

Adaptive Weighted LSTM for Long-Lead Drought Forecasting using Hydroclimatic Time Series in Arid Regions

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Abstract This research work is conducted in Jaisalmer district, located in the western part of Rajasthan, India, an arid region highly vulnerable to persistent drought conditions. The area experiences low and erratic rainfall, making it critical for early drought detection and long-term hydrological forecasting. This research proposes an Adaptive Weighted Long Short-Term Memory (AW-LSTM) model to forecast the Standardized Precipitation Index (SPI) using high-resolution gridded hydroclimatic variables indices of precipitation, vegetation condition index (VCI), and temperature condition index (TCI). AW-LSTM integrates dynamic attention weights that prioritize relevant time steps and input features to enhance the long-term drought forecasting accuracy. The interpolated gridded layered stack of Precipitation-VCI-TCI input features is trained for the period June-September (year 1991 to 2020) and validated for the year 2021 to 2023 across lead times of 1 to 12 months. The AW-LSTM model achieved a high level of predictive accuracy, with an R^2 of ± 0.98 , RMSE of ± 0.02 , and Mean Absolute Error (MAE) of ± 0.08 , successfully capturing the beginning, duration, and severity of droughts. The model revealed that the western and southwestern parts of Jaisalmer are the most drought-prone, whereas the northeastern and central-eastern regions received relatively high rainfall. These findings support the development of real-time drought monitoring systems and enhance adaptive decision making for water resource planning in arid regions.

Index Terms Agricultural drought, sustainable environment, climate smart agriculture, AW-LSTM, SPI, VCI

I. INTRODUCTION

Owing to accelerated changes in climate, a significant challenge facing arid grasslands is the mapping of drought and the analysis of its trends. Improving monitoring techniques enhanced preservation and management of these critical ecosystems. This research aims to assess the utility of Geographic Information System (GIS) and remote sensing technologies in tracking the spatial and temporal progression of agricultural drought, with a focus on precipitation as a core indicator [1]. In arid environments, drought plays a pivotal role in shaping grassland ecosystems and acts as a significant constraint on agricultural productivity [1].

Precipitation serves as the primary determinant of climate variability and impact, directly influencing ecosystem dynamics through its timing and quantity [2][3]. These fluctuations, especially prolonged dry spells, adversely affect agricultural productivity, water resources, and rural livelihoods. As a result, understanding and forecasting drought have become essential for effective resource planning and risk management, particularly in vulnerable regions such as the Indian subcontinent. The increasing frequency and severity of droughts due to climate change have motivated the scientific community to develop various indices and techniques to characterize drought events [4]. Among these, the Standardized Precipitation Index (SPI) has gained widespread acceptance for its simplicity and effectiveness in capturing meteorological drought across varying timescales. Accurate forecasting of SPI enables the early detection of drought onset, thus strengthening drought early warning systems and preparedness strategies [5][6][7].

In recent years, Artificial Neural Networks (ANNs) have emerged as a powerful data-driven technique for drought forecasting, showing competitive results in both short- and long-term predictions [8]. Several studies have demonstrated the applicability of ANNs in forecasting drought indices such as SPI by utilizing lagged climatic variables as input features [9] [10]. However, despite their success, traditional neural networks often face challenges such as overfitting and difficulty capturing non-stationary and nonlinear patterns inherent in time-series climate data.

To address these limitations, researchers have increasingly adopted Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN) specifically designed to capture long-term dependencies through memory gates [11] [12]. LSTM has proven effective in modelling temporal dependencies in drought-relevant variables such as precipitation [13], temperature [14], and vegetation indices [10]. Its architecture allows it to retain crucial climatic patterns over extended periods, which is particularly beneficial for forecasting complex drought dynamics.

While LSTM models have shown promise in drought prediction, many existing approaches still fall short in addressing the nonlinear and dynamic interactions between multiple climate drivers and drought behaviour [17]. Studies such as [9] and [15] have utilized ANN-based models for one-month lead precipitation forecasting, reporting better accuracy than conventional methods. Yet, these models often neglect spatial dependencies and may not generalize well across regions with diverse climatic regimes.

Recent advances in deep learning—highlighted in Nature [16]—underscore the potential of hybrid and ensemble-based architectures in environmental prediction tasks. However, there remains a research gap in designing models that dynamically adapt to changing climatic inputs while effectively learning from both temporal and spatial features. Moreover, very few studies have explored the application of adaptive ensemble LSTM models in drought forecasting, particularly with long-lead-time predictions and complex environmental datasets [5][18].

To fill this gap, the present study proposes an Adaptive Weighted Long Short-Term Memory (AW-LSTM) ensemble model tailored for monthly SPI forecasting in the drought-prone Jaisalmer district. The proposed model incorporates multiple independently trained LSTM networks with varying sequence lengths to enhance temporal diversity. Each network focuses on learning distinct drought-related patterns from input features including SPI, VCI, TCI, and precipitation. A novel attention-based weighting mechanism is integrated to adaptively assign importance to each base learner, thereby improving generalization and reducing prediction error. This dynamic ensemble approach allows the model to adjust to evolving climate patterns and enhances its robustness across varying drought scenarios.

The core aims of this research can be summarized in threefold:

- (1) To examine variations in predicted outcomes by incorporating different drought characteristics, including intensity, duration (in months), and spatial extent;
- (2) To create an ensemble model using adaptive weighted LSTM for drought prediction; and
- (3) To examine the predictive capability of the AW-LSTM model for SPI estimation across multiple timescales in the Jaisalmer region of India.

The paper continues with section 2 that defines the spatial coverage and location-specific characteristics of the Jaisalmer region and outlines the characteristics of the dataset used. Section 3, titled results and discussion, provides insights into SPI calculations, optimal time selection, drought monitoring, drought prediction models, and model evaluation metrics. The following section presents model assessment. The last section presents the key findings and discusses directions for future research.

II. METHODOLOGY**A. LOCATON SITE AND DATASET**

The Jaisalmer district in western Rajasthan, India is selected because of its high vulnerability to agricultural droughts. The region spans approximately 32,401 km² [18] and lies between latitudes 26.25°N and 28.00°N and longitudes 70.25°E and 72.00°E. As shown in Fig. 1, daily gridded precipitation data for 55 grid points, spanning the period from 1991 to 2023, are obtained from the India Meteorological Department (IMD), Pune (<https://www.imdpune.gov.in/>). The data are provided at a spatial resolution of 0.25° × 0.25°. The dataset included 55 spatial grid points distributed across districts. Additionally, satellite-derived vegetation and temperature indices were obtained from NOAA-AVHRR, including SPI, VCI, TCI, VHI. These indices are selected based on their relevance to drought assessment and availability at appropriate temporal and spatial scales [19][20][21][22].

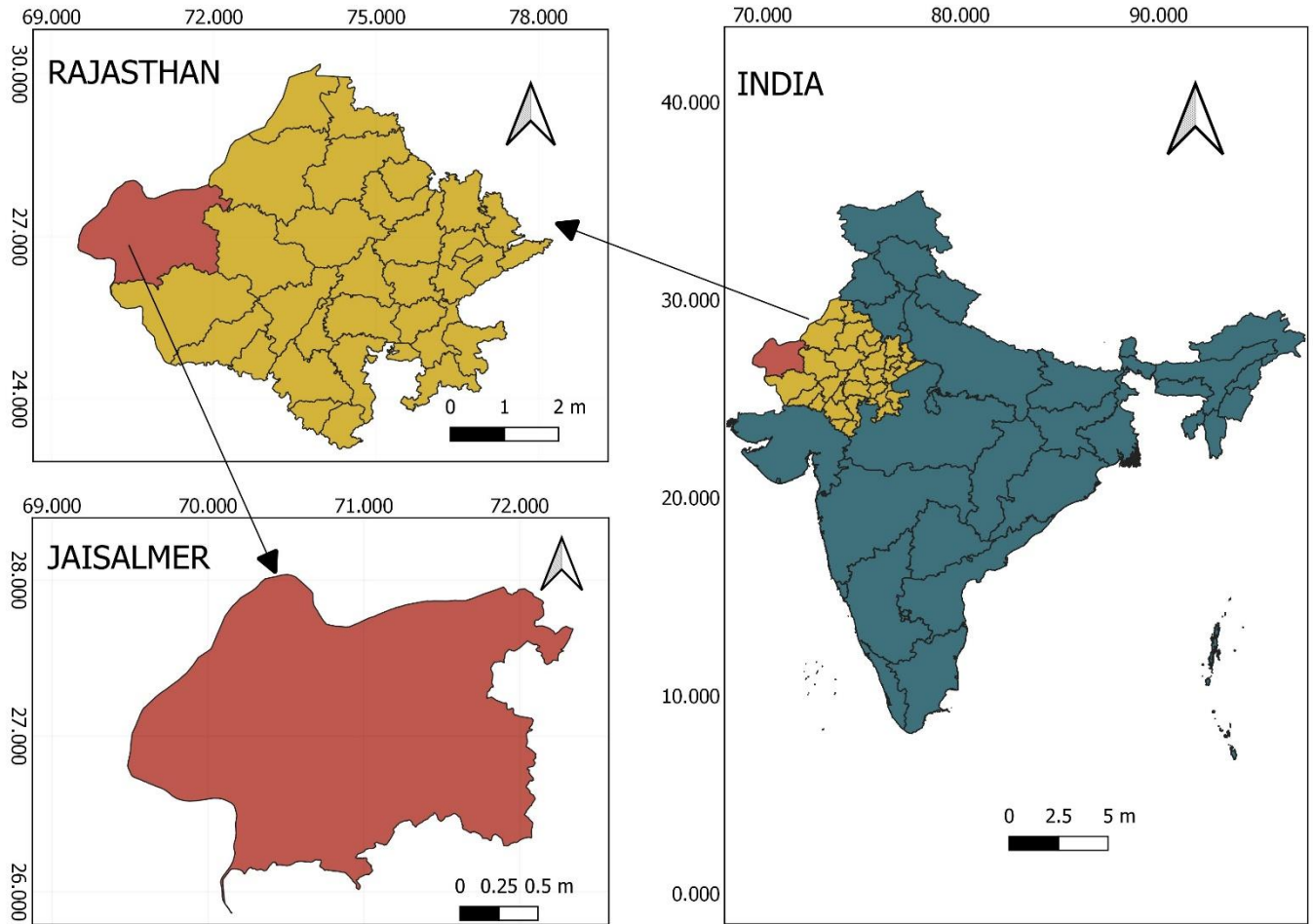


FIGURE 1. Drought Spatial region for Long-Lead Drought Forecasting: Jaisalmer district, Rajasthan, India

SPI-3 has been identified as the most appropriate timescale for drought prediction in this region, based on its responsiveness to seasonal precipitation variability and established relevance in previous studies [23][24][25]. To effectively model the temporal dynamics of drought, a sequence-to-sequence (seq2seq) learning framework is employed. The model utilizes input sequences comprising 12-monthly time steps and five key features: precipitation, SPI, VCI, TCI, and VHI. These vegetation health indices are derived from the NOAA-AVHRR dataset, which provides satellite observations with a temporal resolution of seven days and a spatial resolution of 4 km. This high-resolution data supports a detailed assessment of drought severity and duration, enabling consistent spatial and temporal monitoring.

As shown in Fig. 2, a 55-point spatial grid is applied to align the SPI, VCI, VHI, and TCI inputs across the study area. While the irregular and sparse distribution of ground-based precipitation gauges introduces potential uncertainties in long-term precipitation records, they remain widely adopted due to their affordability, operational reliability, and statistical robustness. However, monitoring large and heterogeneous regions poses inherent challenges. In this context, remote sensing (RS) techniques offer a valuable alternative, particularly for capturing the dynamics of grassland and semi-arid ecosystems [22]. The integration of ground-based precipitation data with satellite-derived vegetation indices enhances the model's capacity to learn both short- and long-term drought patterns across spatial scales, which is crucial for reliable long-lead drought forecasting.

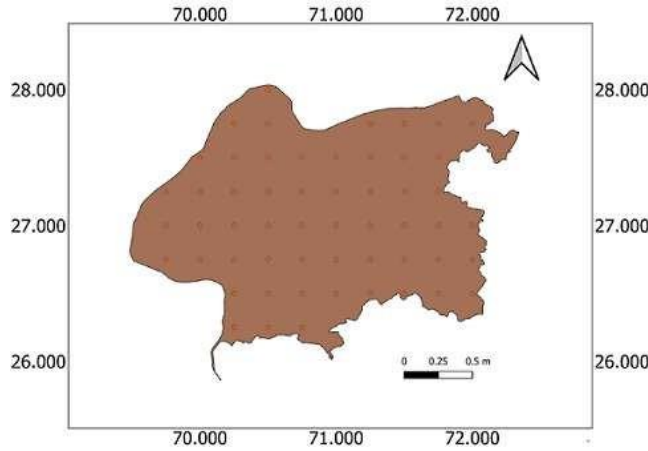


FIGURE 2. Gridded points ($0.5^\circ \times 0.5^\circ$) over Jaisalmer district for drought analysis

The SPI is determined using (1):

$$g(x) = \frac{1}{\beta^\alpha \tau(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \quad (1)$$

Where

α is a shape parameter ($\alpha > 0$)

β is the scale parameter ($\beta > 0$)

x denotes the precipitation amount ($x > 0$)

$\tau(\alpha)$ represents the gamma function [25]

For each calendar month and across various temporal scales (one, three, six, nine, and 12 months), the shape(α) and scale(β) parameters of the gamma probability density function are calculated [10]. The gamma function $\tau(a)$ and the amount of precipitation x , where $x > 0$, are given. Different pixel values acquired from satellite images can yield different indices. The next phase involves identifying the lag duration for climate predictors. The lag duration is not predefined, and various studies have utilized different lag periods. In this research, the optimal lag periods for climatic indices are evaluated using the mean gridded value through cross-correlation. This method is implemented on precipitation data and other predictor variables during the model training phase.

For improved spatial analysis, distinct color ramps are used to denote each drought class. After the classification, the data is exported as maps. June, July, August, and September are the seasonal months that indicate how the drought category varies annually. The Rajasthan Water Resource Department(<https://water.rajasthan.gov.in/>) provided ground data-based meteorological values that is used to validate the results. Fig. 3 illustrates the methodology for long-lead drought forecasting in detail. Based on a literature review [25][26][27], SPI distribution can be classified into five drought classes. The agricultural drought index values are listed in Table I.

TABLE I. CLASSIFICATION OF AGRICULTURAL DROUGHT

Level	Drought Category	Range
1.	NO drought	>0
2.	Mild	0 to -1.0
3.	Moderate	-1.0 to -1.5
4.	Severe	-1.5 to -2.0
5.	Extreme	< -2.0

Quantifying and predicting droughts continue to be a major challenge for those responsible for making decisions on water resources. Time series with values that indicate the severity of drought are known as drought indices. A zero threshold is applied to identify drought episodes, enabling the extraction of detailed information on each event including its peak, duration, and severity. Drought is indicated by SPI values below zero, and its diagnosis can be made more easily if the zero threshold is compatible with this problem.

Following the collection of SPI data, all predictor values are obtained from relevant sources. The following categories apply to the predictors employed in this research: a) hydrometeorological, which comprises elements such as temperature, precipitation, and cloud cover, and b) climatic indicators, which include vegetation.

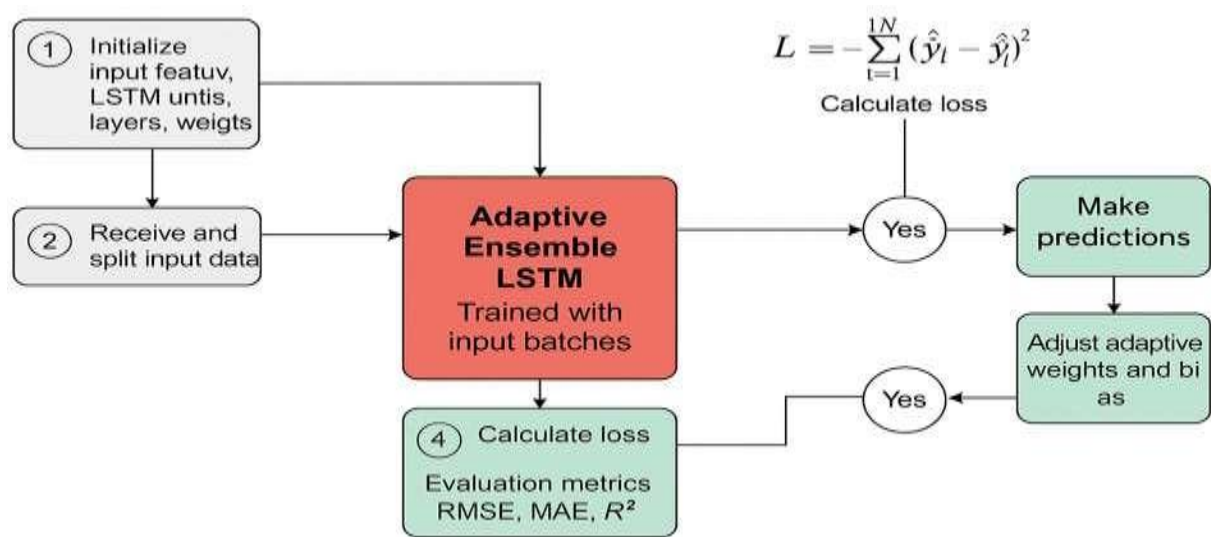


FIGURE 3. Workflow of the Adaptive Ensemble LSTM model for drought prediction

B. LSTM Architecture

The LSTM structure exhibited a chain-like configuration, with a cell functioning as the fundamental building block and its state determining the operational mode [25]. The status of a cell can be ascertained using three types of gates: input, forget, and output gates [28]. The gates use point-wise multiplication operation and sigmoid neural layer to evaluate and regulate the amount of data that can pass through them. The following formulas can be used to express the operation of the gates and information flow:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$c_{\sim t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot c_{\sim t} \quad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (7)$$

In (2), (3), (4), (5), (6) and (7), where σ is the sigmoid function; W_f , W_i , W_c , and W_o denote the weight matrices; And b_f , b_i , b_c , and b_o are their corresponding biases. These parameters had values ranging from 0 to 1. where c_t denotes the current cell state, h_t represents the cell's output information, and c'_t denotes newly generated information.

C. Adaptive weighted ensemble LSTM

The Adaptive Weighted Long Short-Term Memory (AW-LSTM) model is developed to address the key challenges associated with long-lead-time drought prediction, particularly those involving complex temporal dependencies and feature relevance across climate variables. Traditional LSTM models, although capable of learning from sequential data, often treat all temporal features equally, which can dilute the influence of critical indicators such as sudden precipitation drops or vegetation stress responses. The AW-LSTM model mitigates this by embedding an attention mechanism that adaptively assigns weights to the hidden states at each time step. This mechanism enhances the model's ability to focus on the most informative features while suppressing less relevant noise, thereby improving interpretability and prediction accuracy in the presence of multidimensional drought-related data [21].

A key innovation in the proposed approach is the integration of multiple LSTM networks into an ensemble framework, where each network serves as an independent base learner or “foundational prediction model” [29]. To maximize the diversity of the ensemble, each LSTM model is trained with a different sequence length. This variation allows each learner to capture temporal patterns across different time horizons—ranging from short-term fluctuations to more persistent trends—which contributes to the model's capacity to generalize over diverse drought scenarios. The heterogeneous sequence lengths introduce variation in the memory capacity of each LSTM unit, fostering the learning of a broader spectrum of temporal relationships. This ensemble diversity not only enhances robustness but also minimizes overfitting, which is a common issue in deep learning models trained on limited or noisy environmental datasets [30].

The proposed Adaptive Weighted Ensemble LSTM (AW-LSTM) model is composed of ten independently trained LSTM models ($M=10$), each configured to process temporal input sequences spanning twelve months ($n_{\text{time_steps}}=12$). Each input sequence contains four key drought-related features: precipitation, the Standardized Precipitation Index (SPI), the Vegetation Condition Index (VCI), and the Temperature Condition Index (TCI). These features were selected based on their proven relevance in drought detection, with precipitation and SPI reflecting meteorological drought conditions and VCI and TCI capturing vegetation stress responses. The inclusion of both atmospheric and ecological indicators enables the model to more effectively represent the multifaceted nature of drought events.

Each LSTM model in the ensemble learns the temporal dynamics of these variables independently. Once trained, the outputs of the ten models are not simply averaged. Instead, they are aggregated using an adaptive weighting strategy, wherein each model's contribution to the final prediction is determined by its validation loss—models with lower

validation loss receive higher weights. This adaptive mechanism ensures that better-performing models exert more influence on the final prediction, thereby improving the ensemble's overall generalization capability. By combining multiple LSTM models with diverse initialization or training paths and dynamically assigning weights based on performance, the AW-LSTM model enhances robustness, reduces prediction variance, and delivers superior accuracy in long-lead drought forecasting. This design is particularly effective in capturing the non-linear and lagged interactions characteristic of drought phenomena, which often challenge conventional single-model approaches. Fig. 3 illustrates the working model used in this research.

Fig. 4 illustrates the architecture of the AW-LSTM model. It highlights the flow of input sequences through each LSTM base model, the incorporation of the attention mechanism, and the final output stage where predictions are aggregated. The ensemble not only improves accuracy but also provides resilience against temporal shifts and anomalies in the data. By capturing both short-term variability and long-term dependencies, the AW-LSTM framework is well-suited for operational drought forecasting in data-scarce and climate-sensitive regions such as Jaisalmer. Overall, this model demonstrates the benefits of combining deep temporal learning, attention-based feature weighting, and ensemble diversity in a single architecture tailored for real-world climate risk prediction.

This research employs a sliding window approach or sequence-to-sequence (seq2seq) forecasting method, where predictions for time t_i estimate values for time t_i+1 . As the forecast lead time increases, the number of dense layers increases proportionally; a six-month lead time results in six dense layers. The prediction accuracy of the AW-LSTM ensemble is influenced by combining the weights ω^m for $m=1 \dots, M$. A dynamic weighting algorithm proposed to adaptively adjusts the time-varying dynamics of the underlying time series. This ensemble of LSTM models employs an adaptive weight-adjustment strategy that modifies the weight of each model based on its validation loss during training. Models with higher validation losses received greater weight, increasing their influence on ensemble prediction. This procedure involved several steps. First, the validation loss for each LSTM model is computed using a distinct validation dataset following each training epoch. Subsequently, the inverse of the validation loss is calculated for each model, thereby prioritizing the models with lower validation losses. To ensure that the weights add up to one, each inverse validation loss is divided by the total of all inverse losses, normalizing them in the process. Weights are subsequently allocated to the LSTM models based on the normalized inverse validation losses. The weights are updated at the end of each epoch during the training process. In the weighted ensemble prediction phase, the predictions of each LSTM model are multiplied by their respective weights and aggregated. The final prediction is derived from the sum of the weighted forecasts. The AW- LSTM approach emphasizes models that perform well on unseen data by adjusting the weights in response to validation loss, resulting in more accurate ensemble predictions than those produced by a single model. The overall methodology of AW-LSTM for Long-Lead Drought Forecasting is given in Algorithm 1.1.

Algorithm 1.1: AW-LSTM for Long-Lead Drought Forecasting

- step1** Define the number of input features, LSTM units, and layers.
- step2** Initialize weights, biases, and adaptive weights.
- step3** Prepare input data and split into batches.
- step4** Initialize hidden and cell states for each batch.
- step5** For each batch
 - a. Compute the adaptive weighted input
 - b. Calculate forget, input,,,,,,,,, and output gates
 - c. Update cell state using adaptive weights.
 - d. Compute new hidden state and output.
- step6** Calculate loss between predicted and actual outputs.
- step7** Update model parameters using adaptive gradient descent.
- step8** Repeat steps 4–7 for defined epochs or until convergence.
- step9** Apply the trained model to generate predictions on unseen data.

step10 Evaluate performance with RMSE, Mean Absolute Error (MAE,) and R^2 .

step11 Adjust adaptive weights based on performance.

step12 Tune batch size and learning rate for optimal performance.

step13 Save final model parameters for future use.

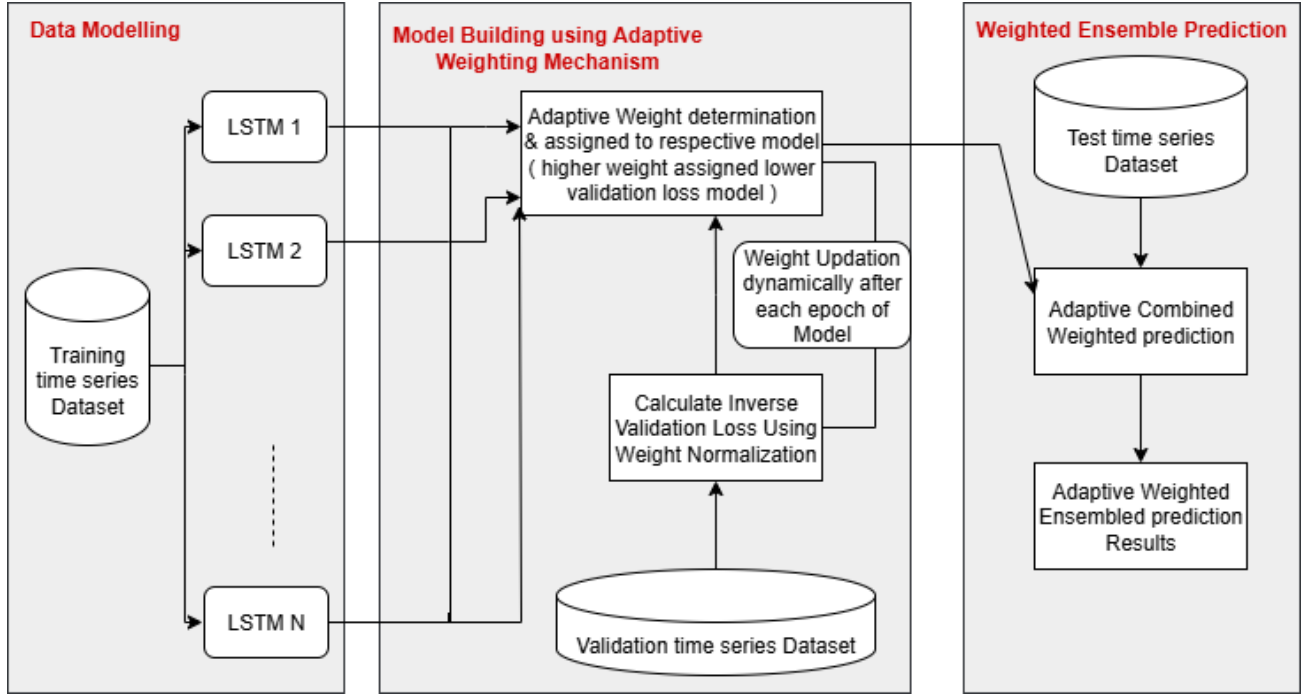


FIGURE 4. Architecture of Adaptive weighted LSTM model

D. Performance evaluation

The effectiveness of the proposed drought forecasting model is quantitatively assessed using three standard statistical metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2), as defined in Equations (14)–(16). These metrics provide a rigorous framework for evaluating the model's predictive accuracy, error distribution, and overall explanatory power.

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n} = \frac{\sum_{i=1}^n |e_i|}{n} \quad (14)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 \quad (15)$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (16)$$

III. RESULTS AND DISCUSSIONS

A visual inspection of the monthly precipitation anomalies from May to September over the period 1991–2023 (Fig. 5) reveals substantial inter-annual variability in monsoonal rainfall. Years such as 2000, 2002, 2009, and 2021 display consistently negative anomalies across all five months, indicating widespread monsoon failure and prolonged drought conditions. Particularly, May and June show early signs of anomaly onset, underscoring their critical role in triggering seasonal drought. This reinforces the utility of early-month indicators for drought

prediction models. The wide spread of positive and negative values further validates the inclusion of multi-month inputs in the proposed AW-LSTM and GNN-LSTM models to better capture these dynamics. Grid colors represent varying levels of drought severity, with the western part of the district consistently emerging as the most affected. Fig. 6 provides a clearer view of the model performance, and a detailed comparison is conducted for the year 2023 using a one-month lead time. The predicted SPI values indicated that the percentages of drought-affected grids in June, July, August, and September are 28.8%, 27.2%, 21.0%, and 27.6%, respectively. August exhibited the lowest drought severity. In July, the northeastern and eastern regions showed the highest SPI values (above 8.0), indicating wet conditions, whereas the southwest region showed red hues (0.15–0.5), reflecting low rainfall. In September, the same southwestern area recorded nearly zero precipitations, suggesting persistent drought. The central-western region in August had SPI values close to 0.32, confirming the consistency of the drought conditions across months. Rainfall peaks are also observed in the north-central grids in August (~3.23) and in the eastern patches of June (above 1.6).

The drought prediction is conducted for 2023 using a model trained on historical data from 1991 to 2020. In addition to forecasting accuracy, analyzing the spatial variability of drought characteristics is essential for understanding pixel-wise variation across the study region. The proposed Adaptive Weighted Ensemble LSTM method outperformed conventional deep learning approaches, as demonstrated in Fig. 6. The model performance is primarily evaluated using the coefficient of determination (R^2), which achieved a high value of 0.98, indicating a strong correlation between the predicted and observed values. Complementary error metrics—MSE and MAE—are also computed, yielding values of 0.02 and 0.08, respectively. These metrics are selected for their distinct advantages: R^2 , ranging from 0 to 1, captures the proportion of variance in the observed data that is explained by the model; MSE amplifies larger errors due to the squaring of residuals, while MAE provides a clear indication of the average magnitude of prediction errors.

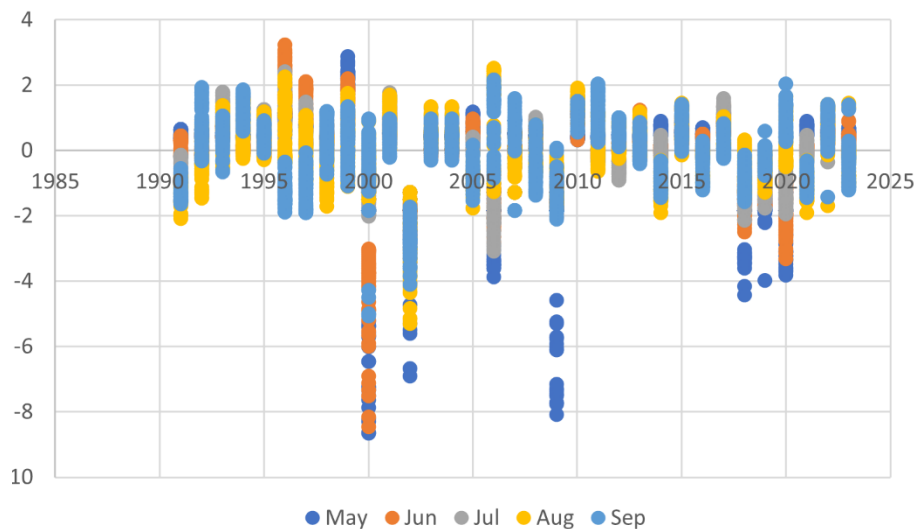
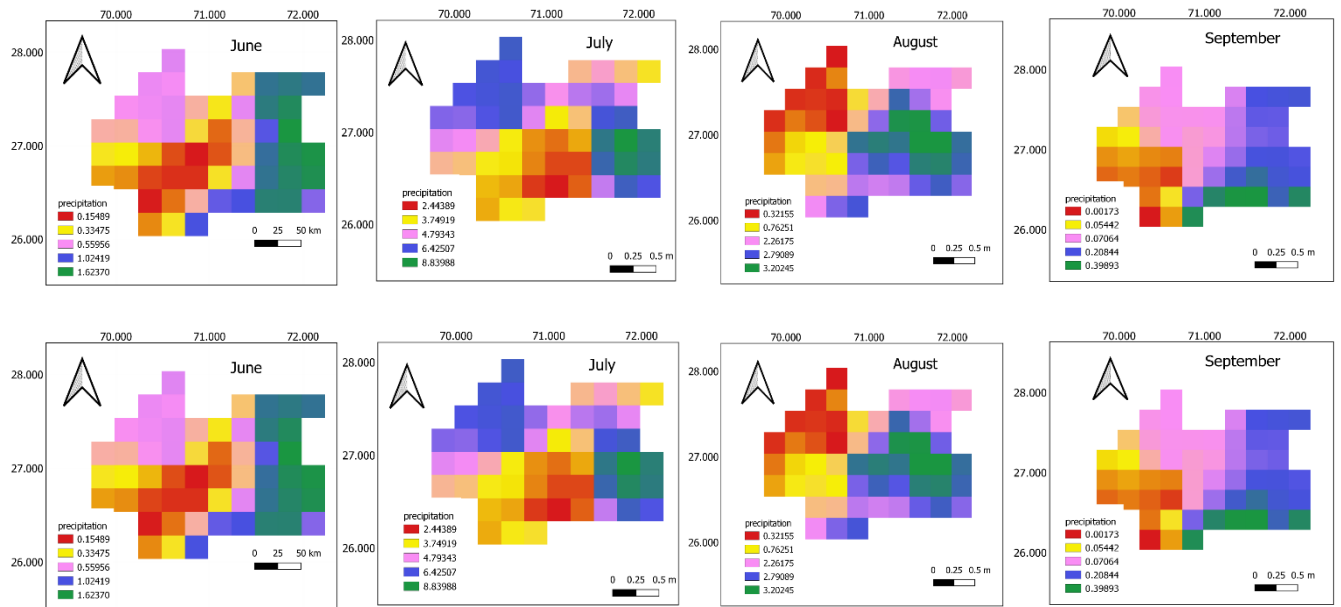


FIGURE 5. Variation in seasonal months during study period (1991-2023)



(a) SPI for June

(b) SPI for July

(c) SPI for August

(d) SPI for September

FIGURE 6. Comparison of the first-instance SPI 3 values observed and predicted, with lead times of one month for months of a) June, b) July, c) August, and d) September. The predicted values are shown in the bottom row, and the observed values are shown in the top row

IV. MODEL ASSESSMENT

The research focused on supplying an extensive training dataset, complemented by an adequately sized testing dataset for reliable evaluation. Therefore, the data is trained between 1991 and 2020 and assessed between 2021 and 2023. The next step involves determining the lag durations of large-scale climate projections. Various lag durations have been used in previous studies, and each has been successful in producing the desired result. For instance, some researchers predicted rainfall using a lag period of three months [32], whereas some predicted SPI using a lag period of 12 months [10].

Rather than exploring various lag durations, this research assessed the lag of climate indicators through cross-correlation, utilizing the mean gridded SPI as a reference. Cross-correlation between the predictor variables and SPI values is employed during the training phase. Climate variables show a strong association with values of 0.94 and 0.78, respectively, and no lag time between rainfall and SPI. The proposed method predicts monthly SPI at various lead times by incorporating climate and meteorological variables as input. Furthermore, it evaluates how lag duration affects the forecasting performance [33][34].

Using hydrometeorological variables as input features, a single-layer Long Short-Term Memory (LSTM) network was employed to forecast the Standardized Precipitation Index (SPI) for Hyderabad, India, with a one-month lead time [11]. The research yielded an accuracy of 94% and an RMSE value of 0.03 and utilized temperature and rainfall as predictor variables. Using a global hydrometeorological dataset and considering the entire state, 0.72 value of R^2 is obtained [35][36][37][38].

V. CONCLUSION

In this study, we introduced a novel Adaptive Weighted Long Short-Term Memory (AW-LSTM) ensemble model for drought forecasting, which dynamically adjusts model weights based on performance, thereby improving the accuracy and robustness of predictions. This ensemble architecture effectively integrates temporal dependencies and nonlinear patterns present in multivariate drought data by utilizing advanced LSTM-based deep learning techniques. Our approach utilized SPI-3 as the primary drought indicator along with vegetation indices such as the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI), collected over a 33-year period (1991–2023) for the Jaisalmer region of Rajasthan, India. The model achieved exceptional predictive performance, recording an R^2 value of 0.996, Mean Squared Error (MSE) of 0.0982, and Mean Absolute Error (MAE) of 0.1906. These metrics demonstrate the model's capability to accurately capture the onset, duration, and severity of drought events, making it a highly reliable tool for early warning systems.

One of the key advantages of the AW-LSTM is its ensemble structure, which includes multiple LSTM base learners trained with varying sequence lengths and initialized with different parameters. This introduces diversity into the modeling process and improves generalization by reducing overfitting. The adaptive weighting mechanism further refines the predictions by assigning greater importance to models with lower validation loss, which is particularly beneficial for handling non-stationary climate data. Furthermore, the short-lead forecasting capability (1-month ahead) of the model demonstrated substantial improvements in early drought detection, offering timely insights for agricultural planning and water resource management. The enhanced short-term accuracy underscores the potential of integrating ensemble deep learning architectures in operational drought monitoring frameworks, especially in data-scarce, arid, and semi-arid regions.

Spatiotemporal analysis of SPI patterns using the model also revealed granular drought dynamics across the study region. The ability to interpret drought evolution at the grid level facilitates localized risk assessments and targeted mitigation strategies. The model's success in the Jaisalmer district, characterized by extreme climatic conditions and sparse rainfall, affirms its scalability and adaptability to other regions facing similar environmental challenges. In essence, the AW-LSTM model provides a comprehensive and scalable framework for drought prediction by effectively combining ensemble deep learning, adaptive weighting, and climatic indices. The findings of this study serve as a foundation for advancing precision drought forecasting and highlight the critical role of data-driven approaches in enhancing climate resilience, supporting policy interventions, and enabling sustainable resource management.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no financial or personal relationships that could be perceived as influencing the work reported in this paper.

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