

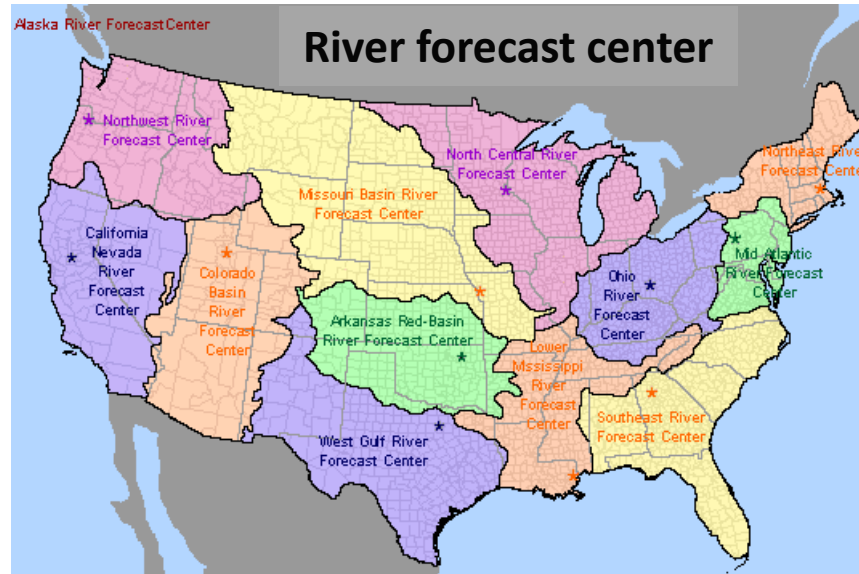
Enhancing Ensemble Streamflow Forecasting through an Integrated Multimodel System

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Aug. 29, 2019

Need of multimodel streamflow forecasting!



❑ River forecast center

- ❑ Regional
- ❑ Probabilistic forecasts (Experimental)
- ❑ Spatially lumped modeling

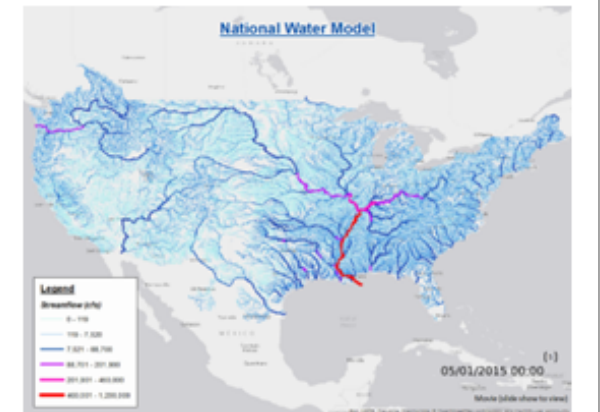
❑ National Water Model

- ❑ Continental
- ❑ Spatially distributed modeling
- ❑ Deterministic forecasts

Current River Forecast Points (~3,600)



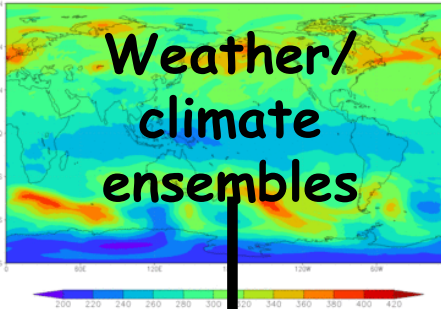
NWM Streamflow Output Points (~2.7 mil)



We assemble, implement and verify a regional hydrological ensemble prediction system [RHEPS]

RHEPS

GFS Entire Atmosphere Total Ozone [Dobson]
00Z12JUL2012+000Hrs



Observing systems
[MPEs, gridded T,
USGS flow, NLDAS]

**Statistical
preprocessor**
[BMA, HCLR]

**Decision-
support tools**

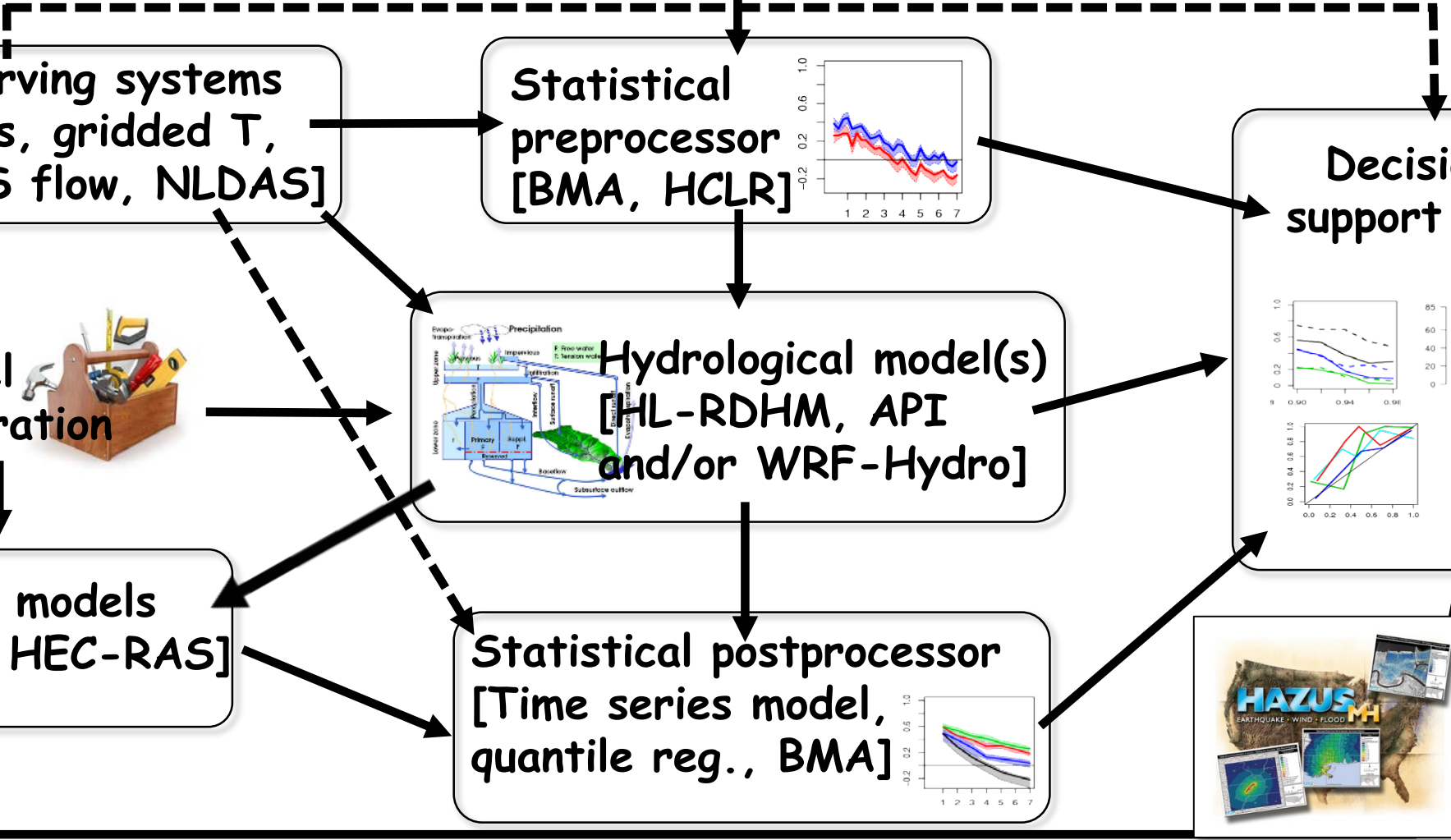
**Model
calibration**

Hydrological model(s)
[HL-RDHM, API
and/or WRF-Hydro]

Hydraulic models
[LISFLOOD, HEC-RAS]

Statistical postprocessor
[Time series model,
quantile reg., BMA]

HAZUS
EARTHQUAKE - WIND - FLOOD - MH



Analysis/Simulation

Short-to-medium range

Subseasonal to seasonal

Long-term projection

Model Initialization

Hourly observations

Daily at 00Z

Every 10 days at 00Z

Daily Ens (13 mem)

Forecast Duration

Hourly
[2002-2017]

1-7 days
[2003-2013]

1-90 days
[2002-2017]

1981-2099

Meteorological/Climatological Forcing

MPEs/Gridded T, NLDAS

GEFSRv2

CFSv2

CMIP5

Number of ensembles

Deterministic

11 ensembles

8 ensembles (time-lagged)

13 ensembles

Applications

Real-time streamflow
information

Flood (inundation) forecast

Drought prediction,
Water quality prediction &
Agricultural planning

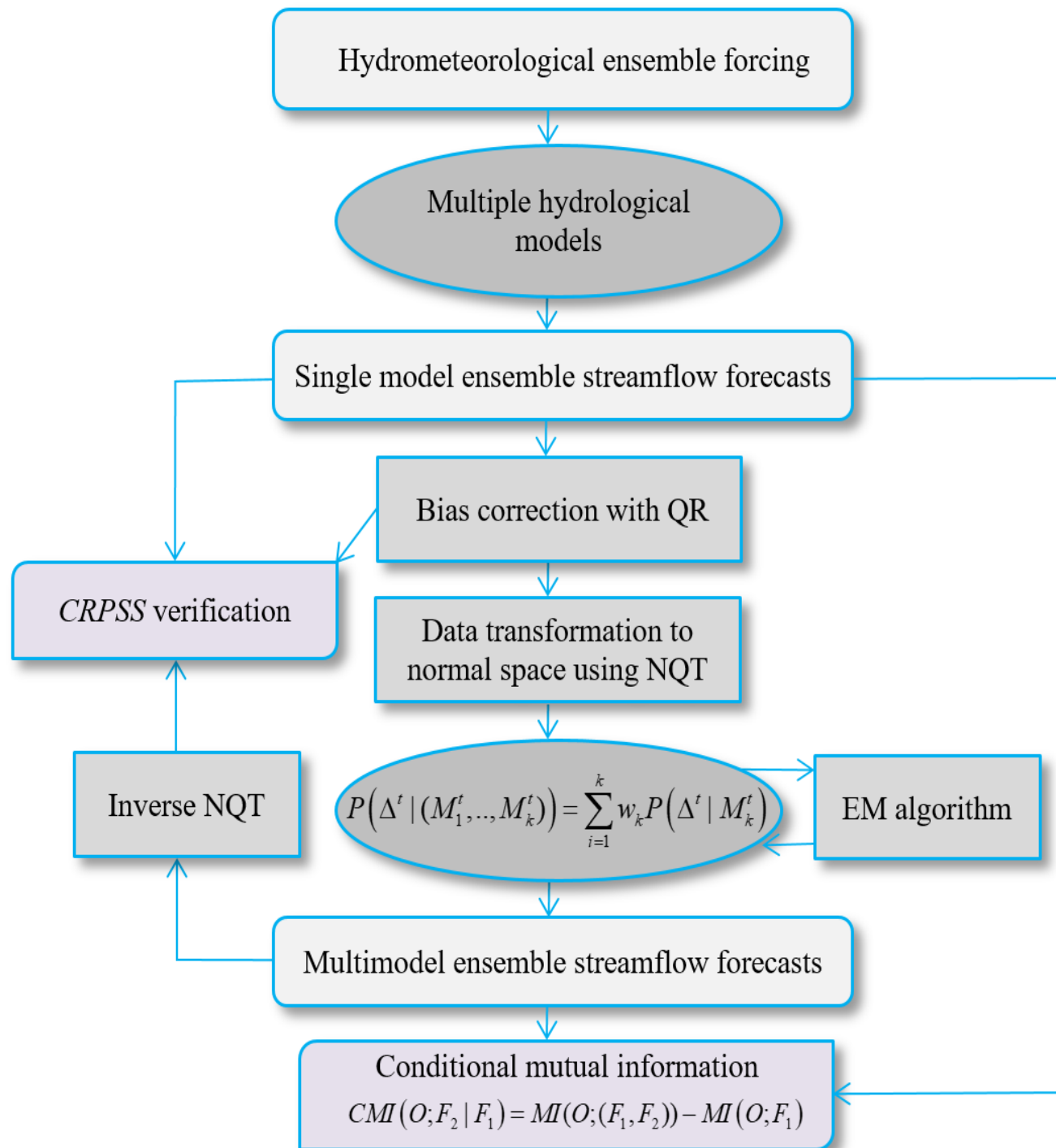
Flood hazard and risk
assessment

RHEPS uses HPC system from Penn State and also tested to run in the cloud

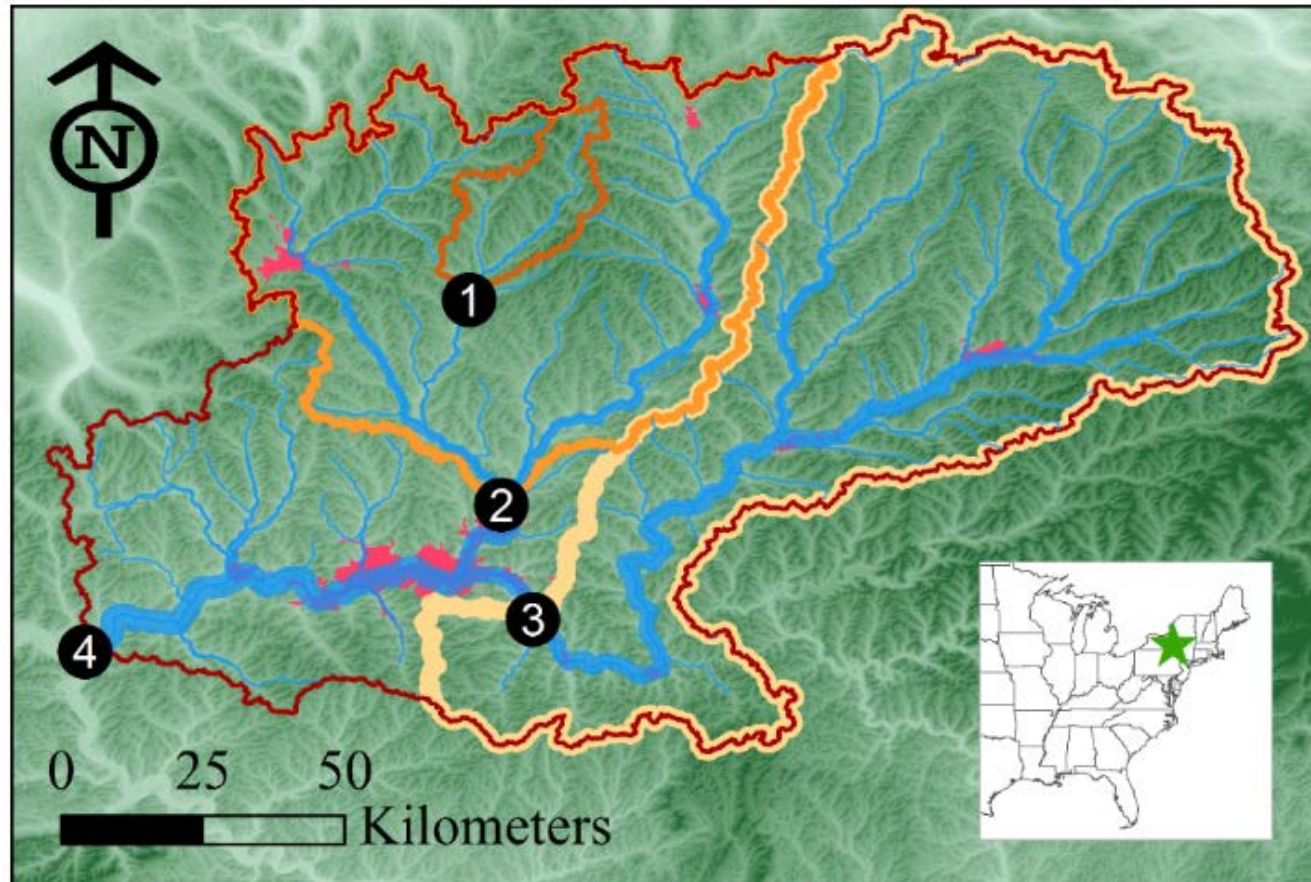
Are multimodel ensemble streamflow forecasts more skillful than single-model forecasts?

Hydrological models considered

- ❑ HL-RDHM (distributed, conceptual)
- ❑ Continuous API (lumped, conceptual)
 - Operational forecasts from NOAA's MARFC
- ❑ WRF-Hydro (distributed, land surface)
 - Employs land surface model NoahMP
 - Gridded wave diffusion routing
 - 1x1 km² resolution
 - Dynamically Dimensioned Search (DDS) used for calibration



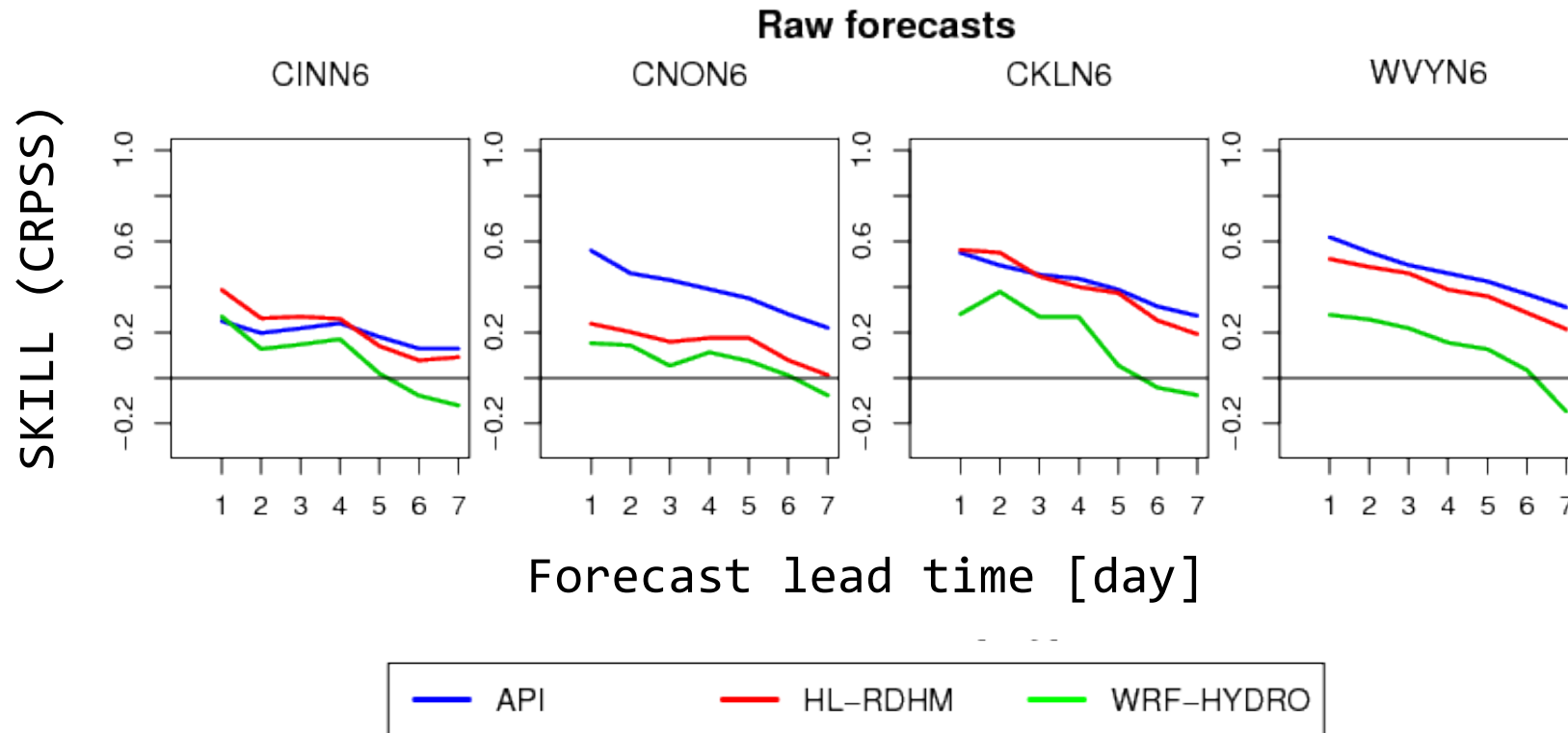
Four nested subbasins are chosen in the Middle Atlantic region



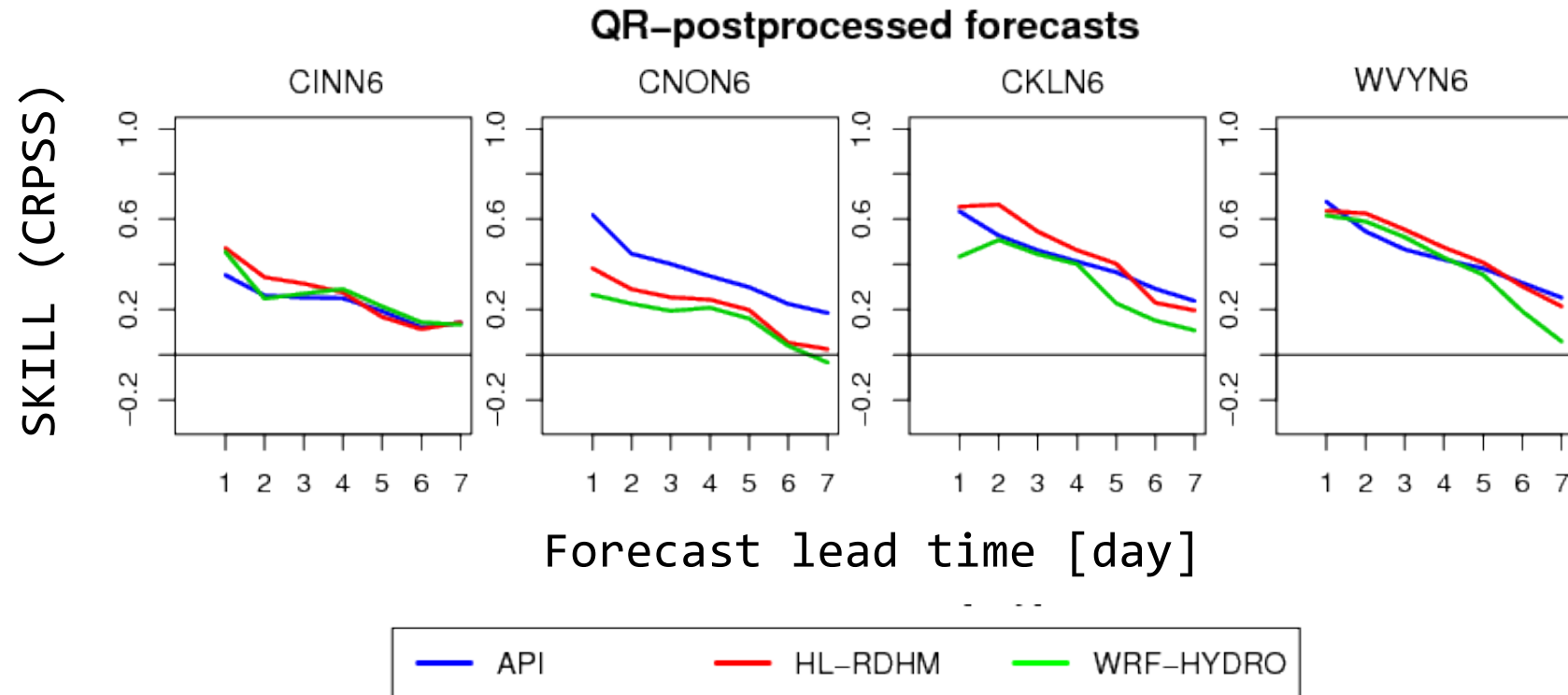
- ❑ Six years of multimodel forecast data are used for verification (2004-2009, warm season only).
- ❑ Verification is performed conditioned on forecast lead times (1-7 days) and basin scale.

- | | |
|------------------|-----------|
| ❶ Cincinnatus | ❸ Conklin |
| ❷ Chenango Forks | ❹ Waverly |

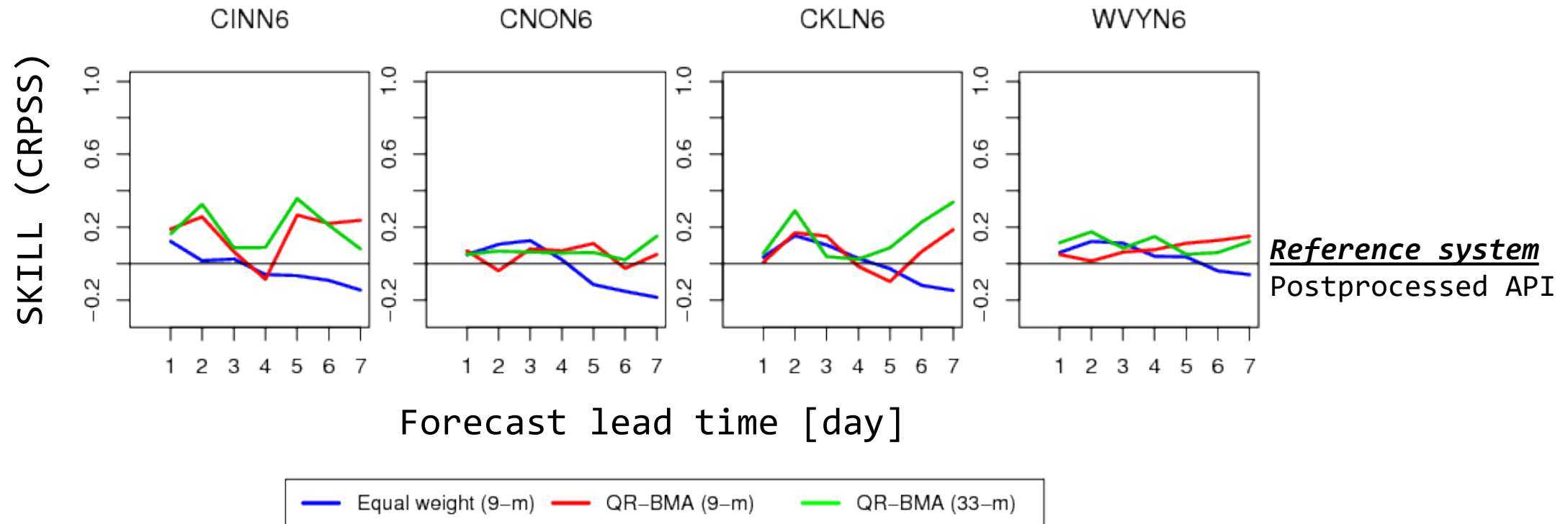
API and HL-RDHM tend to outperform WRF-Hydro for raw forecasts



All the models have comparable skill after QR-postprocessing



Multimodel forecasts have higher skill than the best single model forecast



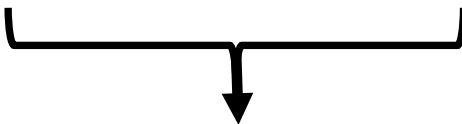
Are any skill improvements in multimodel forecasting dominated by model diversity or the addition of new ensemble members?

Conditional mutual information (CMI) is used as a skill measure

F_1 represents the single model forecast

F_2 represents the multimodel forecasts of the remaining models

$$\text{CMI}(O; F_2 | F_1) = \text{MI}(O; (F_1, F_2)) - \text{MI}(O; F_1)$$


Decrease in uncertainty due to adding a second forecast

CMI can be expressed as a function of partial correlation

$$\text{CMI} \leq -\frac{1}{2} \log(1 - \rho_{02|1}^2)$$

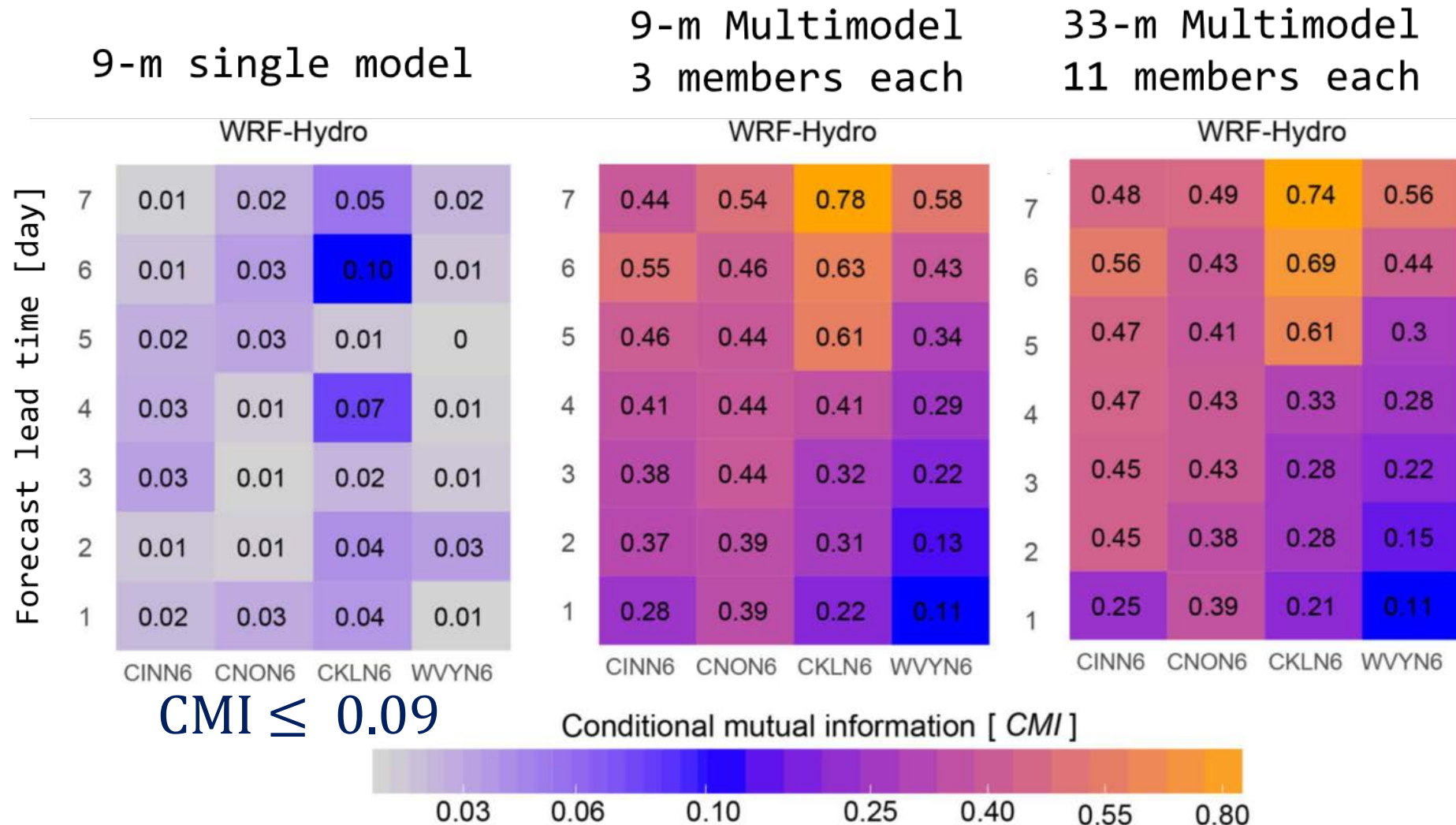
Upper bound on skill improvement due to adding new ensemble member from same model:

$$\rho_{02|1} \leq \sqrt{\frac{E_2}{(E_1 + E_2)(E_1 + 1)}}$$

For $E_1=3$ and $E_2=6$

$$\text{CMI} \leq 0.09$$

Hydrological model diversity enhances forecast skill more than the ensemble size



It is concluded that..

- ❑ Multimodel ensembles are more skillful compared to the best single model forecasts.
- ❑ Each single model contributes additional information to enhance forecast skill.
- ❑ **Skill enhancements obtained by multimodel forecasts are found to be dominated by model diversity, rather than by increased ensemble size alone.**

Thank you for your attention!

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Papers

Sharma*, S., G. Heather, G. Jorge, and A. Mejia (2019): Seasonal hydroclimate predictions anticipate nutrient and sediment loads using a dynamical-statistical approach, *Environmental Research Letter*.

Sharma*, S., R. Siddique, S. Reed, P. Ahnert, and A. Mejia (2019): Hydrological model diversity enhances streamflow forecast skill more than the ensemble size, *Water Resources Research*.

Sharma*, S., Siddique, R., Reed, S., Ahnert, P., Mendoza, P., and A. Mejia (2018): Relative effects of statistical preprocessing and postprocessing on a regional hydrological ensemble prediction system, *Hydrology and Earth System Sciences*.

Sharma*, S., R. Siddique*, N. Balderas*, J. D. Fuentes, S. Reed, P. Ahnert, R. Shedd, B. Astifan, R. Cabrera, A. Laing, M. Klein, and A. Mejia (2017), Eastern U.S. verification of ensemble precipitation forecasts, *Weather and Forecasting*.

