



MACHINE LEARNING-BASED INTELLIGENT WATER MANAGEMENT SYSTEM FOR AGRICULTURE

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ARTICLE ID IJREK-2026-00125	ARTICLE TYPE Research Article	RESEARCH AREA Machine Learning & Deep Learning	PUBLICATION Volume 1, Issue Issue 1 (2026)
RECEIVED 19 October 2026	REVISED 20 October 2026	ACCEPTED 19 October 2026	PUBLISHED 20 October 2026

Abstract

Agriculture depends on reliable access to water, yet irrigation decisions are often affected by changing weather, soil variability, crop growth stages, and limited monitoring. This paper proposes a Machine Learning-Based Intelligent Water Management System for Agriculture that combines soil-moisture observations, weather information, crop and soil profiles, and irrigation history to support timely water-management decisions. The proposed design uses a sensor and controller layer to collect and validate data, a machine-learning module to estimate short-term water need, and a safety layer to determine whether irrigation should be recommended or activated. The system includes rainfall checks, sensor-fault handling, maximum pump-runtime limits, manual override, and post-irrigation feedback. A rule-based threshold controller is retained as a transparent baseline and fallback when model confidence is low or connectivity is unavailable. The paper outlines system architecture, a conceptual algorithm, candidate hardware and software, evaluation metrics, limitations, and future development. This is a design-oriented paper; it does not claim measured water savings, yield improvement, or field-test results. Such benefits must be established through controlled and documented field evaluation.

Keywords: Machine learning; intelligent water management; precision agriculture; smart irrigation; soil-moisture sensing; Internet of Things; water-use efficiency

I. INTRODUCTION

A. Background and Context Water management is a major operational concern in agriculture. Fixed irrigation schedules and decisions based only on visual inspection may not fully reflect current soil moisture, rainfall forecasts, crop growth stage, or local environmental conditions. Excess irrigation can waste water and energy, while insufficient irrigation can expose crops to water stress. A data-driven system can help farmers combine repeated field measurements with contextual information and make irrigation decisions more consistent and explainable. B. Problem Statement The core problem is to determine when and how much water should be supplied to a crop zone using reliable data while avoiding unnecessary irrigation and unsafe pump operation. A single sensor threshold is not sufficient for every crop, soil, or season. Sensors can drift, weather services can fail, and a model trained for one field may not generalize to another. Therefore, the system must combine machine-learning estimates with agronomic settings, validated sensor readings, safety checks, and farmer control. C. Aim and Objectives Design a modular system for collecting soil, weather, crop, and irrigation data. Use machine learning to estimate short-term irrigation need or soil-moisture decline when suitable data are available. Retain a transparent threshold-based controller as a baseline and fallback. Define safety measures for invalid sensors, expected rainfall, water availability, and pump runtime. Propose measurable evaluation criteria without inventing experimental results. Consider affordability, connectivity, maintenance, and usability for small and medium farms. D. Scope and Contribution This paper presents a literature-informed system proposal rather than a report of completed field experimentation. Its main contribution is a hybrid design that separates prediction from safety-critical actuation, incorporates feedback after irrigation, and defines a practical evaluation protocol. The design can be implemented as a student prototype using a microcontroller, moisture sensors, a relay or motor driver, a pump or valve, a data store, and a web or mobile dashboard.

II. LITERATURE REVIEW AND RELATED WORK

TABLE I

Research theme	Implication for the proposed system
Soil-moisture sensing [2], [7]	Calibrate probes and place them representatively; do not rely on one unverified reading.
Machine-learning estimation [3], [4], [6]	Compare models with a threshold baseline and validate across different days or plots.
Multi-source intelligent irrigation [5]	Combine local sensing with weather and crop context while tracking data quality.
Water conservation [1]	Evaluate applied water alongside crop condition; less water is not beneficial if it causes stress.

III. PROPOSED SYSTEM AND METHODOLOGY

TABLE II

Farmer / Web or Mobile Dashboard			
Controller / API Gateway and Safety Rules			
Soil Moisture + Environment	Weather Forecast	Crop Profile	Soil
Decision Engine: Threshold Baseline + Validated ML Prediction			
Pump / Valve Control + Alerts + Event Logs			
Feedback: Post-irrigation sensor readings and reassessment			

Component	Purpose	Design consideration
Soil-moisture sensors	Estimate water availability in the root zone.	Calibration, placement, corrosion, sensor drift.
Weather input	Provide rainfall forecasts and atmospheric variables.	Forecast uncertainty and service outages.
Controller / edge node	Read sensors, validate data, execute local rules.	Safe baseline operation during network loss.
ML decision module	Estimate water need or probability of moisture deficit.	Use validated data; report uncertainty.
Pump / valve driver	Apply irrigation for a bounded duration.	Electrical isolation, dry-run protection, runtime limit.
Dashboard and logs	Show readings, recommendations, status, and override	Readable interface, timestamps, access control.

Fig. 1. Proposed architecture of the machine-learning-based intelligent water-management system.

IV. CONTROL ALGORITHM AND SAFETY LOGIC

A. Conceptual Algorithm Step Operation Read soil-moisture sensors, weather data, crop profile, and actuator status. Check timestamps, sensor ranges, connectivity, and data-quality flags. If a critical reading is invalid, stop automatic actuation and notify the farmer. Estimate moisture deficit and near-term irrigation need using baseline rules and, if validated, an ML model. Check rainfall, water availability, pump status, maximum runtime, and minimum off-time. If all conditions permit, activate irrigation for a bounded duration or request approval. Stop the pump, record runtime or estimated volume, and re-read moisture after a suitable delay. Log the decision and outcome for monitoring and later model evaluation. Read data Validate Estimate need Apply safety checks Act / alert Log and reassess

Step	Operation
1	Read soil-moisture sensors, weather data, crop profile, and actuator status.
2	Check timestamps, sensor ranges, connectivity, and data-quality flags.
3	If a critical reading is invalid, stop automatic actuation and notify the farmer.
4	Estimate moisture deficit and near-term irrigation need using baseline rules and, if validated, an ML model.
5	Check rainfall, water availability, pump status, maximum runtime, and minimum off-time.
6	If all conditions permit, activate irrigation for a bounded duration or request approval.
7	Stop the pump, record runtime or estimated volume, and re-read moisture after a suitable delay.
8	Log the decision and outcome for monitoring and later model evaluation.

Read data	Validate	Estimate need	Apply safety checks	Act / alert	Log and reassess
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Fig. 2. Conceptual control and feedback workflow; field validation is required.

V. IMPLEMENTATION PLAN

TABLE III

Layer	Candidate implementation	Notes
Sensing	Capacitive soil-moisture sensor; optional temperature/humidity sensor.	Select rugged components and calibrate in target soil.
Edge control	ESP32 or comparable microcontroller; relay/driver and pump/valve.	Electrical protection and enclosure are required.
Backend	Python API using FastAPI/Flask or a local service.	Separate model logic from physical actuation.
Data store	SQLite for a prototype; PostgreSQL or MongoDB for larger deployments.	Store readings, events, device health, and configuration.
ML analysis	Python with scikit-learn or another validated library.	Use time-aware validation and avoid data leakage.
User interface	Mobile-friendly dashboard with readings and alerts.	Show units, data freshness, action reason, and override.

VI. EVALUATION PLAN AND DISCUSSION

TABLE IV

Metric	How to measure	Interpretation
Applied irrigation water	Flow meter or calibrated volume per plot and period.	Compare under similar crop and weather conditions.
Soil-moisture stability	Time within crop-specific target band; time below threshold.	Indicates whether water availability is maintained.
Crop response	Yield, plant-health observations, or suitable agronomic measure.	Avoid water savings achieved by harming crops.
Control reliability	Successful commands, missed/false triggers, and fault events.	Measures safety and operational robustness.
Prediction quality	MAE/RMSE for numeric estimates; precision/recall for events.	Compare with a simple baseline using time-aware validation.
Usability and cost	Setup time, maintenance, energy, connectivity cost, user feedback.	Assesses suitability for the intended farm.

VII. LIMITATIONS, ETHICS, AND FUTURE SCOPE

A. Limitations Sensor readings are local and may not represent an entire field; installation and calibration affect reliability. Weather forecasts and network services may be delayed, inaccurate, or unavailable. ML models require representative labelled data and may not transfer across crops, soils, and seasons. Software alone cannot detect every plant stress or hydraulic fault without suitable sensors. Hardware, maintenance, power, connectivity, and farmer training may limit adoption. The proposed design does not establish measured water savings, yield improvement, or cost reduction. B. Responsible Use Irrigation recommendations should complement, not replace, local agronomic advice. The interface should explain why watering is recommended, show the freshness of sensor and weather data, and make manual override accessible. Thresholds and model updates should not change silently. Any field study should obtain informed participation where user data are collected and avoid publishing identifiable farm information without permission. C. Future Scope Future work may incorporate evapotranspiration estimates, satellite or drone observations, crop-growth models, multi-zone optimization, solar-powered sensing, and low-connectivity operation. Further research should examine cross-season validation, robust sensor-fault detection, transparent explanations, and affordability for smallholder farms. Regional-language voice prompts and local agricultural advisories may improve accessibility if tested with intended users.

VIII. CONCLUSION

This paper proposes a Machine Learning-Based Intelligent Water Management System for Agriculture that combines soil-moisture sensing, weather context, crop profiles, decision logic, and bounded pump or valve control. Its central design principle is to separate machine-learning prediction from safety-critical actuation: the model can assist with estimating irrigation need, while sensor validation, local interlocks, maximum runtime, and manual override protect reliable operation. Prior research indicates growing interest in machine learning and IoT for irrigation decisions, while data quality, generalization, and evaluation remain important challenges [2]–[7]. The proposed system should be evaluated against a transparent baseline using measured water volume, soil-moisture behaviour, crop response, reliability, prediction quality, and total cost. No performance improvement should be claimed until supported by a documented field study.

REFERENCES

[1] Food and Agriculture Organization of the United Nations (FAO), “Water Conservation and Smart Irrigation,” FAO in India, 8 October 2026. Available: <https://www.fao.org/india/home/water-conservation-and-smart-irrigation/en>

[2] R. Togneri, R. Prati, H. Nagano, and C. Kamienski, “Data-driven water need estimation for IoT-based smart irrigation: A survey,” *Expert Systems with Applications*, vol. 225, art. 120194, 2023, doi: 10.1016/j.eswa.2023.120194.

[3] Y. Abiadi et al., “The application of machine learning techniques for smart irrigation systems: A systematic literature review,” *Smart Agricultural Technology*, vol. 7, art. 100425, 2024, doi: 10.1016/j.atech.2024.100425.

[4] L. Umutoni and V. Samadi, “Application of machine learning approaches in supporting irrigation decision making: A review,” *Agricultural Water Management*, vol. 294, art. 108710, 2024, doi: 10.1016/j.agwat.2024.108710.

[5] H. Hammouch et al., “A Systematic Review and Meta-Analysis of Intelligent Irrigation Systems,” *IEEE Access*, vol. 12, pp. 128285–128304, 2024, doi: 10.1109/ACCESS.2024.3421322.

[6] M. Del-Coco, M. Leo, and P. Carcagni, “Machine Learning for Smart Irrigation in Agriculture: How Far along Are We?,” *Information*, vol. 15, no. 6, art. 306, 2024, doi: 10.3390/info15060306.

[7] A. E. G. and G. J. Bala, “IoT and ML-based automatic irrigation system for smart agriculture system,” *Agronomy Journal*, vol. 116, no. 3, pp. 1187–1203, 2024, doi: 10.1002/agj2.21344.

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