Data-driven Model Selection in the Next Generation Water Resources Modeling Framework

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Motivation

The modular design of the Next Generation Water Resources Modeling Framework (Nextgen; Ogden et al., 2021) provides a model agnostic platform to mosaic multiple hydrologic models for one modeling task and evaluate their performance using a unifying structure and standard, yet there is no existing methodology for choosing an optimal model (or models) for a given catchment in Nextgen.

The goal is to inform user's decisions about model selection and avoid favoring models that are readily available or that users are familiar with. Ideally, a model selection method would eliminate the need to run several models in order to choose the optimal candidate(s).

Objectives

- Provide a model selection method for Nextgen that is:
  - Adaptable to incorporation of new hydrologic models
  - Applicable to prediction in ungauged basins (PUB)
  - Inclusive of ensemble modeling methods

Methodology

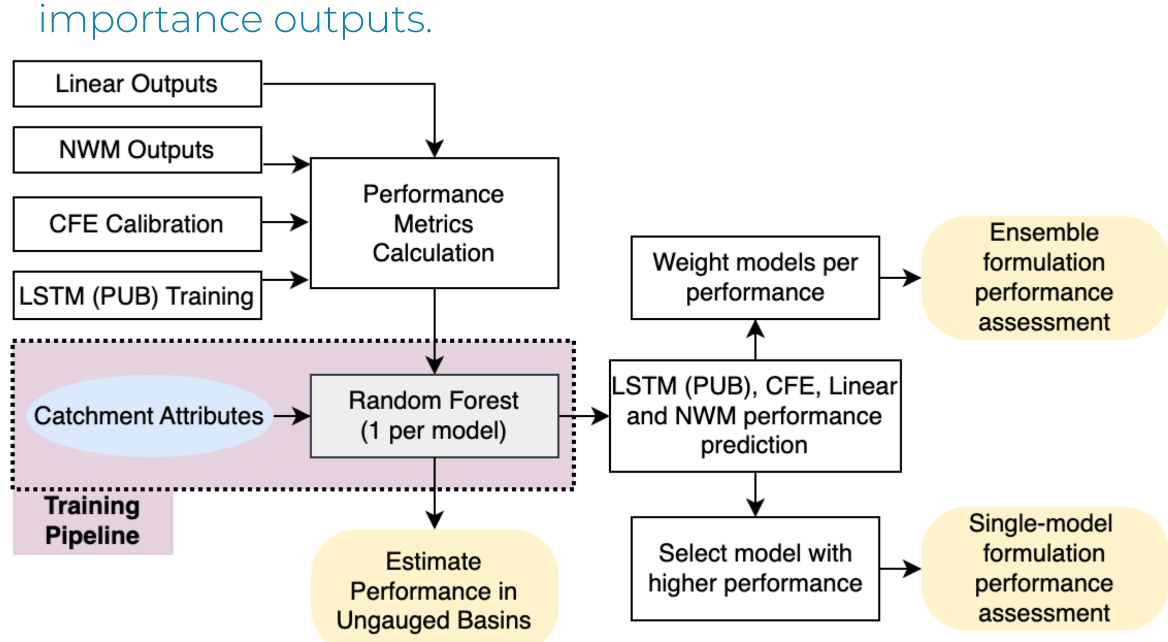
We trained/calibrated and tested/ran 4 models for 495 basins across the US.

We trained a random forest regressor (RFR) to predict normalized Nash-Sutcliffe Efficiency (NNSE) scores for all models using catchment attributes from the CAMELS dataset (Newman et al. 2015, Addor et al. 2017).

$$NNSE = \frac{1.0}{2.0 - NSE}$$

NNSE of 0.5 is equivalent to NSE of 0

We evaluated the accuracy of the RFR predictions compared to actual model performance and evaluated which models perform well in catchments with different climatic and physiographic features using RFR feature importance outputs.



Results: Random Forest Model Selection

Using catchment attributes such as aridity index, soil clay fraction, and percent forest cover, we trained a random forest regressor to predict normalized NSE of 4 hourly rainfall-runoff models, one deep learning model (LSTM) making predictions in ungauged basins (PUB), one autoregressive linear model (Linear), the National Water Model version 2.0 (NWM), and a conceptual model that simplifies the runoff schemes of NWM (CFE).

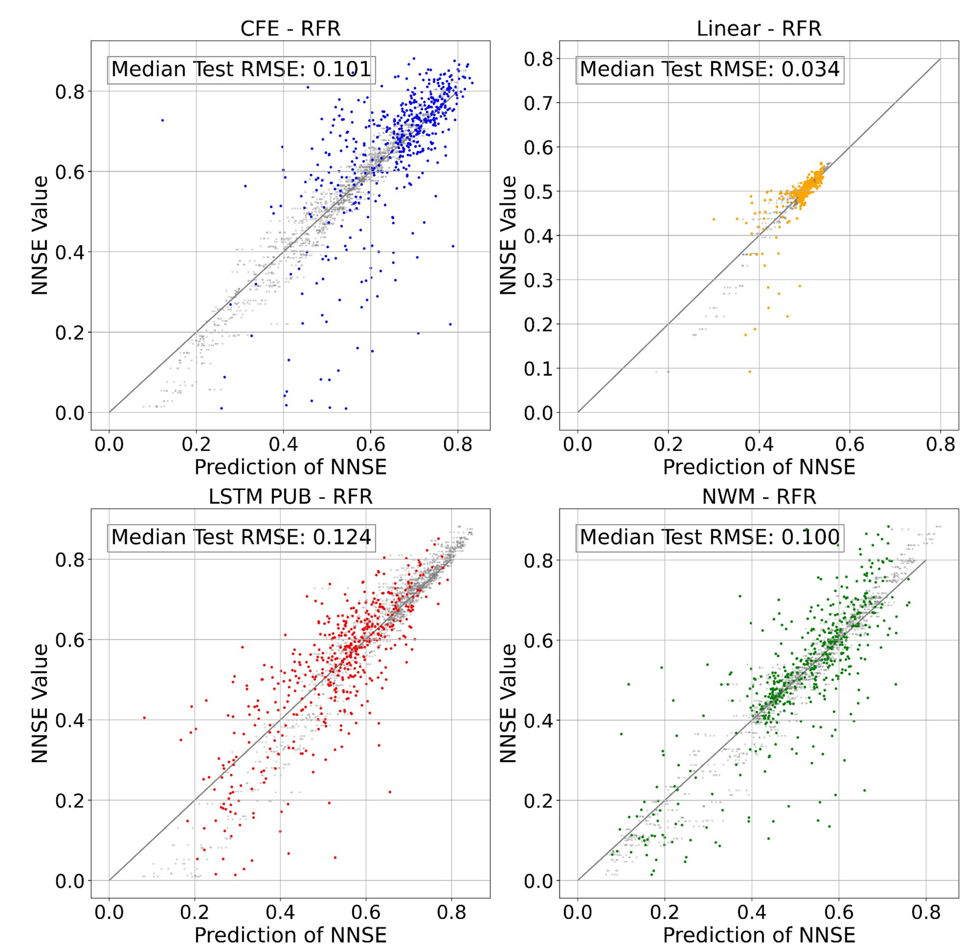


Figure 1. *Comparison of actual model performances and performances predicted by the RFR.*

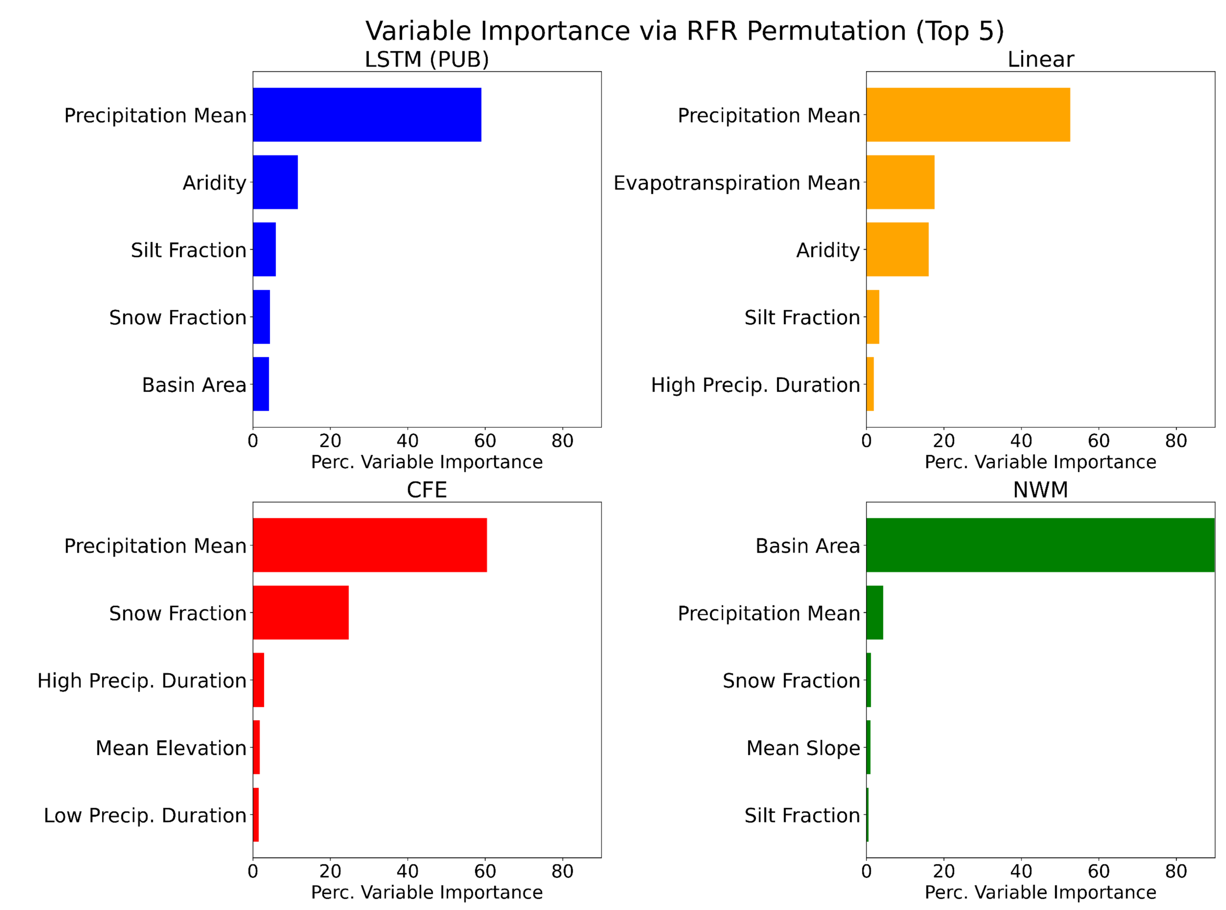
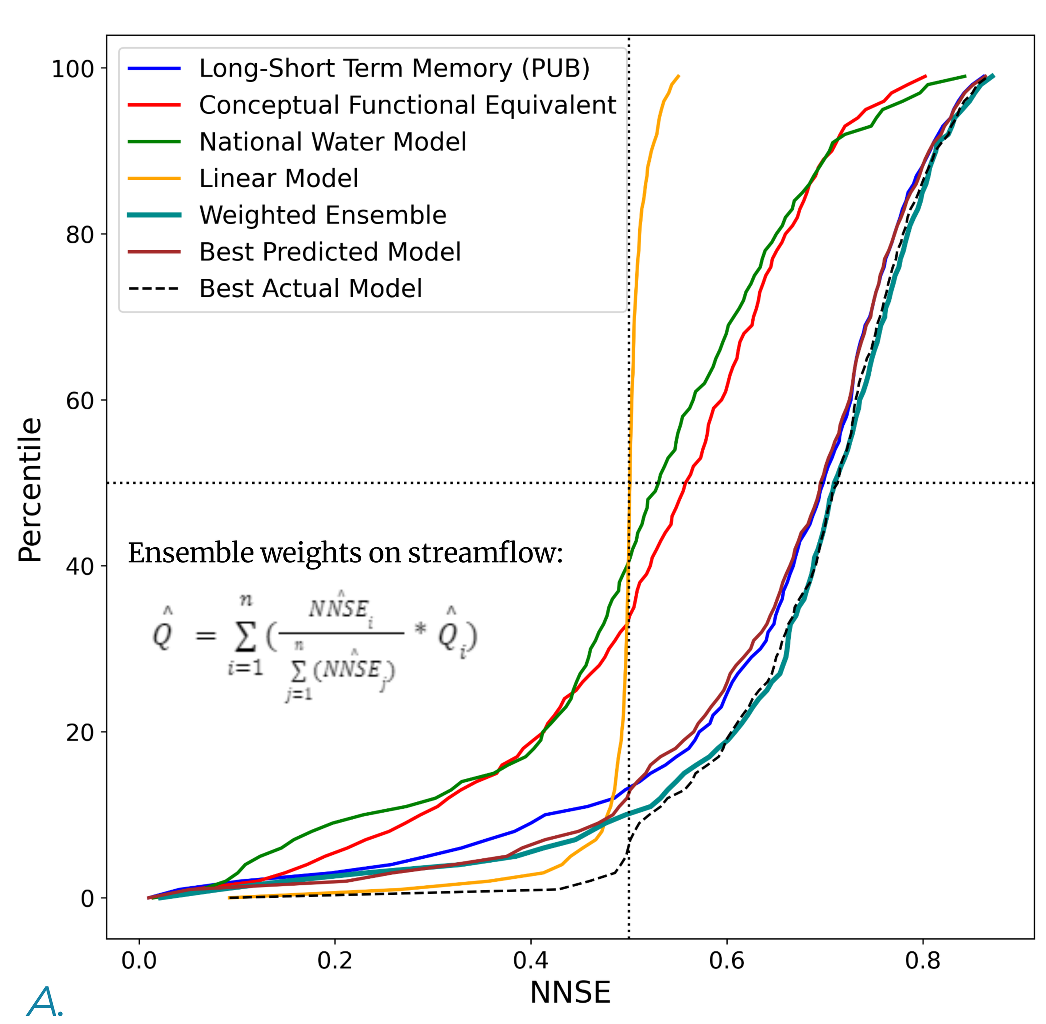


Figure 2. *The top 5 most important catchment attributes for the accuracy of predicted model performances by the RFR.*

Results: Weighted Ensemble Models

- LSTM (PUB) has the highest performance in several cases
- The best predicted model by the RFR is very close to LSTM (PUB)
- Ensemble models weighted based on RFR predicted model performances performed similarly to the best actual model, and in some cases improved overall performance beyond that of any individual model



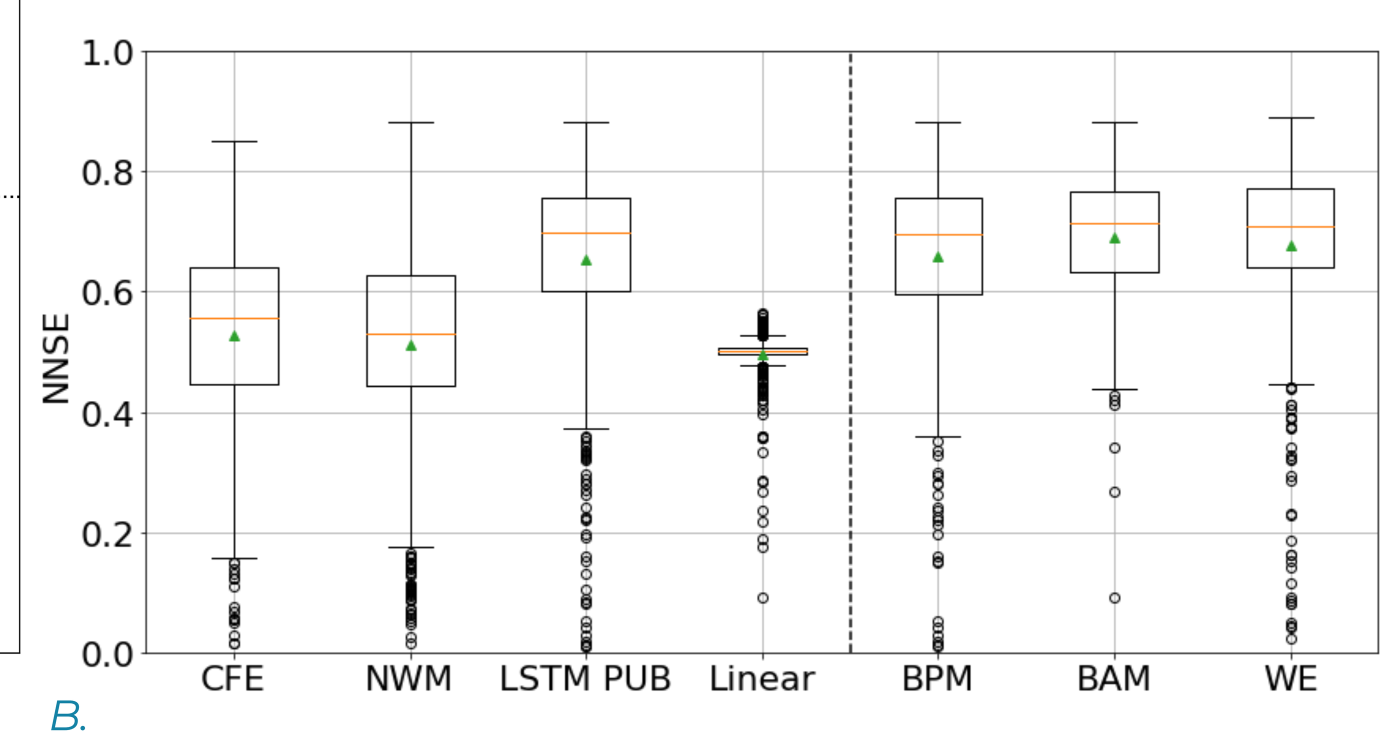
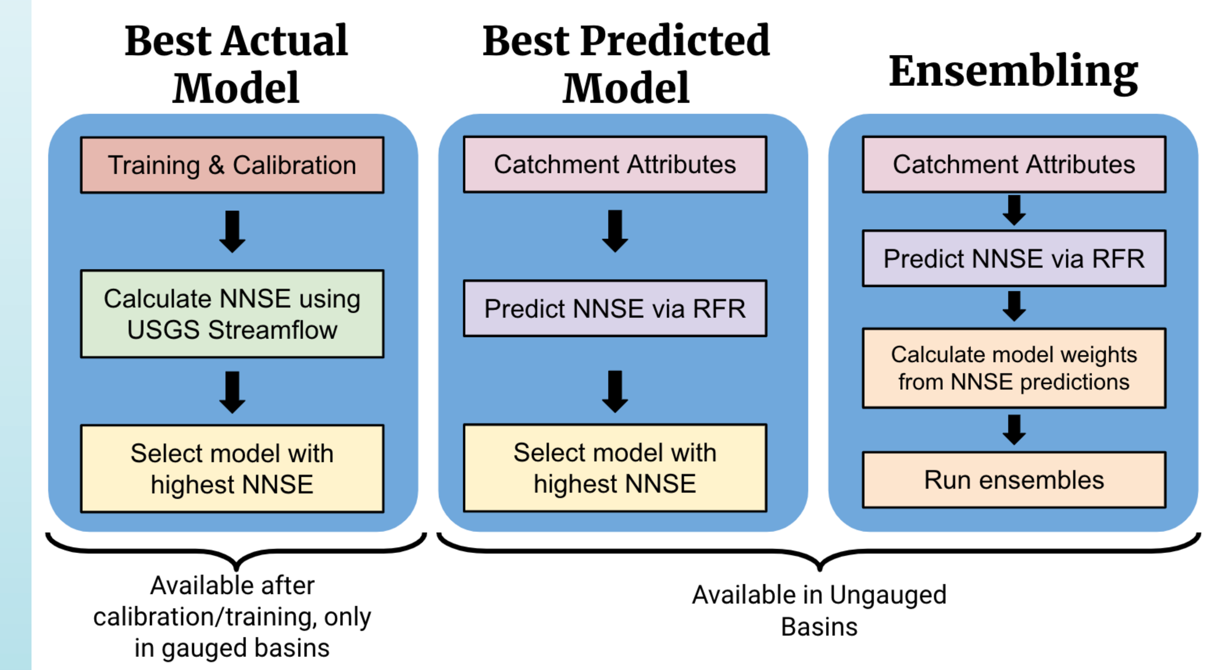


Figure 3. Cumulative distribution function (left, A) and boxplot (below, B) of all individual models, the best actual model for each watershed, the best predicted model for each watershed by the RFR, and ensemble models using weights derived from RFR model performance predictions.

Evaluation of Model Selection Results

We compared: the best actual model (calibrated/trained and run for all basins with performance determined compared to streamflow observations), the best predicted model by the RFR, and an ensemble of models weighted based on each individual model's RFR predicted NNSE.



Conclusion

We developed a data-based model selection method that predicts model performance reasonably well for application in ungauged basins. Future work will further develop the method to promote prediction in ungauged basins. Additionally, we created the method to be adaptable to the addition of new candidate models and new watersheds of interest, given that the catchment attributes we used for the CAMELS watersheds will be available for other watersheds as a part of Nextgen.

We found that in cases where two models perform similarly, weighting the predicted streamflow timeseries from both models according to their predicted NNSE by the random forest regressor improved performance beyond that of either individual model.

Acknowledgements & References

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1. Ogden, F. L. et al. (2021), The next generation water resources modeling framework: Open source, standards based, community accessible, model interoperability for large scale water prediction, Abstract (H43D-01) presented at 2021 AGU Fall Meeting, 13-17 Dec.
2. Addor, N. et al. (2017) The CAMELS Data Set: Catchment Attributes and Meteorology for Large-Sample Studies. Hydrol. Earth Syst. Sci. 21.
3. Newman, A. J. et al. (2015). Development of a Large-Sample Watershed-Scale Hydrometeorological Data Set for the Contiguous USA: Data Set Characteristics and Assessment of Regional Variability in Hydrologic Model Performance. Hydrol. Earth Syst. Sci. 19 (1), 209–223.

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