THE UNIVERSITY OF MELBOURNE

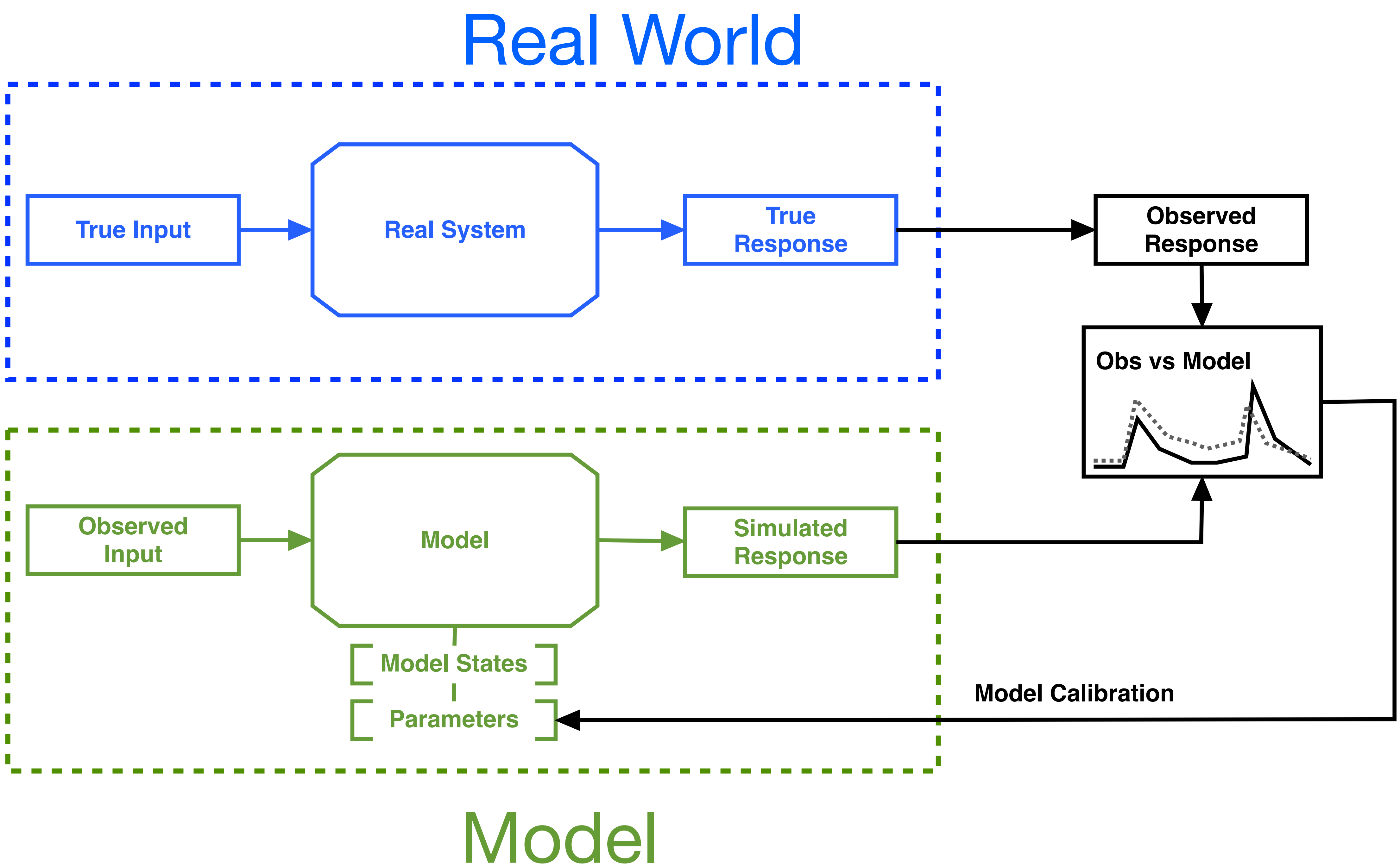
Leveraging Ground and Remotely Sensed Observations for Short-Term Streamflow Forecasting

Dr. Dongryeol Ryu

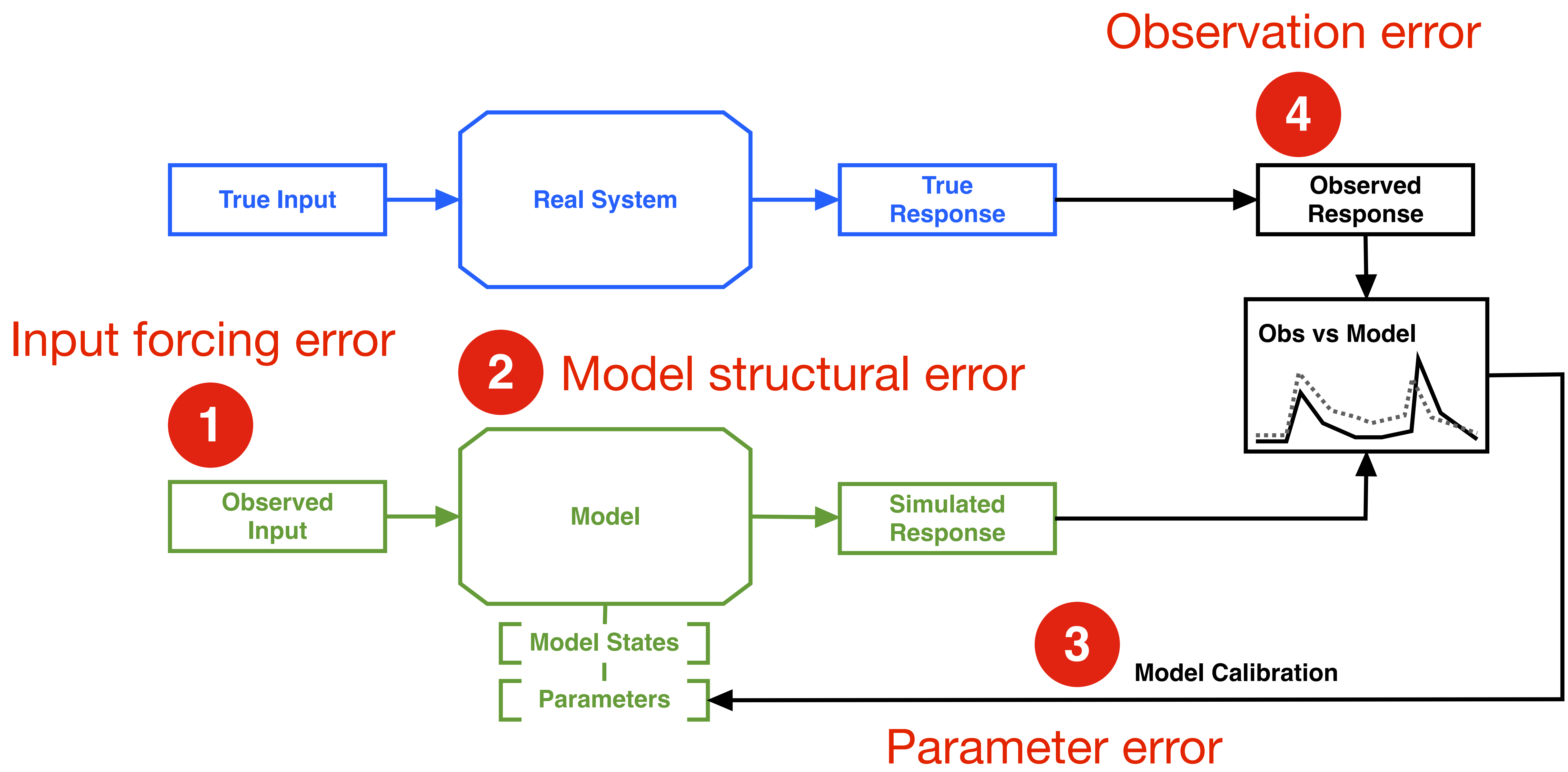
Contributing Members

- Yuan Li (now at Monash), Camila Alvarez-Garreton, Chun-Hsu Su, Andrew W. Western (Univ of Melbourne)
- Wade T. Crow (USDA ARS, HRSL)
- Chris Leahy, Soori Sooriyakumaran (BoM)
- David Robertson, QJ Wang, Luigi Renzullo (CSIRO)
- Jeffrey P. Walker (Monash)

Mechanics of Streamflow Modeling



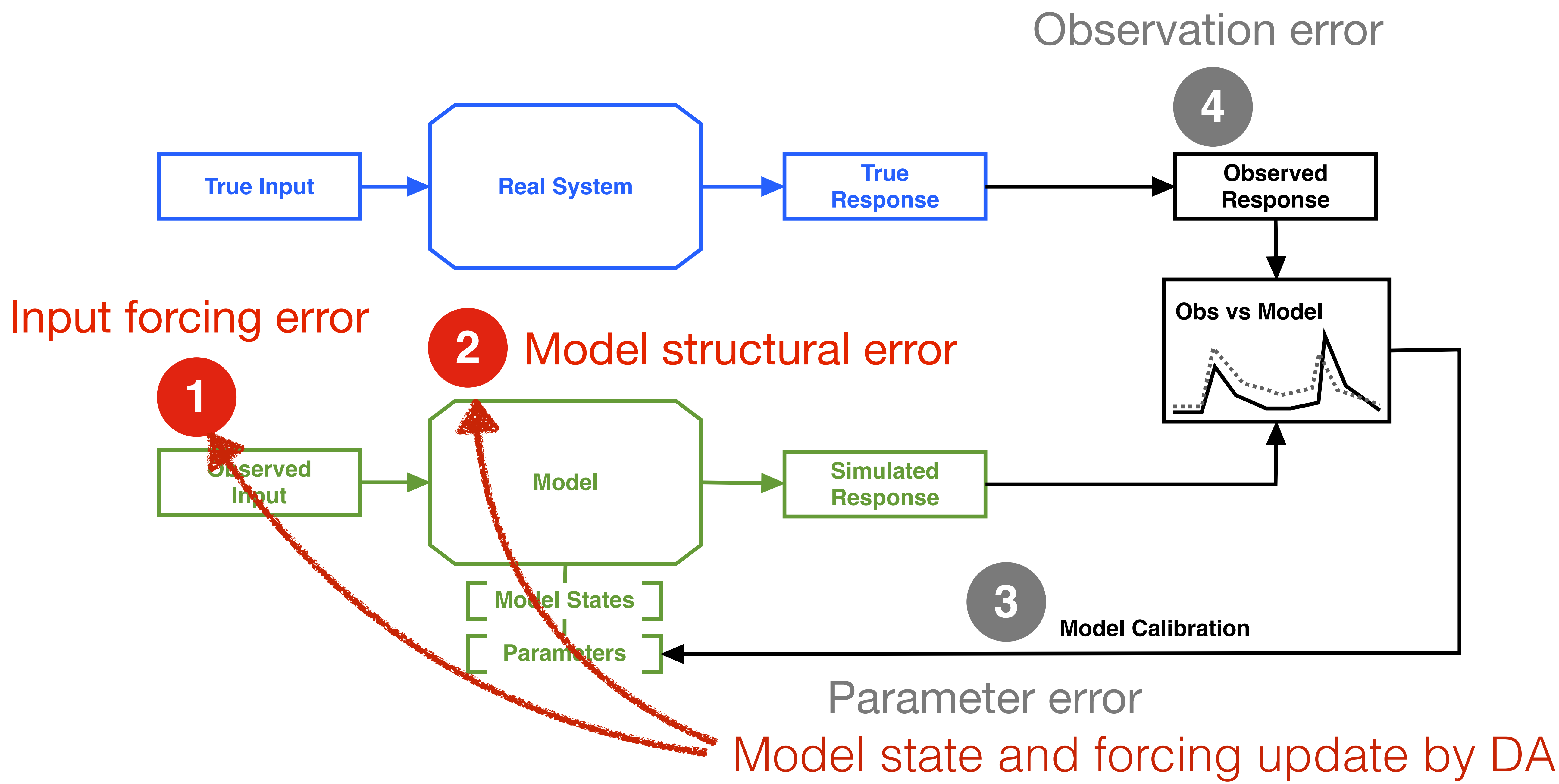
Background Prediction Errors



Background Prediction Errors

- Suppose we have properly calibrated the model with carefully collected observations

Room for Improvement?



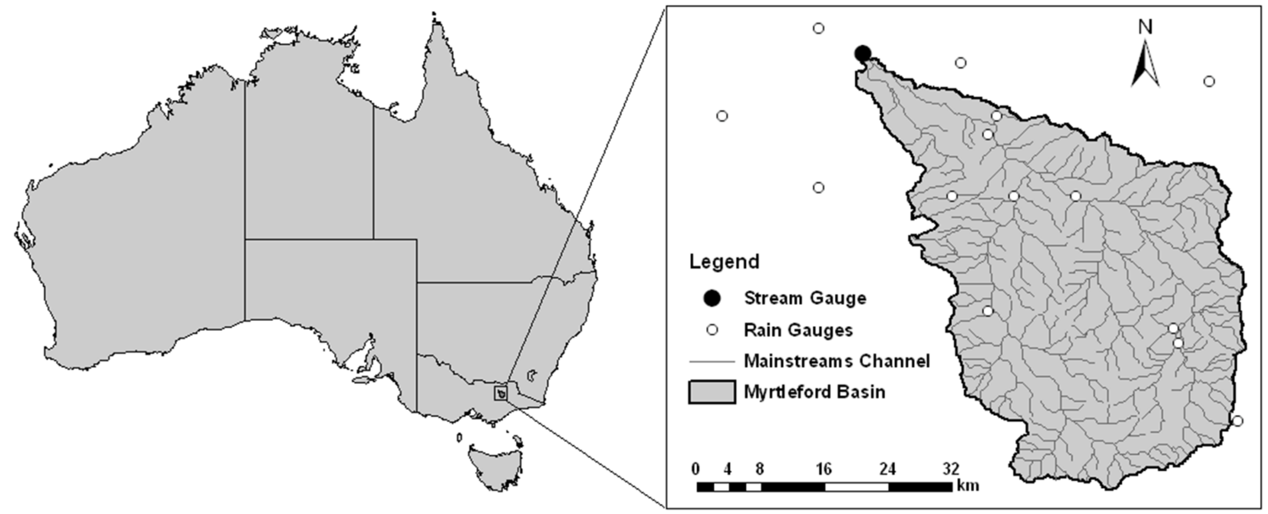
Background Prediction Errors

- This is not a perfect rationale because errors in input forcing and structure would be transferred to the ‘parameters’
- Data assimilation presumes sound model structure and internal processes (sensitivity between updated states and model outputs)

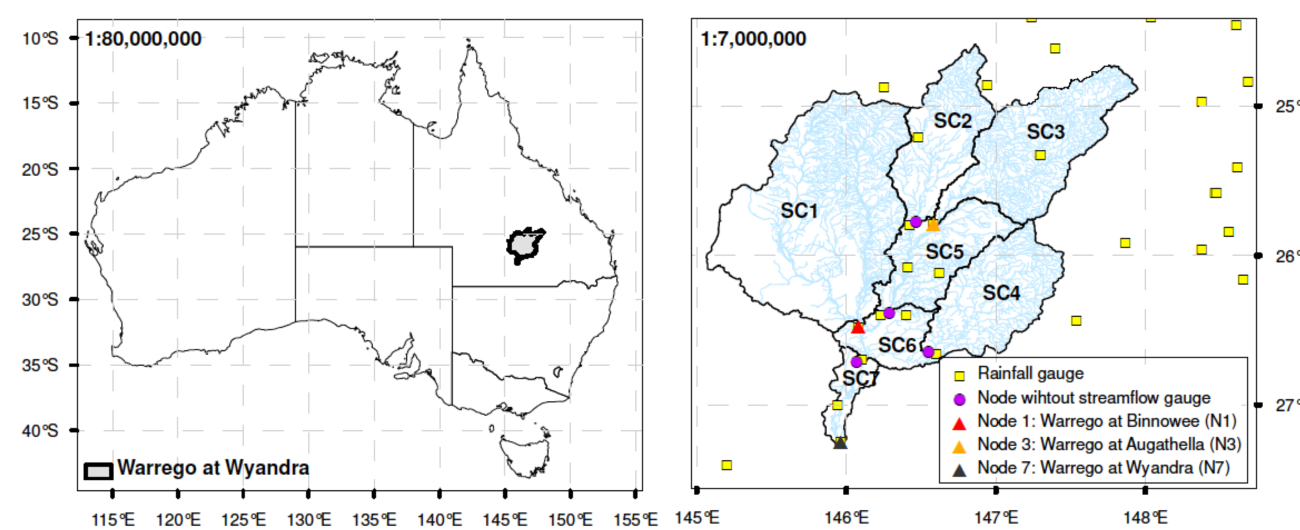
THE UNIVERSITY OF MELBOURNE

Two Examples

- Ovens Catchment - (relatively) data rich site



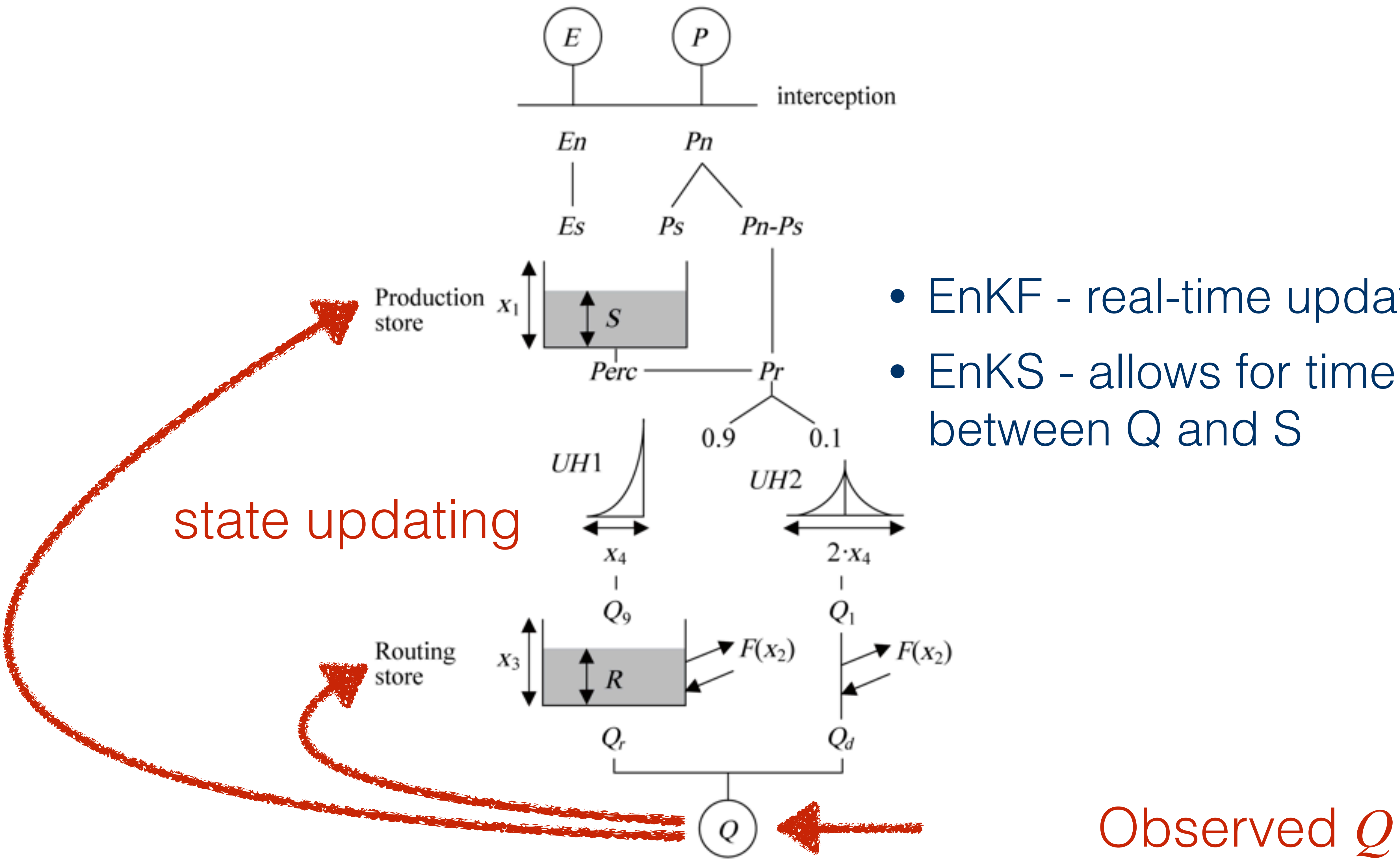
- Warrego Catchment - data sparse semi-arid site



Ovens Catchment

- GR4H over lumped Ovens catchment
- Average of [$NSE_{raw\ flow}$, $NSE_{log\ flow}$, $NSE_{Box\text{-}Cox\ flow}$, Kling Gupta efficiency, bias skill score] in 1999-2004 for objective function
- Stream discharge was assimilated using EnKF and EnKS
- Maximum *a posteriori* (MAP) scheme for rainfall (multiplicative Gaussian) and soil moisture (additive Gaussian) error parameter calibration
- Observed stream discharge error derived from flowmeter vs. water-level-based discharge data

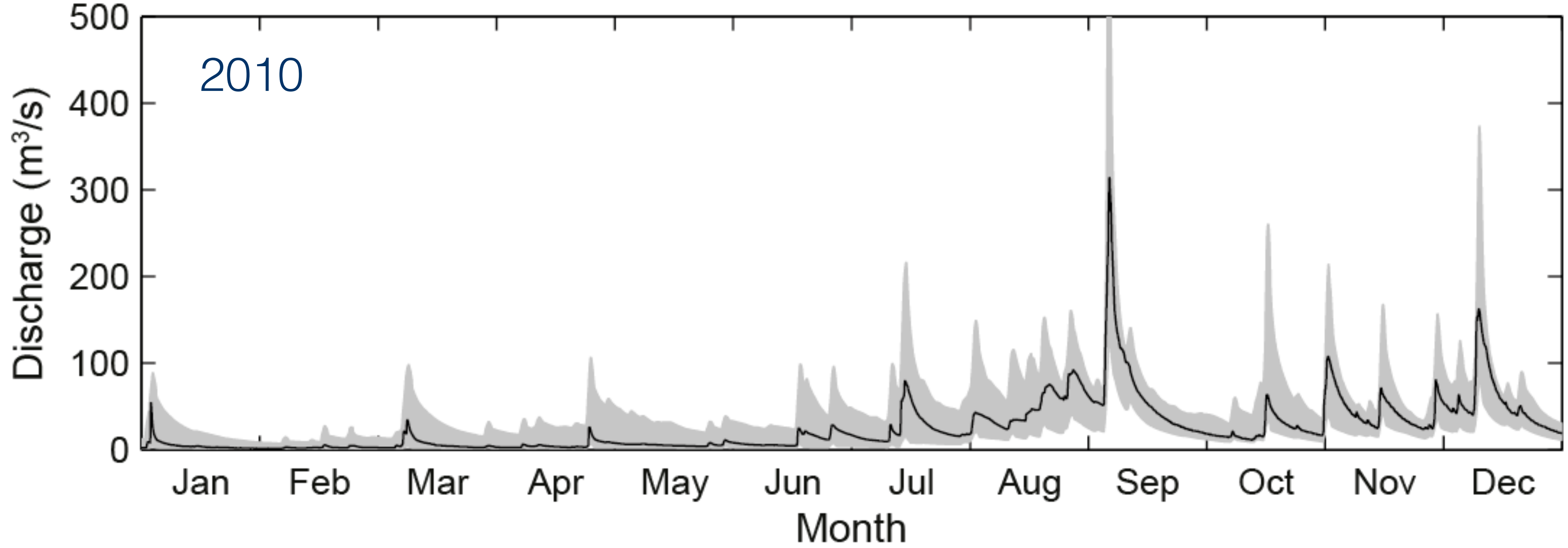
Schematics of EnKF/EnKS

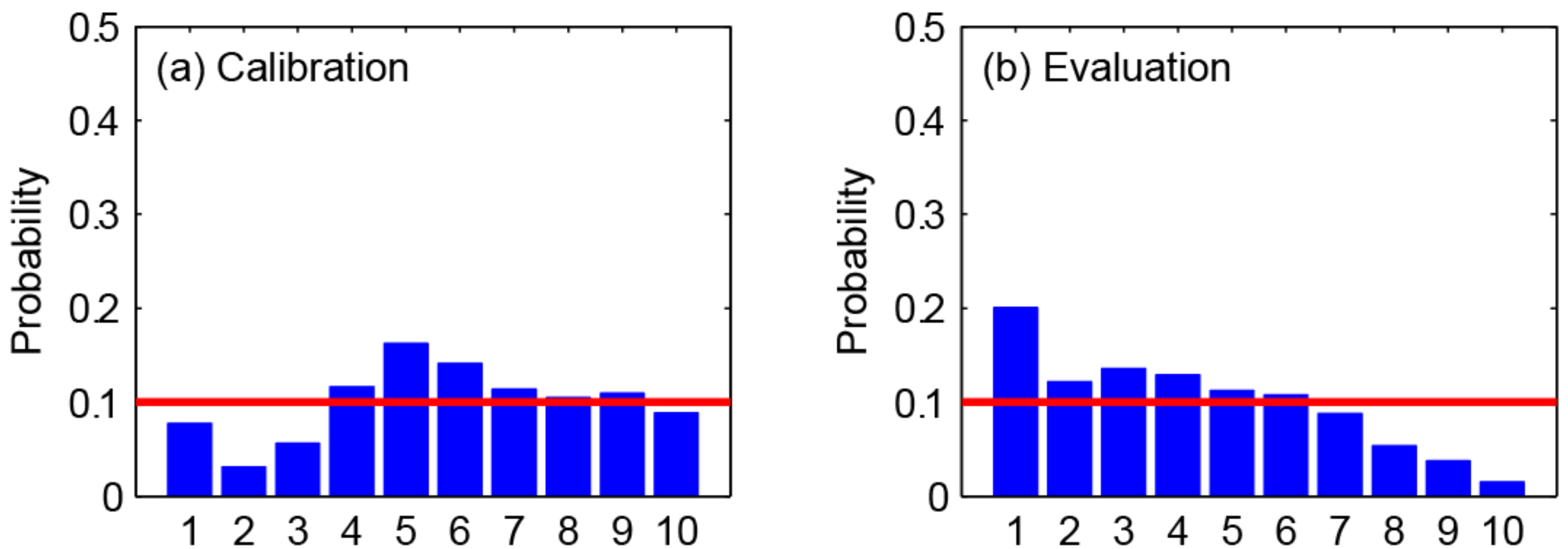


- EnKF - real-time updater
- EnKS - allows for time lag between Q and S

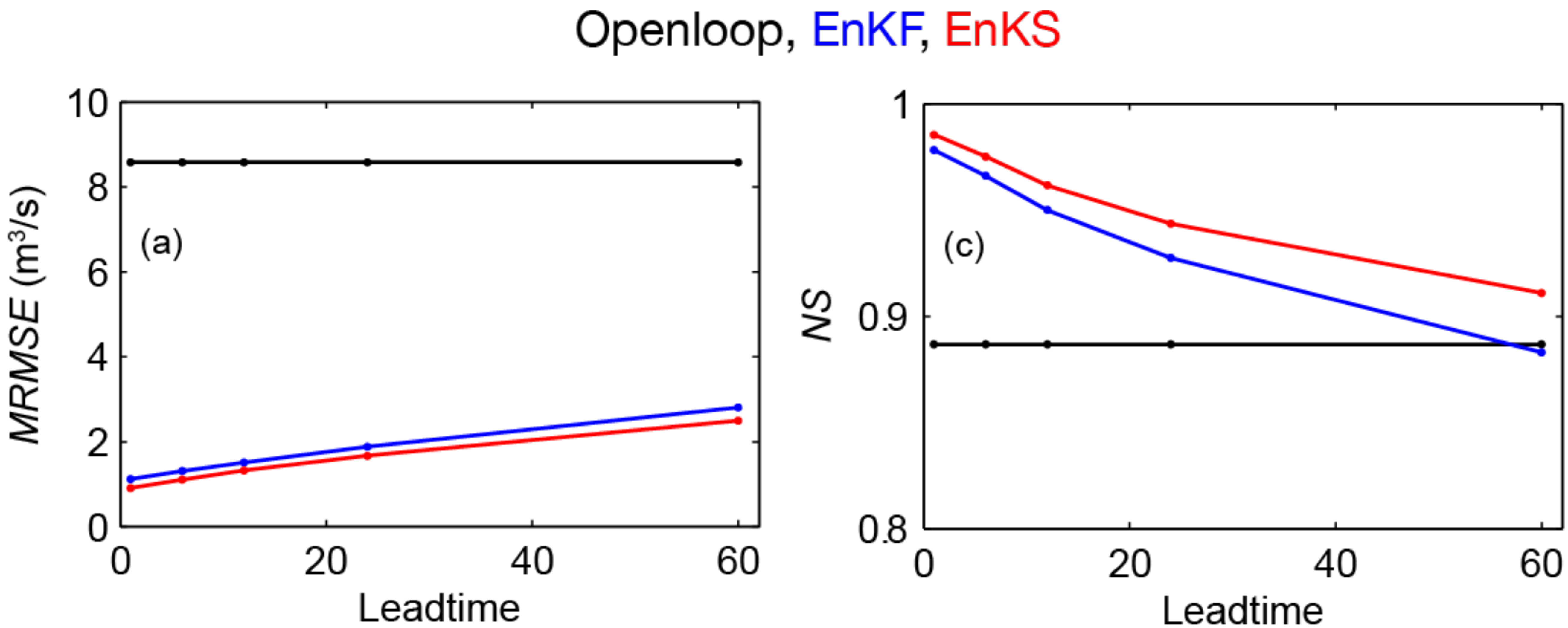
Ovens Catchment - Lumped

Evaluation - 2005~2010

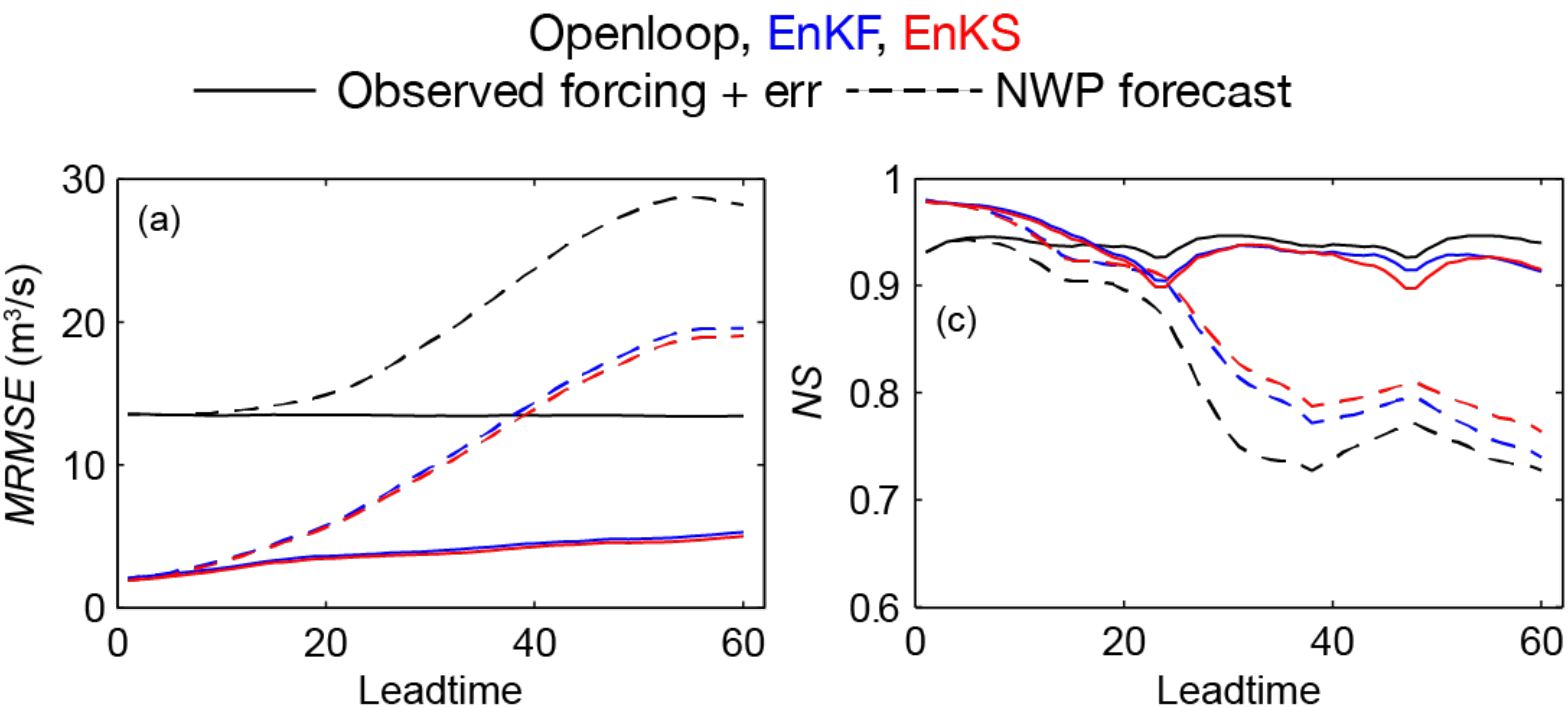




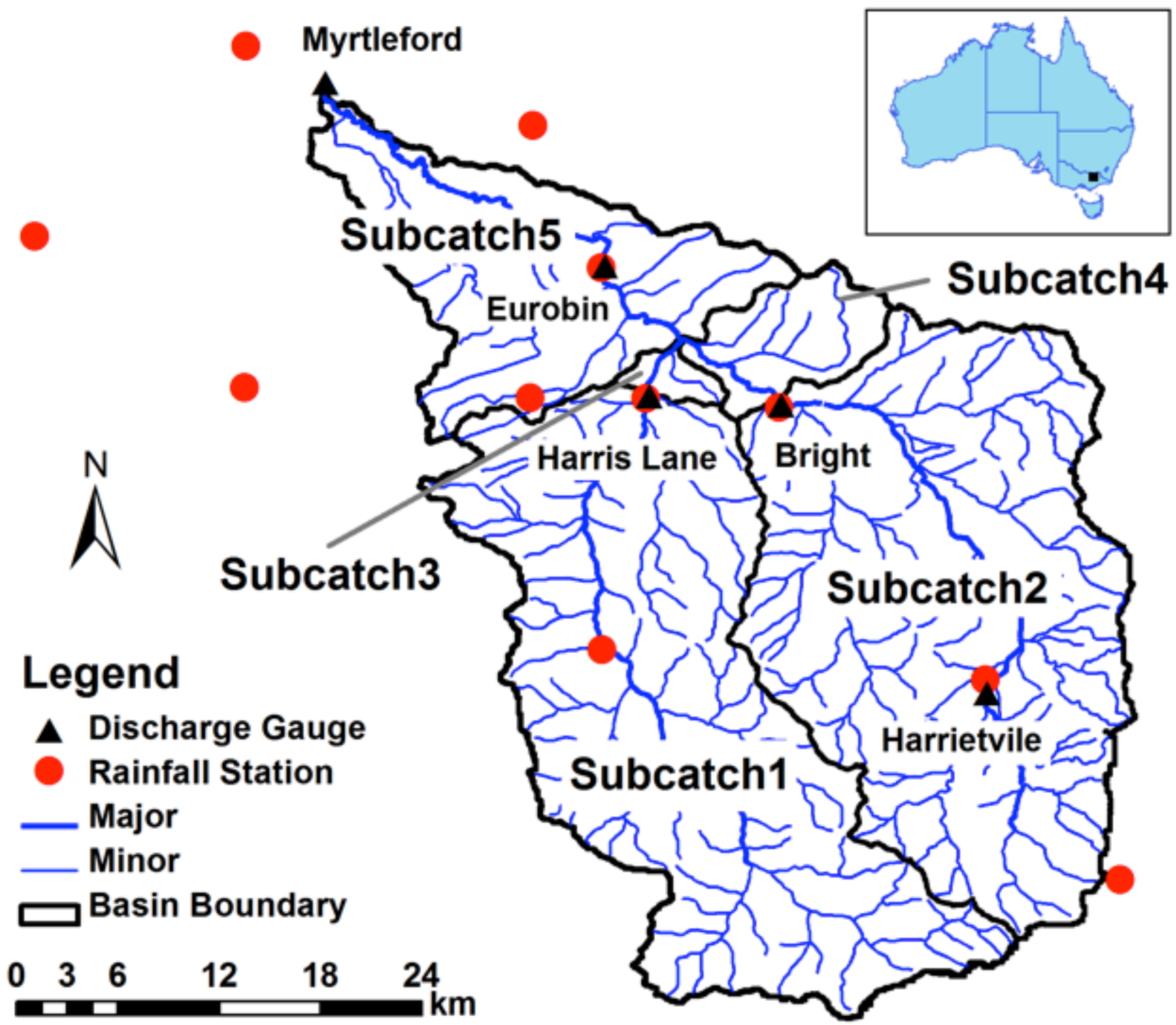
Ovens Catchment - Lumped



Ovens Catchment - Lumped

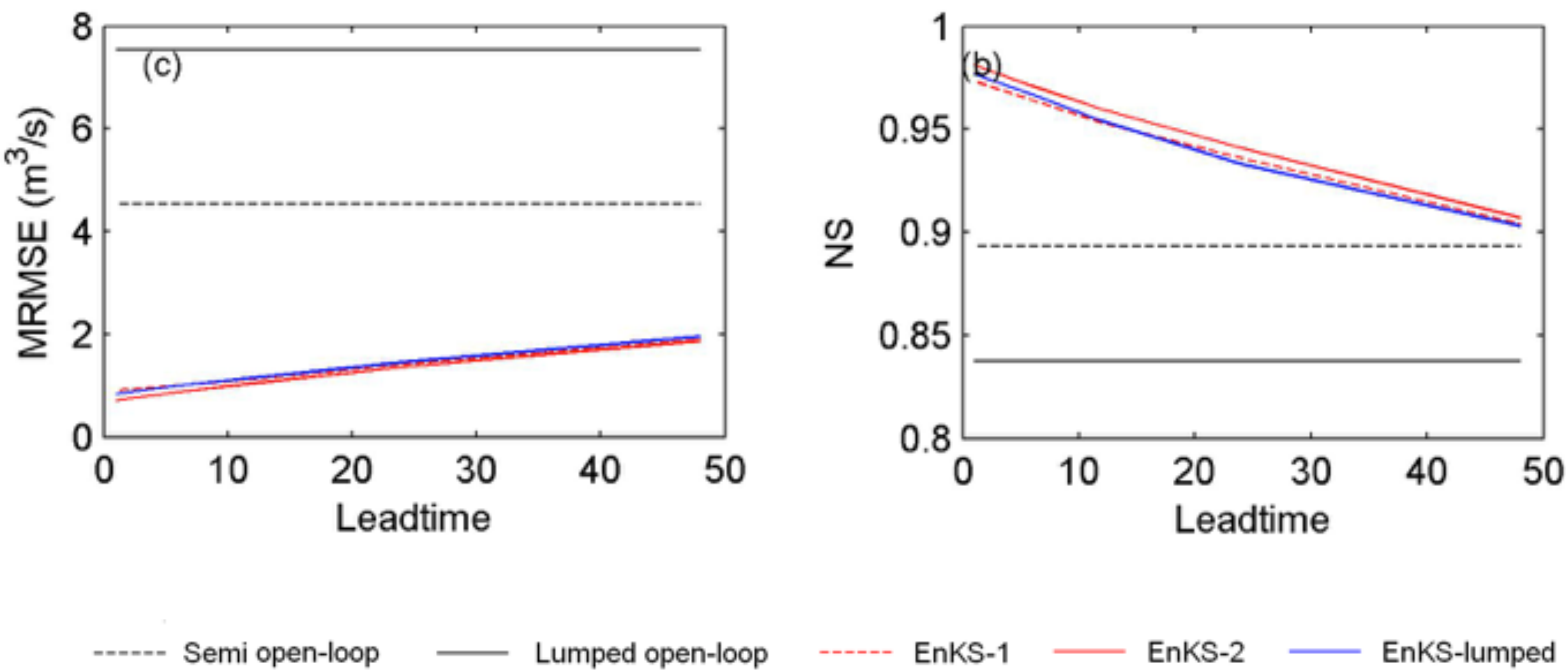


Ovens Catchment - Semi-distributed



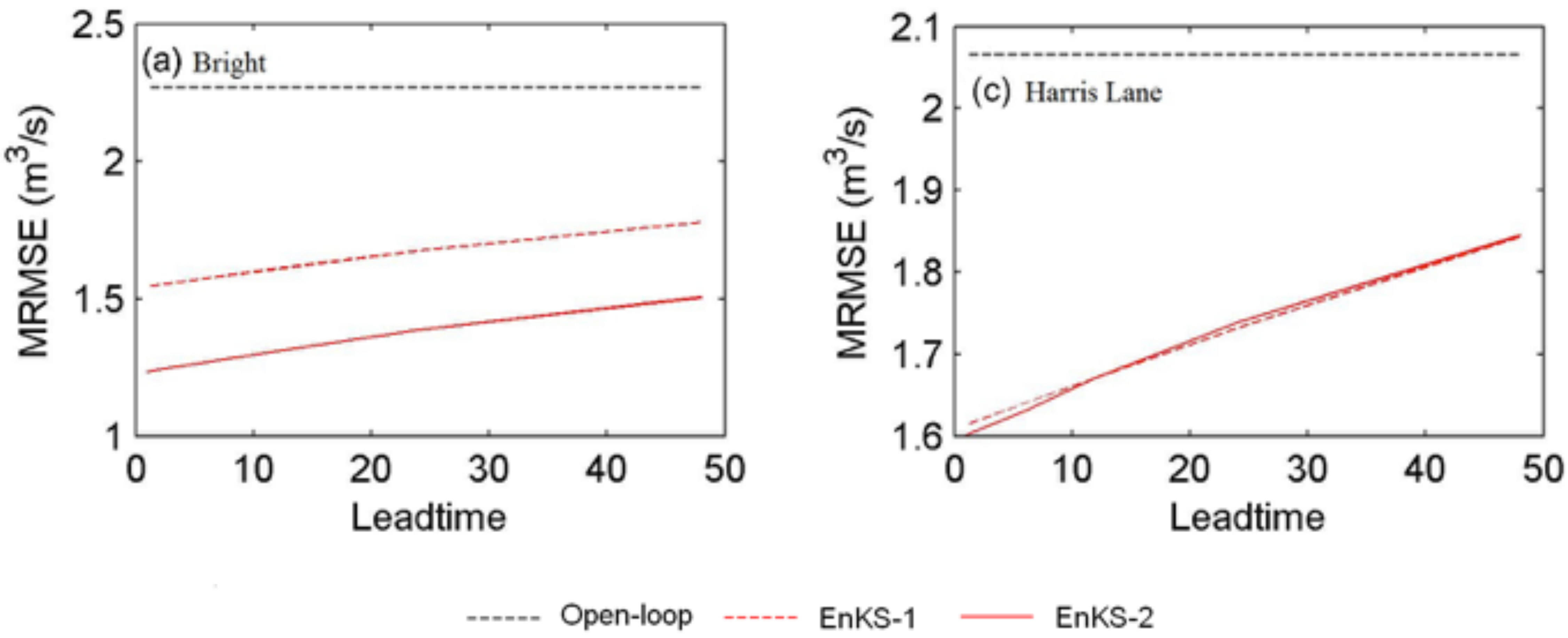
Ovens Catchment - Semi-distributed

- EnKS-1: corrects GR4H states only
- EnKS-2: corrects GR4H states + routing states



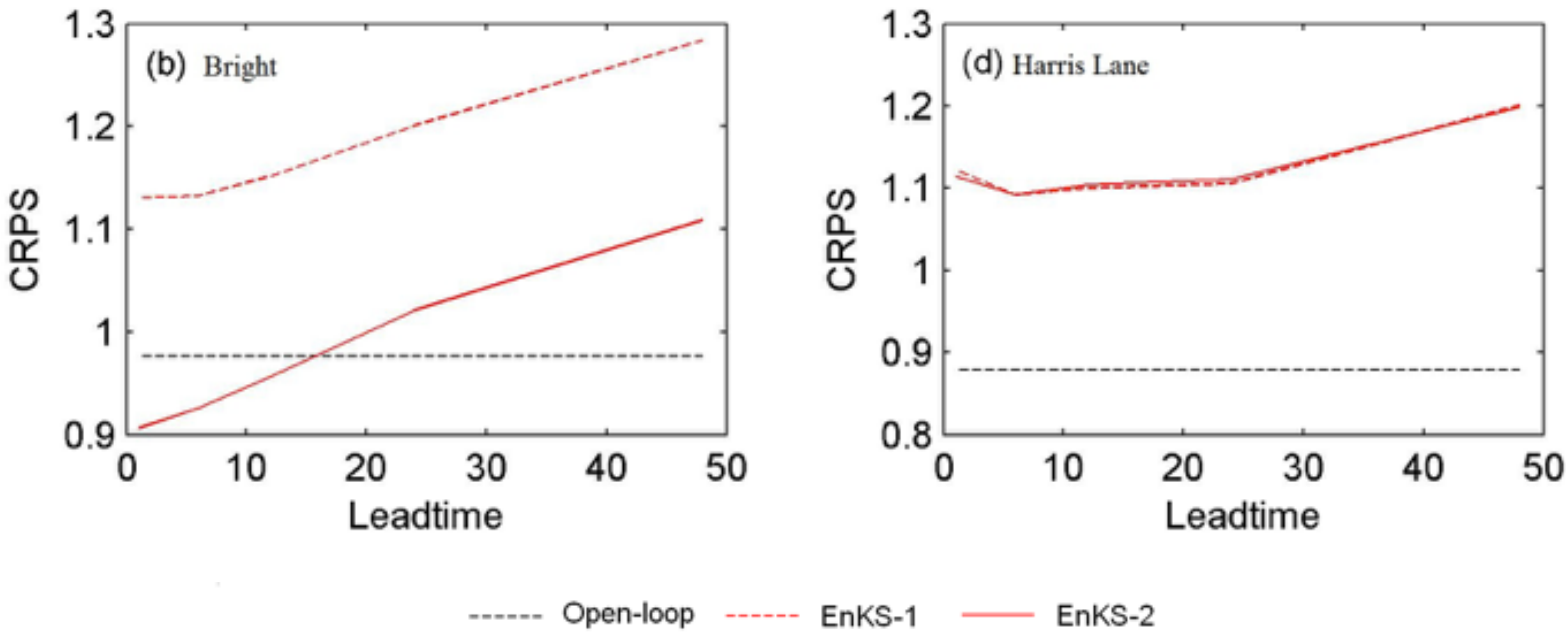
Ovens Catchment - Semi-distributed

- Limited skills for correcting internal (upstream) discharge



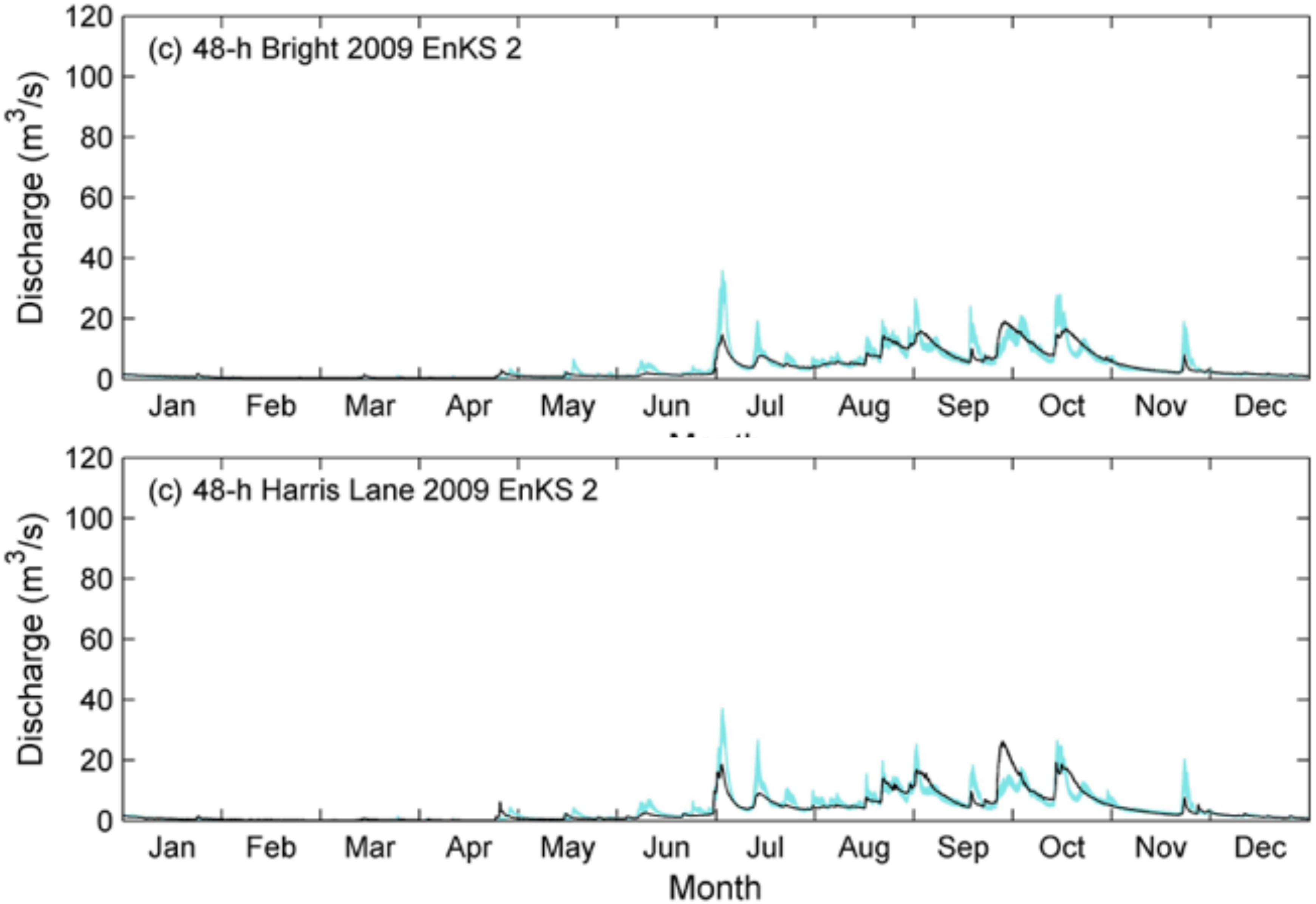
Ovens Catchment - Semi-distributed

- Continuous ranked probability score (CRPS) at upstream gauge locations **worse** after streamflow assimilation



Ovens Catchment - Semi-distributed

- Continuous ranked probability score (CRPS) at upstream gauge locations **worse** after streamflow assimilation



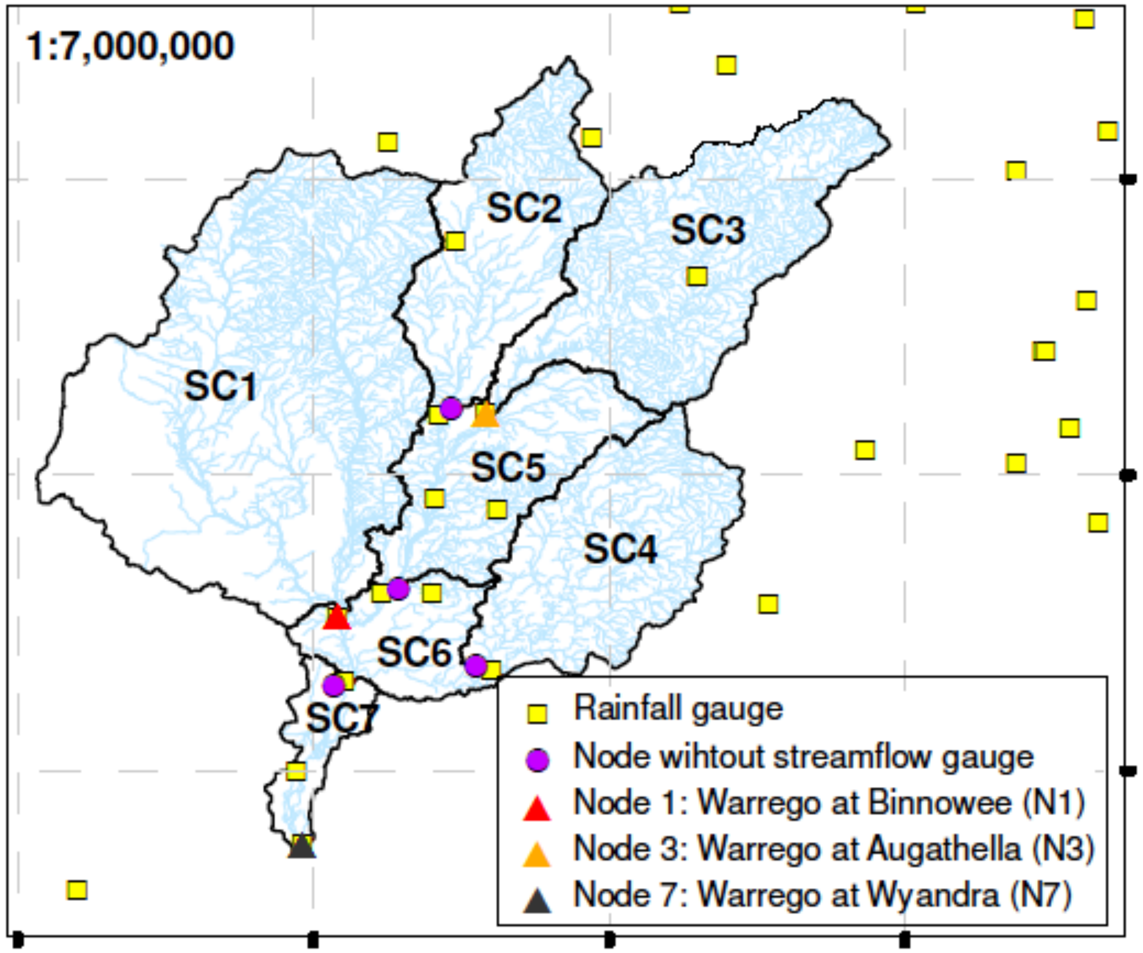
Summary of Ovens Case

- When real-time discharge is assimilated, both EnKF and EnKS improve the forecast accuracy (e.g., MRMSE and NS) by large margin (which decreases with lead time)
- With NWP forecast rainfall, overall forecast accuracy decreases but improvement in MRMSE remains consistent
- Semi-distributed configuration reduces openloop forecast accuracy (~40% reduction of MRMSE)
- No significant difference between lumped and semi-distributed setups after discharge assimilation
- Forecast reliability in upstream gauge locations drops after discharge assimilation

Warrego Catchment

Catchment	Area (km^2)	MAR (mm)
SC1	14,670	492
SC2	4,453	532
SC3	8,070	596
SC4	5,431	524
SC5	4,067	503
SC6	2,130	467
SC7	4,049	418
Total	42,870	512

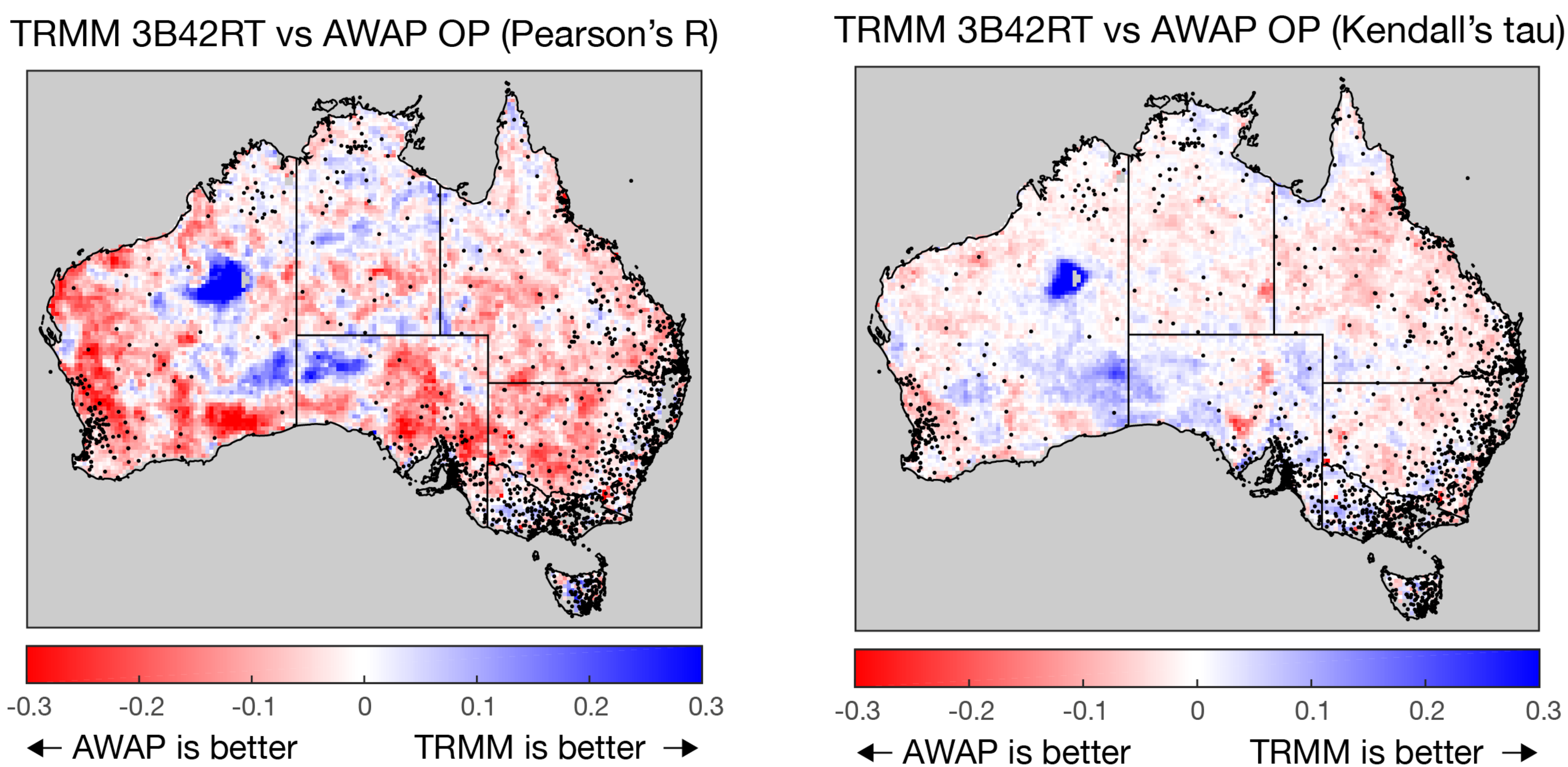
- Chosen assuming no current gauging (no discharge to be assimilated)
- Daily AWAP was used as input to PDM
- We may have to rely on remotely sensed forcing input (e.g., satellite rainfall data) when AWAP accuracy is not guaranteed



AWAP vs TRMM 3B42RT

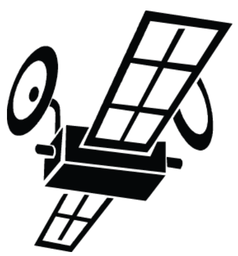
TRMM 3B42RT V7 → API Model → Proxy SM ↔ AMSR-E SM

AWAP Operational → API Model



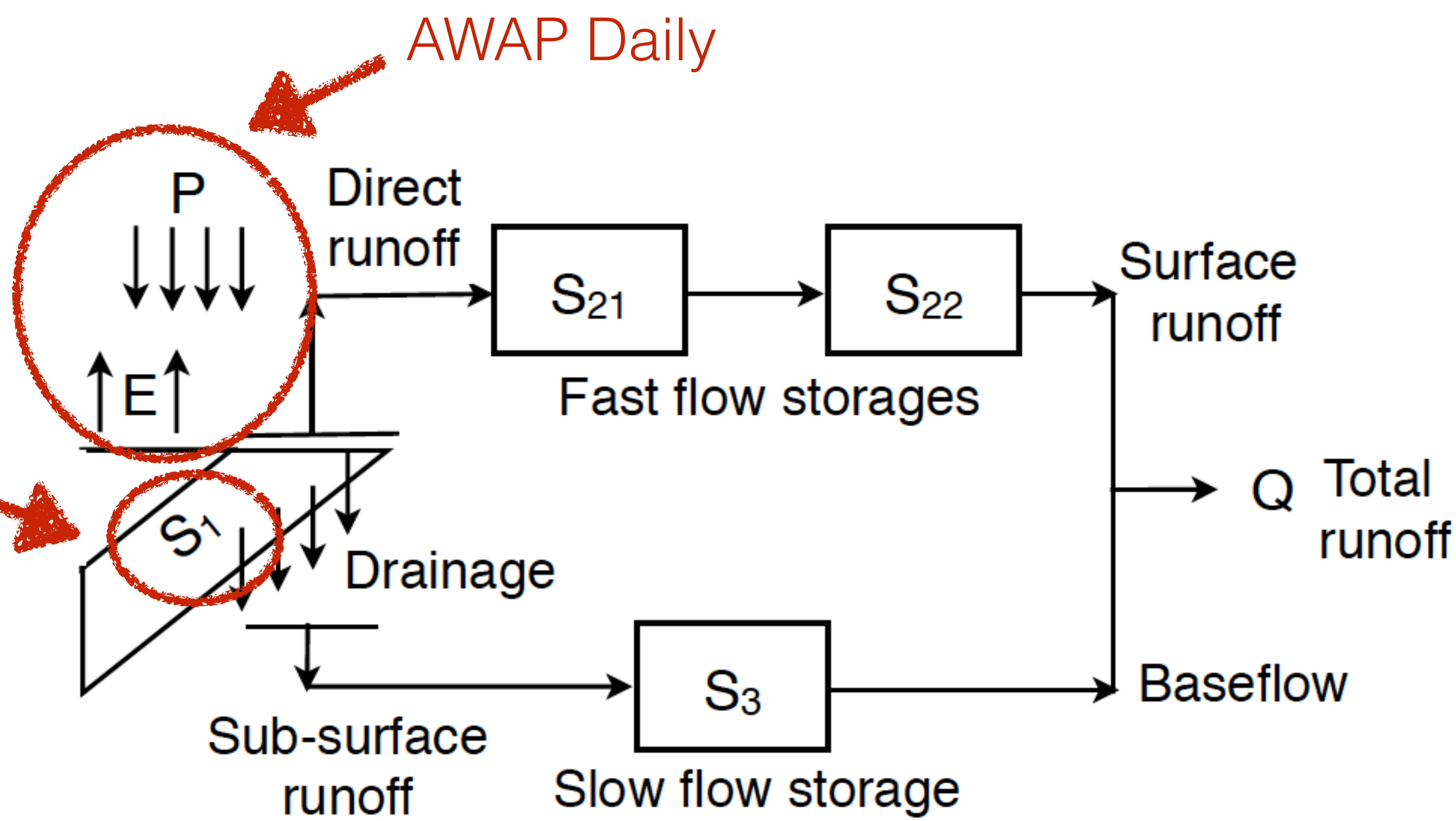
Assimilation of Microwave SM

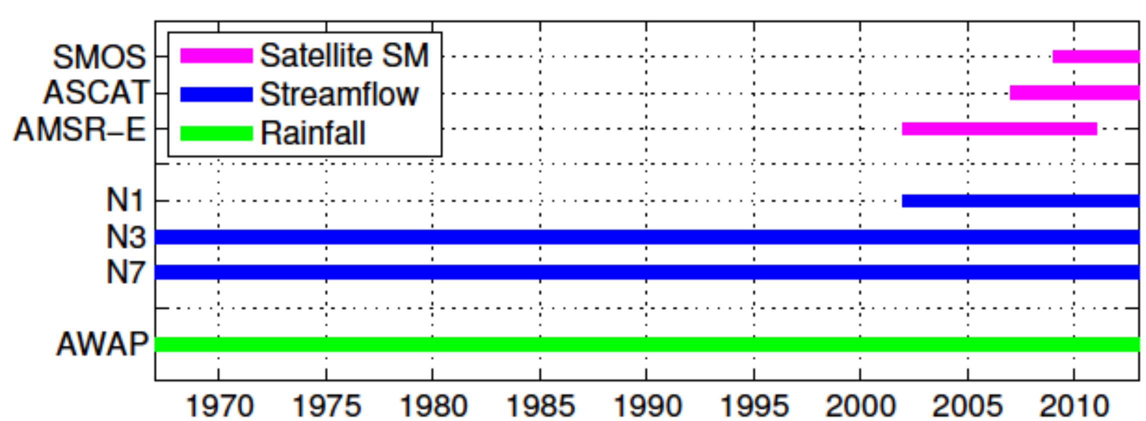
Probability Distributed Model (PDM)



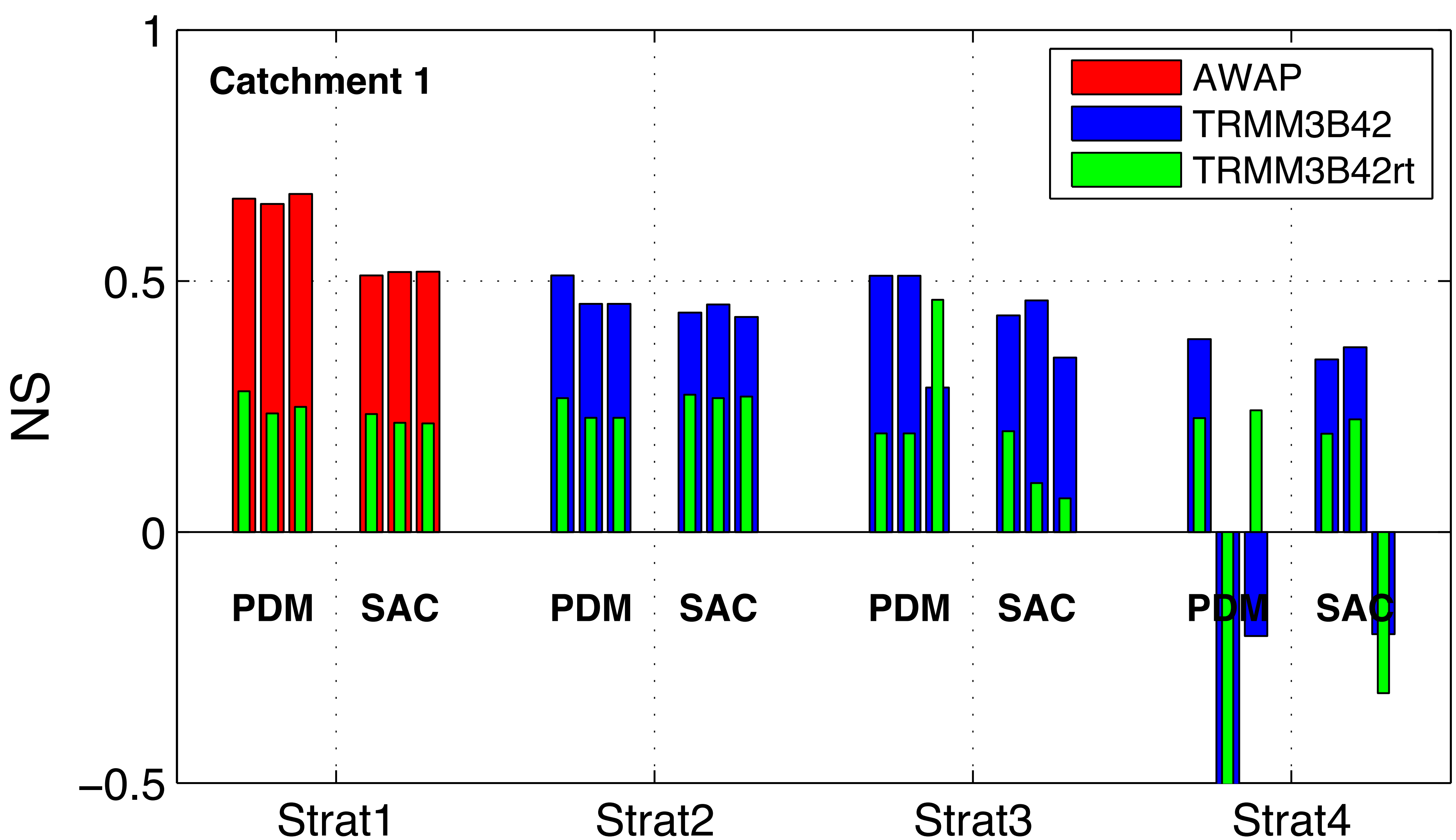
AMSR-E
SMOS
ASCAT

EnKF





Calibration using satellite rainfall products

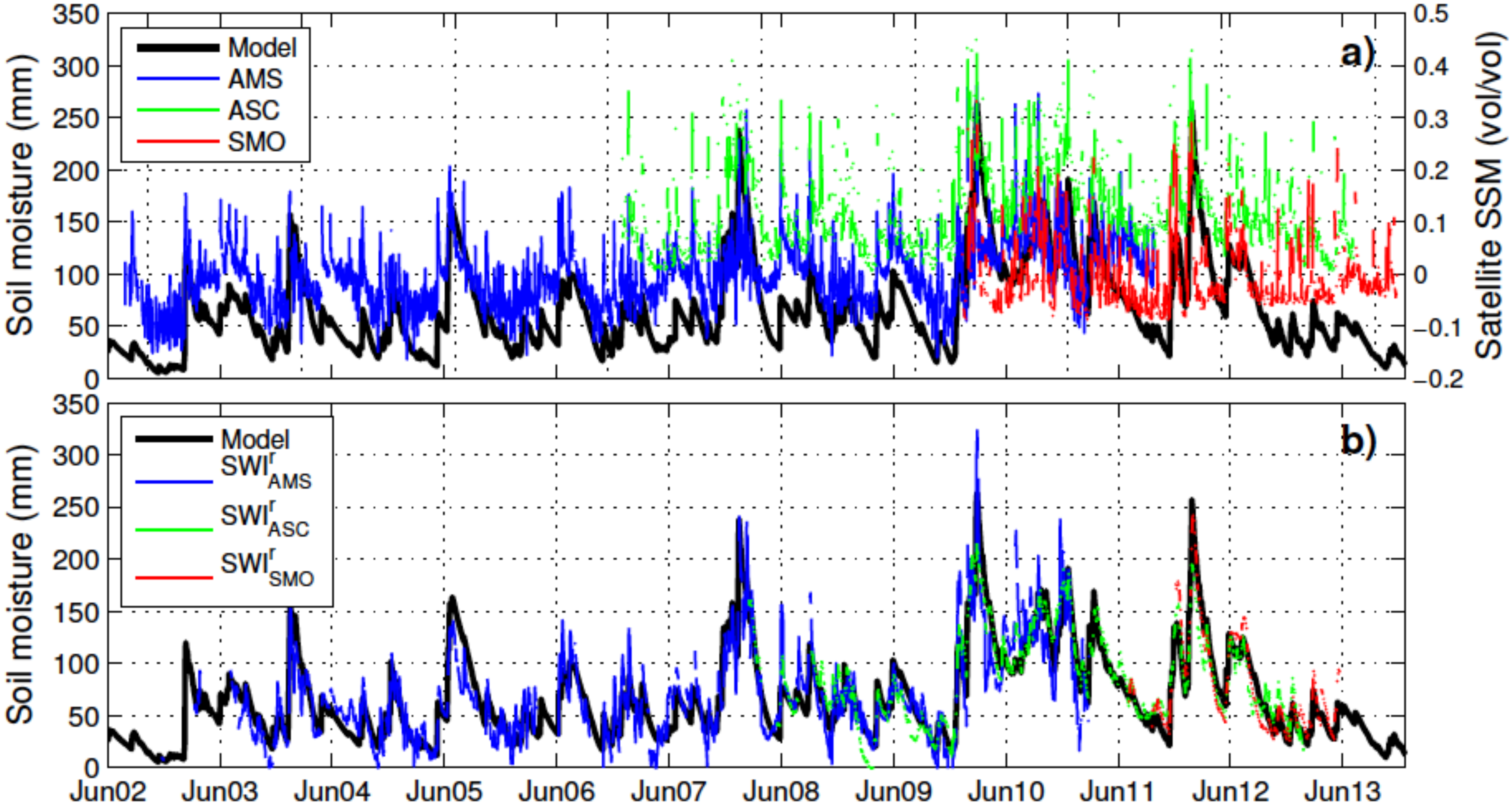


2-fold cal/eval   random cal/eval

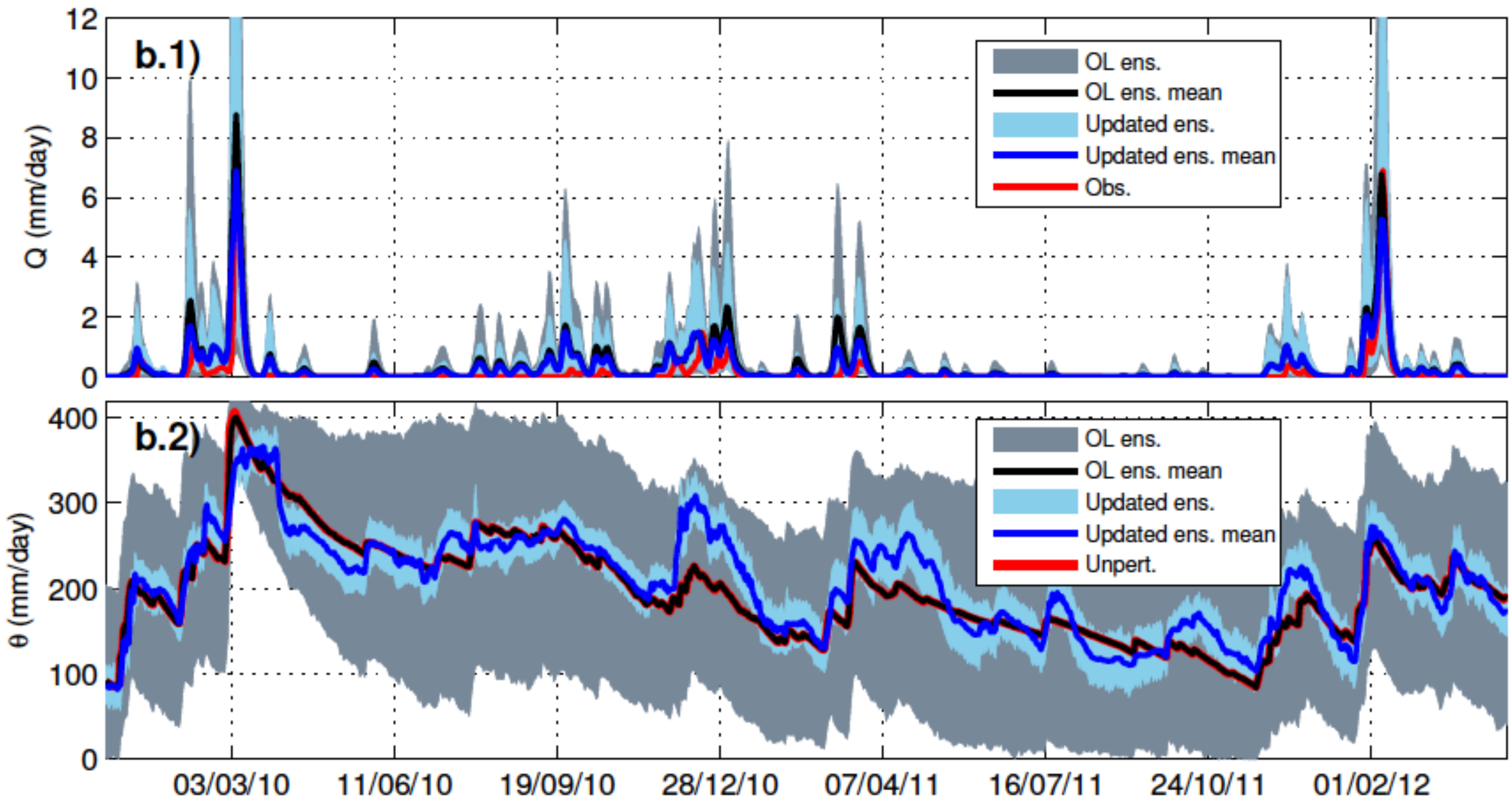
Assimilation of Microwave SM

- AMSR-E, SMOS, and ASCAT soil moisture products bias-corrected by triple collocation (TC) or lagged-variable (LV) scheme
- Seasonally varying observation error specification (byproduct of TC/LV)
- Maximum a posteriori (MAP) to calibrate model perturbation parameters (rainfall and soil moisture)
- Ensemble perturbation bias correction
- Soil water index (SWI) calculated by exponential filter was also tried (no statistically significant difference)

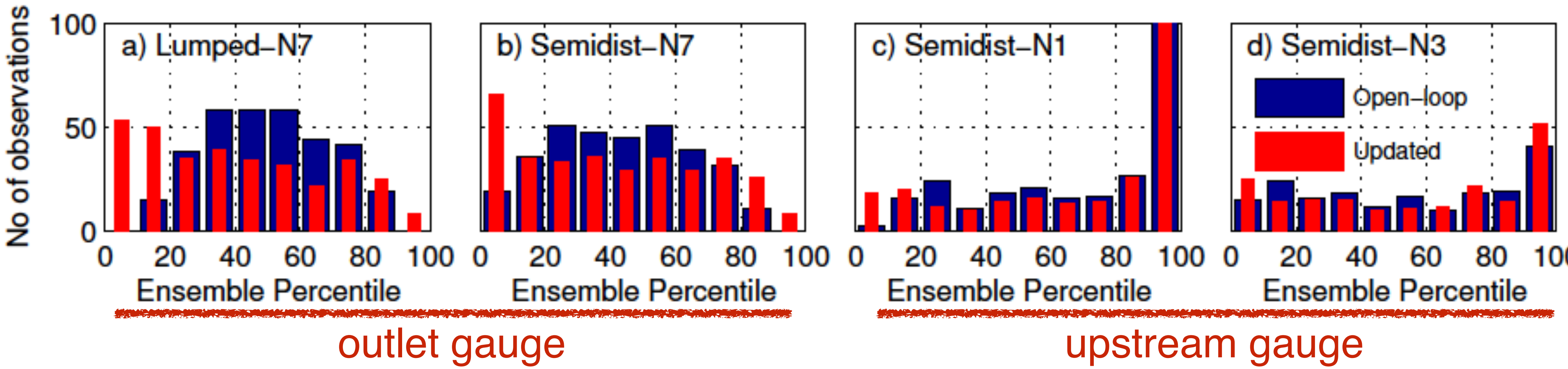
Assimilation of Microwave SM



Output example: semi-distributed, outlet gauge



Assimilation of Microwave SM



Statistic	Lumped scheme (N7)	Semi-distributed scheme (N7)	(N1)	(N3)
NRMSE	0.73	0.69	0.76	0.75
NS_{ol}	0.61	0.53	-0.02	-5.36
NS_{up}	0.65	0.73	0.18	-2.47
POD_{ol}	1.00	0.99	0.61	0.74
POD_{up}	0.99	0.98	0.58	0.71
FAR_{ol}	0.20	0.20	0.13	0.17
FAR_{up}	0.17	0.15	0.10	0.14

Summary of Warrego Case

- In case real-time discharge observation is not available, satellite soil moisture can reduce streamflow prediction error with limited skills (compared to the discharge assimilation)
- Soil moisture assimilation requires very careful handling of biases, model perturbation and observation error specification
- SM DA works better with semi-distributed setup
- Over some part of the country, satellite rainfall shows comparable skills to AWAP (will get better with GMP and other rainfall products)
- Having a small number of rain gauges makes a big difference in ungauged regions

Some Thoughts

- Marginal improvements made by ‘signature information’ are often expensive (start with realistic expectation)
- Real-time integration of observations presumes sound model structure and proper calibration (it will NOT free you from calibration!)
- Mind biases between measurements from difference sources
- Ground and satellite measurements are “complementing”, not “competing” (increasing satellites does not mean we need fewer ground measurements)

THE UNIVERSITY OF MELBOURNE

Results are sourced from:

- Alvarez-Garreton, C., D. Ryu, A. W. Western, C. H. Su, W. T. Crow, and D. E. Robertson (2014), Improving operational ensemble flood prediction by the assimilation of satellite soil moisture: comparison between lumped and semi-distributed schemes, Hydrol. Earth Syst. Sc. (Discuss), 11, 10635-10681, doi:10.5194/hessd-11-10635-2014.

- Li, Y., D. Ryu, A. W. Western, Q. J. Wang, D. E. Robertson, W. T. Crow (2014), An integrated error parameter estimation and lag-aware data assimilation scheme for real-time flood forecasting, J. Hydrol., doi:10.1016/j.jhydrol.2014.08.009, in press.

- Alvarez-Garreton, C., D. Ryu, A. W. Western, W. T. Crow, D. E. Robertson (2014), The impacts of assimilating satellite soil moisture into a rainfall-runoff modle in a semi-arid catchment, J. Hydrol., doi:10.1016/j.jhydrol.2014.07.041, in press.

- Su, C. H., D. Ryu, W. T. Crow, A. W. Western (2014), Stand-alone error characterisation of microwave satellite soil moisture using a Fourier method, Remote Sens. Environ., 154, 115-126, doi:10.1016/j.rse.2014.08.014.

- Su, C. H., D. Ryu, W. T. Crow, A. W. Western (2014), Beyond triple collocation: Applications to soil moisture monitoring, J. Geophys. Res., 119(11), 6419-6439. doi:10.1002/2013JD021043.

- Chen, F., W. T. Crow, D. Ryu (2014), Dual forcing and state correction via soil moisture assimilation for improved rainfall-runoff modeling, J. Hydrometerol., 15, 1832-1848, doi:10.1175/JHM-D-14-0002.1.

- Li, Y., D. Ryu, A. W. Western, and Q. J. Wang (2013) Assimilation of stream discharge for flood forecasting: the benefits of accounting for routing time lags, Water Resour. Res., 49, 1887-1900, doi:10.1002/wrcr.20169.