Evaluating Spatially-Aware Deep Learning Models for Historical Streamflow Reconstruction in Ungauged Basins

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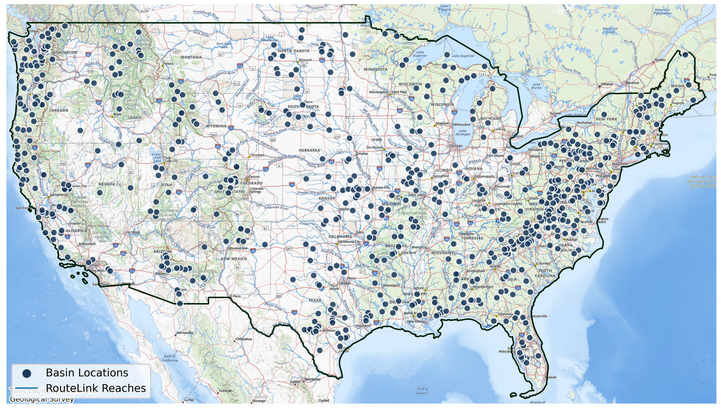
INTRODUCTION

- Streamflow prediction in ungauged basins is difficult due to the lack of in situ discharge measurements.
- Prior studies (Nearling et al., 2024; Kratzert et al., 2019) show LSTMs outperform conceptual models under [2]PUB conditions.
- Standard deep learning models treat basins independently and ignore hydrologic connectivity.
- Our approach integrates upstream and downstream information, modeling basins as a connected river network.

STUDY AREA



- Study focuses on a subset of [1]CAMELS basins with one-reach upstream configuration across CONUS.
- Basins were selected to span diverse hydro-meteorological and physiographic conditions.
- Each basin represents the drainage area of a major river or a combined contributing river system.

OBJECTIVES

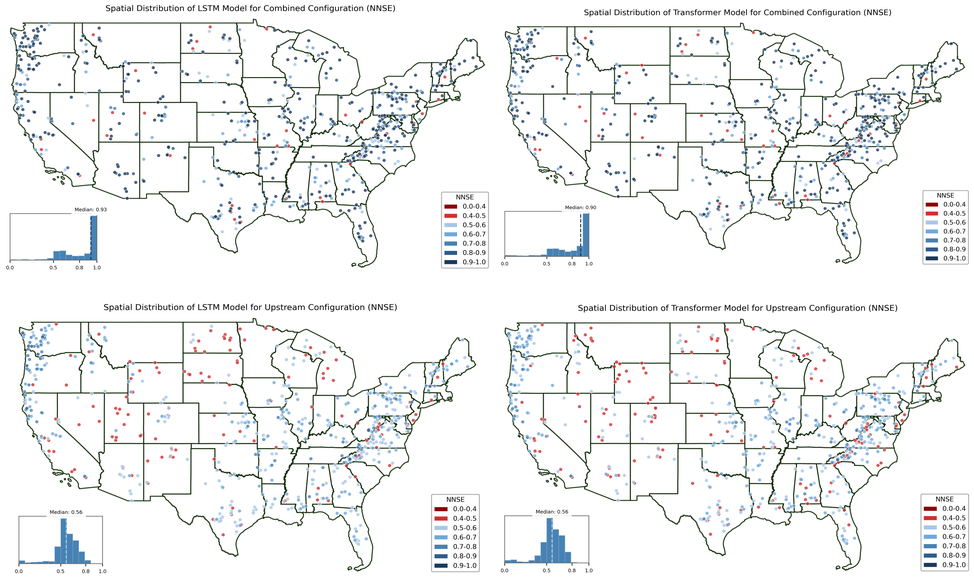
- Design spatially-aware deep learning frameworks for ungauged streamflow reconstruction.
- Evaluate how upstream and downstream information influences reconstruction accuracy.
- Compare the performance of models using the [4]NWM Retrospective dataset.

METHODS

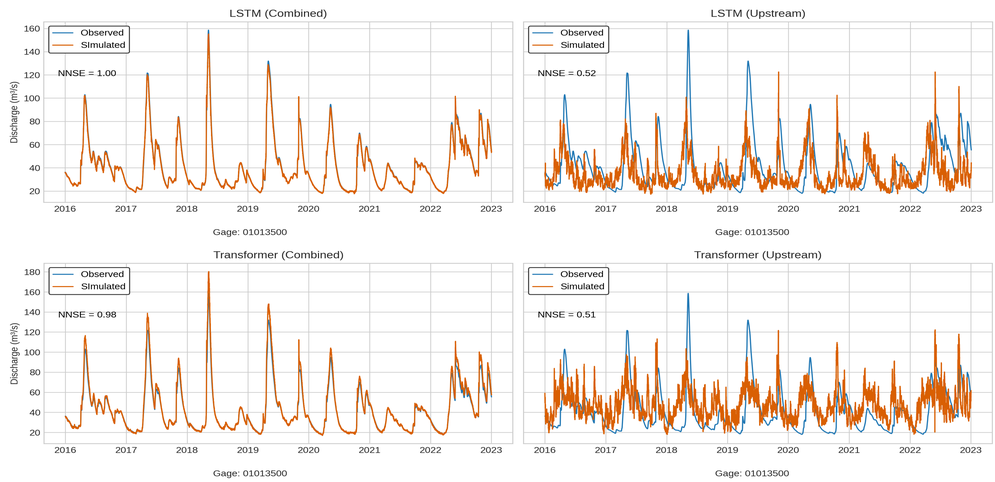
- **Dataset:** NOAA NWM v3.0 (1979–2023, 44 years) with basin-averaged hourly forcings and streamflow for 671 CAMELS basins (70–15–15 split).
- **Topology Linking:** USGS gauges matched to NWM reach identifiers using RouteLink connectivity.
- **Spatial Setup:** Upstream configuration uses n = 1 contributing reach; combined setup includes upstream + downstream inputs.

CAMELS[1] (Catchments Attributes and Meteorology for Large Sample Studies), **PUB[2]** (Prediction in Ungauged Basins), **NWM[4]** (National Water Model)

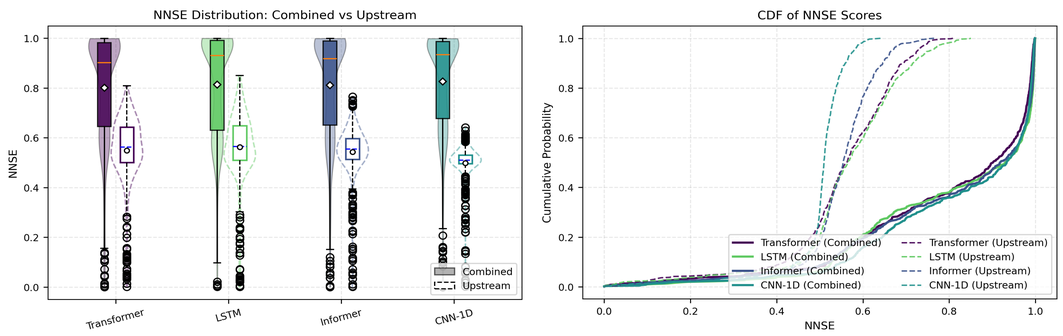
RESULTS



Spatial distribution of NNSE score for LSTM and Transformer models under Combined and Upstream configurations. Each point represents a basin, colored by NNSE performance class.



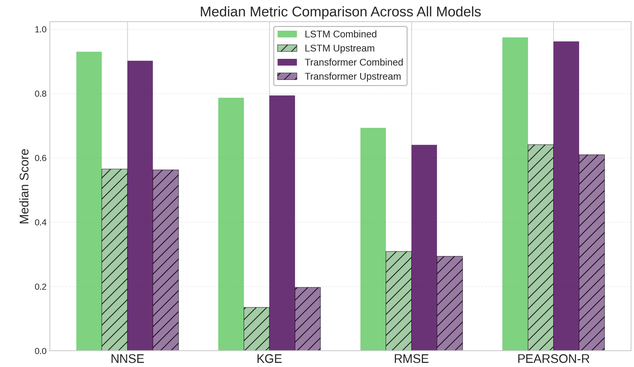
Hydro-graphs of simulated and observed streamflow for LSTM and Transformer models under both configurations with NNSE score.



*NNSE distribution comparison between models under Combined and Upstream configurations. **Left:** violin–box plots showing basin-level NNSE variability. **Right:** cumulative distribution functions (CDFs) highlighting the proportion of basins achieving different NNSE performance levels*

Metrics	Transformer		LSTM	
	Upstream	Combined	Upstream	Combined
NNSE (0:1; 1)	0.56	0.90	0.56	**0.93**
KGE (-inf:1; 1)	0.20	**0.80**	0.20	0.79
RMSE (0:inf; 0)	2.41	0.56	2.24	**0.44**
Pearson-r(-1:1; 1)	0.61	0.96	0.64	**0.98**
% Basins NNSE > 0.5	75.21%	91.68%	79.87%	**93.84%**

Table showing median metrics for Transformer and LSTM performance across all basins, showing stronger results under the Combined configuration and better overall accuracy from the LSTM model.



Median performance comparison across LSTM and Transformer models under Combined and Upstream-only configurations.

CONCLUSION

- Downstream forcings improve performance by capturing hydrologic connectivity.
- Combined upstream–downstream inputs outperform upstream-only across basins.
- Spatial context helps models learn routing and flow dynamics, boosting generalization.
- LSTM shows the highest and most stable accuracy.
- Transformer and Informer perform well but show higher variability.
- Hydrologic connectivity improves accuracy more than model complexity

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