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Enabling Community Contributions in Formulation Selection Decision Support for Continental Hydrologic Modeling

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How might we understand where streamflow predictive models work well or poorly for NextGen?

The **R**egionalization **and** **F**ormulations **T**esting & **S**election (**RaFTS**) analysis framework trains machine learning models on catchment attributes to make predictions on:

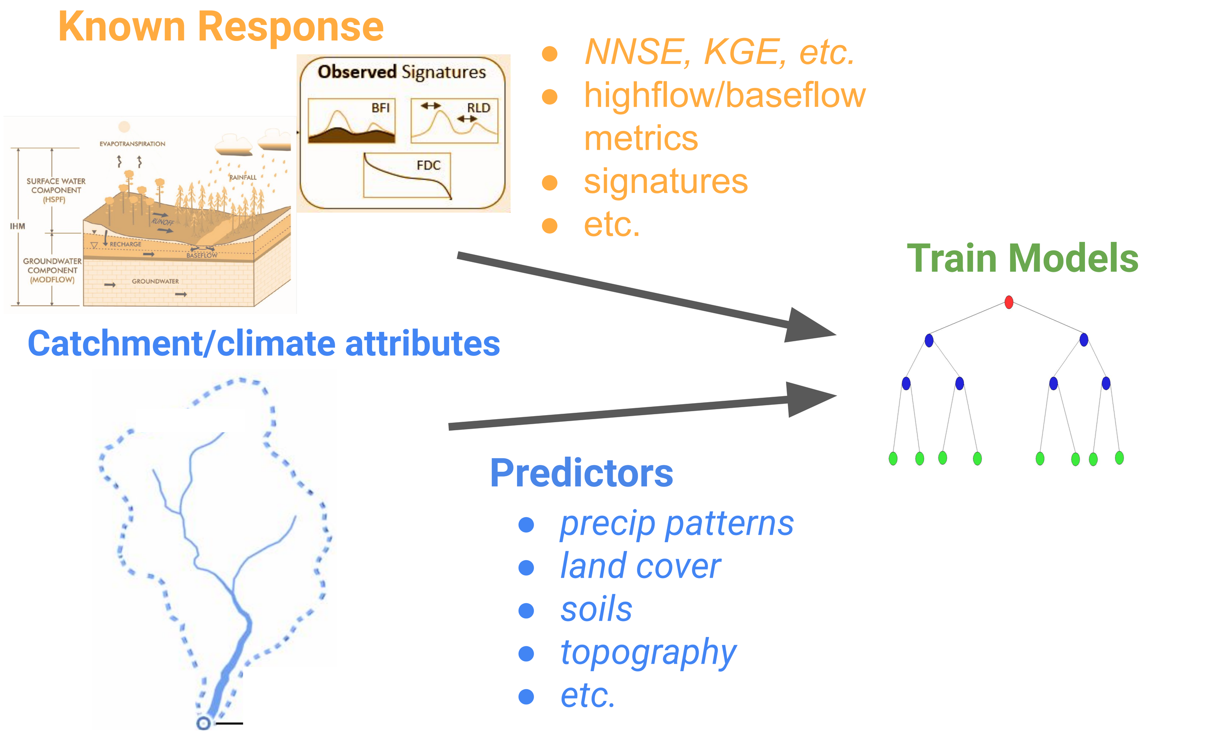
1. Estimated hydrologic formulation performance (e.g. KGE, NNSE) (Frame et al., in-review)
2. Dominant processes (e.g. Sobol' Senstivity)
3. Hydrologic signatures (e.g. runoff ratio, FDC midsegment slope)

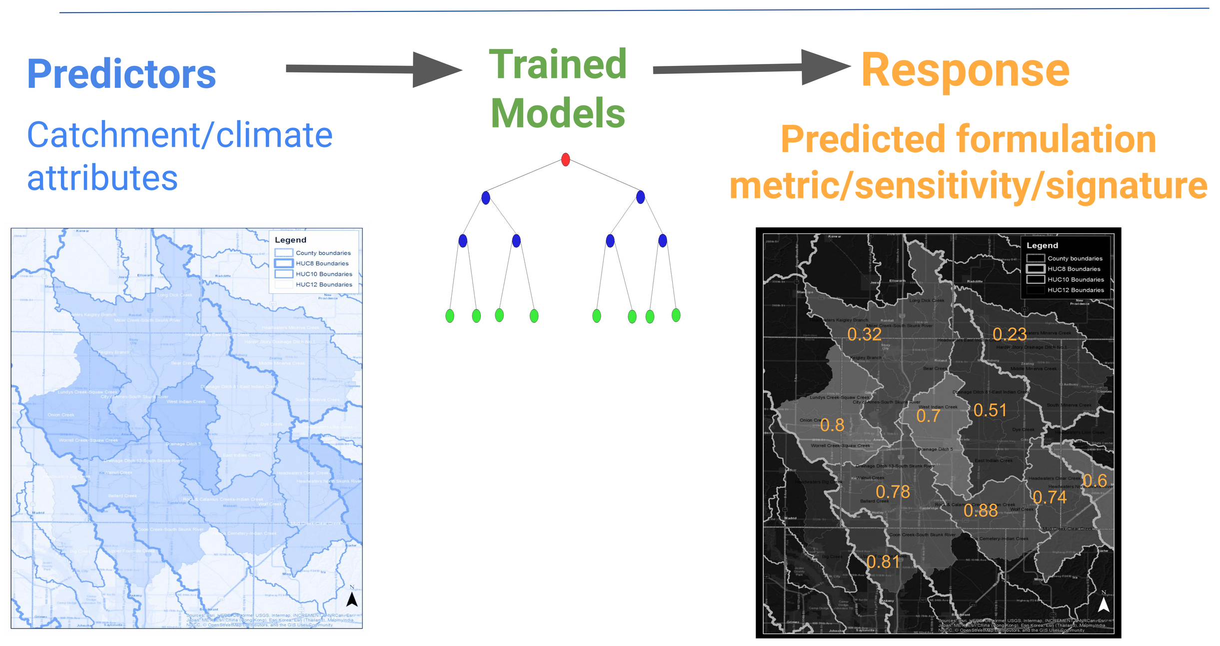
RaFTS relies on publicly available datasets:

1. Catchment attributes (e.g. NHDplus, hydroatlas)
2. Continental-scale reference catchments commonly modeled (e.g. CAMELS - Addor et al 2017)
3. Published hydrologic model results (e.g. Kratzert et al, 2019, Mai et al, 2022)

RaFTS enables hydrologic data-informed decision making across the hydrofabric: >800k catchments across CONUS + AK, HI, & PR

How RaFTS makes predictions

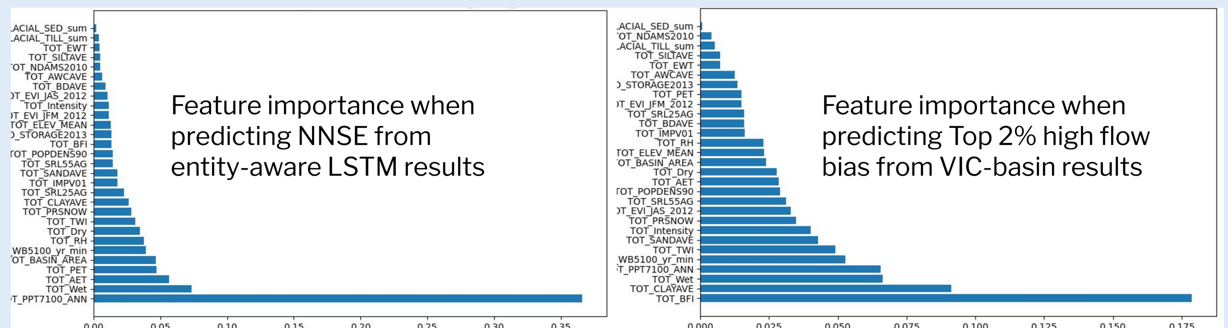




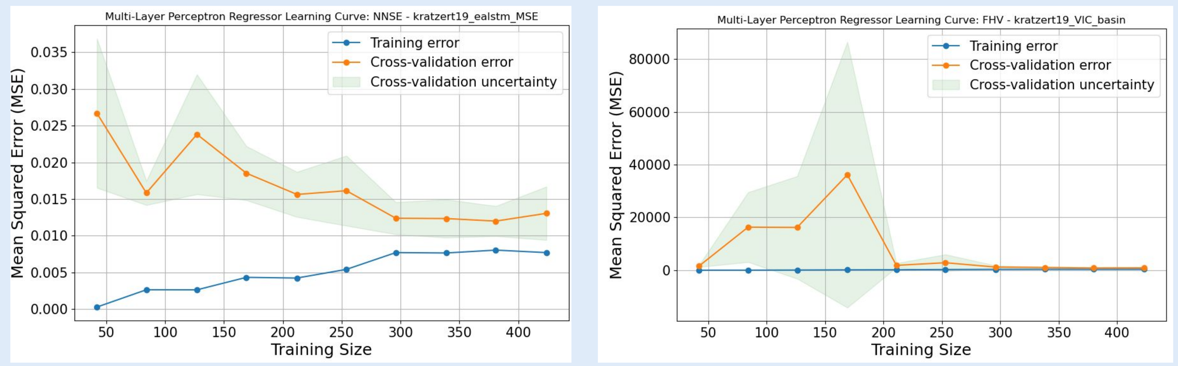
RaFTS: Open-source analytics tool for hydrologic model regionalization & decision making

Data-informed NextGen formulation selection

The importance of catchment attribute data vary by what's being predicted:



The amount of catchments needed to train a machine-learning model vary by what's being predicted:



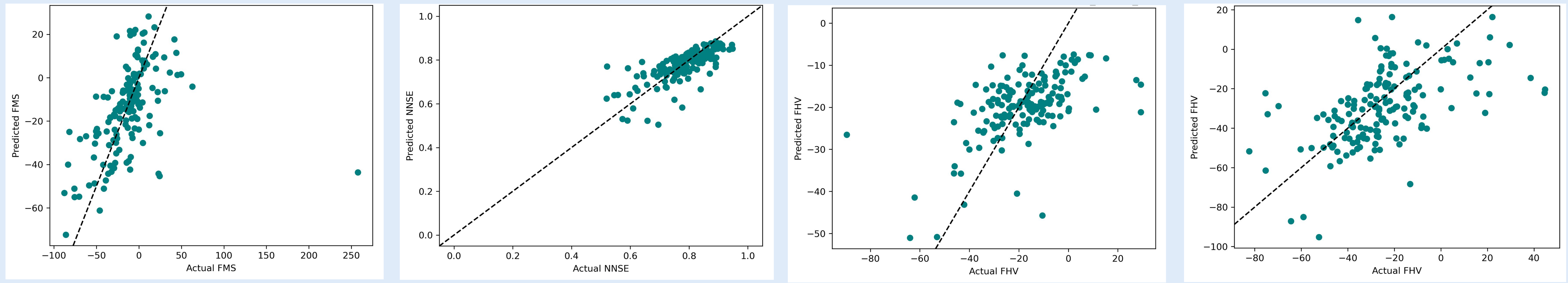
Not all metrics or signatures are predictable with a given dataset:

Bias of FDC midsegment slope, Entity-aware LSTM test dataset predicted vs observed, multilayer perceptron

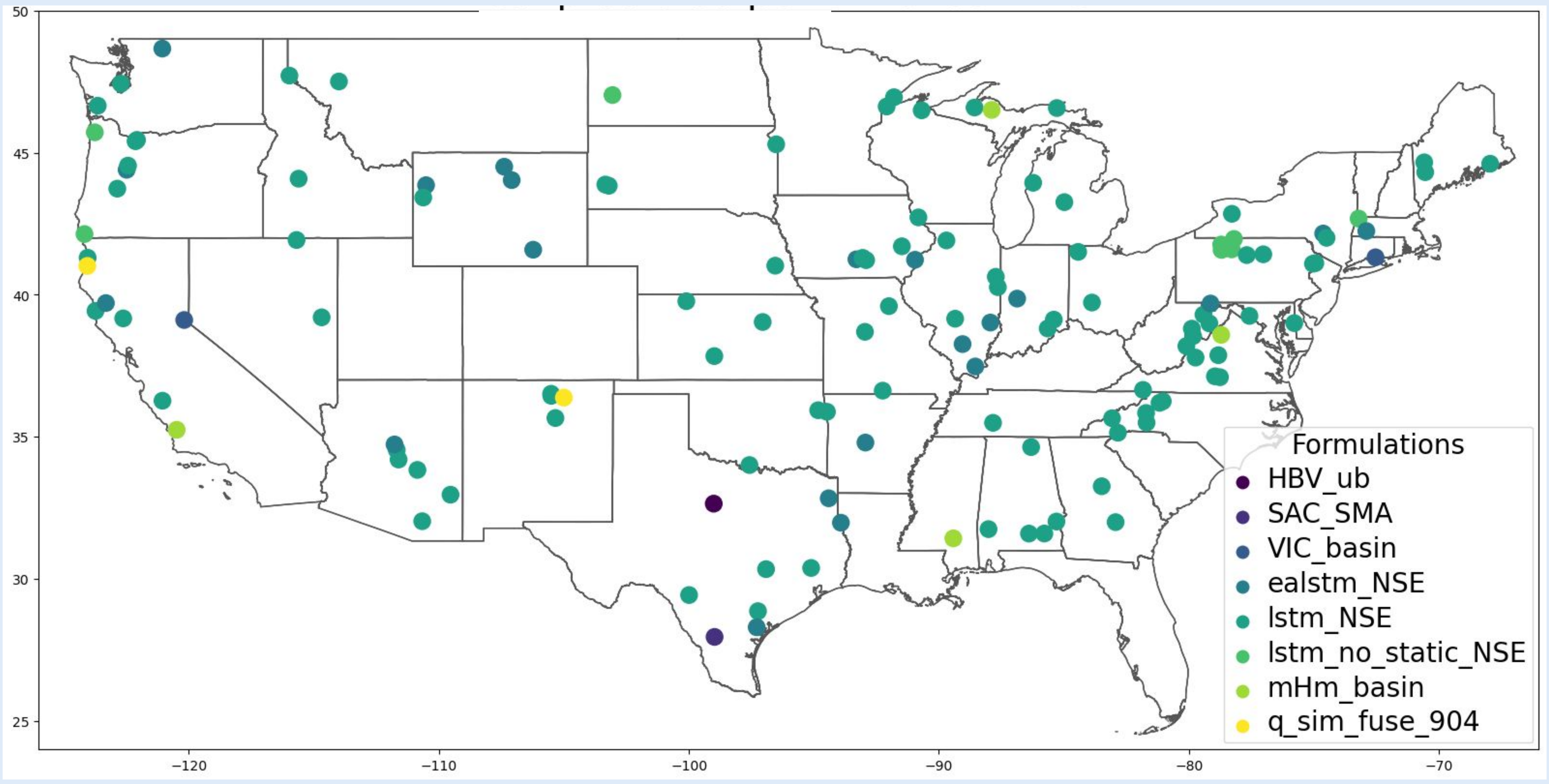
NNSE, Entity-aware LSTM test dataset predicted vs observed, random forest

Top 2% peak flow flow bias, Entity-aware LSTM test dataset predicted vs observed, multilayer perceptron (*Poor predictability*)

Top 2% peak flow bias, VIC basin validation dataset predicted vs observed, multilayer perceptron



The hydrologic formulations with the RaFTS best-predicted normalized Nash Sutcliffe Efficiency:



Current RaFTS Capabilities

- Standardize predictor datasets (e.g. metrics, hydrologic signatures)
- Retrieve and standardize basin attributes
  - USGS NHDplus attributes
  - hydroatlas
- Aggregate/transform standardized attributes
- Train machine learning models on attributes and predictors
  - Random Forest
  - Multi-layer Perceptron
- Grid search hyperparameter optimization
- Evaluate input datasets
  - Principal component analysis
  - Feature importance
- Evaluate machine learning results
  - Learning curve
  - Testing vs. observed regression
  - Prediction maps
- Make predictions in any basin with a USGS comid and retrievable basin attributes

Open source development of RaFTS for community use:
https://github.com/NOAA-OWP/formulation-selector

Possible Future Work:

- Uncertainty quantification
- Containerization
- Optimal best model(s) selector
- Regional-scale analyses
- Cloud-hosted data

Summary

Community-contributed outcomes from continental-scale hydrologic modeling results further improves data-informed decision making using RaFTS, an analysis framework for the community.

RaFTS can predict which hydrologic models may perform best based on a variety of metrics, such as NSE, KGE, high-flow metrics, baseflow metrics, etc, but ***requires careful assessment of appropriate predictive ML models.***

Future applications to RaFTS might:

- Decide which processes should be represented & where, in process-based hydrologic models
- Constrain parameter sets following calibration via hydrologic signatures
- Automate decision-making on regionalization strategies

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formulation-selector repo: