to adapt irrigation schemes in rural environments. The framework utilized clustering algorithms to reduce transmission redundancy, thereby conserving energy and increasing sensor lifespan by 18%.

Theme 3: Predictive Irrigation Modeling and Water Management

The third theme emphasizes the forecasting capabilities of ML models in predicting water requirements. Glória et al. (2021) proposed a sustainable irrigation system that incorporated real-time sensor readings and ensemble learning techniques. The study developed a Random Forest-based model trained on 36,000 readings over 90 days, achieving a water prediction error below 1.9%. Their contribution shows the value of ensemble ML models in minimizing prediction errors in field conditions.

Goldstein et al. (2018) conducted an interpretative ML study to derive irrigation patterns from sensor data and agronomist insights. Using feature importance analysis, they discovered that latent environmental variables like wind speed and radiation intensity, often ignored in rule-based systems, significantly influenced soil moisture dynamics. Their findings reinforce the necessity of incorporating weather-API-based inputs to improve ML model reliability.

Padmanaban and Kannan (2021) developed a groundwater forecasting model using long short-term memory (LSTM) neural networks to anticipate subterranean water availability and adjust irrigation schedules accordingly. Their results showed 85% model reliability in predicting irrigation viability under fluctuating aquifer conditions, offering a proactive approach to sustainable water use.

Theme 4: Full-System Deployment and Automation in Agricultural Environments

Addressing end-to-end automation, Vij et al. (2020) examined ML- and IoT-based irrigation systems leveraging open-source weather databases and sensor feedback to initiate autonomous irrigation. Their results recorded a 30.6% reduction in total irrigation water applied and improved yield per hectare by 11.3%, confirming that decision-driven automation can enhance both water savings and productivity.

Tace et al. (2022) extended this system-level perspective by introducing fault-tolerant edge computing for irrigation logic. They integrated redundancy protocols to reduce data loss and ensure decision continuity during network failures. Such designs are essential in ensuring reliability in remote rural deployments, a consideration vital for our study's focus on scalability.

Despite considerable progress in smart irrigation, a key gap persists in the field-level implementation and empirical validation of unified systems that integrate both WSN and machine learning for irrigation optimization. Most studies either emphasize controlled lab conditions or focus on isolated components—either the sensor network or the algorithmic modeling. This segmented approach undermines the holistic utility of smart irrigation frameworks, especially in semi-arid and resource-constrained agricultural zones.Our research fills this void by designing, deploying, and testing a fully integrated SIS model that spans from sensor deployment to ML-based water forecasting. The significance lies in its potential to contribute actionable insights for policy-makers, agri-tech developers, and smallholder farmers, bridging the gap between conceptual innovation and practical, sustainable water use strategies in precision agriculture.

3. Materials and Methods

3.1 Research Design

This study adopted a quantitative, applied experimental research design focusing on the field deployment of a Smart Irrigation System (SIS) integrating Wireless Sensor Networks (WSN) and Machine Learning (ML) in a controlled agricultural setting. The primary goal was to monitor, predict, and optimize irrigation schedules through real-time data collection and predictive modeling. A single crop field measuring 1.5 acres, located in the Yavatmal district of Maharashtra, India, was selected as the experimental site due to its semi-arid climatic characteristics and water stress challenges.

The methodology was developed to fill the literature gaps related to the lack of integrated, scalable, field-level testing of WSN-ML based systems. The approach ensured empirical rigor in validating the water use efficiency, energy savings, and forecasting accuracy of the proposed model.

3.2 Data Collection System and Tools

Data for the study were collected using a multi-sensor WSN setup deployed uniformly across the selected agricultural plot. Sensors captured key environmental and soil parameters at 30-minute intervals throughout two cropping cycles (Kharif and Rabi seasons, October 2022 to May 2023). The following components were utilized in the data acquisition process:

Table 1: Sensor Configuration and Data Acquisition Tools

Component Type	Model/Specification	Function	Frequency of Reading	Placement	Output Format
Soil Moisture Sensor	Capacitive v1.2 (Analog, 3.3–5V)	Measures volumetric water content	Every 30 minutes	10 sensors, 30 cm deep	Voltage (0–3V)
Ambient Temperature	DHT22	Records field-level temperature	Every 30 minutes	5 locations, 1.5 m height	°C
Relative Humidity	DHT22	Captures air moisture content	Every 30 minutes	Alongside temperature unit	% RH
Soil Temperature	DS18B20 (Waterproof)	Measures soil thermal profile	Every 30 minutes	Same locations as moisture	°C
Light Intensity	BH1750	Captures daylight input	Every 30 minutes	2 per hectare	Lux
Weather	OpenWeatherMap	Collects rainfall,	Hourly	API-based	JSON/CSV

Data API	(Hourly API)	solar radiation & wind		cloud sync	

All sensors were connected to Arduino Uno microcontrollers with LoRaWAN modules, enabling long-range, low-power data transmission to a local Raspberry Pi-based gateway, which stored data in a structured CSV format and relayed it to a centralized Firebase database for ML processing. Power to the sensor units was provided by 5V solar panels with 4400mAh Li-ion battery backups to ensure uninterrupted operation.

3.3 Dataset Overview

The total dataset included over 180,000 data points, consisting of real-time values for five environmental variables and supplemented by hourly weather inputs over two crop seasons. Data cleaning was performed to eliminate sensor anomalies such as spikes or dropouts using a 3-sigma filtering technique, resulting in 168,235 usable observations.

Table 2: Dataset Characteristics Summary

Parameter Category	No. of Data Points	Missing Data (%)	Range (min–max)
Soil Moisture (%)	33,647	1.3	4.8 – 33.9
Soil Temperature (°C)	33,658	0.9	18.2 – 37.1
Humidity (% RH)	33,629	0.7	32 – 97
Ambient Temperature (°C)	33,612	1.0	19.5 – 41.2
Light Intensity (Lux)	33,689	0.4	106 – 45,000

3.4 Machine Learning Model Development

The study utilized Random Forest Regression (RFR) as the primary Machine Learning algorithm for predicting optimal irrigation timing and volume. RFR was selected due to its robust performance in nonlinear, multidimensional regression problems and resistance to overfitting.

Table 3: ML Model and Configuration Details

Parameter	Description
ML Algorithm Used	Random Forest Regressor (Scikit-learn v0.24)
Target Variable	Soil moisture forecast for next 3 hours
Input Variables	Soil temp, air temp, humidity, rainfall, light
Training Data Split	70% training, 15% validation, 15% test
No. of Trees	100 decision trees
Evaluation Metrics	R^2 Score, RMSE, MAE
Forecast Horizon	3 hours (short-term prediction window)

Hyperparameter tuning was conducted using GridSearchCV with five-fold cross-validation to optimize the number of estimators and maximum tree depth.

3.5 Data Analysis Tool

All data processing and analysis were performed using IBM SPSS Statistics v28. Descriptive analytics (mean, SD, coefficient of variation) were computed for environmental variables, and multiple regression diagnostics were conducted to assess the contribution of each input to soil moisture predictions. Results of ML predictions were imported to SPSS for comparative analysis of model output versus observed values under traditional irrigation and ML-controlled scenarios.

Table 4: Summary of Analytical Scope and Tool

Aspect Analyzed	Tool Used	Variables	Outcome Variable	Output Metric
Descriptive Environment Stats	SPSS v28	Soil moisture, temp, humidity	—	Mean, SD, CV
Correlation Analysis		All 5 sensor variables	Soil moisture	Pearson r, p-values
Regression Impact Study		ML-predicted vs actual moisture	Water usage (liters/day)	R^2, F-test, RMSE
Energy Savings Comparison		Pump activation records	Energy (kWh/day)	% difference (traditional vs ML)

This rigorous, real-world method filled the research gap identified in Section 1 by ensuring full-cycle implementation of a hybrid WSN-ML framework and evaluating its actual impact across both biophysical and operational parameters. The use of a single, high-fidelity, sensor-based dataset enabled control and transparency in assessing model reliability and field feasibility.

4. Results and Analysis

4.1 Descriptive Profile of Environmental Variables

Table 1: *Descriptive Statistics for Sensor Variables across Two Cropping Seasons*

Variable	*M*	*SD*	Min	Max	CV (%)
Soil Moisture (%)	18.67	5.21	4.8	33.9	27.9
Soil Temperature (°C)	26.84	3.77	18.2	37.1	14.1
Air Temperature (°C)	29.43	4.08	19.5	41.2	13.9
Relative Humidity (% RH)	61.55	13.92	32	97	22.6
Light Intensity (Lux)	11 986	8 267	106	45 000	68.9

Interpretation.

The descriptive analysis revealed considerable heterogeneity among environmental inputs. Soil moisture averaged 18.67 %, indicating moderately dry field conditions for a semi-arid zone. The coefficient of variation (CV) of 27.9 % suggests pronounced intra-seasonal fluctuations, underlining the need for dynamic irrigation scheduling. Soil temperature's narrow CV of 14.1 % reflects greater thermal stability at 30 cm depth, whereas air temperature varied similarly (13.9 %). Relative humidity displayed moderate dispersion (22.6

%), signifying variable evaporative demand across diurnal cycles. Light intensity showed the highest dispersion (68.9 %), driven by rapid cloud cover changes during late monsoon spells. Collectively, these patterns justify a predictive approach that can accommodate sharp, asynchronous changes in micro-climate drivers affecting plant water demand.

4.2 Pearson Correlations among Predictors and Target Variable

Table 2: *Zero-Order Correlations between Environmental Variables and Soil Moisture*

Predictor	*r*	*p*
Soil Temperature	–0.63	< .001
Air Temperature	–0.51	< .001
Relative Humidity	+0.44	< .001
Light Intensity	–0.39	< .001
Rainfall (mm h^{-1})*	+0.58	< .001

*Rainfall sourced via OpenWeatherMap API.

Interpretation.
Correlation analysis confirmed theoretically consistent relationships. Soil temperature exhibited the strongest negative association with soil moisture (r = –0.63), indicating accelerated moisture depletion at elevated subsurface temperatures. Air temperature also showed a significant negative link (r = –0.51), reinforcing the role of atmospheric heat load on evapotranspiration. Relative humidity correlated positively (r = 0.44), suggesting that higher ambient moisture slows soil water loss. Incident light intensity held a moderate negative correlation (r = –0.39), as increased solar radiation drives evaporative demand. Rainfall showed the expected positive correlation (r = 0.58). All relationships were highly significant (p< .001), validating their inclusion as predictor variables in the Random Forest model and supporting the premise that multivariate, nonlinear interactions govern soil moisture dynamics in the study setting.

4.3 Random Forest Model Performance

Table 3: *Evaluation Metrics for Soil-Moisture Forecasts (Test Set, n = 25 236)*

Metric	Value
R^2	0.912
Root Mean Square Error (RMSE, %)	1.83
Mean Absolute Error (MAE, %)	1.37
Bias (Forecast – Observed, %)	–0.05

Interpretation.
The Random Forest Regressor delivered strong predictive accuracy, explaining 91.2 % of the variance in three-hour-ahead soil moisture values. An RMSE of 1.83 % and MAE of 1.37 % indicate narrow average deviations, well below agronomic decision thresholds (~3 %). The negligible bias (–0.05 %) suggests virtually no systematic over- or under-prediction. These outcomes outperform similar field studies that reported R^2 values around 0.80 and RMSE > 2.5 % using support-vector or k-nearest neighbor models under comparable climates. The high fidelity of short-range forecasts supports confident, data-driven irrigation triggers, a

critical step toward maximizing water use efficiency while preventing water stress or saturation-related yield losses.

4.4 Comparative Water-Use Outcomes

Table 4: Daily Irrigation Water Applied under Conventional vs. SIS Control (Mean of 196 Days)

Season	Method	*M* (L ha^{-1} day^{-1})	*SD*	Min	Max	% Reduction vs. Conventional
Kharif	Conventional	5 720	611	4 680	6 545	—
	SIS (WSN + ML)	4 063	544	3 210	4 892	28.9
Rabi	Conventional	4 815	533	3 956	5 602	—
	SIS (WSN + ML)	3 442	497	2 784	4 126	28.5

Interpretation.
Across 196 observation days, the SIS reduced mean daily irrigation volumes by roughly 29 % in both seasons. In Kharif, conventional farmers applied 5 720 L ha^{-1} day^{-1} on average, versus 4 063 L ha^{-1} day^{-1} under SIS management. Similar proportional savings were observed in Rabi (4 815 L vs. 3 442 L). Standard deviations were proportionately lower in SIS conditions, indicating more consistent application aligned with crop water demand forecasts. Minimum-to-maximum ranges narrowed by ~20 %, reflecting precise control and avoidance of excessive irrigation events common with manual scheduling. The water savings align with, yet slightly exceed, the 25-27 % range cited in the broader literature for comparable WSN-ML interventions, underscoring the benefits of fine-tuned, short-horizon forecasting and localized sensor calibration.

4.5 Energy Consumption of Pump Operations

Table 5: Pump Energy Use under Conventional and SIS Regimes

Metric	Conventional	SIS Control	Difference	% Change
Average Daily Runtime (min)	58.4	42.7	–15.7	–26.9
Mean Energy (kWh ha^{-1} day^{-1})	3.28	2.35	–0.93	–28.4
Peak Load (kW)	1.89	1.57	–0.32	–16.9
Number of Starts per Day	3.6	2.8	–0.8	–22.2

Interpretation.
Energy metrics paralleled water-use gains. Average pump runtime fell from 58.4 to 42.7 minutes per hectare per day, translating to a 28.4 % reduction in electrical consumption. The decline in start–stop cycles (–22.2 %) is particularly important: frequent starts elevate motor wear and peak-demand charges. Lower peak loads (–16.9 %) suggest smoother energy profiles, beneficial where rural feeders suffer voltage variability. The cumulative effect equates to an annual saving of ~340 kWh ha^{-1}—roughly ₹3 400 at prevailing tariffs—demonstrating the system's economic as well as environmental advantages. These findings

substantiate SIS as a dual-resource conservation tool, consistent with sustainability objectives for water-energy nexus management in agriculture.

4.6 Predictor Importance within the Random-Forest Ensemble

Table 6: *Normalized Variable Importance Scores (n = 100 Trees)*

Rank	Predictor	Mean Decrease in Impurity	Relative Weight (%)
1	Rainfall	0.214	28.7
2	Soil Temperature	0.189	25.3
3	Air Temperature	0.142	19.1
4	Relative Humidity	0.109	14.6
5	Light Intensity	0.094	12.3

Interpretation.
Variable-importance diagnostics highlight rainfall as the dominant explanatory factor, accounting for 28.7 % of total split reductions in impurity. This accords with the strong positive correlation observed earlier and validates the model's ability to weight episodic precipitation events appropriately. Subsurface and ambient temperatures jointly contribute 44.4 %, revealing the sensitivity of near-surface moisture flux to thermal drivers. Relative humidity and light intensity, though lower in rank, still supply meaningful incremental information by capturing evaporative demand nuances. The ordered hierarchy underscores the multifactorial nature of soil-water dynamics and supports the premise that integrating weather-API data with in-situ sensing is essential for robust, short-range forecasting. These results also provide agronomists with insight on which variables merit priority when sensor budgets or bandwidth limit the number of monitored parameters.

4.7 Agronomic Outcomes: Yield and Water Productivity

Table 7: *Grain Yield and Water Use Efficiency (WUE) under Conventional vs. SIS Management*

Metric	Conventional	SIS (WSN + ML)	Difference	% Change
Grain Yield (t ha^{-1})	3.42	3.79	+0.37	+10.8
Seasonal Water Applied (m^3 ha^{-1})	1 062	769	–293	–27.6
Water Productivity (kg m^{-3})	3.22	4.93	+1.71	+53.1
Harvest Index (%)	42.1	44.8	+2.7	+6.4

Interpretation.
Beyond resource metrics, SIS deployment translated into tangible agronomic gains. Average grain yield improved by 0.37 t ha^{-1}—an uplift of 10.8 % that farmers attributed to reduced water stress during critical flowering stages. Seasonal irrigation volume fell from 1 062 to 769 m^3 ha^{-1}, consistent with daily savings documented earlier. Consequently, water productivity leapt by 53.1 %, reaching 4.93 kg grain per cubic metre of water—well above regional benchmarks of ~3.5 kg m^{-3} for the same crop. The modest rise in harvest index (2.7 percentage points) hints at improved partitioning toward economic yield under optimized moisture regimes. These findings reinforce the premise that smart irrigation not only

conserves water but also enhances production outcomes, augmenting farm profitability and resilience in water-scarce contexts.

4.8 System Robustness and Network Reliability

Table 8: *Operational Health of WSN Infrastructure over 241-Day Monitoring Window*

Indicator	Mean	SD	Min	Max	Threshold	Status
Sensor Uptime (%)	97.4	2.1	91.1	99.8	≥ 95	Pass
Packet Loss Rate (%)	1.8	0.7	0.5	3.9	≤ 5	Pass
Gateway Downtime (h month^{-1})	0.62	0.31	0.00	1.25	≤ 2	Pass
Battery Voltage Drop (%)	11.3	4.2	3.4	19.6	≤ 25	Pass

Interpretation.

The WSN demonstrated high operational stability, with average sensor uptime of 97.4 %—comfortably exceeding the 95 % reliability benchmark for agronomic DSS applications. Packet loss averaged 1.8 %, largely occurring during sporadic LoRa interference windows at peak humidity, yet remained well under the 5 % tolerance ceiling. Gateway outages were negligible (0.62 h per month), attributable mainly to scheduled firmware updates rather than hardware faults. Solar-battery discharge never exceeded 20 %, affirming the adequacy of the 5 V/4 400 mAh power subsystem under semi-arid insolation profiles. Collectively, these diagnostics verify that the SIS architecture is technically resilient and capable of sustaining continuous data flows essential for dependable ML inference, directly addressing prevailing concerns in the literature about long-term sensor drift and network fragility in remote farming environments.

5. Discussion

5.1 Integration of Environmental Variables and Model Predictive Accuracy

The results from Section 4 demonstrate that the smart irrigation system (SIS) implemented through wireless sensor networks (WSNs) and Random Forest Regression (RFR) achieved high predictive accuracy for short-term soil moisture forecasts. The R^2 value of 0.912, with an RMSE of just 1.83%, substantiates the robustness of the chosen model and validates its use in agricultural decision-making. These findings are in strong agreement with the study conducted by Glória et al. (2021), where an ensemble model showed similar predictive potential in real-time applications. The minimal forecast bias and mean absolute error indicate that the system was finely tuned to respond to short-term environmental fluctuations, a crucial requirement in semi-arid farming contexts.

In the literature review, Tace et al. (2022) emphasized the role of decision-tree-based models in water-saving strategies. Our findings, particularly in terms of model sensitivity to key predictors such as rainfall and soil temperature, expand on this by quantifying their contribution within the Random Forest structure. Rainfall's relative importance of 28.7% aligns with its strong correlation coefficient ($r = 0.58$) and reinforces its weight in any predictive framework. Thus, the predictive modeling component of this study directly addresses the literature gap identified in Section 2.2—namely, the need for integrated, field-validated forecasting systems that account for real-world climatic dynamics.

5.2 Efficacy of Water Use and Energy Optimization

The SIS demonstrated significant reductions in water and energy usage compared to conventional irrigation methods. Daily irrigation volumes decreased by 28.9% in Kharif and 28.5% in Rabi, which is consistent with water-saving rates reported by Sami et al. (2022) and Ndunagu et al. (2022), who noted a 25–30% reduction in similar deployments. The drop in seasonal water applied (from 1 062 to 769 $m^3\ ha^{-1}$) and increase in water productivity by 53.1% provide empirical validation for claims made by Goldstein et al. (2018) that smart systems can substantially enhance agronomic efficiency.

Energy consumption metrics further support the dual resource-efficiency of SIS. A 28.4% reduction in mean daily pump energy usage and a 22.2% decrease in pump start-stop cycles signify not only operational savings but also improvements in system longevity and grid load distribution. These outcomes align with Ding and Du (2024), who stressed energy conservation through intelligent control systems. Our study adds quantitative depth by linking these reductions directly to algorithm-triggered irrigation schedules, substantiating the environmental and economic advantages of smart farming technologies.

5.3 Agronomic Impact and Yield Enhancement

Grain yield improvements under SIS (10.8% increase) reflect a more stable and moisture-appropriate growing environment, especially during flowering and grain-filling phases. These gains echo findings by Vij et al. (2020), who documented similar improvements in productivity through automated irrigation logic. Additionally, the increase in harvest index from 42.1% to 44.8% suggests more efficient biomass partitioning—a probable result of reduced abiotic stress.

This empirical yield enhancement directly addresses the practical needs of smallholder farmers and reinforces the potential of SIS as not merely a water-saving intervention but a crop-improving strategy. These agronomic results validate the broader thesis that technological solutions must simultaneously address productivity and sustainability, thereby fulfilling the dual mandate emphasized by González-Briones (2018) for deploying knowledge-based rural agriculture frameworks.

5.4 Multivariate and Contextual Sensitivity of ML Models

The correlation matrix and variable importance scores emphasize the need for contextualized models that can weigh predictors appropriately. For example, while rainfall emerged as the dominant variable, soil temperature and air temperature together accounted for nearly 45% of model sensitivity. This supports the argument made by Goldstein et al. (2018) about the undervaluation of thermal variables in conventional irrigation models and validates the use of a multi-sensor input matrix.

This finding further deepens the argument that SIS must integrate both in-situ data and cloud-based weather inputs for optimal performance. Our model's hybrid architecture—combining real-time sensors and weather API inputs—demonstrates a practical resolution to the data integration challenge identified by Mekonnen et al. (2019), who had advocated for predictive systems that do not rely solely on single-source datasets.

5.5 System Reliability and Network Stability

One of the critical challenges in WSN-based irrigation systems is maintaining operational stability over extended periods in field conditions. Our system recorded a 97.4% average sensor uptime over 241 days, and a packet loss rate well below 2%. This reliability not only meets but exceeds benchmarks proposed by Padmanaban and Kannan (2021) for autonomous irrigation infrastructure. Furthermore, minimal gateway downtime (0.62 h/month) and acceptable battery discharge rates affirm the technical feasibility of long-term deployment, especially in semi-arid or resource-scarce contexts.

These system performance indicators directly address the often-overlooked literature gap concerning infrastructure resilience. Unlike lab-based or greenhouse experiments, our findings reflect real-world conditions—intermittent cloud cover, variable solar charging, and ambient temperature extremes. Therefore, this component of our study provides unique and much-needed evidence for practitioners and researchers focusing on large-scale SIS deployment.

5.6 Bridging the Literature Gap: Unified SIS Implementation

A recurring issue in the reviewed literature is the fragmentation between sensor-network studies and machine learning applications. While some works, like those of Sami et al. (2022) or Glória et al. (2021), successfully demonstrated either model performance or hardware reliability, few provided a comprehensive framework that spans from data acquisition to field validation.

This research bridges that divide by providing an end-to-end empirical demonstration of a SIS—from data acquisition, model training, and prediction to irrigation control and impact assessment. By capturing over 180,000 field-level data points and validating the ML model under field conditions, the study provides a unified structure that can serve as a blueprint for future implementations. This is in line with the call by Tace et al. (2022) for scalable, validated, and interpretable systems that can move from academic pilot to rural application.

5.7 Implications for Policy, Practice, and Further Research

From a policy perspective, the demonstrated reductions in water and energy use position SIS as a strong candidate for inclusion in agricultural subsidy and sustainability programs. Given India's increasing focus on water conservation under schemes like 'Per Drop More Crop,' technologies validated by this study can support evidence-based scaling initiatives.

In practice, the findings reinforce the importance of investing in local sensor calibration, reliable data transmission, and user training. The economic value—through increased yield and energy savings—offers a compelling case for adoption among small and medium-scale farmers.

As for future research, the model can be expanded to include evapotranspiration indices, real-time NDVI data from satellite imagery, and adaptive control through reinforcement learning. Additionally, longitudinal trials across agro-climatic zones would further validate system adaptability and enhance generalizability.

Ultimately, this study offers a data-rich, empirically grounded demonstration of how SIS can advance sustainable agriculture, directly contributing to Sustainable Development Goals (SDGs) on clean water (SDG 6), sustainable agriculture (SDG 2), and climate resilience (SDG 13).

6. Conclusion

This research demonstrated the feasibility, efficiency, and broader potential of an integrated Smart Irrigation System (SIS) that combines wireless sensor networks (WSN) with machine learning (ML) to improve water use efficiency in agriculture. Through the deployment of a real-time, multi-sensor monitoring network and predictive modeling using Random Forest Regression, the system achieved accurate short-range soil moisture forecasts and significantly optimized irrigation schedules. The empirical results from the two cropping seasons showed not only substantial reductions in water usage—averaging nearly 29% across seasons—but also corresponding improvements in energy efficiency and crop yield. These findings contribute to a growing body of evidence supporting the viability of intelligent, data-driven irrigation frameworks for real-world agricultural applications.

Importantly, this study bridged a critical gap in the existing literature by implementing a full-cycle, field-based SIS that functioned autonomously and reliably over an extended period. The robustness of the system, validated through operational metrics such as sensor uptime and battery performance, underscores the practicality of deploying such solutions in semi-arid and resource-constrained environments. Furthermore, the predictive accuracy and interpretability of the machine learning model provide a strong foundation for its integration into broader agricultural decision support systems.

Beyond technical outcomes, the broader implications of this work extend to sustainability and policy. By reducing dependence on groundwater and minimizing energy consumption, the SIS supports key environmental goals, such as conservation of finite water resources and climate-smart agriculture. Its potential scalability, given its reliance on low-cost components and open-source platforms, makes it an attractive option for smallholder and marginal farmers across developing regions. This opens the door for government and institutional support in embedding smart irrigation practices within national water resource management frameworks.

Future research can build upon this work by incorporating additional data sources, such as satellite imagery and evapotranspiration indices, to enhance spatial coverage and prediction depth. Furthermore, the integration of reinforcement learning and adaptive feedback control could further refine irrigation logic under dynamically changing climatic conditions. Expanding the deployment across diverse agro-climatic zones will also be essential to test the generalizability and resilience of the model. Ultimately, this study establishes a replicable and scalable model for intelligent irrigation, aligning with the evolving intersection of digital agriculture, sustainability, and precision farming.

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