Improving Streamflow Predictions in the Dry Southwestern United States Through Understanding of Baseflow Generation Mechanisms

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1. Introduction & Objectives

Streamflow Prediction Challenges:

- Large-scale models, such as NOAA's NWM, struggle with streamflow predictions in arid southwestern U.S., often overestimating baseflow and failing to capture low-flow conditions.

Key Uncertainties:

- Inconsistent frameworks for flux and infiltration parameters.
- Overlooked soil structure impacts on infiltration and baseflow.
- Errors in precipitation data due to coarse spatial and temporal resolution.
- Limited ability of precipitation to capture localized extreme events critical for recharge.

Hypothesis:

- Baseflow generation processes in hydrological models significantly contribute to streamflow prediction inaccuracies

Objective:

- Provide guidance for selecting reliable hydrological schemes and datasets to improve streamflow predictions in dry regions.

2. Methodology

Model Setup

- Enhanced Noah-MP:
  - Mixed-form Richards equation down to bedrock.
  - Single and dual-permeability physics for macropore flow.
  - Surface ponding thresholds for improved infiltration modeling.
- Coupled Model:
  - Noah-MP outputs routed through RAPID for daily streamflow predictions

Category	Experiment name	Soil Moisture Solver	Ponding depth (mm)	Soil Hydraulics	Forcing	Soil Water Retention Characteristics Parameters
Hydrological Process	CH	Mixed Form RE	50	Brooks-Corey/Clapp-Hornberger	NLDAS-2	Noah-MP Table
	VGM	Mixed Form RE	50	Van-Genuchten		
	VGM0	Mixed Form RE	0	Van-Genuchten		
	DPM	Dual Permeability, Mixed Form RE	50	Van-Genuchten		
Hydraulic Parameters	ML	Mixed Form RE	50	Van-Genuchten	NLDAS-2	ML-Based (Gupta et al., 2022)
	PTF50	Mixed Form RE	50			PFT (Wösten et al., 1999)
	DPMPTF0	Dual Permeability, Mixed Form RE	0			PFT (Wösten et al., 1999)
Precipitation	NLDAS	Mixed Form RE	50	Van-Genuchten	NLDAS-2	Noah-MP Table
	IMERG				NLDAS-2, IMERG	
	AORC				NLDAS-2, AORC	

Table 1. Model Experiments configurations. The surface and subsurface runoff generated from these excrements were routed using RAPID to compute daily streamflow

Metrics:

- Compared Baseflow Index (BFI) from Noah-MP-RAPID and NWM against USGS-derived BFI.
- Assessed streamflow predictions using Kling-Gupta Efficiency (KGE) and low-flow RMSE metrics.

3. Results

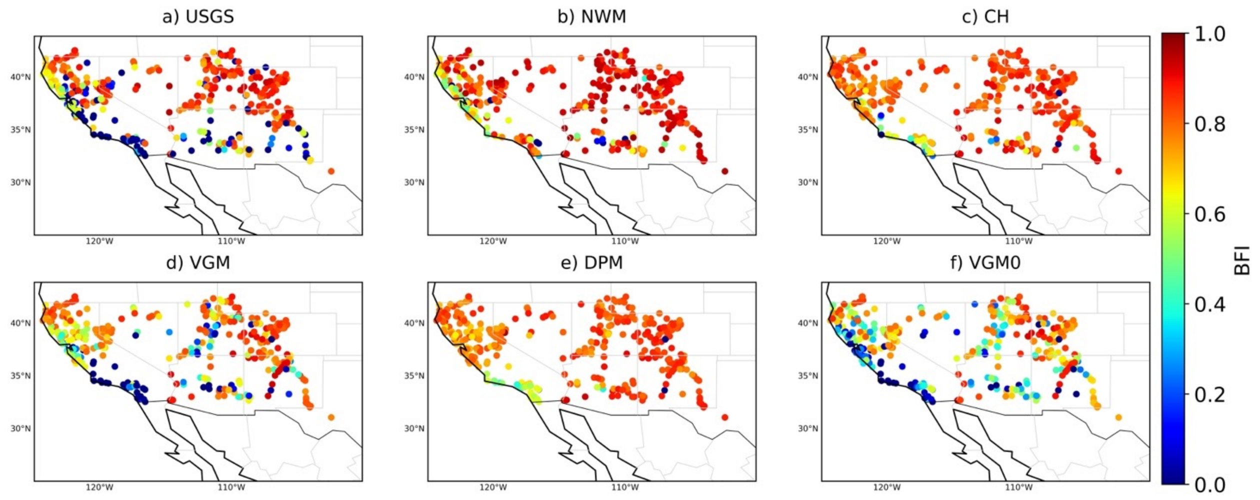

Fig. 1. BFI at 390 gauges (a) derived from USGS gauges (median of 0.78) and those from models (b) NWM (median of 0.88); (c) CH (median of 0.82) (50 mm ponding); (d) VGM (median of 0.78) (50 mm ponding); (e) DPM (median of 0.81); and (f) VGM0 (median of 0.76) (0 ponding).

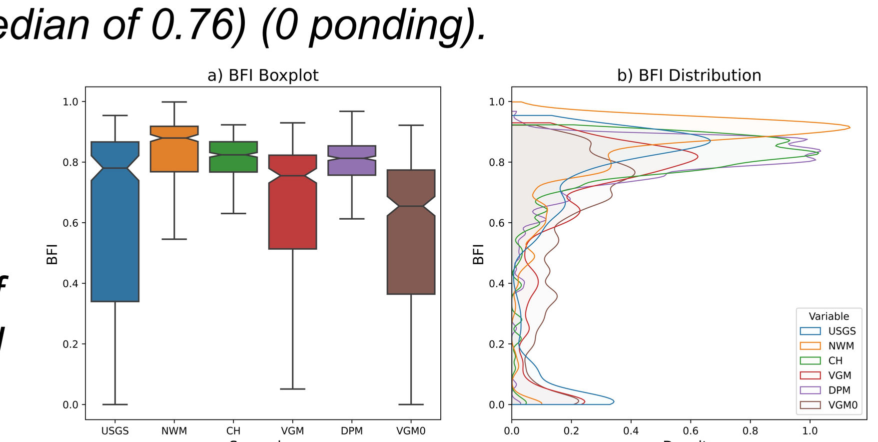

Fig. 2. Boxplot (a) and distribution (b) of BFI for USGS, NWM, VGM, DPM, and VGM0.

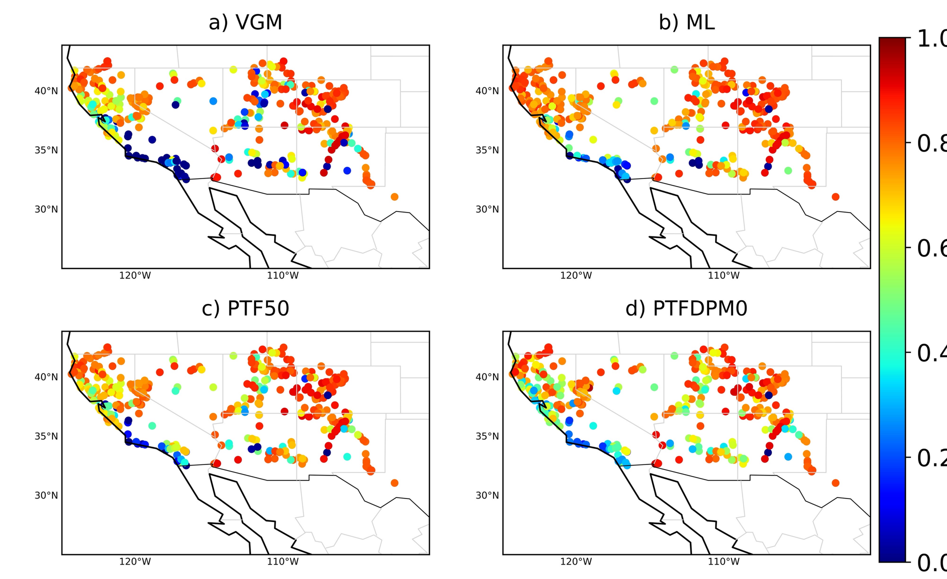

Fig. 3. BFI at 390 gauges (a) derived from VGM (median of 0.78) (50 mm ponding); (b) ML (median of 0.78); (c) PTF50 (median of 0.78); and (d) PTFDPM0 (median of 0.74).

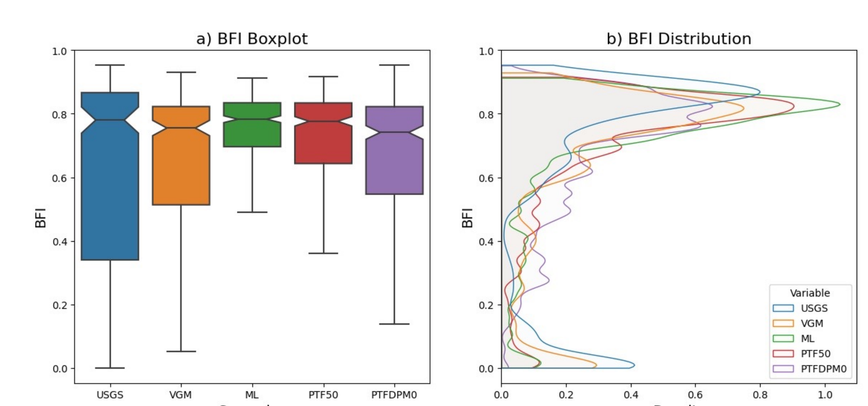

Fig. 4. Boxplot (a) and distribution (b) of BFI for USGS, VGM, and ML-derived and PTF-derived soil hydraulic parameter experiments.

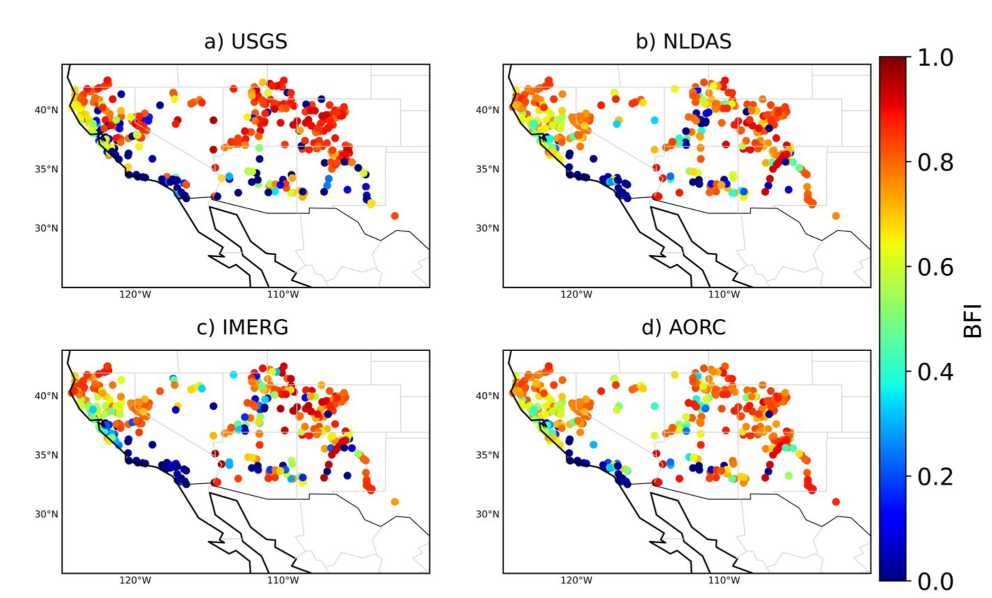

Fig. 5. BFI at 390 gauges (a) USGS (median of 0.78); (b) (b) NLDAS (median of 0.76); (c) IMERG (median of 0.74); and (d) AORC (median of 0.77).

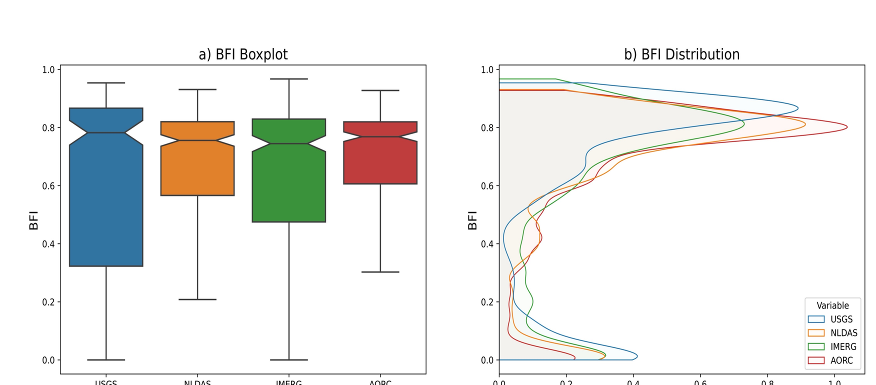

Fig. 6. Boxplot (a) and distribution (b) of BFI for USGS, NLDAS, and IMERG and AORC precipitation experiments.

4. Results

Scenario	Median KGE	Number of stations with positive KGE	Low flow RMSE
NWM	0.16	221	2.35
CH	0.17	227	2.07
VGM	0.28	257	1.62
DPM	0.21	229	1.77
VGM0	0.13	211	2.50
ML	0.29	272	1.57
PTF50	0.28	257	1.62
PTFDPM0	0.06	200	2.62

Table 2. Median KGE, Number of stations with positive KGE, and low flow RMSE for scenarios covering 1980-2019.

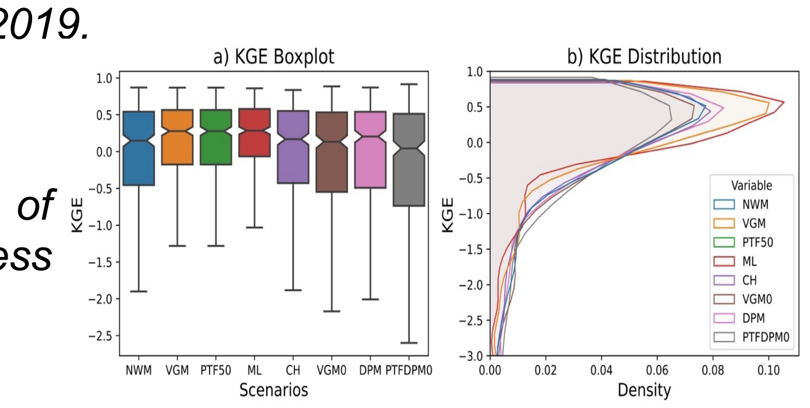

Fig. 7. Boxplot (a) and Distribution of KGE for NWM, and physical process and hydraulic parameter scenarios

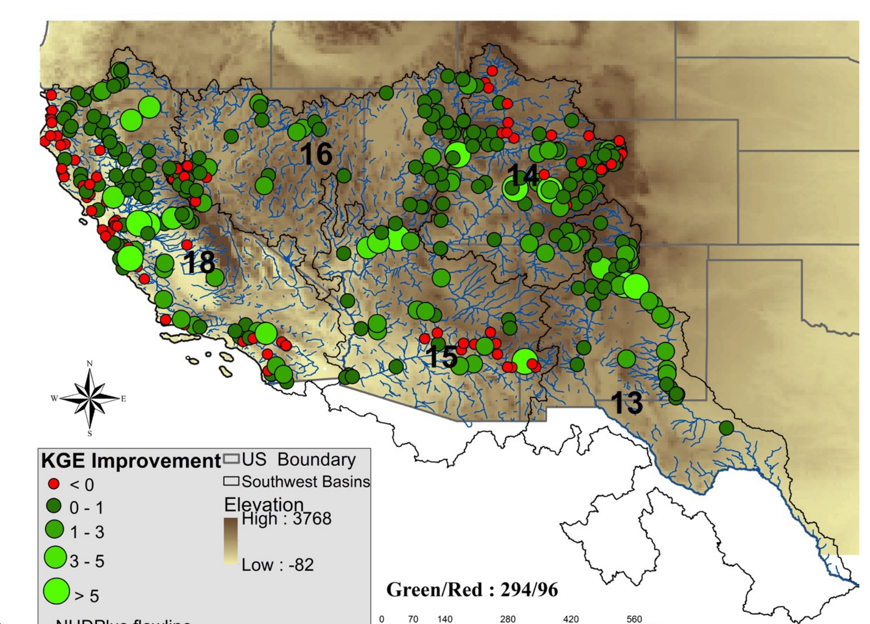

Fig. 8. Streamflow KGE Improvement of the VGM with machine learning (ML) based hydraulic parameters and ***NLDAS-2 precipitation*** *against NWM.*

The ML-based hydraulic parameters performs better than the optimized NWM by a median KGE of 21%

5. Conclusion

- **Improving baseflow representation in hydrological models like Noah-MP leads to better streamflow predictions in the arid southwestern U.S.**
- The Van Genuchten hydraulic scheme (VGM) outperformed Brooks-Corey (CH), reducing BFI overestimation and improving groundwater recharge modeling.
- ML-derived parameters significantly improved streamflow predictions, achieving better alignment with observed data than lookup tables or pedotransfer functions.
- Macropores enhanced baseflow in wet regions but caused overestimation in low-BFI areas, highlighting the need for calibration.
- Ponding depth thresholds increased infiltration and recharge, particularly in wet regions, improving baseflow accuracy.
- High-resolution datasets like IMERG provided the best baseflow predictions, outperforming traditional datasets (e.g., NLDAS-2) by better capturing localized rainfall events and their impacts on recharge.

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