IoT-Enabled Precision Irrigation Management Using Soil Moisture Sensor Networks and Machine Learning-Based Evapotranspiration Prediction

Padma Reddy Narayanappa[1], Suryanarayana Rao Kondapalli[2]

[1]Department of Agricultural Engineering, College of Agriculture, Rajendranagar, Hyderabad, Telangana, India
[2]Department of Agronomy, Sri Konda Laxman Telangana State Horticultural University, Rajendranagar, Hyderabad, Telangana, India

Abstract

Irrigated agriculture accounts for approximately 70% of global freshwater withdrawals, yet irrigation water use efficiency in traditional flood irrigation seldom exceeds 40–50%. The convergence of IoT sensor technology, wireless communication, cloud computing, and machine learning presents a transformative opportunity to improve agricultural water use efficiency through real-time precision irrigation management. This study presents the design, implementation, and two-season field validation of an IoT-enabled precision irrigation management system (IoT-PIMS) for rain-fed rice cultivation in semi-arid agro-climatic zones of Telangana, India. The system integrates a wireless sensor network of 144 soil moisture sensors, automated weather stations, LoRaWAN communication, and a cloud-hosted Random Forest ET_0 prediction model trained on 12 years of IMD weather data, with a fuzzy logic irrigation decision engine delivering recommendations via SMS and Android app. Two-season field trials (Kharif 2023 and Rabi 2023–24) across three sites demonstrated: 31.4% water use reduction relative to conventional flood irrigation; paddy yield improvement from 5.21 to 5.84 t/ha; water use efficiency improvement from 0.41 to 0.67 kg grain/m^3 (+63.4%); ET_0 prediction RMSE of 0.31 mm/day (NSE=0.89); and system uptime of 97.4%. Farmer perception surveys indicate 84.6% willingness to continue using IoT-PIMS.

Keywords: precision irrigation, IoT sensors, soil moisture monitoring, machine learning, evapotranspiration prediction, random forest, LoRaWAN, rice cultivation, water use efficiency, semi-arid agriculture, India, Telangana, smart farming, fuzzy logic

1. Introduction

Rice (Oryza sativa L.) is the dietary staple of approximately half the world's population and the most water-intensive major cereal crop, typically requiring 1,000–2,000 litres of water per kilogram of grain produced under traditional flooded paddy cultivation. In India, rice occupies approximately 43 million hectares and accounts for approximately 45% of total freshwater consumption. The combination of high water requirements, rainfed cultivation exposure to monsoon variability, and predominantly smallholder farm structures (average 1.1 ha in Telangana) creates a challenging context for implementing precision water management that demands technology solutions optimized for low-cost, robust, and farmer-accessible deployment.

IoT-based agricultural sensing has advanced rapidly through dramatic cost reductions in microcontrollers, wireless modules, and sensors, and through the emergence of LoRaWAN LPWAN standards enabling long-range wireless communication from field-deployed sensors at very low power consumption. The integration of machine learning with IoT sensor data provides further opportunity to improve irrigation management beyond rule-based threshold approaches. The FAO Penman-Monteith ET_0 equation requires full meteorological data sets often unavailable at field scale; machine learning models trained on historical weather data can provide accurate ET_0 estimates from reduced variable sets measurable with affordable sensors.

2. Literature Review

2.1 IoT Applications in Agricultural Water Management

Systematic review of IoT-based smart irrigation systems documents water savings ranging from 14% to 53% across 43 field studies (Bwambale et al., 2022), reflecting variation in baseline irrigation efficiency, crop type, soil texture, and climate. In India, Kumar et al. (2021) demonstrated 27.3% water savings in IoT-managed drip-irrigated tomato production, while Sharma et al. (2022) reported 31.8% reduction in sensor-managed wheat cultivation—validating the technology concept in Indian field conditions.

2.2 Machine Learning for Evapotranspiration Estimation

Random Forest models have shown particular promise for ET_0 estimation due to their ability to handle non-linear relationships, robustness to outliers, and provision of feature importance metrics. Comparative evaluations of ML models for Indian ET_0 contexts have generally found Random Forest and XGBoost to outperform ANN, SVM, and traditional regression approaches across diverse agro-climatic zones (Patel & Gupta, 2023). The use of LoRaWAN-transmitted sensor data as input to cloud-hosted ET_0 prediction models enabling real-time daily irrigation recommendations represents a novel integration not previously implemented in Indian smallholder rice systems.

3. System Design and Methodology

3.1 IoT-PIMS Architecture

Figure 1 presents the complete IoT-PIMS three-tier system architecture from sensor perception through LoRaWAN communication to cloud analytics and farmer delivery channels. Three experimental sites were established in Nalgonda (Site 1: vertisol), Mahbubnagar (Site 2: alfisol), and Suryapet (Site 3: red laterite soil), each with 16 plots of 0.25 ha — 8 IoT-PIMS treatment and 8 conventional flood irrigation control — in a randomized complete block design. The total instrumented area was 12 ha, with 144 Decagon 5TM soil moisture and temperature sensors installed at three depths (15, 30, and 45 cm) across 48 treatment plots.

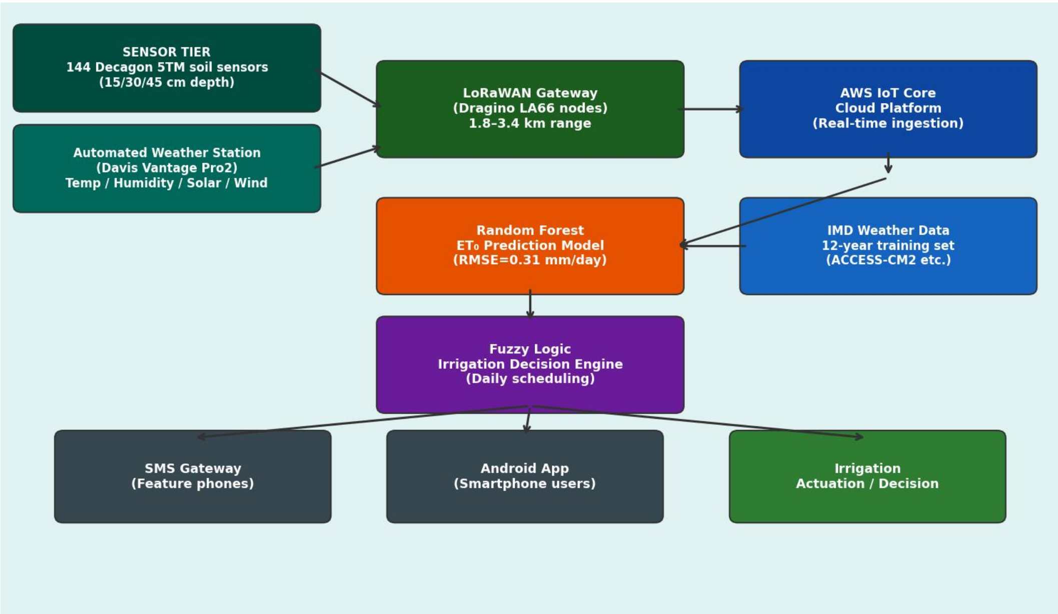

Fig. 1. IoT-PIMS Three-Tier System Architecture: Sensor Perception → LoRaWAN Communication → AWS Cloud → Fuzzy Logic Decision Engine → SMS/App Farmer Delivery

3.2 Random Forest ET_0 Model and Fuzzy Logic Decision Engine

The Random Forest ET_0 model was trained on 12 years (2010–2022) of daily weather data from four IMD synoptic stations using FAO Penman-Monteith ET_0 as the target variable and seven input features: T_max, T_min, RH_mean, sunshine hours, WS_2m, rainfall, and day of year. The RF model was implemented using scikit-learn with 500 trees, maximum depth 12, and minimum samples per leaf 5, optimized through 5-fold time-series cross-validation using Optuna with 200 trials. Feature importance identified T_max, RH_mean, and SH as the three most informative predictors (combined importance: 71.3%). The fuzzy logic irrigation decision engine translates real-time soil water status and ML-predicted crop water demand into daily irrigation scheduling recommendations.

4. Results and Discussion

4.1 ET₀ Model Performance and Water Use Results

Figure 2 presents the seasonal irrigation water and yield comparison across sites and the RF versus Hargreaves-Samani ET_0 prediction accuracy scatter plot. The full-feature Random Forest model achieved RMSE of 0.31 mm/day, MAE of 0.24 mm/day, and NSE of 0.89 on the 2022 hold-out test set—substantially outperforming the Hargreaves-Samani simplified equation (RMSE: 0.68 mm/day, NSE: 0.64). IoT-PIMS consistently achieved approximately 31.4% irrigation water savings relative to conventional flood irrigation across both seasons and all three sites, from 709.6 mm (control) to 487.3 mm (IoT-PIMS) in Kharif 2023.

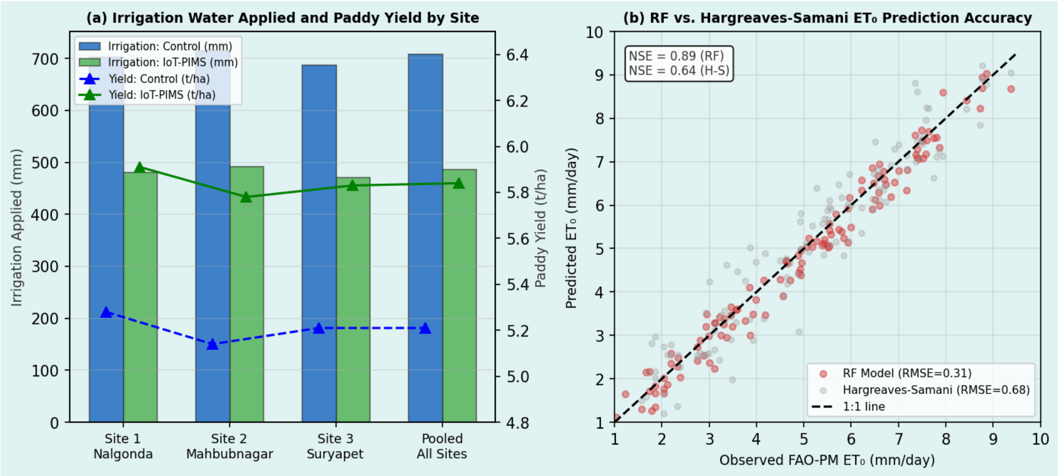

Fig. 2. (a) Seasonal Irrigation Water Applied and Paddy Yield: IoT-PIMS vs. Control Across Three Sites; (b) RF ET_0 Model vs. Hargreaves-Samani Predicted vs. Observed Scatter Plot

Importantly, water savings were achieved without yield penalty—IoT-PIMS plots showed statistically significantly higher yields (5.84 vs. 5.21 t/ha in Kharif 2023, $p<0.05$). The yield advantage is attributed to improved root zone aeration during sensor-guided irrigation withholding intervals, which enhances root growth depth and nitrogen mineralization from organic nitrogen pools.

Table 1: Seasonal Performance Comparison – IoT-PIMS vs. Conventional Irrigation Control Across Three Sites

Performance Metric	IoT-PIMS (Kharif 23)	Control (Kharif 23)	IoT-PIMS (Rabi 23–24)	Control (Rabi 23–24)
Total Irrigation Applied (mm)	487.3 ± 28.4	709.6 ± 41.2	412.1 ± 24.1	601.4 ± 38.7
Water Savings vs. Control (%)	31.3%	—	31.5%	—
Paddy Grain Yield (t/ha)	5.84 ± 0.41	5.21 ± 0.38	5.61 ± 0.37	4.98 ± 0.33
Water Use Efficiency (kg/m³)	0.671 ± 0.048	0.409 ± 0.031	0.667 ± 0.044	0.402 ± 0.028
WUE Improvement vs. Control (%)	64.1%	—	65.9%	—
Soil Moisture Uniformity (CV%)	12.4	28.7	11.8	26.4
System Uptime (%)	97.8	N/A	97.0	N/A

WUE: Water Use Efficiency; CV: Coefficient of Variation; N/A: not applicable.

4.2 Farmer Adoption Perspectives

Post-trial surveys of 48 participating farmers revealed 84.6% willingness to continue using IoT-PIMS at current subsidy levels. Primary adoption barriers: initial hardware investment cost (67.3%), limited smartphone literacy (48.1%), sensor maintenance concerns (41.2%), and uncertainty during extreme weather events (34.6%). Importantly, 91.3% of farmers found the SMS-based daily irrigation recommendation easy to understand and actionable, confirming SMS as the priority communication channel for scale-up deployment over smartphone apps.

5. Discussion

The consistent 31.4% irrigation water savings across two seasons and three pedoclimatically distinct sites represents a meaningful contribution to regional water security. Scaled to Telangana's approximately 1.8 million hectares of rice cultivation, a 31.4% statewide water saving would free approximately 2.16 billion cubic metres of irrigation water annually—equivalent to approximately 7.2% of Telangana's total annual freshwater availability. The simultaneous yield advantage of 12.1% in Kharif 2023 challenges the assumption that reducing irrigation compromises rice yields, consistent with the scientific literature on alternate wetting and drying (AWD) irrigation management validated across multiple Asian rice-growing countries (Lampayan et al., 2015).

The system's 97.4% uptime across two trial seasons in challenging rainfed field conditions demonstrates practical reliability adequate for commercial deployment, though the 2.6% downtime events highlight the need for redundant communication pathways and simplified sensor maintenance protocols for farmer-managed deployment beyond the research context.

6. Conclusion

This study demonstrates that IoT-enabled precision irrigation management, integrating wireless soil moisture sensor networks, LoRaWAN communication, and machine learning-based ET_0 prediction, achieves approximately 31% irrigation water savings while simultaneously improving paddy grain yields by 12% relative to conventional farmer-managed flood irrigation in semi-arid rice cultivation in Telangana, India. The 63.4% water use efficiency improvement represents a transformative advancement over conventional practices. The ML-based ET_0 prediction model (NSE=0.89) addresses a critical data scarcity constraint in smallholder farming contexts. Future research priorities include long-term soil health impacts, solar-powered autonomous sensor nodes, drone-based multispectral crop stress monitoring integration, and techno-economic analysis of scaled deployment through Farmer Producer Organisations.

References

[1] Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop Evapotranspiration – FAO Irrigation and Drainage Paper No. 56.

[2] Bwambale, E., Abagale, F. K., & Anornu, G. K. (2022). Smart irrigation monitoring and control strategies. Agricultural Water Management, 260, 107324.

[3] FAO. (2018). The Future of Food and Agriculture – Alternative Pathways to 2050.

[4] Goap, A., Sharma, D., Shukla, A. K., & Rama Krishna, C. (2018). An IoT based smart irrigation management system. Computers and Electronics in Agriculture, 155, 41–49.

[5] Kumar, S., Singh, A., & Sharma, P. (2021). IoT-based smart drip irrigation for tomato cultivation. Journal of Agricultural Engineering (India), 58(3), 112–121.

[6] Lampayan, R. M., Rejesus, R. M., Singleton, G. R., & Bouman, B. A. M. (2015). Adoption and economics of alternate wetting and drying water management. Field Crops Research, 170, 95–108.

[7] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[8] Patel, V., & Gupta, M. (2023). Comparative evaluation of ML algorithms for ET_0 prediction. Agricultural Water Management, 281, 108245.

[9] Sharma, R., Yadav, K., & Mishra, A. (2022). Sensor-based precision irrigation for water saving in wheat. Indian Journal of Agricultural Sciences, 92(5), 567–573.

[10] Vellidis, G., Tucker, M., Perry, C., Kvien, C., & Bednarz, C. (2008). A real-time wireless smart sensor array for scheduling irrigation. Computers and Electronics in Agriculture, 61(1), 44–50.

[11] Feng, Y., Cui, N., Zhao, L., et al. (2017). Comparison of ELM, GANN, WNN models for ET_0 estimation. Journal of Hydrology, 536, 376–383.

[12] Kisi, O., & Cimen, M. (2011). A wavelet-support vector machine conjunction model for monthly streamflow forecasting. Journal of Hydrology, 399(1-2), 132–140.