TC-GTN: Temporal convolution graph transformer network for hydrological forecasting

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NEURAL INFORMATION PROCESSING SYSTEMS

Motivation

Climate change and **global warming** amplify hydroclimatic extremes, leading to more frequent and **severe floods** that threaten **human lives**, **ecosystems**, and **critical infrastructure** [1]. In this context, reliable **streamflow forecasting** is essential for **early warning systems**. Moreover, accurate discharge predictions support more effective planning and **real-time management of hydropower** plant operations, playing a key role in the **sustainable production** and **management of green energy** [2].

Conventional models often struggle to capture the **complex spatio-temporal dynamics** of river networks under changing climatic conditions. By combining **temporal convolution** with **graph transformers**, **TC-GTN** provides robust and interpretable hydrological predictions, supporting **climate adaptation strategies**, enhancing **flood resilience**, and enabling more efficient and **sustainable hydropower operation**.

Contributions

- Novel Spatio-Temporal Hybrid Model — **TC-GTN**
- Structured Graph Representation of Hydrological Systems
- A quantile loss targeting high-flow events critical for flood prediction

Graph Structure

The study area is modeled as a graph with meteorological and hydrological stations as nodes. Three edge types capture spatial dependencies: **Meteo-Meteo (undirected)** for weather correlations, **Meteo-Hydro (directed)** for meteorological influence on discharge, and **Hydro-Hydro (directed)** for downstream flow propagation.

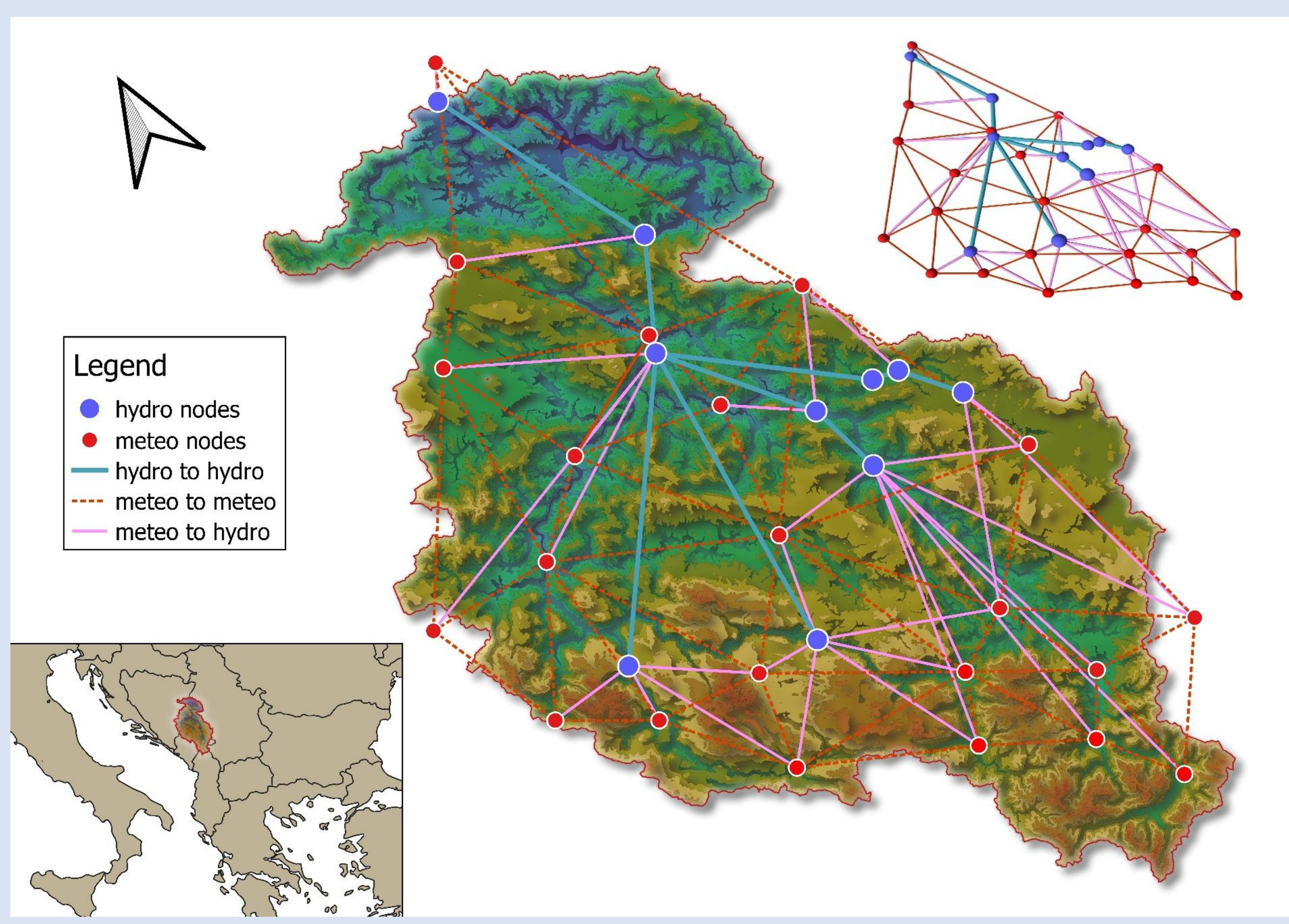


Figure 1. Graph representation of the Case Study (Drina River Basin): blue nodes denote hydrological stations, red nodes represent meteorological stations, and edges (varying by type) indicate connections.

TC-GTN Architecture

TC-GTN combines temporal convolution and graph transformers to capture both temporal dynamics and spatial dependencies in river networks.

It includes three key components:

Temporal Encoder: 1D convolutions extract short-term patterns from each station's time series and project them into latent features.

Graph Transformer [3]: Multi-head attention models directional relationships between meteorological and hydrological nodes and learns complex, long-range dependecies.

Decoder: A two-layer feedforward network maps node embeddings to multi-step streamflow forecasts.

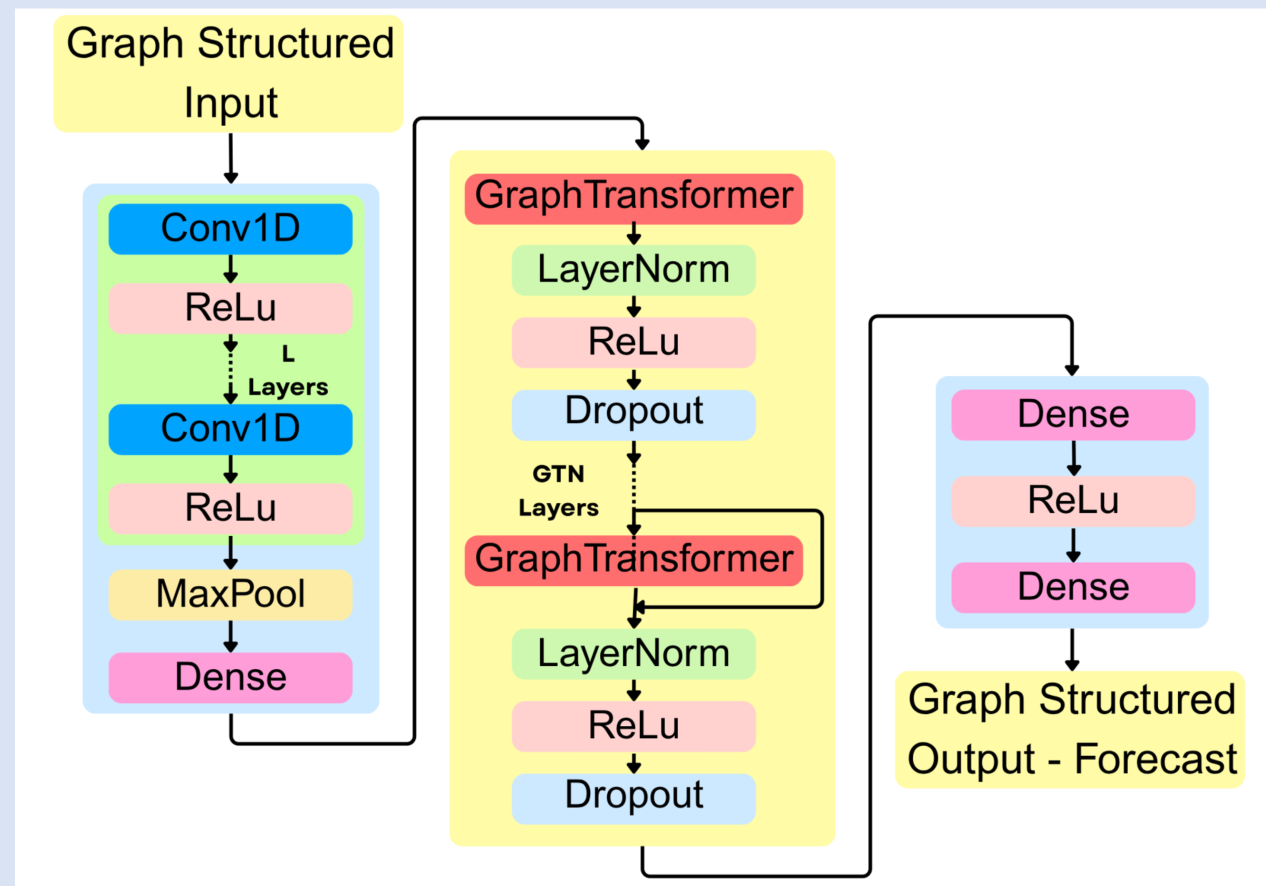
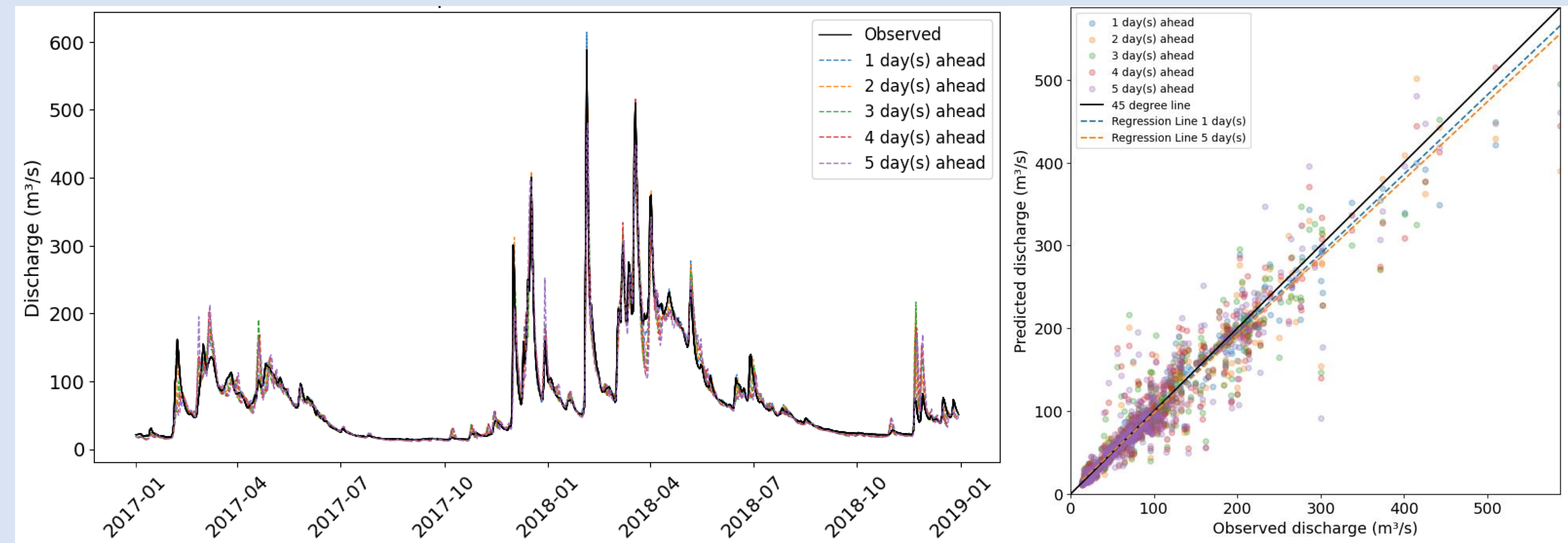


Figure 2 Architecture of the TC-GTN model

Results & Conclusion

Our proposed **TC-GTN consistently outperforms** baseline models (GTN and LS-GTN) across most stations and prediction horizons. Temporal convolutional layers **enhance feature extraction**, **improving long-horizon forecasts** and **low-flow station accuracy**, with average **gains** of **~11.6% RMSE**, **16% MAE**, **40.4% MAPE**, and **21% R²** over the best baseline. In **high-flow scenarios (>75th percentile)**, **TC-GTN** also **reduces errors (~6–10%)** and provides more **stable predictions**, highlighting its advantage over baseline models.



TC-GTN model demonstrates robust performance for high-flow events critical for predicting extreme hydrological events such as floods. High model accuracy supports **efficient hydropower plant operation, up to 5 days in the future**, providing smart, green-energy framework.

Datasets & Experimental Setup

The dataset comprises daily time series from **10 hydrological** and **22 meteorological stations** in the **Drina River basin** (Southeastern Europe). Meteorological stations record mean daily temperature and precipitation, while hydrological stations measure river discharge, totaling $\boldsymbol{V} =$ **54 nodes**. The dataset spans the period from 1968 to 2018 and is divided into training (1968–2015), validation (2016), and test sets (2017-2018). The temporal input sequence spans 7 days, previous 7 days for hydrological nodes and 2 past plus 5 future days for meteorological nodes.

Acknowledgments

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