

Deep Learning Applications in Forecasting Agricultural Water Demand Under Climate Variability

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ABSTRACT

Agriculture accounts for the largest share of global freshwater consumption, making accurate forecasting of agricultural water demand a critical component of sustainable resource management. Climate variability—characterized by fluctuations in rainfall patterns, temperature, and evapotranspiration—poses significant challenges to conventional forecasting models. Recent advances in deep learning provide powerful tools to address these challenges by capturing complex, non-linear relationships between climate variables and crop water requirements. This study investigates the application of deep learning models, including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and hybrid architectures, to forecast agricultural water demand under varying climatic conditions. A dataset comprising historical weather records, soil moisture indices, and irrigation data was used to train and validate the models. The results demonstrate that LSTM-based models outperform traditional statistical methods and machine learning approaches in terms of predictive accuracy, particularly in capturing seasonal variability and extreme events. This work highlights the potential of deep learning in supporting data-driven irrigation planning, improving resilience to climate change, and ensuring efficient water resource management in agriculture.

Key words: Agriculture, LSTM, CNN

INTRODUCTION

1. Background

Water is an indispensable resource for agriculture, which consumes nearly 70% of global freshwater withdrawals. Ensuring optimal water allocation has become increasingly challenging due to climate variability, population growth, and rising food demand. Climate variability manifests in altered rainfall

distribution, frequent droughts, heatwaves, and unpredictable evapotranspiration patterns, all of which complicate the estimation of crop water demand. Accurate forecasting of agricultural water requirements under such uncertain conditions is therefore essential for sustainable irrigation planning and water governance.

2. Limitations of Conventional Approaches

Traditional methods of forecasting agricultural water demand rely on statistical models, crop simulation models, and empirical equations such as the FAO Penman–Monteith approach. While these techniques have been widely applied, they are often constrained by assumptions of linearity, stationarity, and simplified representations of climate–crop interactions. Moreover, they may struggle to integrate high-dimensional datasets such as satellite imagery, soil moisture variability, and multi-scale weather patterns. As a result, conventional approaches often fail to capture the non-linear, dynamic relationships that characterize climate–agriculture interactions, especially under extreme climate events.

3. Emergence of Deep Learning in Forecasting

In recent years, deep learning has emerged as a transformative technology for time series forecasting and spatiotemporal data analysis. Models such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) excel at learning non-linear dependencies, temporal dynamics, and spatial patterns from large-scale data. Their ability to process multi-source datasets—including weather records, remote sensing data, and soil parameters—makes them particularly suited for agricultural water demand prediction. Furthermore, hybrid architectures that combine CNNs for feature extraction with LSTMs for temporal sequence modeling have shown superior performance in capturing complex variability across different climate zones.¹

4. Research Gap and Need

Despite growing research in deep learning applications for hydrology and crop yield forecasting, relatively few studies have focused specifically on **agricultural water demand forecasting under climate variability**. Existing studies often address either irrigation scheduling or climate forecasting in isolation, without integrating both aspects to provide holistic water demand predictions. This gap highlights the need for a comprehensive framework that leverages deep learning to link climate variability with crop water requirements.

5. Objectives of the Study

The primary objectives of this research are to:

1. Explore the effectiveness of deep learning models (LSTM, CNN, and hybrid architectures) in forecasting agricultural water demand under variable climatic conditions.
2. Compare their performance with traditional statistical and machine learning methods in terms of accuracy and robustness.
3. Evaluate the ability of these models to capture seasonal variability, extreme climate events, and non-linear relationships between climate drivers and irrigation demand.
4. Demonstrate the potential of deep learning-based forecasting for sustainable irrigation planning and adaptive water resource management.

6. Significance

By integrating climate variability into agricultural water demand forecasting, this study contributes to climate-resilient agricultural practices. The findings can support policymakers, water managers, and farmers in making informed decisions about irrigation scheduling, resource allocation, and long-term adaptation strategies. Ultimately, the application of deep learning offers a pathway toward more efficient, reliable, and sustainable water management in agriculture under the pressures of climate change.²

Case Study: Forecasting Agricultural Water Demand in a Semi-Arid Canal Command, India (2005–2024)

1. Study Area

A 110,000-ha canal-irrigated command in semi-arid central India (black-cotton soils; Kharif: cotton & soybean; Rabi: wheat & chickpea; hot-season vegetables on ~8% area). Mean annual rainfall ~700–800 mm, ~85% during June–September. Inter-annual climate variability is high with frequent monsoon onset shifts and episodic droughts.

2. Data and Pre-Processing

Period: Jan-2005 to Jun-2024 (monthly horizon; weekly internal resolution).

Hydro-agricultural records

- Canal releases & tail-end deliveries (m³), pump electricity proxies for groundwater (kWh→m³ via calibrated factors), and block-level irrigated area (ha).

Weather & climate

- Daily Tmax/Tmin, RH, wind, solar radiation (station + reanalysis); Penman–Monteith ET₀ computed daily then aggregated.
- Rainfall (gauges blended with gridded products).
- Teleconnections: Niño3.4, IOD, MJO phase (monthly).

Remote sensing

- NDVI/EVI (16-day composites), surface soil moisture (L-band), land-surface temperature.
- Actual ET (AET) from energy-balance products used for ex-post evaluation, not as features.

Derived features

- Lags (1–12 months) of rainfall, ET₀, soil moisture, NDVI.
- Seasonal encodings (sine/cosine), crop calendars, irrigation price signals.
- Rolling stats (7–90 day means), SPI/SPEI drought indices.

Target variable

- **Monthly agricultural water demand (MCM)** = canal releases + estimated groundwater abstraction needed to meet crop water requirement.

3. Models

Baselines

- SARIMA (seasonal), Multiple Linear Regression (ET₀, rainfall, area), Gradient Boosted Trees (XGBoost).

Deep learning

- Univariate LSTM (demand only).
- Multivariate BiLSTM (all features, 12-month look-back).
- **Temporal Fusion Transformer (TFT)** with static embeddings (soil, canal, crop mix), known future inputs (crop calendar), and attention for interpretability.
- ConvLSTM on 2-D gridded features (NDVI/rain/soil moisture), aggregated to command demand.

Training

- Huber loss; Adam optimizer; early stopping on validation MAPE; dropout 0.2–0.3; look-back window 52 weeks; batch size 64.
- Feature scaling with time-series aware normalization (fit on train only).³

4. Performance

Table no 1: Metrics on 2022–2024 test set (monthly forecasts one month ahead)

Model	MAE (MCM)	RMSE (MCM)	MAPE (%)	NSE
SARIMA	17.3	24.9	18.6	0.62
MLR	15.1	22.7	16.2	0.68
XGBoost	11.6	17.9	12.5	0.79
LSTM	9.2	14.8	9.4	0.86
ConvLSTM	8.7	13.9	8.8	0.88
TFT (proposed)	7.6	12.1	7.8	0.91

- During peak Kharif (Aug–Sep), TFT reduced RMSE by 33% vs. XGBoost.
- For abrupt demand spikes (heatwave in Apr-2023), TFT absolute error = **+6.1 MCM** vs. LSTM **+9.4 MCM**.

5. Robustness to Climate Variability

Extreme year's analysis

- **Monsoon deficit (2023, Niño positive):** Demand rose **+14%** vs. climatology; TFT MAPE **9.1%** (others $\geq 12\%$).
- **Wet monsoon (2022, late withdrawal):** Demand decreased **–8%**; TFT tracked tail-season canal cuts with MAPE **6.5%**.

Scenario stress tests (counterfactual simulations using learned model)

- **+2 °C Tmax & +5% VPD:** **+12–15%** monthly demand in hot months.
- **–20% JJAS rainfall:** **+18–22%** Rabi groundwater reliance.
- **Monsoon onset delayed by 2 weeks:** Kharif peak shifts by ~ 1 month; storage drawdown **+11%** in Aug–Sep.⁴

6. Ablation & Interpretability

Table no 2: Feature ablation (Δ MAPE on TFT):

Removed group	Δ MAPE (pp)
ET ₀ & VPD	+3.1
NDVI/EVI	+1.8
Soil moisture	+1.4
Teleconnections (Niño3.4, IOD)	+0.7
Seasonality encodings	+0.6

Attention/SHAP insights

- Top drivers in Kharif: ET₀ (current), rainfall lag-1 to lag-2, soil moisture lag-1, NDVI current.
- In Rabi: ET₀ lag-1, NDVI lag-1, canal allocation policy indicator.

7. Operational Trial (Jan-2024–Jun-2024)

- Weekly TFT forecasts fed to gate scheduling.
- **Outcome:** Canal releases reduced 9–12% relative to historical policy for comparable weather, while maintaining tail-end adequacy $\geq 90\%$ of weeks. Reported pump hours fell 8%.

8. Error Diagnostics

- Residuals near-white with mild positive skew during dust-storm weeks.
- Largest underestimation in April heatwave weeks with abrupt crop water stress (LST anomalies $> +3$ K).
- No significant bias across distributaries; slight over-prediction at sandy sub-command (K-sat high).

9. Reproducibility Notes

- Horizon: 1-month-ahead (updated weekly); recursive strategy for 3-month horizon.
- Missing-data handling: bidirectional temporal imputation + uncertainty flag as an input.
- Model uncertainty: Monte-Carlo dropout (50 passes) to compute 80% prediction intervals; PICP on test = 0.83.

10. Practical Implications

- **Policy:** Use forecasts to announce **indented releases** two weeks earlier; integrate with rotational canal schedules.
- **Farmer advisories:** Couple demand forecasts with plot-level ET deficits from remote sensing to nudge deficit-irrigation on tolerant crops.
- **Infrastructure:** Prioritize lining/repair for distributaries with highest error-to-loss correlation.

11. Limitations

- Groundwater estimates rely on calibrated energy-to-discharge factors; introduce 5–10% uncertainty.
- Transferability to non-canal or high-rainfed systems requires retraining with local features.
- Teleconnection indices are coarse; sub-seasonal MJO effects could be better represented.

MATERIALS AND METHODS

1. Study Area and Context

The present study was conducted in a semi-arid agricultural region characterized by high dependence on irrigation for crop production. The area lies between 21°N–23°N latitude and 77°E–79°E longitude in central India, covering nearly 110,000 hectares of canal- and groundwater-irrigated farmland. The region experiences a **subtropical monsoon climate** with average annual rainfall of 700–800 mm, approximately 85% of which occurs during June–September (Kharif season). Cropping is dominated by **soybean and cotton** in Kharif, followed by **wheat and chickpea** in Rabi, with hot-season vegetables covering smaller fractions. Due to frequent rainfall variability, water demand often exceeds supply, creating a suitable case for deep learning-based forecasting.⁵

2. Data Sources

2.1 Climatic Data

Daily weather records for the period 2005–2024 were obtained from the **India Meteorological Department (IMD)** and supplemented with reanalysis data (ERA5) for missing intervals. Variables included:

- Maximum and minimum temperature (°C)
- Relative humidity (%)
- Wind speed (m/s)
- Solar radiation ($\text{MJ m}^{-2} \text{d}^{-1}$)
- Rainfall (mm)

Reference evapotranspiration (ET_0) was computed using the **FAO Penman–Monteith equation**.

2.2 Hydrological and Irrigation Data

Historical irrigation demand was quantified using:

- **Canal release records** (monthly, million cubic meters, MCM)
- **Groundwater abstraction** estimates derived from electricity consumption records calibrated against discharge rates
- **Crop acreage and irrigation schedules** reported by local water resource authorities

The **target variable** for modeling was defined as **monthly agricultural water demand (MCM)**.

2.3 Remote Sensing Data

Satellite-derived datasets were incorporated to capture land surface and crop dynamics:

- **Normalized Difference Vegetation Index (NDVI)** and **Enhanced Vegetation Index (EVI)** (MODIS, 16-day composites)
- **Soil Moisture (SM)** (SMAP Level-3, 36 km)
- **Land Surface Temperature (LST)** (MODIS, daily products)
- Actual evapotranspiration (AET) used only for validation

2.4 Climate Variability Indicators

To represent large-scale drivers of variability:

- **El Niño–Southern Oscillation (ENSO)** (Niño3.4 index)
- **Indian Ocean Dipole (IOD)**
- **Madden–Julian Oscillation (MJO) phase indices**

3. Data Preprocessing

- **Temporal aggregation:** Daily data were aggregated into monthly time steps.
- **Lag features:** Climate and remote sensing variables were lagged (1–12 months) to capture delayed crop and soil responses.
- **Normalization:** All features were standardized using z-score normalization, fit only on training data to avoid leakage.
- **Missing values:** Filled using time-series interpolation (linear for short gaps, seasonal averages for long gaps).
- **Seasonal encoding:** Month and cropping-season indicators were added using sine/cosine transformations.⁶

4. Model Development

4.1 Baseline Models

- **Statistical:** Seasonal Autoregressive Integrated Moving Average (SARIMA).
- **Machine Learning:** Multiple Linear Regression (MLR) and Gradient Boosted Trees (XGBoost).⁷

4.2 Deep Learning Models

1. **Long Short-Term Memory (LSTM):** Captures sequential temporal dependencies.
2. **Convolutional Neural Networks (CNN):** Extracts local spatial patterns from NDVI, soil moisture, and LST gridded features.
3. **Hybrid CNN–LSTM:** CNN layers for feature extraction followed by LSTM layers for temporal learning.
4. **Temporal Fusion Transformer (TFT):** Combines attention mechanisms, static embeddings, and multi-horizon forecasting for interpretable predictions.

5. Model Training and Validation

- **Data Split:** Training (2005–2018), Validation (2019–2021), Testing (2022–2024).
- **Loss Function:** Mean Absolute Error (MAE) and Huber loss (for robustness to outliers).
- **Optimizer:** Adam with learning rate scheduler (initial = 0.001).
- **Regularization:** Dropout (0.2–0.3) and early stopping based on validation loss.
- **Evaluation Metrics:**
 - Mean Absolute Error (MAE, MCM)
 - Root Mean Square Error (RMSE, MCM)
 - Mean Absolute Percentage Error (MAPE, %)
 - Nash–Sutcliffe Efficiency (NSE)^{8,9}

6. Scenario Analysis under Climate Variability

To test robustness, the best-performing model was subjected to **climate perturbation scenarios**:

- **+2 °C increase in mean temperature**
- **−20% rainfall during monsoon (JJAS)**
- **Delayed monsoon onset by 2 weeks**

Predicted demand changes were compared against historical climatology to assess model sensitivity.

7. Software and Tools

- **Python 3.11** with **TensorFlow/Keras**, **PyTorch**, and **scikit-learn** for model implementation.
- **Pandas** and **NumPy** for preprocessing.
- **Matplotlib** and **Seaborn** for visualization.
- **QGIS** for spatial data processing and map generation.¹⁰

RESULTS

1. Model Performance Comparison

All models were evaluated on the independent **2022–2024 test set** using four metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Nash–Sutcliffe Efficiency (NSE).

Table no : Comparative performance of forecasting models on agricultural water demand (2022–2024 test period)

Model	MAE (MCM)	RMSE (MCM)	MAPE (%)	NSE
SARIMA	17.3	24.9	18.6	0.62
Multiple Linear Regression (MLR)	15.1	22.7	16.2	0.68
Gradient Boosted Trees (XGBoost)	11.6	17.9	12.5	0.79
LSTM	9.2	14.8	9.4	0.86
CNN-LSTM Hybrid	8.7	13.9	8.8	0.88
Temporal Fusion Transformer (TFT)	7.6	12.1	7.8	0.91

The results indicate that **deep learning models consistently outperformed traditional statistical and machine learning methods**. The TFT model achieved the highest accuracy, reducing RMSE by 33% compared to XGBoost and 51% compared to SARIMA.

2. Seasonal Forecasting Accuracy

Performance varied across cropping seasons.

- During **Kharif (June–September)**, when rainfall and ET_0 fluctuations are highest, the TFT maintained a MAPE of 8.1%, compared to 12–15% for baseline models.
- In **Rabi (October–February)**, demand was more stable, and deep learning models captured seasonal irrigation needs effectively (TFT MAPE = 7.0%).
- Peak demand during **April–May heatwaves** was underestimated by most models; however, TFT predictions remained closer to observed values (error = +6.1 MCM) than LSTM (+9.4 MCM).

3. Impact of Climate Variability on Forecasting

The models were stress-tested under **simulated climate variability scenarios**.

Table 4: Forecasted change in agricultural water demand under climate perturbations (relative to baseline climatology)

Scenario	Predicted Change in Water Demand
+2 °C mean temperature	+12–15% increase (April–June)
−20% monsoon rainfall (JJAS)	+18–22% increase in Rabi demand
Delayed monsoon onset (2 weeks)	+11% increase in August–September storage drawdown

These results show that **climate anomalies significantly alter irrigation demand**, especially reduced rainfall leading to heavy dependence on groundwater during Rabi.

4. Feature Importance and Model Interpretability

Interpretability analysis using **attention weights** and **SHAP values** revealed the most influential predictors:

- **Kharif season:** ET_0 (current), rainfall lag-1, soil moisture lag-1, NDVI current.
- **Rabi season:** ET_0 lag-1, NDVI lag-1, irrigation allocation policies.

- **Extreme events:** sudden temperature anomalies (+3–4 °C) were strongly weighted in demand spikes.

5. Operational Validation

A pilot trial (Jan–Jun 2024) integrated TFT-based forecasts into weekly canal gate scheduling. Compared to historical allocation practices, the system achieved:

- **9–12% reduction in canal water releases,**
- **8% decrease in groundwater pumping hours, and**
- **90% reliability in tail-end water delivery.**

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