Exploring Deep Learning Techniques in Daily Streamflow Simulation

Machine Learning in Water and Environmental Modeling Workshop
May 2, 2025
Module #2

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Outline

1. Overview
2. Methodology
3. Results
4. Key Messages

Overview

- **Hydrologic process-based models (PBMs)**
  - Traditional method of streamflow generation in climate planning studies
- **Concerns**
  - Selection of PBMs
  - Rigidity of model structures
- **Deep Learning (DL) models: a viable alternative**
  - Rapid runtime
  - Structural flexibility
- **Overarching goal**
  - Daily streamflow prediction for use in planning studies
  - Generate streamflow predictions for the *Gridded Weather Generator Perturbations* dataset (DWR, 2023)
- **Scope of the current effort**
  - Pilot using adapted existing DL models
  - Historical period
  - DL model performance
  - Hybrid DL and PBM performance

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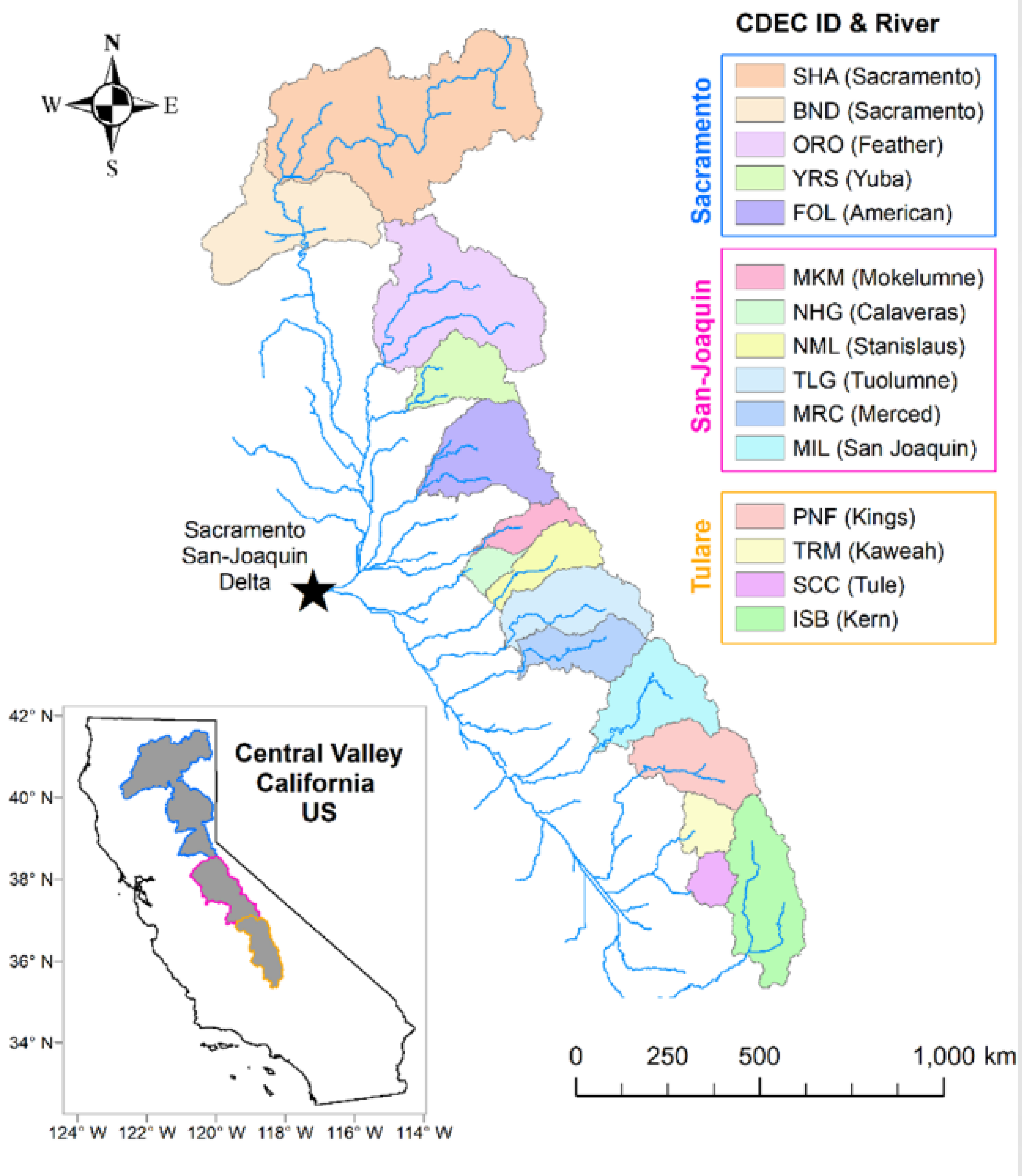
Study Area/Data



- **14 Watersheds**
  - Excluding BND as it highly correlates to SHA
- **Study Period**
  - Jan.10, 1987 to Dec.31, 2018
- **Daily Streamflow observations**
  - CDEC observed
- **Daily Precipitation/Temperature**
  - Historical gridded (4km) Livneh dataset
  - Temperature (Tmax and Tmin) bias-corrected to PRISM
  - Precipitation: unsplit 2021 Livneh dataset
- **Static attributes**
  - Watershed elevation
  - Land cover class
  - Soil type

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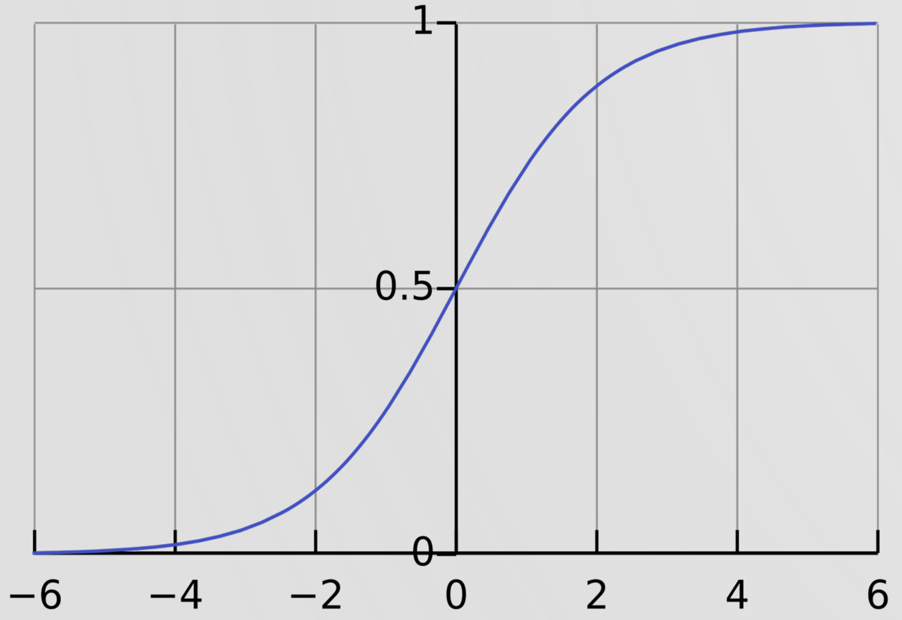
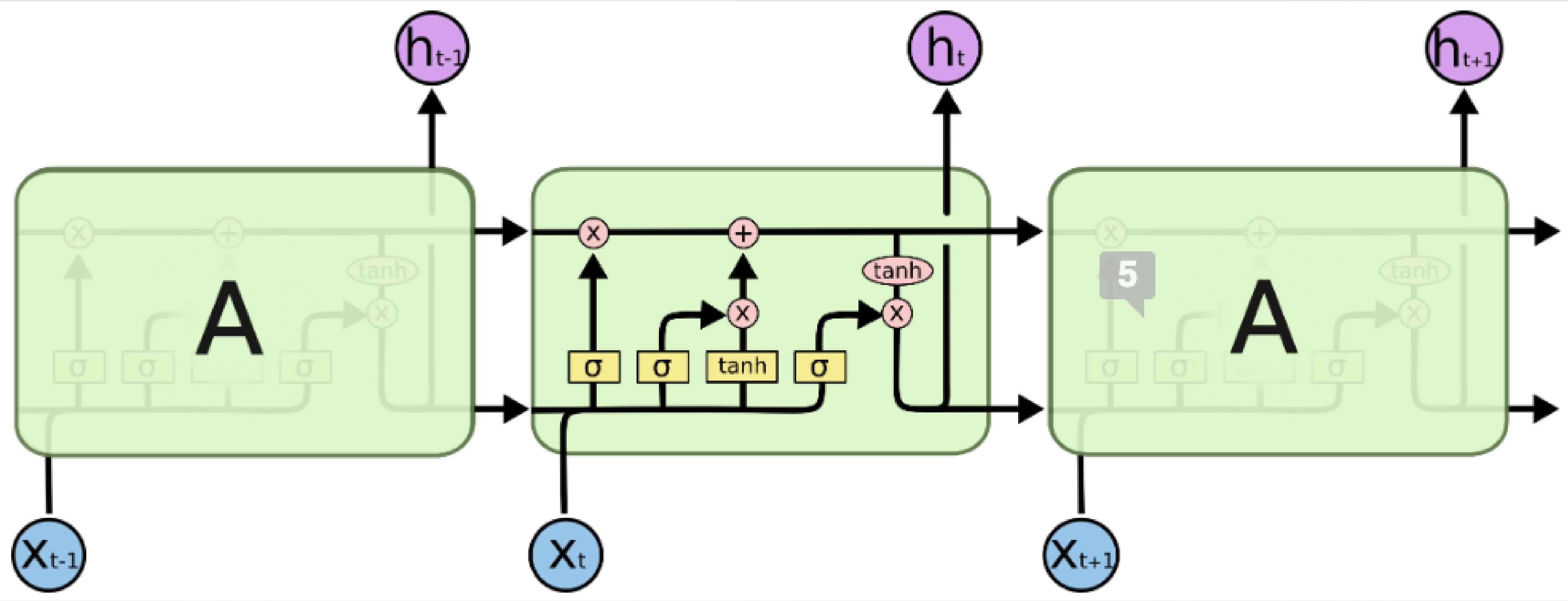
Long-Short Term Memory (LSTM) Architecture

➢ Main concept

- **Update** the memory based on the given information at this step
- **Forget** irrelevant information
- **Pass** the updated memory to the next step



Day 3
- Streamflow discharge



Day 1
- Dynamic inputs
- Static attributes

Day 2
- Dynamic inputs
- Static attributes

Day 3
- Dynamic inputs
- Static attributes

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[1] "Long short-term memory." *Supervised sequence labelling with recurrent neural networks,* Graves, Alex, and Alex Graves, *1997*

Methodology: Workflow

➢ Workflow

dynamic
- Prcp
- Tmax
- Tmin

365 days

static
- Elev.
- Soil
- Land
- …

↓

LSTM

↓

target
- Streamflow

365th day

Static attributes

- Elev.
  - Max_Elev
  - Min_Elev
  - SD_Elev
- Soil
  - Soil_Class
  - Percent_Area
- Land
  - Land_Class
  - Percent_Area
- Flow Length

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Methodology: Study Metrics

➢ Study Metrics

NSE: Nash-Sutcliffe Efficiency

MSE: Mean Squared Error

RMSE: Root Mean Squared Error

KGE: Kling–Gupta efficiency

Pearson-r: Pearson Correlation Coefficient

FHV: Peak Flow Bias

FLV: Low Flow Bias

Peak MAPE: Mean Absolute Percent Error of the Peak Values

Peak Timing: Timing error of the Peak Values

General Fitting (Skill) Performance
• NSE • MSE • RMSE • KGE • Pearson-r

Extreme Flow Performance
• FHV • FLV • Peak-MAPE • Peak-Timing

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Methodology: Study Metrics

General Fitting (Skill) Performance

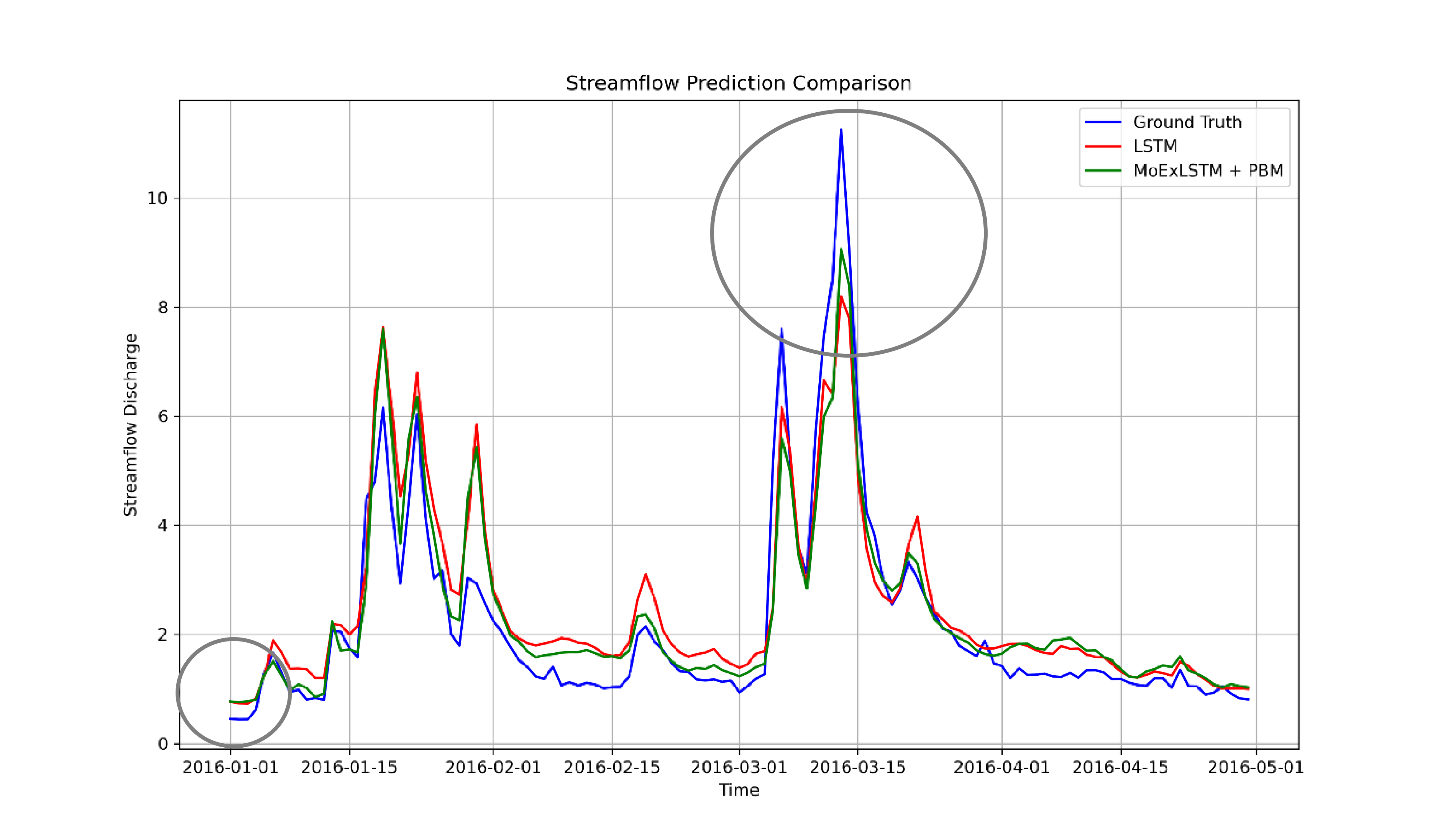
- NSE
- MSE
- RMSE
- KGE
- Pearson-r

Extreme Flow Performance

- FHV
- FLV
- Peak-MAPE
- Peak-Timing

$$MSE = \frac{1}{n}\sum(y_i - \hat{y}_i)^2$$

$$\text{Pearson-r} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2}\sqrt{\sum(y_i-\bar{y})^2}}$$



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Methodology: Experimental Design

- **Experiment 1:** Static attributes selection
- **Experiment 2:** LSTM vs. PBM
- **Experiment 3:** Mixture of LSTMs (MoLSTM)
- **Experiment 4:** Hybrid MoLSTM and PBM

Experiment 1 – Static Attributes Selection

	Features	NSE ↑ (-∞, 1]	MSE ↓ [0, ∞)	RMSE ↓ [0, ∞)	KGE ↑ (-∞, 1]	FHV (-∞, ∞) (closer to 0)	FLV (-∞, ∞) (closer to 0)	Pearson-r [-1, 1] ↑	Peak-MAPE [0, ∞) ↓	Peak-Timing (-∞, ∞) (closer to 0)
PBM		0.762	1.296	1.026	0.799	**7.695**	8.958	0.911	36.574	0.466
MoLSTM	**Elev + Land**	**0.864±0.001**	**0.843±0.028**	**0.832±0.007**	**0.837±0.005**	-11.052±1.162	-14.277±29.379	**0.936±0.002**	28.418±1.008	0.423±0.043
	Elev + Land + Soil	0.858±0.007	0.863±0.029	0.849±0.019	0.836±0.015	-10.626±1.244	-26.498±9.433	0.932±0.003	27.828±1.492	0.424±0.029
	Elev + Land + Soil + FL	0.857±0.008	0.925±0.058	0.865±0.029	0.826±0.005	-10.782±0.790	**8.585±31.575**	0.932±0.005	27.330±1.678	0.425±0.049
	Std. + Elev + Land + Soil + FL	0.858±0.004	0.872±0.011	0.850±0.007	0.827±0.014	-11.446±1.260	-62.620±38.641	0.932±0.002	**27.095±1.017**	0.429±0.046
	elband + Elev + Land + Soil + FL	0.847±0.003	0.928±0.022	0.881±0.009	0.828±0.014	-12.881±0.558	-51.818±18.743	0.926±0.002	29.233±0.760	**0.369±0.030**
	Std. + elband + Elev + Land + Soil + FL	0.848±0.016	0.953±0.038	0.881±0.024	0.813±0.004	-11.780±2.723	-79.566±3.914	0.929±0.005	28.108±1.029	0.426±0.018

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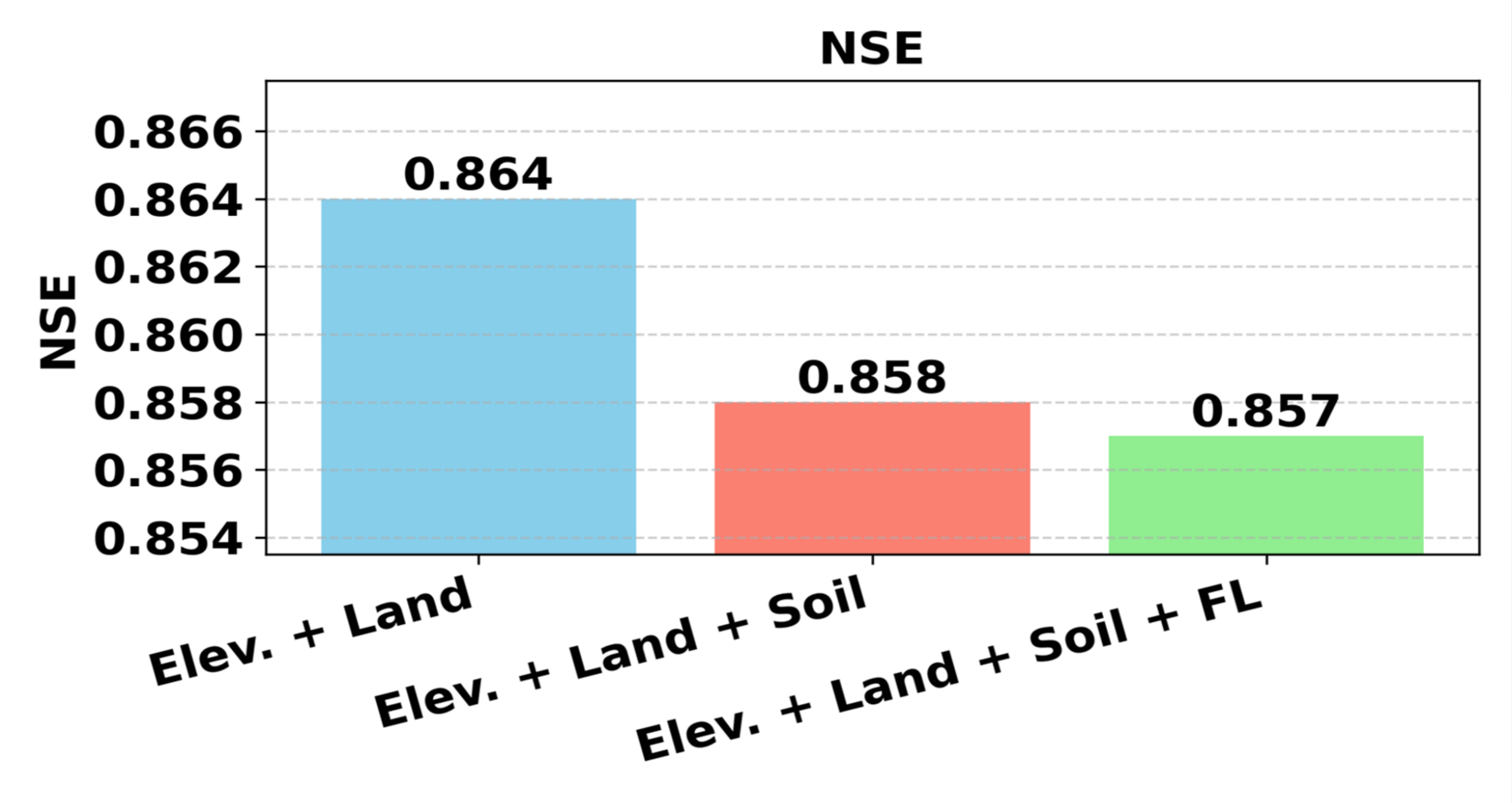
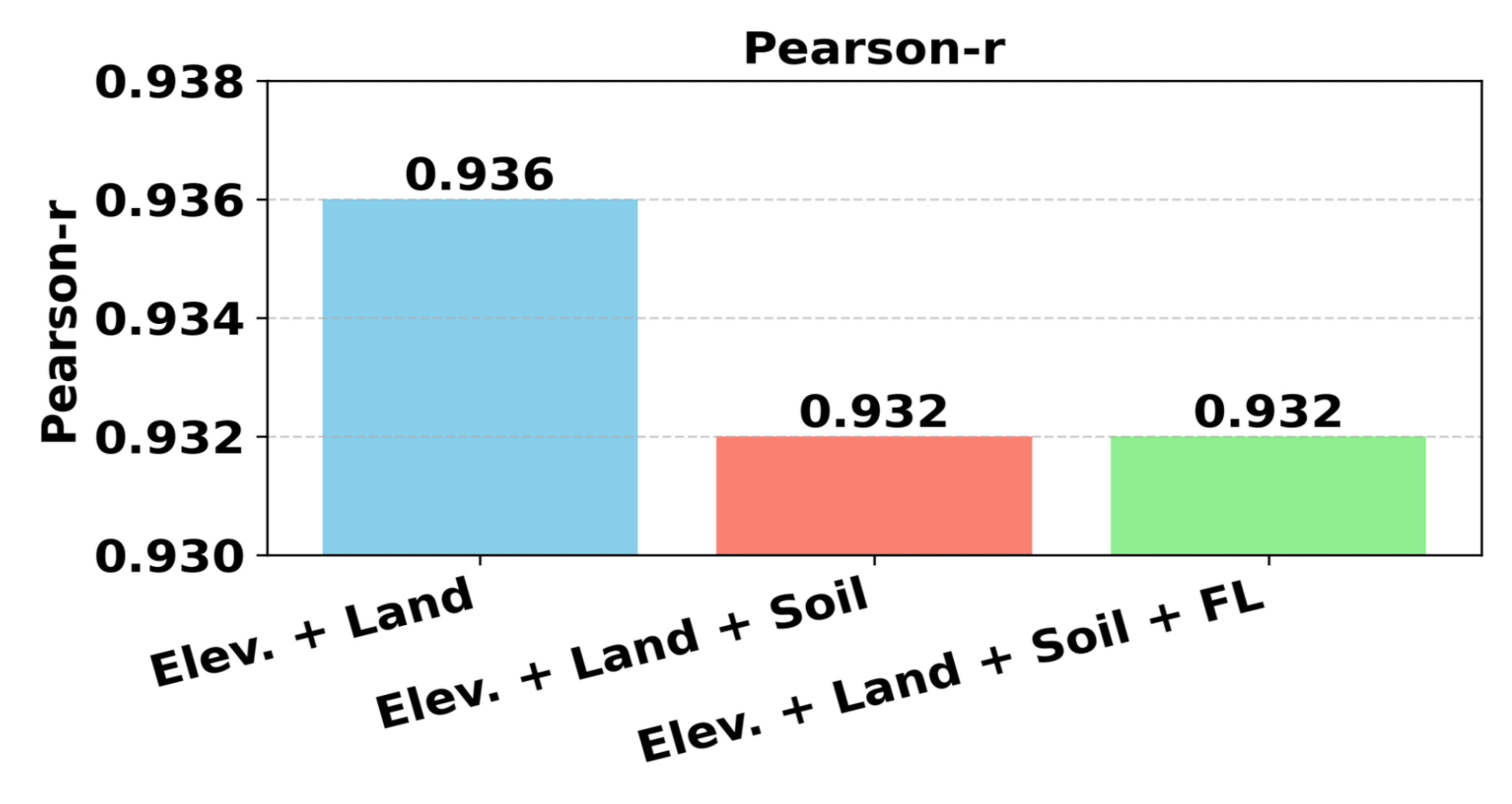
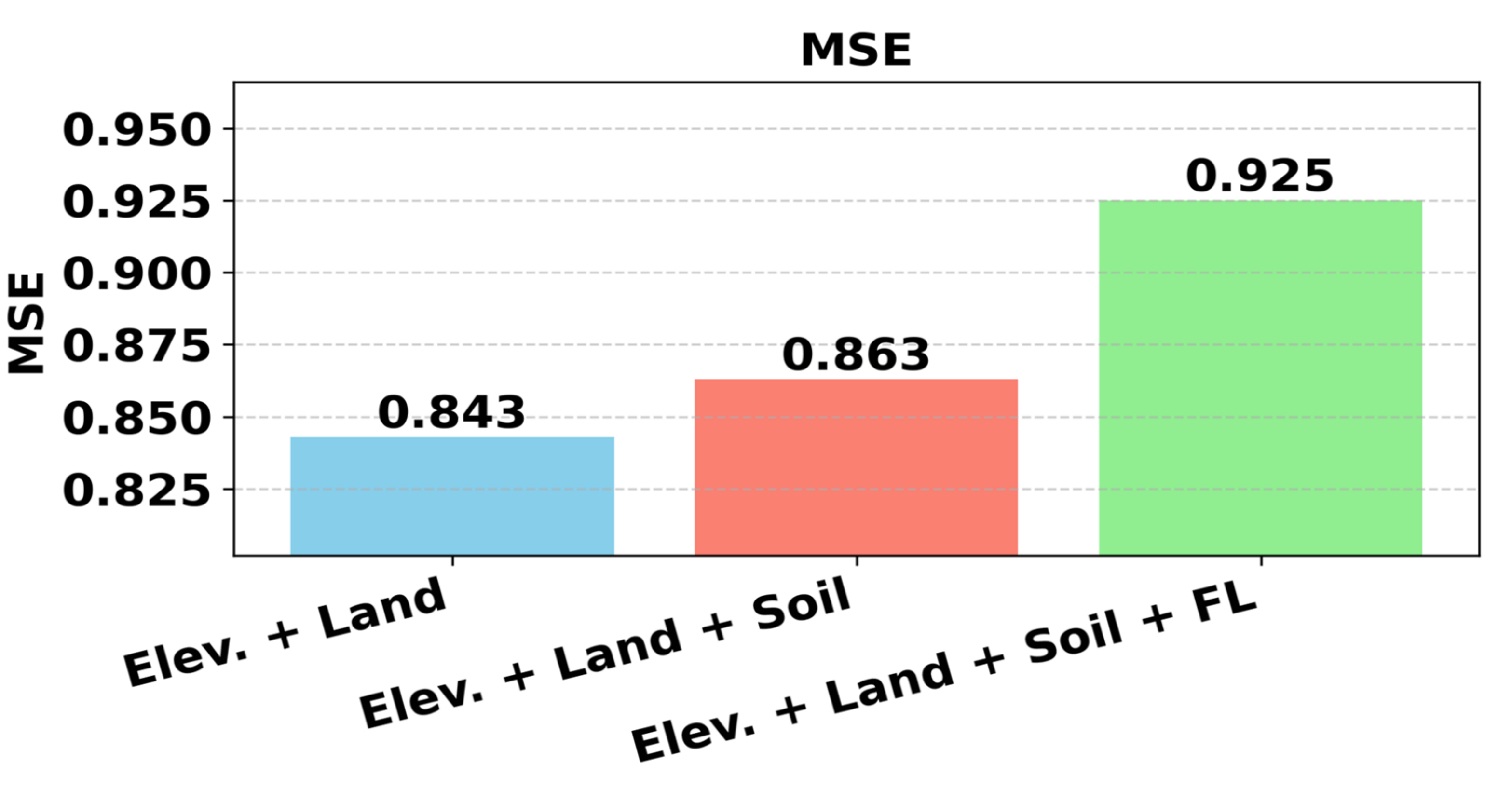
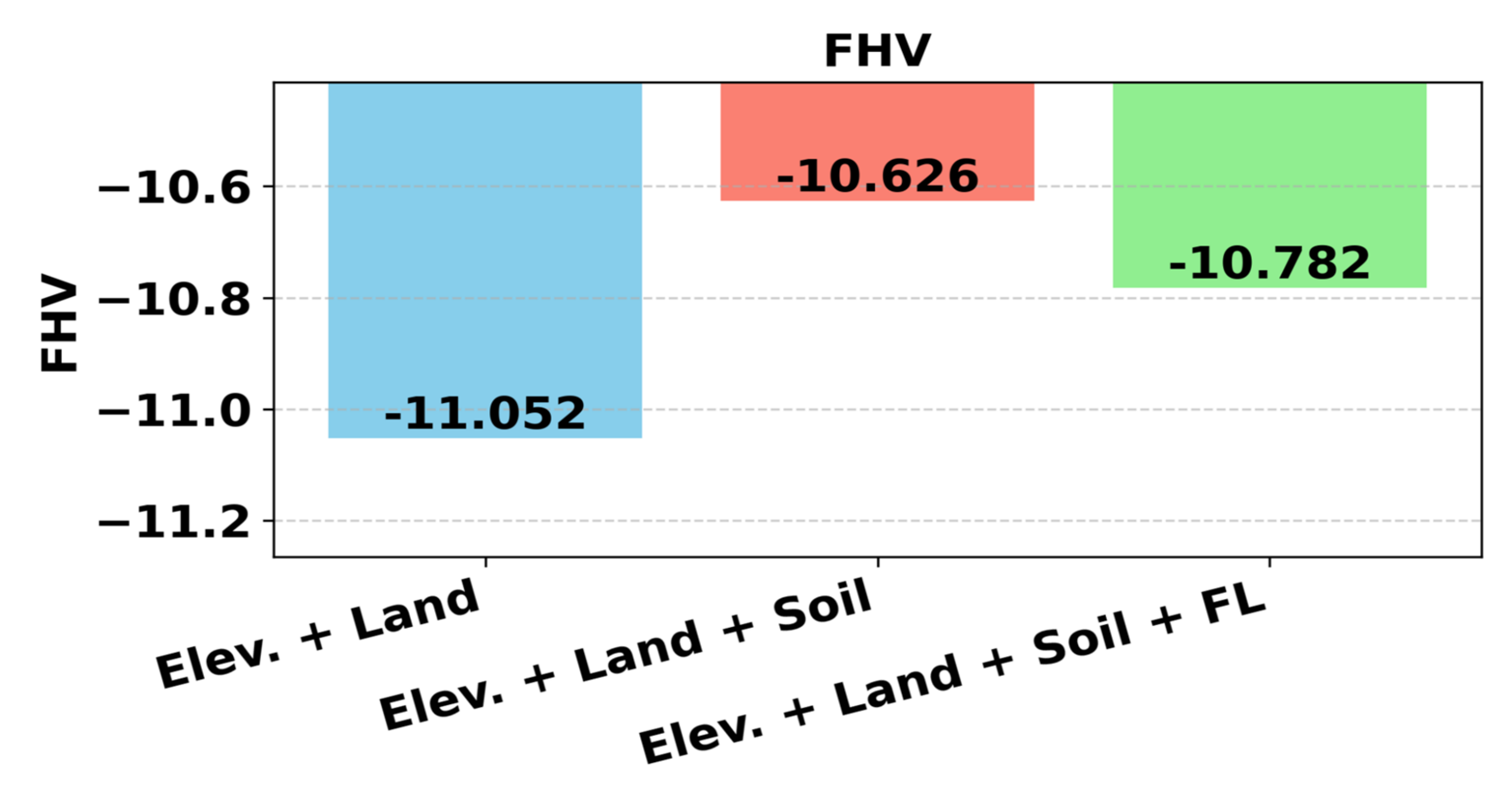
[**Bold**: Best Performance; Blue: Second Best Performance]

Experiment 1 – Static Attributes Selection









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Experiment 2 – LSTM vs. PBM

Elev. + Land	NSE ↑ (-∞, 1]	MSE ↓ [0, ∞)	RMSE ↓ [0, ∞)	KGE ↑ (-∞, 1]	FHV (-∞, ∞) (closer to 0)	FLV (-∞, ∞) (closer to 0)	Pearson-r [-1, 1] ↑	Peak-MAPE [0, ∞) ↓	Peak-Timing (-∞, ∞) (closer to 0)
PBM	0.762	1.296	1.026	0.799	**7.695**	**8.958**	0.911	36.574	0.466
LSTM	**0.847**±0.012	**0.927**±0.075	**0.880**±0.034	**0.815**±0.017	-10.863±1.534	-14.750±44.104	**0.928**±0.005	**31.067**±0.284	**0.374**±0.012

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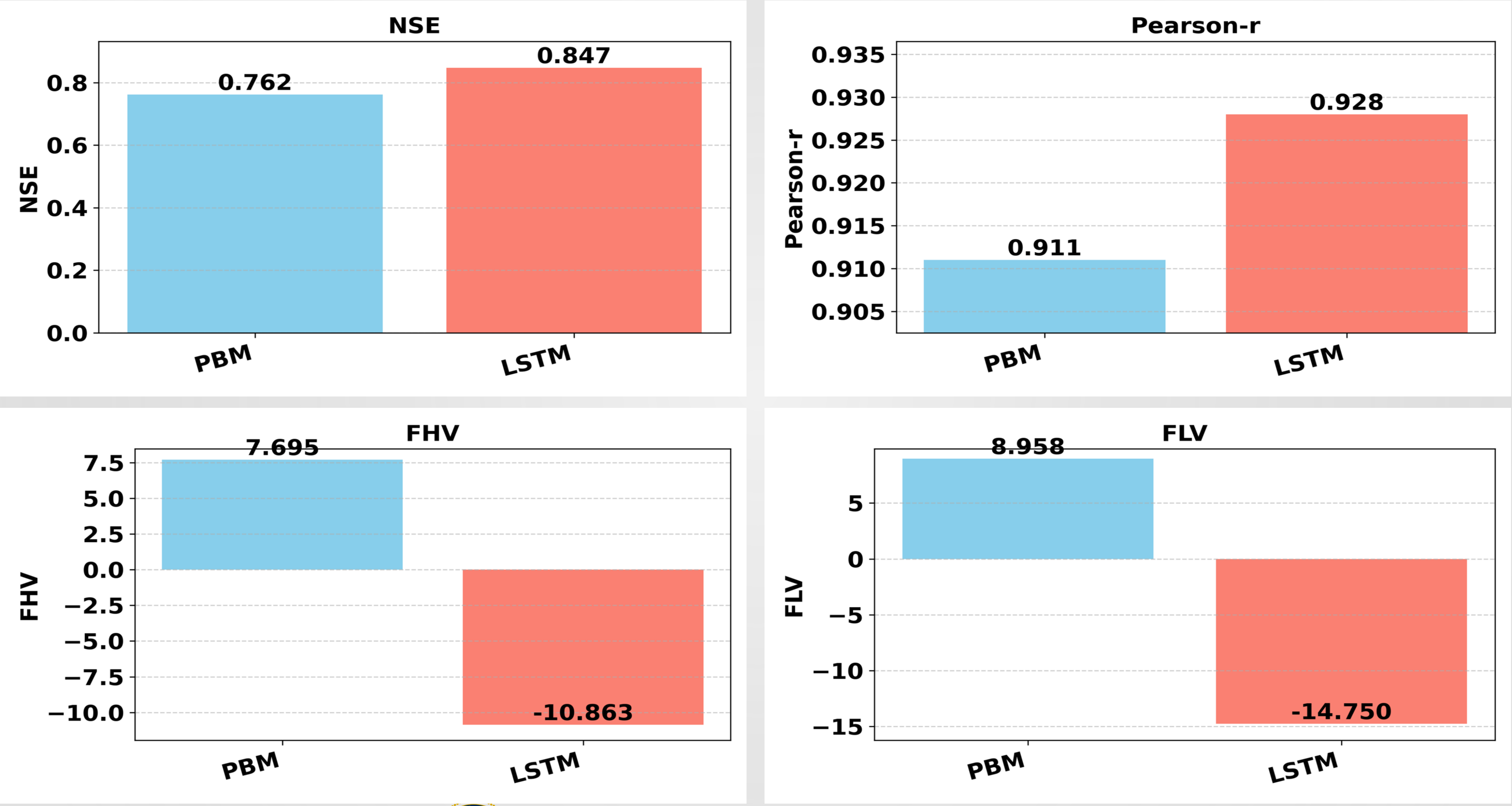


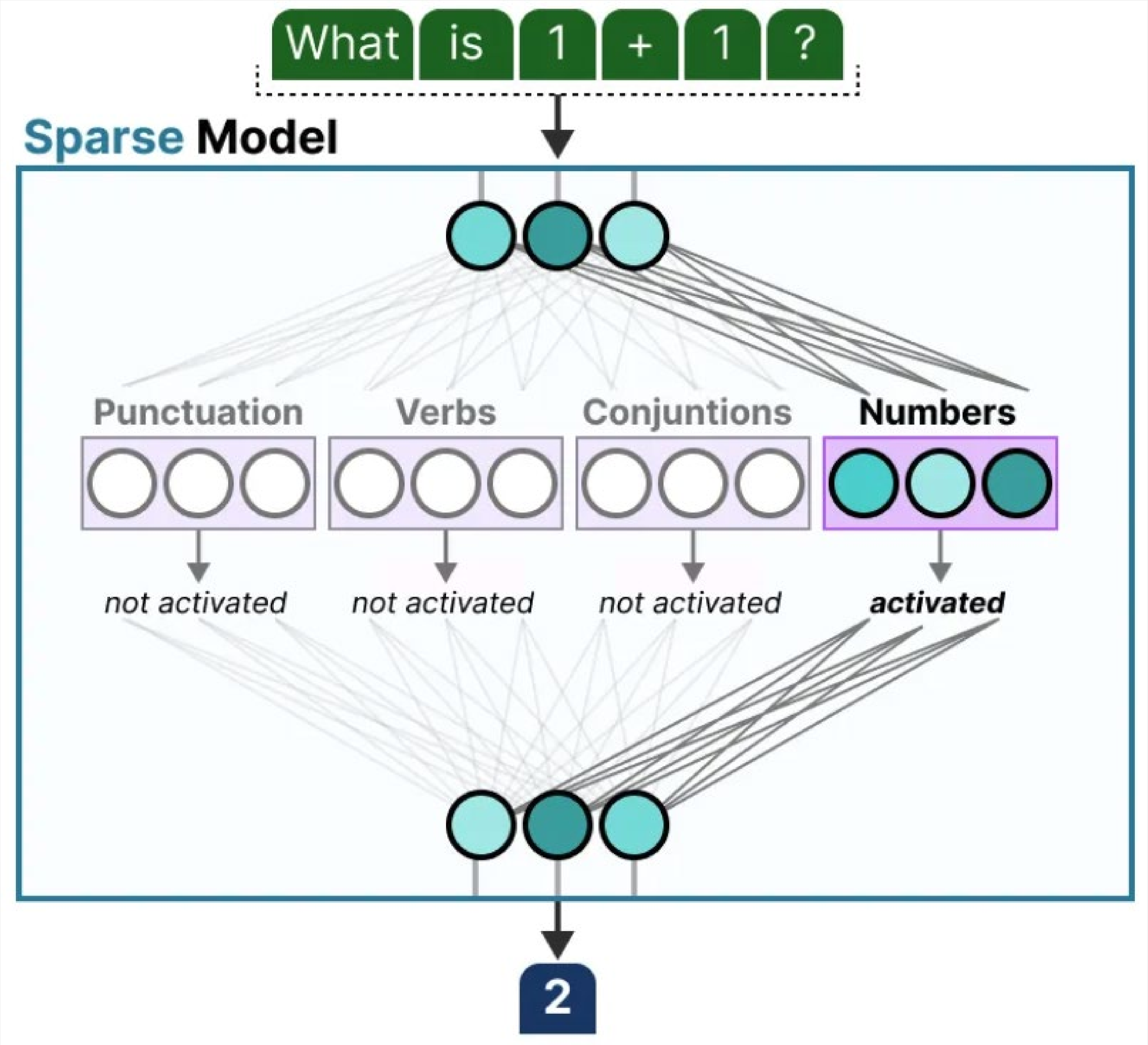
Experiment 3 – Mixture of LSTMs (MoLSTM)

- **Hypothesis**
  It is difficult for a single LSTM to learn both common & extreme events

- **Concept**
  Each expert (LSTM) is in charge of one task:

  Common streamflow

  Extreme streamflow



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[2] Learning Factored Representations in a Deep Mixture of Experts, Eigen, David, Marc'Aurelio Ranzato, and Ilya Sutskever, 2013

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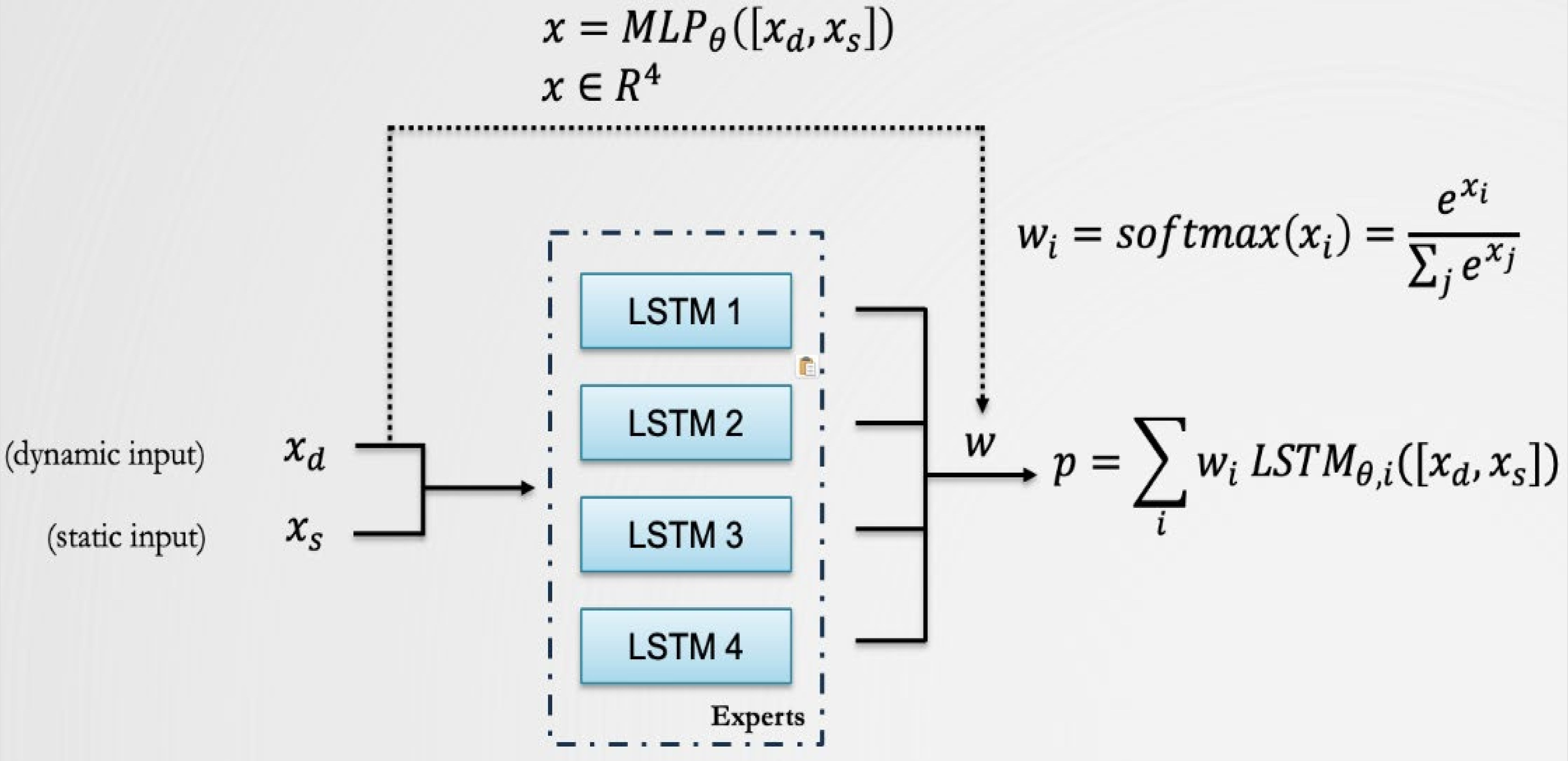

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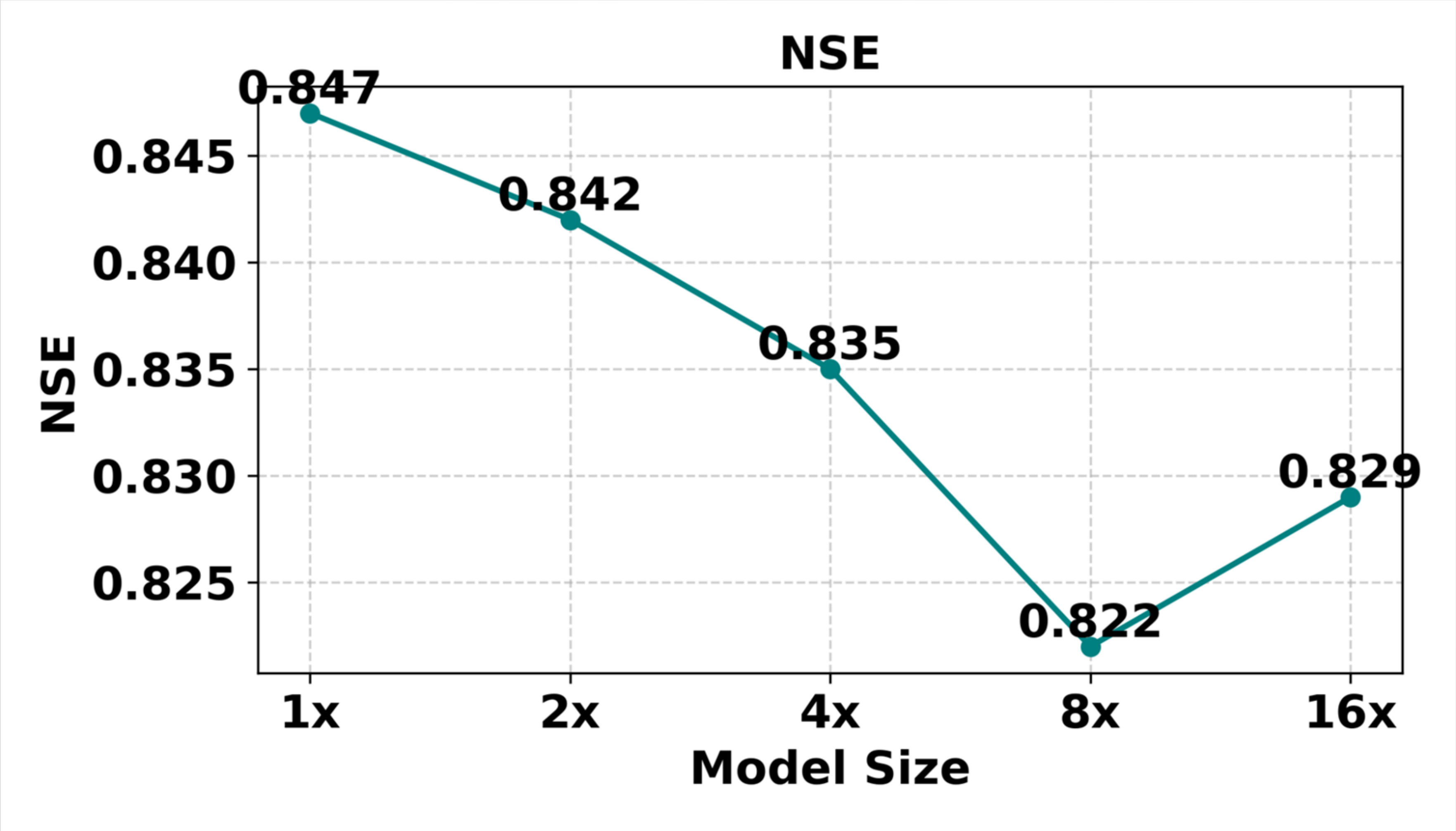

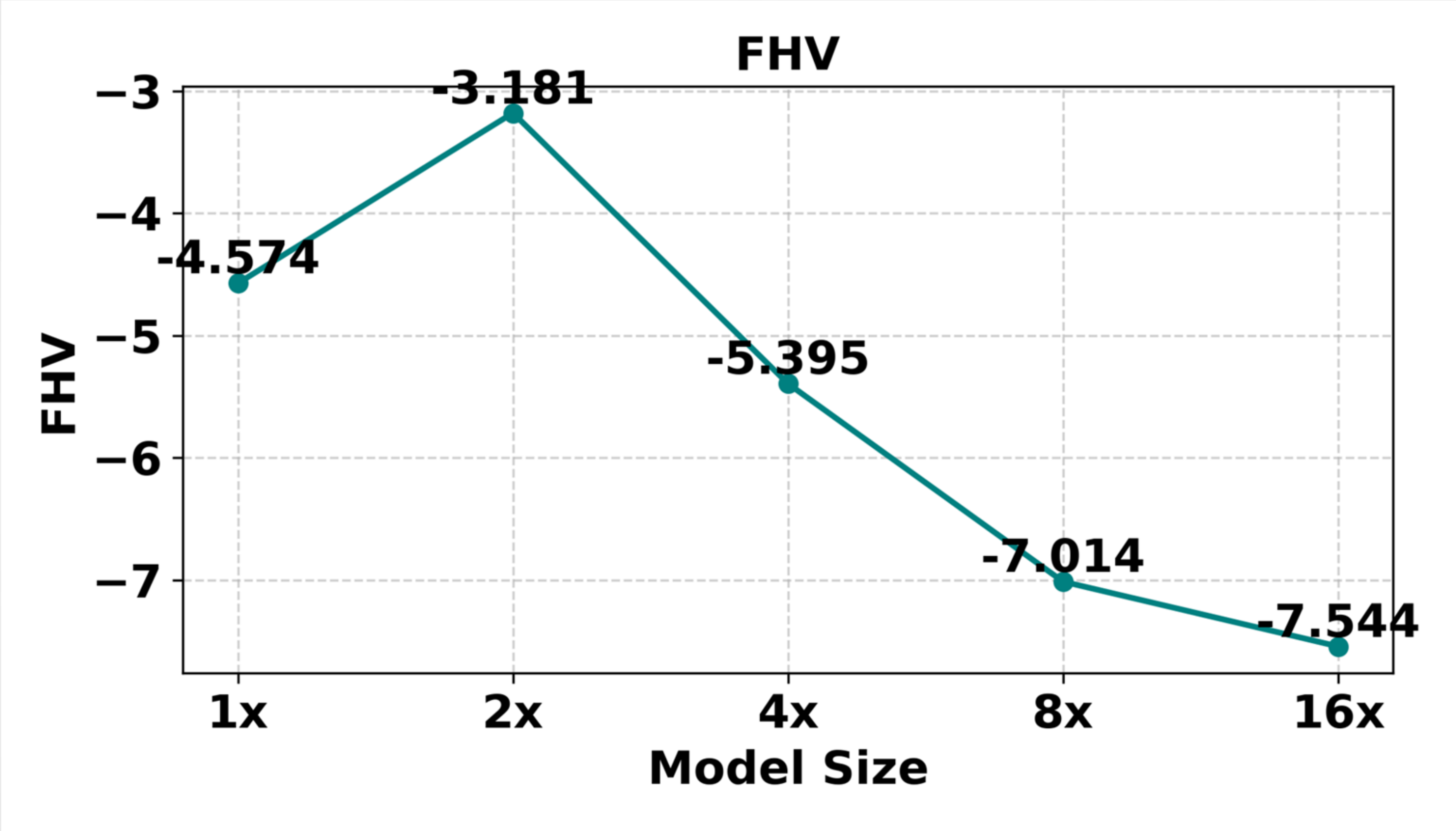

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MoLSTM	**0.859**±0.006	**0.873**±0.048	**0.848**±0.020	**0.826**±0.005	-12.851±1.218	**-8.236**±1.218	**0.932**±0.003	**29.460**±1.660	0.377±0.058

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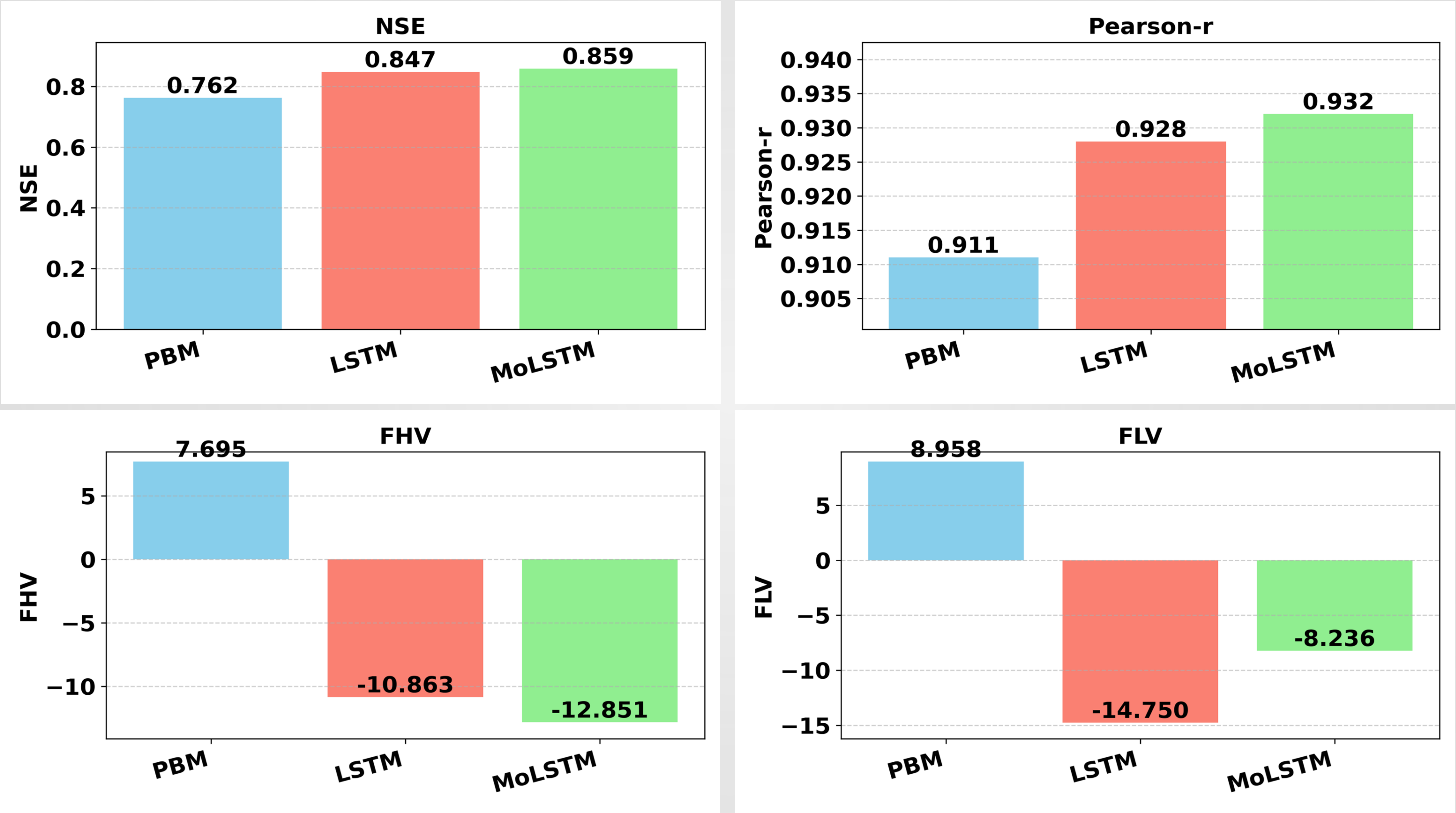

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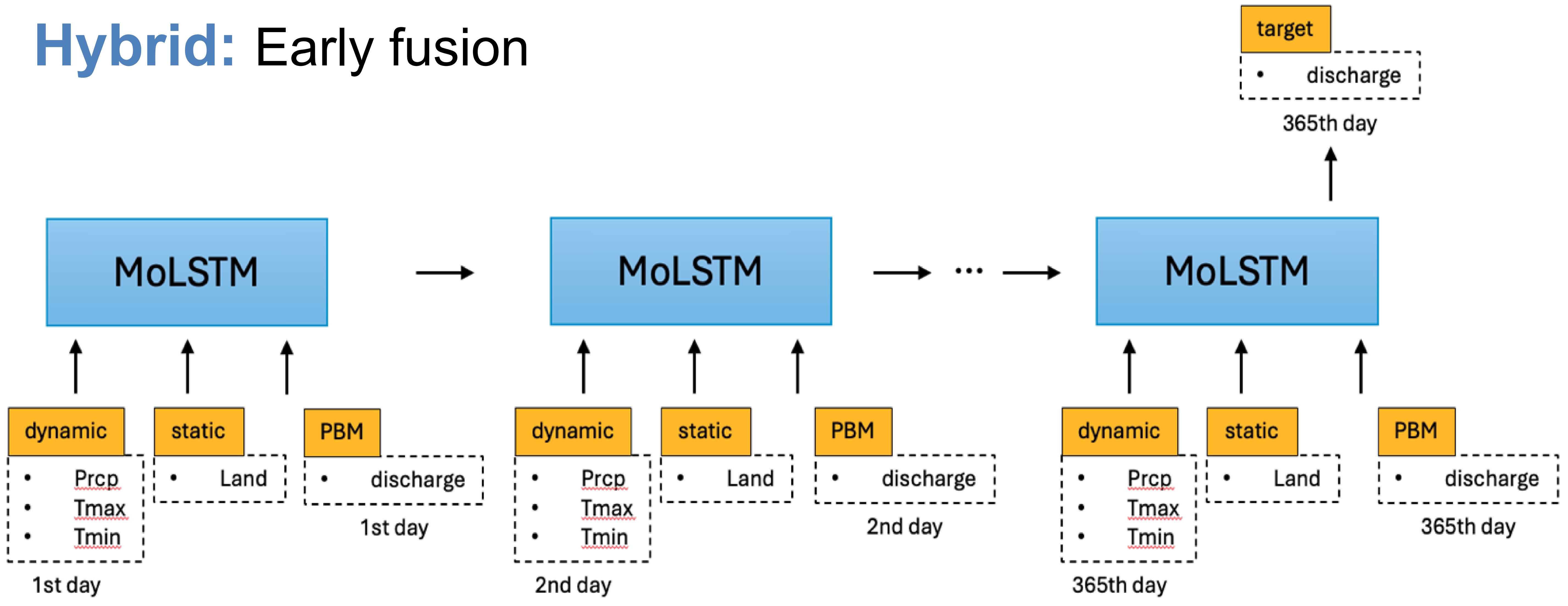
Experiment 4 – Hybrid MoLSTM and PBM

	Pros.	Cons.
Process-Based Methods (PBM)	• Embed physical knowledge of watershed streamflow processes • Good at forecasting extreme events	• Poor at general curve fitting (hard to capture unknown patterns)
Neural Networks (e.g., LSTM)	• Excellent at curve fitting complex and unknown relationships	• Lack physical understanding (no built-in hydrological knowledge)

Hybrid: Early fusion



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MoLSTM + PBM	0.855±0.004	0.891±0.008	**0.848**±0.004	0.816±0.015	**-5.496**±1.711	**-8.225**±40.519	**0.936**±0.002	**25.892**±0.995	**0.364**±0.035

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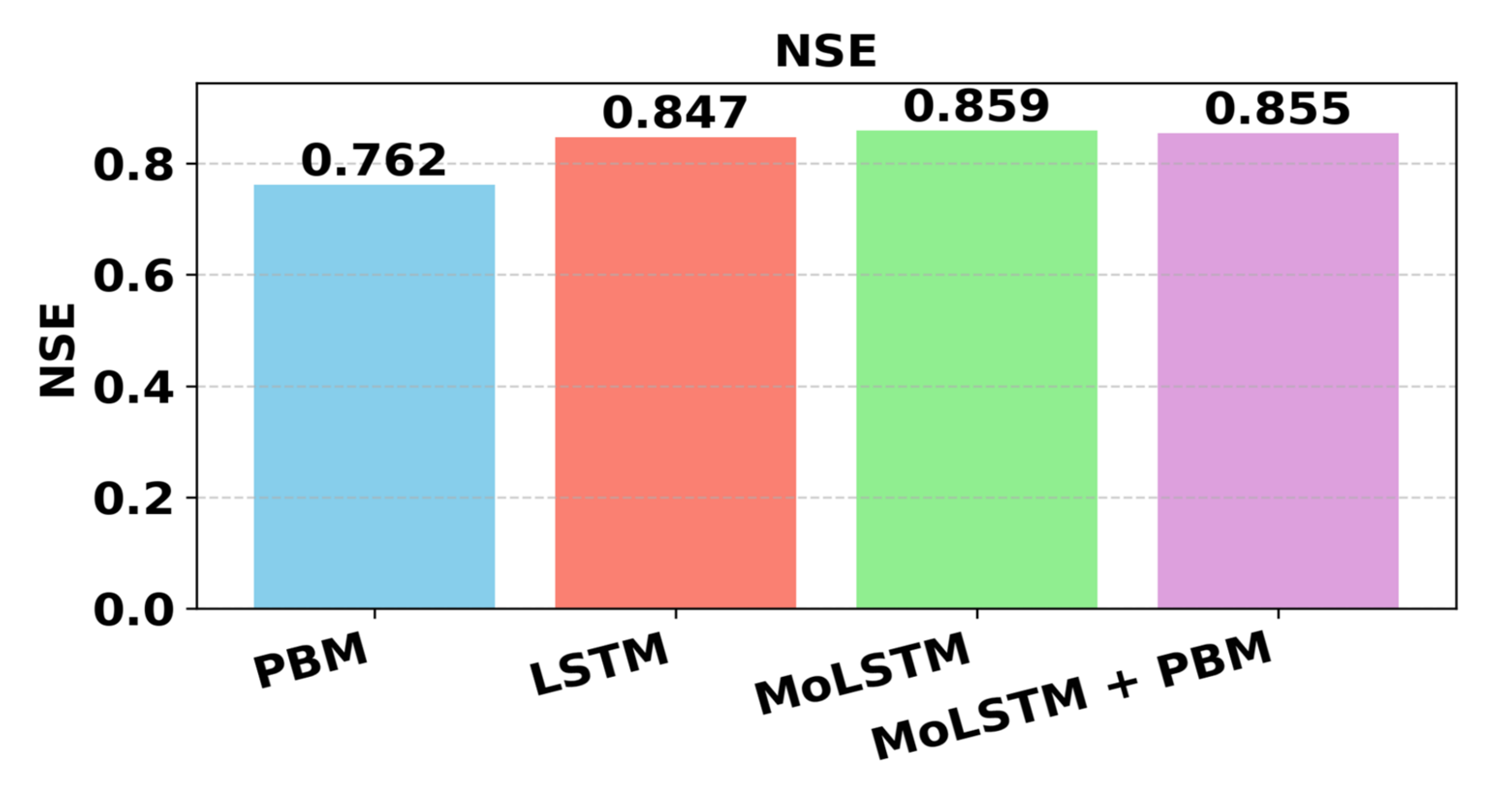
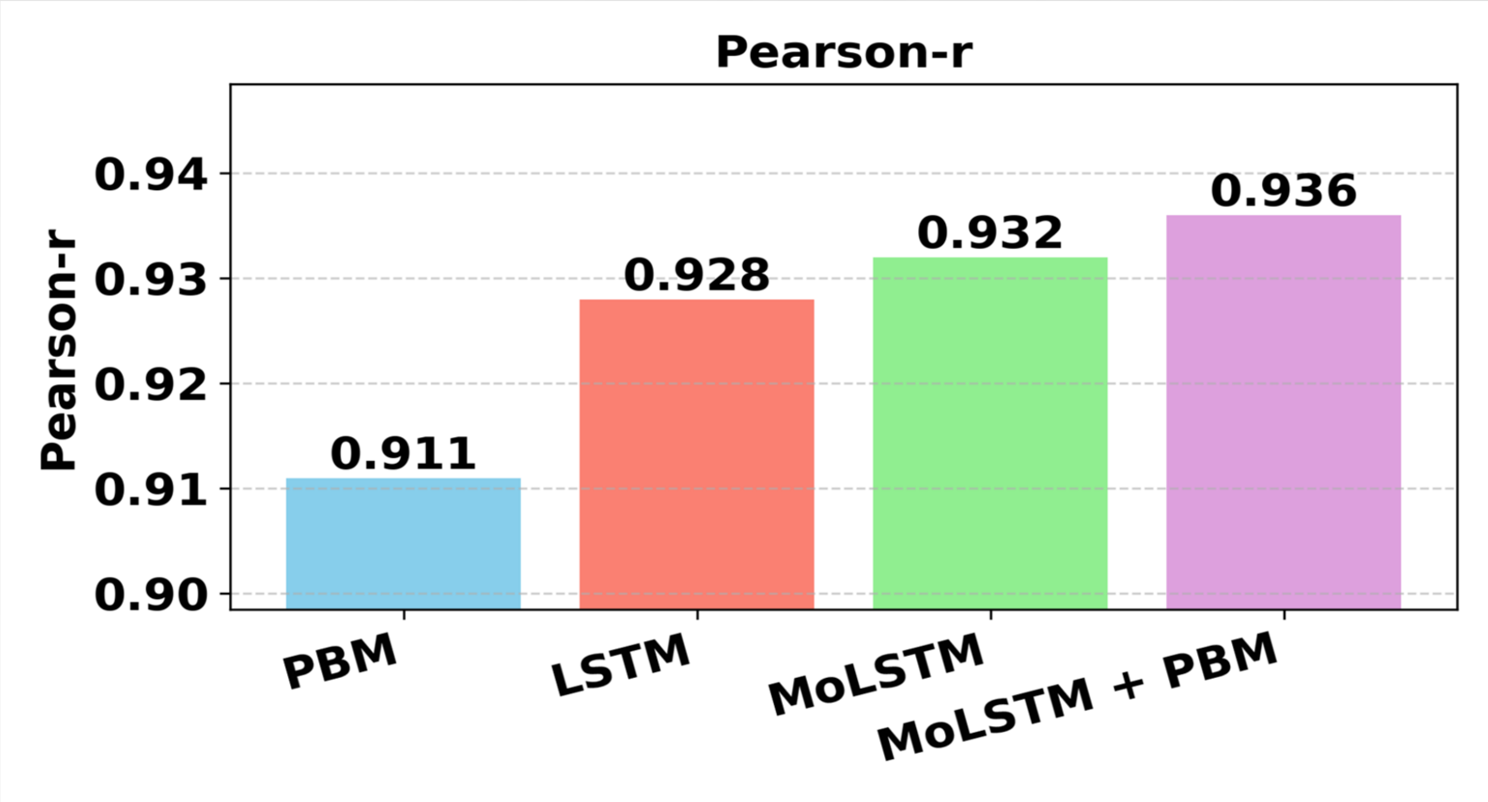
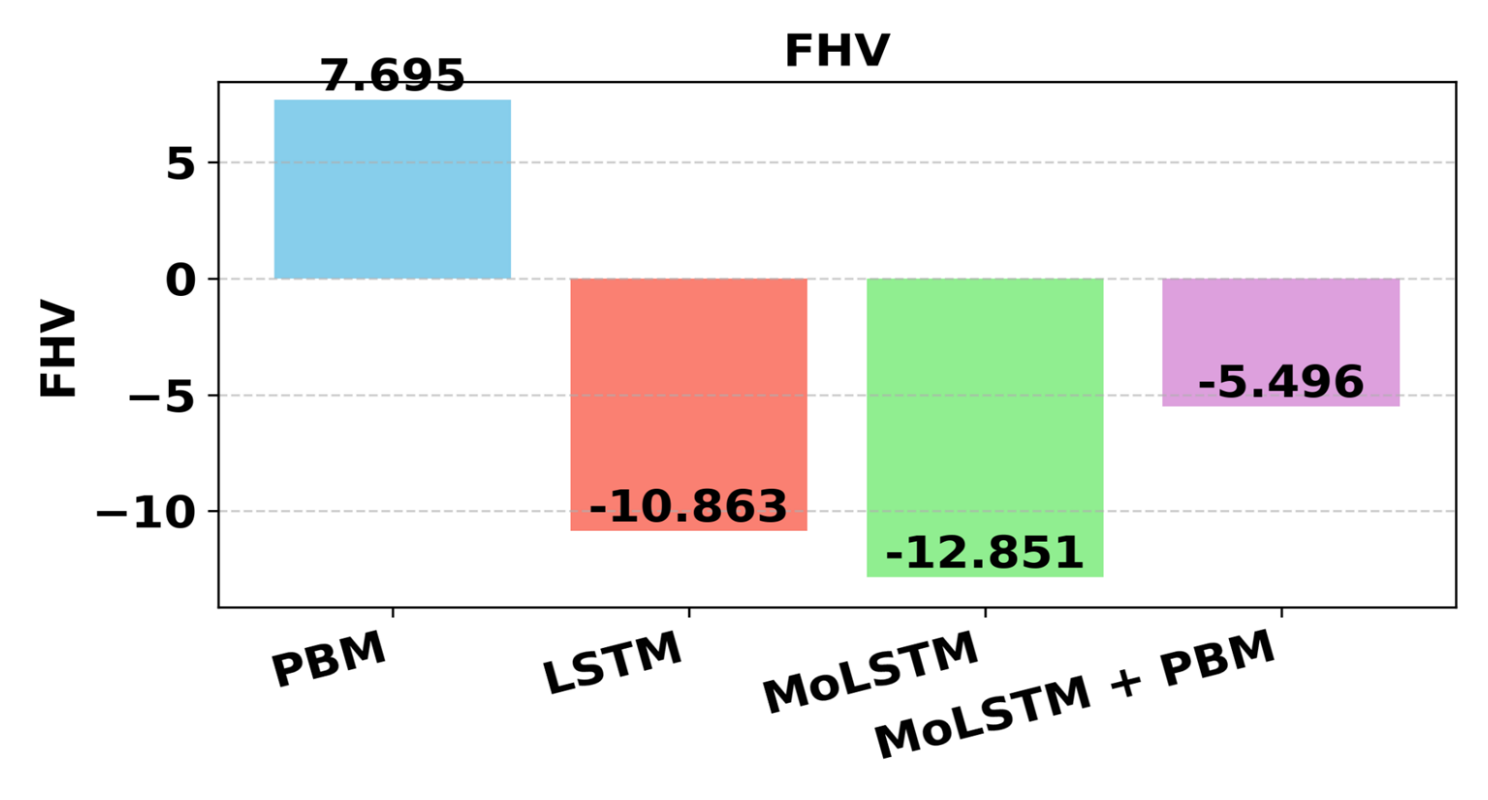
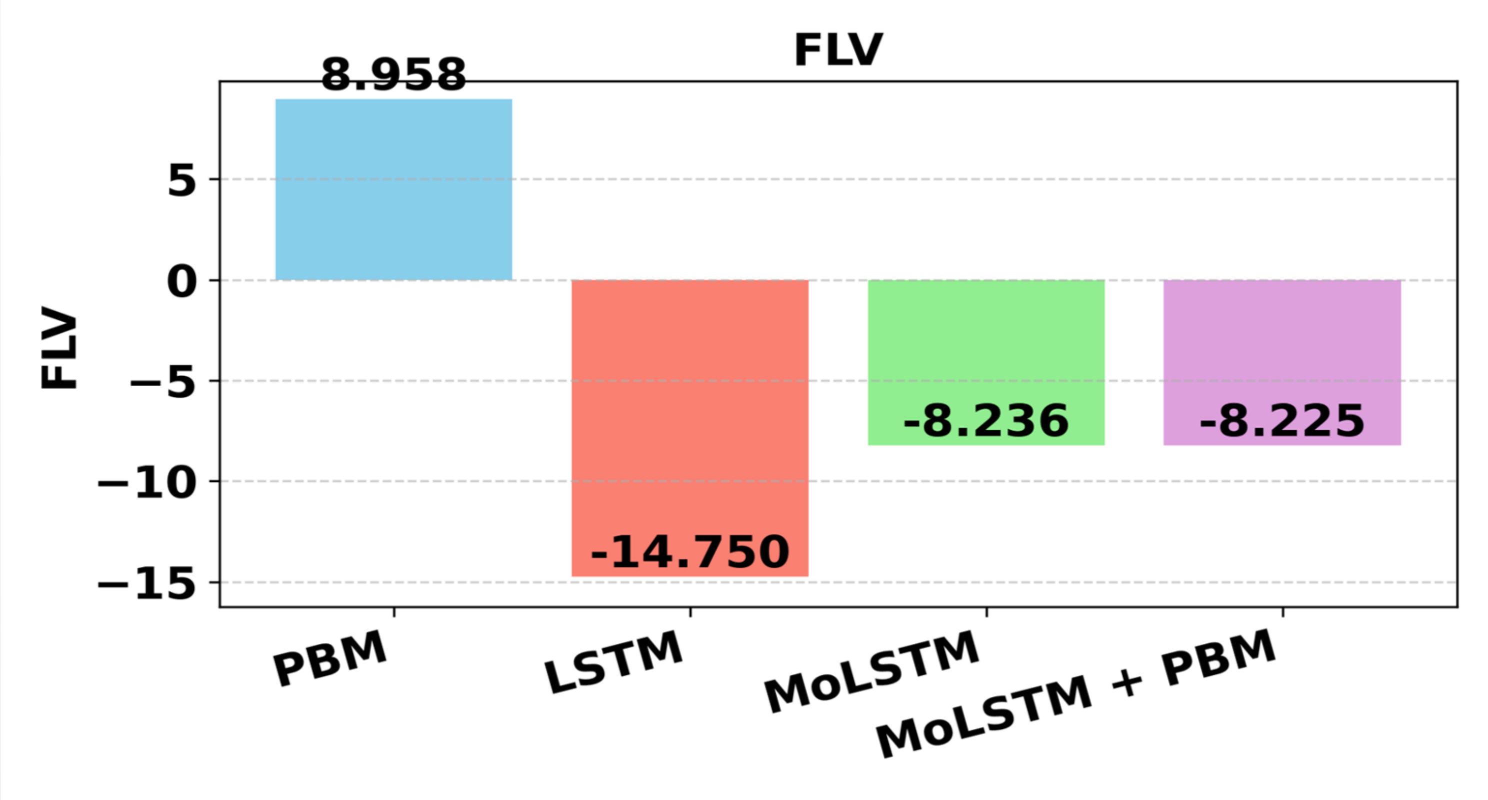
Experiment 4 – Hybrid MoLSTM and PBM









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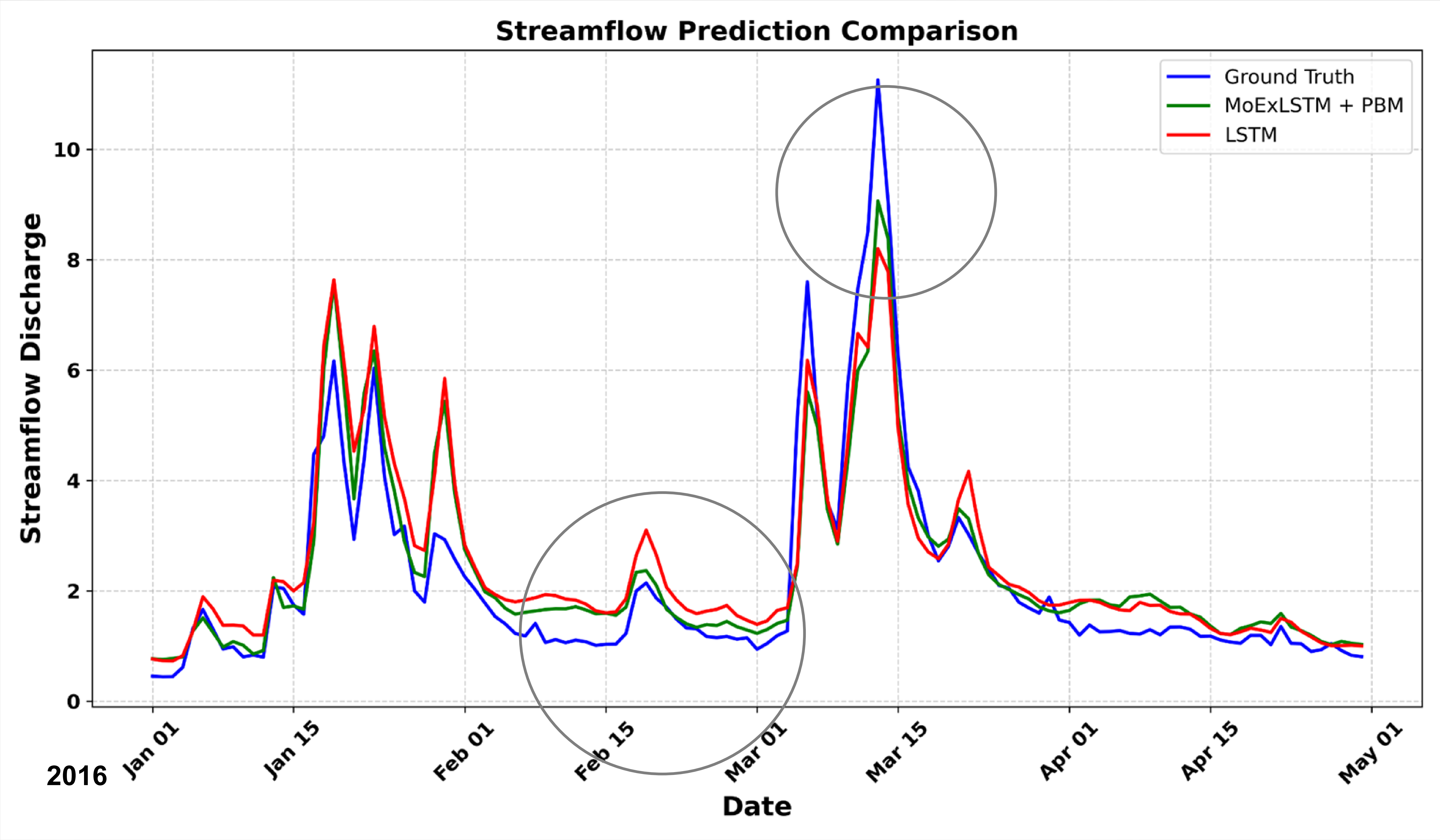
Experiment 4 – Hybrid MoLSTM and PBM

SHA watershed



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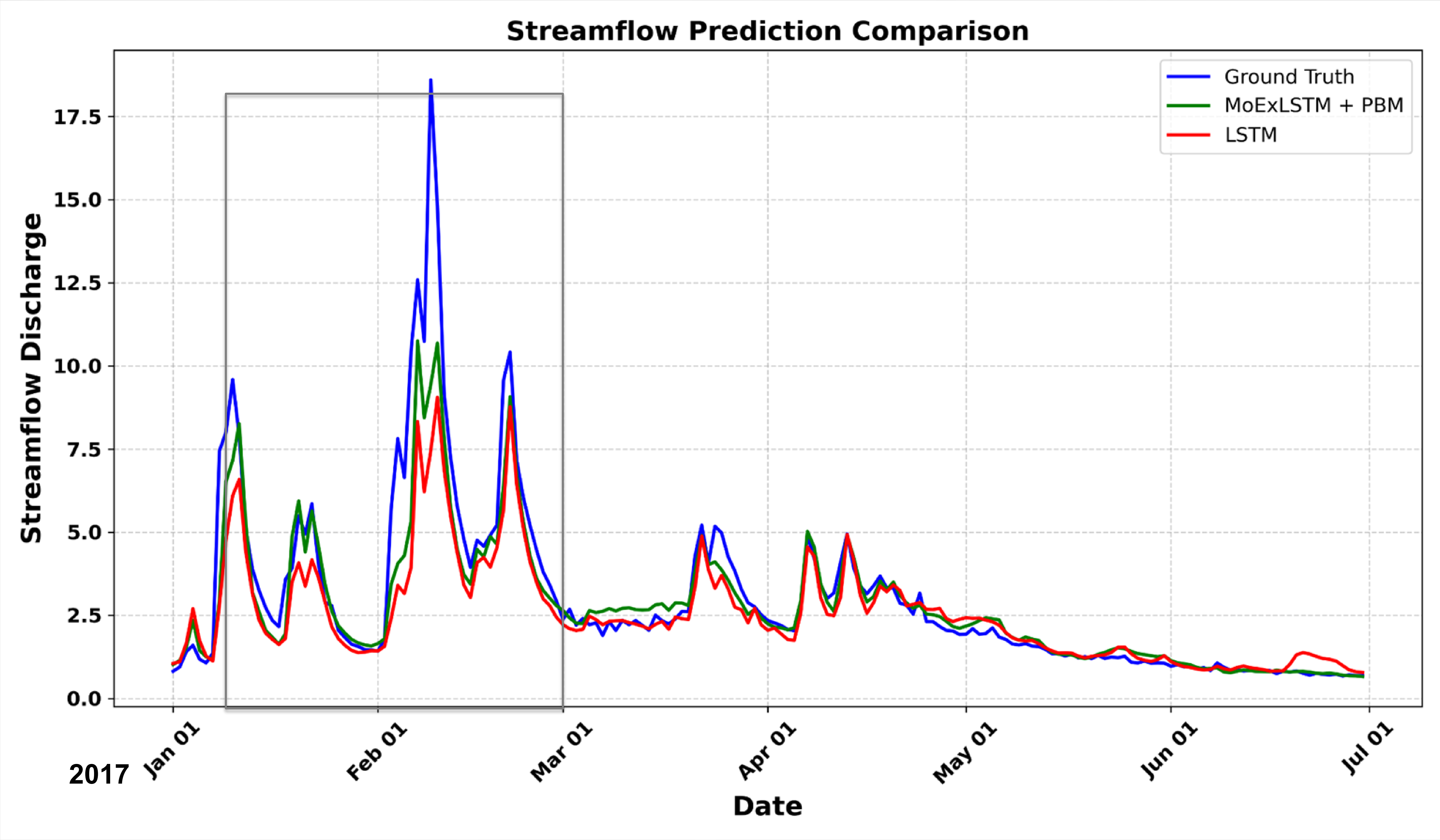

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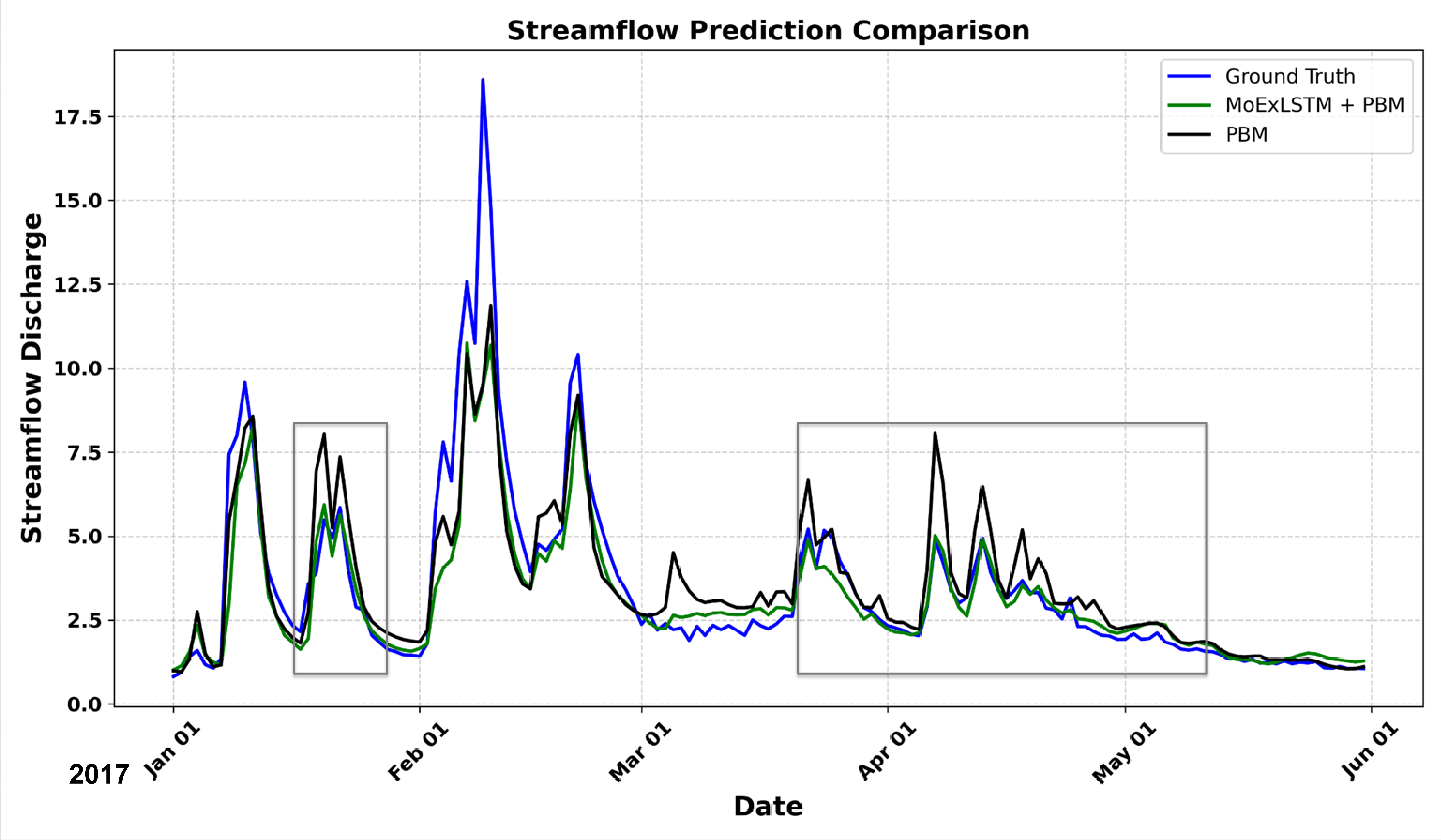

Key Messages

- **Static attributes** → LSTM performance

  Key attributes: Elevation & Land Cover

- **LSTM vs. PBM:** LSTM better skill metrics; PBM better on extremely high/low values

- **Mixture of LSTM (MoLSTM)** → notable improvement

- **Hybrid MoLSTM & PMB** → further improvement, particularly on extreme values

Questions?

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