Evaluation of a Gaussian regression based streamflow postprocessor using simulated streamflows for test basins in the southeast U.S.

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Research Problem Definition

- Quantify the predictive uncertainty of a hydrologic model simulation, i.e., conditional distribution of observed flow given simulation , *f*(obs|sim)
  - ensemble members vs. quantiles of the conditional distribution
  - parametric vs. non parametric methods

- Key requirements
  - produce flow ensembles
  - preserve the skill that is present in simulation
  - correct systematic and conditional biases
  - generate reliable ensemble streamflows that discriminate events vs. non-events

Gaussian Regression Technique

- The *f*(obs|sim) is modeled in normal space via simple linear regression (Seo, et al., 2006)

  observation = *f* (simulation, recent observation)

- Calibration

  - Convert flow variables into normal variates via NQT
  - Develop a regression in normal space

  $$Z_{obs,t} = (1\text{-}b_t)\, Z_{obs,\,t\text{-}1} + b_t\, Z_{sim,\,t} + E_t$$

  $Z_{obs,t}$ – observed flow ; $Z_{obs,\,t\text{-}1}$ – prior observed flow;

  $Z_{sim,\,t}$ – simulated flow; E_t – Error; b_t – regression parameter

  - Estimate ‘b’ in normal space by minimizing CRPS of ensemble flow simulations in the original flow space

Gaussian Regression Technique

- Account for some dependency between $Z_{obs,\, t-1}$ and E_t
- Classify simulated flows into different groups, then calibrate the technique separately for each group
- For NQT modeling, use hyperbolic approximation (λ and ω parameters) for the uppermost–tail of the flow distribution (Deutsch and Journel, 1992)

- Operational considerations:
  - Simple technique
  - Data-driven and parsimonious

Application of the technique

- 12 test locations (here 4 locations in NC, MD, TX, MO)
- 9 model simulations (here sac, prms and multi-model mean)
- Period of the record
  - January 1, 1962 – December 31, 1997 (36 years)
- Calibration scheme
  - Two categories: flow threshold is 90th percentile of sample climatology
- Evaluation (against raw simulations)
  - Dependent validation (36 years)
  - Leave-one year out cross-validation (36 years)
- Verification metrics
  - Correlation, Relative Mean Error and Mean Absolute Error
  - CRPS Skill Score, Reliability Diagram, Relative Operating Characteristic (ROC)

In this presentation …

- Research questions
  - Value of regression parameter ‘b’ with respect to calibration period and model
  - Quality of ensembles generated from the technique
  - Performance of the technique with respect to different hydrologic models and locations

Regression parameter ‘b’

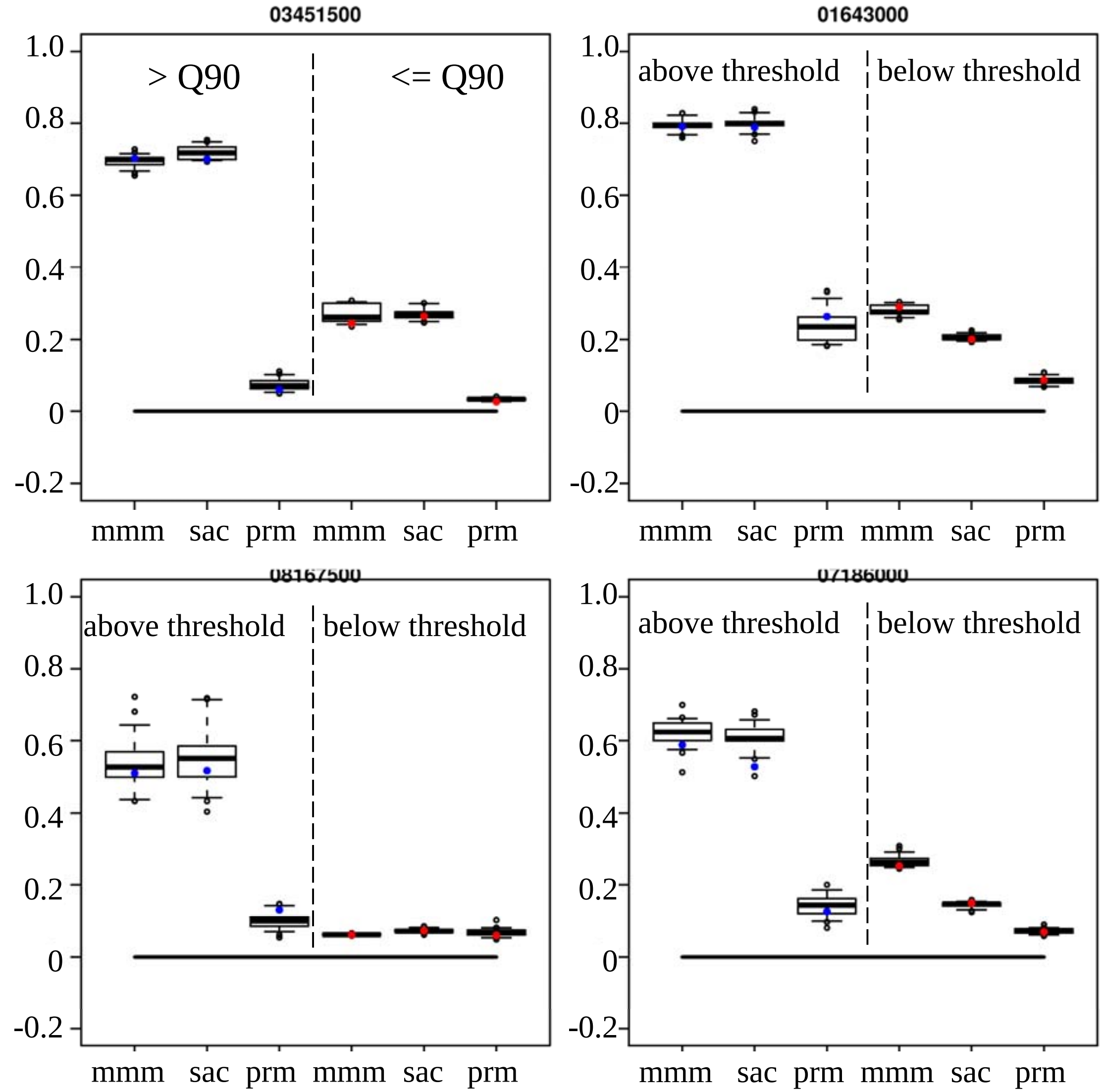
$$Z_{obs,t} = (1-b_t)\, Z_{obs,\, t-1} + b_t\, Z_{sim,\, t} + E_t$$

b = 1: all info from sim.

b = 0: all info from obs.

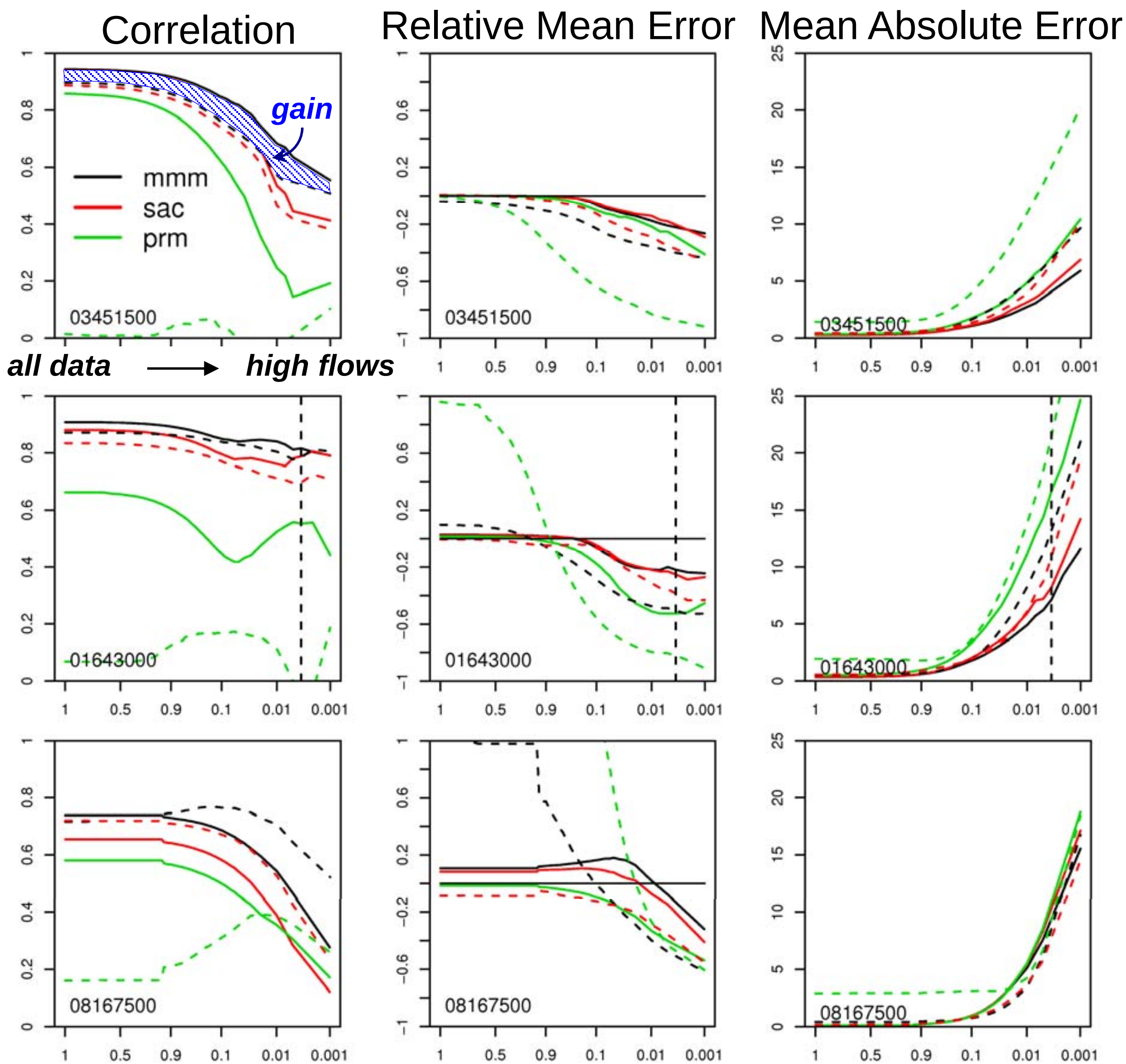
Filled circle: ‘b’ from dependent validation

Box-whiskers: ‘b’ from cross validation



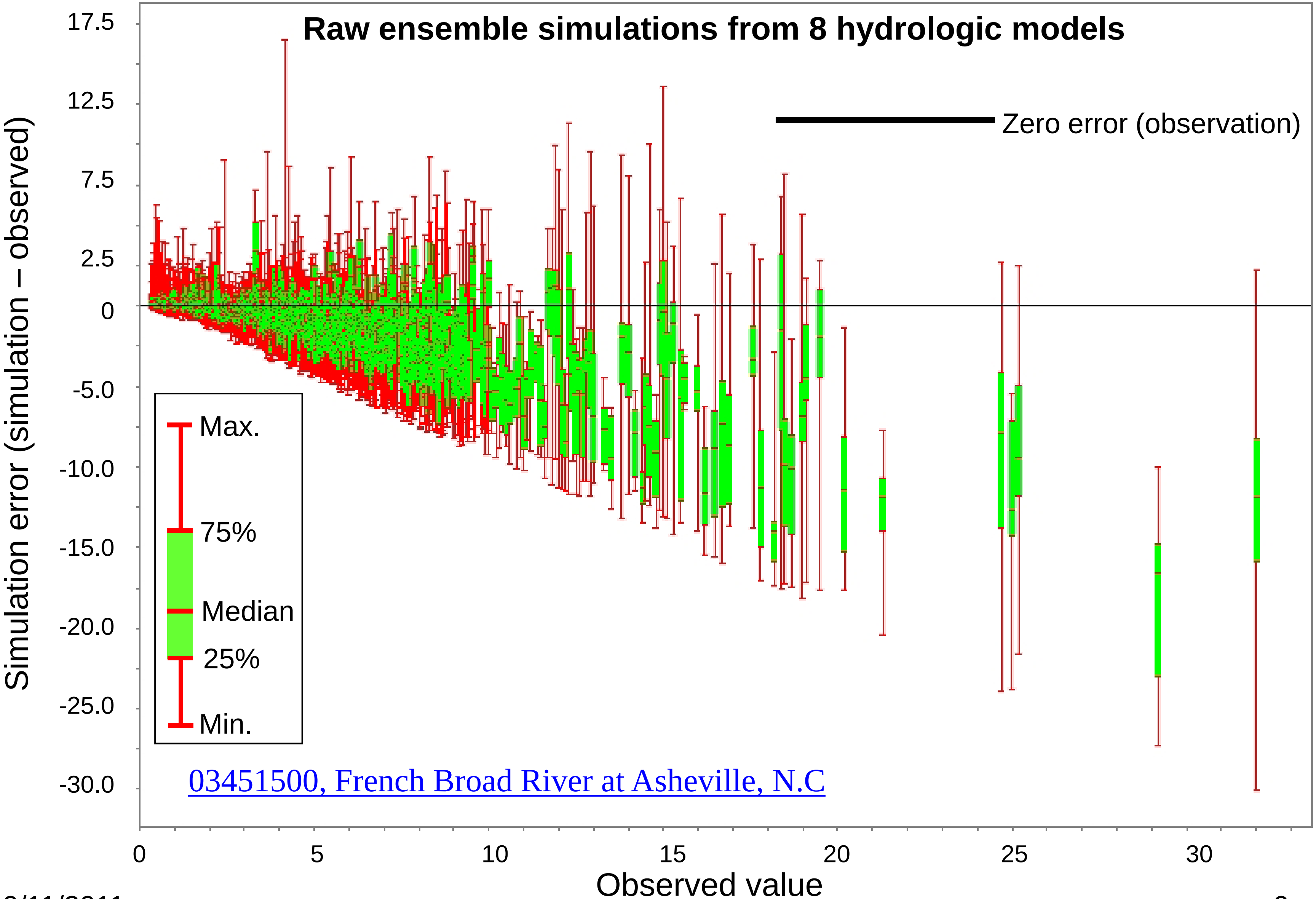
Forecast accuracy and bias

- Ensemble mean (solid) vs. raw single-valued simulations (dashed)
- Ensemble mean exhibited
  - ➢ improved accuracy (i.e., correlation and MAE)
  - ➢ reduced biases except for a few locations

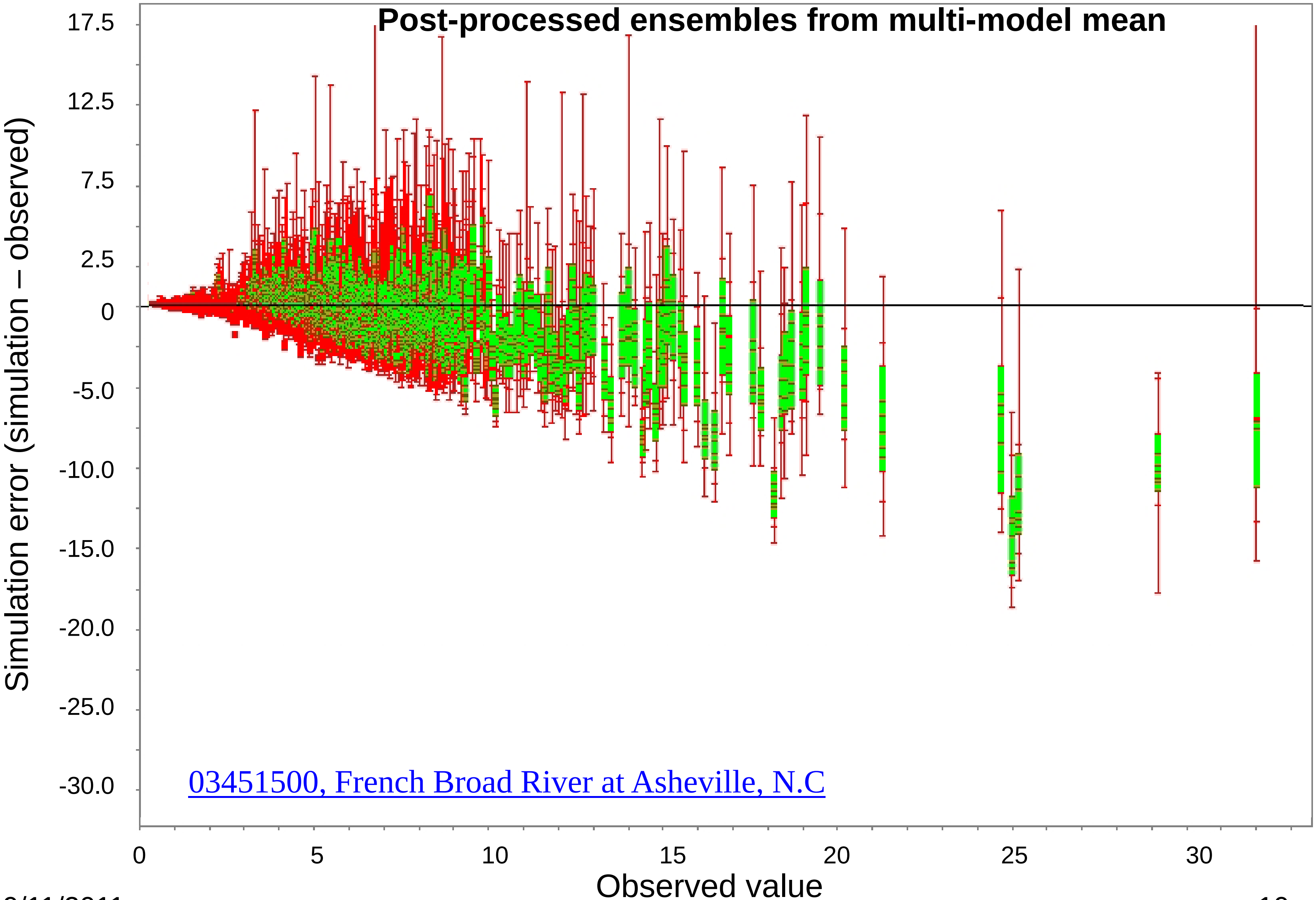


Climatological exceedence probability (logit scale)

Errors in raw ensemble simulations



Errors in post-processed flow ensembles



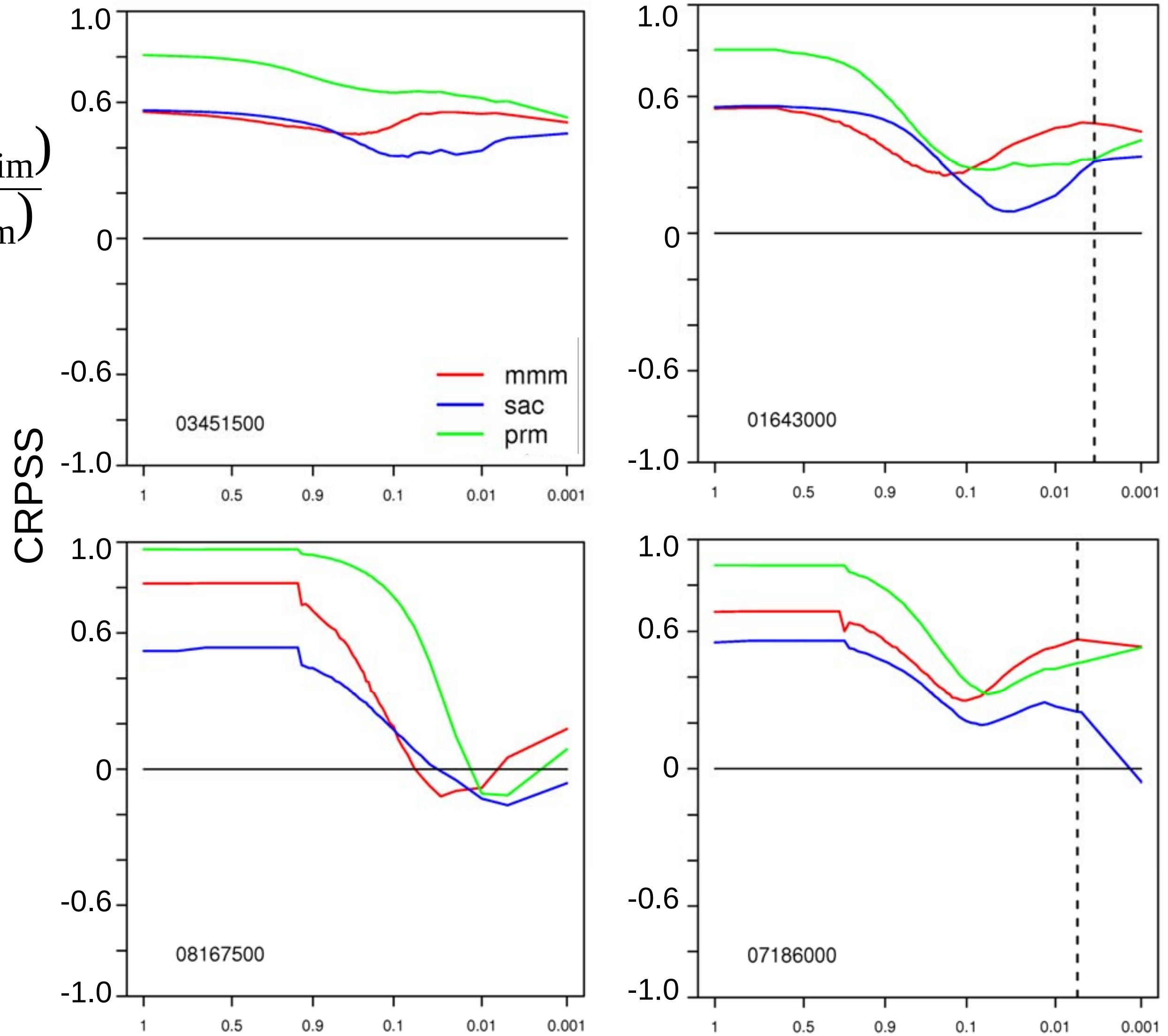
Verification metrics: CRPSS

Post-processed flow ensembles vs. raw single-valued simulation

CRPSS =

$$\frac{(CRPS_{ens.fcst} - MAE_{raw\ sim})}{(CRPS_{per.fcst} - MAE_{raw\ sim})}$$

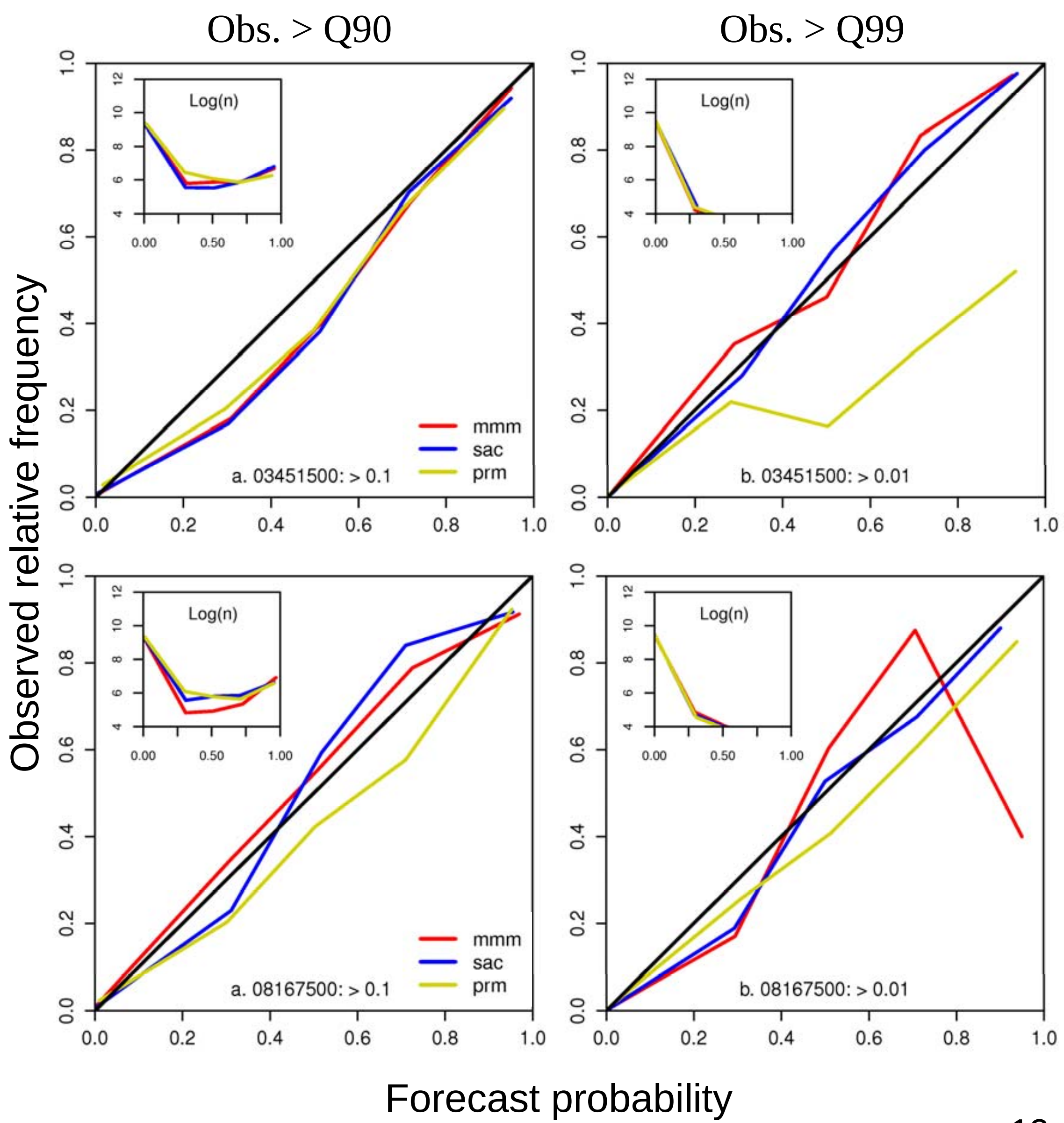
- Positive CRPSS for improved forecasts
- Gain in skill depends on model and flow magnitude
  - ➢ significant gain even for high flows



Climatological exceedence probability (logit scale)

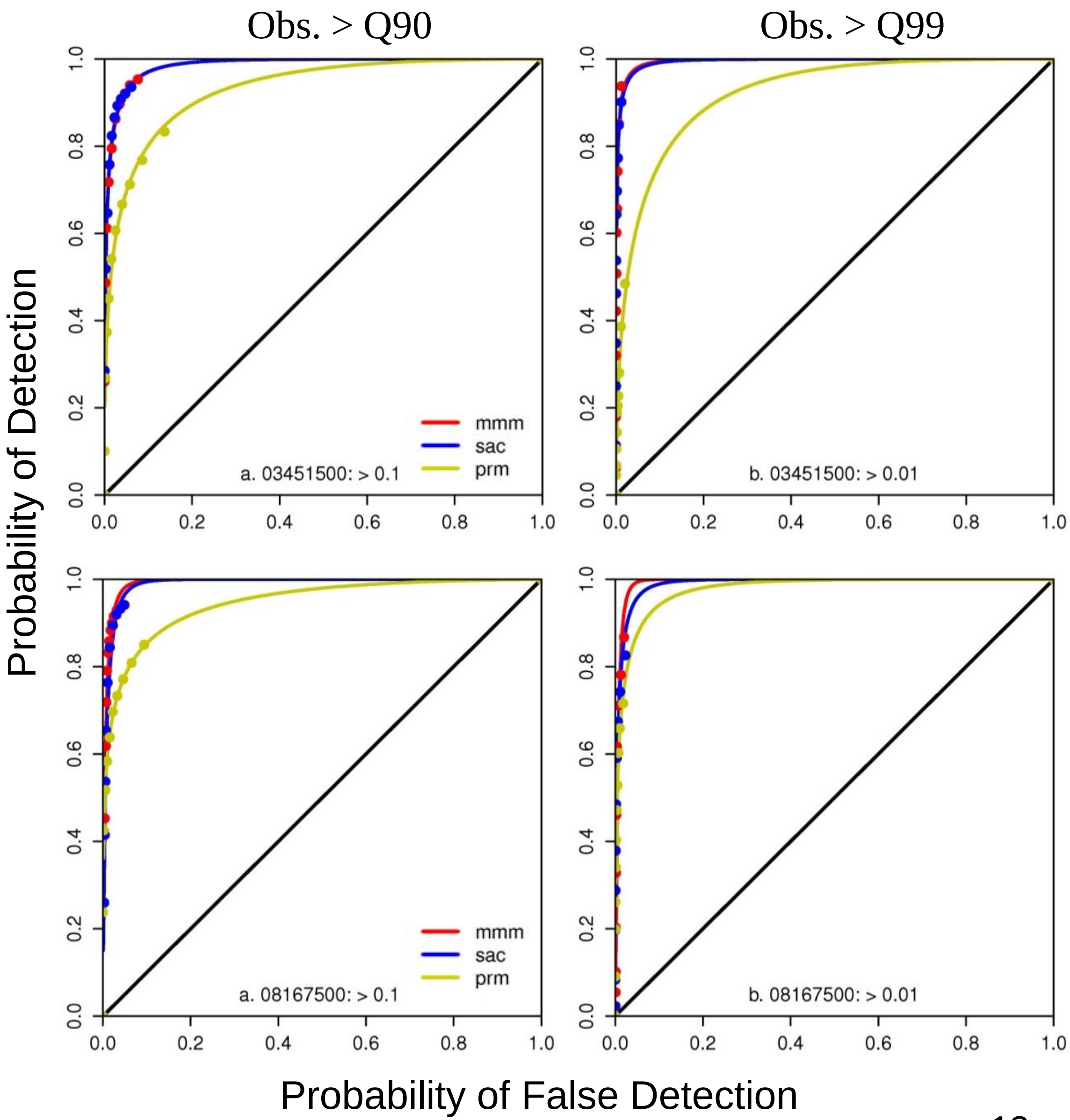
Verification metrics: reliability diagrams

- Below diagonal: over forecasting biases
=>overconfident forecast
- Ensembles are reliable for rare events
- Similar performance between sac and mmm
- Good reliability and sharpness even for higher events



Verification metrics: ROC

- Good discrimination between events and non-events
- Similar performance between sac and mmm



Findings

- The Gaussian regression technique
  - preserves correlations and often times exhibits improved correlations compared to raw simulations
  - maintains accuracy of raw simulations
  - exhibits reduced biases compared to raw simulations
- The generated ensembles are reliable and yield good discrimination between events and non-events.
- Quality of ensembles varies with location (possibly with flow distribution) and hydrologic model (accuracy and bias of raw simulations)

Future work

- Optimization of regression parameter ‘b’ using a multi-objective function to address key requirements of users
- Enhancement of flow stratification criterion (multiple thresholds, seasons, additional variables - precipitation, rising/falling limb)
- Improvement of hyperbolic approximation for the uppermost-tail of the distribution (parameters λ and ω)
- Next steps
  - Evaluation study with flow ensembles
  - Implementation in NWS Hydrologic Ensemble Forecast System

Thank you

Questions ?

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Reference:

Seo, D.-J., Herr, H. D., and Schaake, J. C.: A statistical post-processor for accounting of hydrologic uncertainty in short-range ensemble streamflow prediction, *Hydrol. Earth Syst. Sci. Discuss.*, 3, 1987-2035, doi:10.5194/hessd-3-1987-2006, 2006.