Confronting total uncertainty in Hydrologic Prediction: An Integrated Bayesian Multi-Model Hydrologic Ensemble Prediction System

Newsha Ajami[1], Q. Duan[2], S. Sorooshian[1], P. Duffy[2]

[1.] University of California at Irvine
[2.] Lawrence Livermore National Laboratory

Funding provided by:

What is happening in our world!

?

•What if my model is not perfect … I bet it is!
•What about the states, how should I estimate those?

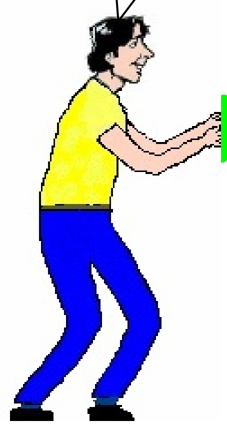
WHAT ABOUT UNCERTAINTY !!!!?????

Bias removal
Downscaling

f my forcing data was perfect!
if my parameters were correct!

Data Assimilation

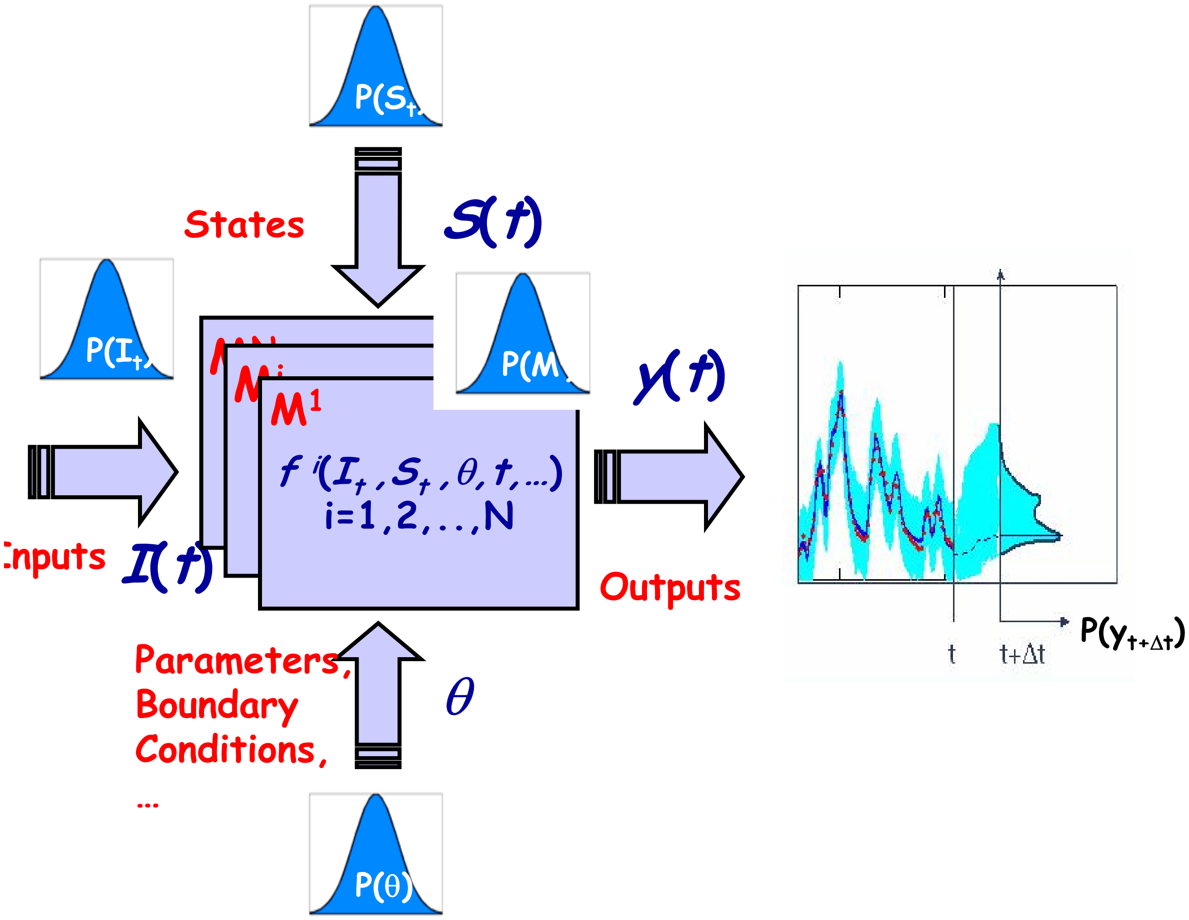
Calibration, MCMC, Equifinality



HYDROLOGIC MODELS

The Need For An Integrated Approach To Account For Total Uncertainty

- The Problems:
  - Observed input uncertainty not addressed
  - Model structural uncertainty ignored, or inadequately addressed
  - Different sources of uncertainty are addressed independently



Integration of multiple sources of Uncertainty

- Input, Parameter and model uncertainty are integrated, in two steps:
  - Accounting for Input and parameter uncertainty in a single model using Shuffled Complex Evolution Metropolis (SCEM-UA - Vrugt et al. 2003)
  - Accounting for Model uncertainty using modified version of Bayesian Model Averaging (Medigan et al. 1996) – This step integrates the Input and parameter uncertainty of different models as well as model structural uncertainty at the same time.

Accounting for Input and Parameter Uncertainty

We can formulate the problem here as follows:

Model k

Streamflow estimate
From model k at time t $\leftarrow$ $y_{k,t} = y(I_t, \theta, M_k, t)$

Input at time t **Model parameters**

So,

what do we want? → probability of the estimated streamflow based on the available data (D=[I, y_{obs}])

$$p(y_t | \theta, D, M)$$

Accounting for Input and Parameter Uncertainty

Step 1: Input and parameter uncertainty for each individual model using SCEM:

$$p(y|\theta, D, M_k)$$

Step 2: Model structure uncertainty , integration of all sources of uncertainty:

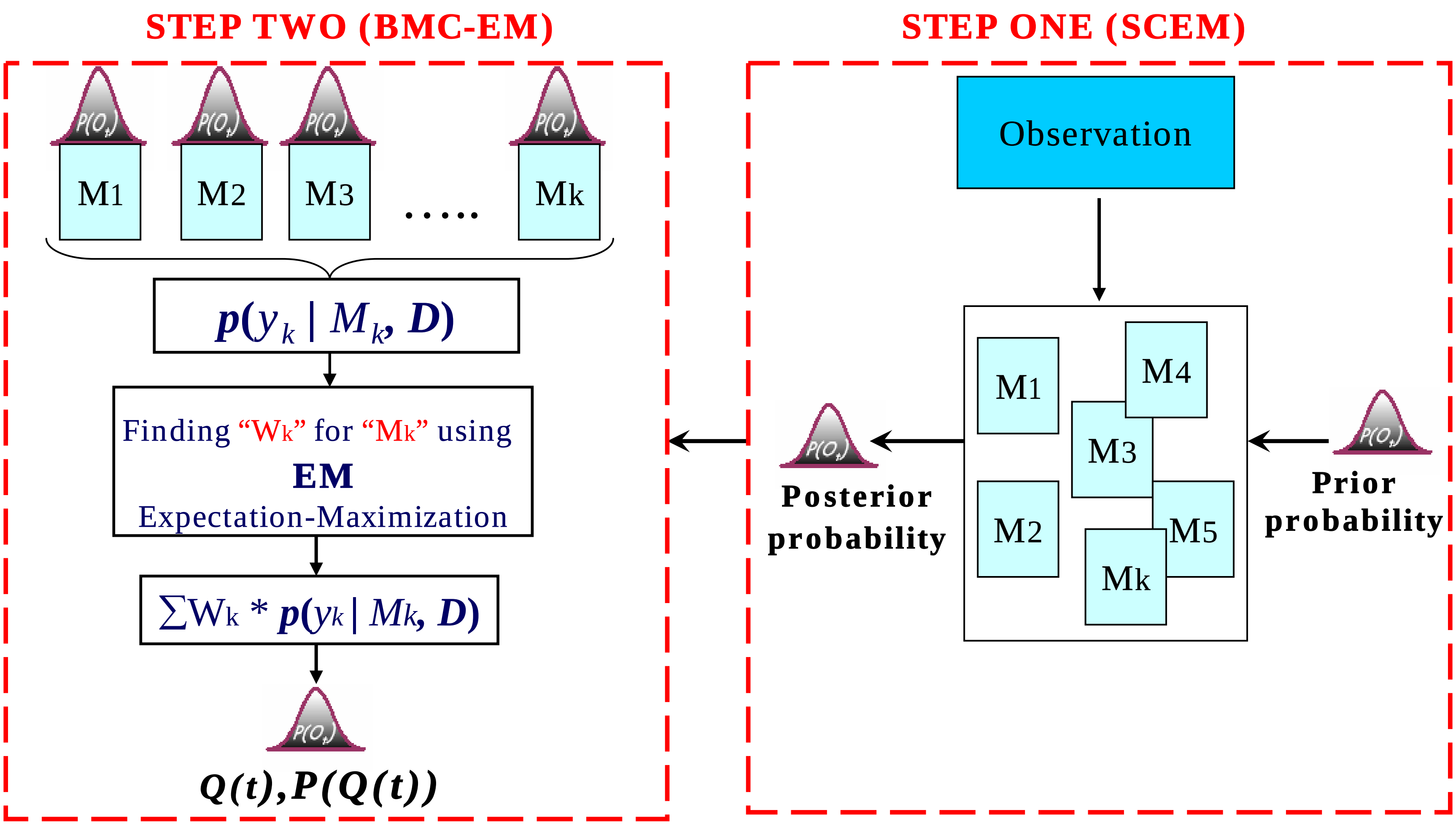
$$p(y \mid M_1, \ldots, M_k, D) = \sum_{k=1}^{K} p(M_k \mid D) \cdot p_k(y \mid M_k, D)$$

$wk = p(M_k|D)$

Likelihood of model *Mk* being a true model -- > Weights represent physical meaning and

$\sum_{k=1}^{K} w_k = 1$

Schematic of the methodology

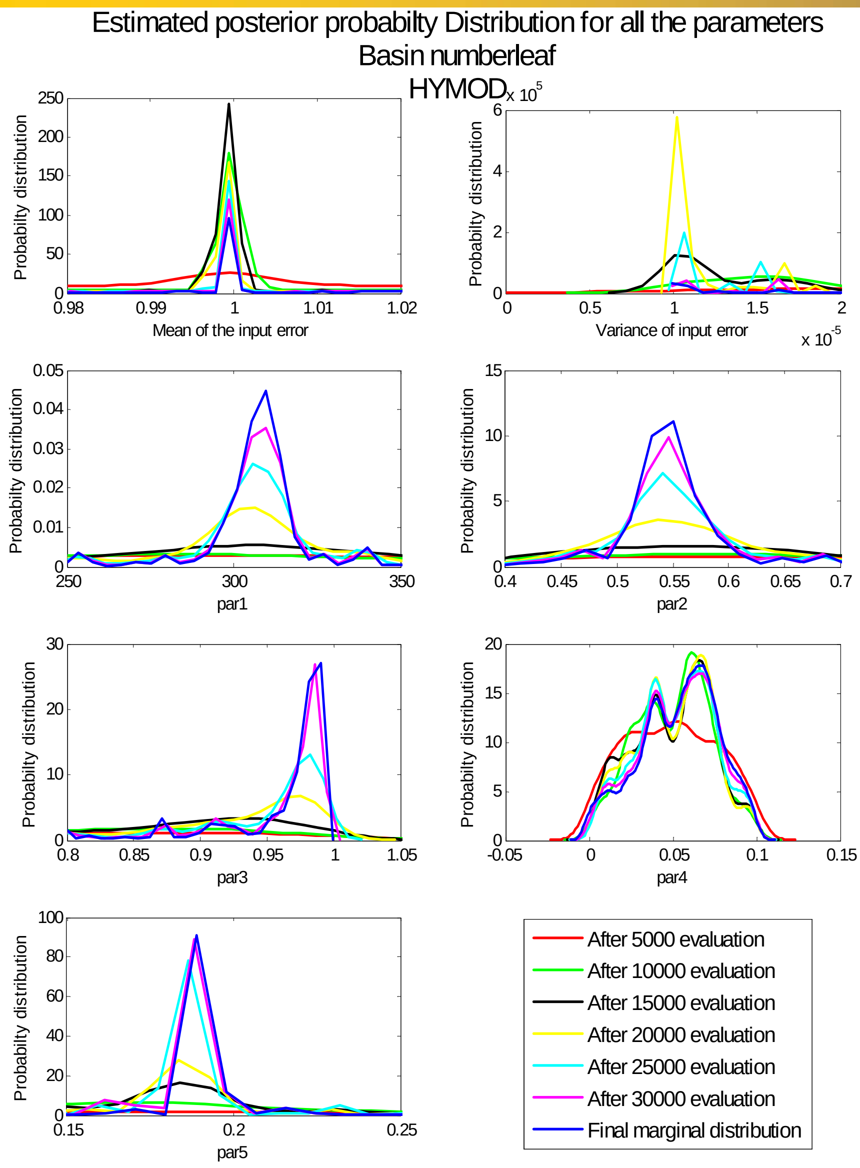


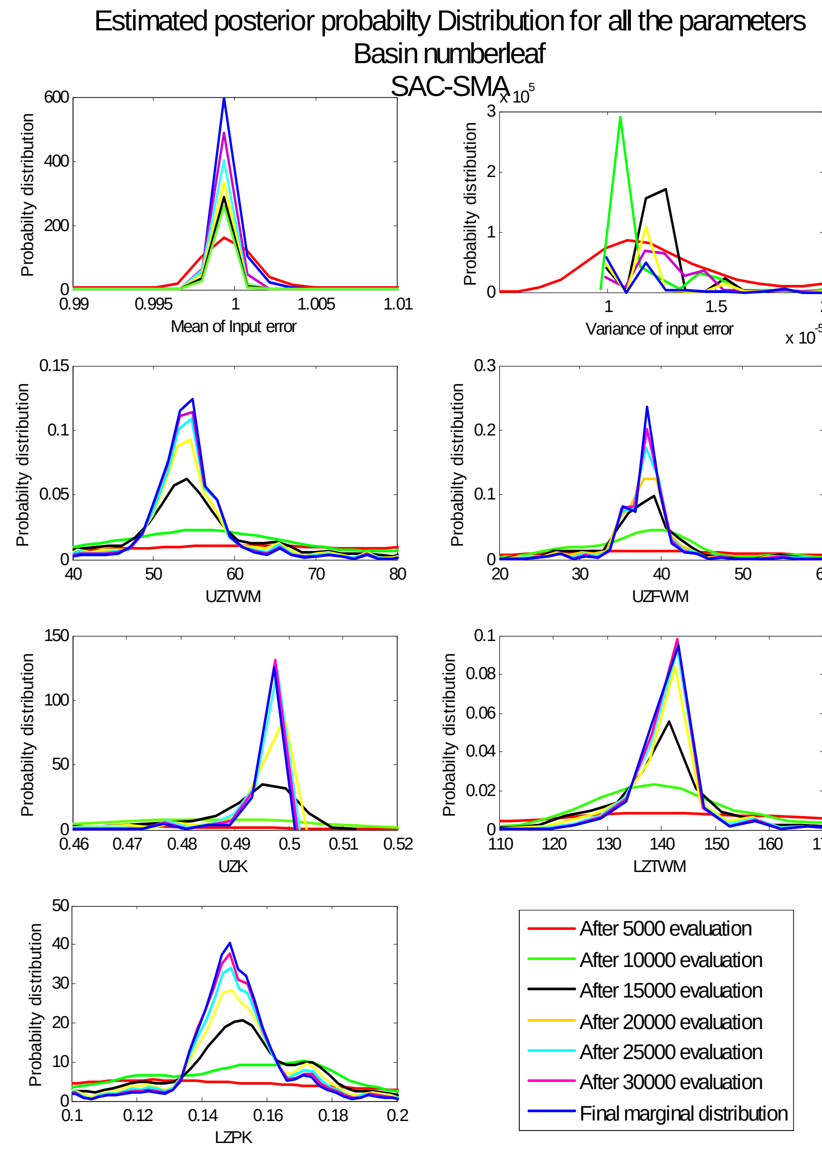
Study plan

- Study Basin: Leaf River in Mississippi
- Hydrologic Data: 6 years of precipitation and streamflow data (one year for warming up and another year for model identification)
- Models used: SAC-SMA, HYMOD and SWB
- Input Error Model: $I_t = \phi_t \cdot I_t^{obs}$, $\phi_t \sim f(m_\phi, \sigma_\phi)$
- Seven parameters optimized: two input error model parameter and five hydrologic model parameters

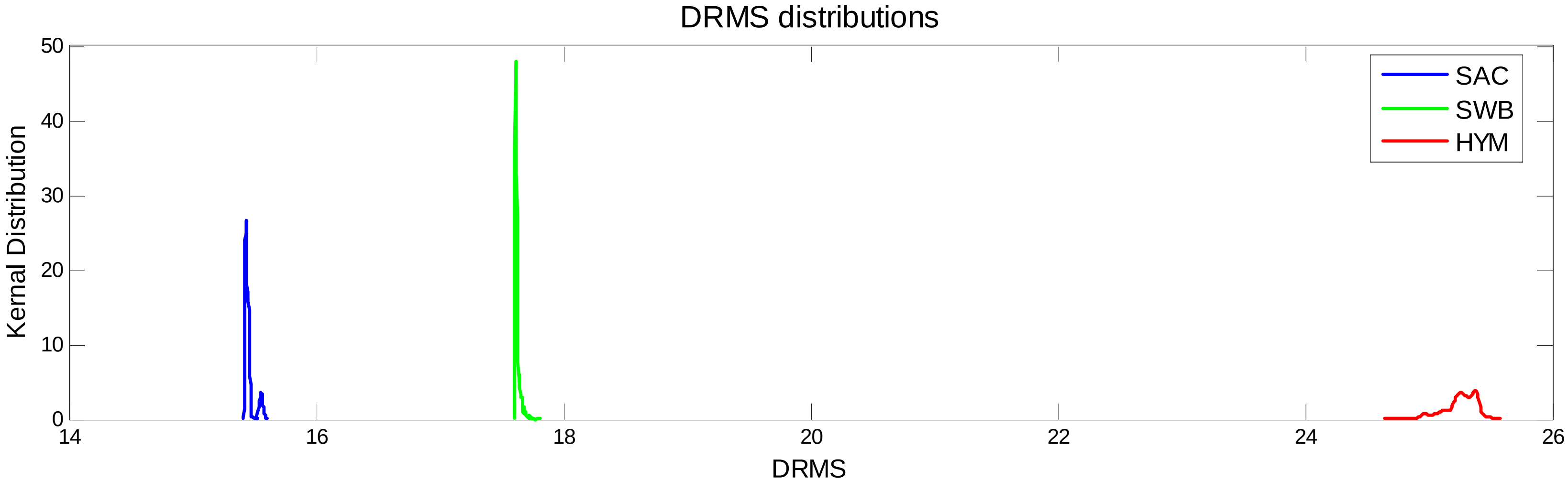
Results from Step one

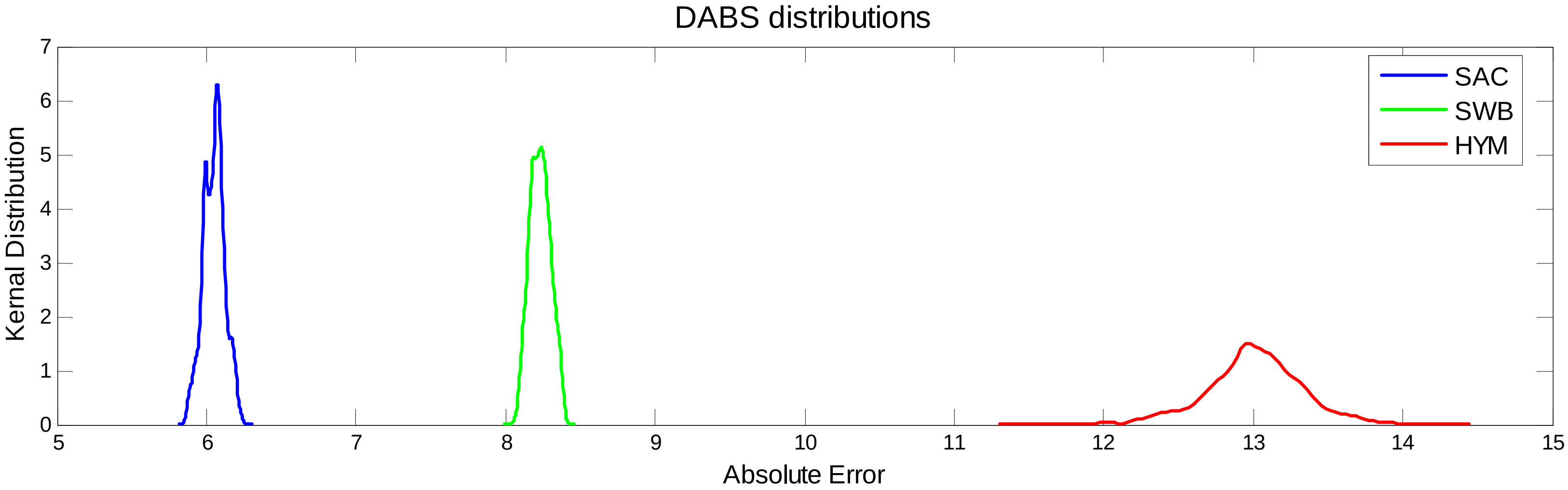
Convergence of posterior Distribution of model parameters





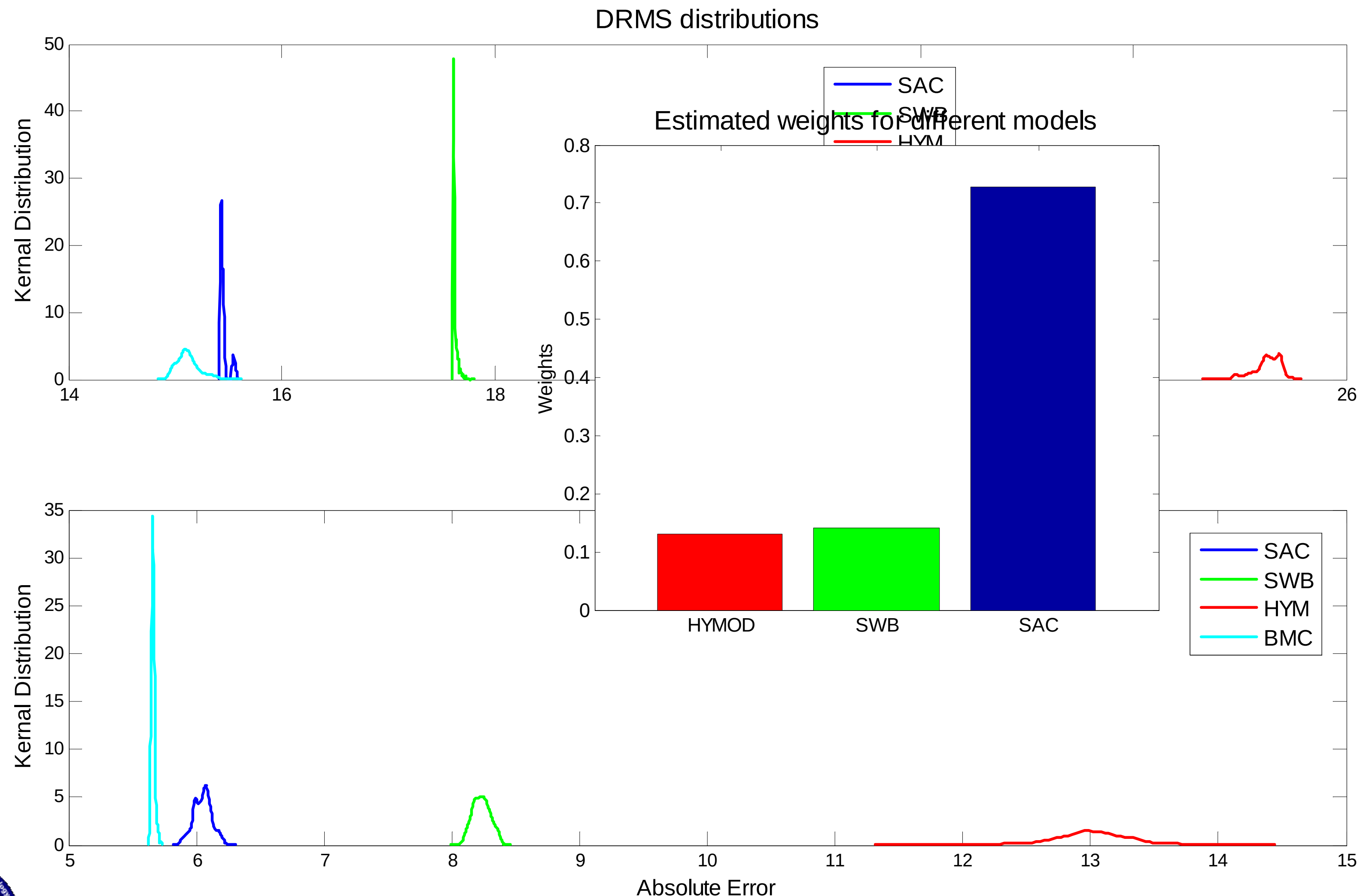
Distribution of Model performances



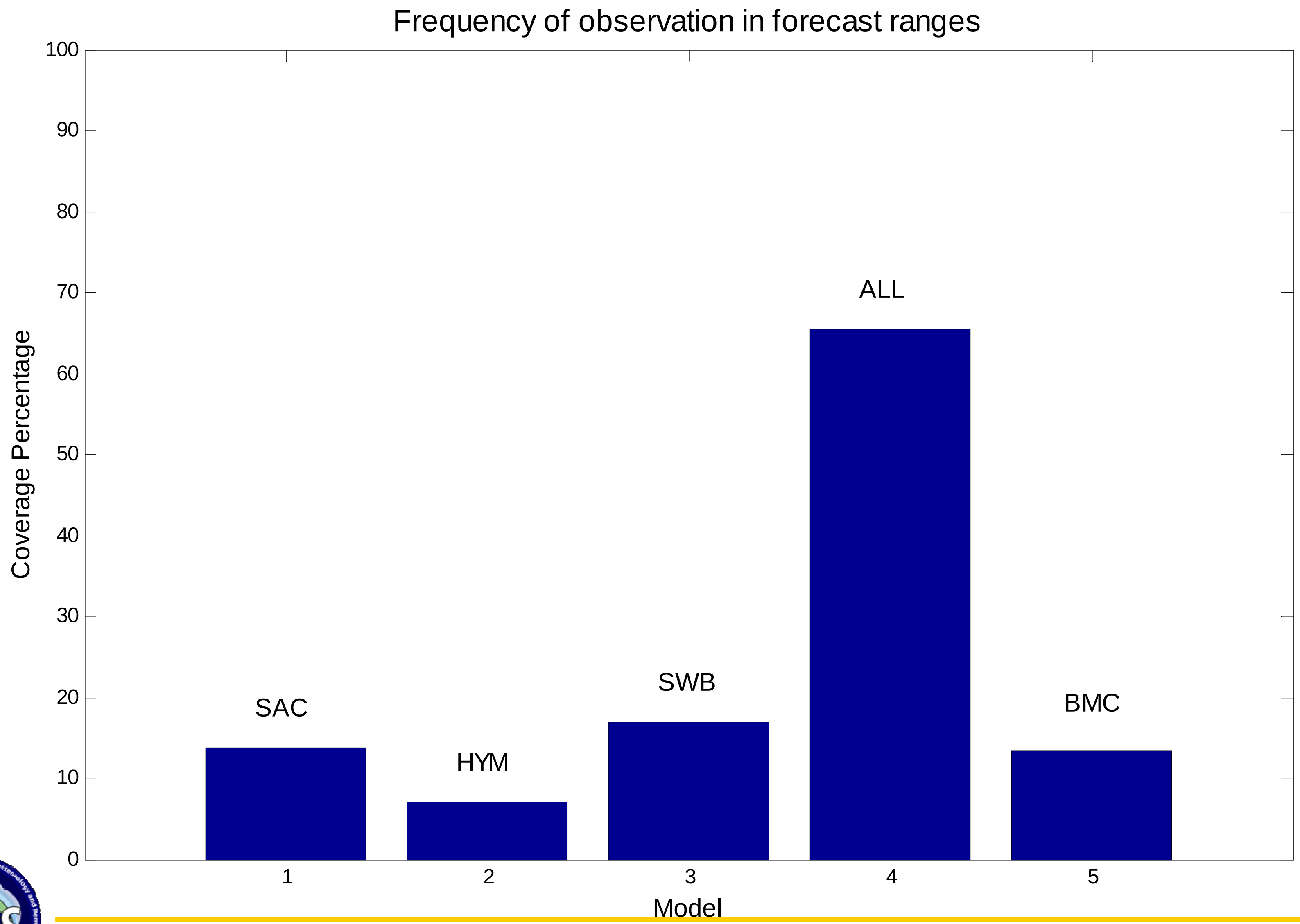


Results from Step two
“Combination”

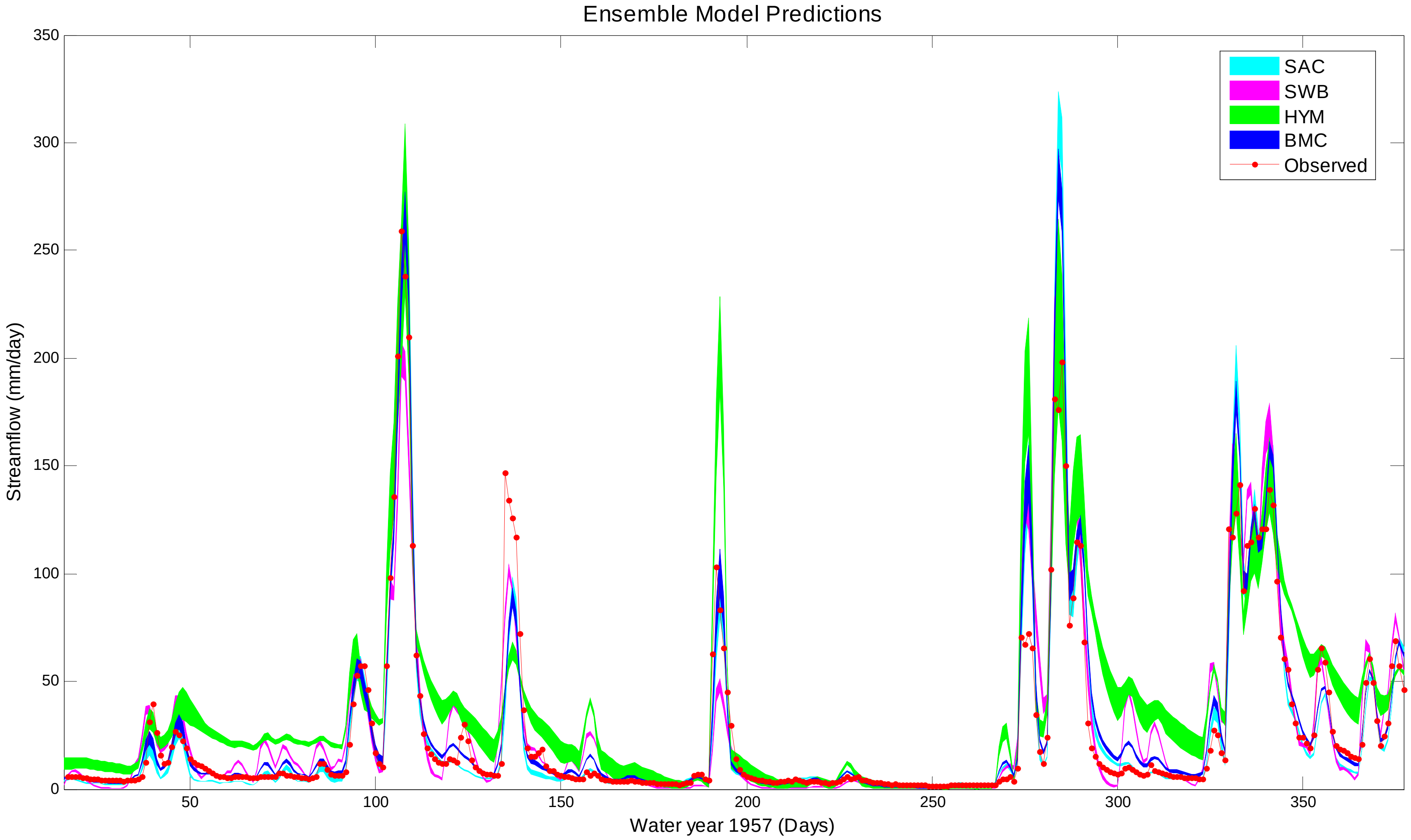
Distribution of model versus BMC performance



Frequency of uncertainty ranges bracket observation



An Excerpt of the hydrographs



Summary

- Outlined an integrated strategy to account for input, model parameter and model structural uncertainties

- Demonstrated the model identification methodology that consider both input and model parameter uncertainties:
  - Input error model
  - Three models

- Demonstrated the multi-model combination approach to obtain consensus predictions:
  - Single model prediction too confident
  - Weights represent model performance and reliability
  - Multi-model consensus prediction more skillful and with better description of total uncertainty

Ongoing and future research

- Verification of the methodology over several other hydrological basins.
- Extend the algorithm to directly using ensemble forcing inputs
- Extend the methodology to consider state and initial condition uncertainties