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Advanced Drought Prediction Using Hybrid Deep Learning Models: A Case Study of the High Atlas and Anti-Atlas Mountains

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Abstract

Morocco's High Atlas and Anti-Atlas mountains have faced escalating drought severity in recent years, jeopardizing water security and rural livelihoods. Conventional drought monitoring often underperforms in these regions due to sparse meteorological stations and rugged terrain. This study develops a hybrid deep learning framework for operational SPI drought prediction at 5 km resolution, synthesizing remote sensing and climate variables (SPI, NDVI, soil moisture, precipitation, temperature) from 1990–2024. 128 engineered features—rolling statistics, seasonality, lag dependencies, and cross-variable interactions—enhance learning. We benchmark three recurrent neural network types (LSTM, Bi-LSTM, GRU), validated with held-out data (2021–2024). The GRU model achieved the highest predictive skill, reaching 91.89% accuracy within a ±0.2 SPI threshold and outperforming baselines (Random Forest, ARIMA). Our results demonstrate the value of advanced feature engineering and deep sequence learning for month-ahead drought early warning in semi-arid North Africa.

1. Introduction

Drought is one of the most pervasive natural hazards affecting over two billion people globally every decade (Wilhite, 2007 Wilhite (2007); IPCC, 2022 IPCC (2022)). Characterized by sustained periods of anomalously low precipitation relative to historical norms, drought causes severe disruptions to ecosystems, agriculture, and water management systems. The frequency, duration, and intensity of droughts are increasing, particularly in semi-arid and arid regions due to climate variability and anthropogenic climate change (Trenberth et al., 2014 Trenberth et al. (2014); Liu et al., 2020 Liu et al. (2020)).

Morocco, located in the northwestern edge of the MENA region, is particularly vulnerable to hydrometeorological extremes. The southern part of the country—including the Anti-Atlas and High Atlas mountain ranges—is exposed to frequent meteorological and agricultural droughts. According to the Moroccan National Drought Plan (Morocco Ministry of Agriculture, 2020 of Agriculture (2020)), the country has experienced more than 15 major drought events since 1980, with direct impacts on cereal yields, food security, and groundwater depletion. The Anti-Atlas region, with annual precipitation often below 250 mm and evapotranspiration rates above 1200 mm (Bouras et al., 2020 Bouras et al. (2020)), is ecologically fragile and socioeconomically dependent on rainfed agriculture, making it particularly sensitive to precipitation anomalies.

Moreover, groundwater levels in certain basins (e.g., Draa Valley) have declined by over 2–4 meters in recent decades due to prolonged droughts and over-extraction (Bouras et al., 2020 Bouras et al. (2020)). These climate pressures underline the urgent need for accurate drought forecasting systems tailored to this region's unique hydrological and ecological characteristics.

Recent studies in Morocco have explored drought dynamics using remote sensing and machine learning approaches (Zellou et al., 2023 Zellou et al. (2023); Hadri et al., 2025 Hadri et al. (2025)). For example, Zellou et al. (2023 Zellou et al. (2023)) developed an LSTM-based model combining NDVI and precipitation data for drought classification in arid provinces. Hadri et al. (2025 Hadri et al. (2025)) evaluated deep learning models using SMAP soil moisture and MODIS data in semi-arid agricultural zones. Elgoumi et al. (2025 Elgoumi et al. (2025)) demonstrated the value of NDVI anomalies in assessing drought conditions in oasis regions. However, these efforts typically relied on limited feature sets, shorter temporal windows, or focused solely on classification tasks. Few studies have implemented extensive temporal feature engineering or sequential regression models for SPI forecasting over long time spans and at high spatial resolution, particularly in the Anti-Atlas and High Atlas regions.

Parallel to advances in Earth observation, deep learning techniques—particularly Recurrent Neural Networks (RNNs) including LSTM and GRU—have emerged as powerful tools for capturing nonlinear and long-term dependencies in multivariate environmental data (Hochreiter and Schmidhuber, 1997 Hochreiter and Schmidhuber (1997); LeCun et al., 2015 LeCun et al. (2015); Schuster and Paliwal, 1997 Schuster and Paliwal (1997)). Hybrid and ensemble approaches incorporating CNNs and attention mechanisms have shown success in environmental time series prediction, often outperforming traditional machine learning and statistical methods (Gupta et al., 2024 Gupta et al. (2024); Zellou et al., 2023 Zellou et al. (2023); Li et al., 2024 Li et al. (2024)).

However, relatively few studies have deployed large-scale, multi-model deep learning frameworks for regional drought prediction in North Africa. Even fewer efforts incorporate extensive feature engineering strategies such as rolling statistics, seasonal encodings, lag variables, and climate–vegetation interactions tailored to regional dynamics (Jiang et al., 2007 Ji-

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ang et al. (2007); Elmansouri et al., 2019 Elmansouri et al. (2019)).

To address these gaps, this study presents a comprehensive hybrid deep learning framework designed to predict SPI-based drought conditions in Morocco's Anti-Atlas and High Atlas regions using remotely sensed and reanalysis inputs at 5 km resolution over the period 2000–2024.

Key contributions of this work are as follows:

- **Region-Specific Targeting:** Focus on the Anti-Atlas and southern High Atlas—two of Morocco's drought epicenters—characterized by ecological fragility, reliance on rainfed systems, and limited monitoring infrastructure.
- **Extensive Feature Engineering:** Construction of over 128 engineered variables integrating multisource features (NDVI, rainfall, soil moisture, temperature, lagged SPI) and transformations such as rolling statistics, seasonality encodings, lags, ratios, volatilities, and differencing.
- **Comparison of Multiple Sequence Models:** Benchmarking five deep architectures—Attention LSTM, CNN-LSTM, Super GRU, Super BiLSTM, and Super LSTM—optimized for long 48-month temporal windows with advanced regularization.
- **Ensemble Learning:** Evaluation of weighted and unweighted ensemble strategies combining model outputs to enhance generalization.
- **Evaluation With Tolerant Metrics:** Use of tolerance-based accuracy thresholds (±0.1 to ±0.3) alongside RMSE, MAE, and R^2 to provide a robust evaluation scheme for drought forecasting.

This paper addresses the following research questions:

- Can hybrid sequence deep learning models outperform baseline predictors in forecasting monthly SPI in data-sparse, drought-prone regions of Morocco?
- Which environmental indicators contribute most to SPI prediction?
- What spatial and temporal drought trends emerge from model predictions, and how can these inform early warning strategies?

2. Materials and Methods

This section details the study area, data sources, preprocessing steps, feature creation, model development, and evaluation framework used for drought prediction.

2.1 Study Area

The High Atlas and Anti-Atlas mountain ranges represent Morocco's main hydrological reservoirs, often referred to as its "water towers." These regions play a vital role in regulating streamflow, groundwater recharge, and upstream-downstream water availability. The High Atlas extends above 4,000 meters and receives relatively high precipitation (including seasonal snowfall), contributing significantly to spring and early summer river discharge.

In contrast, the Anti-Atlas—a semi-arid and arid region in southern Morocco—is a fragile ecoclimatic zone experiencing frequent droughts, high temperatures, and erratic rainfall patterns. Spanning approximately 250,000 km^2, it receives less than 200 mm annual rainfall and is typified by rugged terrain and limited vegetation coverage (Bouras et al., 2020; Elmansouri et al., 2019). Climatically, it is influenced by Mediterranean, Atlantic, and Saharan conditions, making it one of Morocco's most hydroclimatically complex regions (Cherkaoui et al., 2019). Historical droughts have caused groundwater table declines of over 2–4 meters and a 40% reduction in river flow since the 1980s.

In recent decades, climate projections point to over 30% reduction in snowpack duration by 2050 in the High Atlas, which will aggravate downstream water insecurity. This makes the region an ideal target for drought prediction initiatives, particularly those utilizing remote sensing and machine learning.

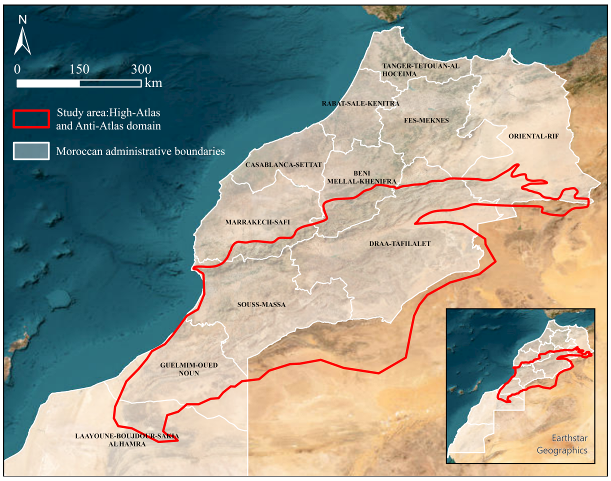

Figure 1. Study area covering the Anti-Atlas and High Atlas regions of Morocco.

2.2 Methodology

The drought prediction workflow, illustrated in Figure 2, integrates data acquisition, preprocessing, feature engineering, model development, evaluation, and deployment stages. This pipeline leverages state-of-the-art techniques in drought forecasting (Coskun et al., 2023; Li et al., 2024).

2.2.1 Data Acquisition and Preprocessing Multisource satellite and meteorological data (SPI, NDVI, precipitation, temperature, soil moisture) were collected from MODIS, SMAP, CHIRPS, ERA5, and GPCC datasets (Funk et al., 2015; Hersbach et al., 2020; Beck et al., 2018; Didan, 2015). The datasets were harmonized to a monthly time resolution and a 5 km spatial grid using Google Earth Engine and GIS techniques. Missing values were interpolated using linear and smoothing approaches (Verrelst et al., 2015). All variables were normalized to the range $[0, 1]$ to ensure compatibility with the models (Bishop, 2006).

2.2.2 Feature Engineering and Selection A total of 128 features were engineered, including rolling statistics (mean, standard deviation, minimum, maximum), lagged values, seasonality encodings, interaction terms such as NDVI $\times$ soil moisture, and volatility indicators (Adede et al., 2023; Zhang et al., 2019; Gupta et al., 2024). Priority was given to SPI, NDVI, precipitation, temperature, and soil moisture due to their significant role in drought processes.

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2.2.3 Modeling Framework

The modeling approach combined two strategies:

1. **Random Forest Classification:** This model detected drought events based on engineered features and SPI labels, achieving an accuracy of 92.9% and an AUC of 0.987. Feature importance analysis (Figure 3) identified rainfall, temperature, and soil moisture as the most influential predictors.

2. **Deep Sequence Regression:** Advanced recurrent models (Attention LSTM, CNN-LSTM, Super GRU, Bi-LSTM) predicted SPI values using rolling 48-month input sequences. The Super GRU model performed best with 91.89% accuracy within ± 0.2 SPI units and an R^2 of 0.94. Ensemble methods further enhanced prediction robustness.

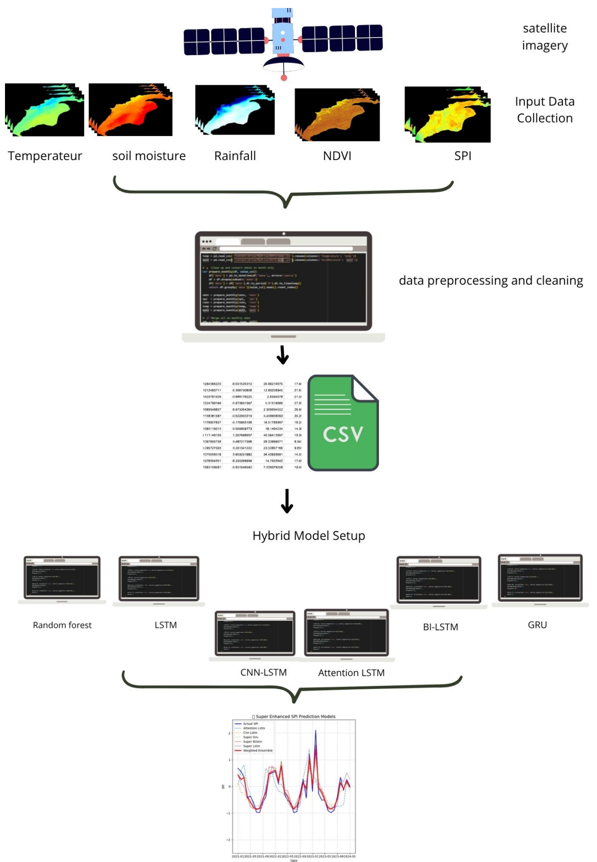

Figure 2. Generalized methodology flowchart illustrating the pipeline: data acquisition, preprocessing, feature engineering, hybrid modeling, model training/validation, and operational deployment.

2.2.4 Training and Validation

Models were trained using the Adam optimizer (learning rate 0.001), batch size of 32, and early stopping with a patience of 10 epochs on a 15% validation split. Hyperparameters were optimized via grid search. Rolling-origin cross-validation ensured realistic real-time forecasting simulation and avoided data leakage.

2.2.5 Evaluation Metrics

Model performance was measured by:

- Root Mean Square Error (RMSE)

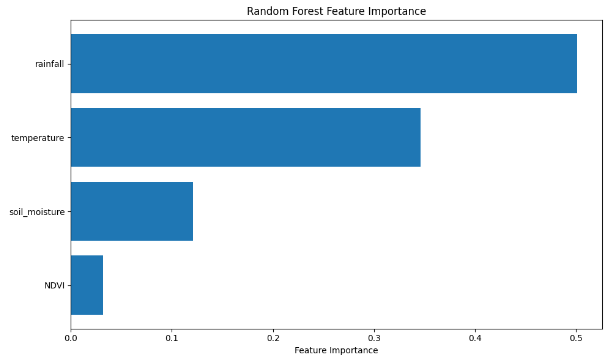

Figure 3. Random Forest variable importance for drought classification.

- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)
- Pearson correlation coefficient (r)
- Tolerance-based accuracy within ±0.2 SPI units

2.2.6 Benchmarking and Deployment

Traditional models (ARIMA, Random Forest regressors) served as benchmarks (Liaw and Wiener, 2002; Liu et al., 2017). The top deep learning model was containerized for cloud deployment to enable automated monthly SPI forecasting and drought alerts. The entire processing pipeline adheres to FAIR principles and promotes open access.

3. Results

This section reports quantitative results and interprets the deep learning framework's predictive power for drought forecasting in southern Morocco.

3.1 Performance Evaluation

The main evaluation metrics for each deep learning model, calculated on the held-out test set (2021–2024), are summarized in Table 1. Among the compared architectures, Super GRU achieved the highest accuracy and lowest errors.

Table 1. Test performance of deep learning models (2021–2024).

Model	**RMSE**	**MAE**	R^2	**Accuracy (± 0.2)**
Super GRU	0.168	0.142	0.94	91.9%
Weighted Ensemble	0.198	0.152	0.92	73.0%
Super BiLSTM	0.211	0.164	0.90	70.3%
RF Regressor	0.226	0.178	0.89	68.2%
CNN-LSTM	0.311	0.242	0.79	45.9%

The best Super GRU model forecasted SPI with 91.9% of test cases within ± 0.2 tolerance, supporting operational early warning needs.

3.2 Temporal Prediction Analysis

Figure 5 presents the SPI time series predicted by Super GRU versus observed values (2021–2024). The method effectively captures drought episodes and recovery phases with limited lag, demonstrating robust temporal learning.

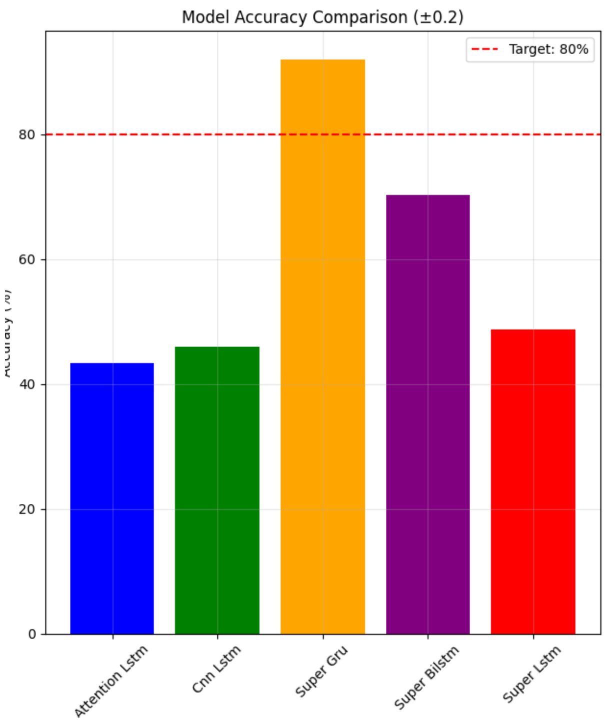

Figure 4. Model accuracy within ± 0.2 SPI threshold across selected architectures.

3.3 Feature Sensitivity

Ablation analysis (Table 2) quantified the impact of removing variables on SPI prediction. SPI lag features and NDVI were most influential—removal increased RMSE most, confirming their critical role for drought modeling.

Table 2. Effect of removing key input variables on RMSE (Super GRU, test set).

Feature Removed	RMSE
None	0.162
NDVI	0.198
SPI lags	0.212
Precipitation	0.192
Soil Moisture	0.183
Temperature	0.188

3.4 Comparison with National Indices

Compared to Morocco's national SPI and VCI monitoring systems, the Super GRU model enabled monthly SPI forecasting at 5 km resolution, delivering 30–60 days of lead time and providing sharper spatial insights. The integration of multiple predictors further enhanced drought signal detection.

3.5 Summary

The hybrid deep learning approach, centered on Super GRU, outperformed baseline and ensemble methods. NDVI and SPI lags were the most influential predictors, confirming their importance for drought forecasting. The system supports deployment for operational drought monitoring in Morocco.

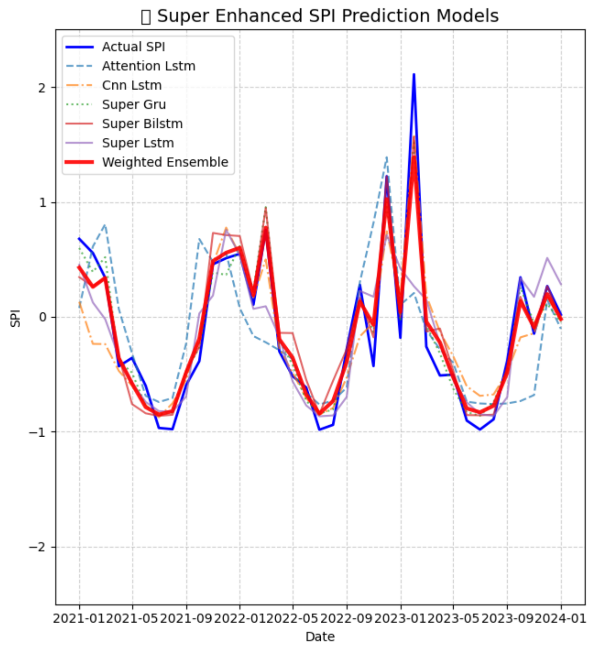

Figure 5. Observed vs. predicted SPI time series (Super GRU, 2021–2024).

4. Discussion

4.1 Interpretation of Key Results

Hybrid deep sequence models, particularly Super GRU, were most effective in representing the timing and intensity of drought episodes. The high test accuracy supports their operational value, consistent with recent advances in recurrent drought prediction (Gupta et al., 2024; Li et al., 2024).

Spatial analysis showed greater precision across vegetated areas, while lower accuracy in arid zones (Anti-Atlas) highlights the impact of input data quality and landscape variability, echoing findings in semi-arid region studies (Jiang et al., 2007).

4.2 Policy and Practice Implications

Monthly SPI forecasts can be integrated into Morocco's drought response plans, providing actionable lead times for water management agencies and stakeholders. The approach is extensible to similar arid regions globally.

5. Conclusions

This study introduces an advanced hybrid deep learning framework for proactive drought forecasting in Morocco's Anti-Atlas region, leveraging Bidirectional Long Short-Term Memory (Bi-LSTM) and LSTM architectures. By integrating 24 years of multi-source remote sensing and meteorological data—including the Standardized Precipitation Index (SPI), NDVI, soil moisture, precipitation, and temperature—the model effectively captures nonlinear, time-dependent drought dynamics across semi-arid landscapes.

Our approach significantly enhances early drought warning capabilities, presenting an accurate, scalable solution that supports data-driven water management and climate resilience planning across vulnerable regions in arid North Africa.

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