Toward Improved and Interpretable Extreme Flood Prediction with Deep Learning: A Novel Combined MSE–Quantile–Tail–Huber Loss Function Tested on the Seine River Basin

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Résumé

Flooding remains a critical global hazard, increasingly intensified by climate change, especially in complex urbanized watersheds like the Seine River Basin in France. This study advances flood forecasting by integrating model optimization and interpretability using deep learning techniques applied to daily maximum water level data from 2000 to 2024. We propose and optimize a novel loss function that combines Quantile, Tail, Huber, and Mean Square Error components to improve model sensitivity to extreme events (outliers) while maintaining accuracy for typical conditions. This custom loss function demonstrates significant improvements in forecasting performance across various architectures, including GRU, Bidirectional GRU, Bidirectional GRU with Attention, and CNN-BiGRU-Attention, improving flood detection F1 scores by 22% and AUC by 15% over standard loss functions for a 7-day lead time.

To address the interpretability challenge in deep learning models, we conduct a multi-pronged analysis combining scenario testing, model comparisons, and SHAP (SHapley Additive exPlanations) analysis. We find that key predictors of downstream flooding, particularly near Rouen, include upstream signals (e.g., Alfortville), sea level variations, and inputs from tributaries such as the Eure and Epte rivers. Groundwater interactions near Rouen also emerge as significant, while broader meteorological data contribute marginally beyond local signals. Notably, we observe a trade-off between model complexity and interpretability, resembling a 'paradox' in model selection: while attention-based models improve predictive accuracy, simpler GRU models offer more transparent insights into feature importance due to their greater sensitivity to input selection. We recommend combining both approaches, leveraging the accuracy of complex models alongside the transparency of simpler ones to better understand flood dynamics and optimize monitoring networks.

Our findings highlight the critical but often overlooked role of carefully designing and optimizing loss functions to improve extreme event prediction in hydrological models. By integrating

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advanced modeling techniques with interpretability-focused diagnostics and optimized loss functions, this work provides a scalable framework for enhancing flood forecasting systems, refining hydrological monitoring, and supporting risk-informed decision-making in highly anthropized river basins.

Mots-Clés: Deep Learning, Loss Function, Flood Forecasting, Extreme Events, Seine River