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A Smart Irrigation Advisory System Using Hybrid Rainfall Forecasting And Iot-Based Soil Moisture Monitoring

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Abstract: Climate variability and inefficient irrigation contribute to water stress and reduced crop productivity worldwide. This paper presents a Smart Irrigation Advisory System that integrates a hybrid rainfall forecasting model with an IoT-based soil moisture monitoring network to provide timely, actionable irrigation recommendations. The forecasting module fuses statistical and machine-learning (deep learning) approaches to improve short- and medium-term rainfall prediction. The sensing module comprises distributed low-cost soil moisture sensors (multi-depth), connected via low-power wireless links to a cloud backend. A decision-support engine fuses forecasted rainfall, real-time soil moisture, crop-specific crop water requirements and evapotranspiration estimates to produce irrigation advisories delivered through a mobile/web interface. A pilot deployment in a semi-arid region evaluated the system for one crop season: the hybrid forecasting reduced rainfall prediction MAE by ~14% versus single-model baselines, and advisory-driven irrigation scheduling reduced water usage by ~22% while maintaining yield within 3% of conventional scheduling. The results demonstrate that combining hybrid forecasting and IoT sensing enables more efficient, climate-resilient irrigation.

Keywords: Smart Irrigation, IoT, Soil Moisture Monitoring, Hybrid Rainfall Forecasting, Decision Support System, Precision Agriculture, Water-Use Efficiency.

I. INTRODUCTION

Water scarcity is a major constraint on agricultural productivity in many regions. Precision irrigation — applying the right amount of water, at the right time and place — is a proven approach to increase water-use efficiency and maintain yields while reducing resource waste. Recent advances in IoT sensing and machine learning have enabled automated decision systems that exploit both local soil status and weather forecasts to optimize irrigation scheduling. Reviews of precision irrigation and IoT in smart farming underline the potential gains from integrated sensing and predictive analytics. [1]

However, practical systems face two core technical challenges: (1) accurately forecasting short-term rainfall events that influence irrigation needs, and (2) acquiring reliable, timely soil moisture data at field scale using durable, low-cost sensors and robust connectivity. This work addresses both by (a) developing a hybrid rainfall forecasting pipeline that combines statistical and deep learning models for enhanced prediction accuracy, and (b) deploying an IoT soil moisture network with multi-depth sensing and low-power telemetry. The outputs feed a decision-support engine to generate farmer-facing advisories.

1.1.Contributions of this paper:

1. Design and implementation of a hybrid rainfall forecasting model combining statistical decomposition and LSTM/CNN hybrids for short-term prediction.
2. A practical IoT soil moisture sensing and communications architecture optimized for low-cost, field deployment.
3. A decision-support algorithm that fuses forecasted rainfall, soil moisture, crop coefficients, and ET estimates to produce irrigation advisories.
4. Results from a pilot study demonstrating reduced water use and improved irrigation timing.

II. RELATED WORK

IoT-based smart irrigation systems and sensor networks have been surveyed extensively; prior works show clear benefits of soil-moisture-driven irrigation and discuss typical architectures and communication protocols. [1] Precision irrigation reviews summarize technological trends and water saving potentials and stresses the need for decision-support layers. [1]

For rainfall forecasting, hybrid approaches combining statistical time-series (e.g., SSA, ARIMA) with machine learning or deep learning (LSTM, CNN-LSTM) have shown improved short-term precipitation forecasts over single-model solutions. Recent hybrid frameworks use decomposition (MSSA/MSSA variants) and sequence models to capture temporal patterns. [3]

Several recent implementations have combined IoT sensing with predictive analytics in irrigation contexts; however, few works tightly integrate hybrid rainfall forecasting with multi-depth soil moisture sensing plus a user-friendly advisory interface in real field trials—this paper aims to fill that gap. [4]

III. SYSTEM OVERVIEW AND REQUIREMENTS

3.1 SYSTEM GOALS

- Maximize water-use efficiency (minimize unnecessary irrigation) while maintaining crop yield.
- Provide reliable short-term rainfall predictions to reduce needless irrigation before forecasted rains.
- Deliver easy-to-understand advisories to farmers (mobile/SMS/local language).
- Use low-cost, maintainable hardware suitable for smallholder contexts.

3.2 HIGH-LEVEL ARCHITECTURE

The system has four layers:

1. **Sensing layer:** Distributed soil moisture sensors (capacitance or TDR-based low-cost sensors) at multiple depths, local microcontroller nodes (e.g., ESP32/Arduino) for data acquisition.
2. **Communication layer:** LoRaWAN/NB-IoT/LoRa point-to-point or GSM depending on site, to relay data to the gateway/cloud. [8]
3. **Analytics layer:** Hybrid rainfall forecasting engine, ET and water-balance models, fusion-based decision engine.
4. **Application layer:** Mobile/web dashboard, SMS gateway, advisory generation and logging.

IV. HYBRID RAINFALL FORECASTING MODULE

4.1 RATIONALE

Short-term irrigation decisions hinge heavily on accurate rainfall forecasts. Hybrid models typically outperform single methods by combining the strengths of statistical decomposition (to extract trend/seasonality) with machine learning’s ability to capture non-linearities. Recent studies report improvements in error metrics (MAE, RMSE) with hybrid techniques. [3]

4.2 MODEL PIPELINE

1. **Input data:** Historical hourly/daily rainfall from the nearest Automatic Weather Station (AWS), local gauge data, satellite-based precipitation products (for spatial context).
2. **Preprocessing:** Missing-value imputation, outlier filtering, normalization, feature engineering (lags, rolling statistics, meteorological covariates like humidity, pressure).
3. **Decomposition/Feature extraction:** Use MSSA or seasonal-trend decomposition to separate components (trend/seasonality/noise) and extract principal components as inputs. [3]
4. **Machine Learning core:** A CNN-LSTM hybrid that uses convolutional layers to learn short-term spatial/temporal feature transforms and LSTM layers to model sequential dependencies. Alternative candidates: MLP optimized with PSO or SVR optimized by ABC; we evaluated CNN-LSTM and LSTM ensembles.
5. **Model Ensemble & Postprocessing:** Combine statistical forecast (e.g., ARIMA or MSSA residual model) and ML output via weighted ensemble (weights derived from cross-validation performance) to produce probabilistic forecasts (quantiles) for 1–7 day horizons.

6. **Evaluation metrics:** MAE, RMSE, NSE (Nash–Sutcliffe), and Brier score for probabilistic aspects.

4.3 TRAINING AND VALIDATION

- Training on multi-year local data (5–10 years if available), with walk-forward cross validation to mimic operational forecasting.
- Benchmark models: ARIMA, LSTM, CNN-LSTM, and the hybrid ensemble.

V. IOT SOIL MOISTURE MONITORING NETWORK

5.1 HARDWARE & SENSING STRATEGY

- Sensors: Cost-efficient capacitance-based soil moisture probes (or low-cost TDR where budget allows) installed at multiple depths (e.g., 10 cm, 30 cm, 60 cm) to capture root-zone moisture dynamics. Recent reviews highlight multi-depth sensing as critical for crop water assessment. [4]
- Nodes: Microcontroller (ESP32 or similar) with ADC or sensor interface, a local power solution (solar + battery), a low-power radio (LoRa/LoRaWAN) for long-range low-power transmission or NB-IoT/GSM where coverage exists. [2]
- Gateway & Cloud: Data aggregated at a gateway, forwarded to cloud for storage and analytics (timeseries DB + processing pipelines).

5.2 DATA QUALITY & CALIBRATION

- Field calibration against volumetric water content (VWC) measured with gravimetric methods or commercial TDR during deployment to convert sensor raw units to VWC.
- Filtering and sensor health checks (outlier rejection, drift detection). Use redundancy and sensor ensembles at representative locations to reduce noise.

5.3 COMMUNICATIONS & POWER CONSIDERATIONS

- LoRaWAN recommended for rural deployments with central gateways; NB-IoT or cellular for dispersed, low-density fields. Tradeoffs: range vs cost vs power. [2]
- Solar panels + small battery for autonomous operation; duty-cycling sensors and radios to extend lifetime.

VI. DECISION SUPPORT AND ADVISORY ALGORITHM

6.1 INPUTS

- Real-time soil moisture at multiple depths.
- Forecasted rainfall (probabilistic) for next 1–7 days.
- Crop type and growth stage (crop coefficient Kc).
- Reference evapotranspiration (ETo) estimated from local weather (Penman-Monteith or Hargreaves when limited data).
- Irrigation system constraints (pump capacity, water availability).

6.2 ALGORITHM

1. **Soil Water Balance:** Compute current root-zone available water (AW) and forecast depletion considering ETo and crop Kc.
2. **Rainfall Adjustment:** Use probabilistic rainfall forecasts; if probability of ≥X mm exceeds threshold P (e.g., P>0.6 for ≥5 mm), postpone irrigation. Otherwise, schedule irrigation to refill AW to target field capacity or crop-specific threshold.
3. **Optimization Objective:** Minimize total irrigation volume subject to AW≥criticalLimit and avoiding irrigation immediately before expected rainfall (to prevent runoff/waste).
4. **Advisory Generation:** Translate optimization output into farmer-friendly messages (e.g., “Irrigate 30 minutes at 4 m^3/h tonight; postpone if >5 mm rain occurs before 06:00 tomorrow”), and provide confidence and rationale.

6.2.1.Algorithm: End-to-End Smart Irrigation Decision Framework

1. Inputs

1. Historical rainfall data R(t−n:t)R(t-n:t)R(t−n:t)
2. Meteorological variables (Temperature, Humidity, Wind speed, Solar radiation)
3. Real-time soil moisture readings SMd(t)SM_d(t)SMd(t), d=1,2,...,Dd = 1,2,...,Dd=1,2,...,D
4. Field parameters: Field Capacity (FC), Wilting Point (WP)
5. Root-zone depth ZrZ_rZr
6. Crop coefficient Kc(t)K_c(t)Kc(t)
7. Reference evapotranspiration ETo(t)ETo(t)ETo(t)
8. Irrigation pump discharge rate QQQ
9. Field area AAA
10. Rainfall threshold XXX mm
11. Rain probability threshold PthP_{th}Pth

2. Outputs

- Irrigation decision (Irrigate / Postpone / No irrigation)
- Irrigation volume VVV
- Irrigation duration TTT
- Farmer advisory message

6.2.2.Phase I: Hybrid Rainfall Forecasting

Step 1: Data Preprocessing

1. Perform missing value imputation (linear interpolation).
2. Detect and remove outliers using Z-score filtering.
3. Normalize rainfall series.
4. Generate lag features and rolling statistics.

Step 2: Time-Series Decomposition

Decompose rainfall series using MSSA:

$$R(t) = T(t) + S(t) + E(t) \qquad (1)$$

Where:

- T(t)T(t)T(t) = Trend component
- S(t)S(t)S(t) = Seasonal component
- E(t)E(t)E(t) = Residual component

Principal components are extracted and used as features.

Step 3: Deep Learning Prediction

1. Apply CNN layers for short-term pattern extraction.
2. Feed extracted features into LSTM to capture temporal dependencies.
3. Generate forecast:

$$\hat{R}_{DL}(t+1:t+7)$$

Step 4: Statistical Forecasting

Apply ARIMA to residual component:

$$\hat{R}_{ARIMA}(t+1:t+7)$$

Step 5: Ensemble Fusion

Combine forecasts:

$$\hat{R}_{final} = w_1\hat{R}_{DL} + w_2\hat{R}_{ARIMA}$$

Where:

w1+w2=1w_1 + w_2 = 1w1+w2=1

Weights selected using cross-validation minimizing MAE.

Step 6: Probabilistic Rainfall Estimation

Compute:

$$P(RF \geq X)$$

for the next irrigation decision window.

6.2.3. Phase II: Soil Moisture and Water Balance Modeling

Step 7: Sensor Calibration

Convert raw readings to volumetric water content (VWC):

$$VWC_d = a \cdot SM_d + b$$

Step 8: Root-Zone Moisture Calculation

$$SM_{root} = \frac{\sum_{d=1}^{D}(VWC_d \cdot depth_d)}{Z_r}$$

Step 9: Available Water Estimation

$$AW = (SM_{root} - WP) \cdot Z_r$$

Total available water:

$$TAW = (FC - WP) \cdot Z_r$$

Readily available water:

$$RAW = p \cdot TAW$$

where p is crop depletion fraction.

Step 10: Crop Water Requirement

$$ET_c = K_c \cdot ETo$$

6.2.4. PHASE III: IRRIGATION DECISION LOGIC

Forecast depletion over next k days:

Step 11: Rainfall Adjustment Rule

$$AW_{forecast} = AW - \sum_{i=1}^{k} ET_c(i)$$

If: $P(RF \geq X) > P_{th}$

Then:
→ Postpone irrigation
→ Generate postponement advisory
Else proceed.

Step 12: Irrigation Requirement Check
If: $AW_{forecast} \leq RAW$
Then irrigation required.
Else:
→ No irrigation needed.

6.2.5.PHASE IV: IRRIGATION OPTIMIZATION

Step 13: Required Irrigation Volume

$$V_{req} = (TAW - AW_{forecast}) \cdot A$$

Apply system constraint:

$$V = \min(V_{req}, Q \cdot T_{max})$$

Step 14: Irrigation Duration

$$T = \frac{V}{Q}$$

6.2.6.PHASE V: ADVISORY GENERATION

If irrigation postponed: "Rain probability exceeds threshold. Irrigation postponed. Re-evaluation after 24 hours." If irrigation required: "Apply irrigation for T minutes (Volume V liters). Soil moisture below optimal threshold. Rain probability low."

Include:

- Current soil moisture status
- Forecast rainfall
- Confidence level

6.2.7.PSEUDOCODE SUMMARY

```
BEGIN

Collect rainfall and meteorological data
Preprocess rainfall series
Decompose using MSSA
Train CNN-LSTM
Train ARIMA
Ensemble predictions
Compute rainfall probability
Read soil moisture sensors
Convert to VWC
Compute root-zone moisture
Calculate AW, TAW, RAW
```

```
Compute ETc
Forecast soil depletion

IF Rain_Probability > Threshold THEN
    Decision = POSTPONE
ELSE
    IF AW_forecast <= RAW THEN
        Compute irrigation volume
        Compute irrigation time
        Decision = IRRIGATE
    ELSE
        Decision = NO_IRRIGATION
    ENDIF
ENDIF
```

VII. RESULTS AND DISCUSSION

- Mobile app and SMS fallback (for low-smartphone users) with advisories in local language. Provide visualization of soil moisture trends and forecasted rainfall probabilities.

Category	Metric	Conventional / Baseline	Proposed Hybrid Advisory System	Improvement / Outcome
Rainfall Forecasting	48-hr MAE (mm)	4.60 (LSTM)	**3.95**	↓ 14% error reduction
	RMSE (mm)	6.10	**5.34**	Improved accuracy
	Nash–Sutcliffe Efficiency (NSE)	0.78	**0.86**	Better model fit
	Brier Score	0.22	**0.16**	Improved probabilistic calibration
Soil Moisture Network	Sensor Uptime	–	**>95%**	High reliability
	VWC Accuracy	–	**±4%**	Post-calibration accuracy
	Communication Success Rate	–	**97%**	Stable telemetry
Irrigation Performance	Total Water Applied (m^3/ha)	4,850	**3,780**	↓ 22% water saving
	Irrigation Events	17	**14**	↓ 18% fewer events
	Irrigation Before Rain	5 events	**1 event**	Significant reduction
Crop Performance	Yield (kg/ha)	5,240	**5,110**	Within ±3% (no significant loss)
	Water Productivity (kg/m^3)	1.08	**1.35**	↑ 25% improvement
Overall System Impact	Forecast Improvement	–	~14%	Reduced uncertainty
	Water Use Efficiency	–	~22%	Resource conservation
	Farmer Feedback	–	Positive	Improved decision confidence

The overall system performance demonstrates that integrating hybrid rainfall forecasting with IoT-based soil moisture monitoring significantly improves irrigation decision-making accuracy. The hybrid model reduced short-term rainfall prediction error by approximately 14% compared to standalone LSTM, achieving lower MAE and RMSE values along with improved Nash–Sutcliffe Efficiency and probabilistic calibration. The soil moisture sensing network exhibited strong field reliability, with over

95% sensor uptime, ±4% volumetric water content accuracy after calibration, and a 97% communication success rate. These results confirm that the forecasting and sensing components operated robustly under real field conditions and provided dependable inputs for irrigation scheduling.

From an agricultural impact perspective, the advisory-driven irrigation strategy reduced total seasonal water usage by approximately 22% and decreased irrigation events by about 18%, while successfully avoiding unnecessary irrigation before forecasted rainfall events. Importantly, crop yield remained within ±3% of conventional farmer scheduling, indicating no significant productivity loss despite reduced water application. Water productivity improved by roughly 25%, demonstrating enhanced efficiency per unit of water used. Overall, the system achieved meaningful water conservation, maintained yield stability, and improved farmer confidence in irrigation timing, highlighting its potential for climate-resilient precision agriculture deployment.

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