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Enhancing Flash Flood Prediction Accuracy with Bi-LSTM and Satellite Rainfall Estimates

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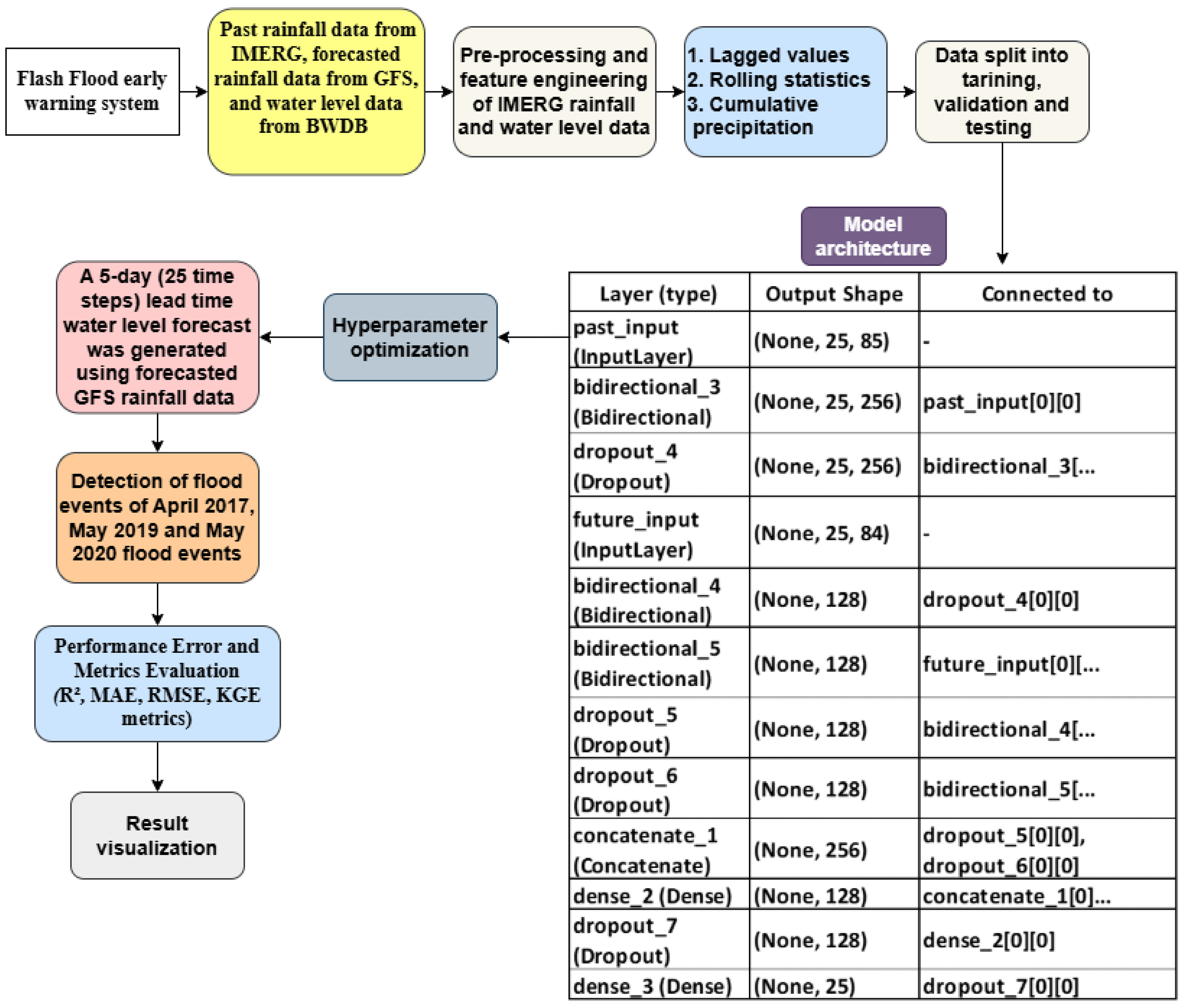
INTRODUCTION & AIM

Flash floods represent one of the most severe and unforeseen hydro-meteorological risks, particularly in mountainous catchments where heavy rainfall and rugged topography accelerate runoff, leading to rapid rises in water levels [1]. Flash flood occurrences leave scant time for an effective response, with major risks to lives, infrastructure, agriculture, and local economies. Flash floods are a yearly threat in Bangladesh's northeastern haor area, where rainfall from surrounding nations and intense rainfall within the region could lead to a sudden rise in rivers in just a matter of hours. More traditional flood forecasting methods, typically grounded in hydrological and hydrodynamic models, may not provide sufficient lead times or simulate nonlinear flash flood dynamics. Recent advances in deep learning offer robust alternatives by enabling data-driven approaches to learn sophisticated temporal relationships from historical and real-time data, thereby enhancing the accuracy and timeliness of forecasts [2,3]. This study develops and examines a deep learning–based flash flood early warning system for the BWDB (Bangladesh Water Development Board) station at Muslimpur, located on the Jhalukhali River in Sunamganj, Bangladesh. It employs a supervised Bidirectional Long Short-Term Memory (Bi-LSTM) neural network to forecast river water levels 25 time steps (5 days) ahead with every day divided into five time slots (06:00, 09:00, 12:00, 15:00, and 18:00). The model integrates a comprehensive set of input features, including IMERG (Integrated Multi-satellitE Retrievals for GPM) and GFS (Global Forecast System) satellite rainfall estimates for five spatial locations, temporal indicators (hour, day of year, month, and monsoon flags), lagged river water levels, rolling statistics, and cumulative precipitation.

METHOD



Layer (type)	Output Shape	Connected to
past_input (InputLayer)	(None, 25, 85)	-
bidirectional_3 (Bidirectional)	(None, 25, 256)	past_input[0][0]
dropout_4 (Dropout)	(None, 25, 256)	bidirectional_3[...
future_input (InputLayer)	(None, 25, 84)	-
bidirectional_4 (Bidirectional)	(None, 128)	dropout_4[0][0]
bidirectional_5 (Bidirectional)	(None, 128)	future_input[0][...
dropout_5 (Dropout)	(None, 128)	bidirectional_4[...
dropout_6 (Dropout)	(None, 128)	bidirectional_5[...
concatenate_1 (Concatenate)	(None, 256)	dropout_5[0][0], dropout_6[0][0]
dense_2 (Dense)	(None, 128)	concatenate_1[0]...
dropout_7 (Dropout)	(None, 128)	dense_2[0][0]
dense_3 (Dense)	(None, 25)	dropout_7[0][0]

Figure 1. Methodological flowchart.

STUDY AREA

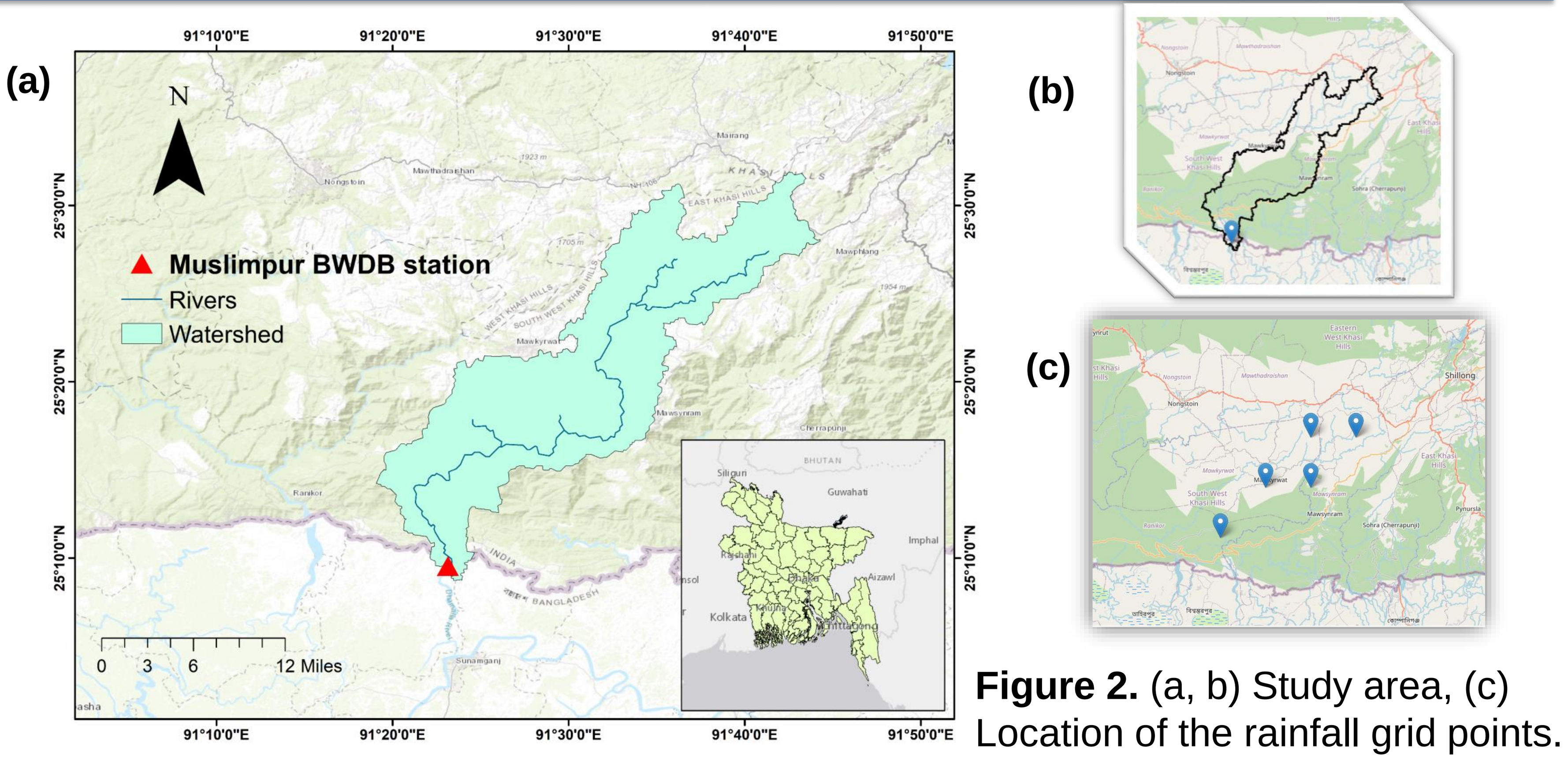


Figure 2. (a, b) Study area, (c) Location of the rainfall grid points.

RESULTS & DISCUSSION

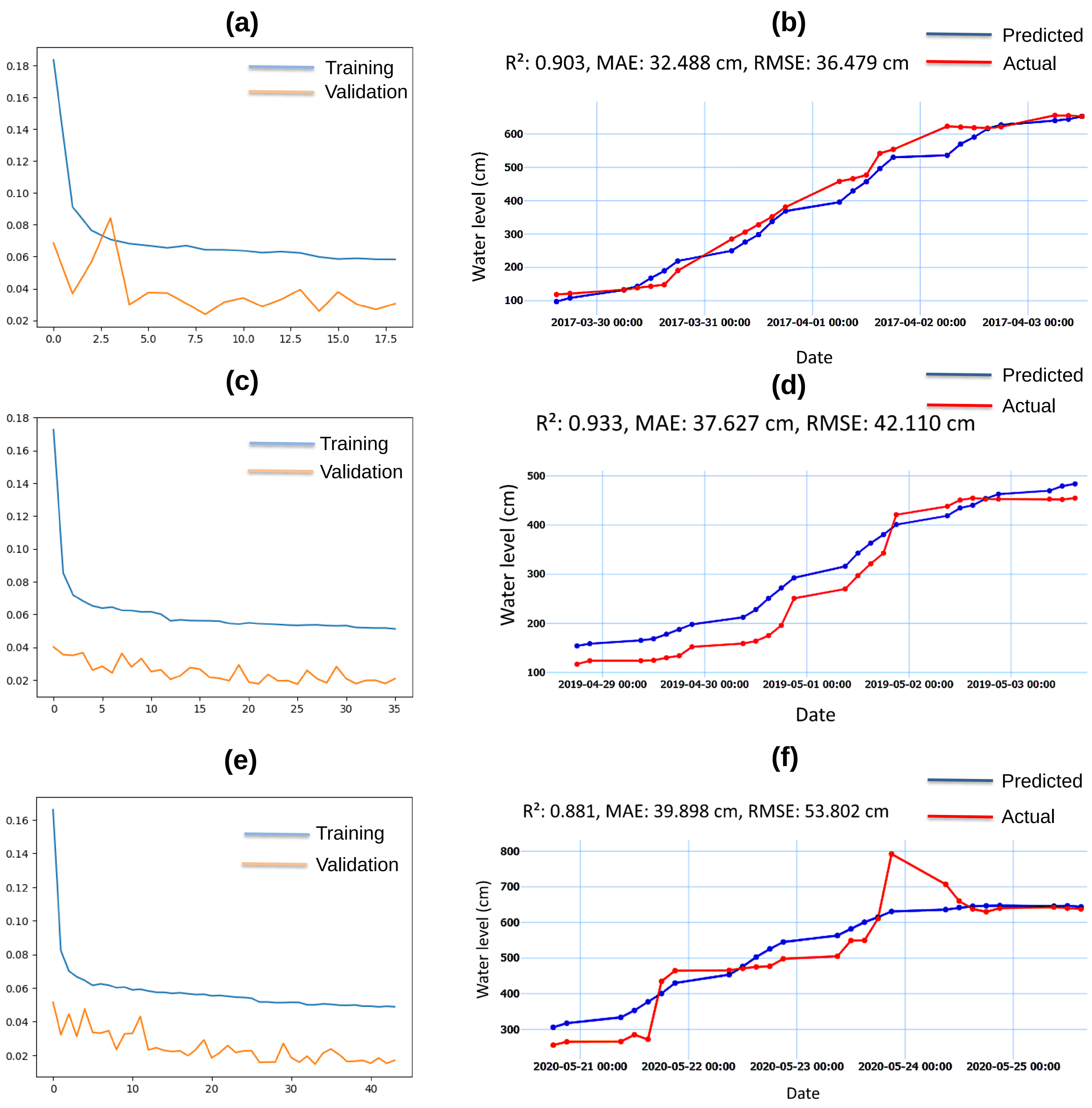


Figure 3. Model performance evaluation: (a, b) April 2017 event loss curves and water level predictions, (c, d) May 2019 event loss curves and water level predictions, (e, f) May 2020 event loss curves and water level predictions.

The Bi-LSTM model demonstrated strong predictive performance across three distinct flash flood events, achieving R^2 values ranging from 0.881 to 0.933, which indicates that the model explained 88-93% of the variance in water level fluctuations. The Mean Absolute Errors (MAE) varied between 32.488 cm and 39.898 cm, while Root Mean Square Errors (RMSE) ranged from 36.479 cm to 53.802 cm, with the April 2017 event showing the best performance (R^2=0.903, MAE=32.488 cm, RMSE=36.479 cm) and the May 2020 event exhibiting slightly lower accuracy (R^2=0.881, MAE=39.898 cm, RMSE=53.802 cm), likely due to the abrupt spike in water levels reaching approximately 790 cm. Despite the higher RMSE in the 2020 event, the model successfully captured the rapid onset and peak dynamics characteristic of flash floods, demonstrating its capability to provide reliable 5-day lead time forecasts. These error metrics confirm the model's operational viability for early warning systems in hilly catchments where timely alerts are critical for disaster preparedness and mitigation.

CONCLUSION & FUTURE WORK

This study presents a deep learning–based flash flood early warning framework tailored for the BWDB Muslimpur station on the Jhalukhali River, Sunamganj, Bangladesh, leveraging a Bi-LSTM architecture to forecast river water levels with a 5-day lead time. Future research will focus on adding additional hydro-meteorological inputs (e.g., evapotranspiration, surface pressure, temperature), improving model generalizability through transfer learning, physics-based model integration, uncertainty analysis, and developing an operational forecasting and alert dissemination system in real-time for mass and more reliable flash flood early warning.

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