

A Multi-Scalar SPEI Drought Index and Desertification Prediction Using Different Deep Learning Neural Network Models

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Abstract: Drought is a slow-developing hazard that significantly affects agriculture and water resources in semi-arid regions such as Anantapur, Andhra Pradesh, India. This study presents a multi-scalar drought and desertification prediction framework based on the Standardized Precipitation Evapotranspiration Index (SPEI) at 1-, 3-, 6-, 9-, and 12-month time scales integrated with deep learning models. Climate and vegetation datasets spanning 2000–2024, including CHIRPS rainfall, ERA5 temperature, soil moisture, and MODIS NDVI, were processed using Google Earth Engine. Three recurrent neural network models—Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BiLSTM)—were trained using data from 2000–2022 and evaluated on 2023–2024 observations. Model performance was assessed using RMSE, MAE, R², and MAPE. Results indicate that GRU achieves consistently lower prediction errors for SPEI across multiple time scales, demonstrating strong generalization capability. BiLSTM effectively captures short-term vegetation variability in NDVI prediction, while LSTM shows comparatively higher errors. The proposed framework provides a reliable approach for drought monitoring, early warning, and decision support in agriculture and water resource management.

Keywords: SPEI, Drought Prediction, NDVI, LSTM, GRU, BiLSTM, Multi-Scalar Analysis, Anantapur.

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I. INTRODUCTION

Drought is a gradual natural hazard characterized by the prolonged water deficiency, significantly impacting agriculture, water resources, and ecosystems. Its slow onset and large spatial extent make an early detection challenging, especially under climate change conditions that increase evapotranspiration and rainfall variability. Desertification, closely linked to persistent drought, leads to land degradation, reduced vegetation cover, and declining soil productivity. Satellite-based indices such as the Normalized Difference Vegetation Index (NDVI) are widely used to monitor vegetation health, while multi-scalar indices like the Standardized Precipitation Evapotranspiration Index (SPEI) enable drought assessment across different time scales. Anantapur district in Andhra Pradesh, characterized by low rainfall (<550 mm) and high temperatures (>40°C), is highly vulnerable to drought due to its dependence on rainfed agriculture.

Traditional statistical models often fail to capture the nonlinear behaviour of climatic data, whereas deep learning models such as LSTM, GRU and BiLSTM effectively model

temporal dependencies in the time-series data. This study proposes a multi-scalar drought and desertification prediction framework integrating SPEI and NDVI using deep learning models. The approach includes dataset preparation (2000–2024), multi-scale SPEI computation, model development and evaluation, and forecasting of drought conditions for 2025.

II. LITERATURE REVIEW

Drought monitoring commonly uses indices such as SPI and SPEI, where SPEI provides improved assessment by incorporating evapotranspiration along with precipitation [6]. Multi-scalar SPEI enables analysis of both short-term agricultural and long-term hydrological drought conditions.

Remote sensing techniques, particularly NDVI, are widely used to evaluate vegetation health and detect land degradation in semi-arid regions [3], [4]. Deep learning models, including LSTM, GRU, and BiLSTM, have shown strong performance in time-series drought prediction, outperforming traditional methods such as ARIMA by effectively capturing temporal dependencies [1], [2], [5].

However, limited work has focused on integrating multi-source satellite data with deep learning models for multi-scalar drought prediction in regions like Anantapur. This study addresses this gap through a unified SPEI–NDVI-based framework.

III. STUDY AREA AND DATA

The study is conducted in Anantapur district, Andhra Pradesh, India (13°40'–15°15' N, 76°50'–78°30' E), a semi-arid region located in the rain-shadow zone of the Western Ghats. The area receives low and highly variable rainfall

(≈500–550 mm annually) and experiences high temperatures exceeding 40°C, leading to increased evapotranspiration and frequent drought conditions. The dependence on rainfed agriculture further increases vulnerability to climatic variability, making the region suitable for drought analysis. Climate and environmental data for the period 2000–2024 were obtained from Google Earth Engine. The datasets include CHIRPS rainfall, ERA5-Land temperature, GLDAS soil moisture, and MODIS NDVI. All data were processed and aggregated into monthly time series for consistent analysis and model development.

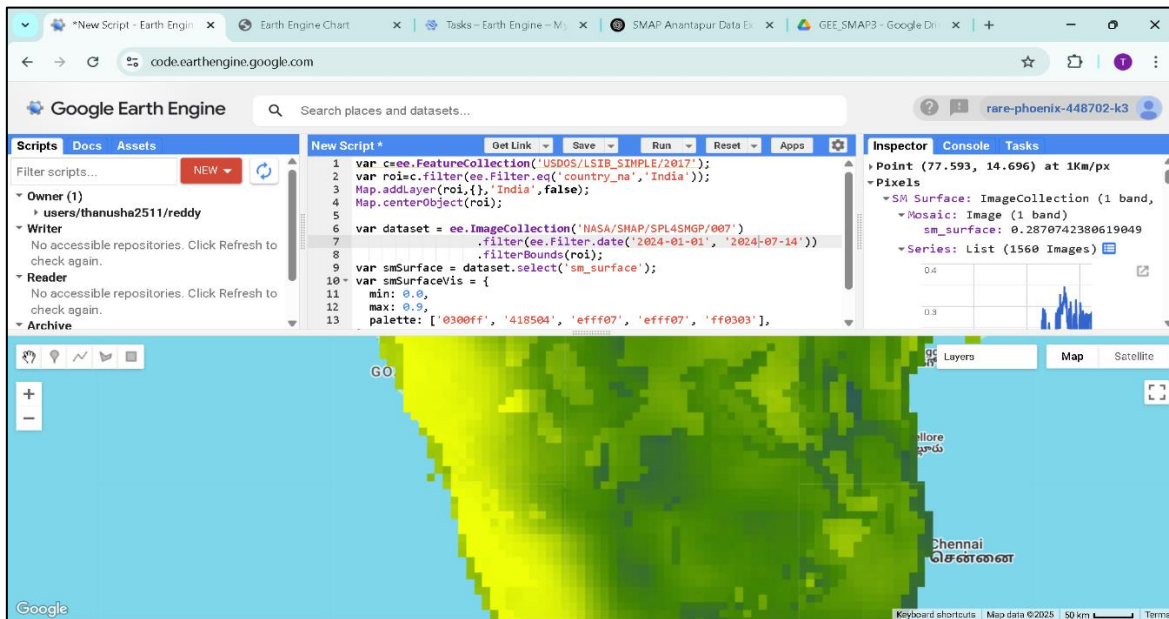


Fig 1 Satellite Data Acquisition and Preprocessing Workflow Using Google Earth Engine.

IV. METHODOLOGY

Drought prediction involves complex interactions among climatic and environmental variables, making deep learning suitable for time-series modelling. The proposed framework includes data preprocessing, feature extraction, sequence generation, model training, evaluation, and forecasting.

The dataset (2000–2024) consists of monthly variables including rainfall, temperature, soil moisture, NDVI, and multi-scalar SPEI (1–12 months). Data preprocessing involved handling missing values, removing inconsistencies, and applying Min–Max normalization.

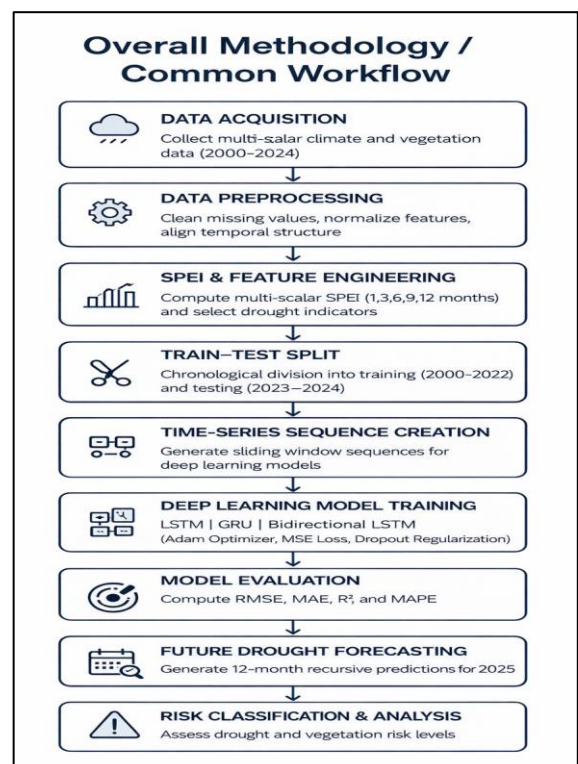


Fig 2 Methodology for Multi-Scalar Drought Prediction.

The dataset was split chronologically into training (2000–2022) and testing (2023–2024), and a sliding window approach was used to generate input sequences.

Three recurrent models—LSTM, GRU, and BiLSTM—were implemented to capture temporal dependencies. The models were trained using the Adam optimizer with MSE loss

and evaluated using RMSE, MAE, R^2 , and MAPE. Finally, the best-performing model was used to forecast drought and vegetation conditions for 2025. The predicted SPEI and NDVI values were used to assess drought severity and vegetation stress, supporting early warning and resource management.

V. RESULTS

➤ Multi-Scalar Drought Prediction

- SPEI-1 Prediction

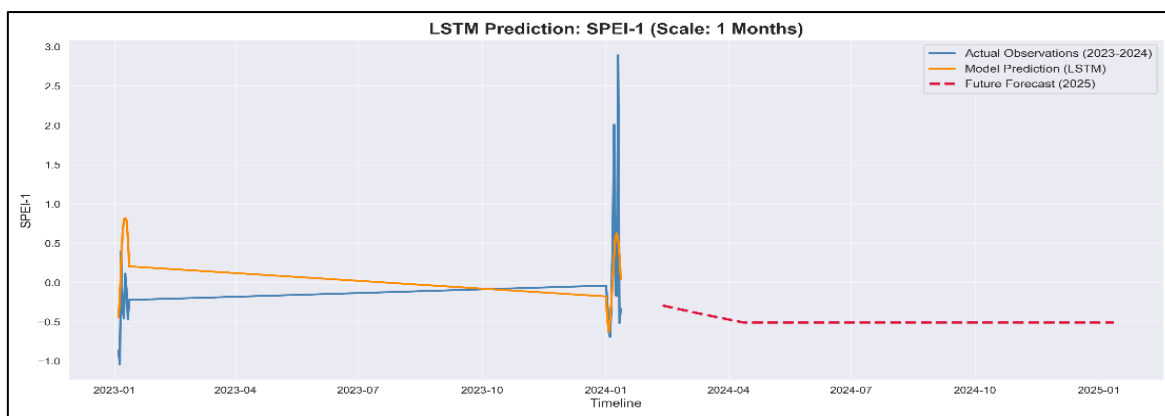


Fig 3 SPEI-1 Prediction Using LSTM Model (1-Month Scale)

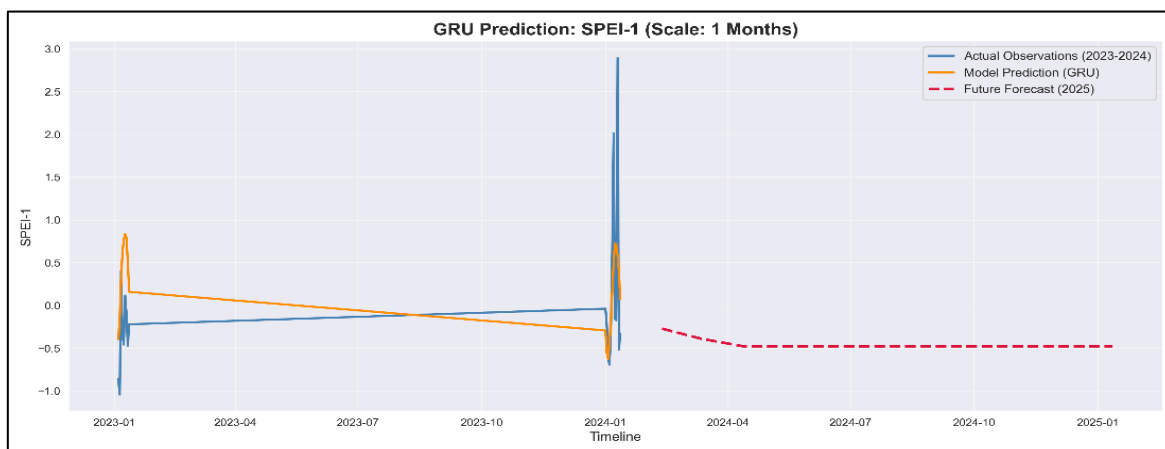


Fig 4 SPEI-1 Prediction Using GRU Model (1-Month Scale)

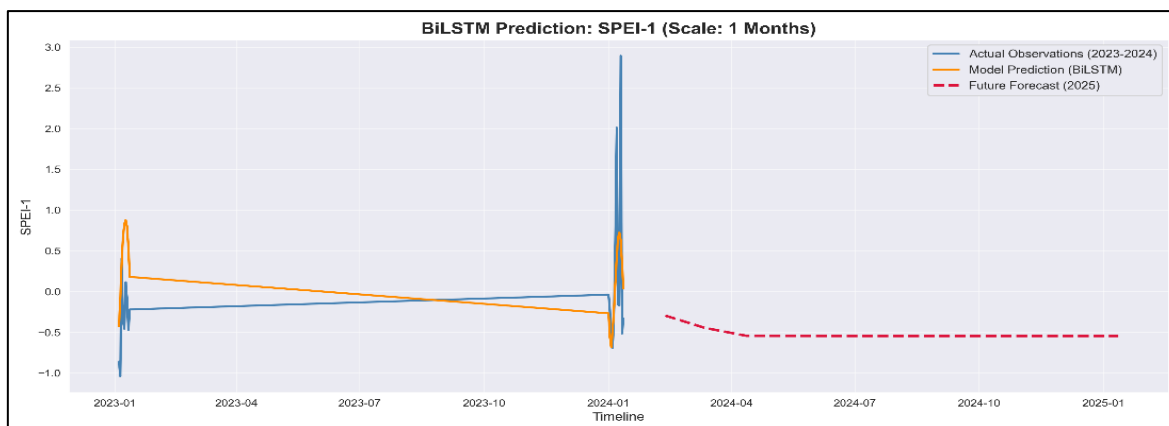


Fig 5 SPEI-1 Prediction Using BiLSTM Model (1-Month Scale)

The models were evaluated for predicting SPEI at a one-month timescale. The results show that all models are able to follow the drought fluctuations between 2023 and 2024, However, GRU produces smoother predictions with lower error compared to LSTM and BiLSTM.

- *SPEI-3 Prediction*

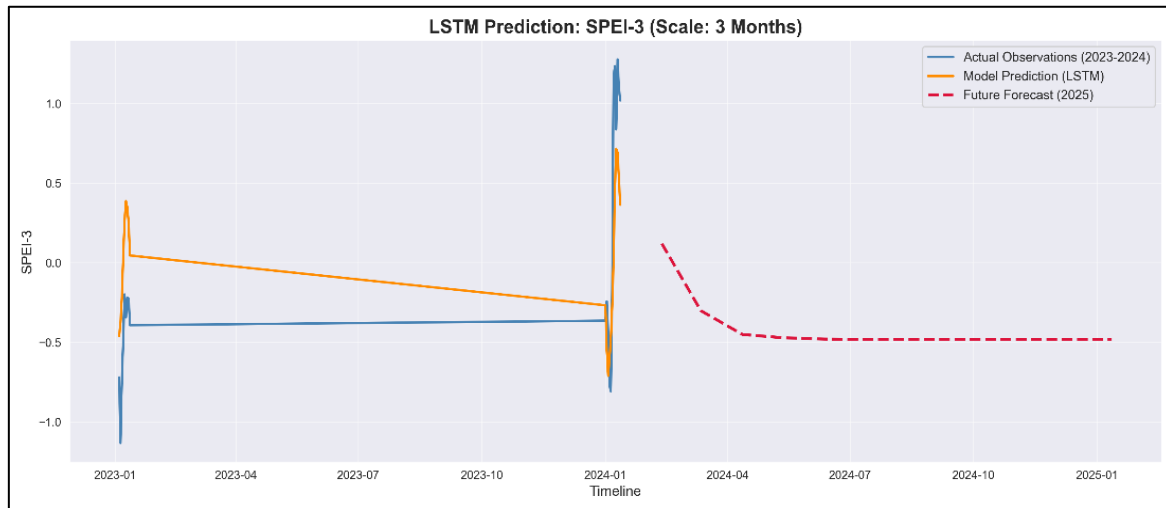


Fig 6 SPEI-3 Prediction Using LSTM Model (3-Month Scale)

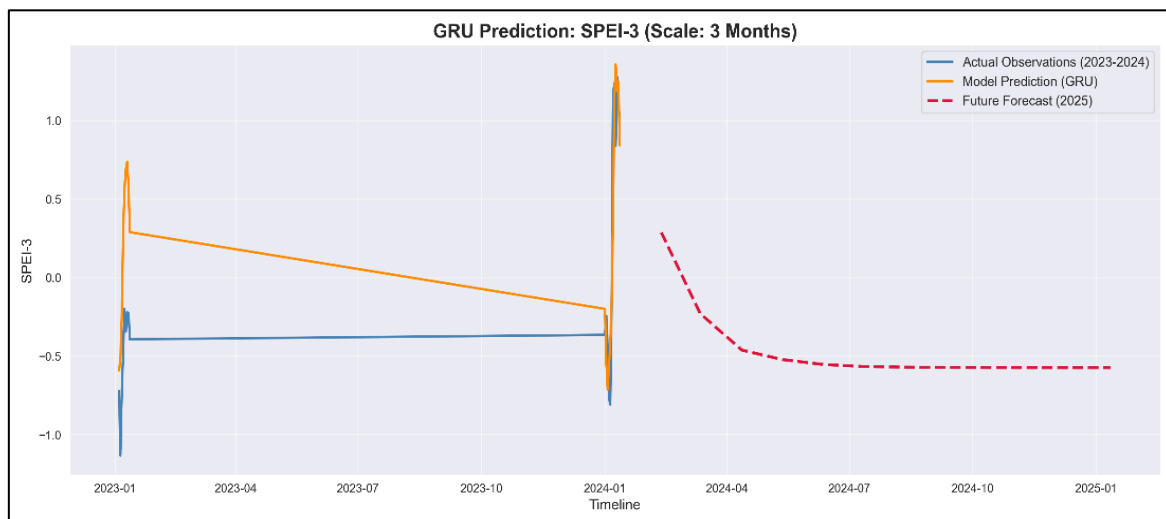


Fig 7 SPEI-3 Prediction Using GRU Model (3-Month Scale)

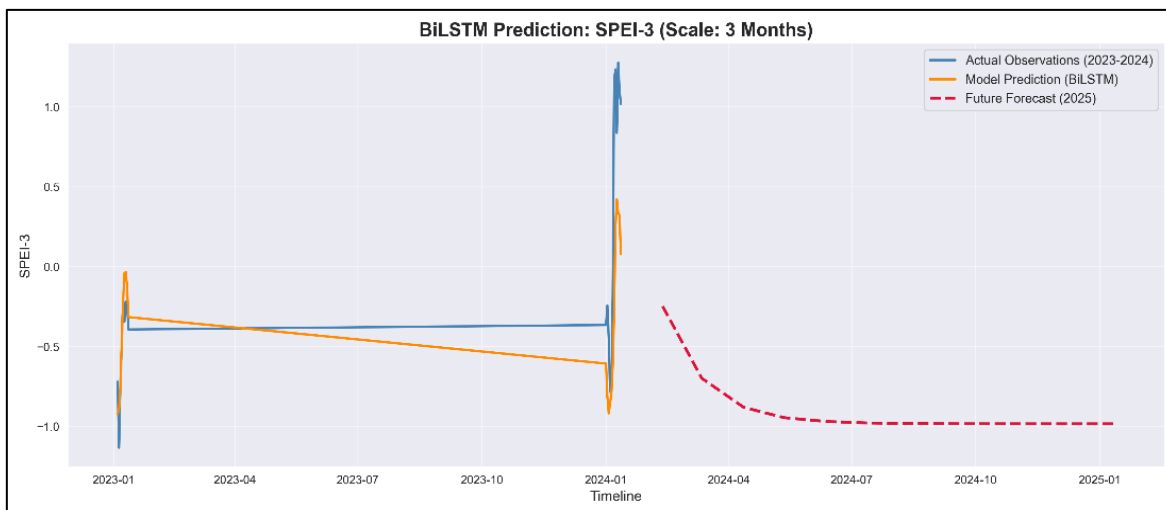


Fig 8 SPEI-3 Prediction Using BiLSTM Model (3-Month Scale)

At the 3-month timescale, the models capture seasonal drought variations. The predictions follow the general trend of observed drought conditions.

- *SPEI-6 Prediction*

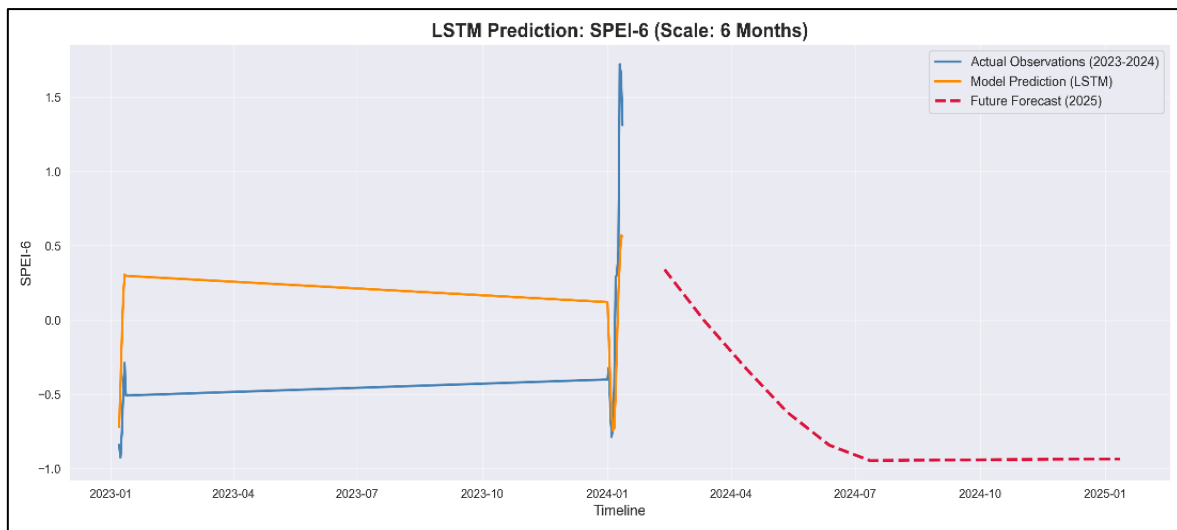


Fig 9 SPEI-6 Prediction Using LSTM Model (6-Month Scale)

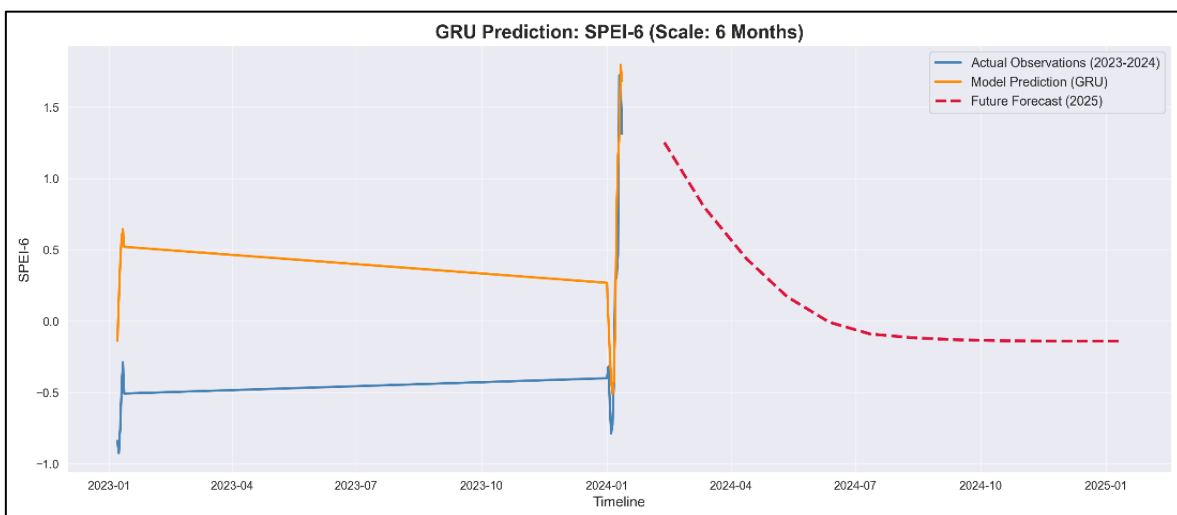


Fig 10 SPEI-6 Prediction Using GRU Model (6-Month Scale)

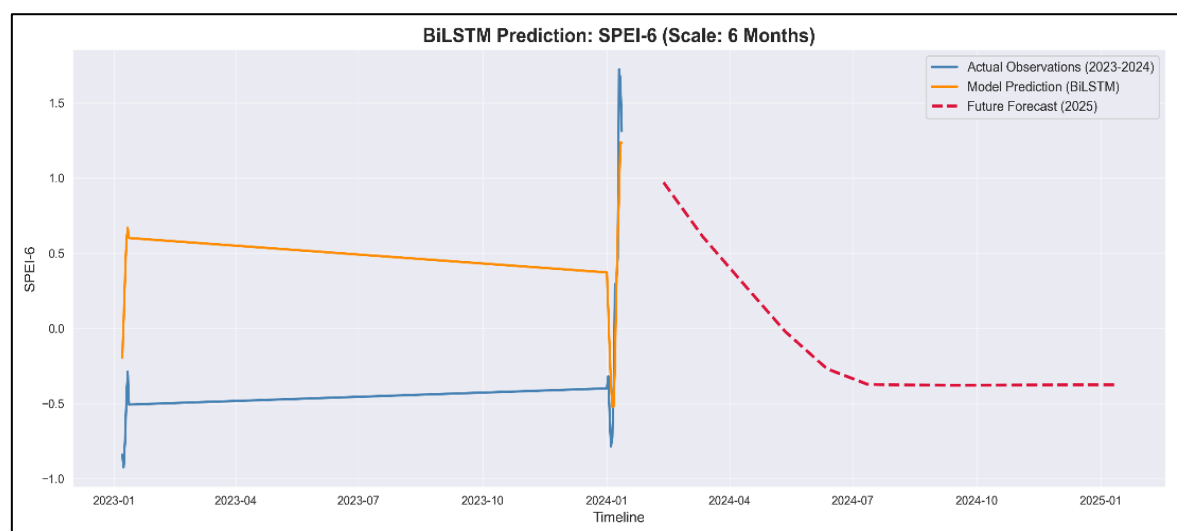


Fig. 11: SPEI-6 Prediction Using BiLSTM Model (6-Month Scale)

The 6-month timescale represents medium-term drought behaviour. The models demonstrate improved stability compared to short-term predictions.

- *SPEI -9 Prediction*

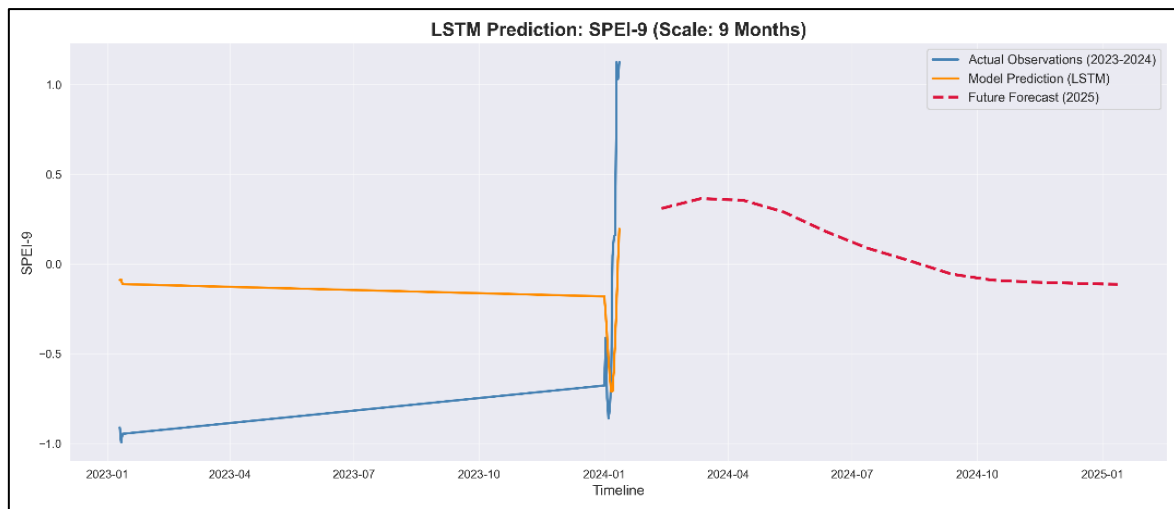


Fig 12 SPEI-9 Prediction Using LSTM Model (9-Month Scale)

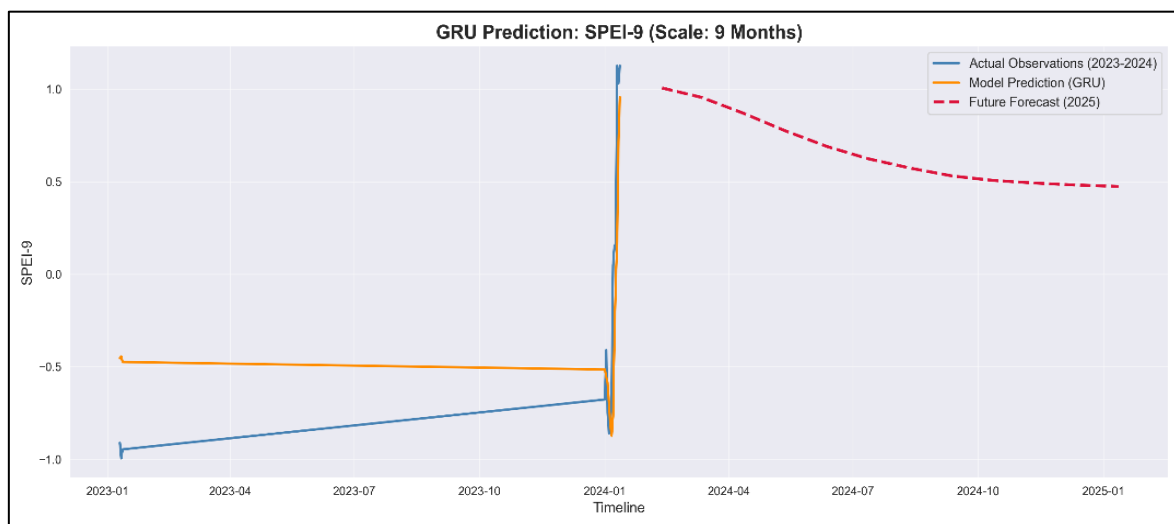


Fig 13 SPEI-9 Prediction Using GRU Model (9-Month Scale)

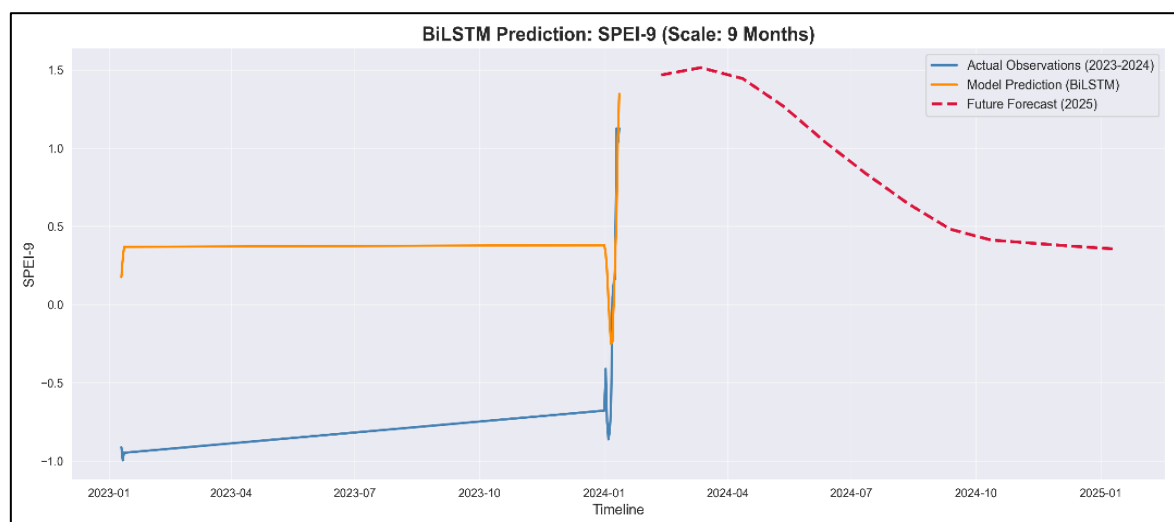


Fig 14 SPEI-9 Prediction Using BiLSTM Model (9-Month Scale)

The 9-month SPEI results capture long-term drought persistence. BiLSTM shows better pattern tracking due to its bidirectional learning capability.

- *SPEI-12 Prediction*

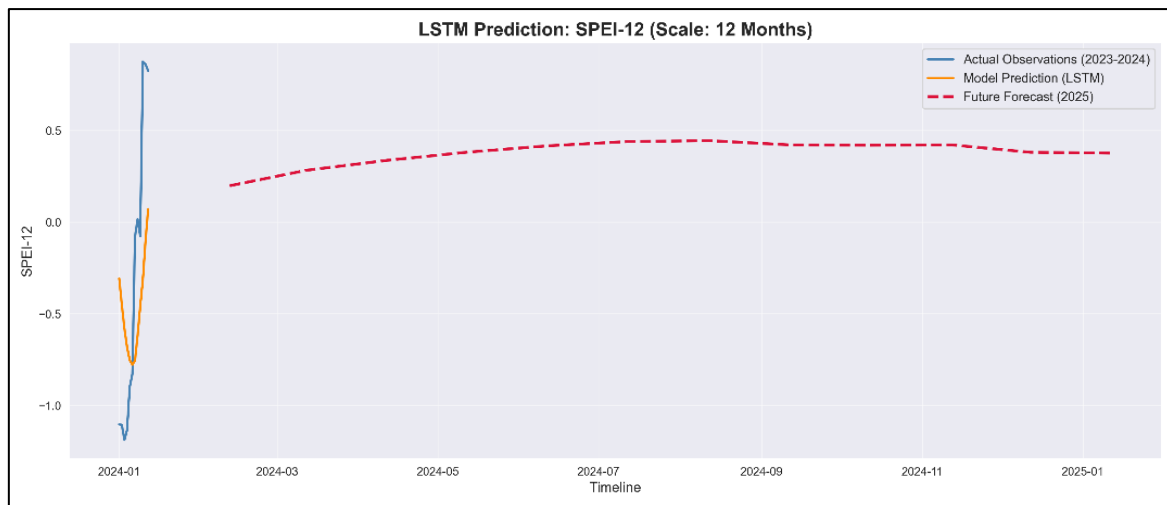


Fig 15 SPEI-12 Prediction Using LSTM Model (12-Month Scale)

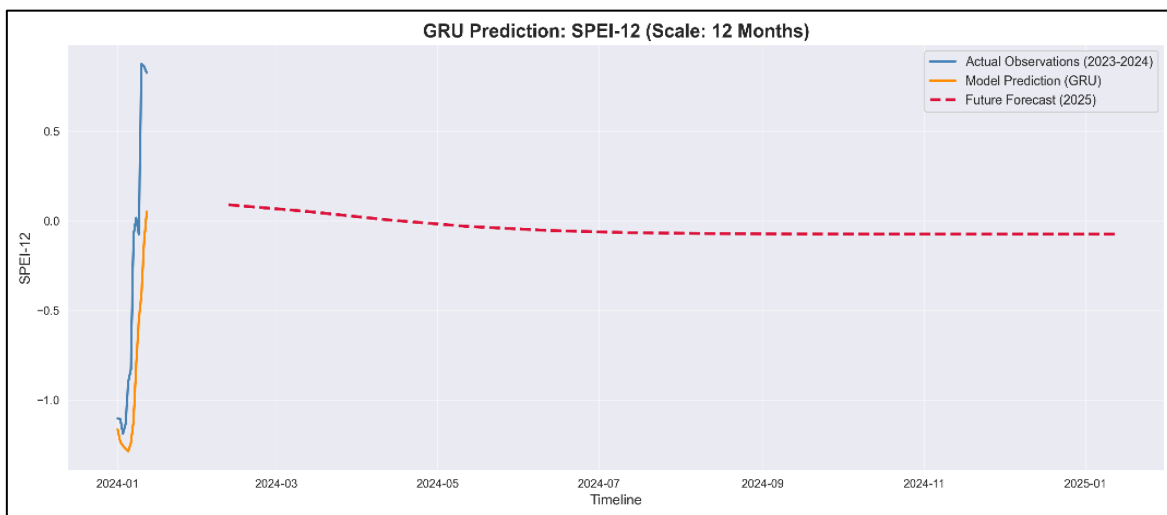


Fig 16 SPEI-12 Prediction Using GRU Model (12-Month Scale)

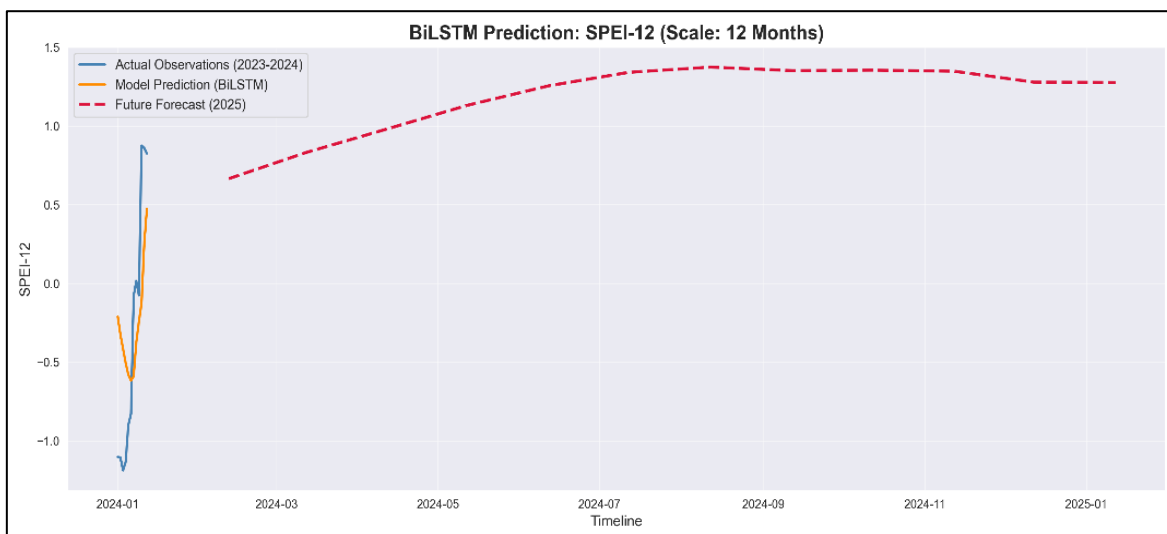


Fig 17 SPEI-12 Prediction Using BiLSTM Model (12-Month Scale)

The 12-month SPEI results represent long-term drought conditions. The models successfully capture long-term drought trends with reduced fluctuations.

➤ *Vegetation-Condition Prediction (NDVI)*

• *NDVI-1 Prediction*

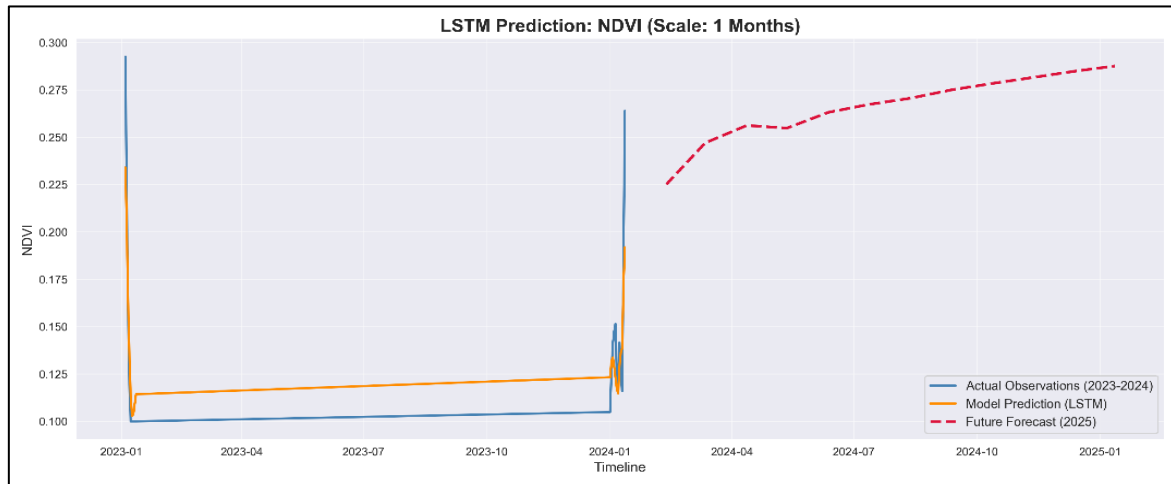


Fig 18 NDVI-1 Prediction Using LSTM Model (1-Month Scale)

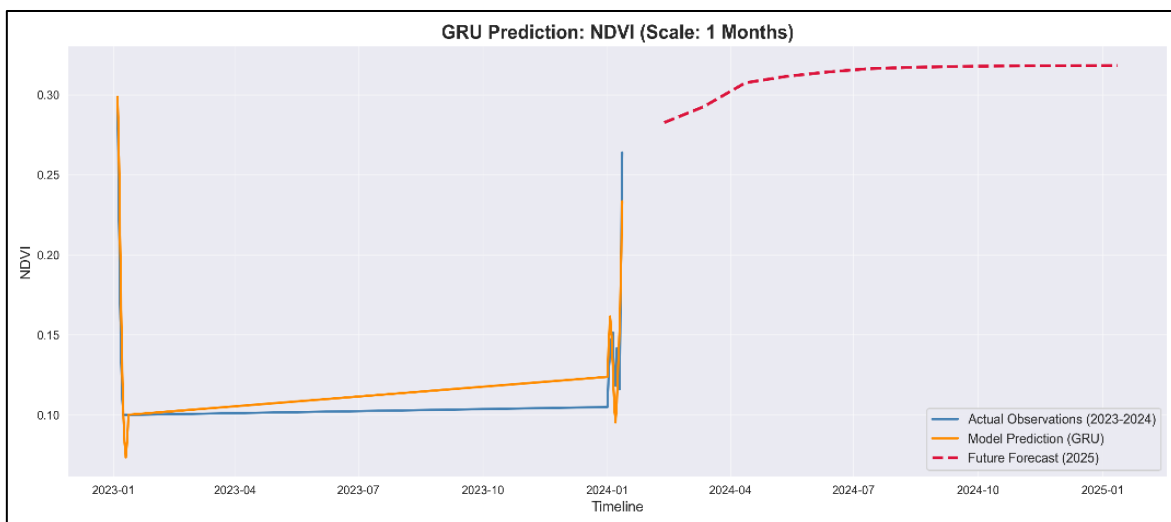


Fig 19 NDVI-1 Prediction Using GRU Model (1-Month Scale)

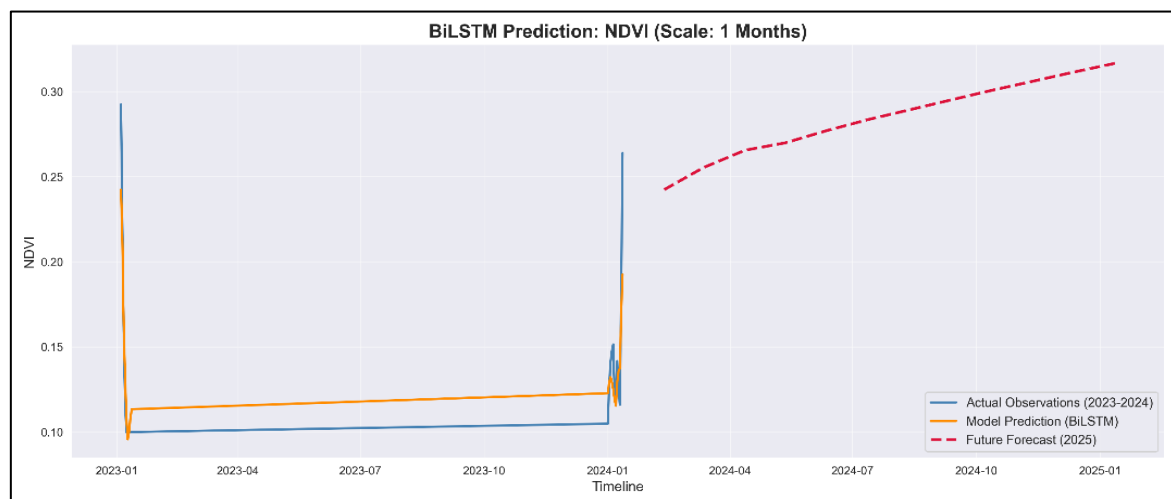


Fig 20 NDVI-1 Prediction Using BiLSTM Model (1-Month Scale)

The NDVI-1 prediction captures short-term vegetation changes influenced by rainfall and soil moisture.

- *NDVI-3 Prediction*

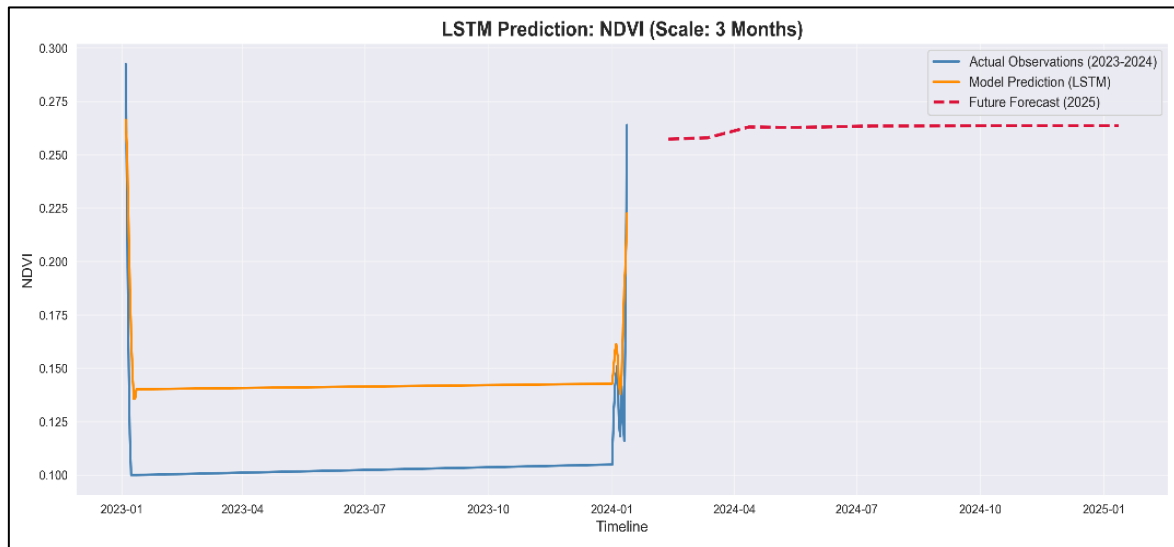


Fig 21 NDVI-3 Prediction Using LSTM Model (3-Month Scale)

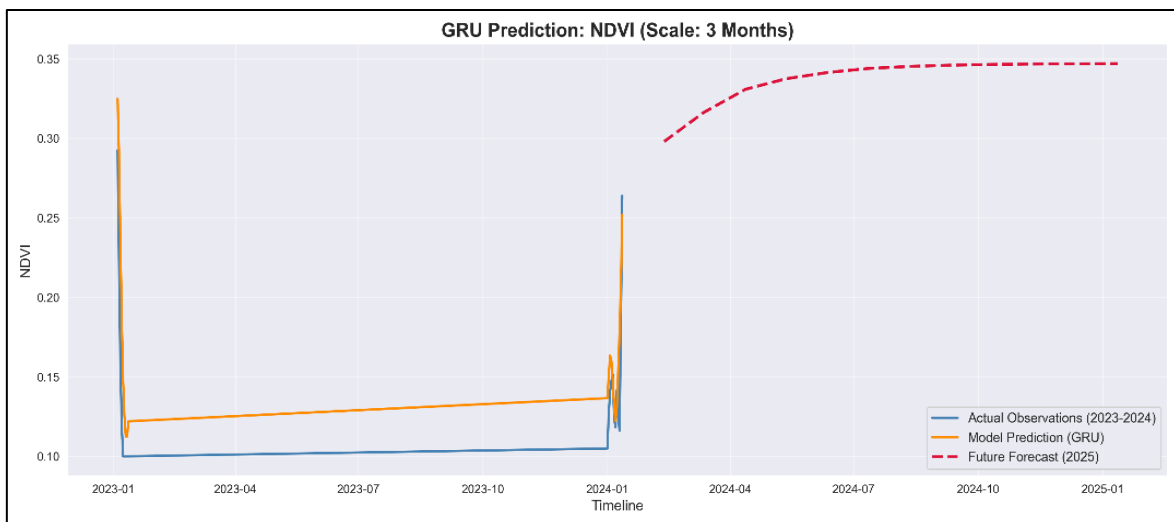


Fig 22 NDVI-3 Prediction Using GRU Model (3-Month Scale)

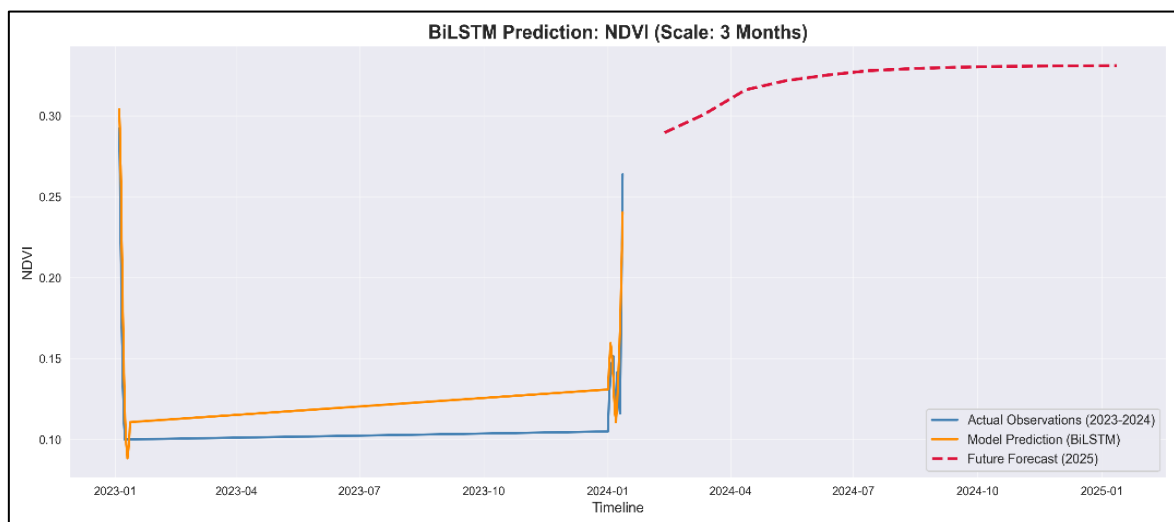


Fig 23 NDVI-3 Prediction Using BiLSTM Model (3-Month Scale)

At the 3-month scale, NDVI predictions show seasonal vegetation variations and crop growth patterns.

- *NDVI-6 Prediction*

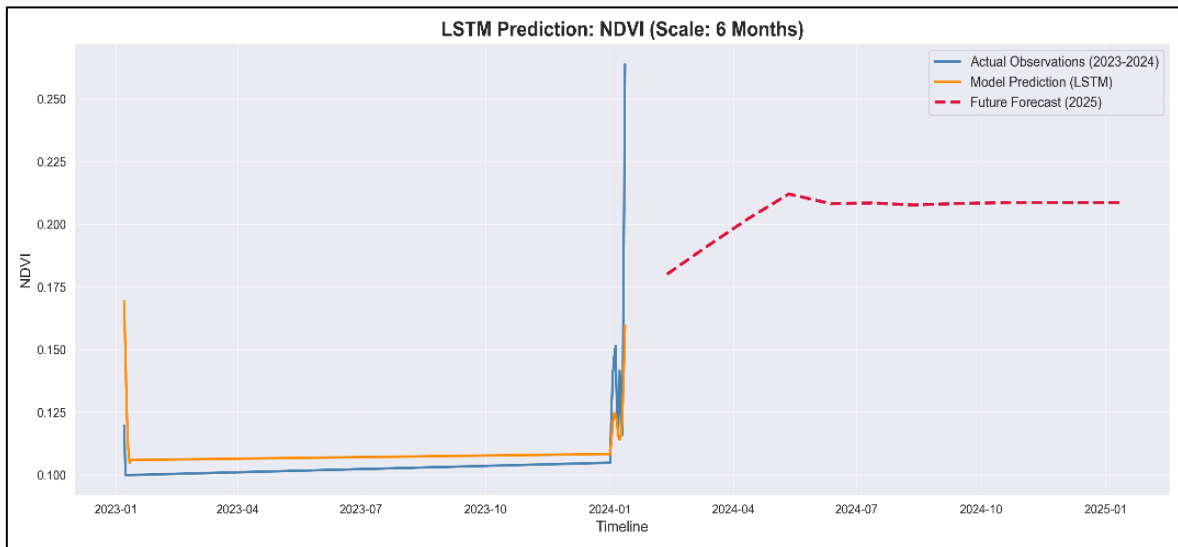


Fig 24 NDVI-6 Prediction Using LSTM Model (6-Month Scale)

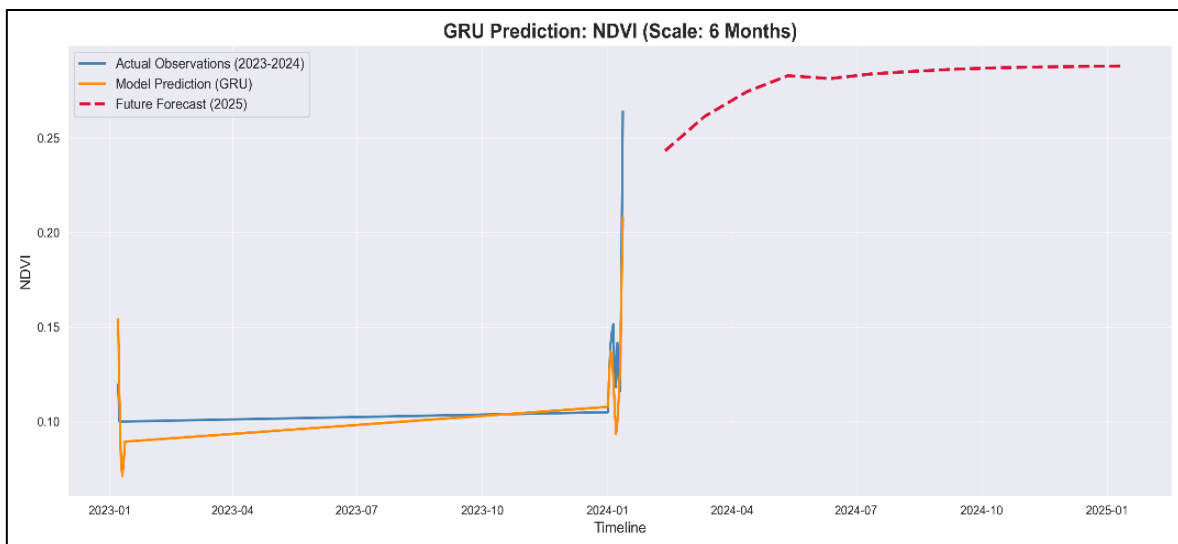


Fig 25 NDVI-6 Prediction Using GRU Model (6-Month Scale)

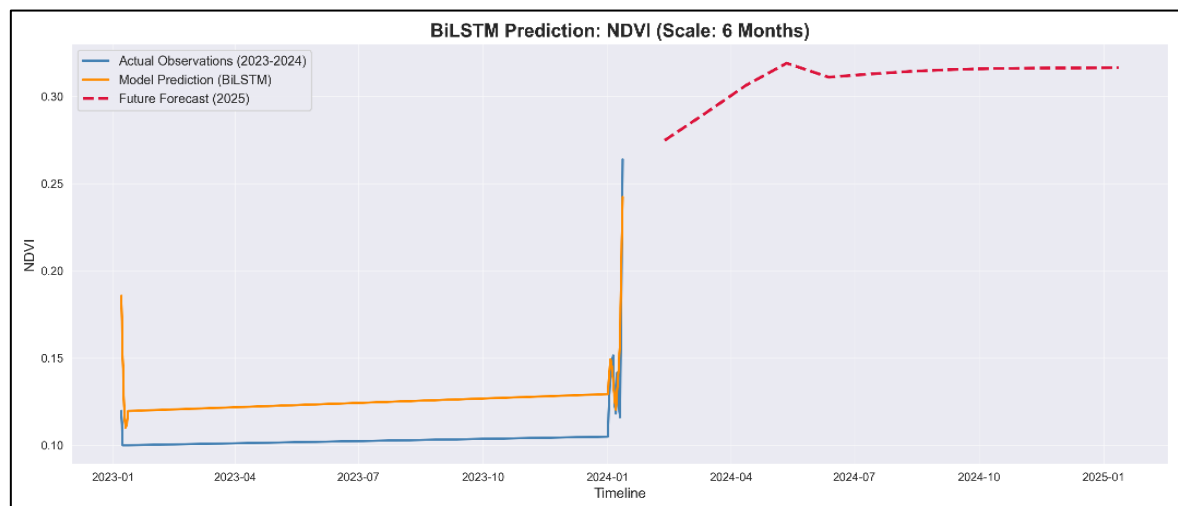


Fig 26 NDVI-6 Prediction Using BiLSTM Model (6-Month Scale)

The NDVI-6 results capture medium-term vegetation response to drought conditions.

• *NDVI-9 Prediction*

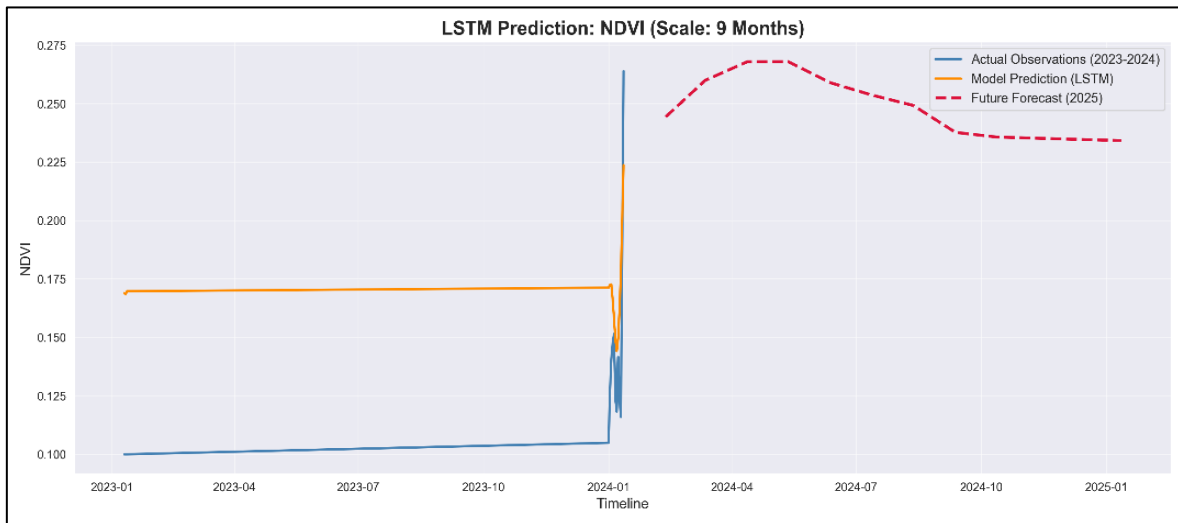


Fig 27 NDVI-9 Prediction Using LSTM Model (9-Month Scale)

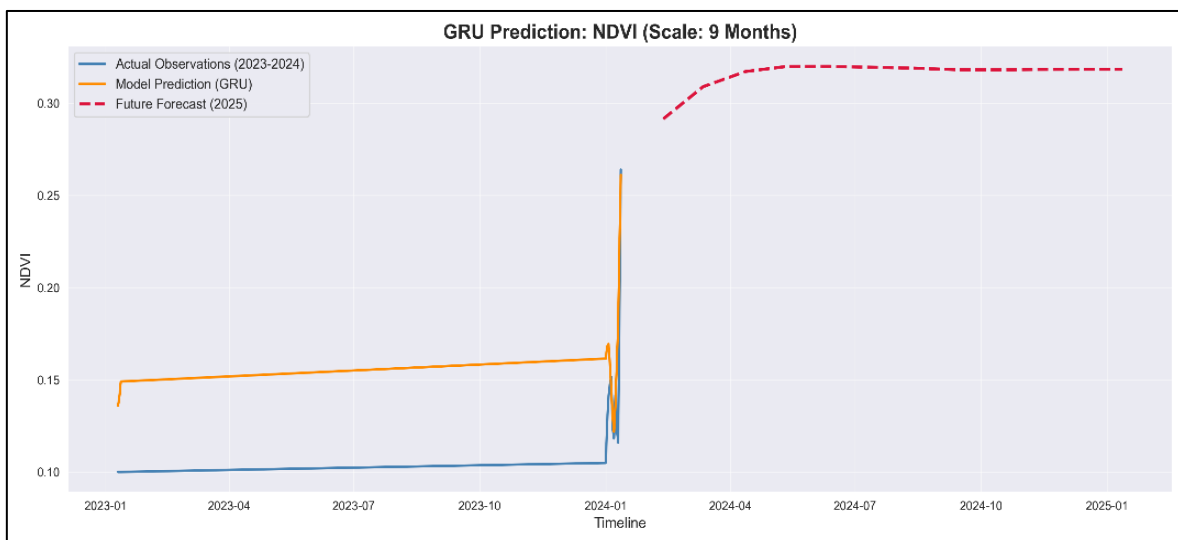


Fig 28 NDVI-9 Prediction Using GRU Model (9-Month Scale)

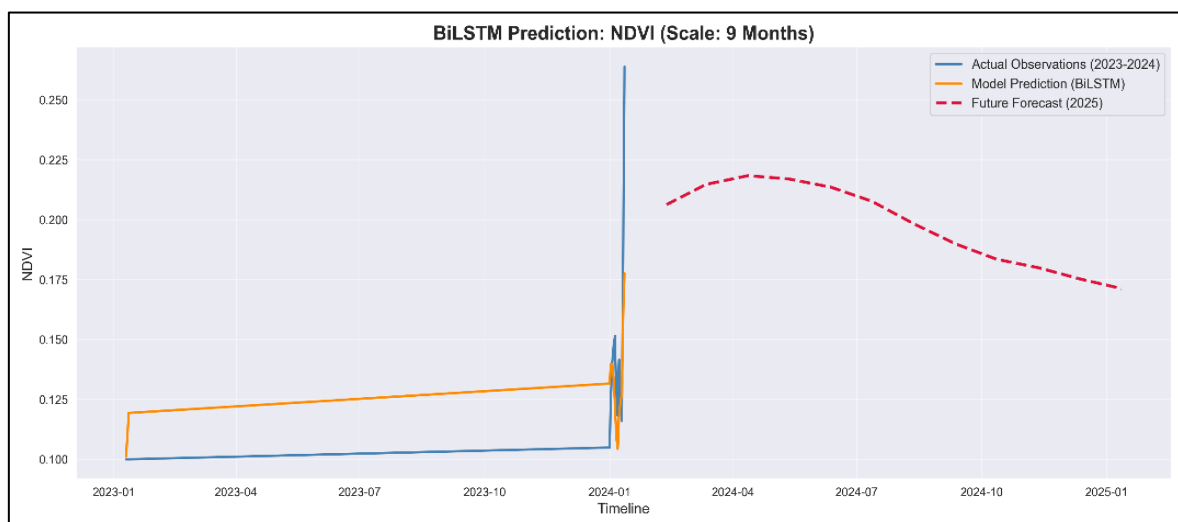


Fig 29 NDVI-9 Prediction Using BiLSTM Model (9-Month Scale)

The NDVI-9 scale reflects long-term vegetation stress patterns associated with prolonged drought.

- *NDVI-12 Prediction*

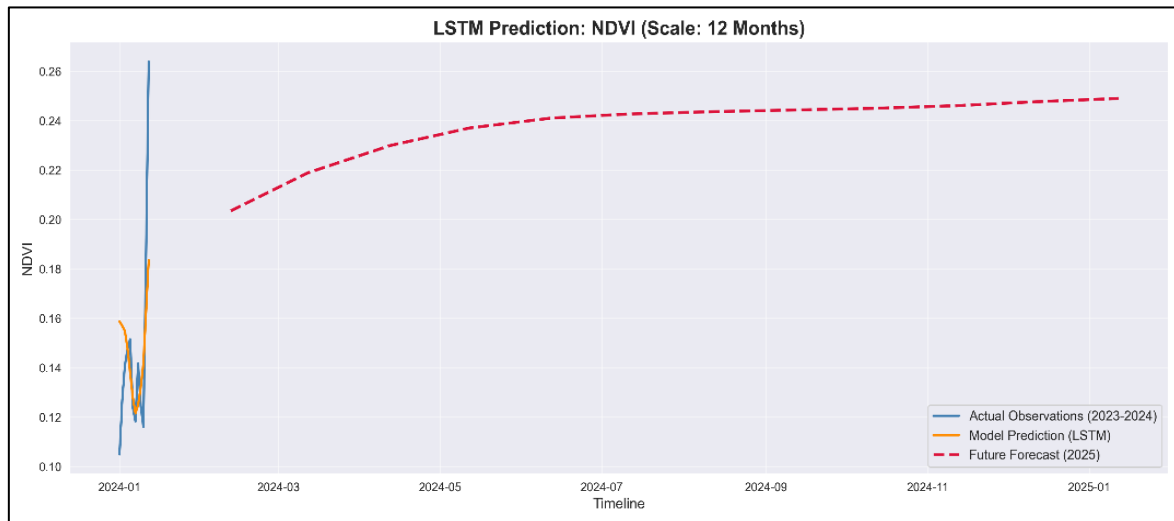


Fig 30 NDVI-12 Prediction Using LSTM Model (12-Month Scale)

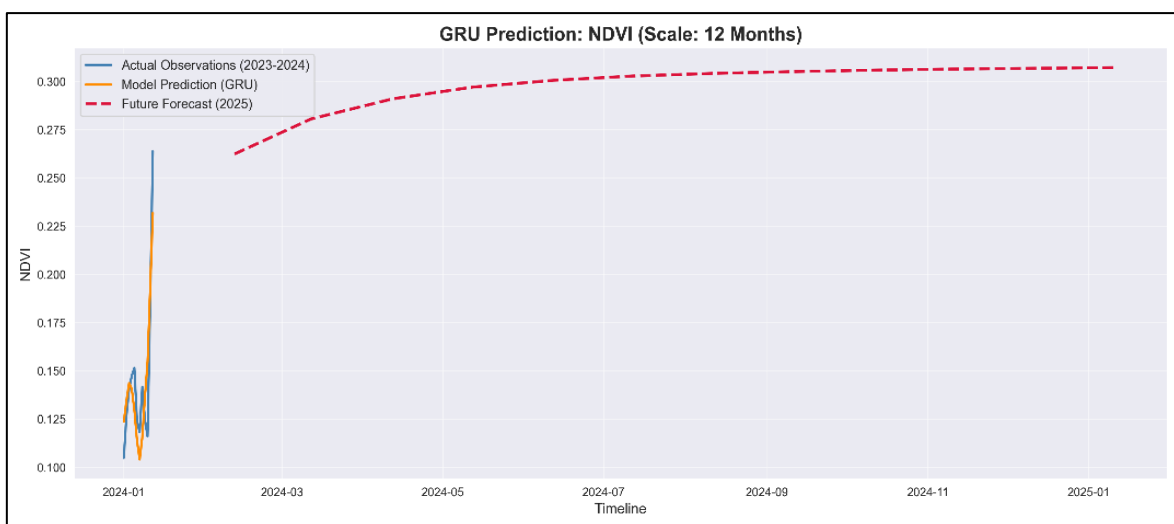


Fig 31 NDVI-12 Prediction Using GRU Model (12-Month Scale)

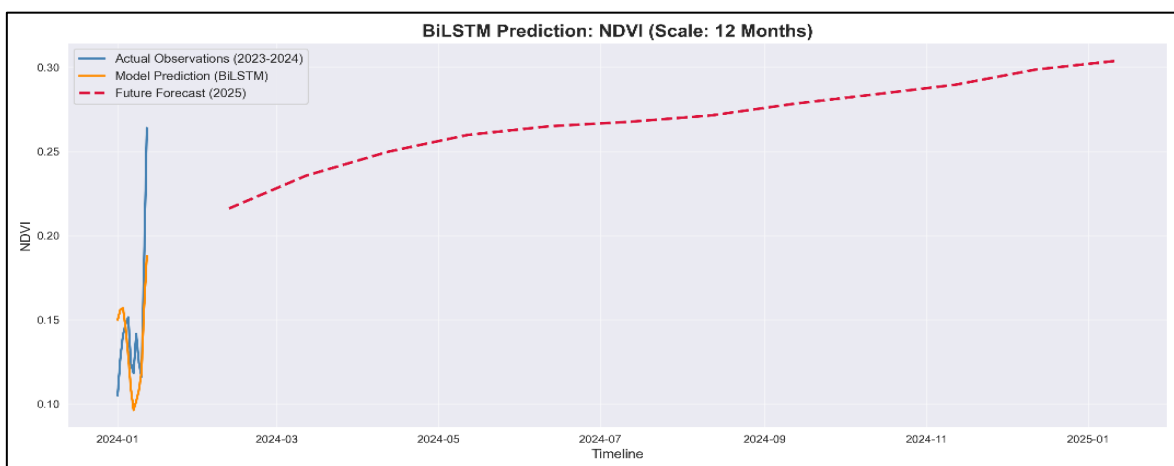


Fig 32 NDVI-12 Prediction Using BiLSTM Model (12-Month Scale)

The NDVI-12 predictions represent long-term vegetation dynamics and desertification risk.

➤ *Model-Performance Comparison*

To evaluate the prediction accuracy of the models, several statistical metrics were calculated using RMSE.

• *SPEI RMSE Comparison*

- ✓ The RMSE comparison confirms the relative performance of the models.
- ✓ GRU and BiLSTM demonstrate improved accuracy compared to the standard LSTM model.

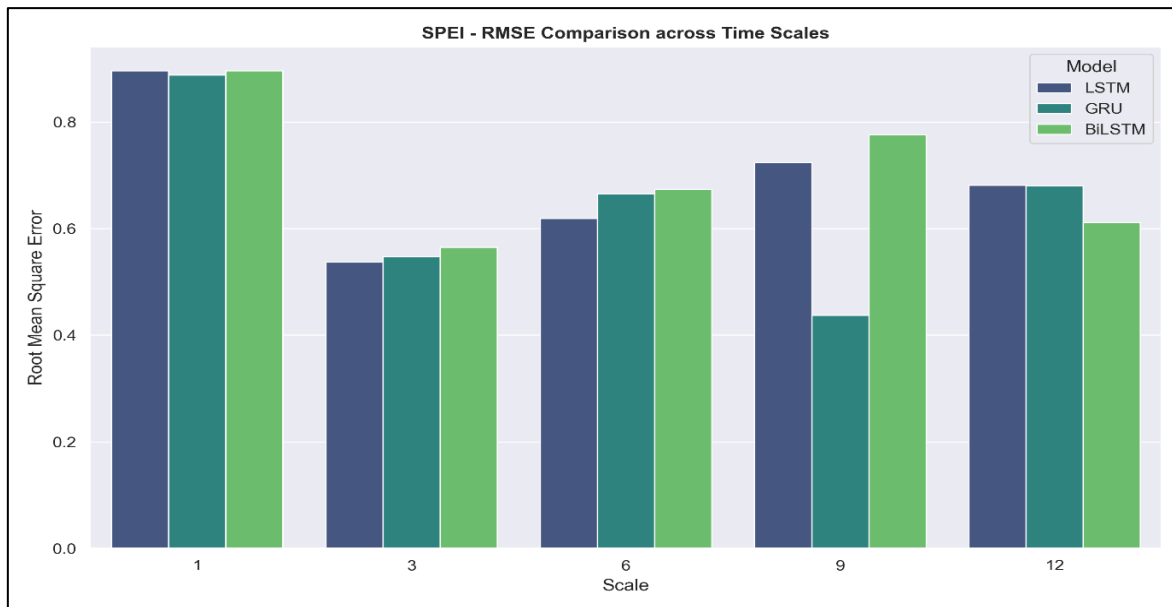


Fig 33 SPEI-RMSE Comparison

• *NDVI RMSE Comparison*

The RMSE comparison provides additional insight into prediction stability. Lower RMSE values suggest that the GRU model produces more consistent NDVI predictions compared to the other models.

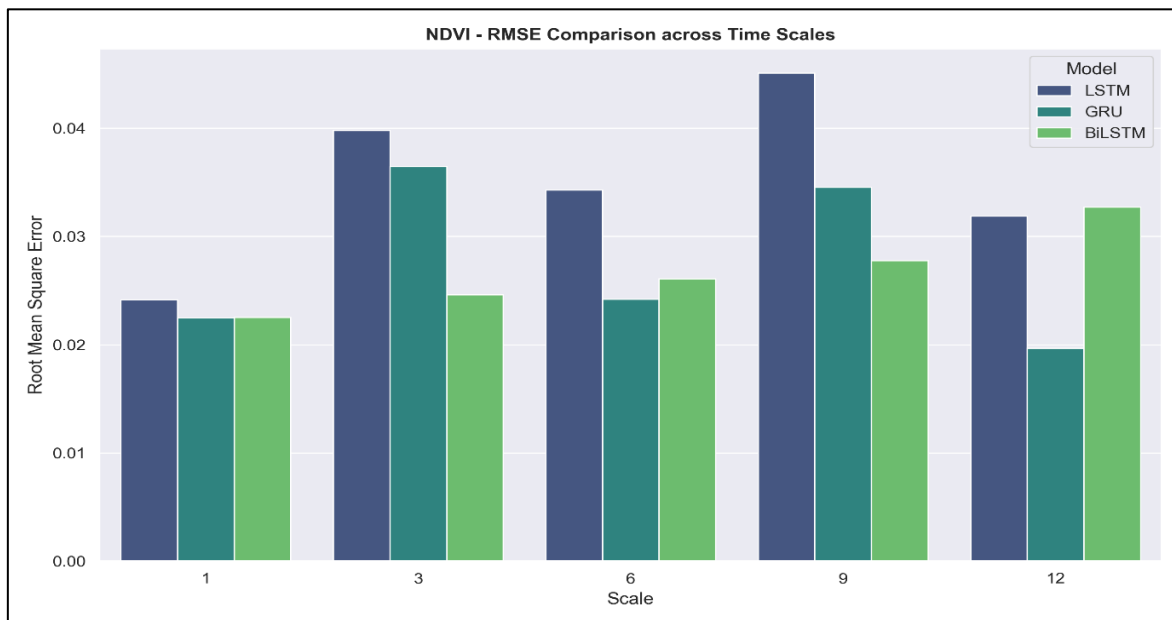


Fig 34 NDVI RMSE Comparison

VI. QUANTITATIVE EVALUATION AND FUTURE PREDICTION RESULTS

The performance of the proposed models was evaluated using Mean Absolute Error (MAE) and Root Mean Squared

Error (RMSE), which measure the difference between predicted and observed values of SPEI and NDVI across multiple time scales (1–12 months). The results, summarized in Table 1.

Table 1 compares LSTM, GRU, and BiLSTM across multiple time scales for SPEI and NDVI prediction. GRU achieves the lowest error for SPEI, especially at longer scales (e.g., RMSE = 0.4376 at 9 months), indicating better accuracy and stability. For NDVI, BiLSTM performs better at shorter scales, while GRU shows improved consistency at longer

scales (RMSE = 0.0197 at 12 months). LSTM generally shows higher errors.

The models were also used to forecast drought and vegetation conditions for 2025, supporting early warning and resource planning.

Table 1 Compares LSTM, GRU, and BiLSTM Across Multiple Time Scales for SPEI and NDVI

Model	Scale	Target	RMSE	MAE	R2	MAPE	Forecast_Avg	Risk_Level
LSTM	1	SPEI-1	0.8959	0.7023	-0.001	222.9957	-0.4809	Low
GRU	1	SPEI-1	0.8877	0.7134	0.0173	244.9894	-0.4521	Low
BiLSTM	1	SPEI-1	0.8958	0.7168	-0.0008	243.0712	-0.5157	Medium
LSTM	1	ndvi	0.0242	0.0171	0.7924	10.7513	0.2659	Medium
GRU	1	ndvi	0.0225	0.0192	0.8203	14.2025	0.311	Medium
BiLSTM	1	ndvi	0.0225	0.0154	0.82	9.602	0.2844	Medium
LSTM	3	SPEI-3	0.5371	0.4698	0.5001	93.809	-0.4137	Low
GRU	3	SPEI-3	0.5475	0.4508	0.4806	116.5127	-0.4563	Low
BiLSTM	3	SPEI-3	0.5649	0.4058	0.4469	69.212	-0.8842	Medium
LSTM	3	ndvi	0.0398	0.0344	0.4369	27.5674	0.2624	Medium
GRU	3	ndvi	0.0365	0.029	0.5271	21.6466	0.3372	Medium
BiLSTM	3	ndvi	0.0246	0.0198	0.7847	14.2936	0.322	Medium
LSTM	6	SPEI-6	0.619	0.5161	0.4414	90.6346	-0.6685	Medium
GRU	6	SPEI-6	0.6654	0.5704	0.3546	109.0546	0.1478	Low
BiLSTM	6	SPEI-6	0.6735	0.5687	0.3388	106.191	-0.0878	Low
LSTM	6	ndvi	0.0343	0.0238	0.2341	16.4835	0.2044	Medium
GRU	6	ndvi	0.0242	0.0199	0.6193	15.0674	0.2791	Medium
BiLSTM	6	ndvi	0.0261	0.0201	0.5569	16.7795	0.3091	Medium
LSTM	9	SPEI-9	0.7238	0.631	0.0878	216.2645	0.095	Low
GRU	9	SPEI-9	0.4376	0.3528	0.6666	173.7365	0.6647	Low
BiLSTM	9	SPEI-9	0.7758	0.6493	-0.0479	128.5268	0.8523	Low
LSTM	9	ndvi	0.0451	0.0393	-0.2121	33.3134	0.2483	Medium
GRU	9	ndvi	0.0345	0.0282	0.2896	23.9678	0.3156	Medium
BiLSTM	9	ndvi	0.0278	0.0193	0.5402	12.7959	0.198	High
LSTM	12	SPEI-12	0.6809	0.6084	0.2684	495.6363	0.3765	Low
GRU	12	SPEI-12	0.6805	0.5476	0.2693	635.1141	-0.0373	Low
BiLSTM	12	SPEI-12	0.611	0.5529	0.4108	324.6081	1.1828	Low
LSTM	12	ndvi	0.0319	0.0227	0.3963	15.2778	0.2374	Medium
GRU	12	ndvi	0.0197	0.0166	0.7701	11.9129	0.2975	Medium
BiLSTM	12	ndvi	0.0327	0.0263	0.3649	17.722	0.2683	Medium

VII. CONCLUSION

This study proposes a deep learning framework for multi-scalar drought and desertification prediction using climate and vegetation data. Models including LSTM, GRU, and BiLSTM were trained on 2000–2022 data and evaluated on 2023–2024.

Results show that GRU achieves lower errors for SPEI prediction, indicating better stability, while BiLSTM performs well for short-term NDVI prediction. LSTM shows comparatively higher errors. The analysis also indicates that NDVI prediction becomes more challenging at longer time scales.

The models were further used to forecast drought and vegetation conditions for 2025, demonstrating their applicability for early warning systems. Overall, the framework provides an effective tool for drought monitoring and resource management.

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