CHIORI - Climate-informed Hydrologic Intelligence for Operational River Infrastructure

Program Riset Unggulan ITB

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Background and Objectives

Flood inundation prediction is essential for supporting early warning systems and emergency response, particularly in areas prone to recurrent flooding. However, conventional hydraulic models, such as HEC-RAS 2D, require substantial computational time to generate spatial flood inundation maps, limiting their application for rapid prediction. This study aims to developing a machine-learning surrogate model capable of directly predicting flood inundation depth using satellite data and spatial information.

Keyword: Flood Inundation Prediction, Machine Learning, Random Forest, Long Short-Term Memory, GSMaP, HEC-RAS 2D, Flood Early Warning.

Methodology

This study used Random Forest (RF) and Long Short-Term Memory (LSTM), to rapidly predict flood inundation using GSMaP v7 hourly rainfall data and spatial information. The surrogate model are trained using inundation maps generated by coupled HEC-HMS and HEC-RAS simulations.

Study Area

This study focuses on the urban areas downstream of the Ciliwung River system. The selected area has a complex network of urban drainage and flood-control infrastructure, allowing the model to adequately represent flow conveyance within the hydraulic model.

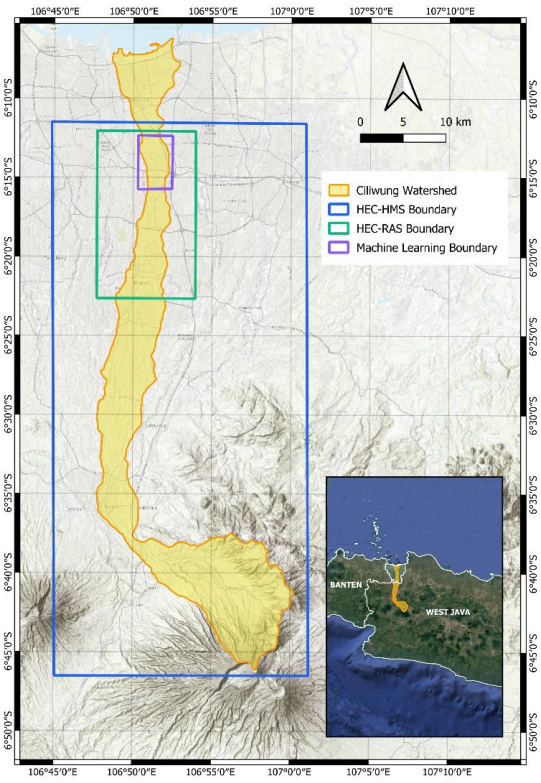


Figure 1. Study area and modeling domain of the Ciliwung River, Jakarta, Indonesia

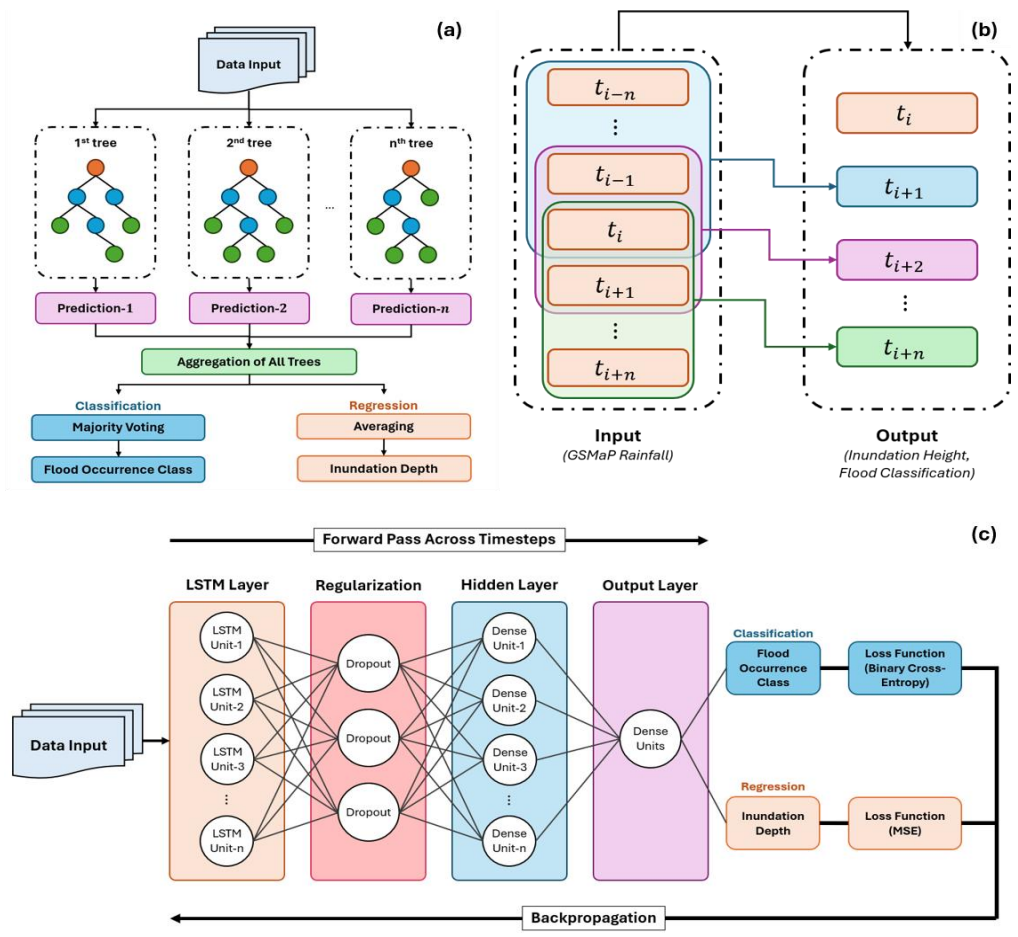


Figure 2. Schematic representation of the Random Forest model (a). Sequence Generation Scheme in the LSTM Model (b). LTSM Architecture (c).

Results & Discussion

RF and LSTM reduced the inference time by approximately 99.88% and 96.91%, respectively, compared with the HEC-RAS simulations. RF achieved a higher accuracy of 96.69% than LSTM 96.31%. RF obtained a higher precision by 1.78& compared to LSTM. In contrast, LSTM demonstrating higher recall by 6.52% and F1-score by 2.17%..

RF performed better at identifying inundated areas during the analyzed short-duration events. For the analyzed long-duration extreme event, LSTM producing fewer false negatives but more false positives than RF. The regression performance evaluation indicates that LSTM outperformed RF with evaluation metrics of MAE (0.06 m), RMSE (0.16 m), and NSE (0.96), meanwhile RF achieved 0.07 m MAE, 0.25 m RMSE, and 0.88 NSE.

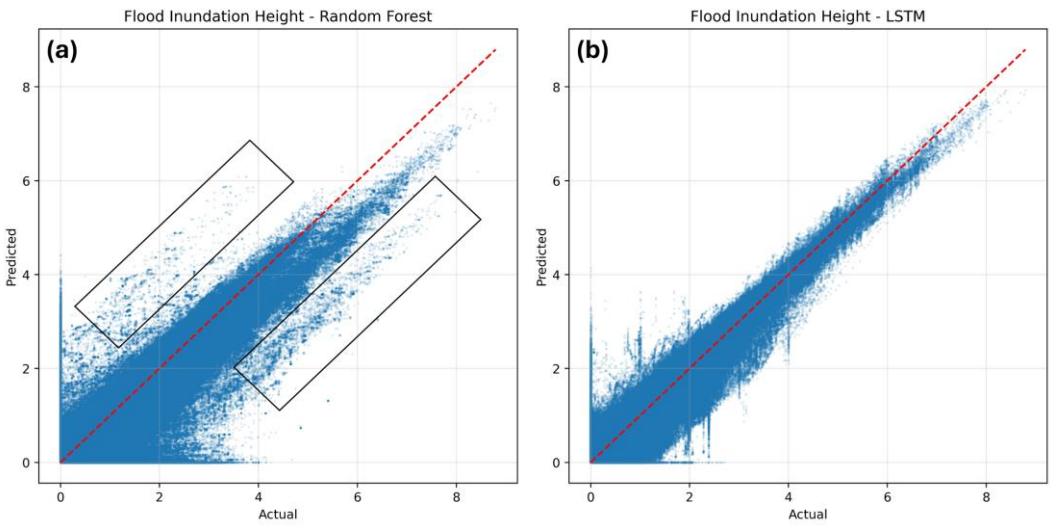


Figure 3. Comparison of actual and predicted flood inundation height (a) RF and (b) LSTM

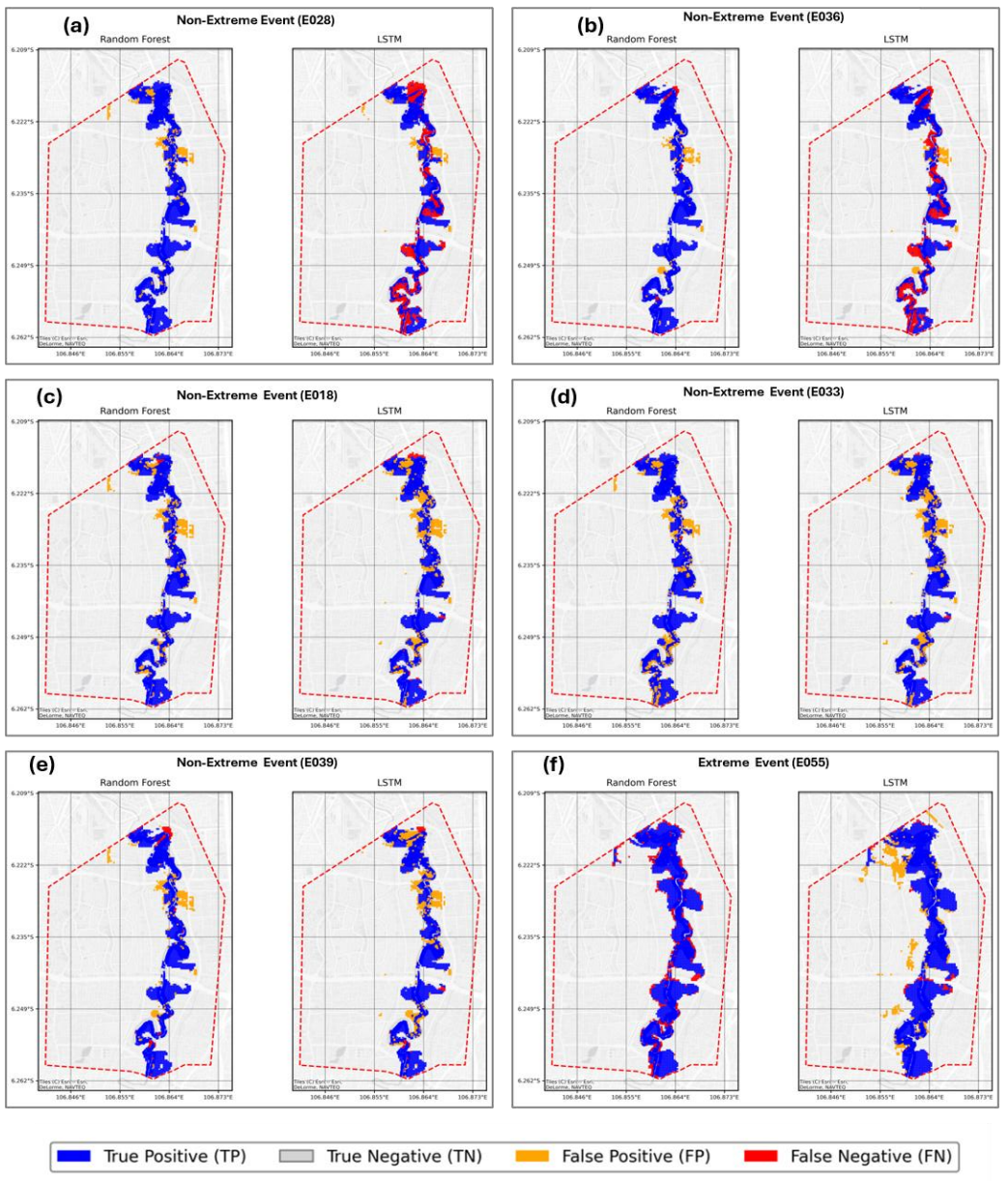


Figure 4. Comparison of actual and predicted flood inundation across non-extreme and extreme events: (a) non-extreme event E028, (b) non-extreme event E036, (c) non-extreme event E018, (d) non-extreme event E033, (e) non-extreme event E039, and (f) extreme event E055.

Conclusion

This study proves the potential of machine learning-based surrogate models to provide substantially faster spatial flood inundation predictions while reproducing the physics-based model's general inundation patterns. Further research should evaluate the models' transferability across different watersheds and a wider range of flood events, incorporate uncertainty in satellite rainfall estimates and hydraulic simulations, and integrate rainfall forecasts to enable predictions with explicit lead times

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