Supplement of Hydrol. Earth Syst. Sci., 30, 5173–5193, 2026
https://doi.org/10.5194/hess-30-5173-2026-supplement

Hydrology and Earth System Sciences
Open Access

Supplement of

An argument for parsimony in differentiable hydrologic models

Sandeep Poudel and Scott Steinschneider

Correspondence to: Sandeep Poudel (sp2596@cornell.edu)

S1: Ensemble MLP-based differentiable model trained and tested on the same period as Feng et al. (2022)

In the main article, we used a different training and testing period than Feng et al. (2022). It is worth noting, however, that there is no consistent temporal split among reference studies. For instance, Feng et al. (2022) trained on 1980–1995 and tested out-of-sample in time for 1995–2010, while Feng et al. (2023) used a different training period (1989–1999) for out-of-sample-in-space evaluation. Nonetheless, we also trained and evaluated the ensemble-based MLP differentiable model using the same periods as Feng et al. (2022), and the results are consistent with those reported in the main article (Figure S1).

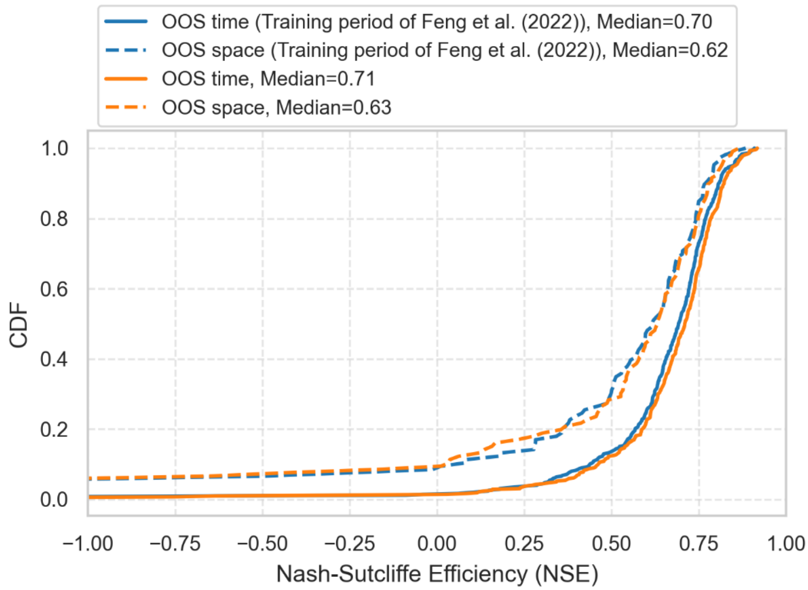

Figure S1: Cumulative distributions of Nash-Sutcliffe Efficiency (NSE) for out-of-sample in time and out-of-sample in space evaluations of MLP-based differentiable model architecture using training and testing period of 1990-2005 and 1980-7989 as used in our main article versus 1980-1995 and 1995-2010 used in Feng et al. (2022).

S2: Model simulation using a stride length of 1 day

In the main article, results are presented using a stride length of 60 days, meaning parameters are allowed to vary every 60 days. This choice was made because no improvement in validation performance was observed when using strides shorter than 60 days. Here we present additional results using a stride of 1 day, where the estimated process-based model parameters are allowed to vary at every time step. The results for both the temporal variability of process-based parameters (Figure S2) and the performance comparison of time-varying parameters against a single parameter set from the last time step (Figure S3) are consistent with those obtained using a 60-day stride in the main article.

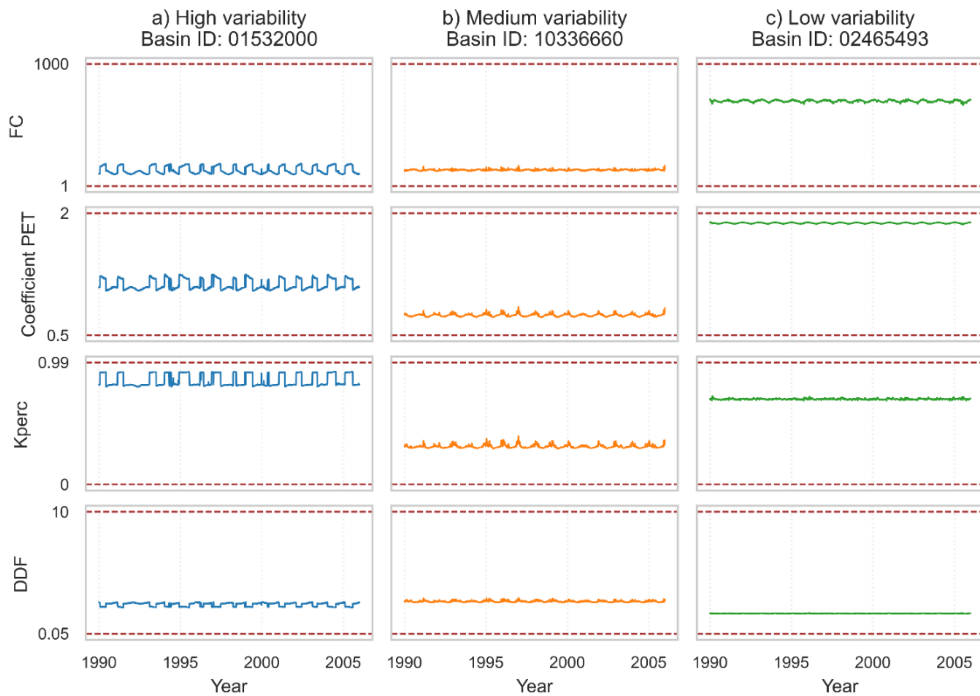

Figure S2: Temporal variability of four selected HBV parameters inferred by the LSTM+HBV differentiable model for basins exhibiting (a) high, (b) medium, and (c) low average coefficients of variation. The red dashed line shows the lower and upper bound for each parameter. These results are for a model with a stride of 1 day (i.e., parameters vary each day), compared to a stride of 60 days, which was used in the main article and shown in Figure 7.

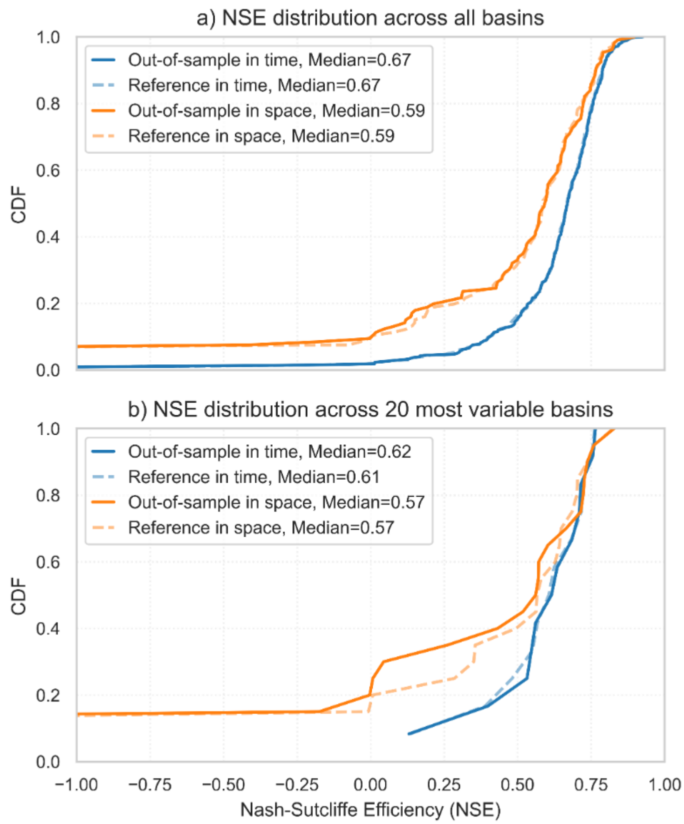

Figure S3: Cumulative distributions of NSE for out-of-sample in time and out-of-sample in space evaluations for the differentiable LSTM+HBV model using time-varying parameters for (a) all study basins, and (b) the 20 basins with highest parameter variability. Dotted lines indicate reference performance using a single static parameter from the final LSTM time step. These results are for a model with a stride of 1 day (i.e., parameters vary each day), compared to a stride of 60 days, which was used in the main article and shown in Figure 8.

References

Feng, D., Liu, J., Lawson, K., & Shen, C. (2022). Differentiable, Learnable, Regionalized Process-Based Models With Multiphysical Outputs can Approach State-Of-The-Art Hydrologic Prediction Accuracy. Water Resources Research, 58(10), e2022WR032404. https://doi.org/10.1029/2022WR032404

Feng, D., Beck, H., Lawson, K., & Shen, C. (2023). The suitability of differentiable, physics-informed machine learning hydrologic models for ungauged regions and climate change impact assessment. Hydrology and Earth System Sciences, 27(12), 2357–2373. https://doi.org/10.5194/hess-27-2357-2023