Data-Centric ML-based flood forecasting system of the Drina-Lim hydropower system (south-east Europe)

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ABSTRACT

Climate change has intensified extreme hydrological events in South-East Europe, increasing flood risk in the Sava River Basin. The Drina River, a key hydroenergetic system within the Sava River basin, requires reliable inflow forecasting to support hydropower operations and flood management. Existing platforms rely on physics-based models that face limitations under non-stationary climatic conditions. This study introduces the first data-centric, ML-based operational inflow forecasting system for the Drina–Lim hydropower cascade. The framework integrates hydrological observations, ERA5 reanalysis data, satellite-derived inputs, and bias-corrected meteorological fields to enhance data quality prior to model training. Four ML architectures (LSTM, TCN, TKAN, GNN) were evaluated using assimilated meteorological variables for the 2019–2023 period. All models achieved high predictive accuracy, with NSE values between 0.86 and 0.90 and low MAPE across reservoirs. Upstream HPPs exhibited particularly low absolute errors, while downstream stations maintained strong performance despite larger flow magnitudes. The results show that ML-based forecasting provides a robust and accurate alternative to traditional hydrological models and is well-suited for operational flood risk management in the Drina River Basin.

KEYWORDS: ML flood forecasting, hydropower plants, ERA5, data-centric approach, river flow

1 INTRODUCTION

Climate change and climate variability have intensified the frequency and severity of hydrometeorological extremes across southeastern Europe, leading to more frequent heavy-rainfall events, accelerated snowmelt episodes, and prolonged wet periods (Stojković et al. 2014;

Stojković et al. 2017a; Stojković at al. 2017b; Stojković and Simonović, 2020). These shifts have significantly increased flood risk in river basins, within the considered area, where mountainous terrain and rapid runoff magnify the impacts of extreme precipitation.

Within this context, the Sava River Basin is recognized as one of the most flood-prone regions in the area (Brilly et al., 2014). Due to its complex hydrological regime, steep tributaries, and recurrent extreme precipitation, the basin experiences regular and often severe flooding, threatening local communities, infrastructure, and hydropower operations across multiple countries. A major sub-basin of the Sava is the Drina River catchment, which contains one of the most important hydroenergetic systems in South-East Europe (Stojković and Simonović, 2019, Milivojević at al. 2014). The river hosts a cascade of hydropower plants (HPPs) whose reliable and safe operation critically depends on accurate inflow forecasting. Over the past decade, several forecasting and monitoring platforms have been developed to support water authorities and hydropower operators. The HIS Drina system (Milivojević et al, 2014) provides integrated acquisition and visualization of meteorological and hydrological data, and streamflow forecast while the Sava FEWS system (ISRBC, 2018), built on the Delft-FEWS platform, delivers operational hydrological forecasts for the entire Sava Basin and supports transboundary flood management

However, these systems rely on physics-based hydrological models, which can struggle to maintain performance under non-stationary climate conditions. Increased variability in precipitation patterns, increased air temperatures, and shifts in seasonal runoff have made model calibration more challenging and increased predictive uncertainty. In response to these challenges, this study presents the first ML-based operational inflow forecasting system developed for the Drina–Lim hydropower cascade, marking an advancement in flood forecasting for South-East Europe. The system adopts a data-centric design philosophy (Ng, 2021; Liu et al. 2023), where the quality, completeness, and representativeness of input data are prioritized as key drivers of model performance. To achieve this, the framework integrates not only recent hydrological observations and ERA5 (Hersbach et al. 2020) climate reanalysis datasets but also enhanced input data produced through satellite-derived observations (Ilić et al., 2025) and bias-correction procedures (Vinokić et al., 2023; Stojković et al, 2019). As a result, the ML models operate on higher quality, harmonized datasets that more accurately represent real hydrometeorological conditions.

Unlike traditional models, the proposed ML flood forecasting system demonstrates high predictive accuracy, strong robustness to reanalysis-driven meteorological inputs, and stable performance across varying hydrological regimes, including conditions influenced by climate variability and extremes. These results highlight the potential of ML-based forecasting as both a complement and a viable alternative to classical hydrological modeling approaches in complex river systems.

2 MATERIALS & METHODS

2.1 Data collection

In the Drina River basin, there are 9 reservoirs with their corresponding hydropower plants (Figure 1). The most upstream reservoir is Mratinje on the Piva River, equipped with a storage hydropower plant. Along the main course of the Drina River, three reservoirs with storage hydropower plants are located: Višegrad, Bajina Bašta, and Zvornik. An additional reservoir, Lazići, represents the upper reservoir of the Bajina Bašta pumped-storage hydropower plant. In the Lim River basin, there are four reservoirs in total. Three of them are situated on the Uvac River (Kokin Brod, Uvac, and Radojna), while the Potpeć reservoir is located on the Lim River. All reservoirs are associated with storage hydropower plants, while the Radojna reservoir is directly connected to the Bistrica diversion hydropower plant. In Table 1, the HPPs located at the Drina-Lim hydropower systems are presented, along with their catchment areas.

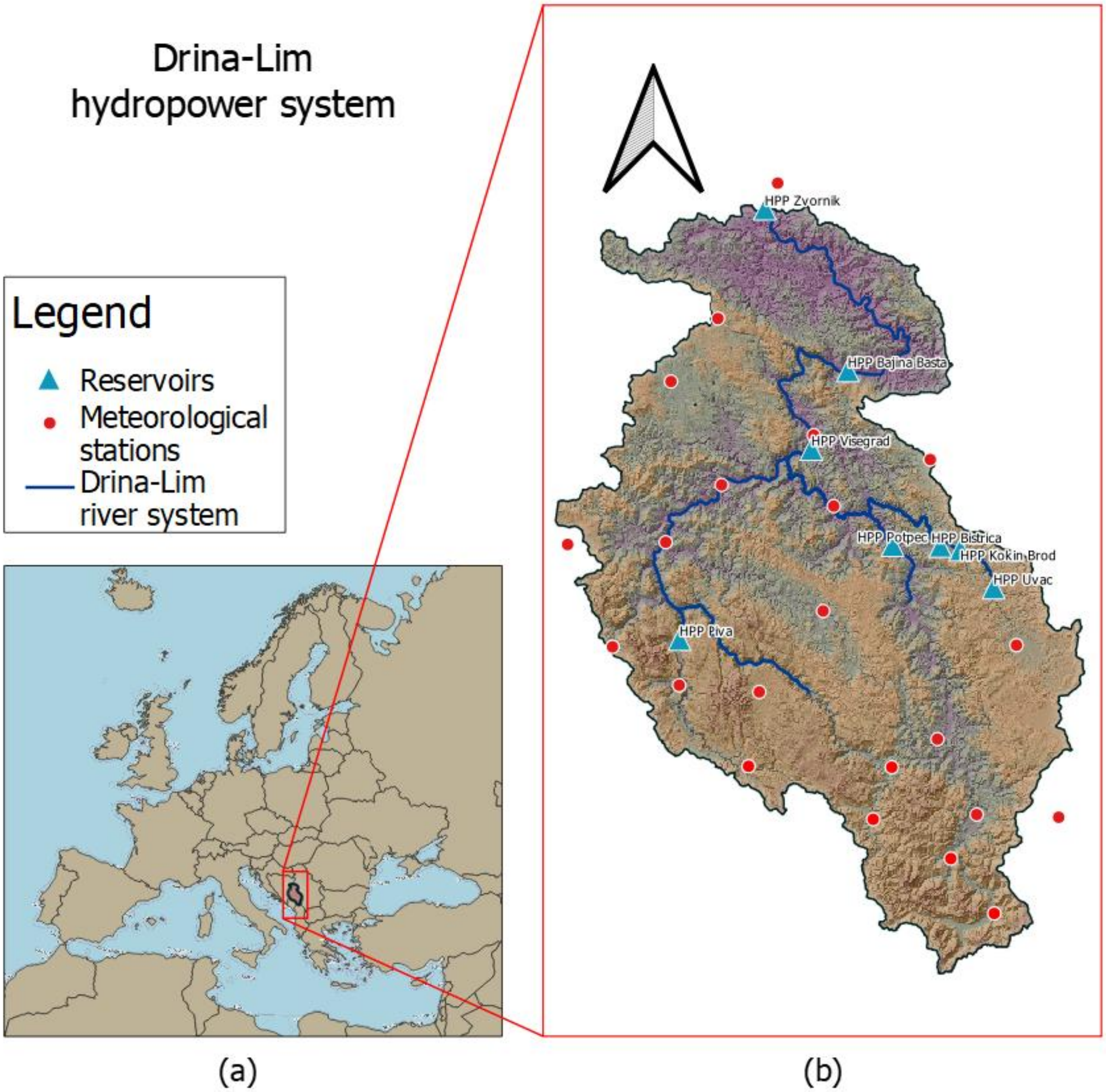


Figure 1. Drina-Lim hydropower system river basin based with associated HPPs.

Table 1. Reservoirs at the Drina-Lim hydropower system alongside catchment area.

Reservoir:	**River:**	**Catchment Area (km²):**
Mratinje	Piva	1500
Višegrad	Drina	13300
Bajina Bašta	Drina	15200

Zvornik	Drina	17400
Uvac	Uvac	1050
Kokin Brod	Uvac	1300
Radojnja	Uvac	1400
Potpeć	Lim	3600

Naturalized inflows in reservoirs, precipitation and air temperature are collected for ML model developing and functioning in real time. Hydrological data are collected from: HPP Višegrad, HPP Bajina Bašta, HPP Zvornik, HPP Piva, HPP Uvac, HPP Kokin Brod, HPP Bistrica, and HPP Potpeć (Figure 1, Table 1). Meteorological data (precipitation and air temperature) with stations equipped with real-time data acquisition, are collected within the Drina river basin covering each representative part (Figure 1).

2.2 A methodology for flood forecasting at the Drina-Lim hydropower system

A core component of the flood-forecasting system of Drina-Lim hydropower system (Figure 2) is the acquisition of recently observed historical hydrological releases under the naturalized river regime, together with key meteorological parameters (precipitation and air temperature). In addition, the system collects meteorological forecasts (precipitation and air temperature). All collected data are stored in a central database and formatted into the required structure, after which the previously trained ML models are executed. A description of the developed models is provided in Table 2, while the data needed for ML model operation can be specified as follows:

- Daily Air Temperature – historical data for the previous two days;
- Daily Air Temperature – forecast for five days ahead, including the current day (ECMWF (2025), GFS (2025), Open-Meteo ensemble (2025));
- Daily precipitation sums – historical data for the previous two days;
- Daily precipitation sums – forecast for five days ahead, including the current day;
- Naturalized streamflows from HPPs – historical data for the previous seven days.

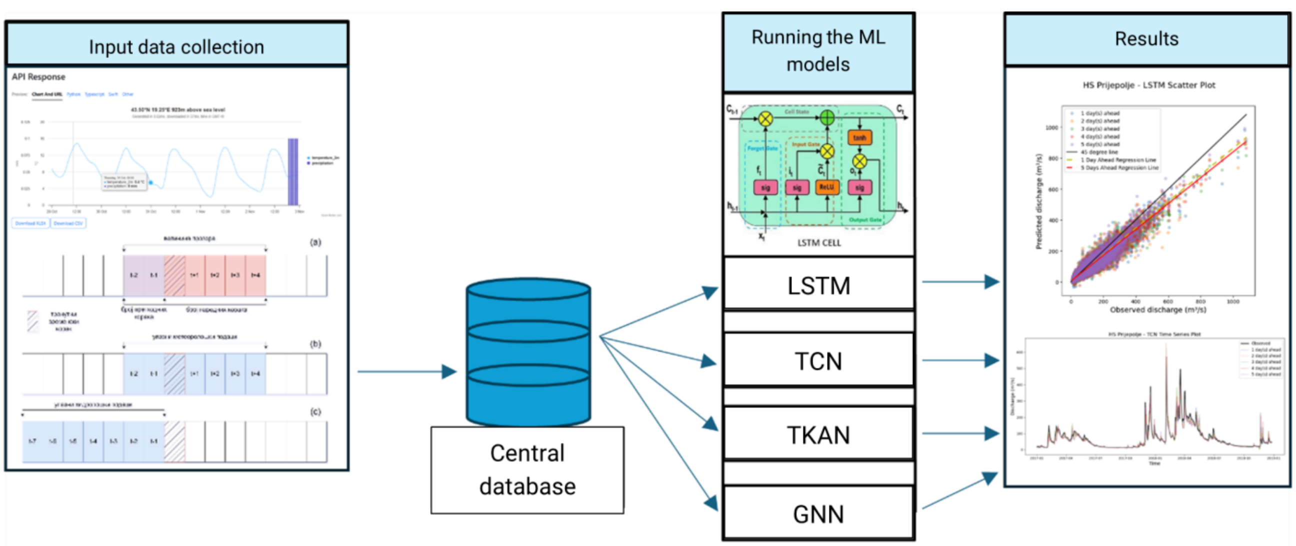


Figure 2. Data-centric flood forecasting system: Drina-Lim hydropower system.

Table 2. Overview of ML Models used in the Drina-Lim flood forecasting system.

ML models	Full name	Key underlying mechanism	Relevance for hydrological predictions	References
LSTM	Long Short-Term Memory	Recurrent neural network with memory cells governed by input, forget, and output gates that regulate information flow over long sequences.	Captures long-term temporal dependencies; effective for delayed hydrological responses (e.g., runoff after precipitation).	Vinokić et al. (2025)
TCN	Temporal Convolutional Network	Uses 1D dilated causal convolutions and residual connections to model sequential data while ensuring temporal causality.	Learns both short- and long-range temporal patterns; stable training and strong performance in time-series forecasting.	Vinokić et al. (2025)
TKAN	Temporal Kolmogorov–Arnold Network	Extends KANs by using learnable univariate functions on edges and adapting them for temporal dependencies.	Highly flexible nonlinear transformations with fewer parameters; promising for hydrological forecasting.	Vinokić et al. (2025)
GNN	Graph Neural Network	Encodes spatial dependencies using graph structures where nodes represent stations and edges represent hydrological or spatial connectivity.	Explicitly models spatial interactions; captures basin-wide spatiotemporal dynamics.	Dodig et al. (2025)

3 RESULTS

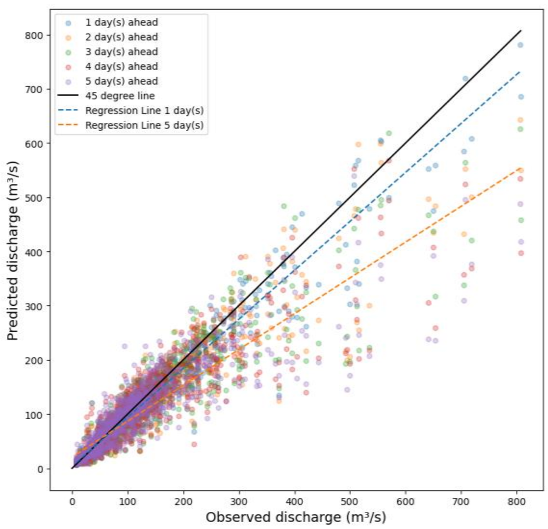
The verification period does not belong to the measured dataset. Instead, the period from 2019 through 2023 without available datasets was selected. During this period, meteorological data from the ERA5 dataset is used. ERA5 provides assimilated meteorological parameters for the European domain, based on observational data collected by hydrometeorological institutes across the region. For the hydrological data required for verification, the estimated naturalized streamflows of the Drina–Lim hydropower plants are used.

The model performance is presented through visualizations and metrics (MAE- Mean Absolute, MAPE- Mean Absolute Percentage Error; RMSE- Root Mean Square Error; NSE - Nash–Sutcliffe Efficiency) that enable a comprehensive assessment of predictive skill. Comparative scatter plots are provided for the Lim river example, showing the dynamics of predicted and observed values (Figure 3).

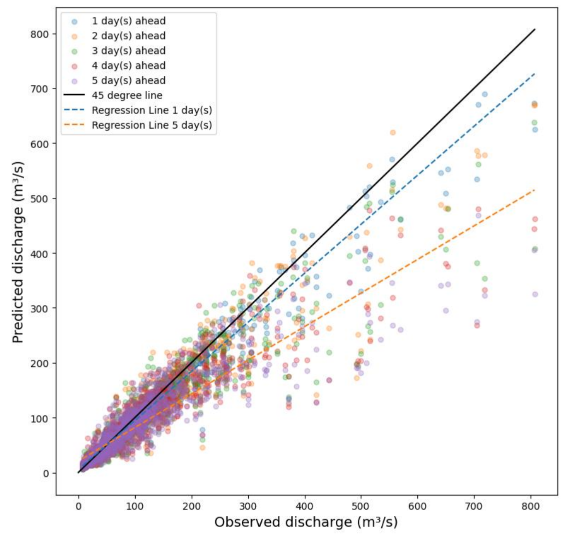
Table 3. Performance metrics for each ML model estimated using the ERA5 meteorological datasets from 2019 to 2023.

HPPs:	MAE (m3/s)	MAPE (-)	RMSE (m3/s)	NSE (-)
Uvac	0.95	0.17	1.85	0.88
Kokin Brod	1.07	0.12	2.28	0.89
Bistrica	1.20	0.13	2.70	0.86
Potpeć	17.08	0.21	27.32	0.88
Piva	8.11	0.14	18.49	0.89
Višegrad	46.75	0.17	71.53	0.89
Bajina Bašta	55.01	0.32	75.64	0.90
Zvornik	65.77	0.24	88.46	0.87

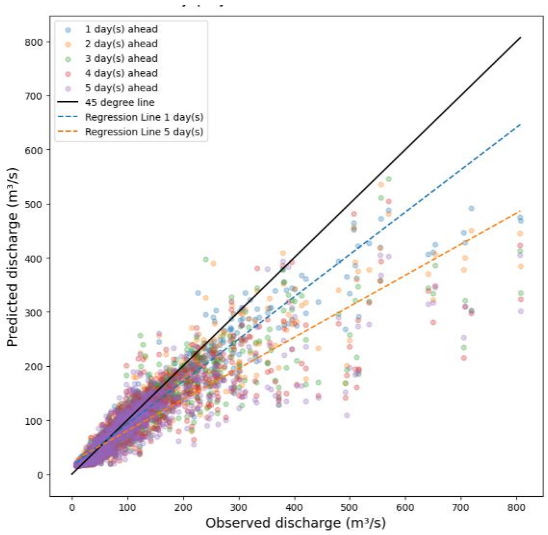
(a) LSTM



(b) TCN



(c) TKAN



(d) GNN

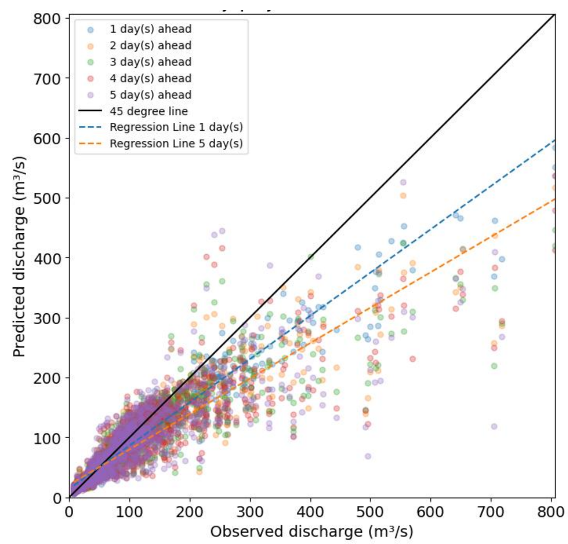


Figure 3. Example of model verification for the Drina-Lim hydropower system using LSTM, TCN, TKAN, and GNN.

The results from Table 3 and Figure 3 demonstrate high predictive skill of ML models, with NSE values ranging from 0.86 to 0.90, indicating that the models reproduce observed inflows with strong fidelity. The upstream HPPs (Uvac, Kokin Brod, Bistrica) exhibit very low absolute errors (MAE between 0.95 and 1.20 m³/s). Correspondingly low RMSE values further confirm high model precision in these sub-basins. For mid- to downstream reservoirs (Potpeć, Piva, Višegrad, Bajina Bašta, Zvornik), the models maintain consistently strong performance despite substantially larger flow magnitudes. Although MAE and RMSE naturally increase with the scale of the system, the models continue to show excellent relative accuracy, with MAPE ranging between 0.14 and 0.32 and NSE values ≥ 0.87. The highest absolute errors occur at Bajina Bašta and Zvornik due to the cumulative upstream contributions and larger catchment variability, yet their NSE values (0.90 and 0.87, respectively) confirm high reliability.

4 CONCLUSIONS

The results demonstrate that a data-centric, ML-based inflow forecasting framework can substantially enhance predictive accuracy within the Drina–Lim hydropower system. By integrating multiple sources of meteorological and hydrological information, including ERA5 reanalysis data, satellite-derived observations, and bias-corrected datasets, the system effectively overcomes limitations associated with traditional physics-based hydrological models, particularly under conditions influenced by climate variability and extremes. All evaluated ML architectures exhibited strong performance across both upstream and downstream reservoirs, confirming the robustness of the proposed approach for real-time flood forecasting and hydropower decision support in complex mountainous catchments. The key conclusions may be summarized as follows:

- the ML-based forecasting system achieves high predictive skill (NSE 0.86–0.90) and outperforms classical hydrological models.
- the data-centric approach, incorporating data assimilation, satellite inputs, and bias correction, significantly improves input data quality and model robustness.
- the framework is operationally suitable for flood forecasting and hydropower management, even when driven by reanalysis datasets rather than direct measurements.

Despite these promising results, several limitations should be acknowledged. The ML models are trained on historical data that may not fully capture the statistical properties of unprecedented extreme events, raising questions about transferability to flood scenarios under a shifting climate. Additionally, operational deployment introduces constraints related to quality of real-time meteorological inputs, where forecast uncertainty propagates through the ML pipeline and may degrade prediction skill at longer lead times. Finally, the relatively short training record may restrict the ability to learn the full range of hydrological variability, particularly for rare, high-magnitude events.

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