Journal of Agrometeorology

(A publication of Association of Agrometeorologists)

ISSN : 0972-1665 (print), 2583-2980 (online)

Vol. No. 27 (3) : 332-337 (September - 2025)

https://doi.org/10.54386/jam.v27i3.3010

https://journal.agrimetassociation.org/index.php/jam

Research Paper

Hybrid SARIMA–Bi-LSTM model for monthly rainfall forecasting in the agroclimatic zones of Chhattisgarh

DIWAKAR NAIDU[1*] and SURENDRA KUMAR CHANDNIHA[2]

[1]Swami Vivekananda College of Agricultural Engineering and Technology and Research Station, Indira Gandhi Krishi Vishwavidyala, Raipur, Chhattisgarh, India

[2]Bhawani Ramlal Sao Memorial College of Agricultural Engineering and Technology and Research Station, Indira Gandhi Krishi Vishwavidyala, Mungeli, Chhattisgarh, India

**Corresponding author email: diwakar.naidu@igkv.ac.in*

ABSTRACT

This study proposes a hybrid Seasonal Autoregressive Integrated Moving Average (SARIMA)–Bidirectional Long Short-Term Memory (Bi-LSTM) model for monthly rainfall forecasting in the agroclimatic zones of Chhattisgarh, India. Accurate rainfall prediction is critical for agricultural planning and water resource management, especially under increasing climate variability. The analysis utilizes 120 years (1901–2020) of monthly rainfall data, preprocessed for time series modeling. SARIMA serves as a statistical baseline, effectively capturing linear and seasonal trends, while Bi-LSTM, a deep learning model, is adept at learning long-term and non-linear dependencies. The hybrid SARIMA–Bi-LSTM model leverages the strengths of both approaches to improve forecasting accuracy. Model performance was evaluated using standard metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Results show that Bi-LSTM outperforms SARIMA, and the hybrid model delivers the best generalization across agroclimatic zones. In the Chhattisgarh Plains, the hybrid model achieved the lowest validation RMSE (41.70 mm), MAE (25.93 mm), and the highest R^2 (0.906). The study highlights SARIMA's limitations in capturing non-linearities and Bi-LSTM's tendency to overfit, both addressed in the hybrid approach. This work demonstrates the effectiveness of hybrid models in enhancing rainfall forecasting and informs climate-resilient agricultural practices.

Keywords: Rainfall prediction, Bi-LSTM, SARIMA, Hybrid modeling, Agroclimatic zones, Deep learning.

Rainfall prediction plays a critical role in agricultural planning, water resource management, and disaster preparedness. In agrarian regions like Chhattisgarh, where agriculture forms the economic backbone, accurate rainfall forecasting is vital for ensuring food security and efficient resource allocation. The state encompasses diverse agroclimatic zones, each exhibiting distinct rainfall patterns, making region-specific predictive models essential.

Traditional statistical models, particularly the SARIMA, have long been employed for time series forecasting. SARIMA is effective in identifying seasonality and linear trends (Box and Jenkins, 1976). For instance, Dabral and Murry (2017) applied SARIMA to forecast rainfall in Northeast India, where it successfully modeled monsoon patterns but underperformed during extreme events. Several studies have explored enhancing SARIMA's performance by incorporating exogenous climate variables like temperature and humidity (Han and Park, 2020; Pandey, 2018). Despite such efforts, SARIMA remains limited in capturing highly nonlinear climatic behavior (Smith and Taylor, 2023).

To address these limitations, machine learning (ML) and deep learning (DL) techniques have gained prominence. Algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) have shown promise in rainfall forecasting (Choi *et al.,* 2021; Martinez and Lee, 2019). Among DL models, Long Short-Term Memory (LSTM) networks have become popular due to their ability to learn long-term temporal dependencies (Hochreiter and Schmidhuber, 1997). Studies by Ahmed and Sreedevi (2023) and Rajalakshmi (2023) revealed that LSTM models outperform SARIMA in monsoon-heavy regions by delivering more accurate forecasts with lower errors. Patro and Bartakke (2024) further demonstrated LSTM's effectiveness

Article info - DOI: *https://doi.org/10.54386/jam.v27i3.3010*

Received:17 April 2025; Accepted: 21 May 2025; Published online : 1 September 2025

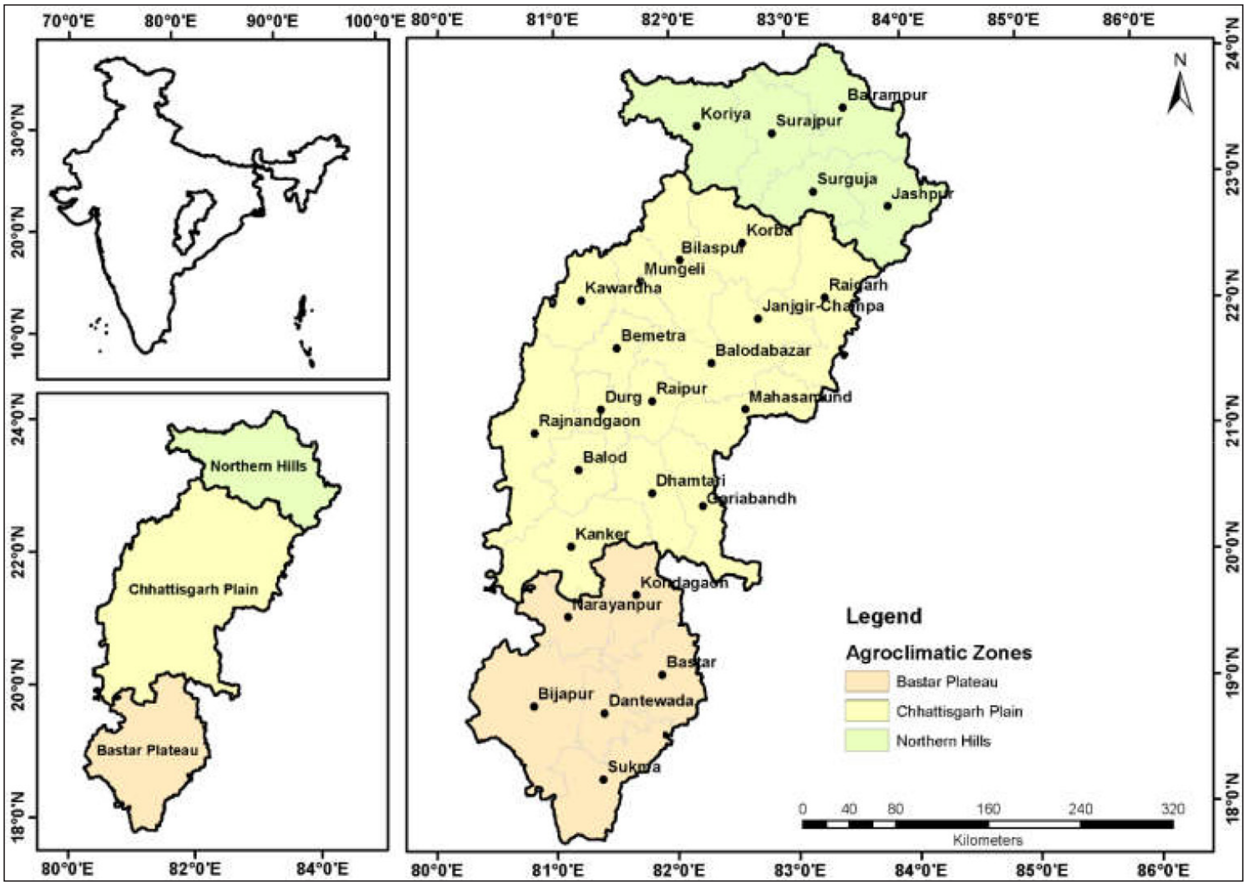

Fig. 1: Location map of the study area covering the three agroclimatic zones of Chhattisgarh

in modeling daily rainfall, though its performance is sensitive to dataset size and hyper-parameter tuning (Zhou *et al.,* 2023; Kumar and Singh, 2021).

Recent advancements have introduced hybrid modeling frameworks that integrate SARIMA and deep learning techniques to leverage the strengths of both. Wu and Zhang (2022) and Yadav and Verma (2022) proposed SARIMA-LSTM models where SARIMA first modeled the linear seasonal components, and LSTM captured the residual nonlinear patterns, resulting in reduced forecasting errors. Similarly, Singh and Patel (2023), in a meta-analysis, concluded that hybrid models consistently outperform standalone methods in accuracy and robustness. Gupta and Sharma (2021) confirmed this by evaluating climate forecasting models and highlighting the superior performance of hybrid structures. In parallel, Ray *et al.,* (2023) showcased the potential of time-delay wavelet neural networks (TDWNN) in forecasting rainfall and managing agrometeorological risks.

This study develops monthly rainfall prediction models for Chhattisgarh's agroclimatic zones using SARIMA, Bi-LSTM, and a hybrid SARIMA–Bi-LSTM model. The hybrid approach first fits SARIMA to capture linear trends and seasonality, then trains Bi-LSTM on the residuals to model complex nonlinear dependencies. This layered modeling ensures improved accuracy in both short- and long-term forecasting. Enhanced rainfall prediction supports hydrological planning, climate adaptation, and disaster risk reduction. By comparing SARIMA, Bi-LSTM, and their hybrid, this study offers valuable insights for researchers, policymakers, and agricultural planners working toward sustainable and climate-resilient development.

MATERIALS AND METHODS

Study area and data

This study examines monthly rainfall patterns across Chhattisgarh's three agroclimatic zones, Chhattisgarh Plains, Bastar Plateau, and Northern Hills (Fig. 1), which exhibit notable seasonal variability. The Chhattisgarh Plains, characterized by extensive paddy cultivation, experience moderate rainfall. The Bastar Plateau, with its undulating topography, receives higher precipitation, while the Northern Hills, with rugged terrain, exhibit the highest annual rainfall. A 120-year (1901–2020) monthly rainfall dataset from the India Meteorological Department (IMD), with a spatial resolution of 0.25° × 0.25°, was aggregated at the district level to create time series for each zone. This extensive dataset supports the development of robust models that capture both short-term variations and long-term climatic trends (Hyndman and Athanasopoulos, 2018; Shumway and Stoffer, 2017).

Data preprocessing

Before model training, the dataset was preprocessed to ensure quality and consistency. As the IMD gridded dataset had no missing values, imputation was unnecessary. Outliers were detected using the z-score method and removed based on their deviation from historical patterns. Due to high seasonal variance, Min-Max normalization was applied to scale values between 0 and 1, preventing extreme values from skewing the training process, particularly important for deep learning models sensitive to input ranges (Chollet, 2017; Goodfellow *et al.,* 2016).

Dataset structuring for prediction

The dataset was structured into sequences using a sliding window approach, where the past 12 months of rainfall data were utilized as input features to predict the rainfall for the subsequent month. This one-month-ahead forecasting strategy effectively captures temporal dependencies within the time series data. To ensure unbiased model training and evaluation, the dataset was partitioned into training (80%), testing (10%), and validation (10%) subsets, following the methodology outlined by Pasini (2020).

Predictive modeling approaches

This study utilizes three models for rainfall forecasting: SARIMA, Bi-LSTM, and a hybrid SARIMA-Bi-LSTM. SARIMA, a statistical model, captures linear trends and seasonality in time series data (Box and Jenkins, 1976; Brown, 2004), optimized here using Auto-ARIMA based on the Akaike Information Criterion (Hyndman and Athanasopoulos, 2018). It effectively models monsoonal patterns with a 12-month seasonal period. Bi-LSTM, a deep learning model, captures nonlinear, long-term dependencies through memory cells and bidirectional processing (Hochreiter and Schmidhuber, 1997; Greff *et al.,* 2017). The hybrid SARIMA-Bi-LSTM model combines both methods: SARIMA forecasts are fed as additional inputs into the Bi-LSTM, enabling it to refine predictions by learning residual nonlinear patterns. This integration leverages SARIMA's strength in modeling seasonality and Bi-LSTM's capacity for complex pattern recognition, leading to enhanced forecasting accuracy (Zhang, 2003).

Model architectures and hyper-parameter selection

The SARIMA model in this study was designed to effectively capture both non-seasonal and seasonal variations in monthly rainfall data. The chosen configuration included non-seasonal parameters: autoregressive order (p) = 1, differencing order (d) = 1, and moving average order (q) = 1. Seasonal components were also incorporated, with seasonal autoregressive order (P) = 1, seasonal differencing (D) = 1, and seasonal moving average (Q) = 1. The seasonal period (s) was set to 12, corresponding to the annual cycle of rainfall. This configuration, denoted as SARIMA(1,1,1)(1,1,1)[12], was selected based on diagnostic evaluation, and the Auto-ARIMA algorithm was employed to confirm the optimal parameters.

For the Bi-LSTM component, hyper-parameter tuning was performed using grid search on the training dataset. The search space included LSTM units (ranging from 50 to 200), dropout rates (0.2 to 0.5), learning rates (0.0001 to 0.01), and batch sizes (32, 64, 128). The optimal configuration identified consisted of 150 LSTM units and a dropout rate of 0.4, providing the best validation performance. The final model architecture comprised two stacked bidirectional LSTM layers with tanh activation functions, each followed by dropout layers (0.4) to prevent overfitting. A dense output layer with linear activation was used to generate rainfall predictions. The model was compiled using the Adam optimizer and Mean Squared Error (MSE) loss function, with a batch size of 64. Early stopping with a patience of 25 epochs was implemented to enhance generalization and prevent overfitting.

The proposed hybrid SARIMA–BiLSTM rainfall forecasting model follows a structured, multi-stage process. Monthly rainfall data are first acquired from a CSV file and normalized using MinMaxScaler. The dataset is then split into training, testing, and validation subsets. A SARIMA(1,1,1)(1,1,1)[12] model, selected using diagnostic evaluation and confirmed via Auto-ARIMA, is fitted to the training data to generate forecasts for the entire series. These forecasts are normalized and concatenated with the original normalized rainfall values, forming a two-dimensional multivariate time series that integrates observed and SARIMA-inferred patterns. Input-output sequences are prepared using a sliding window of 12 months to capture temporal dependencies. A stacked Bi-LSTM model with 150 units and a 0.4 dropout rate is constructed, followed by a dense output layer with linear activation. The model is trained using the Adam optimizer and Mean Squared Error loss function, with early stopping (patience = 25) to prevent overfitting. Final predictions are inverse-transformed to their original scale, and model performance is evaluated using appropriate accuracy metrics and visualized for interpretation.

Model evaluation and performance metrics

Model performance was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). RMSE reflects the average prediction error magnitude, MAE measures absolute deviations between predicted and actual values, and R^2 indicates the proportion of variance explained by the model. These metrics were calculated separately for training, testing, and validation datasets to ensure robust assessment. Comparative analysis across SARIMA, Bi-LSTM, and the hybrid SARIMA-Bi-LSTM models identified the most accurate and reliable forecasting approach

RESULTS AND DISCUSSION

Rainfall variability across agroclimatic zones

The analysis of monthly rainfall across the three agroclimatic zones of Chhattisgarh reveals distinct seasonal and spatial variations. Table 1 presents the statistical summary of rainfall data, highlighting trends crucial for agricultural planning and water resource management.

The Chhattisgarh Plains exhibit moderate rainfall, with the monsoon months (June to September) contributing the majority of annual precipitation. July records the highest average rainfall (376.4 mm), with a relatively low coefficient of variation (CV) of 24.2%, indicating consistent monsoonal patterns. In contrast, winter and summer months record minimal rainfall with high variability, making them unreliable for agricultural activities. The Bastar Plateau experiences higher precipitation, particularly in July and August (exceeding 400 mm), with moderate CV values (27.8%

Table 1: Monthly rainfall and CV (%) in three zones of Chhattisgarh

Month	Chhattisgarh Plains		Bastar Plateau		Northern Hills	
	Rainfall (mm)	CV (%)	Rainfall (mm)	CV (%)	Rainfall (mm)	CV (%)
January	12.8	140.5	7.6	178.4	21.3	131.8
February	18.6	122.0	11.0	188.9	26.2	116.4
March	15.2	139.3	13.0	137.5	17.9	120.4
April	14.2	122.2	35.9	75.0	13.8	111.5
May	18.4	103.5	45.4	71.0	22.3	91.2
June	190.7	50.4	212.6	40.9	198.3	56.1
July	376.4	24.2	399.9	27.8	415.4	26.8
August	371.4	23.0	402.9	29.0	398.3	28.2
September	209.9	39.3	245.4	35.0	221.8	40.8
October	54.8	82.8	93.4	71.2	62.1	82.3
November	9.5	187.7	20.4	130.1	11.7	192.0
December	5.1	224.9	6.3	218.5	6.5	203.5

Table 2: Performance metrics for monthly rainfall prediction models in three zones of Chhattisgarh

Model	Dataset	Chhattisgarh Plains			Bastar Plateau			Northern Hills		
		RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
Bi-LSTM	Train	57.64	36.39	0.853	66.31	42.90	0.825	70.80	44.05	0.817
	Test	56.45	35.46	0.826	66.43	42.34	0.823	60.66	36.45	0.820
	Validation	49.36	31.82	0.869	63.05	39.33	0.852	59.93	38.20	0.810
SARIMA	Train	58.32	37.79	0.849	65.79	42.16	0.828	69.24	45.04	0.825
	Test	53.59	31.03	0.844	67.96	44.00	0.817	62.94	39.32	0.804
	Validation	49.24	31.99	0.868	67.45	43.60	0.832	59.54	40.35	0.815
Hybrid	Train	50.04	31.69	0.889	59.38	38.39	0.859	60.48	37.81	0.866
	Test	46.36	27.76	0.883	61.52	40.12	0.848	51.82	30.98	0.869
	Validation	41.70	25.93	0.906	59.60	38.00	0.856	51.78	31.50	0.859

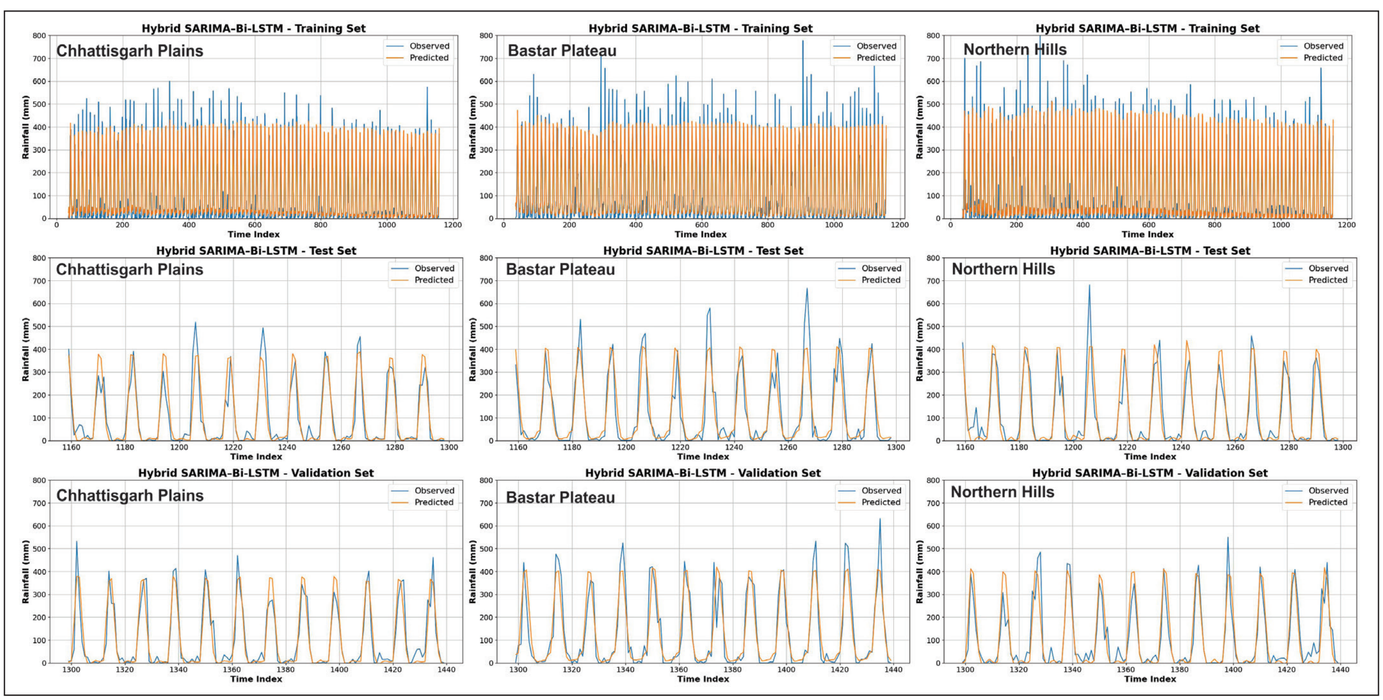

Fig. 2: Observed versus predicted monthly rainfall using the Hybrid SARIMA Bi-LSTM model for Chhattisgarh Plains, Bastar Plateau, and Northern Hills agroclimatic zones during training, testing, and validation periods.

and 29.0%). The early onset of rainfall in April and May provides a significant advantage for pre-monsoon crops, supporting early sowing and soil moisture conservation. The Northern Hills receive the highest rainfall among the three regions, with August recording a peak of 810.5 mm. Despite abundant monsoonal rainfall, some months display high CV values, indicating erratic precipitation patterns largely driven by western disturbances during winter and pre-monsoon thunderstorms in summer. A common pattern observed across all three zones is the high variability in rainfall during winter and summer months, with CV values often exceeding 100%. This unpredictability outside the monsoon season underscores the need for adaptive water management strategies and resilient agricultural planning to mitigate the risks associated with erratic precipitation.

Comparative interpretation of model performance across agroclimatic zones

This study systematically evaluates the performance of three forecasting models—Bi-LSTM, SARIMA, and a hybrid SARIMA-Bi-LSTM—applied to monthly rainfall prediction across three distinct agroclimatic zones of Chhattisgarh: the Chhattisgarh Plains, Bastar Plateau, and Northern Hills. The comprehensive evaluation is based on standard metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R-squared). The detailed performance metrics for each model and region are presented in Table 2.

In the Chhattisgarh Plains, characterized by fertile soils and heavy dependence on monsoonal rainfall, the Bi-LSTM model demonstrated robust performance in modeling non-linear rainfall fluctuations. It achieved R-squared values of 0.853, 0.826, and 0.869 during training, testing, and validation phases, respectively. RMSE values were 57.64 (training), 56.44 (testing), and 49.36 (validation), with corresponding MAEs of 36.24, 35.98, and 32.47. These values reflect Bi-LSTM's strength in capturing complex rainfall variability. The SARIMA model, although slightly less accurate, delivered competitive results with R-squared values of 0.849, 0.844, and 0.868, and RMSEs of 58.32, 53.59, and 49.24. However, it exhibited marginally higher MAEs of 37.89, 31.03, and 31.99, indicating a modest increase in prediction deviation. The hybrid SARIMA-Bi-LSTM model showed superior performance in this zone, with R-squared values reaching 0.889, 0.883, and 0.906, and significantly lower RMSEs of 50.04, 46.36, and 41.70. The MAEs were also the lowest among all models, at 31.69, 27.76, and 25.93, highlighting the hybrid model's ability to minimize prediction errors.

In the Bastar Plateau, known for its undulating terrain and erratic rainfall patterns, Bi-LSTM produced R-squared values of 0.825, 0.823, and 0.852, with RMSEs of 66.31, 66.43, and 63.05. MAE values ranged from 39.33 to 42.90, slightly elevated due to the presence of extreme rainfall events. SARIMA's performance was relatively weaker, with R-squared values of 0.828, 0.817, and 0.832, and RMSEs of 65.79, 67.96, and 67.45. The corresponding MAEs of 42.16, 44.00, and 43.60 signaled a higher average prediction deviation. The hybrid model again led in performance, improving R-squared values to 0.859, 0.848, and 0.856 and lowering RMSEs to 59.38, 61.52, and 59.60. MAEs also declined to 38.39, 40.12, and 38.00, showcasing its robustness even in regions with high variability.

In the Northern Hills, marked by steep slopes and complex topography, Bi-LSTM attained moderate R-squared values of 0.817, 0.820, and 0.810. The RMSEs (70.80, 60.66, 59.93) and MAEs (44.05, 36.45, 38.20) were comparatively higher, reflecting the challenges posed by abrupt rainfall variations. SARIMA marginally improved upon these results with R-squared values of 0.825, 0.804, and 0.815 and slightly lower RMSEs (69.24, 62.94, 59.54). MAEs stood at 45.04, 39.32, and 40.35. The hybrid model, once again, outperformed both, with R-squared values of 0.866, 0.869, and 0.859, RMSEs of 60.48, 51.82, and 51.78, and MAEs of 37.81, 30.98, and 31.50.

In conclusion, across all three agroclimatic zones, the hybrid SARIMA-Bi-LSTM model consistently demonstrated superior accuracy, effectively balancing the seasonal trend modeling strength of SARIMA and the deep learning capabilities of Bi-LSTM. This integrated approach significantly reduced prediction errors and improved correlation with observed rainfall patterns. As evidenced by the results in Table 2, the hybrid model offers a reliable and accurate solution for monthly rainfall forecasting, with strong potential to support climate-resilient agricultural planning and water resource management in the region. The hybrid approach, which combines the advantages of SARIMA and Bi-LSTM, demonstrated enhanced predictive accuracy and stronger alignment with observed rainfall across the training, testing, and validation phases. A representative output showcasing the hybrid model's performance is provided in Fig. 2. The results confirm the model's ability to produce reliable and smooth forecasts, especially during periods of high variability, underscoring its robustness and improved performance over the individual models

CONCLUSION

This study demonstrates that while SARIMA effectively captures seasonal trends and Bi-LSTM models better accommodate nonlinear rainfall patterns, the hybrid SARIMA-Bi-LSTM approach offers superior accuracy by integrating the strengths of both. The hybrid model provides a more reliable and context-sensitive solution for rainfall forecasting across Chhattisgarh's agroclimatic zones, supporting applications in agriculture and water management. However, the study is limited by the use of a single climatic variable (rainfall), and model performance may vary under rapidly changing climate conditions. Future research should focus on incorporating additional climatic factors such as temperature, humidity, and atmospheric pressure, and exploring advanced deep learning architectures like Transformers. The adoption of AI-based hyper-parameter tuning and ensemble methods could further enhance the robustness and adaptability of rainfall prediction model.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the IMD for providing access to the gridded monthly rainfall data through their online data portal.

Funding: No funding was received for conducting this study.

Data Availability: The monthly rainfall data used in this study is publicly available on the IMD website: https://mausam.imd.gov.in/

Conflict of Interests: The authors declare that there is no conflict of interest related to this article.

Authors Contribution: **D. Naidu**: Conceptualization and development of model, coding, data analysis, and interpretation of results; **S. K. Chandniha**: Data collection, data curation, graphical representation

Disclaimer: The contents, opinions and views expressed in the research article published in the Journal of Agrometeorology are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

Publisher's Note: The periodical remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

REFERENCES

Ahmed, I. and Sreedevi, T. (2023). Comparative analysis of deep learning models for rainfall prediction. *J. Climate Inform.,* 12(3): 45-58.

Box, G.E.P. and Jenkins, G.M. (1976). Time series analysis: Forecasting and control. Holden-Day.

Brown, R.G. (2004). Smoothing, forecasting and prediction of discrete time series. Dover Publications. (Original work published 1963)

Choi, J., Kim, H. and Lee, D. (2021). Application of machine learning techniques for seasonal rainfall prediction. *Environ. Model. Softw.,* 145: 105205.

Chollet, F. (2017). Deep learning with Python. Manning Publications.

Dabral, P.P. and Murry, M. (2017). Rainfall forecasting using SARIMA models in Northeast India. *Indian J. Hydrol.,* 34(2): 120-132.

Goodfellow, I., Bengio, Y. and Courville, A. (2016). Deep learning. MIT Press. ISBN: 978-0262035613. https://www.deeplearningbook.org

Greff, K., Srivastava, R.K., Koutník, J., Steunebrink, B.R. and Schmidhuber, J. (2017). LSTM: A search space odyssey. *IEEE Trans. Neural Netw. Learn. Syst.,* 28(10): 2222-2232. https://doi.org/10.1109/TNNLS.2016.2582924

Gupta, R. and Sharma, A. (2021). Comparative performance of SARIMA and deep learning models in climate forecasting. *Meteorol. Adv.,* 19(4): 78-92.

Han, J. and Park, S. (2020). Enhancing time-series forecasting accuracy with multivariate SARIMA models. *J. Climate Res.,* 28(1): 35-50.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Comput.,* 9(8): 1735-1780.

Hyndman, R.J. and Athanasopoulos, G. (2018). Forecasting: Principles and practice (2nd ed.). OTexts.

Kumar, V. and Singh, P. (2021). Deep learning for climate time series analysis: A review. *Int. J. Data Sci.,* 17(2): 205-225.

Martinez, F. and Lee, J. (2019). Ensemble learning techniques for improved rainfall prediction. *J. Artif. Intell. Climate Stud.,* 11(3): 67-79.

Pandey, S. (2018). Improving SARIMA forecasting accuracy using GARCH models. *Indian J. Stat. Anal.,* 22(1): 45-59.

Pasini, A. (2020). Artificial intelligence for applied sciences. Springer.

Patro, B.S. and Bartakke, P.P. (2024). Daily rainfall prediction using long short-term memory (LSTM) algorithm. *J. Agrometeorol.,* 26(4): 509-511. https://doi.org/10.54386/jam.v26i4.2745

Rajalakshmi, M. (2023). Evaluating the effectiveness of LSTM models for monsoon rainfall prediction. *J. Hydrometeorol.,* 15(4): 98-115.

Ray, M., Singh, K.N., Pal, S., Saha, A., Sinha, K. and Kumar, R.R. (2023). Rainfall prediction using time-delay wavelet neural network (TDWNN) model for assessing agrometeorological risk. *J. Agrometeorol.,* 25(1): 151-157. https://doi.org/10.54386/jam.v25i1.1895

Shumway, R.H. and Stoffer, D.S. (2017). Time series analysis and its applications (4th ed.). Springer. https://doi.org/10.1007/978-3-319-52452-8

Singh, R. and Patel, V. (2023). A meta-analysis of rainfall forecasting models: SARIMA vs. deep learning. *J. Climate Anal.,* 21(2): 112-129.

Smith, B. and Taylor, J. (2023). Challenges of time series forecasting with traditional statistical models. *Int. J. Forecast.,* 39(1): 23-37.

Wu, L. and Zhang, Y. (2022). A hybrid SARIMA-LSTM model for improved time-series forecasting. *J. Comput. Meteorol.,* 25(3): 55-72.

Yadav, N. and Verma, K. (2022). Comparative study of SARIMA and deep learning models for rainfall prediction. *Environ. Data Sci. Anal.,* 14(2): 88-101.

Zhang, G.P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomp.,* 50: 159-175. https://doi.org/10.1016/S0925-2312(01)00702-0

Zhou, Y., Wang, X. and Chen, L. (2023). Advances in deep learning for climate time series forecasting. *Artif. Intell. Meteorol.,* 30(1): 67-85.