Spatio-Temporal Deep Learning for Flood Forecasting in Sparsely-Gauged Niger River Basin
(Oral)

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ABSTRACT

The Niger River Basin exhibits extreme hydrological heterogeneity, which spans from the humid Guinean highlands to the arid Sahelian region, the semi-arid Sudan region and the complex Niger Delta. Conventional hydrological and data-driven models often struggle to generalize across these diverse climatic regimes and geophysical settings. This study introduces a robust, transboundary flood early-warning framework designed to overcome the challenges posed by sparse historical records. The objectives of the study are to: (i) employ self-supervised masked reconstruction to address multi-sensor data gaps, (ii) identify critical climatic and biophysical drivers across sub-basins, and (iii) develop an interpretable hybrid forecasting model.

We propose an Interpretable Graph-Based Mixture of Experts (MoE) Transformer, a novel deep learning architecture for watershed-scale flood forecasting in data-scarce environments. This framework integrates a Transformer encoder to capture long-range temporal dependencies with a Graph Attention Network (GATv2) to enforce spatial connectivity and physical routing through the HydroATLAS sub-basin network.

Missing data gaps in historical datasets such as GPM, CHIRPS, and CHIRTS are bridged through a self-supervised masked reconstruction phase, followed by supervised fine-tuning. The daily time-series of the input data (features) are processed through a Variable Selection Network (VSN) to determine their feature importance before entering the Transformer encoder. The sub-basins are represented as nodes in a directed graph, with edges derived from their physiographic attributes. Spatial connectivity is enforced as the Transformer's latent states are fed into the GATv2 for routing across the network. The MoE component dynamically routes these latent states to specialized neural experts, with each representing distinct hydrological regimes. In order to ensure reliability, the model incorporates a Monotonic Quantile Head for the output quantiles (0.05, 0.50 and 0.95), for nowcasts and 1–day to 7-day lead forecasts. Calibrated with Conformal Prediction with Jackknife-after-Bootstrap (JAB) resampling to provide statistically guaranteed uncertainty intervals. Inactive gauges in the GRDC dataset were filtered using a binary flag system, that ensured training was restricted to valid observations.

This framework builds directly on previous Transformer-based research that achieved Kling–Gupta Efficiency (KGE) and Nash–Sutcliffe Efficiency (NSE) scores of 0.80–0.96 across vital stations in the Niger River Basin, including Lokoja, Jiderebode, and Niamey. The incorporation of self-supervised masked reconstruction in the new framework has enhanced the predictive accuracy of the model during sensor outages, and also strengthened the resilience of flood forecasting in data-scarce regions. The results of the study indicates that the MoE-GATv2 model maintains high skill scores across nowcasts and 1-day to 7-day lead times, and have also improved the model's interpretability by revealing the dominant climatic and biophysical drivers of flood peaks in different sub-basins. This evolution represents a significant advancement in reliable, uncertainty-aware flood forecasting for the transboundary Niger River system, thereby providing a scalable pathway for operational flood early-warning services in Africa's data-constrained river basins.

Keywords: Transboundary Flood Forecasting; Spatio-Temporal Graph Networks; Transformer-based Hydrology; Uncertainty Quantification (Conformal Prediction).