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

Ana Samac, Milan Dotlić, Luka Vinokić, Milan Stojković, Veljko Prodanović

The Institute for Artificial Intelligence Research and Development of Serbia, Novi Sad, Serbia

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 for flood mitigation strategy
- Real-time hydropower management
- Sustainable management of green energy [2]

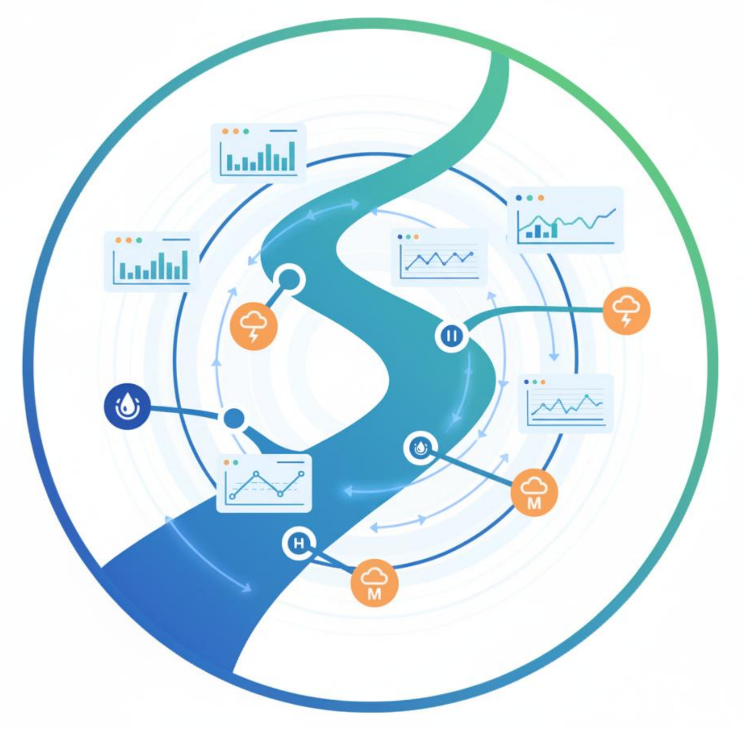
Conventional models often struggle to capture the **complex spatio-temporal dynamics** of river networks under changing climatic conditions.

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**.

[1] Martinez-Villalobos, C., Neelin, J.D., 2023. Regionally high risk increase for precipitation extreme events under global warming. Scientific Reports 13, 5579

[2] Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A.S., Maharaj, T., Sherwin, E.D., Mukkavilli, S.K., Kording, K.P., Gomes, C.P., Ng, A.Y., Hassabis, D., Platt, J.C., Creutzig, F., Chayes, J., Bengio, Y., 2022. Tackling climate change with machine learning. ACM Comput. Surv. 55. URL: https://doi.org/10.1145/3485128, doi:10.1145/3485128

Research gaps



River basins form **directional** and **hierarchical** networks connecting **meteorological** and **hydrological** stations, where streamflow exhibits complex **spatial** and **temporal** dynamics.

Many models:

- Use **GNNs, transformers or temporal models**, but not all together effectively.
- Ignore **domain-specific graph structure** (upstream–downstream, meteo–hydro links)

Need for a model that:

- Jointly learns **spatial and temporal dependencies**,
- Handles **extreme events** (high flows),
- Leverages **graph structure knowledge**.

Objective and contributions

Objective: Develop a hybrid model for accurate and robust streamflow forecasting.

Key Contributions:

1. **Structured graph representation** with three hydrological edge types (Meteo–Meteo, Meteo–Hydro, Hydro–Hydro).
2. **Hybrid architecture:** Temporal Convolution + Graph Transformer + residual connections.
3. **Quantile loss** for better performance on high-flow (extreme) events.

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.

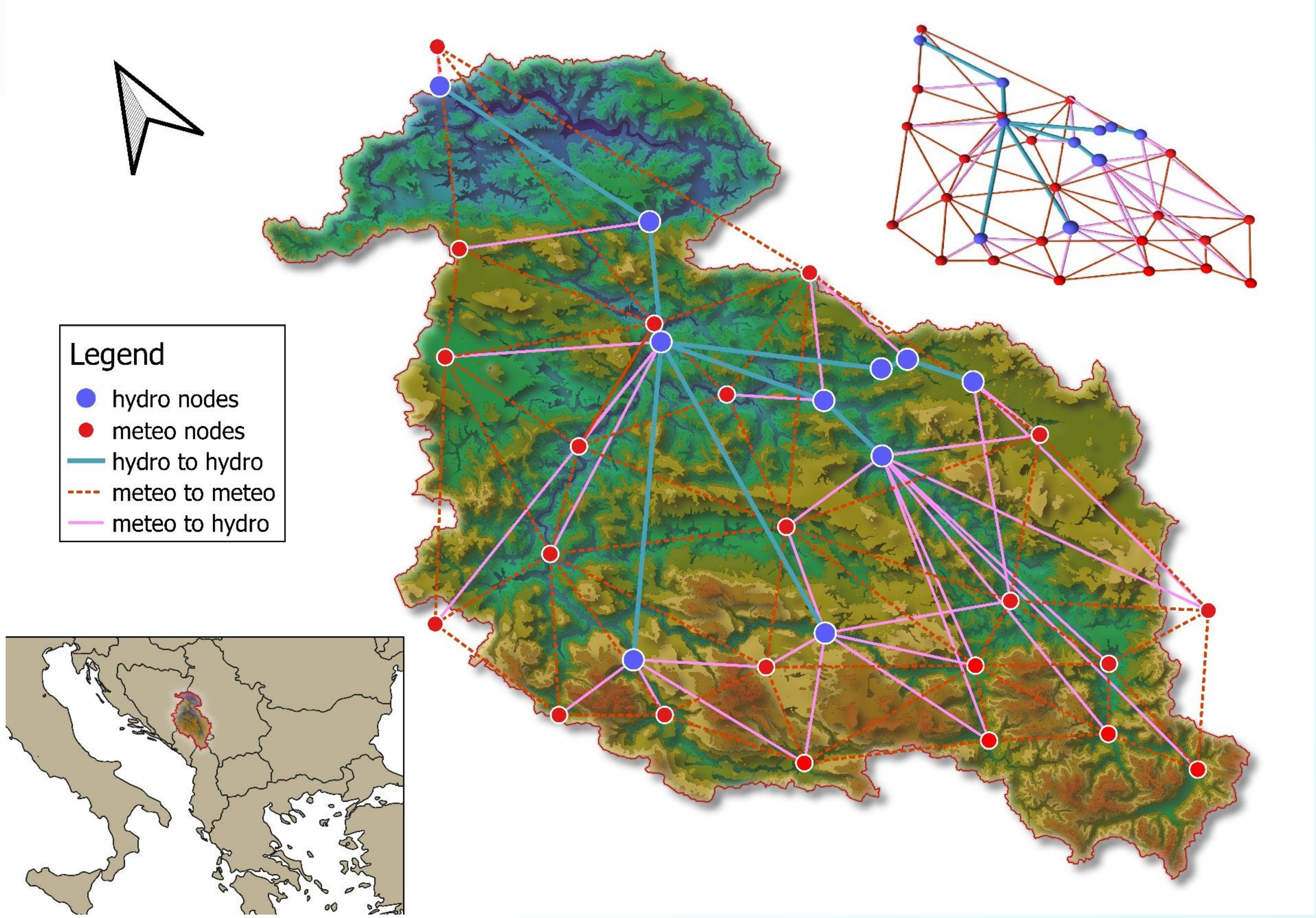
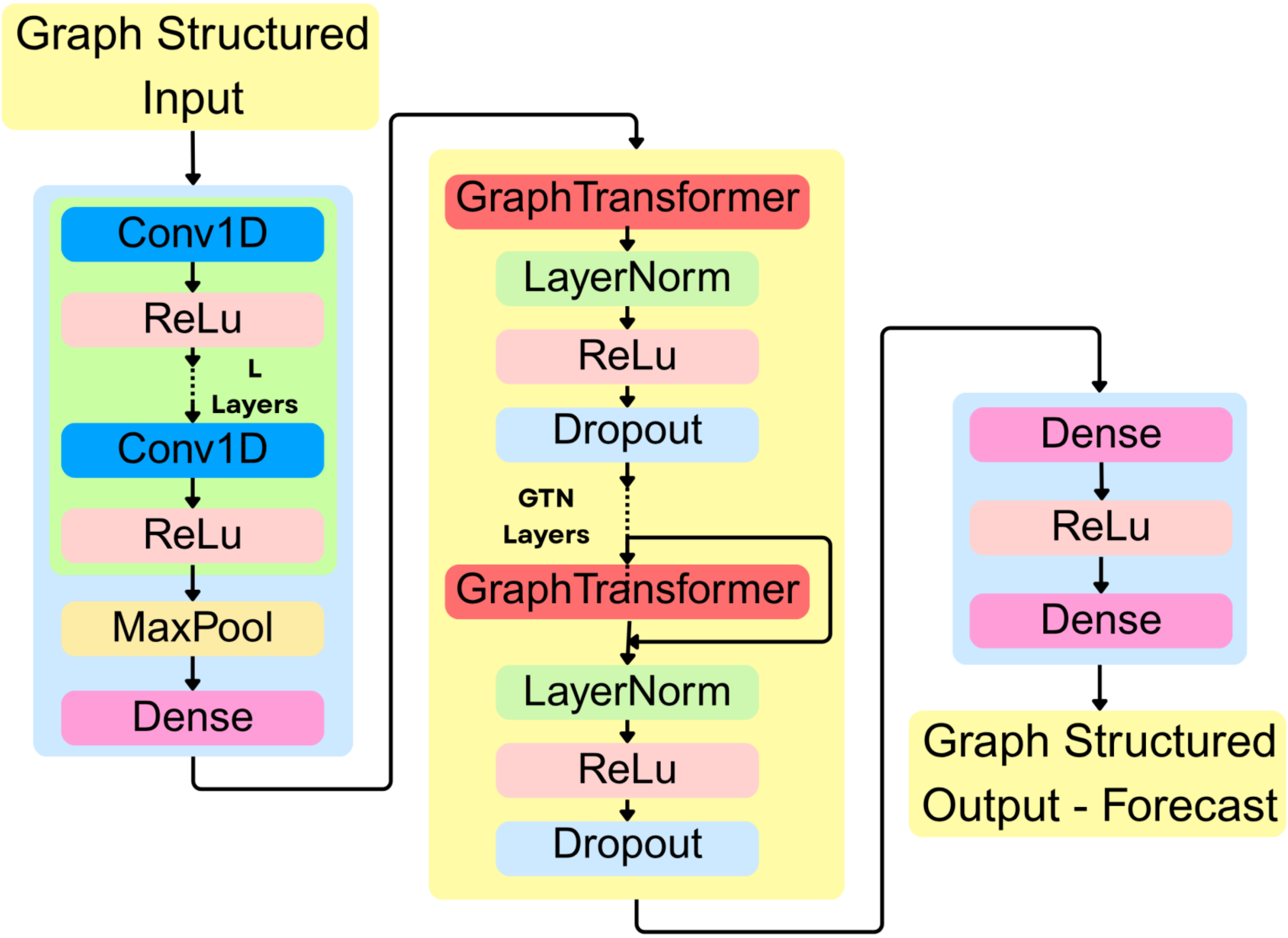


Figure 1. Graph representation of the Case Study (Drina River Basin): blue nodes denote hydrological stations, red nodes represent meteorological stations, and edges (varying by type) indicate connections.

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.

[3] Shi, Y., Huang, Z., Feng, S., Zhong, H., Wang, W., Sun, Y., 2020. Masked label prediction: Unified message passing model for semi-supervised classification. arXiv preprint arXiv:2009.03509

Datasets & Experimental Setup

Dataset: Drina–Lim River Basin (Southeastern Europe)

- 10 hydrological + 22 meteorological stations → 54 nodes
- Daily data (1968–2018)
- Train: 1968–2015, Validation: 2016, Test: 2017–2018

Input: 7 days sequence

- Previous 7 days for hydrological nodes
- 2 past plus 5 future days for meteorological nodes

Metrics: RMSE, MAE, R^2, MAPE (+ filtered for high-flow events)

Baselines:

- Graph Transformer (GTN)
- LSTM + GTN (LS-GTN)

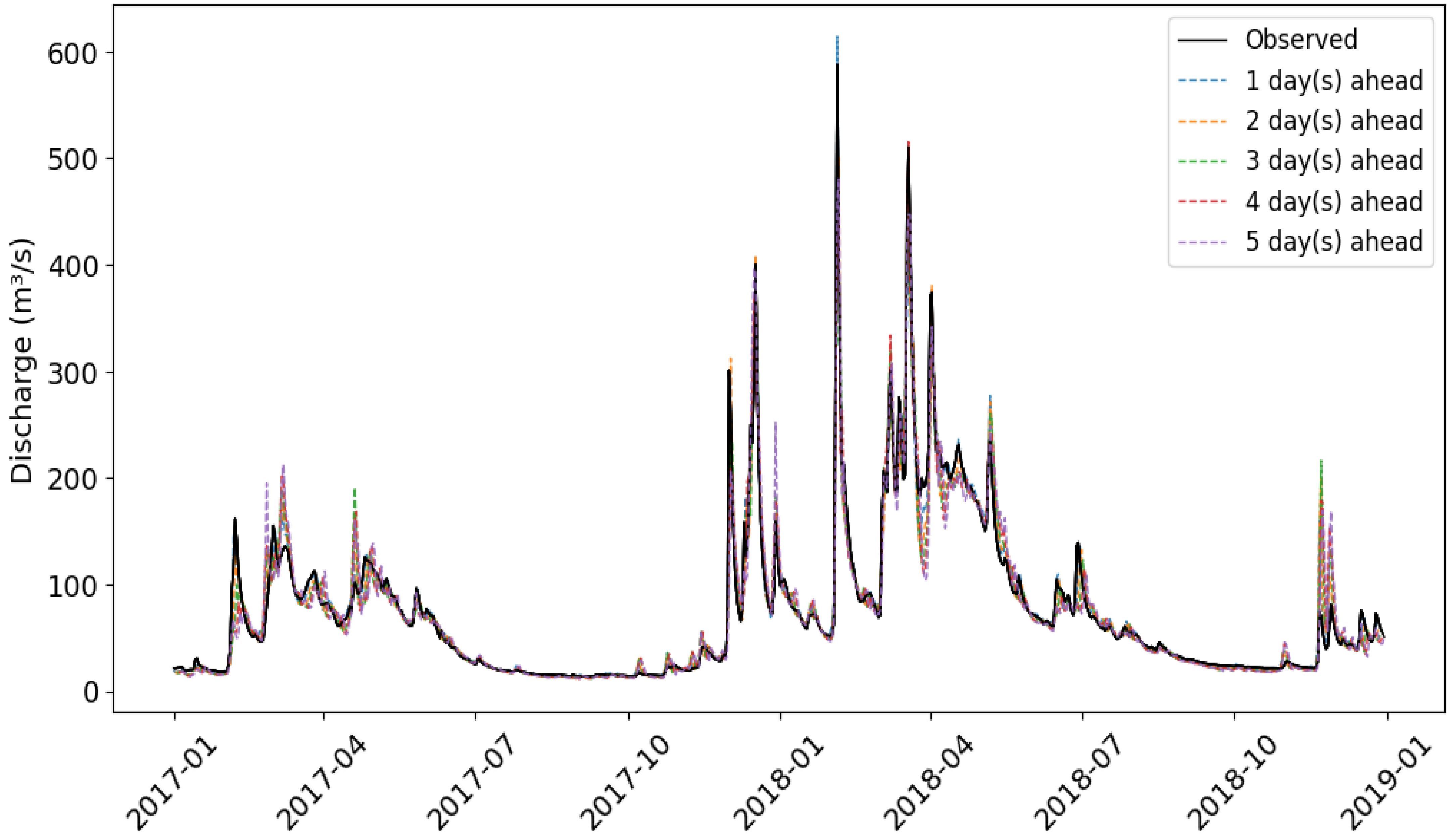
Results

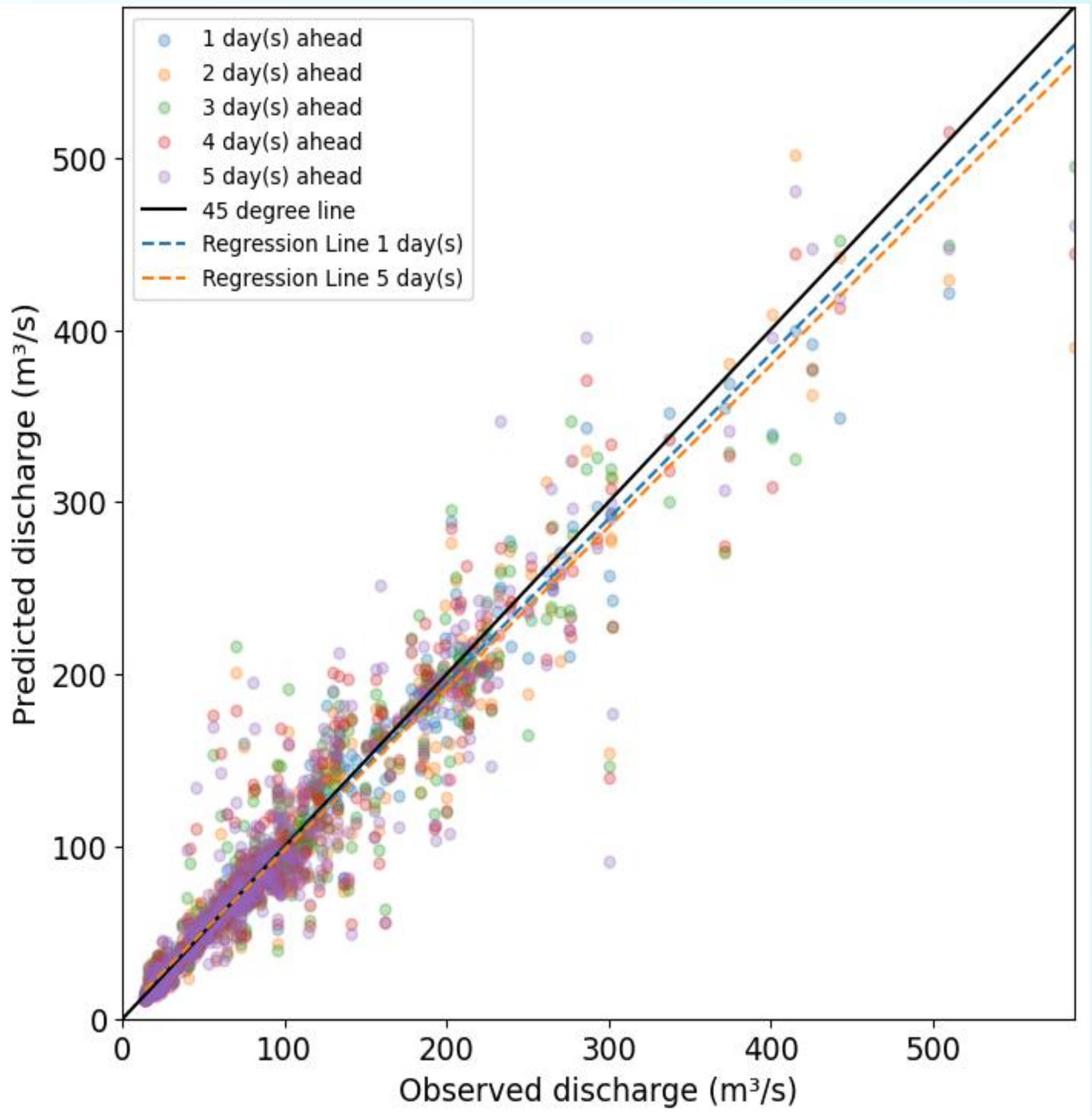
Overall Performance:
- TC-GTN consistently outperforms baselines across all metrics.
- Average improvement over best baseline (LS-GTN):
  - RMSE ↓ 11.6%
  - MAE ↓ 16%
  - MAPE ↓ 40.3%
  - R^2 ↑ 21.0%
- Stronger performance on longer prediction horizons.
- Especially effective on low-flow stations, where GNNs underperform.

High Flow Events Performance:
- Metrics computed on values > 75th percentile.
- TC-GTN achieves:
  - RMSE ↓ 6.9%
  - MAE ↓ 8.8%
  - MAPE ↓ 10.4%
  - R^2 ↑ 6.0%
- Superior stability and lower median errors in 95–99 percentile flow events.
- Demonstrates improved flood event prediction capability.

Station	Day	MAE			RMSE			R^2			MAPE		
		GTN	LS-GTN	TC-GTN	GTN	LS-GTN	TC-GTN	GTN	LS-GTN	TC-GTN	GTN	LS-GTN	TC-GTN
Station 1	1	7.84	7.37	**5.75**	16.12	16.35	**13.92**	0.949	0.947	**0.962**	0.112	0.109	**0.070**
	2	10.27	9.36	**8.28**	21.82	**19.91**	19.99	0.906	**0.921**	**0.921**	0.137	0.131	**0.102**
	3	11.59	10.43	**9.85**	24.21	21.21	**20.97**	0.884	0.911	**0.913**	0.157	0.148	**0.126**
	4	11.86	11.42	**10.79**	23.38	22.60	**21.78**	0.892	0.899	**0.906**	0.164	0.160	**0.141**
	5	12.40	12.14	**11.32**	23.52	22.83	**22.25**	0.890	0.897	**0.902**	0.176	0.170	**0.150**

Results


Observed
1 day(s) ahead
2 day(s) ahead
3 day(s) ahead
4 day(s) ahead
5 day(s) ahead
Discharge (m³/s)
600
500
400
300
200
100
0
2017-01
2017-04
2017-07
2017-10
2018-01
2018-04
2018-07
2018-10
2019-01


1 day(s) ahead
2 day(s) ahead
3 day(s) ahead
4 day(s) ahead
5 day(s) ahead
45 degree line
Regression Line 1 day(s)
Regression Line 5 day(s)
Predicted discharge (m³/s)
Observed discharge (m³/s)
0
100
200
300
400
500

Conclusions

- Introduced TC-GTN, a hybrid Temporal Convolution Graph Transformer Network for spatiotemporal streamflow forecasting.
- Achieves state-of-the-art performance in streamflow forecasting, outperforming baseline models.
- Enhances predictive accuracy during high-flow (flood) events, contributing to improved flood risk assessment.
- Enables early warning systems for climate-resilient water management and optimized hydropower operations, supporting a smart, sustainable energy framework.

Acknowledgments
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Code available at:

https://github.com/dodi007/TC-GTN-Spatio-temporal-Graph-Transormer www.ivi.ac.rs

Thank you

ana.samac@ivi.ac.rs milan.dotlic@ivi.ac.rs luka.vinokic@ivi.ac.rs milan.stojkovic@ivi.ac.rs veljko.prodanovic@ivi.ac.rs