

Use of LSTM machine learning technique to forecast monthly rainfall for selected districts of Nagaland (India)

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Abstract: The current study attempted to predict rainfall on a monthly basis using sequential Long short-term memory (LSTM) algorithm for four selected stations (Kohima, Mon, Phek and Wokha) of Nagaland, India. The LSTM model was built using Python, with data split 80% for training and 20% for testing. Numerous trials with varying LSTM hyperparameters were conducted to identify the best-performing model. For monthly rainfall predictions, the model showed strong performance during training and testing. The value of MAE, MSE, RMSE near-zero errors values and NSE values close to 1.0 during training and testing indicated the model's suitability for making reliable predictions. Ultimately, using the developed sequential LSTM model, monthly rainfall was forecasted for the selected four stations from the year 2023 to 2026. Monthly forecasted value of rainfall may be useful for agricultural and water resource planning of the study area.

Keywords: LSTM model, monthly rainfall forecasting, Nagaland (India)

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1 Introduction

One of the main extreme phenomena in the climate system is rainfall. It directly affects agriculture, management, water resources, ecosystems and for those whose entire livelihood depends on water rainfall is the primary source. Rainfall prediction is still a serious topic that has drawn interest from the scientific community, governments, businesses, and risk management organizations. Rainfall is one of the primary complex meteorological phenomena. Rainfall predictions were made using a variety of techniques in the past. The dynamical and the empirical approaches are the two main methods for forecasting rainfall. The dynamical approach uses physically constructed

models based on the system's rainfall forecasting equations to carry out forecasts. The empirical method's foundation is the examination of historical weather data and how they relate to different atmospheric variables over a range of geographical areas. Deep learning algorithms, fuzzy logic, and regression are the most commonly used empirical approaches. Since RNNs can handle time series data well, they are the superior choice for managing rainfall data.

Because of its potential to sense long-term dependencies and efficiently capture temporal dynamics, LSTM, a type of recurrent neural network (RNN), has demonstrated exceptional performance in

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a variety of time-series forecasting tasks (Richardson, 2007; Marchuk, 2012). LSTM can effectively capture the cyclic and seasonal patterns in the data. This is particularly useful for rainfall data which typically exhibits such patterns. Numerous studies have demonstrated that LSTM models can faithfully represent the cyclical and seasonal patterns seen in rainfall data. LSTM maintains its short-latency capabilities while learning to bridge time periods longer than 1000 steps, even when dealing with noisy input sequences.

Examining later and more recent research on deep learning for rainfall forecasting, we discovered that Poornima and Pushpalatha (2019) employed an intensified LSTM based RNN to forecast rainfall. A typical rainfall dataset was employed to train and test the neural network, and the outcomes showed that the model could produce accurate predictions using the data (root mean square error (RMSE): 0.33, model accuracy: 87.01, losses: 0.1274, learning rate: 0.5). Man et al. (2023) predicted daily runoff in China's upper Huai River basin using enhance LSTM model taking precipitation, pan evaporation, and temperature as input and the results showed that the enhanced LSTM did well in predicting daily runoff, (attaining the greatest Nash Sutcliffe Efficiency (NSE) of 0.924). Shi et al. (2015), Akbari Asanjan et al. (2018), Kumar et al. (2019) and Chai and Goh (2022) used convolutional LSTM for forecasting precipitation. Moreover, LSTM models also used for different hydro-meteorological parameters forecasting (Yang et al., 2017; Kratzert et al., 2018; Zhang et al., 2018; Chen et al., 2022; Suebsombut et al., 2021; Majhi et al., 2020; Li et al., 2022).

Although numerous studies have applied LSTM and other deep learning models for rainfall forecasting, several limitations remain. Many previous studies focused on short-term daily forecast rather than monthly-scale forecasting, which is more relevant for agricultural and water resource planning. Additionally, limited research has specifically addressed rainfall

prediction in northeastern India, particularly in Nagaland, where complex topography and spatial variability present additional modelling challenges. Furthermore, some studies emphasized model accuracy without systematically evaluating model robustness across multiple stations within the same climatic region. Therefore, there remains a need for region-specific, station-level validation of LSTM models for reliable monthly rainfall forecasting.

Keeping in view of the recent applications of LSTM model, present study was attempted to forecast monthly rainfall using LSTM algorithm for four selected stations of Nagaland. This study's primary goals are to create an LSTM model for rainfall forecasting and use that model to forecast rainfall on a monthly basis.

2 Methods and material

2.1 Study area and collection of data

North-East India's mountainous state of Nagaland is located between latitudes 25.67° N and longitudes 94.12° E. The climate of Nagaland varies, ranging from subtropical to submontane temperate with high humidity level. The average annual rainfall is between 1800 mm to 2500 mm, occurring over a period of 6 months from May to October. There are 15 meteorological observatories spread all over the state at various altitudes ranging from 160 metres to 1780 metres above sea level. As per availability of data, 4 meteorological observatories were chosen namely Kohima, Mon, Phek, Wokha and can be seen in Figure 1. The summarized details of the study area are provided in Table 1. For the present study, monthly rainfall data for 122 years (1901-2022) and weekly data (1997-2022) for 26 years were collected from India Meteorological Department (IMD) and Directorate of Soil and Water Conservation Nagaland respectively. A plot has been developed to better illustrate the temporal rainfall distribution over 122 years across the selected stations in Nagaland (Figure 2).

2.2 LSTM model architecture

According to Salman et al. (2018), a unique type of RNN model created specifically to replicate temporal series is the LSTM model. Hochreiter and Schmidhuber (1997) originally introduced this unique architecture in 1997 to fix the issues of vanishing and expanding gradients, or the backpropagation algorithm's error backflow issue, in RNNs. This is mostly due to the fact that the gradient vector component deteriorates quickly over long distances,

making it impossible for the typical RNN model to learn the complicated correlation in an extended sequence (Bengio et al., 1994; Hochreiter, 1998). This is addressed by the LSTM model, which integrates units of memory. The LSTM model will be able to determine when to update the hidden states with the recently provided information and when to disregard the earlier hidden states thanks to these memory units.

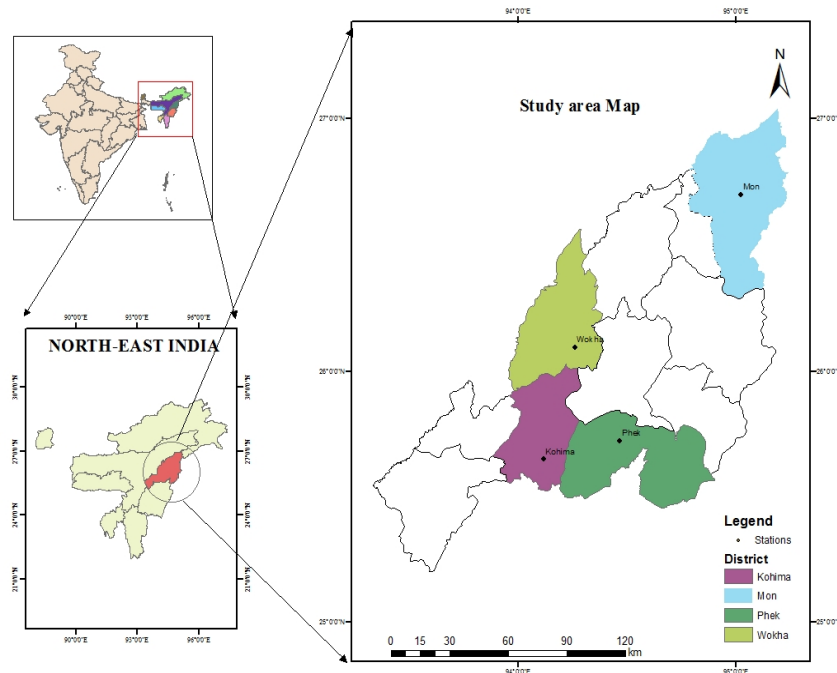


Figure 1 Location map of study area

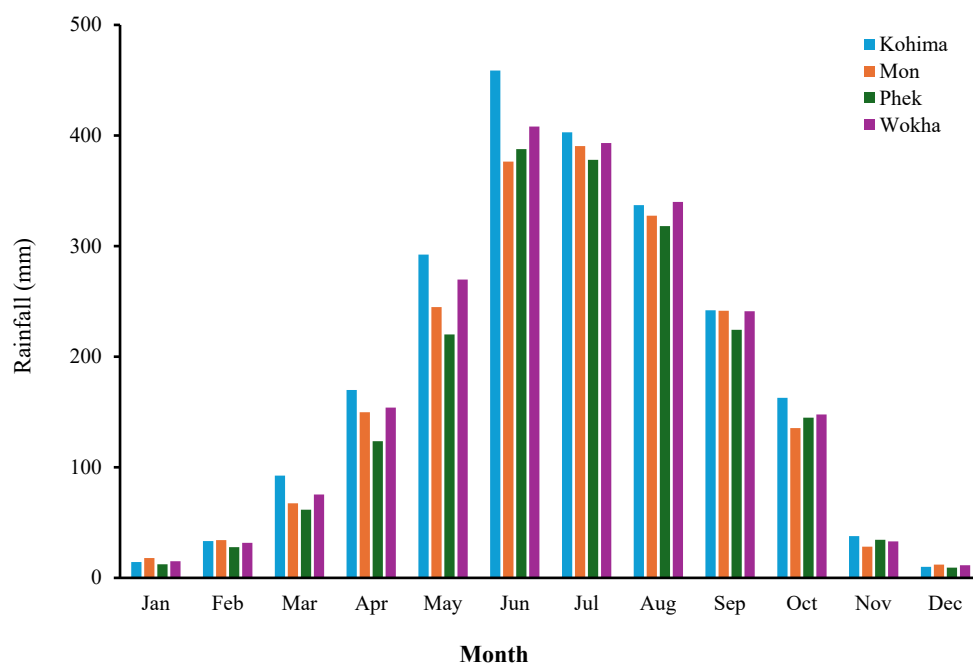


Figure 2 The monthly average rainfall distribution for selected stations of Nagaland (1901-2022)

Table 1 Details of study area

Station	Lat.	Long.	Altitude (m)	Data period		Average annual rainfall (mm)
Kohima	25.6586° N	94.5309° E	1444	1901-2022	1997-2022	2280
Mon	26.8038° N	94.9796° E	655	1901-2022	1997-2022	2028
Phek	25.7375° N	94.4388° E	2133	1901-2022	1997-2022	1966
Wokha	26.2168° N	94.1923° E	1313	1901-2022	1997-2022	2128

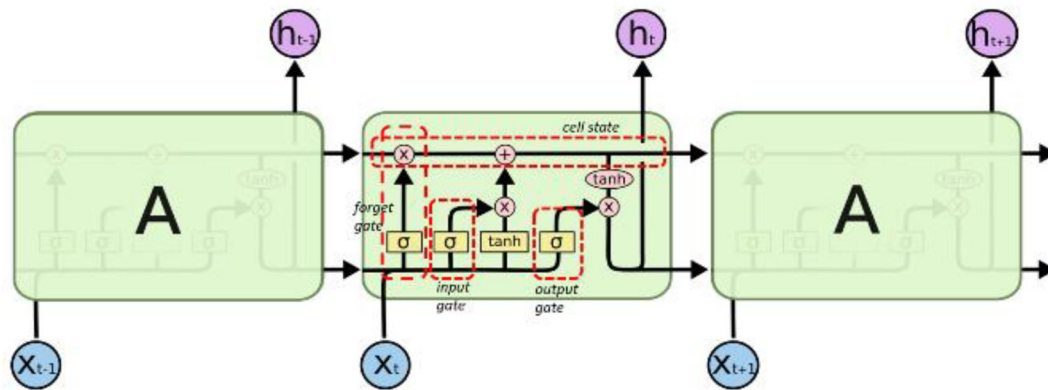


Figure 3 A typical LSTM block (Sakinah et al., 2019)

The standard RNN model's hidden states also exist in an LSTM block. As seen in Figure 3, the LSTM block is then added on top of this, along with a cell state and three distinct gates: an input gate, an output gate, and a forget gate. Relative information is carried down the sequence chain via the cell state, which also serves as the network's "memory". To determine which information on the memory cell should be kept or erased, the Sigmoid activation function in the forget gate will be used to examine the data entered into the LSTM model. The choice of what fresh data will be kept in the cell state will be decided in the following phase. There are two stages to this process: (a) A decision regarding which values will be updated must be made using the sigmoid layer, also known as the input gate layer. (b) A new value vector must be created using the $\tanh$ activation function and stored in the memory cell. The former value in the cell gate's memory cell will be replaced by the sum of the values from the input and forget gates. The output gates will be used for two procedures. The sigmoid activation function will be used in the first operation to determine which portion of the memory cell should be released. In the second action, the $\tanh$ activation function will be used to insert a new value into the memory cell.

These two functions will be multiplied to determine this new value. The input and the LSTM block/layer are the two primary components of an LSTM network. Time series or sequence data are entered into the model using the input layer, and the long-term relationships among time steps in sequence data are ascertained by the LSTM block or layer. Figure 3 shows the repeating modules (abbreviated A) of an LSTM architecture. At time point $t - 1$, an input and input x_t are received by the core block depicted in Fig. 3. Next comes the output h_t , which at time point $t + 1$ is likewise an input.

The LSTM model is trained using the Adaptive Moment Estimation (ADAM) optimizer (Kingma and Ba, 2014). The learning rates for each and every parameter will be determined using the adaptive learning rate algorithm, or ADAM. One of ADAM's benefits was its effective stochastic optimization, which required only first-order gradients and used minimal memory (Jiang and Chen, 2017).

2.3 Workflow of LSTM model

In the present study, LSTM was designed as predictive model for forecasting rainfall. The flow chart (Figure 4) shows the workflow for LSTM modelling and forecasting.

2.3.1 Data pre-processing

Data pre-processing is a crucial step when working with LSTM (Long Short-Term Memory) models or

any other machine learning models. The following are the main steps in LSTM data pre-processing: Data splitting and normalization/scaling.

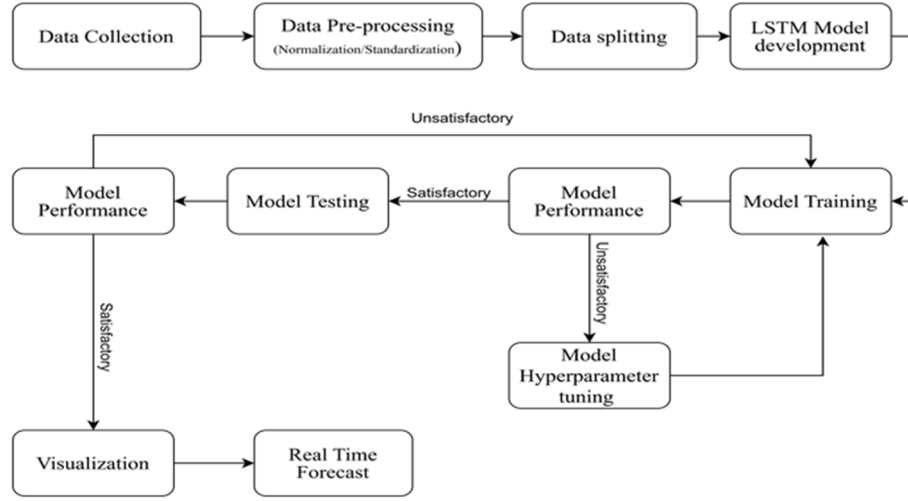


Figure 4 Process Flow Diagram for LSTM model

2.3.2 Normalization/Scaling

In order to limit the data related to an attribute to a smaller range between 0 and 1 or -1 and 1, normalization helped with data scaling. Equation 6's formula was utilized to apply the min-max normalizing procedure.

$$Y_{normalized} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

Where,

$Y_{normalized}$ is the normalized data;

Y is the series' actual value to be normalized;

Y_{min} is the minimum value;

Y_{max} is the max value of data of the series.

2.3.3 Data splitting

Two subgroups were created from the dataset: training and testing. The ability of the model to generalize the new, unobserved input will be assessed with the help of this division. 20% of the data used in this study was for testing, while the remaining 80% was for training.

2.3.4 Model training

The model discovers links and patterns in the data during this phase. The 80% training dataset was used to train the LSTM model to produce predictions.

2.3.5 Model testing

In this step, the model's performance was evaluated using the remaining 20% test dataset. This is done to ensure that the model can accurately

forecast new, untested data.

2.3.6 Model evaluation criterion

Statistical measures such the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and Nash Sutcliffe efficiency (NSE) were used as prediction error statistics to assess the performance of the developed models.

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_{est_i} - x_{obs_i}| \quad (2)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n |x_{est_i} - x_{obs_i}|^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{est_i} - \bar{x}_{obs_i})^2} \quad (4)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (x_{est_i} - x_{obs_i})^2}{\sum_{i=1}^n (x_{obs_i} - \bar{x}_{obs})^2} \quad (5)$$

Where,

n is the number of observations;

x_{obs_i} and x_{est_i} are observed and predicted value, respectively.

The average values of the observed and predicted data are $\bar{x}_{obs_i}$ and $\bar{x}_{est_i}$.

2.3.7 Model hyperparameter tuning

Hyperparameter of the model is adjusted to optimize its performance. This was obtained by altering the parameters such as number of LSTM layer, number of dense layers, number of hidden units, dropout, activation function, number of epochs, batch size. After many trials, the optimum values of different

parameters were selected and are described in results and discussion section.

2.3.8 Visualization

Visualization is done to interpret and communicate the results. This might include plotting training and validation curves, visualizing predictions compared to

actual values, or other relevant visualizations.

2.3.9 Real-time forecast

This step is applicable in scenarios where the model needs to provide forecasts or prediction continuously. The trained model was deployed to make predictions on new, real-time data.

Table 2 The model architectures utilized for monthly rainfall forecasting across the four stations

Stations	No. of Layers	Dropout	Dense Layer	Epochs	Batch size
Kohima	Three LSTM layers with 208, 109, and 79 units, respectively.	Each LSTM layer is followed by a Dropout layer having value 0.2.	A Dense layer with 1 unit and ReLu activation function.	91	8
Mon	Three LSTM layers with 241, 109, and 82 units, respectively.	Each LSTM layer is followed by a Dropout layer having value 0.2.	Two dense layers with 50 units and 1 unit and ReLu activation function.	81	8
Phek	Three LSTM layers with 142, 95, and 86 units, respectively.	Each LSTM layer is followed by a Dropout layer having value 0.2.	Two dense layers with 60 units and 1 unit and ReLu activation function.	15	4
Wokha	Three LSTM layers with 155, 111, and 75 units, respectively.	Each LSTM layer is followed by a Dropout layer having value 0.2.	A Dense layer with 1 unit and ReLu activation function.	80	12

3 Results and discussion

For developing long short-term memory model, we considered 122 years monthly rainfall data. Out of which 80% was utilized for training and the remaining 20% was used for testing. The selected data were normalized using min-max scaler and split into training and testing data using random splitting method. After undergoing many trials with different hyperparameter values, number of LSTM layers, number of dense layers, the best suited model architectures are described in Table 2.

The long short-term memory model's performance statistics for monthly rainfall during training and testing are displayed in Table 3. For monthly rainfall analysis, the range of values for MAE, MSE, RMSE

and NSE, were found to be 0.228 to 0.241, 0.01 to 0.014, 0.103 to 0.117, and 0.755 to 0.796 respectively for training dataset. The range of values for MAE, MSE, RMSE and NSE, were found to be from 0.196 to 0.245, 0.009 to 0.013, 0.097 to 0.116, and 0.71 to 0.75 for testing dataset. These values indicate good model fitness during training and testing (Table 3).

Figure 5(a) to 5(d) shows the rainfall values that were observed and predicted for Kohima, Mon, Phek, and Wokha throughout the training period. The scatter plots and 1:1 line of observed and predicted rainfall values of four selected stations indicated that the predicted values were overestimated and underestimated by the model during training and are shown in Figure 6 and Figure 7.

Table 3 Performance statistics of LSTM for monthly rainfall during training and testing across the four stations

Stations	Dataset	MAE	MSE	RMSE	NSE
Kohima	Training	0.228	0.012	0.110	0.755
	Testing	0.199	0.009	0.097	0.714
Mon	Training	0.237	0.01	0.103	0.796
	Testing	0.226	0.013	0.113	0.710
Phek	Training	0.233	0.014	0.117	0.757
	Testing	0.196	0.01	0.102	0.710
Wokha	Training	0.241	0.011	0.105	0.784
	Testing	0.245	0.013	0.116	0.750

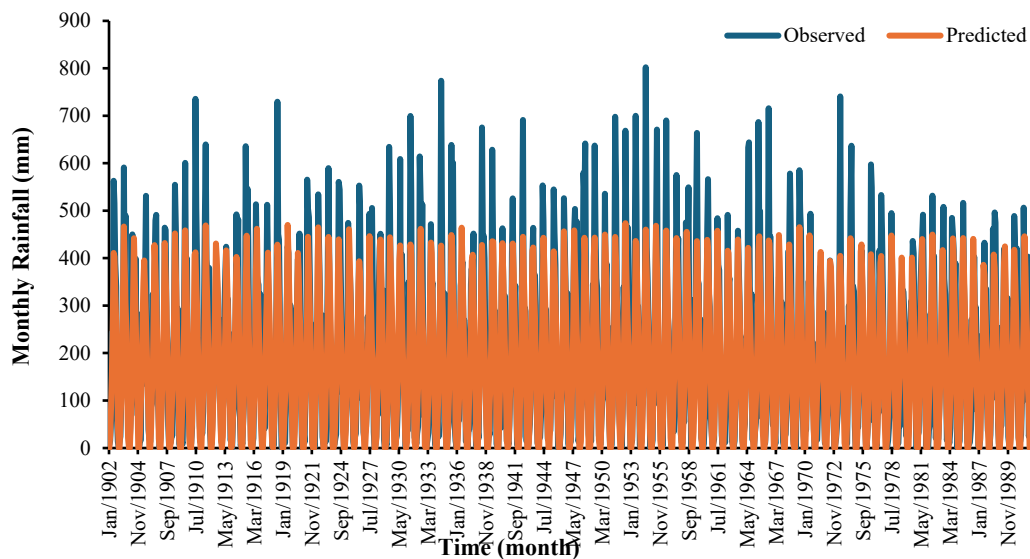


Figure 5(a) Observed and predicted monthly rainfall for Kohima during training

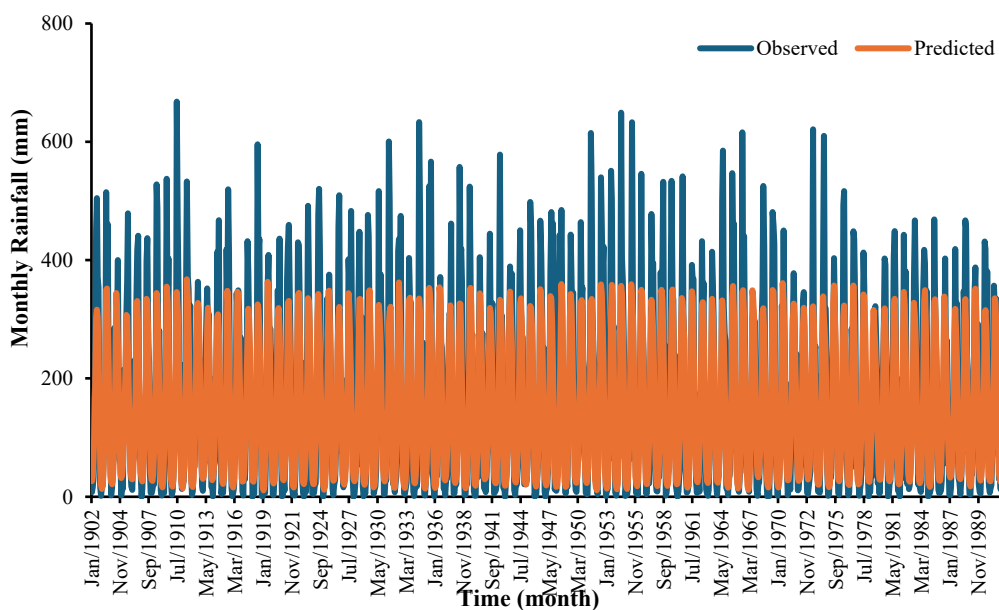


Figure 5(b) Observed and predicted monthly rainfall for Mon during training

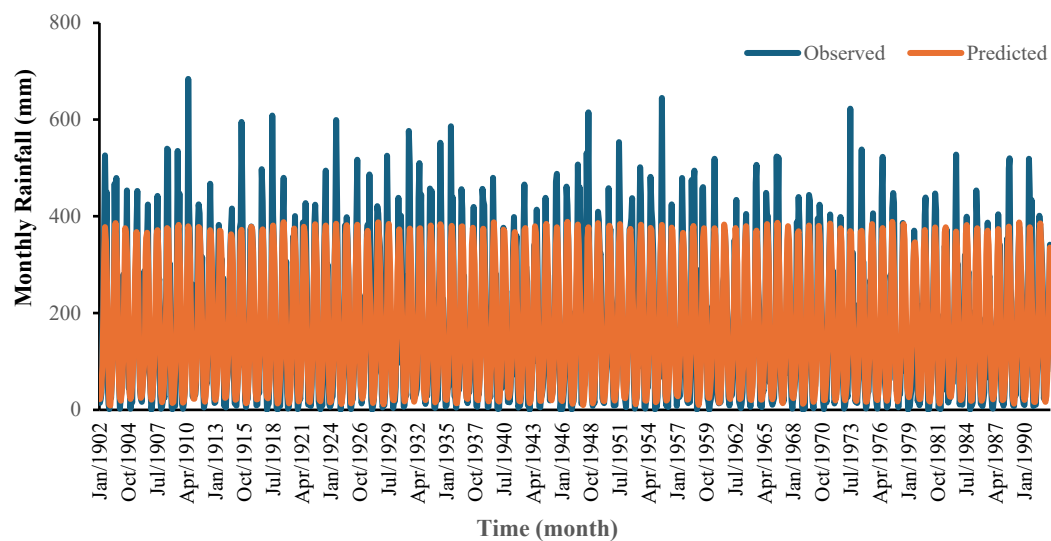


Figure 5(c) Observed and predicted monthly rainfall for Phek during training

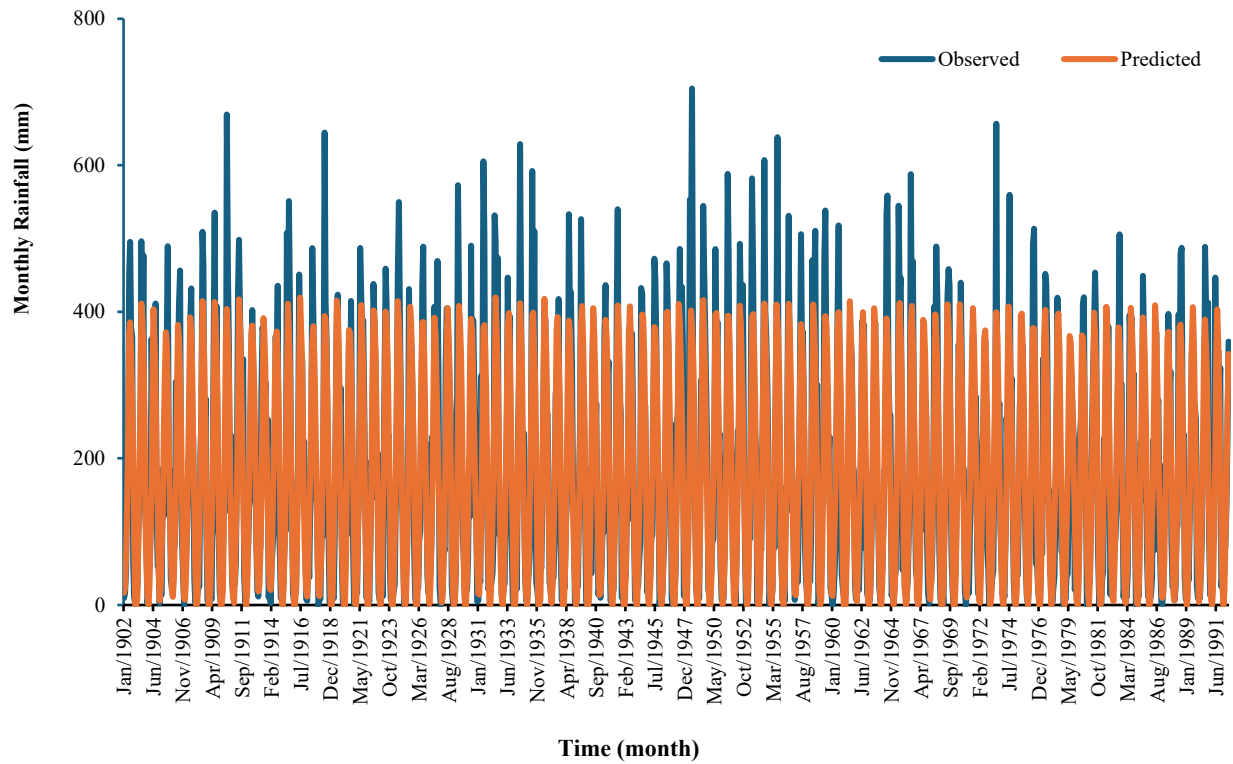


Figure 5(d) Observed and predicted monthly rainfall for Wokha during training

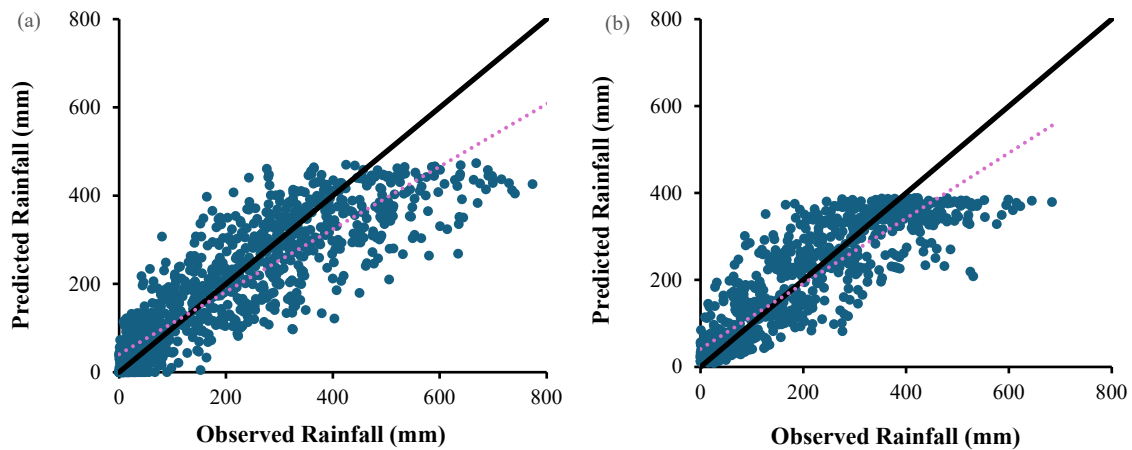


Figure 6 Scatter plot of observed and predicted monthly rainfall during training for (a) Kohima and (b) Mon

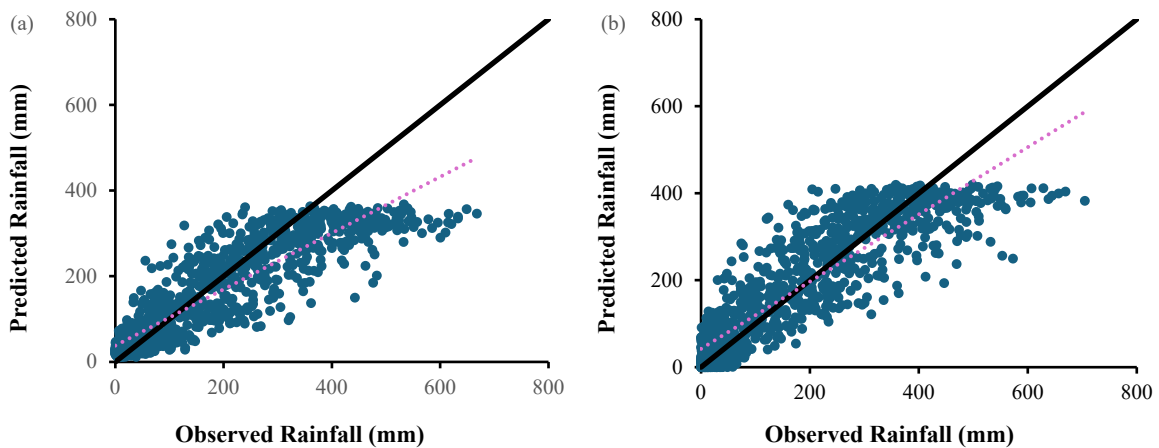


Figure 7 Scatter plot of observed and predicted monthly rainfall during training for (a) Phek and (b) Wokha

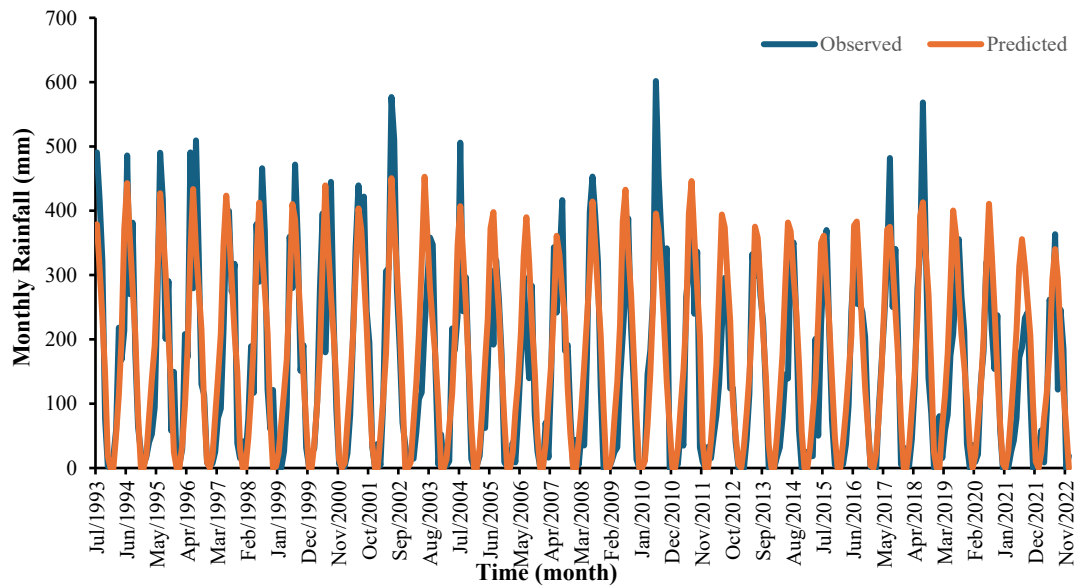


Figure 8(a) Observed and predicted monthly rainfall for Kohima during testing

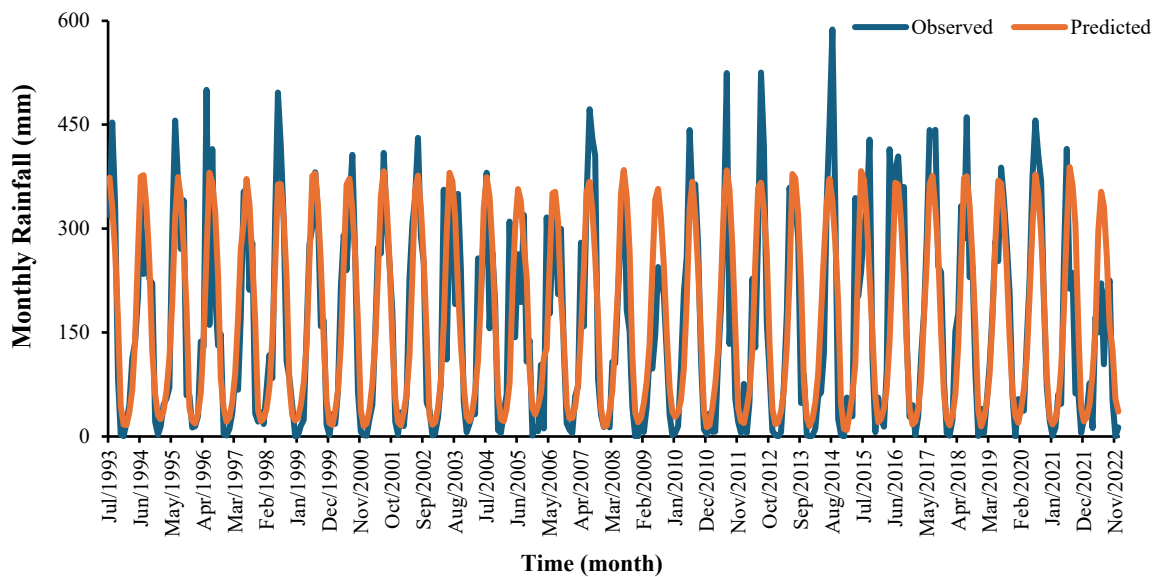


Figure 8(b) Observed and predicted monthly rainfall for Mon during testing

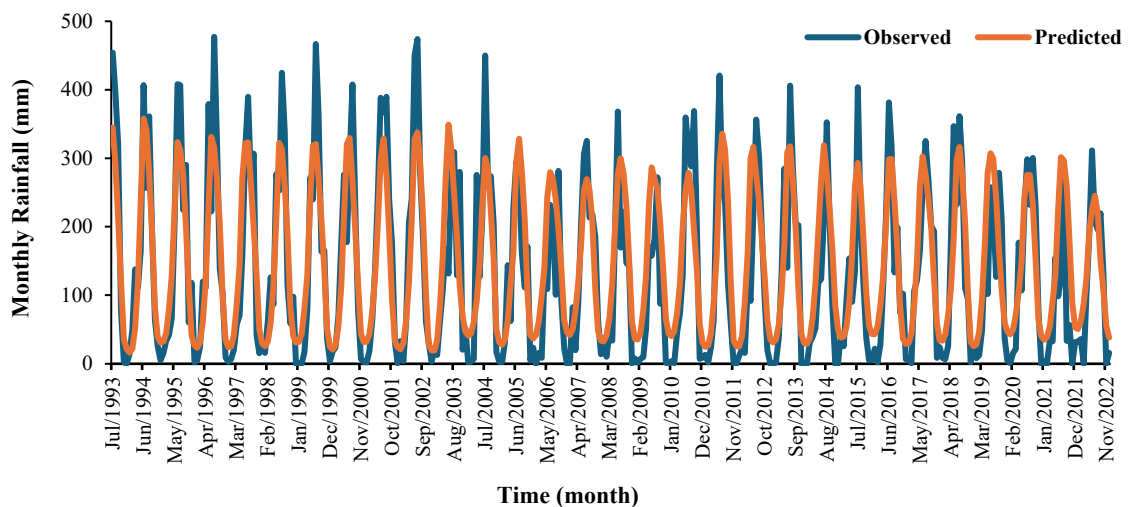


Figure 8(c) Observed and predicted monthly rainfall for Phek during testing

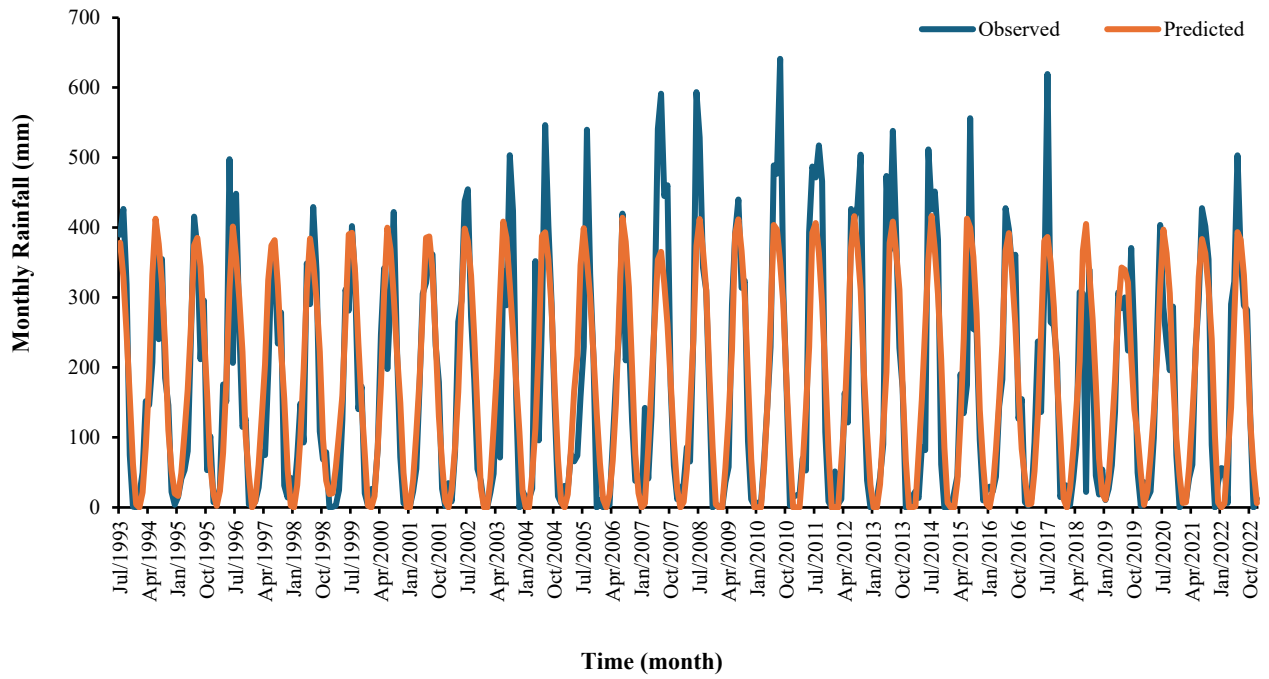


Figure 8(d) Observed and predicted monthly rainfall for Wokha during testing

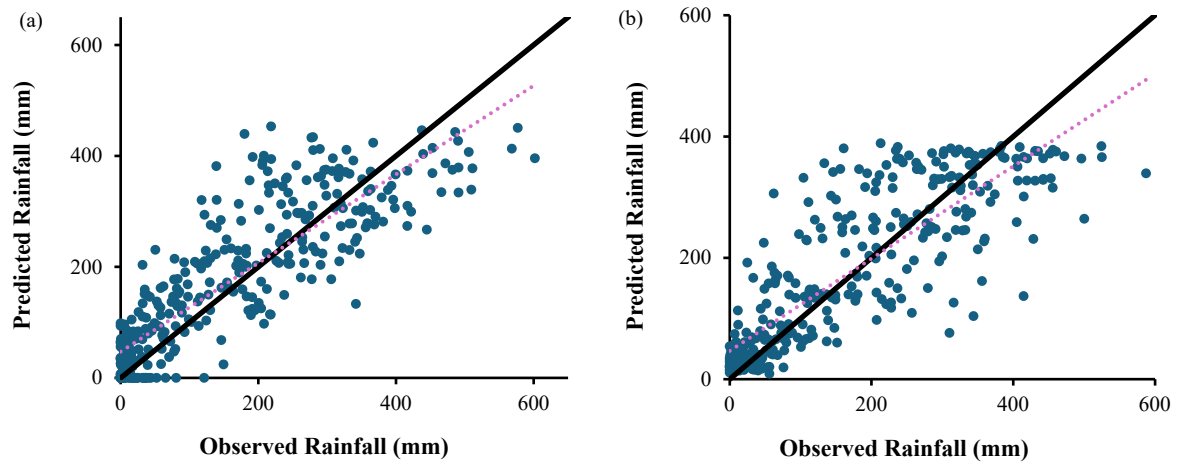


Figure 9 Scatter plot of observed and predicted monthly rainfall for (a)Kohima and (b)Mon during testing

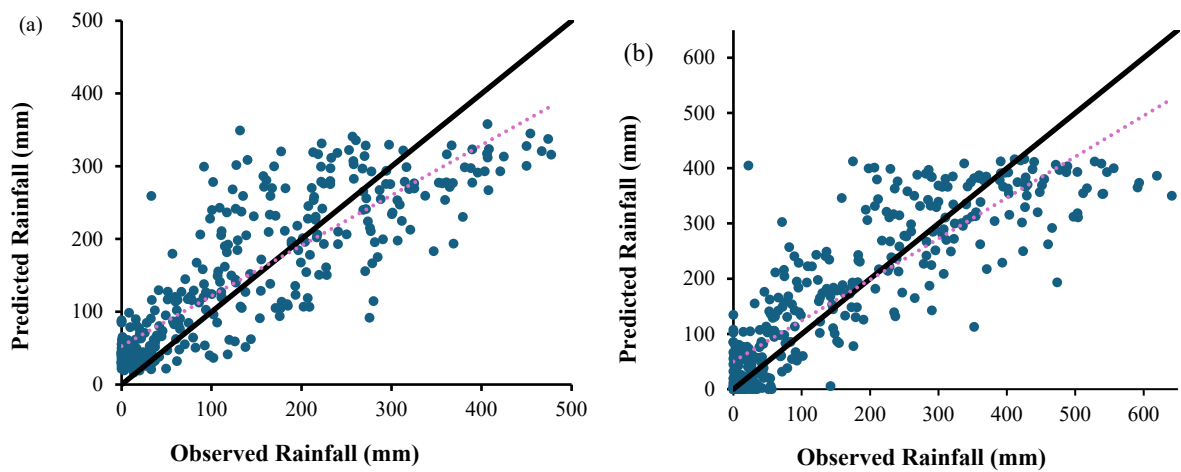


Figure 10 Scatter plot of observed and predicted monthly rainfall for (a) Phek and (b) Wokha during testing

Figure 8(a) to 8(d) shows the rainfall values that were observed and predicted for Kohima, Mon, Phek, and Wokha during the testing period. The scatter plots and 1:1 line of observed and predicted rainfall values of four selected stations indicated that the predicted values were overestimated and underestimated by the model during testing and are shown in Figure 9 and Figure 10.

Anelu Puro (2018) used the monthly rainfall data of Kohima, Mon, Phek and Wokha and carried out the time series analysis for forecasting rainfall using

SARIMA model. During training and testing, she reported the values of NSE as 0.79 and 0.76; 0.83 and 0.70; 0.83 and 0.80 and 0.80 and 0.79 for Kohima, Mon, Phek and Wokha respectively.

Using the observed monthly rainfall (1901-2022) for each of the four stations namely, Kohima, Mon, Phek and Wokha, the rainfall for the next 4 (2023-2026) years has been forecasted using the developed LSTM model. The graph has been plotted to show the trends between observed and forecasted rainfall values and is shown in Figure 11(a) to Figure 11(d).

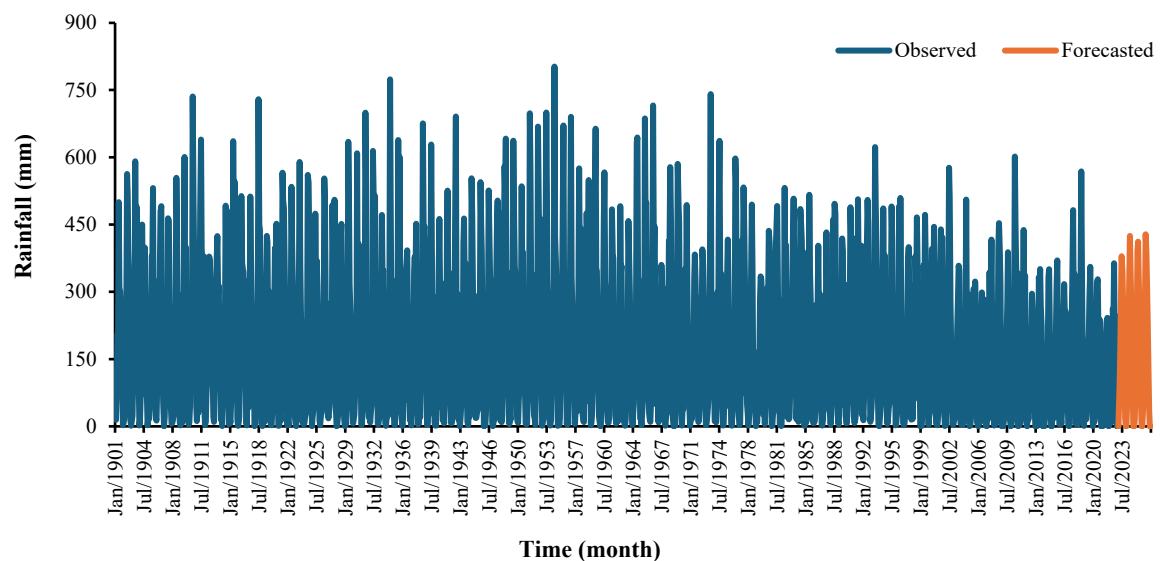


Figure 11(a) Observed (1901-2022) and forecasted (2023-2026) monthly rainfall for Kohima

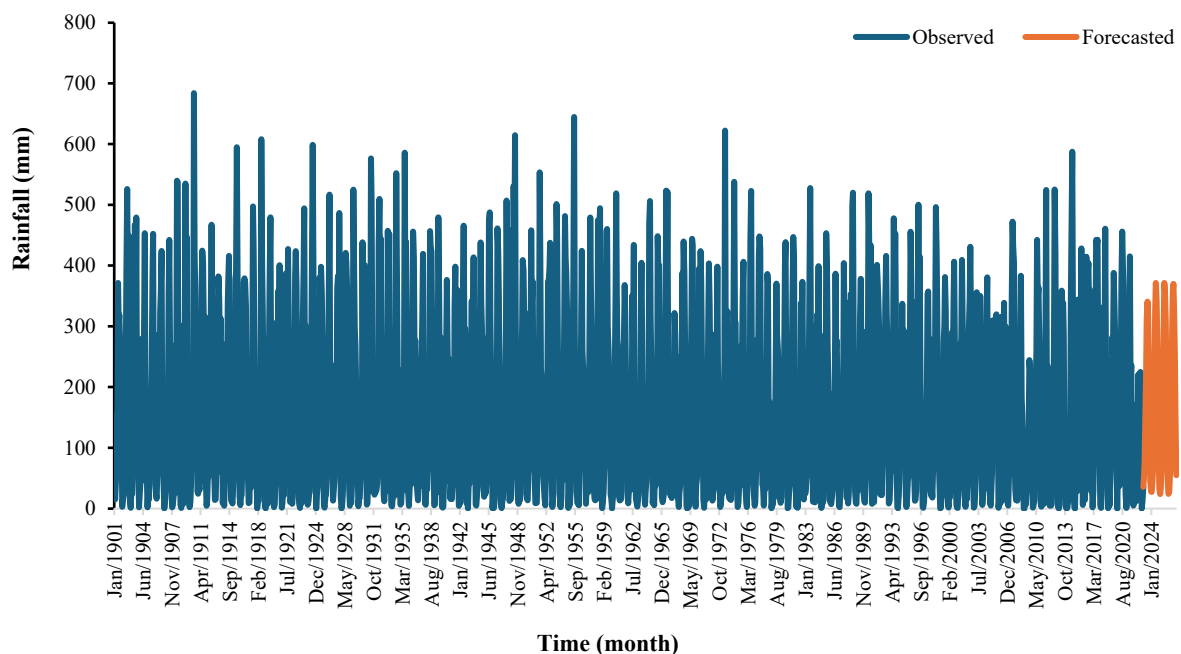


Figure 11(b) Observed (1901-2022) and forecasted (2023-2026) monthly rainfall for Mon

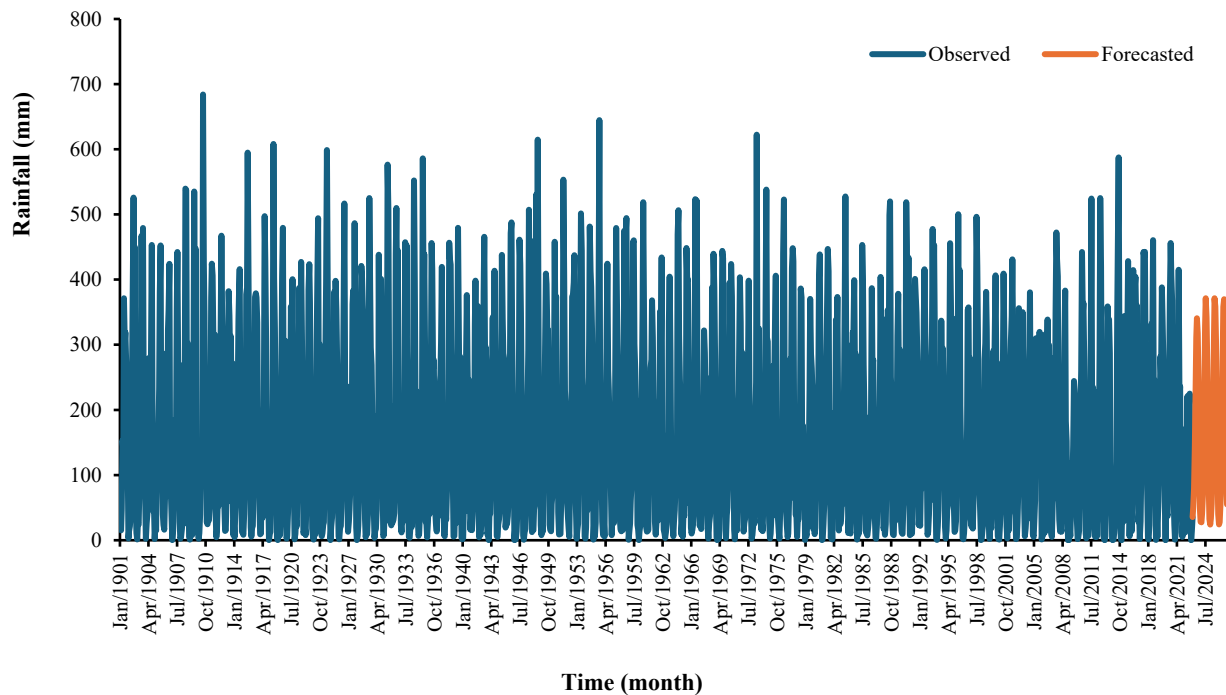


Figure 11(c) Observed (1901-2022) and forecasted (2023-2026) monthly rainfall for Phek

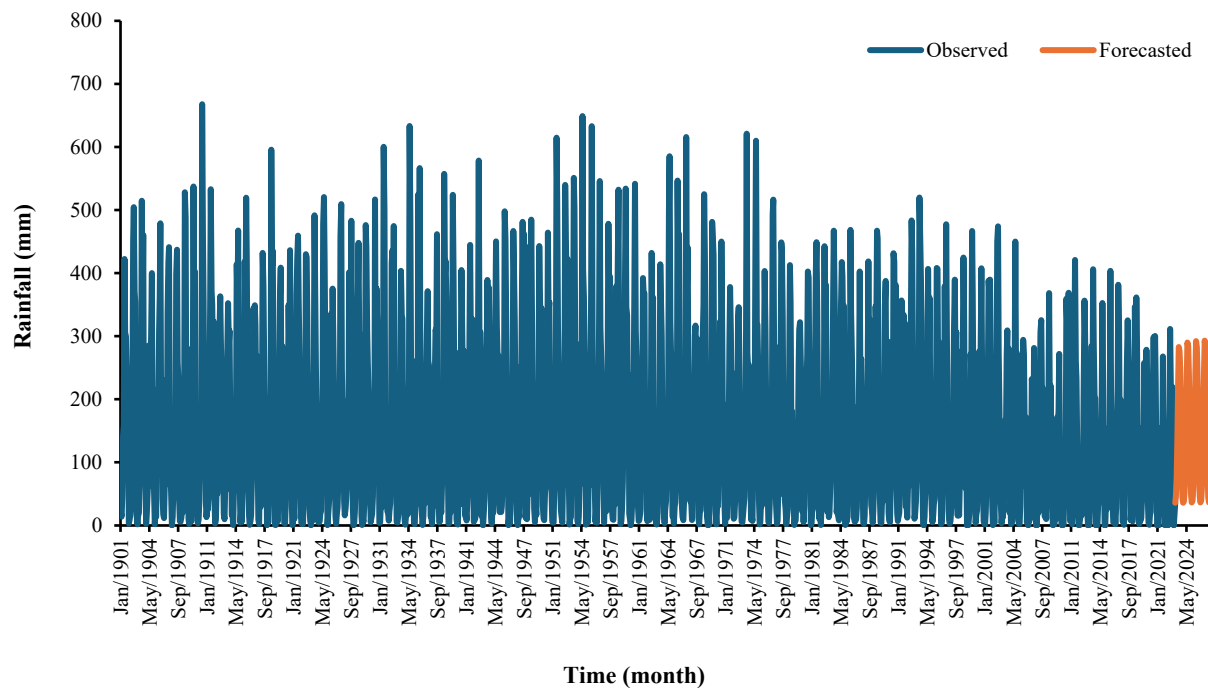


Figure 11(d) Observed (1901-2022) and forecasted (2023-2026) monthly rainfall for Wokha

It was observed that forecasted values as reported by Anelu Puro (2018) using SARIMA model were same in all years (2023-2026) whereas values forecasted by LSTM were different in different years for Kohima, Mon, Phek and Wokha (Figures 12 to 15).

The improved performance of the LSTM model compared to SARIMA indicates its ability to capture

nonlinear and temporal dependencies present in long-term rainfall data. The variation in forecasted values across different years suggests that the LSTM model can better represent inter-annual variability in rainfall patterns. Such monthly rainfall forecasts can be useful for agricultural planning, crop scheduling, irrigation management, and local water resource planning in the

selected stations of Nagaland.

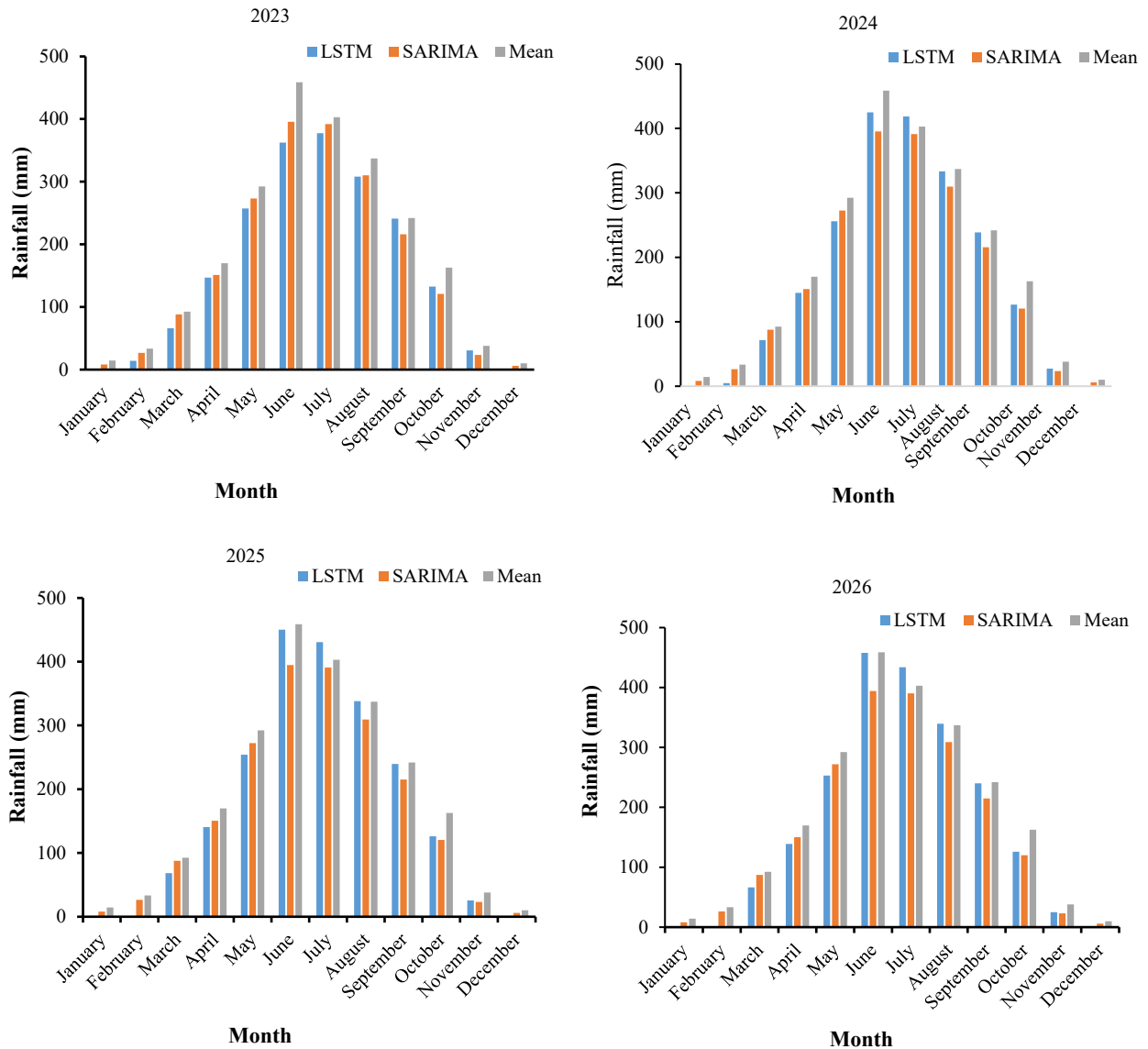
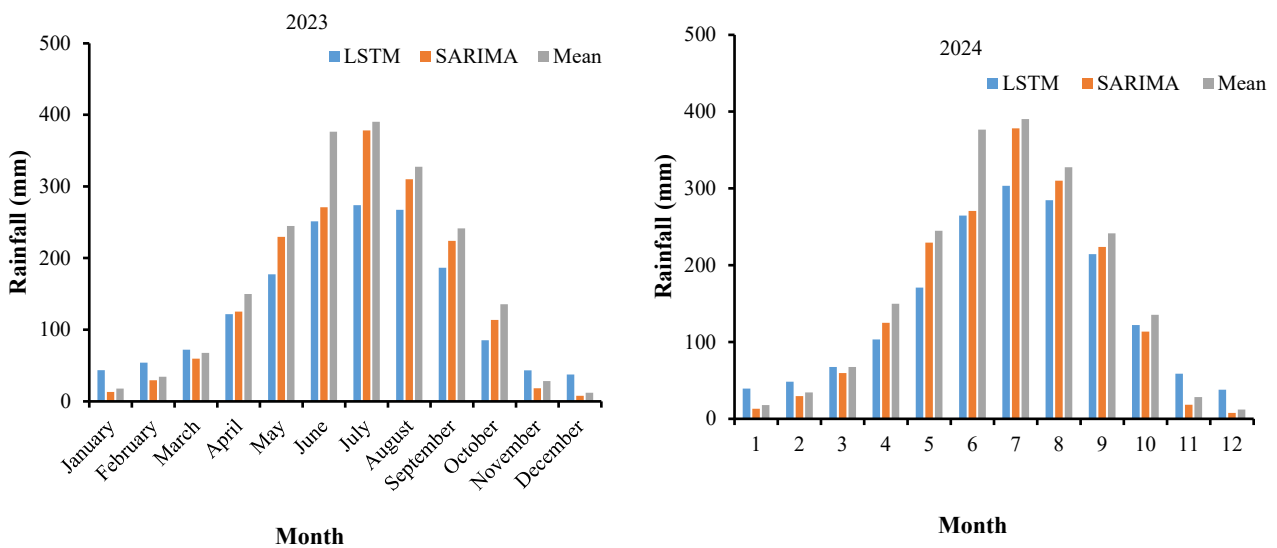


Figure 12 Forecasted value of monthly rainfall (mm) for Kohima using LSTM and SARIMA model for the years 2023, 2024, 2025 and 2026



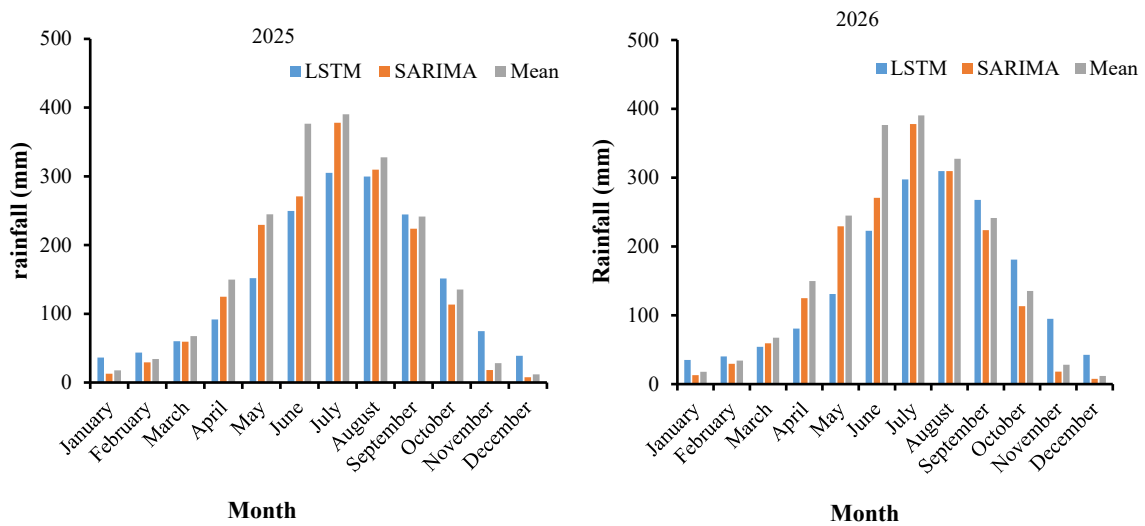


Figure 13 Forecasted value of monthly rainfall (mm) for Mon using LSTM and SARIMA model for the years 2023, 2024, 2025 and 2026

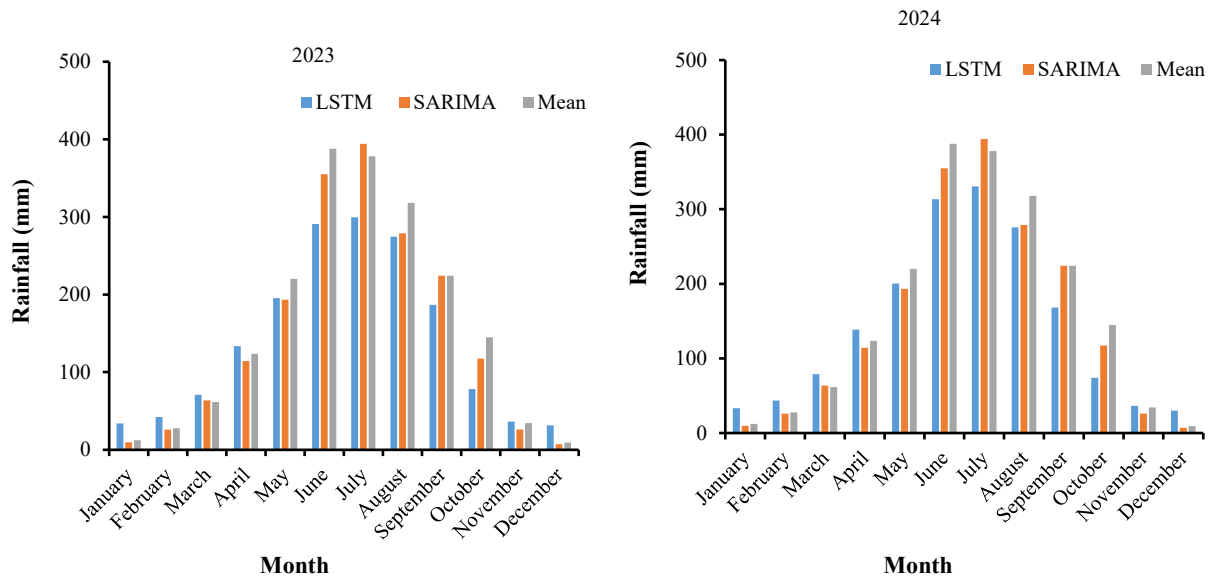
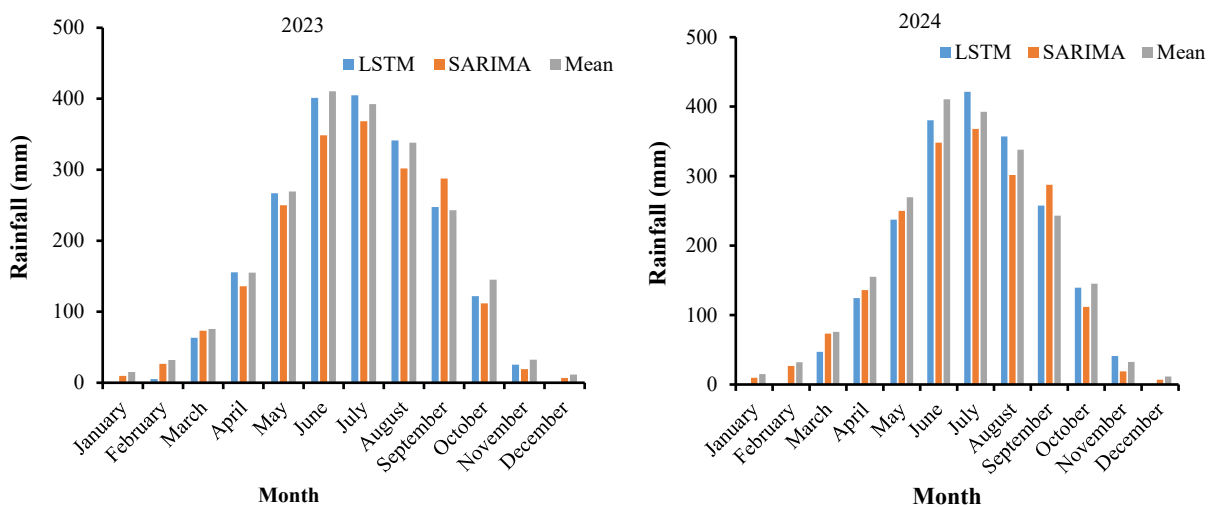


Figure 14 Forecasted value of monthly rainfall (mm) for Phek using LSTM and SARIMA models for the years 2023, 2024, 2025 and 2026



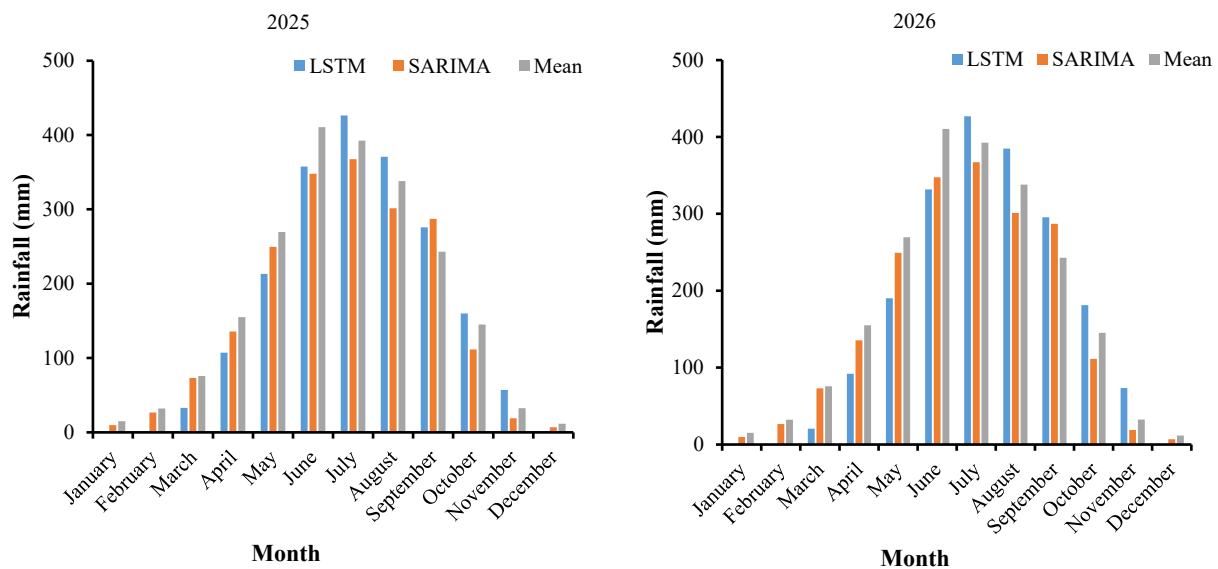


Figure 15 Forecasted value of monthly rainfall (mm) for Wokha using LSTM and SARIMA models for the years 2023, 2024, 2025 and 2026

4 Conclusions

In order to produce accurate monthly rainfall forecasts, this study sought to create an efficient model for rainfall forecasting utilizing LSTM networks. The methodology involved selecting relevant input variable, optimizing hyperparameters, and validating the model through rigorous testing on both training and testing datasets.

The LSTM model demonstrated robust performance. The observed and predicted values graphs and the 1:1 scatter plot for monthly rainfall forecasts revealed high accuracy and reliability. The results demonstrate that LSTM networks effectively capture the temporal dependencies of rainfall data, with the model achieving the value of MAE, MSE, RMSE, NSE ranged from 0.228 to 0.241, 0.01 to 0.014, 0.103 to 0.117, and 0.755 to 0.796 respectively during training and 0.196 to 0.245, 0.009 to 0.013, 0.097 to 0.116, and 0.71 to 0.75 respectively during testing. The near-zero errors values (MAE, MSE, RMSE) and NSE values close to 1.0 indicated the model's suitability for making reliable predictions.

The key findings from this study highlight several important implications. Accurate rainfall forecasts are crucial for various sectors, particularly agriculture and water resource management. Accurate rainfall

forecasts in agriculture can help farmers make well-informed choices on planting, irrigation, and harvesting, increasing crop yields and decreasing losses. In water resource management, reliable rainfall forecasts can help in planning and managing water supply, mitigating the impacts of droughts and floods, and enhancing overall water security.

However, the study has certain limitations. The model was developed using historical rainfall data without incorporating additional climatic variables such as temperature, humidity, or atmospheric circulation indices, which may further improve prediction accuracy. Moreover, the model was applied for station-level forecasting and did not consider real-time prediction with continuous monitoring.

Future research may focus on integrating multiple climatic parameters, exploring hybrid deep learning architectures, and implementing real-time rainfall forecasting systems for operational use. Such improvements may further enhance the robustness and applicability of rainfall prediction models in climate-sensitive regions.

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