

High-flow forecasting in the Severn river basin, using deep learning and dynamic multimodal fusion



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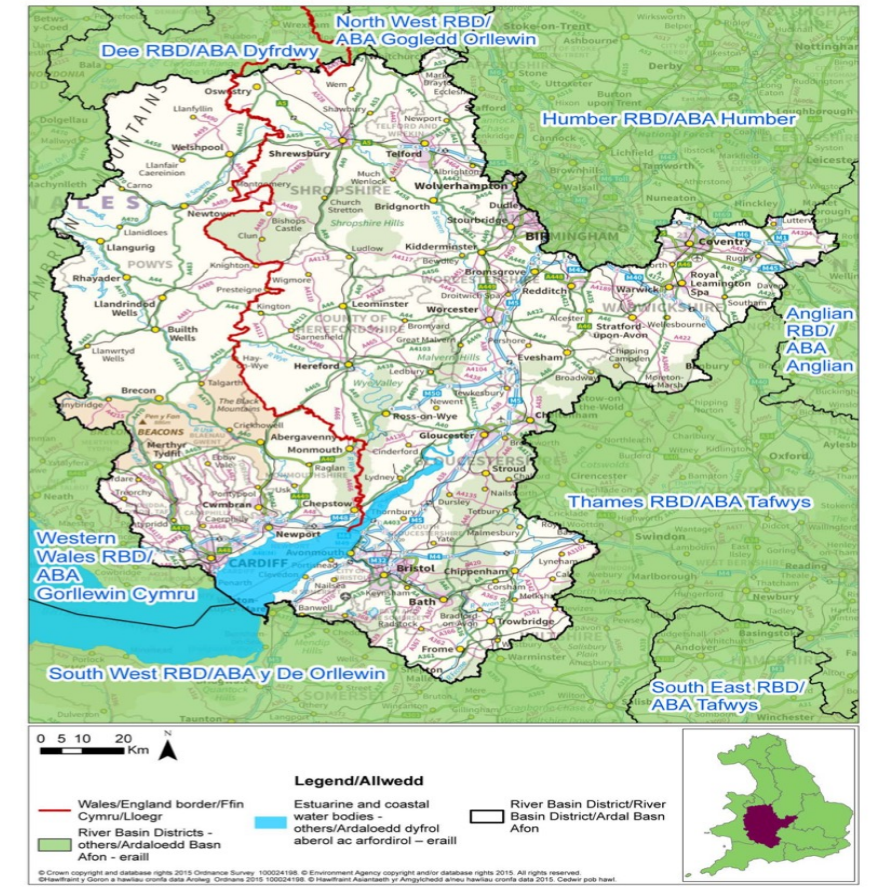
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1. Introduction

Climate change leads to more intense rainfall, imposing greater flood-risk in existing high-flow areas. For such areas, improving short-term daily streamflow forecasts is vital for effective warning alerts. With the known success of machine learning, particularly deep learning methods in hydrology, we leverage multisource data by exploring dynamic multimodal fusion methods applied in a deep-learning LSTM-based architecture.

2. Study area

The Severn River Basin [1], is one of the highest-flow in Great Britain. The average annual rainfall in the area lies from app. 600 mm in lowland areas to over 1200 mm in upland parts. 6 river stations are selected, based on the top maximum flow and data completeness, in rivers Severn and Wye.

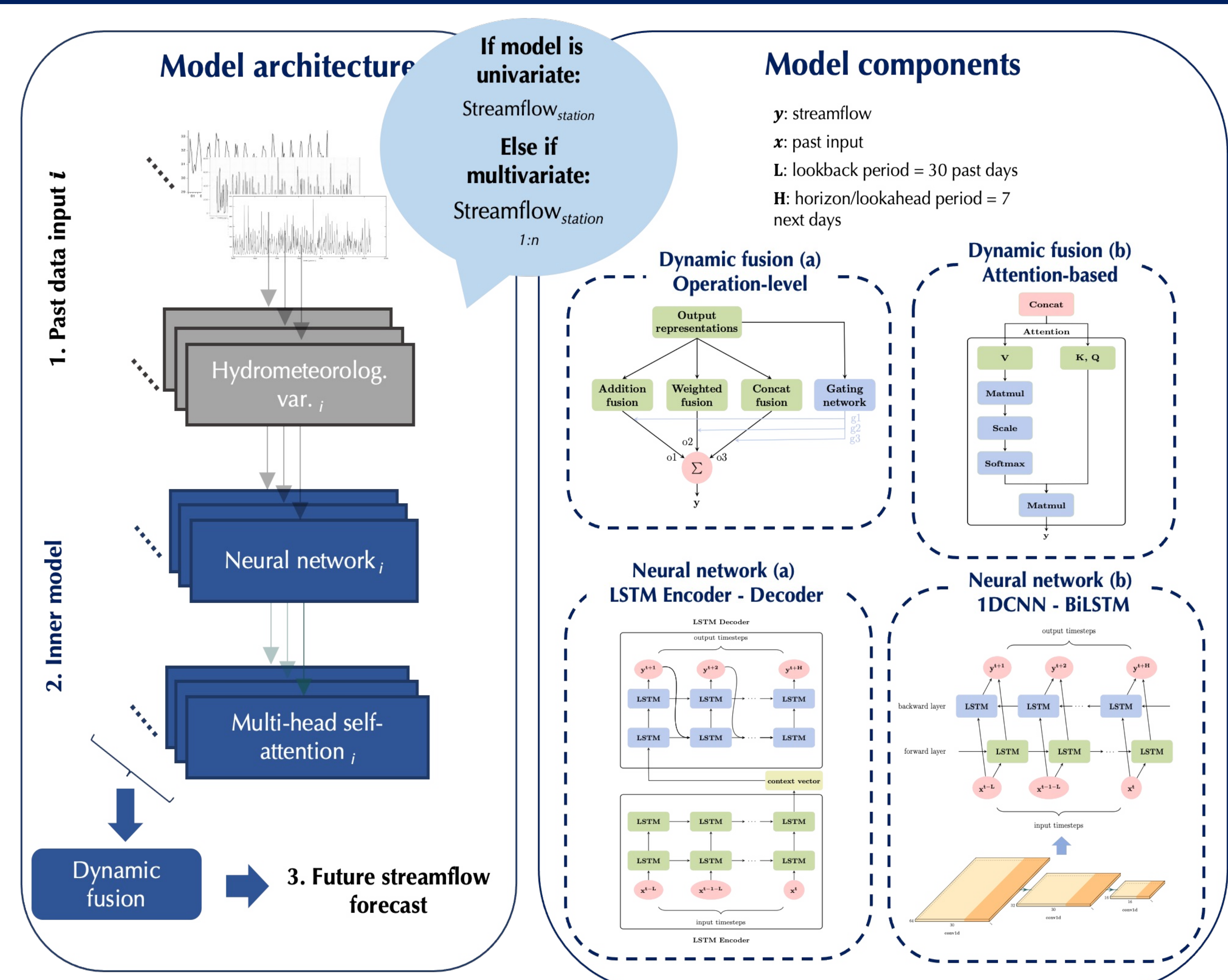


3. Methods & data

- We compare two multimodal fusion strategies for adaptively integrating multiple past input variables within an LSTM Encoder-Decoder or a 1DCNN-BiLSTM time-series model.
 - The first uses a gated network that combines different merging operations. (operation-level)
 - The second uses attention, fusing modalities based on their inter-dependencies. (attention-based)
- Also, we use two training approaches: (a) a univariate model, trained for each station (single-site), and (b) a multivariate model, trained across all stations at once (multi-site).
- We use the following multisource data:

Data source	Variables
DEFRA/NRFA	Gauged daily river flow (from river stations 54002, 54095, 54001, 54032, 54057, 55005)
ERA5-Land	Complementary daily climatic variables

4. Model



5. Results

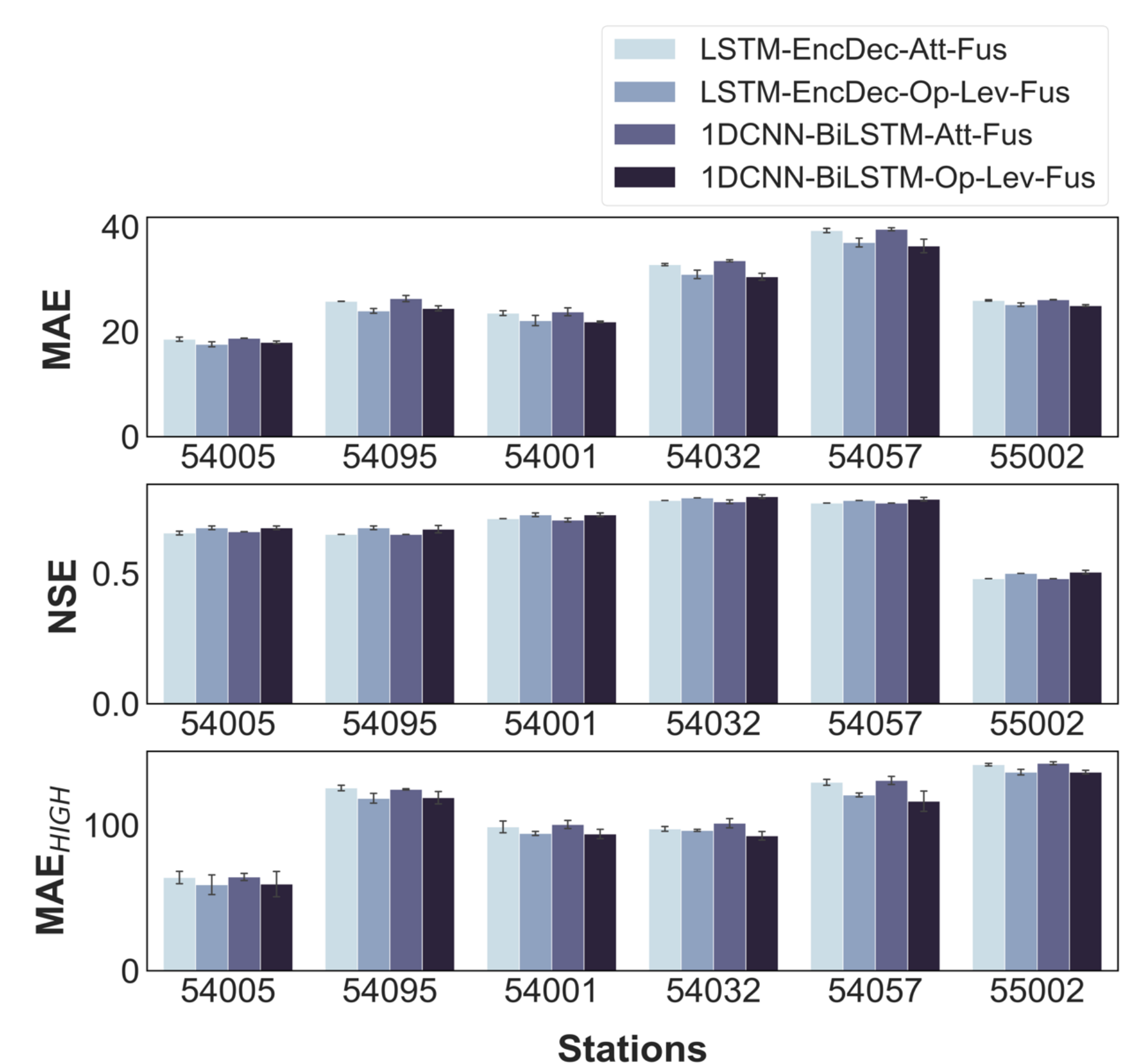
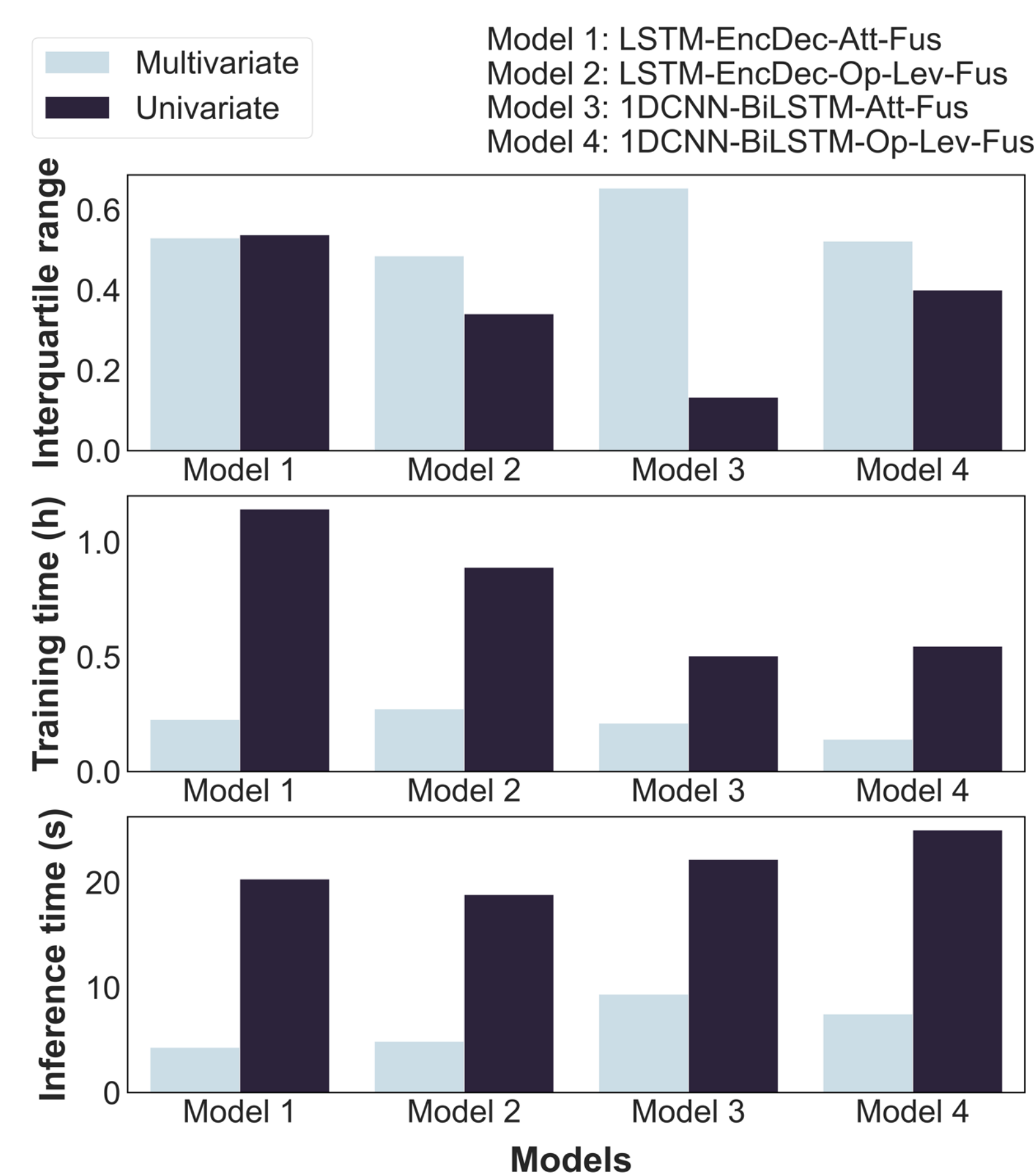
A. Operation-level fusion for univariate and multivariate models compared to attention-based fusion leads to improved MAE & MAE_{High} by 6.32% & 4.48%.

B. Multivariate models are similar, slightly more accurate by 1.33% (MAE) than univariate models and faster by 76%, but twice as unstable on average (IQR).

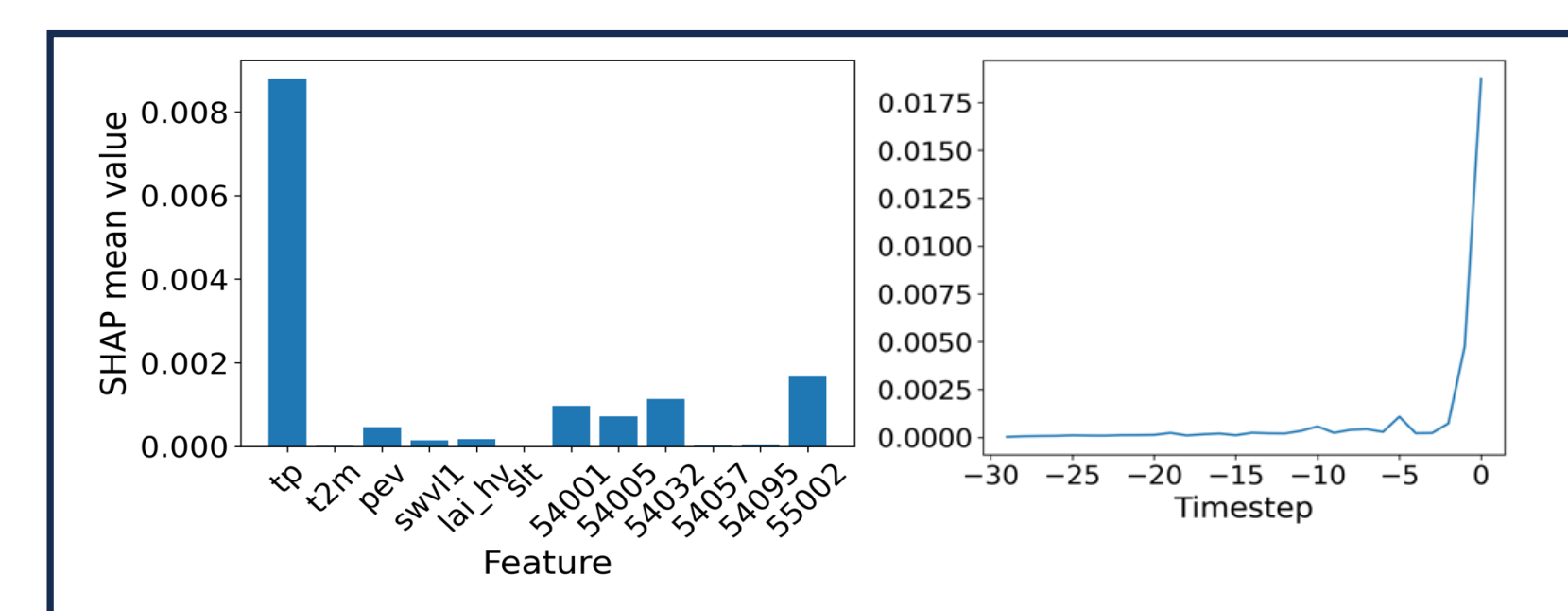
C. Station 55002 shows the lowest NSE and highest MAE_{High}, due to its more diversity and its less hydrological relation to other stations.

D. A multi-site LSTM-EncDec-Op-Lev-Fus balances accuracy, training and inference times and stability (IQR).

Univariate				Multivariate		
Metric	MAE	NSE	MAE _{High}	MAE	NSE	MAE _{High}
LSTM-Enc-Dec						
Att-Fus	27.73	0.75	109.59	27.60	0.75	112.82
Op-Lev-Fus	26.29	0.76	105.62	25.97	0.76	108.88
1DCNN-BiLSTM						
Att-Fus	28.22	0.75	111.07	27.80	0.75	115.93
Op-Lev-Fus	26.32	0.76	106.85	25.73	0.77	107.70



E. For this model, SHapley Additive exPlanations show that rainfall is the dominant feature contributing to the predictions, along with the most past recent timesteps.



6. Conclusion

We compared two fusion strategies for adaptively integrating multiple past input variables within LSTM-based multimodal models for streamflow forecasting. Our findings recommend that a **multi-site LSTM Encoder-Decoder model with operation-level fusion** balances accuracy and efficiency aspects against all model combinations, with explainability tests being satisfying. In the future, we will consider adding spatiotemporal inputs and focusing on uncertainty-aware methods for mixed-quality data.

