Machine Learning Post-Processing Enhances NWM Accuracy in Watersheds with Extensive Water Infrastructure

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Savalan Neisary[1], Ryan Johnson[3], Md Shahabul Alam[2], Steven Burian [1,2]

[1]Department of Civil Engineering, University of Alabama, Tuscaloosa, AL, USA, [2]Alabama Water Institute, University of Alabama, Tuscaloosa, AL, USA, [3]The University of Utah, Salt Lake City, Utah

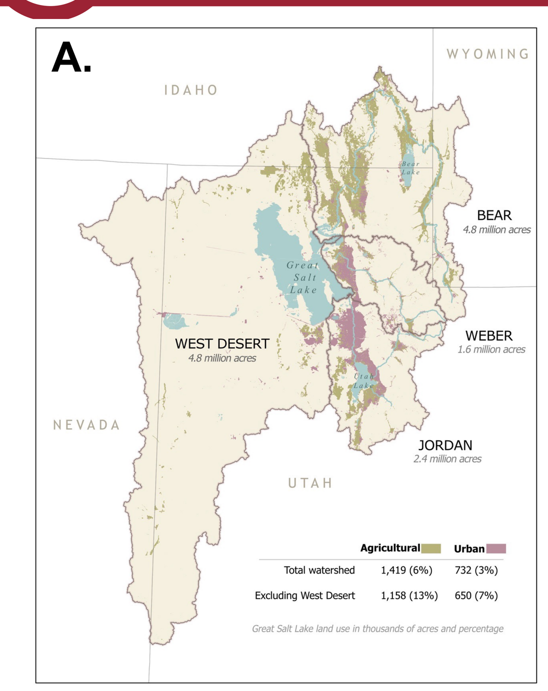
Accurate Streamflow Prediction

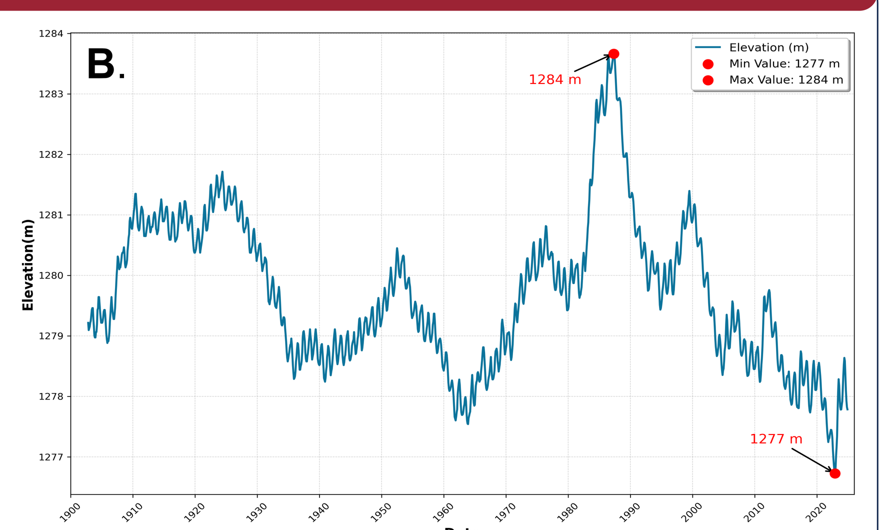
- Accurate streamflow prediction is critical for sustainable water resource management in drought-prone western US with extensive water resources infrastructure.
- The National Water Model (NWM) provides large-scale, consistent streamflow predictions across the US but struggles in low-flow prediction in regions with extensive water infrastructure, such as reservoirs, particularly west of the 95th meridian.
- Post-processing methods can enhance hydrological model outputs by correcting biases and quantifying uncertainties without modifying the original model structure.
- The rise of Machine Learning (ML) in hydrology highlights their potential to improve hydrological predictions, with successful applications as a post-process

Can ML Improve the Accuracy?

Develop a post-processing machine-learning (PP-ML) framework to enhance hydrological models, including NWM streamflow data, by accounting for the primary hydrological processes, such as snow melt dynamics and water resources management.

GSL with Extensive Water Infrastructure





- The GSL watershed is nearly 55,000 km^2, and the lake is the terminus of the Bear, Weber, and Jordan Rivers. The Bear River is the largest tributary (~55% of flow volume), and the West Desert provides negligible inflow (A).[1]
- GSL is very important because it provides economic opportunities for people in the region, but it has been shrinking due to drought and increasing demand (1.2 MAF water deficit in 2020).
- The GSL watershed has numerous water infrastructures, including reservoirs, diversions, and inter-basin water transfers.
- The highest recorded lake elevation occurred in 1986, reaching 1,283.8 m, while the lowest was observed in 2022 at 1,276.7 m (B).[2]
- Our analysis shows that the NWM has lower accuracy in downstream parts of GSL with extensive water management infrastructures.

[1] Great Salt Lake: An Overview of Change. (2002). United States: Utah Geological Survey.
[2] Abbott, B. W., Baxter, B. K., Busche, K., de Freitas, L., Frei, R., Gomez, T., ... & Carling, G. T. (2023). Emergency measures needed to rescue Great Salt Lake from ongoing collapse. Brigham Young University: Provo, UT, USA.

Post-Processing Machine Learning (PP-ML) Framework

Data Collection
- Snow Water Equivalent (SWE)
- NWM Data
- Catchment Characteristics (e.g., mean area)
- Reservoir Storage
- Meteorological Variables (precipitation and temperature)
- Seasonality Index
- Streamflow Characteristics (e.g., mean historical streamflow)
- Day of Year

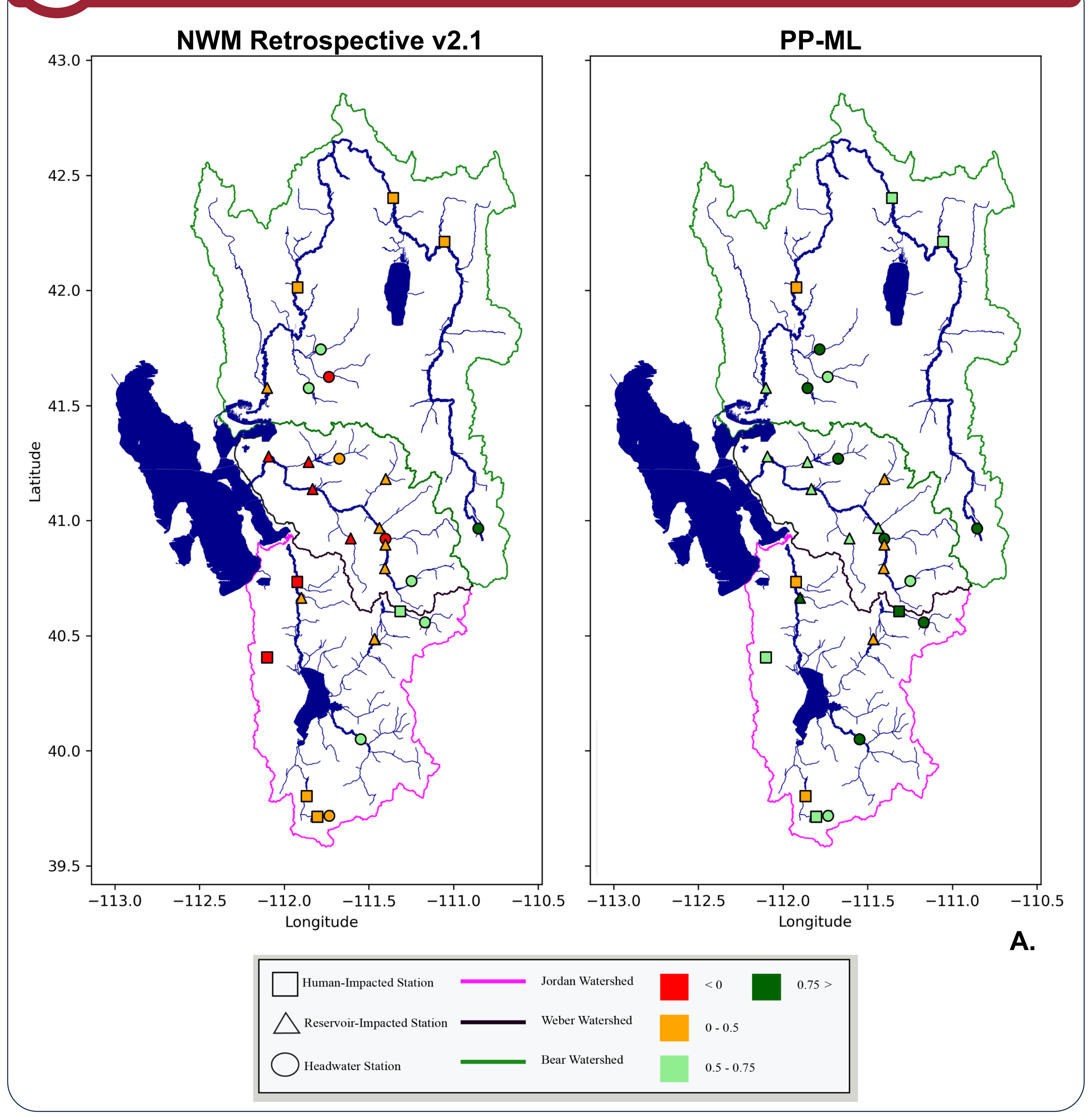
Hyperparameter Tunning
- Bayesian Optimization
- Cross-validation

Feature Analysis
- XGBoost Feature Importance

Model Training
- XGBoost
- Training: 2007 – 2020
- Testing: 1990 – 2006
- 30 stations.

Model Evaluation
- KGE, PBias, and RMSE
- Streamflow Regimes (Low, High, Normal)
- Feature Analysis
- Hydrological Signatures
- Drought Severity
- Transferability of the Framework

Results and Conclusions



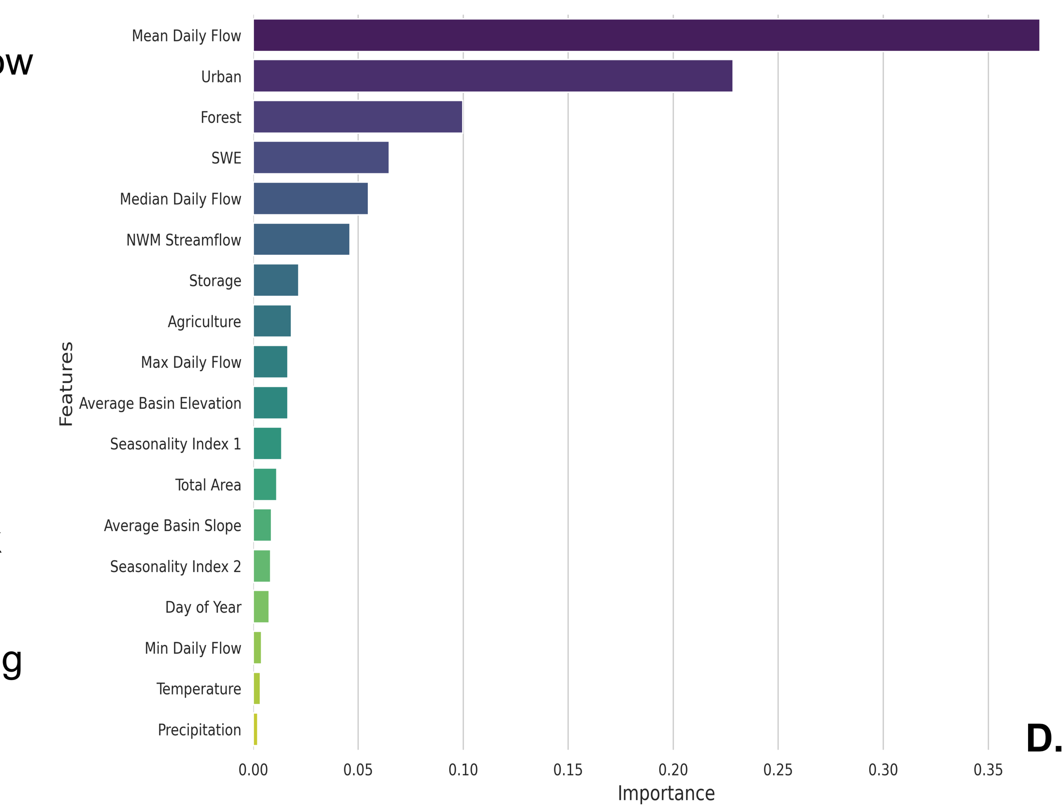
Station Type	Model Name	KGE				PBias				RMSE			
		All	Low Flow	Normal Flow	High Flow	All	Low Flow	Normal Flow	High Flow	All	Low Flow	Normal Flow	High Flow
All Stations	NWM	0.24	-5.72	-0.46	0.15	-27.04	-292.83	-43.11	5.76	5.32	3.32	2.70	11.02
	PP-ML	0.69	-1.76	-0.06	0.44	6.21	-53.58	-6.58	23.08	4	0.7	1.61	8.28
Headwater	NWM	0.55	-2.14	0.11	0.30	9.74	-56.71	-16.78	21.76	4.66	0.69	1.42	8.46
	PP-ML	0.78	-1.14	0.04	0.56	4.27	-31.2	-10.02	11.56	2.7	0.48	1.48	5.15
Human Impacted	NWM	0.26	-4.76	-0.67	-0.54	-25.74	-311.67	-63.56	19.44	10.12	5.4	5.61	18.73
	PP-ML	0.57	-1.97	-0.12	0.24	9.98	-52.85	-2.31	29.10	4.38	1.08	2.15	8.68
Reservoir Impacted	NWM	0.14	-15.31	-2.12	0.16	-48.94	-1104.6	-65.26	-18.78	6.38	4.36	5.41	11.12
	PP-ML	0.62	-6.91	-0.04	0.38	7.09	-113.4	-6.28	72.96	5.16	1.39	3.00	9.91

B.

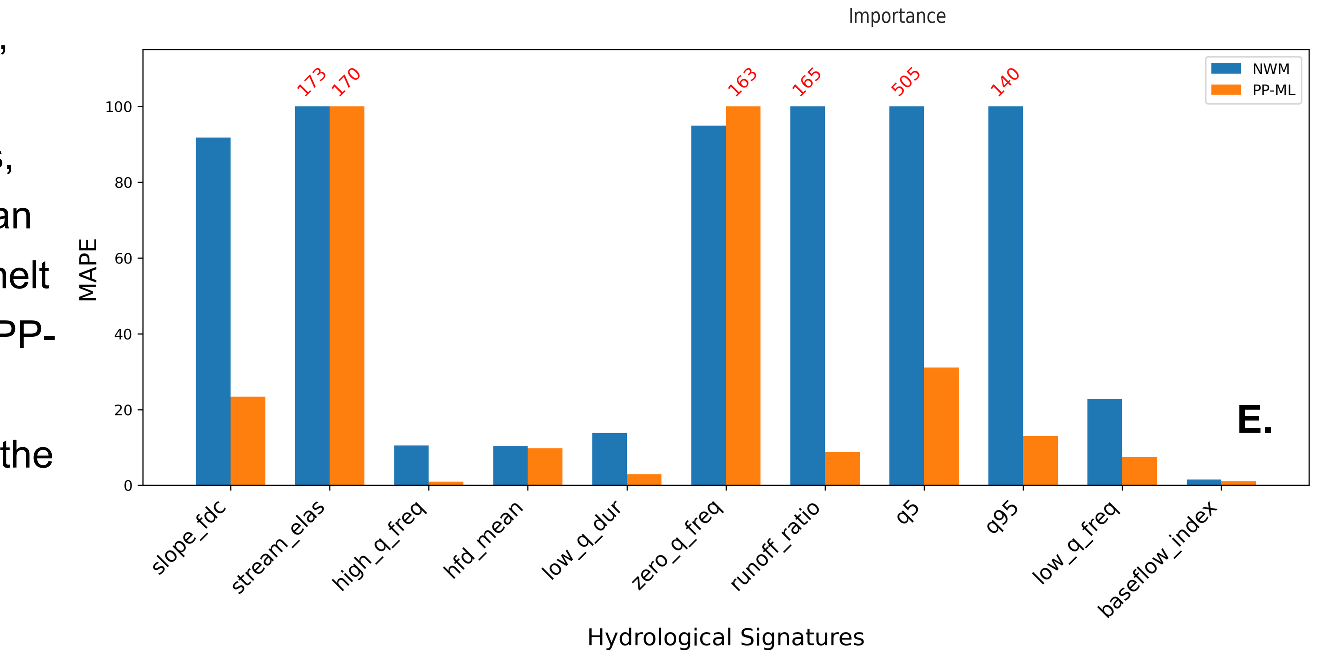
Station Type	Model Name	KGE		PBias		RMSE	
		Version 3.0	Version 2.1	Version 3.0	Version 2.1	Version 3.0	Version 2.1
All Stations	NWM	0.20	0.24	-20.76	-27.04	5.70	5.32
	PP-ML	0.68	0.69	5.37	6.21	3.86	4.00
Headwater	NWM	0.49	0.55	23.24	9.74	3.96	4.66
	PP-ML	0.77	0.78	3.11	4.27	2.54	2.70
Human Impacted	NWM	-0.13	0.26	-66.16	-25.74	12.88	10.12
	PP-ML	0.64	0.57	8.66	9.98	4.22	4.38
Reservoir Impacted	NWM	-0.03	0.14	-58.03	-48.94	8.07	6.38
	PP-ML	0.63	0.62	6.76	7.09	5.27	5.16

C.

A. The PP-ML model results for NWM v.2.1 show a significant improvement overall and among different station groups, including Headwater (HW), Human-Impacted (HI), and Reservoir-Impacted (RI). The number of stations with negative KGE decreases from eight to zero. **B.** The PP-ML model can improve all the flow regimes in NWM v2.1., particularly the low-flow regime in RI stations. **C.** The PP-ML framework can improve the results of different NWM versions, including v3.0, significantly highlighting its transferability to other hydrological models.



D. The PP-ML model shows SWE, reservoir storage, and catchment characteristics as important inputs, demonstrating that these inputs can help the model account for snowmelt and infrastructure impact. **E.** The PP-ML model can improve all the hydrological signatures, including the ones indicating low-flow intensity.



Key Findings:
- The prototype PP-ML model can learn dominant hydrological processes (e.g., snow-to-flow) and water regulation impact on streamflow to correct NWM streamflow for stations under various hydrological dynamics.
- PP-ML shows significant improvement in the low-flow regime and reservoir-impacted stations.
- The PP-ML model can comprehend the interaction between static and dynamic features.
- The PP-ML framework is transferable to different hydrological models.

Future Work will investigate other ML models to post-process monthly (sub-season) NWM predictions for water supply management. We will also expand our research area to other western regions, such as the Upper Colorado Basin.

Acknowledgments

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Savalan Naser Neisary

PP-ML GitHub