CALIFORNIA DEPARTMENT OF WATER RESOURCES

Exploring Deep Learning Techniques in Daily Streamflow Prediction

CWEMF Annual Meeting, May 13, 2025

CALIFORNIA DEPARTMENT OF WATER RESOURCES

UCDAVIS UNIVERSITY OF CALIFORNIA

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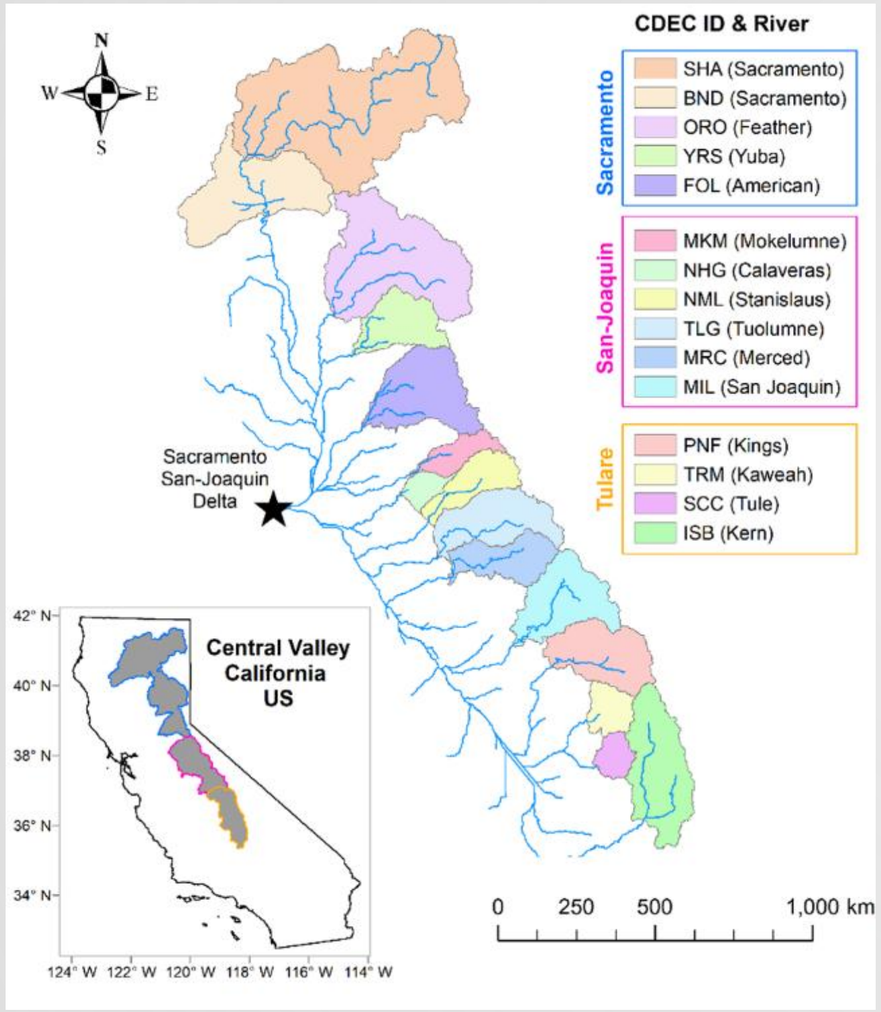
Outline

1. Overview
2. Methodology
3. Results
4. Summary

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

Methodology: Study Area/Data



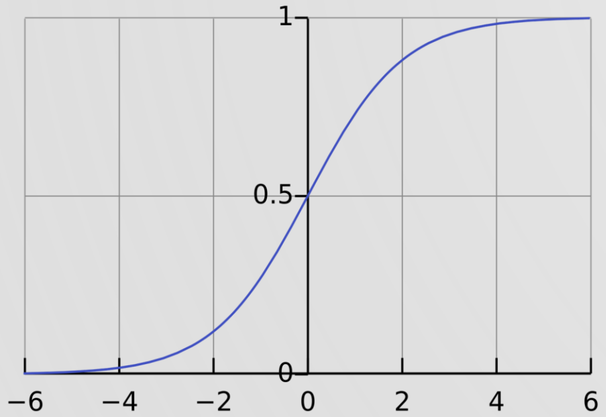
- **14 Watersheds**
  - Excluding BND as it highly correlates to SHA
- **Study Period**
  - Jan.10, 1987 to Dec.31, 2018
- **Daily Streamflow observations**
  - CDEC observed
- **Daily Precipitation/Temperature**
  - Historical gridded (4km) Livneh dataset
  - Temperature (Tmax and Tmin) bias-corrected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

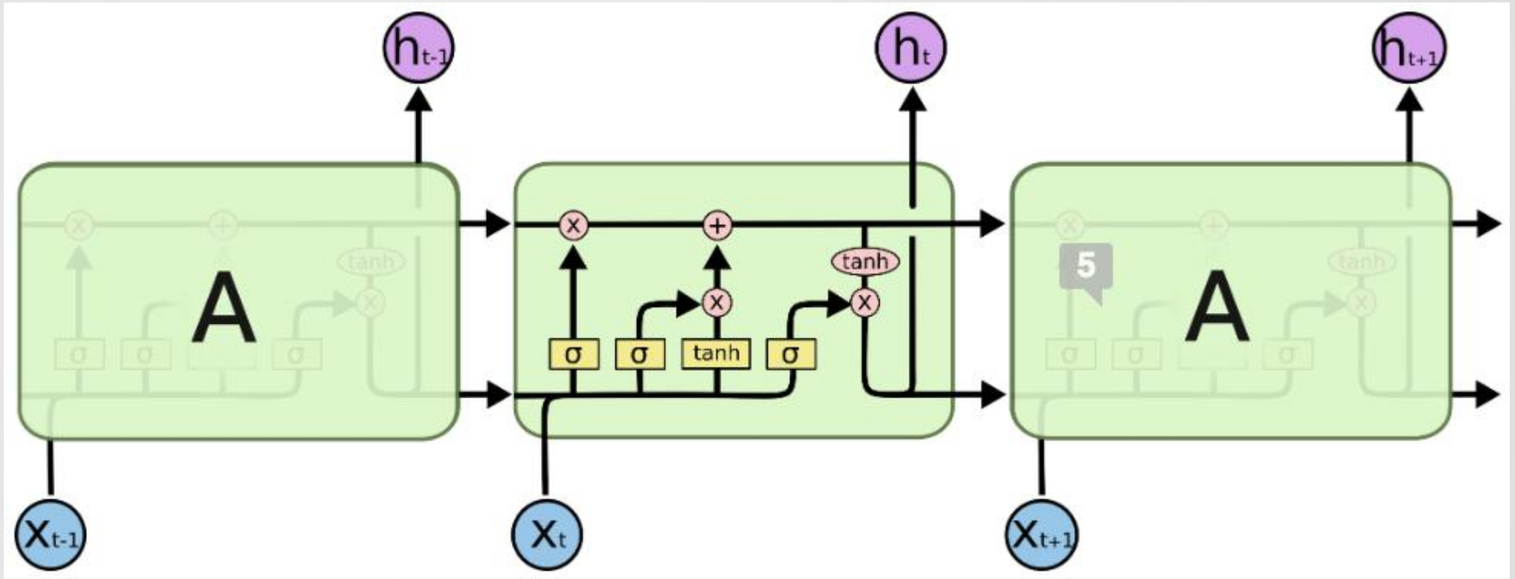
Methodology: Long-Short Term Memory (LSTM) Architecture

Day 3
- Streamflow discharge

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 1
- Dynamic inputs
- Static attributes

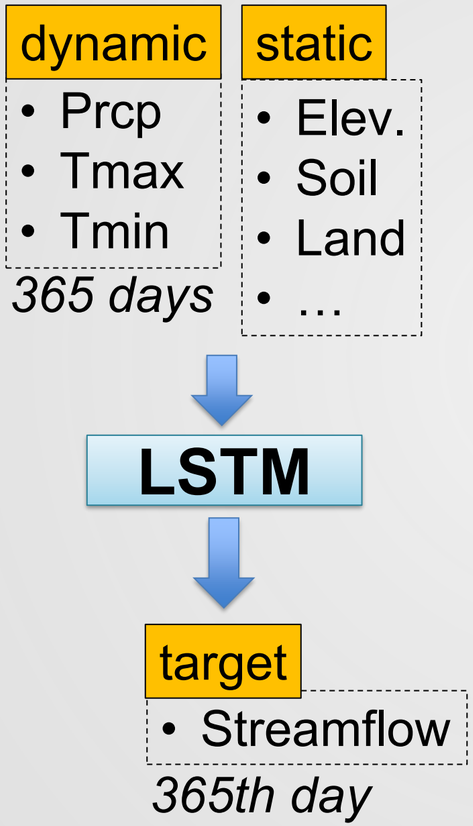
Day 2
- Dynamic inputs
- Static attributes

Day 3
- Dynamic inputs
- Static attributes

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

Methodology: Workflow

➢ Workflow



Static attributes

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

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

Methodology: Experimental Design

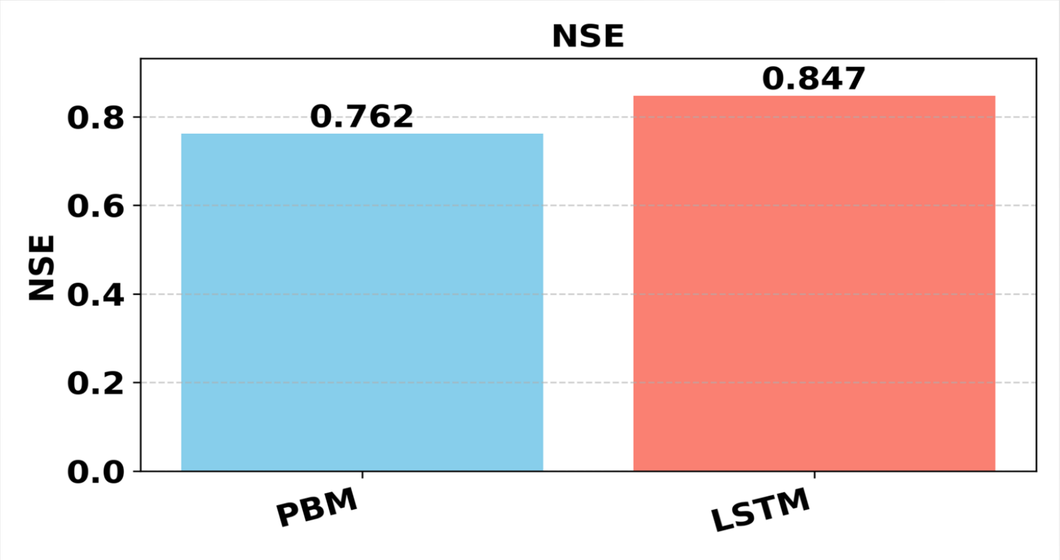
- **Experiment 1:** LSTM vs. PBM
- **Experiment 2:** Mixture of LSTMs (MoLSTM)
- **Experiment 3:** Hybrid MoLSTM and PBM

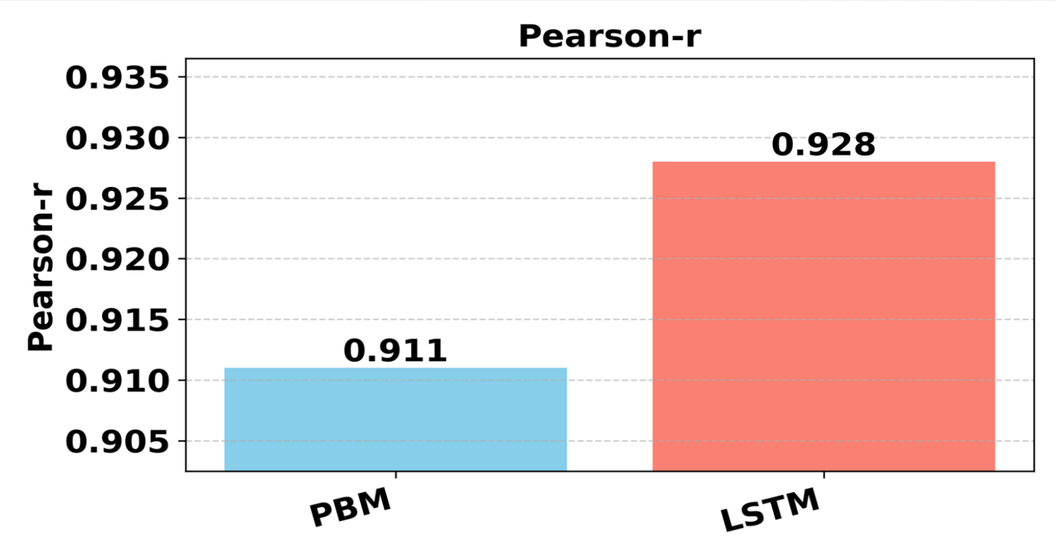
Experiment 1 – LSTM vs. PBM

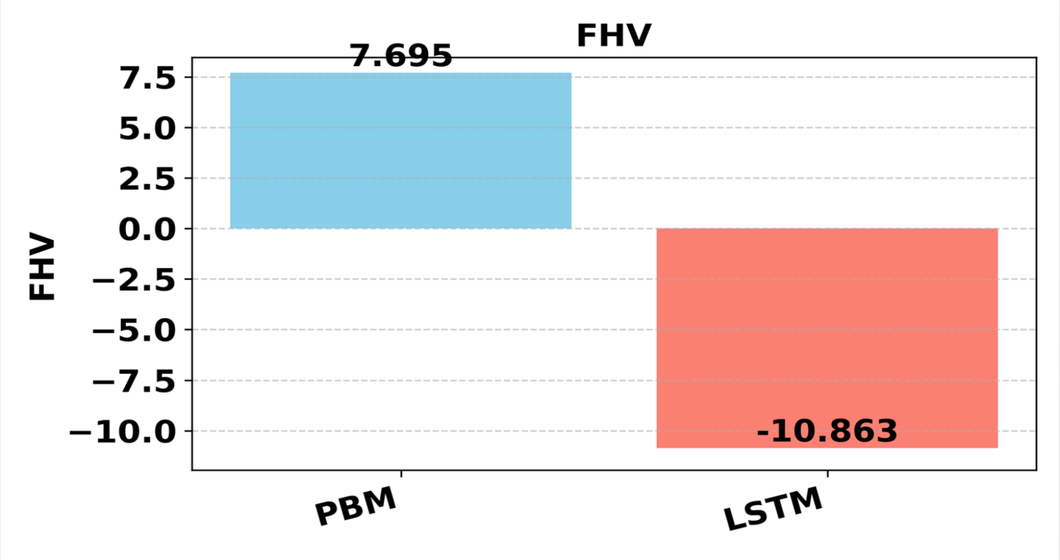
Elev. + Land	NSE ↑ (-∞, 1]	MSE ↓ [0, ∞)	RMSE ↓ [0, ∞)	KGE ↑ (-∞, 1]	FHV (-∞, ∞) (closer to 0)	FLV (-∞, ∞) (closer to 0)	Pearson-r [-1, 1] ↑	Peak-MAPE [0, ∞) ↓	Peak-Timing (-∞, ∞) (closer to 0)
PBM	0.762	1.296	1.026	0.799	**7.695**	**8.958**	0.911	36.574	0.466
LSTM	**0.847**±0.012	**0.927**±0.075	**0.880**±0.034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

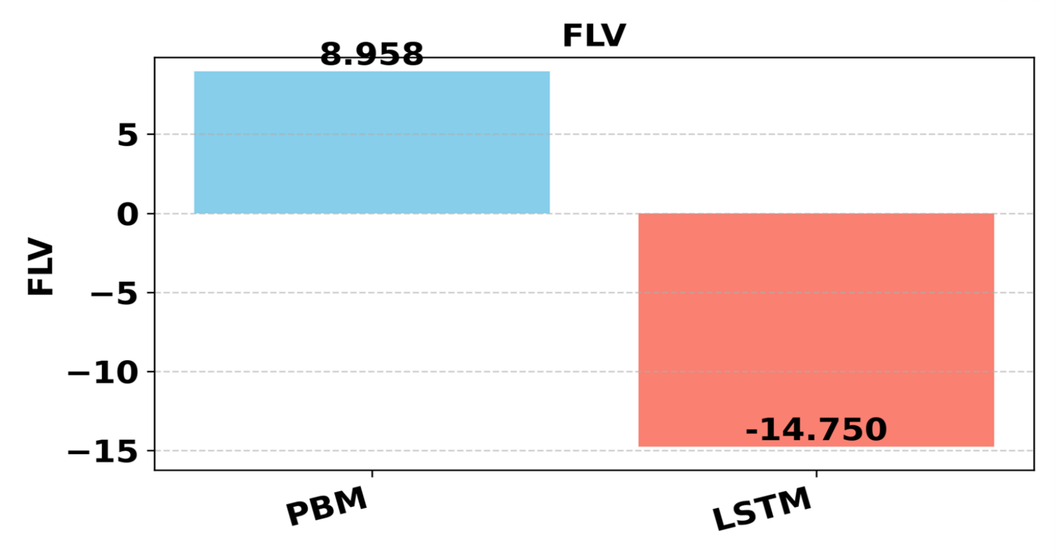
[**Bold**: Best Performance]

Experiment 1 – LSTM vs. PBM









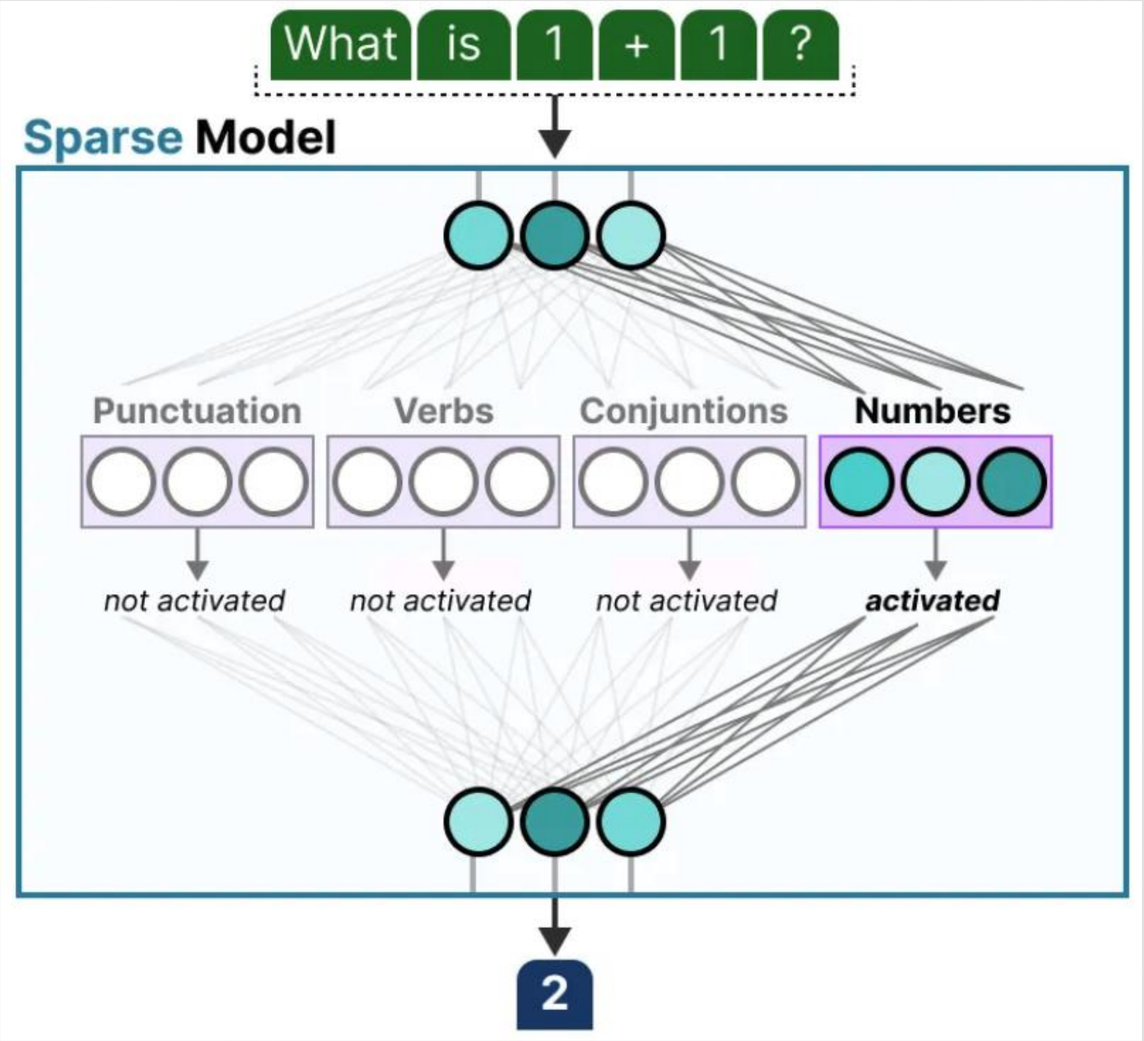
Experiment 2 – Mixture of LSTMs (MoLSTM)

- **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

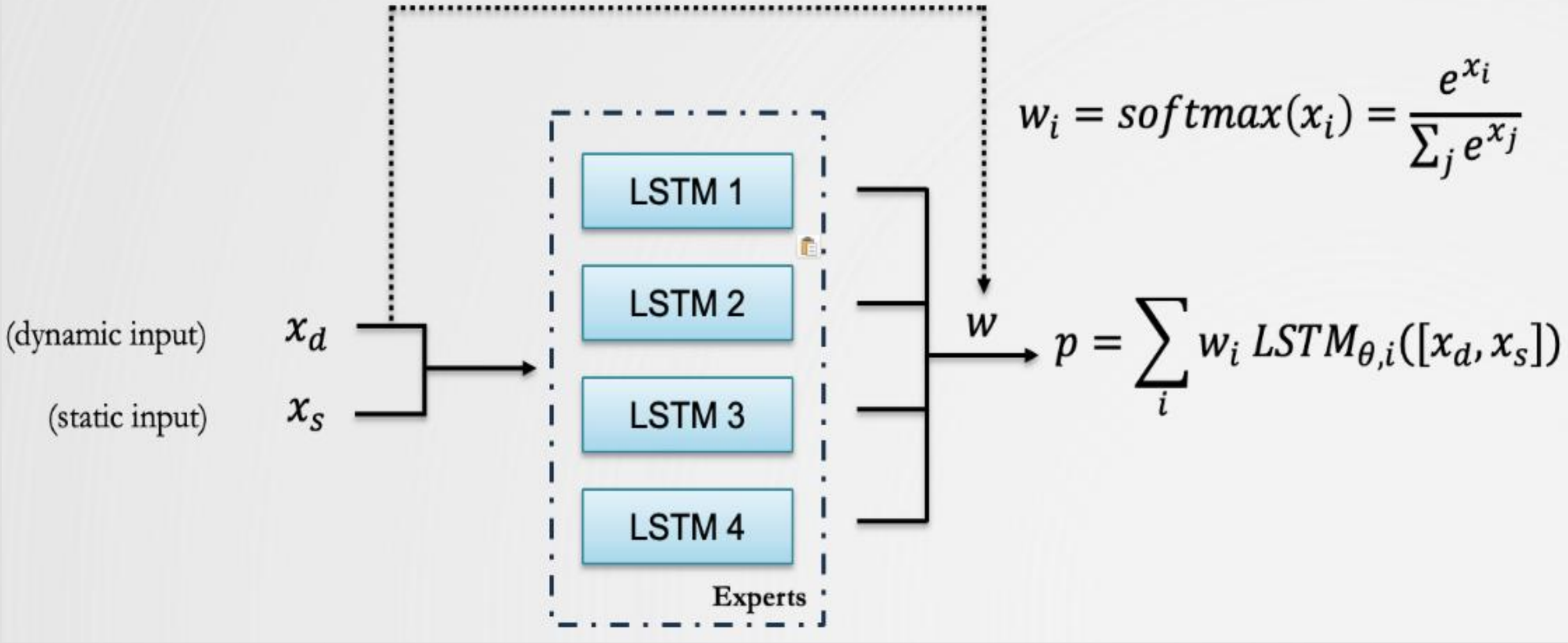
  Extreme streamflow



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

Experiment 2 – Mixture of LSTMs (MoLSTM)

$$x = MLP_\theta([x_d, x_s])$$
$$x \in R^4$$



$$w_i = softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

$$p = \sum_i w_i \, LSTM_{\theta,i}([x_d, x_s])$$

Experiment 2 – Mixture of LSTMs (MoLSTM)

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)
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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

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

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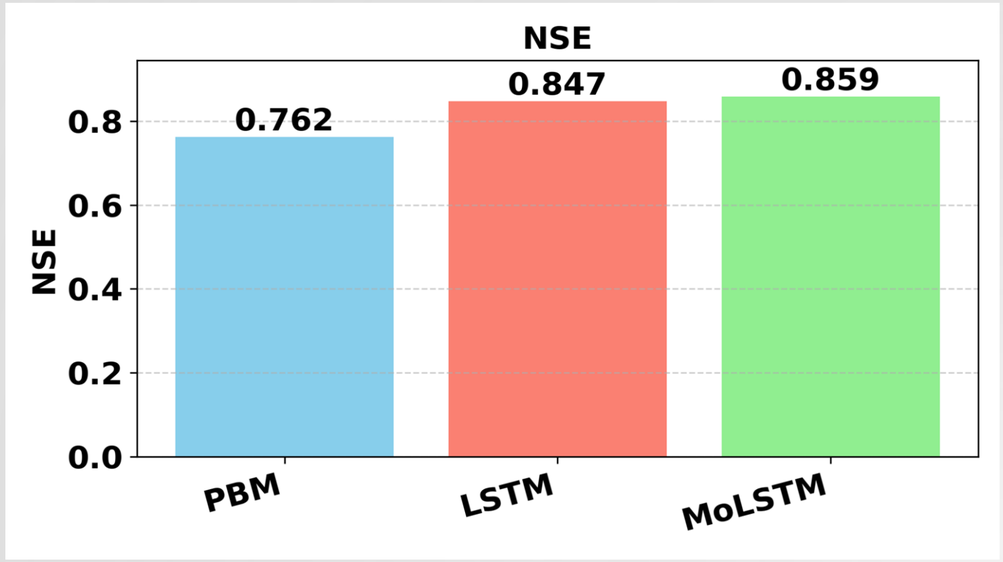
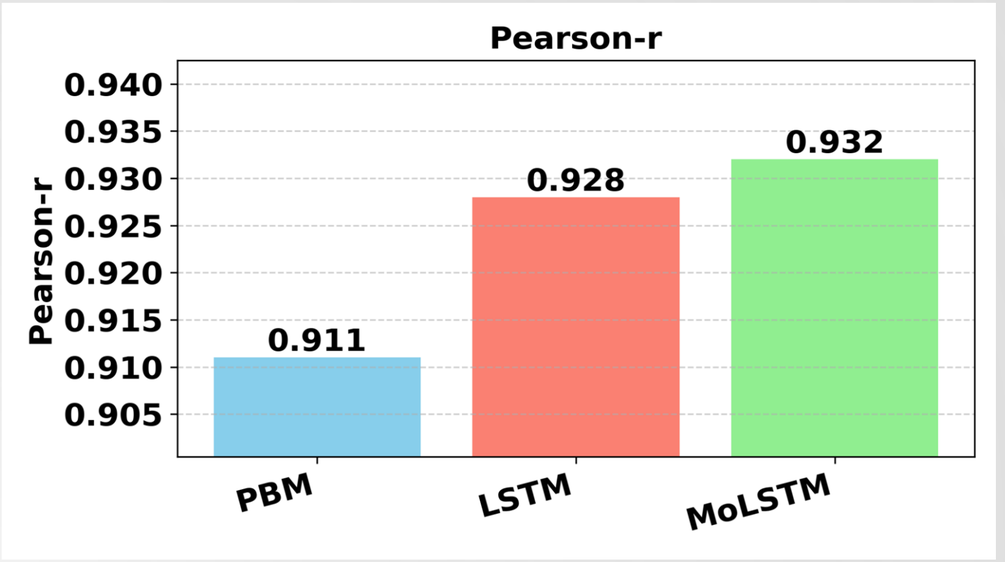
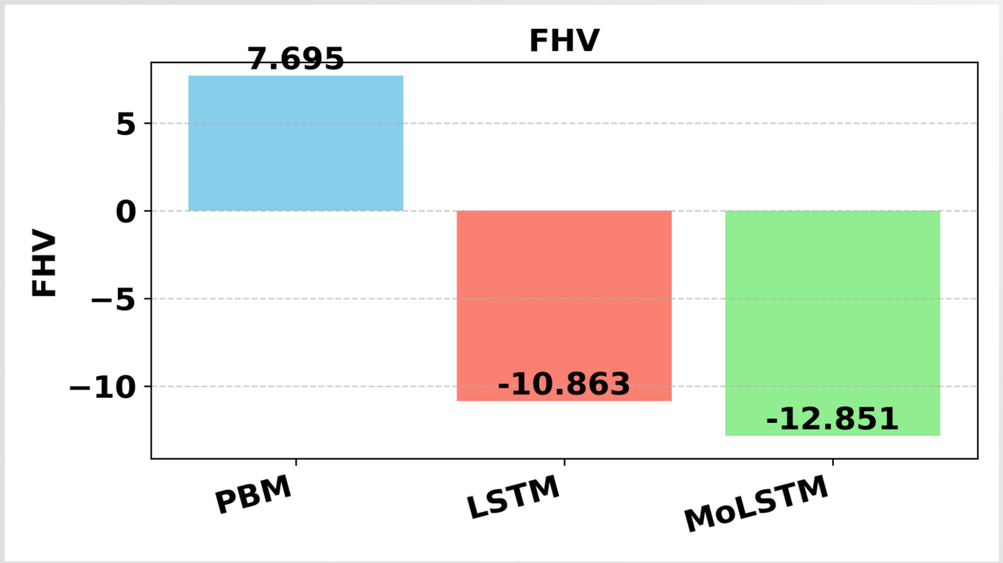
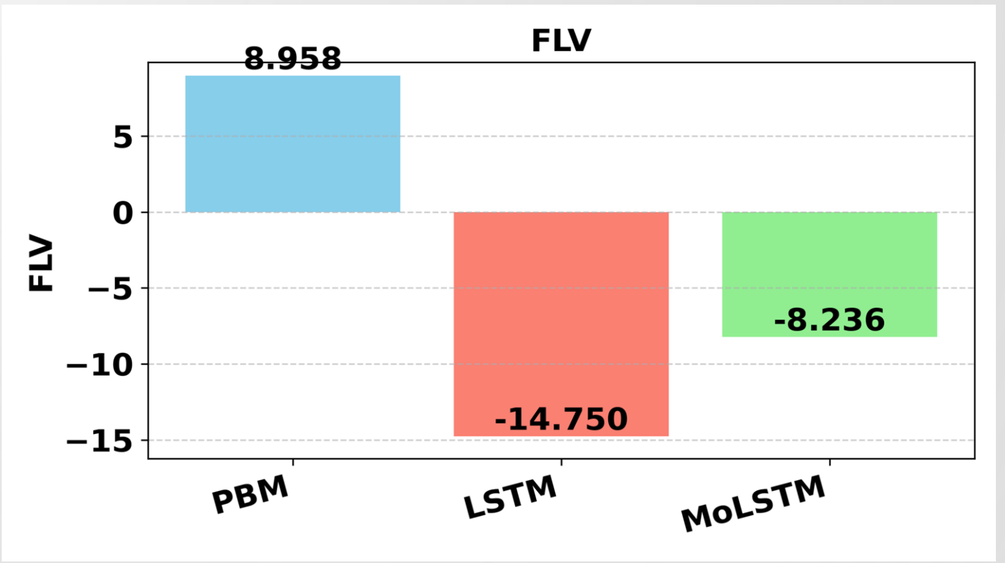




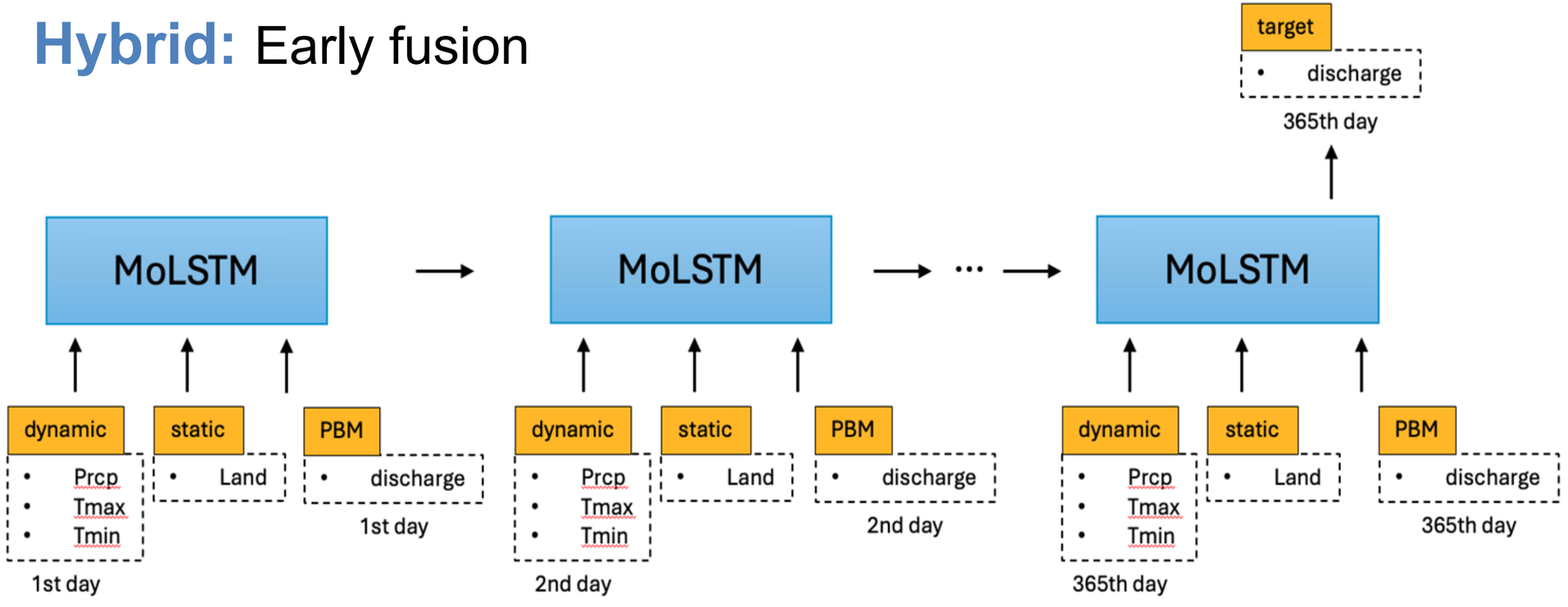




Experiment 3 – Hybrid MoLSTM and PBM

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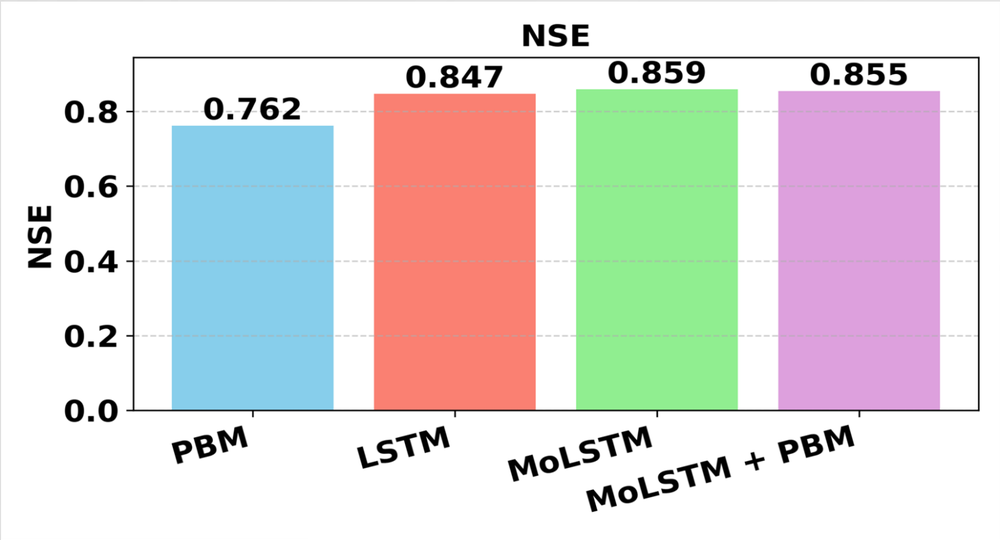
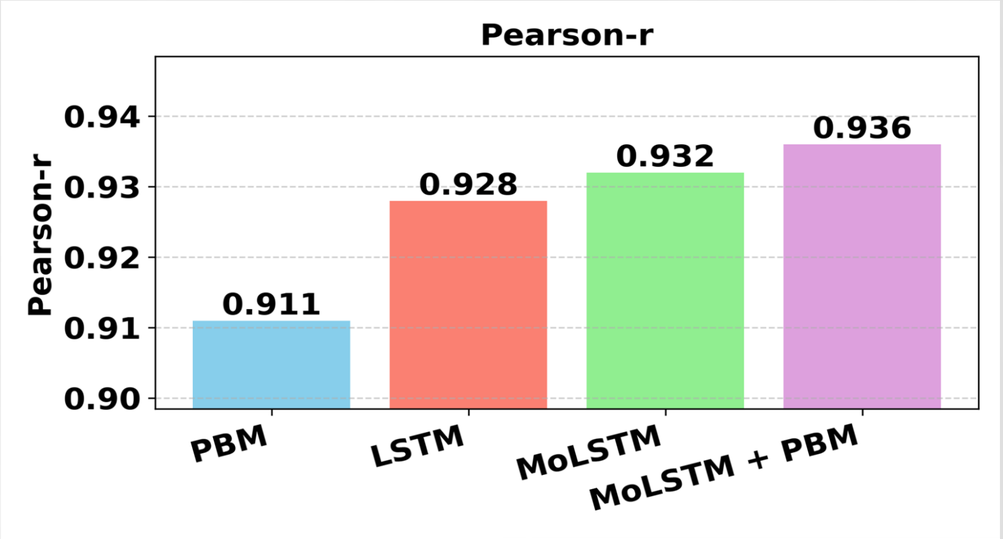
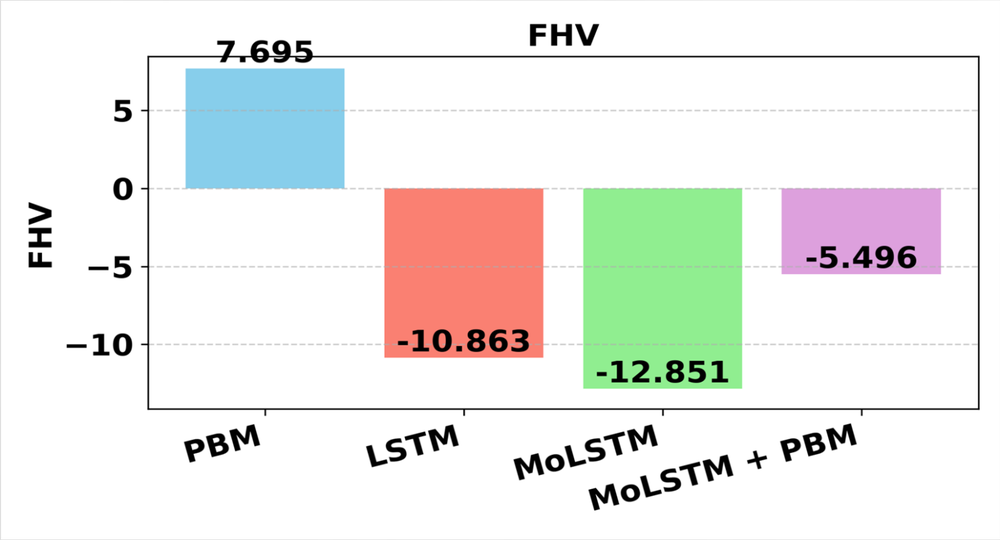
MoLSTM + PBM	**0.855**±0.004	**0.891**±0.008	**0.848**±0.004	**0.816**±0.015	**-5.496**±1.711	**-8.225**±40.519	**0.936**±0.002	**25.892**±0.995	**0.364**±0.035

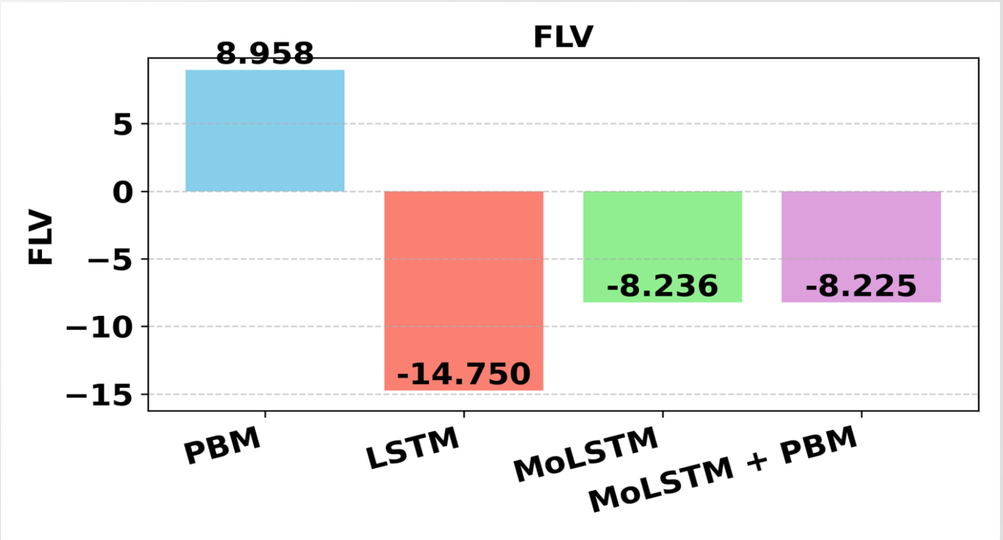
[**Bold**: Best Performance; **Blue**: Second Best Performance]

Experiment 3 – Hybrid MoLSTM and PBM



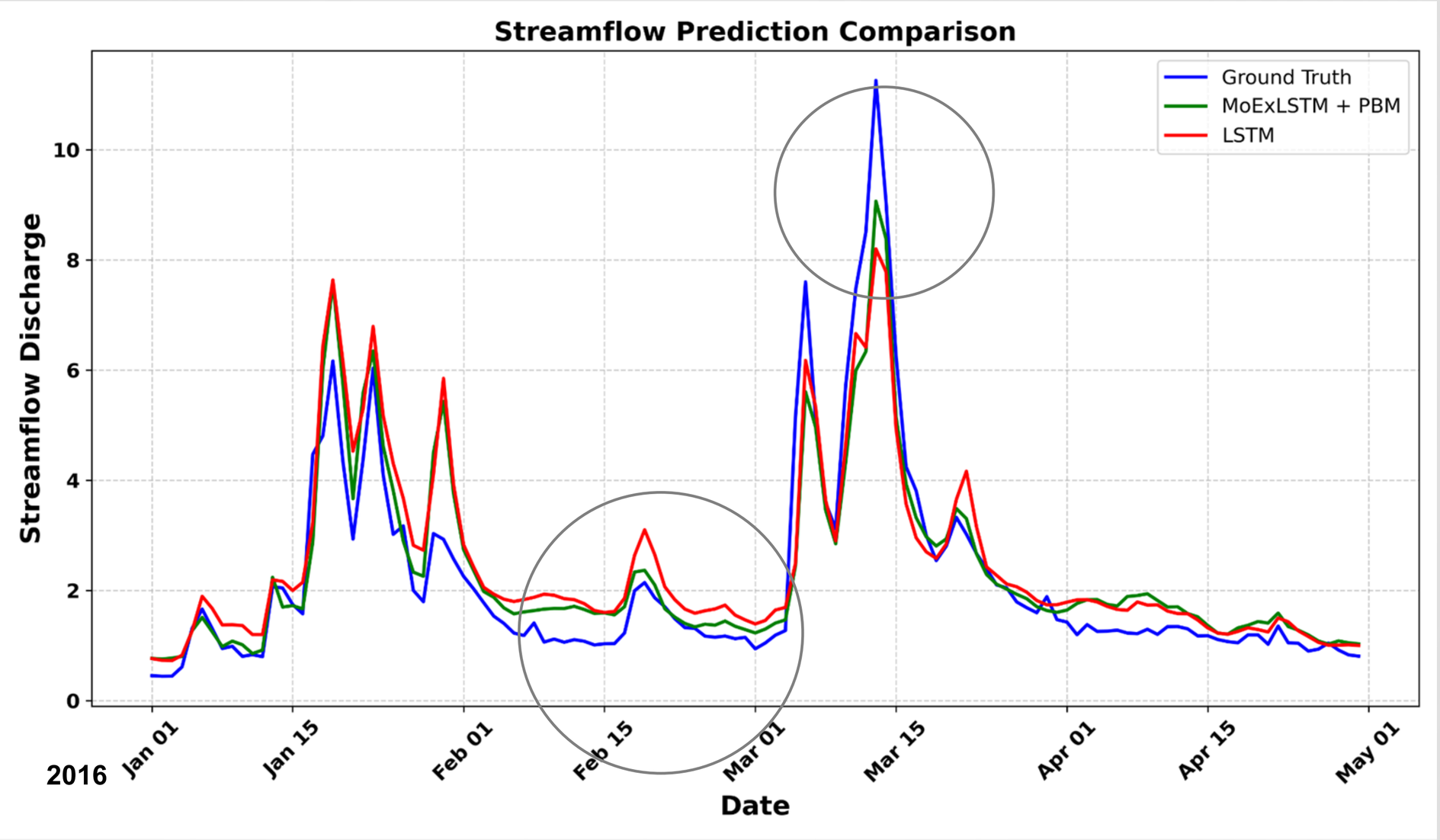






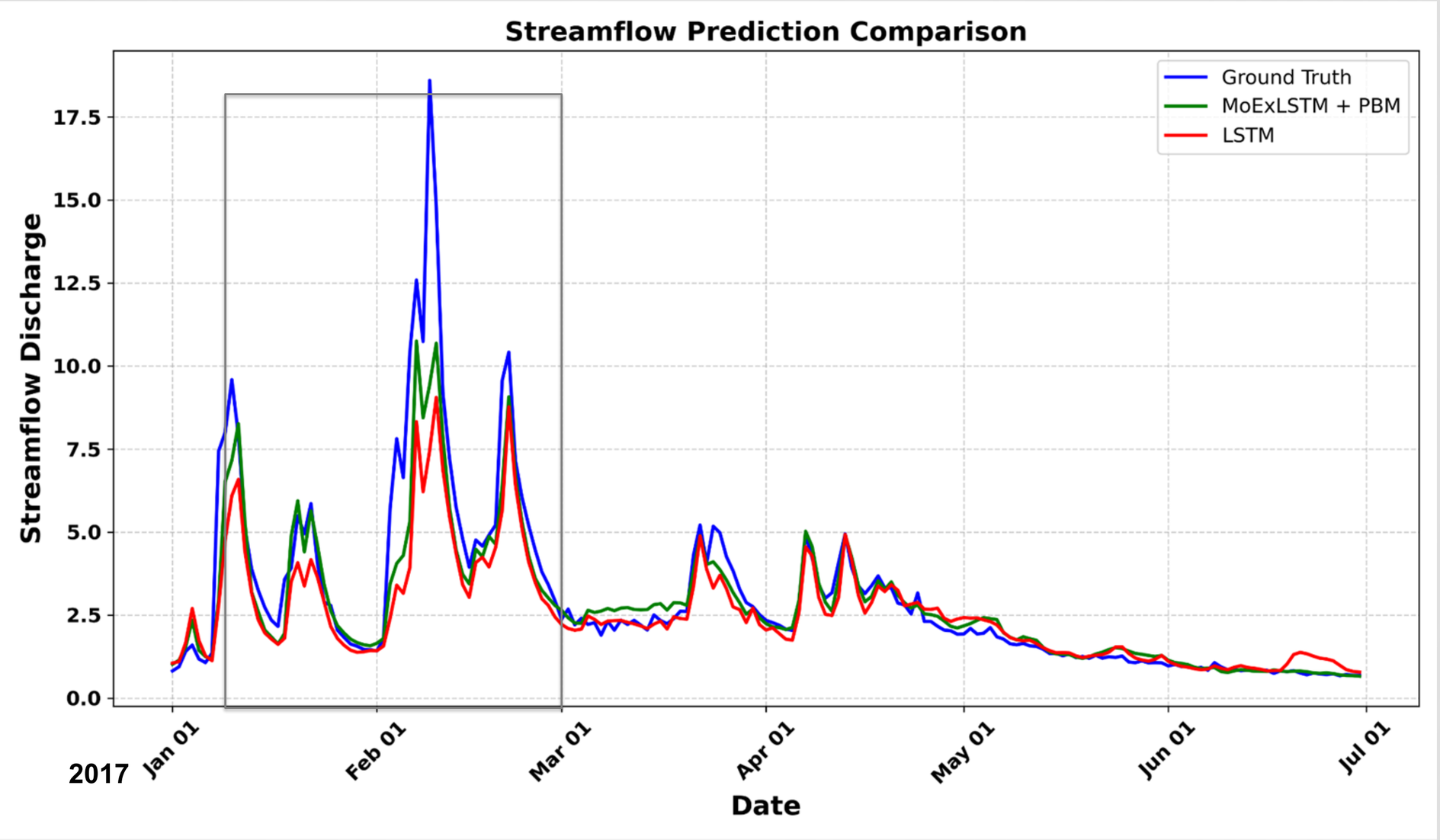
Experiment 3 – Hybrid MoLSTM and PBM

SHA watershed



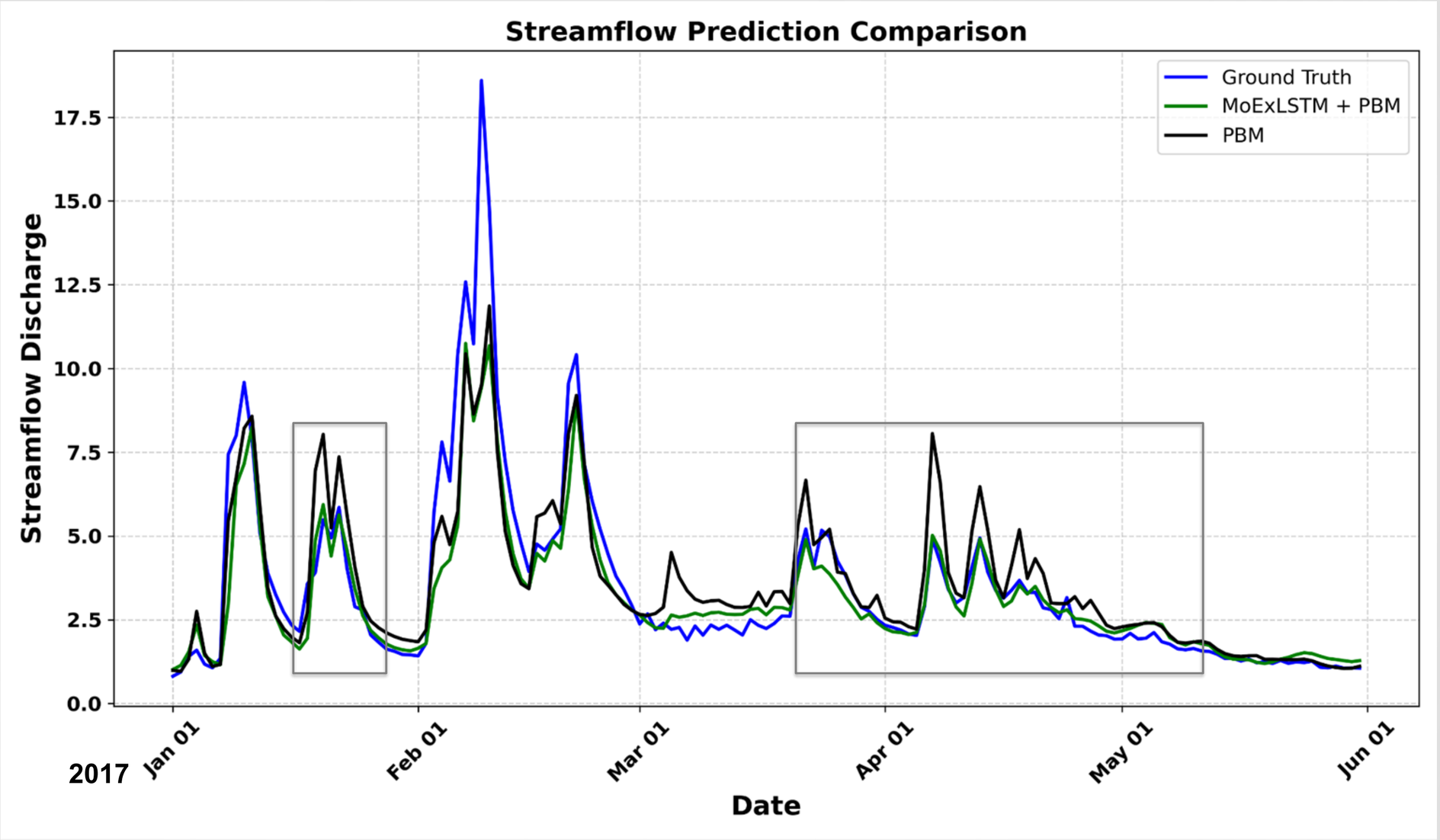
Experiment 3 – Hybrid MoLSTM and PBM

SHA watershed



Experiment 4 – Hybrid MoLSTM and PBM

SHA watershed



Summary

❑ Key Messages

- **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

❑ Future Directions

- **LSTM enhancements:**
  - Loss function refinement
  - Mixture architecture optimization

Questions?

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