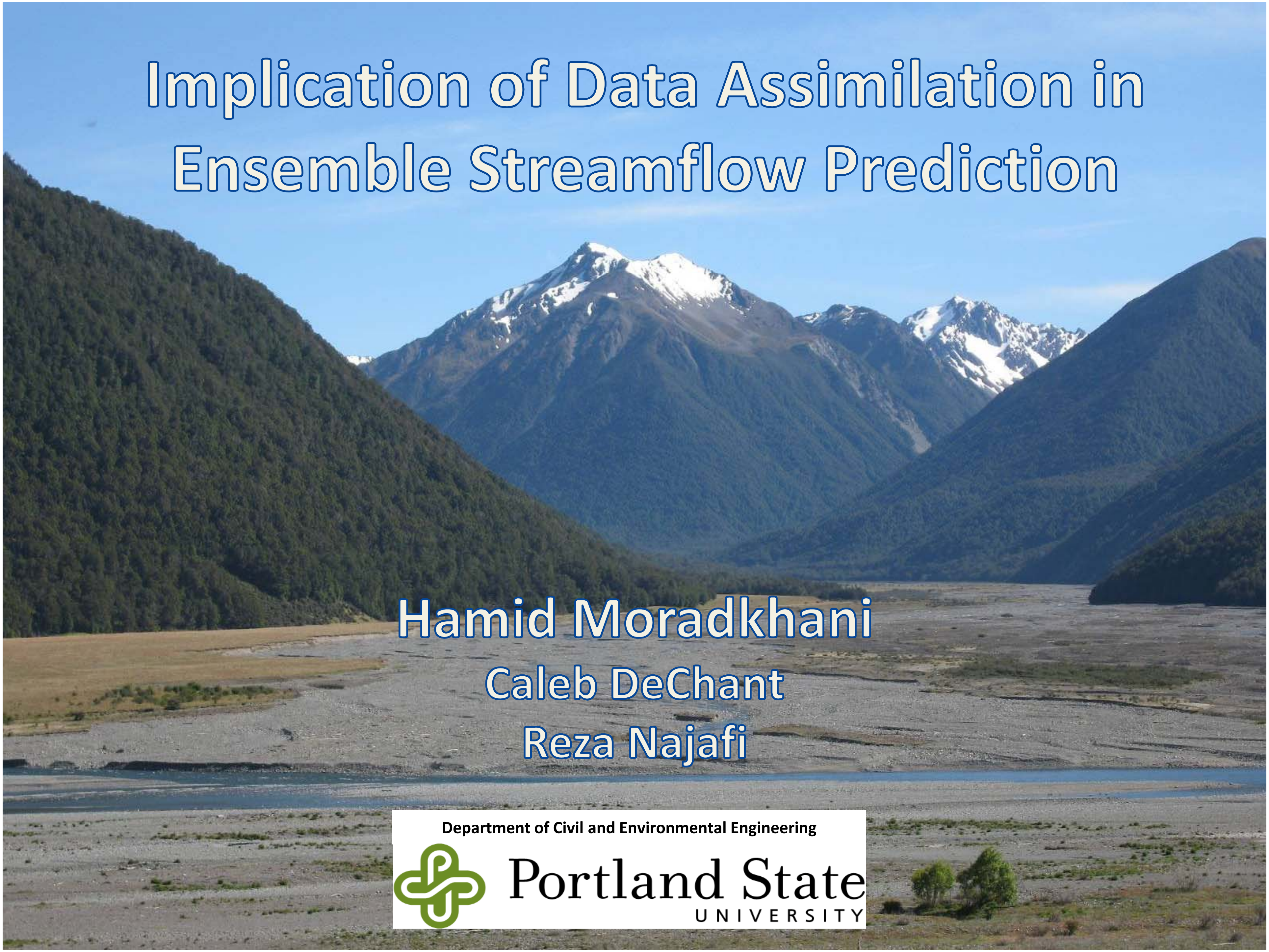


Implication of Data Assimilation in Ensemble Streamflow Prediction

Hamid Moradkhani

Caleb DeChant

Reza Najafi

Department of Civil and Environmental Engineering

Portland State University

Difficulties in Hydrologic Predictions

- Space-time variability of climatic inputs
- Heterogeneity of the land surface condition: vegetation, land use, soils, snow extent, etc.
- Selection of one or multiple plausible model/s that can provide reliable and skillful prediction under all circumstances

Motivation

- Ensemble based data assimilation provides a framework for estimating uncertainty
- Can be used to calibrate models (dual state-parameter estimation) to reliably estimate the total uncertainty in streamflow estimation
- Can be used to estimate the uncertainty in system states for initialization of forecasts
  - will demonstrate in a case study for Ensemble Streamflow Prediction (ESP)

Global Optimization or Ensemble Inference and Data Assimilation?

Moradkhani 2008

Parameter Estimation: Improve estimates of a set of poorly known model parameters leading to an exact model solution that is close to the measurements.

- All errors in the model are associated with uncertainties in the selected model parameters.
- The model initial conditions, boundary conditions, and the model structure are all exactly known

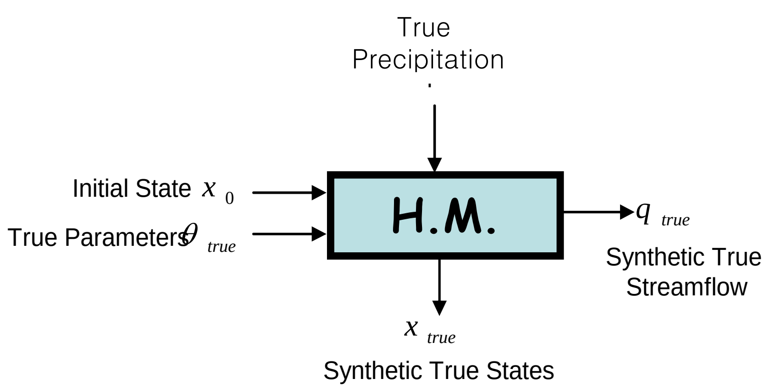
State Estimation using Data Assimilation: Defined as finding the estimate of the model state that in some weighted measure best fits the observation, the initial and boundary conditions.

Combined Parameter and State Estimation: An improved state estimate and a set of improved model parameters are searched for simultaneously.

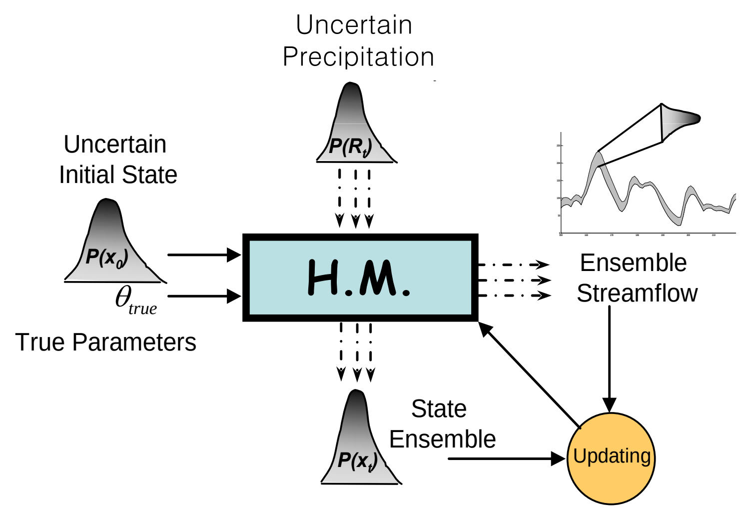
Hydrologic Modeling and Uncertainty Analysis Scenarios using Data Assimilation

Moradkhani et al., 2006

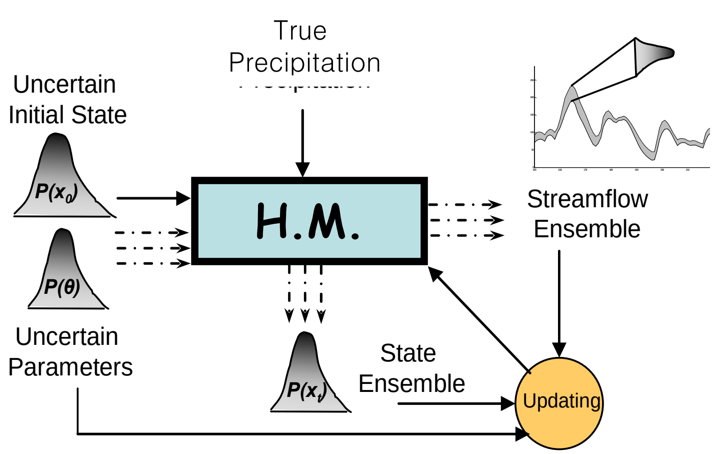
(a) Synthetic True



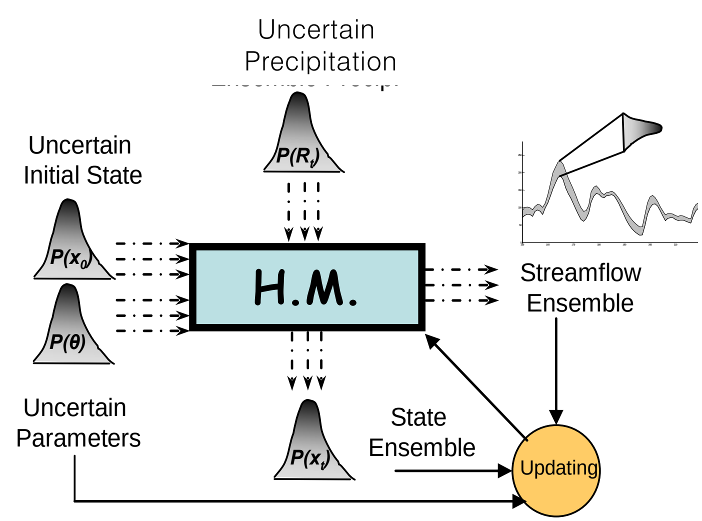
(b) Forcing Data Error



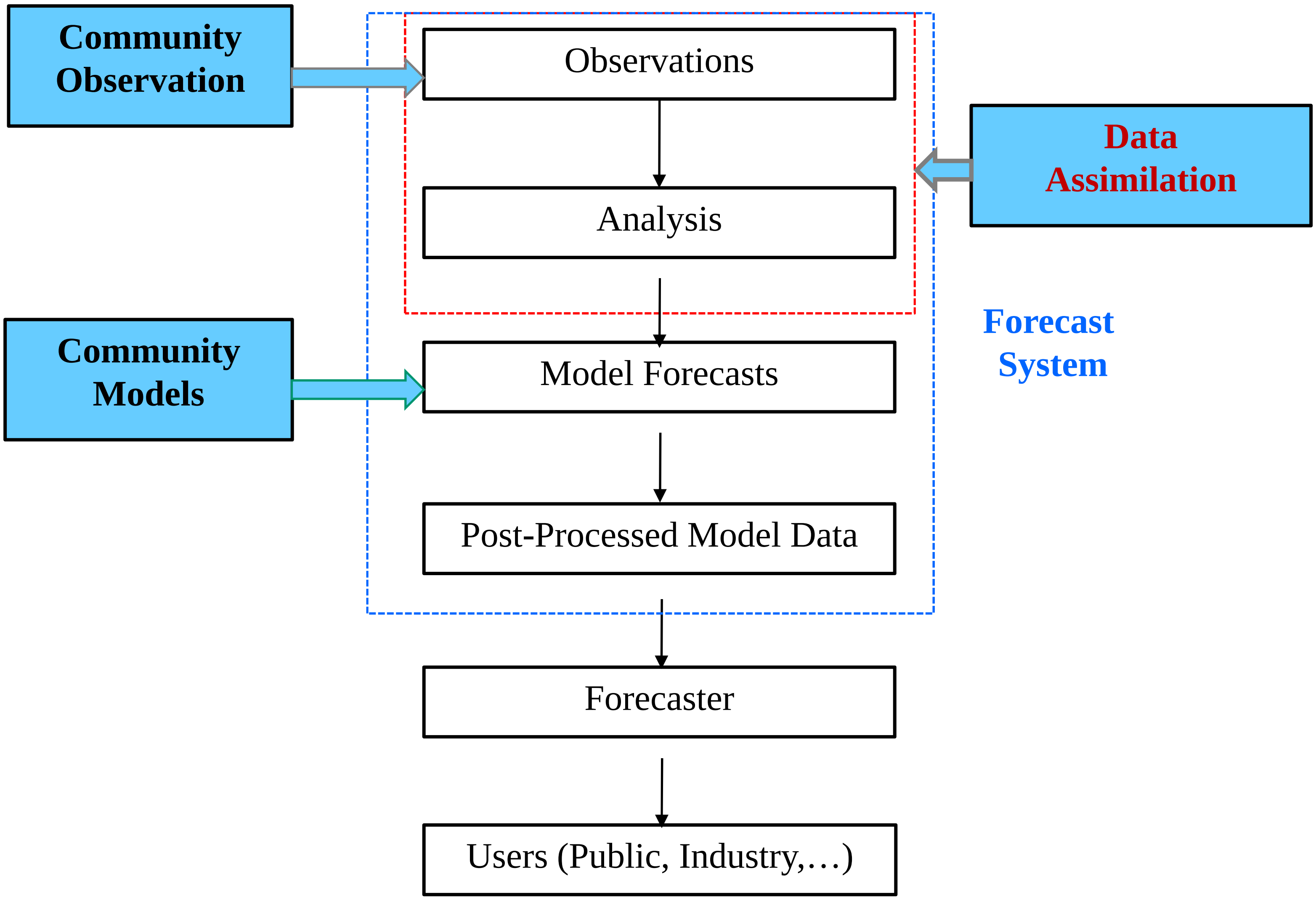
(c) Parameter Uncertainty



(d) Combined Uncertainties



Community Hydrologic Prediction System (CHPS)



Bayes Law and Data Assimilation

Likelihood

$$P(X,\theta \,|\, Data) = P(X,\theta)\,\frac{P(Data \,|\, X,\theta)}{P(Data)}$$

Posterior Probability

Prior Probability

Evidence

Sequential Ensemble Data Assimilation

Moradkhani et al., 2005

Likelihood

Forecast Density (Prior)

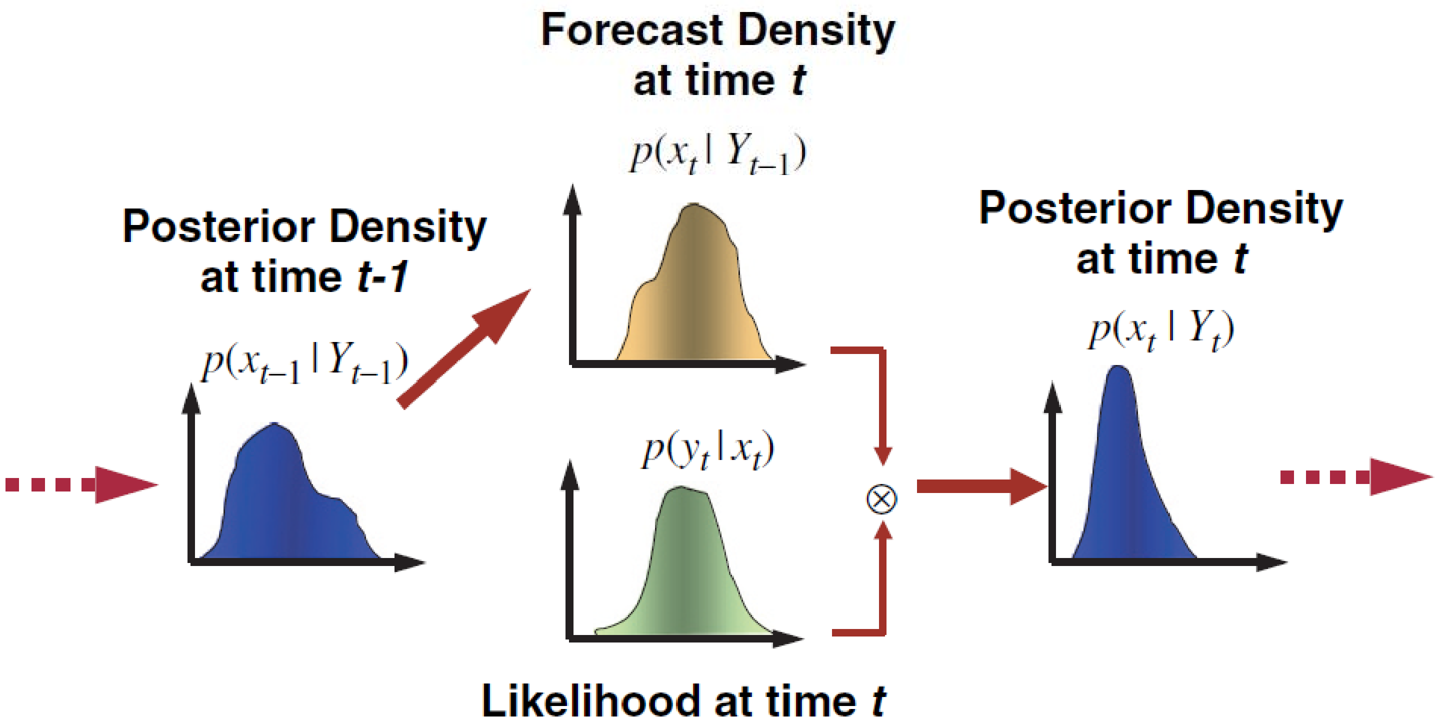
Analysis Density (Posterior)

$$\boxed{p(x_{k+1} \mid Y_{k+1}) = \frac{p(y_{k+1} \mid x_{k+1})\, p(x_{k+1} \mid Y_k)}{p(y_{k+1} \mid Y_k)}}$$

Evidence

$$p(x_{k+1} \mid Y_k) = \int_{x_k} p(x_{k+1} \mid x_k)\, p(x_k \mid Y_k)\, dx_k$$

$$p(y_{k+1} \mid Y_k) = \int_{x_{k+1}} p(y_{k+1} \mid x_{k+1})\, p(x_{k+1} \mid Y_k)\, dx_{k+1}$$



Using Data Assimilation to Initialize Seasonal Forecasts

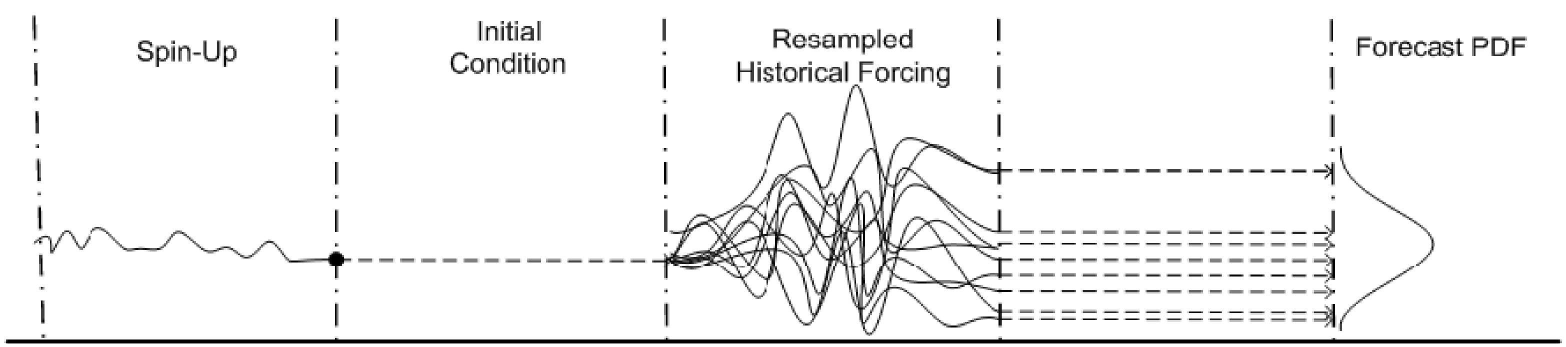
- Performed within the ESP framework
  - May be improved through better characterization of future forcing or initial states
- This study uses in-situ snow observations (SNOTEL) to constrain model estimates of SWE
- Implemented with a coupled SNOW-17 and SAC-SMA model
- Compares against the method currently used at the NWS for seasonal streamflow prediction
  - Analyzes the effect of SWE uncertainty estimation

Ensemble Streamflow Prediction

- Run the model through a spin-up period to characterize the initial condition (current watershed states)

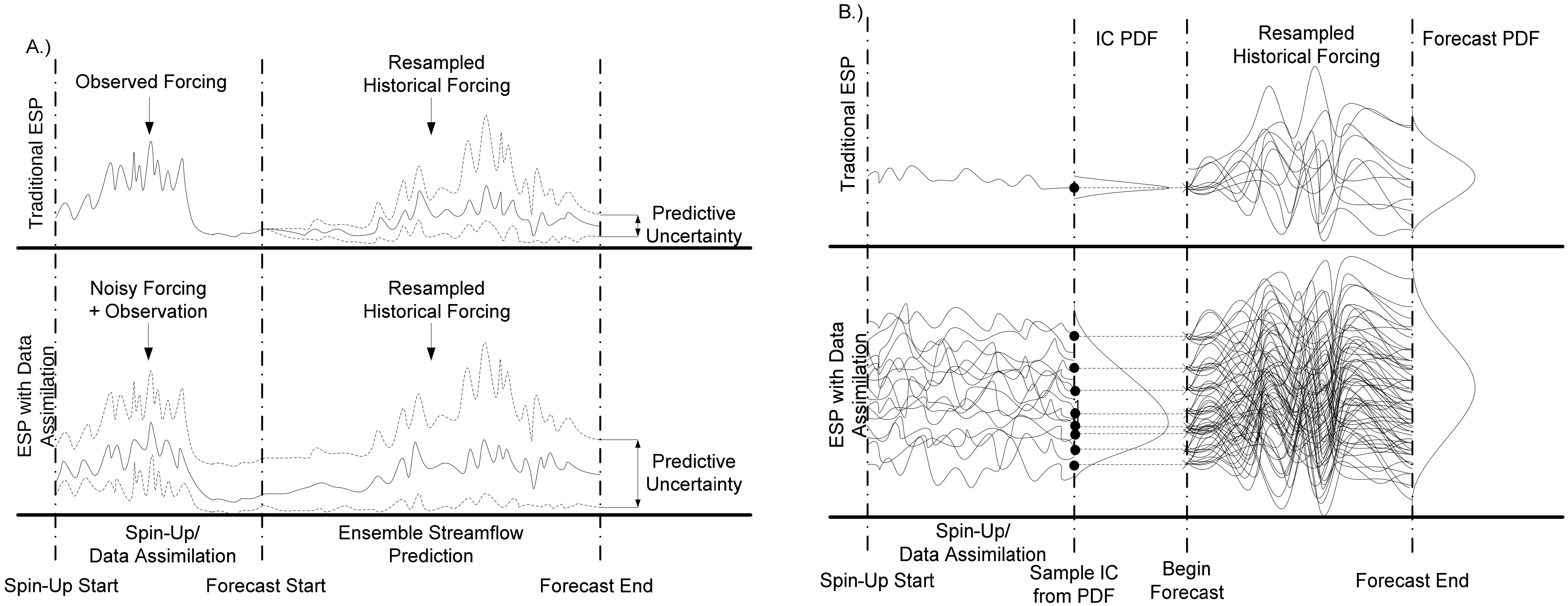
- From the initial states, run the model using resampled historical forcing
  - Assumes that historical forcing is an indicator of the possible future forcing
- Creates an ensemble forecast considered as probabilistic prediction of the water that will flow off of the land surface in a given season

Run the model to current time-step with observed data	→	Run model from current time-step with historical data	→	Calculate the probability of different runoff scenarios



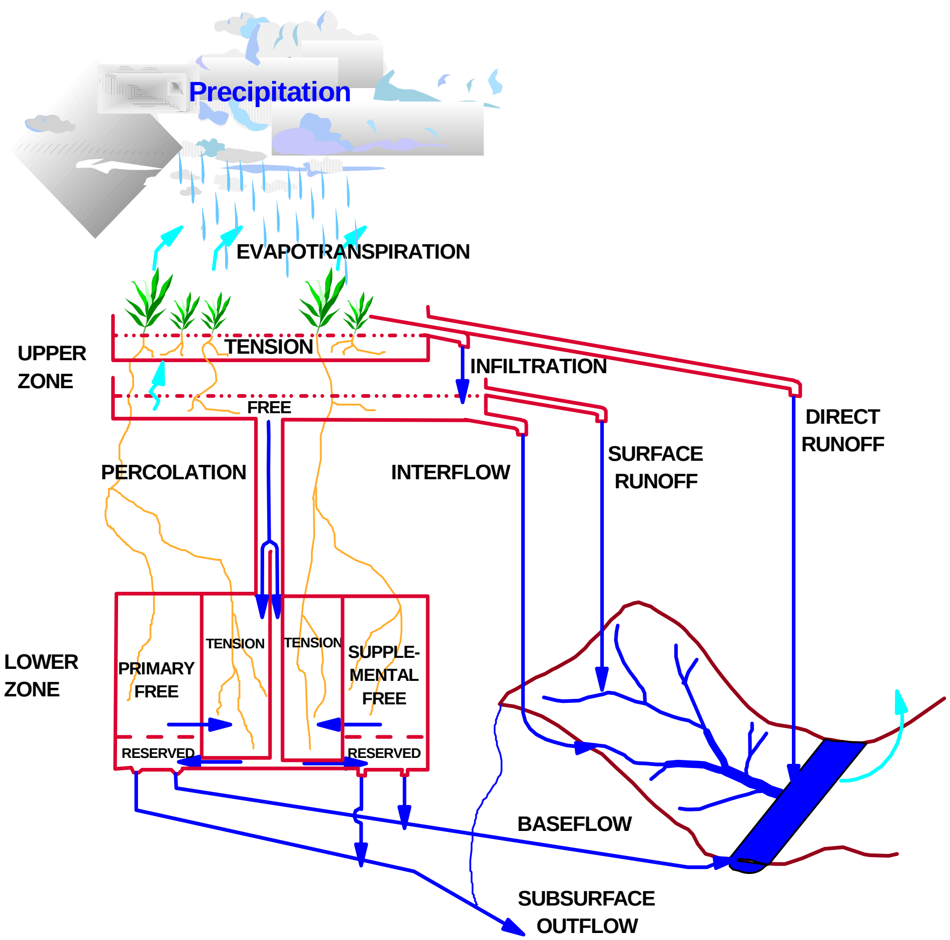
ESP with Data Assimilation (ESP-DA)

- Use Data Assimilation to characterize the uncertainties in initial conditions
- More completely characterizes the uncertainty in seasonal streamflow predictions
- Greatest potential for improvement is in snow-dominated regions

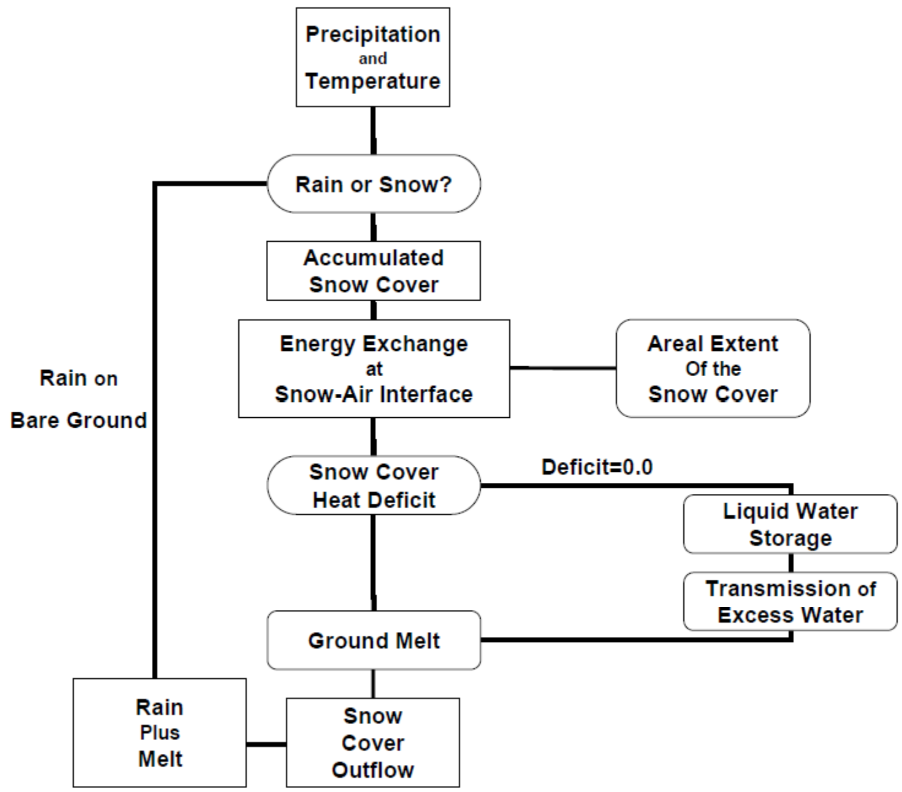


Operational Hydrologic Models

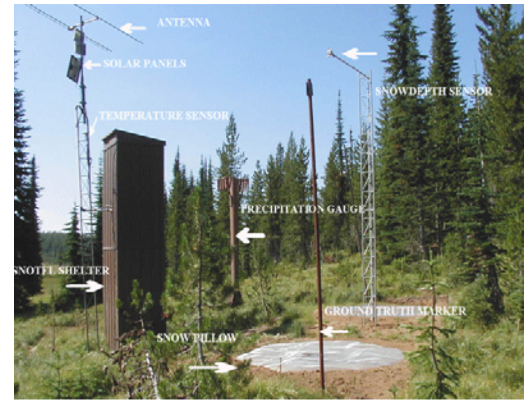
SAC-SMA

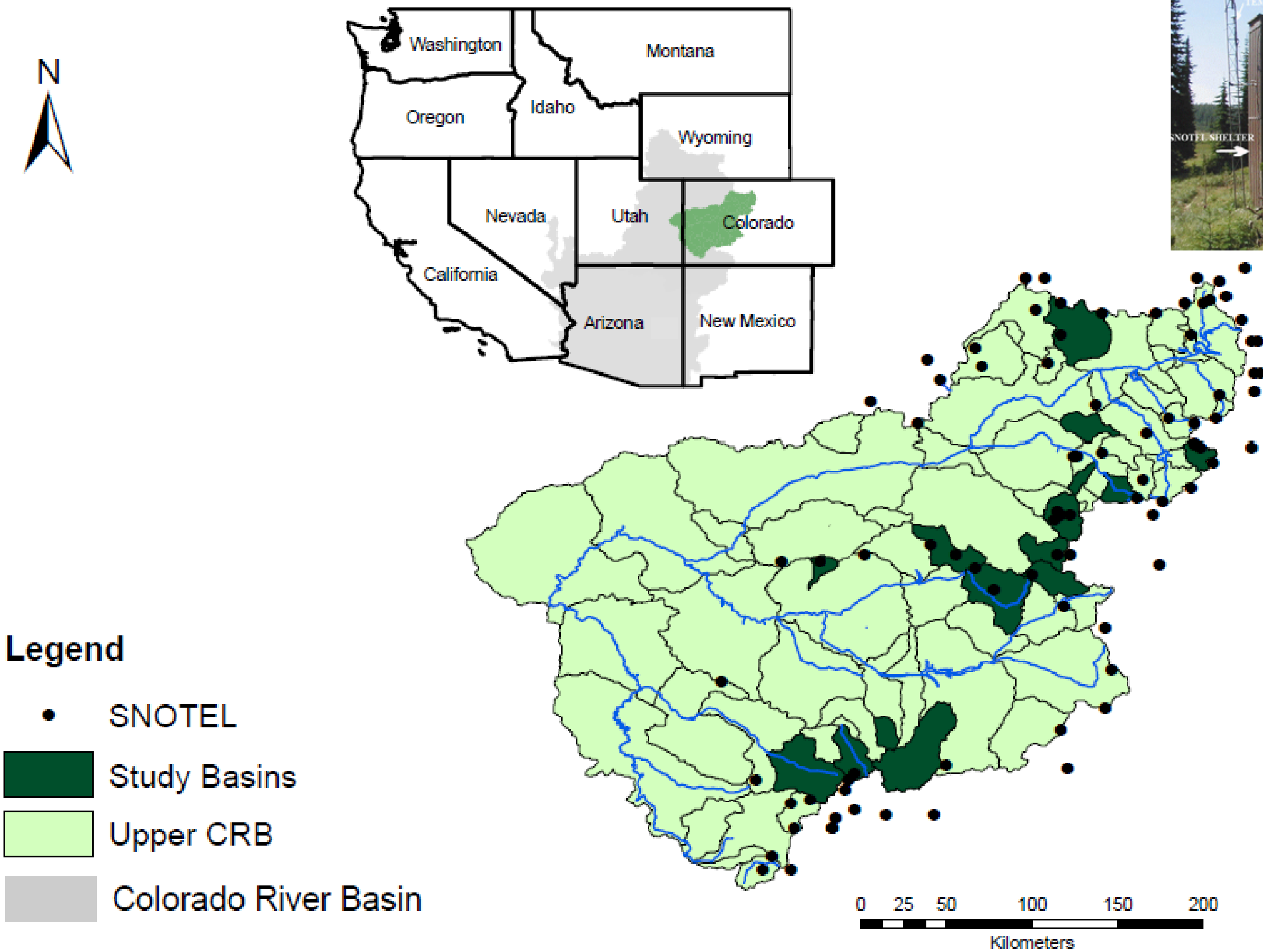


Snow-17

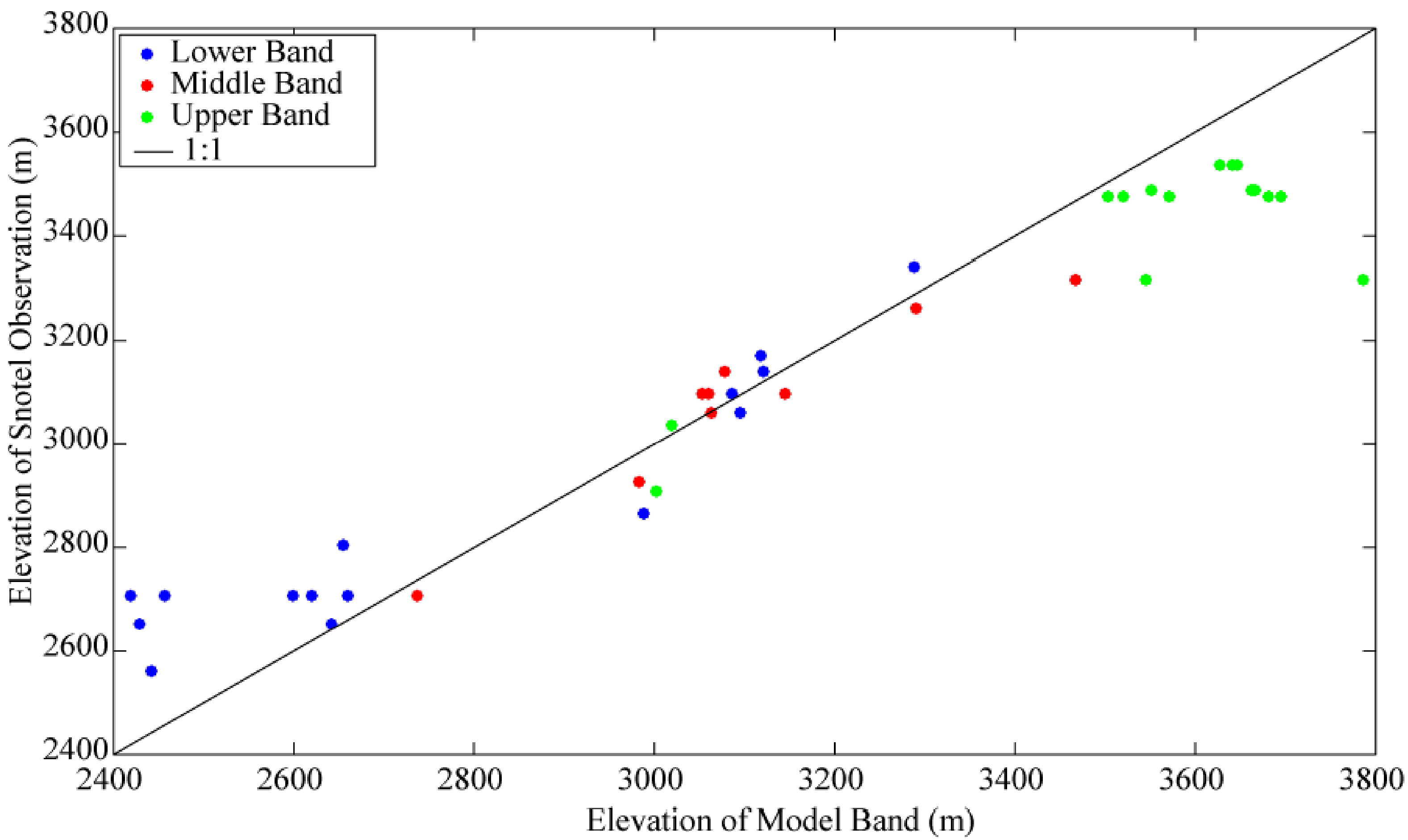


Study Area

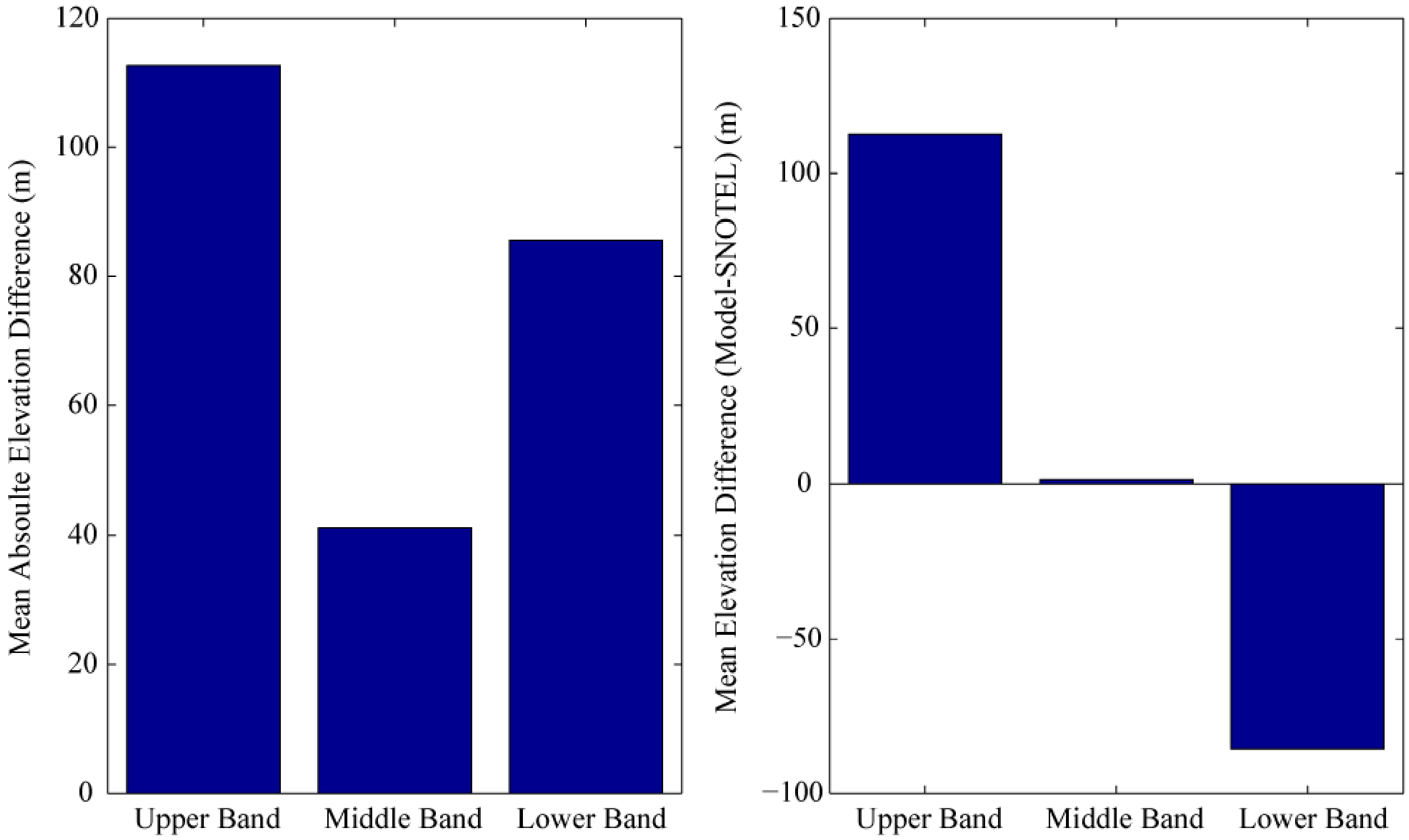

ANTENNA
SOLAR PANELS
TEMPERATURE SENSOR
SNOWDEPTH SENSOR
PRECIPITATION GAUGE
SNOTEL SHELTER
GROUND TRUTH MARKER
SNOW PILLOW


N
Washington
Montana
Oregon
Idaho
Wyoming
Nevada
Utah
Colorado
California
Arizona
New Mexico
0 25 50 100 150 200
Kilometers
Legend
SNOTEL
Study Basins
Upper CRB
Colorado River Basin

SNOTEL Representativeness

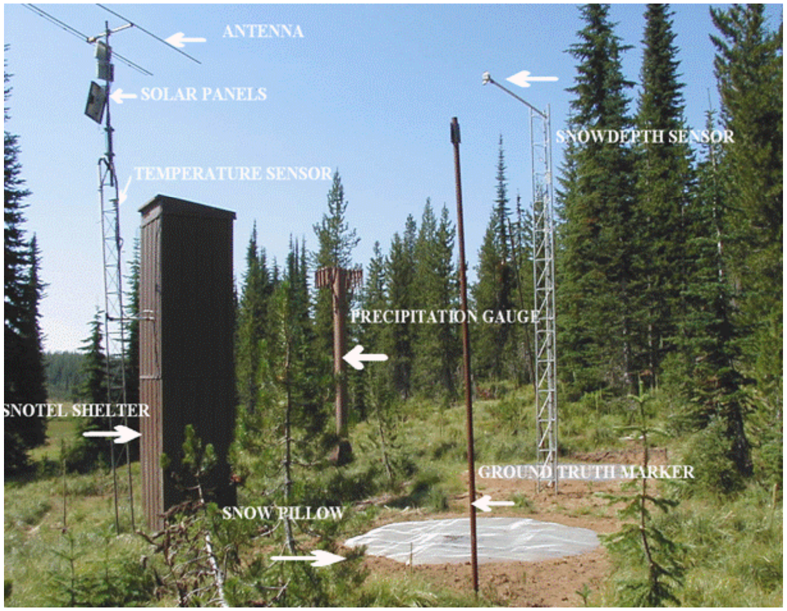


SNOTEL Representativeness

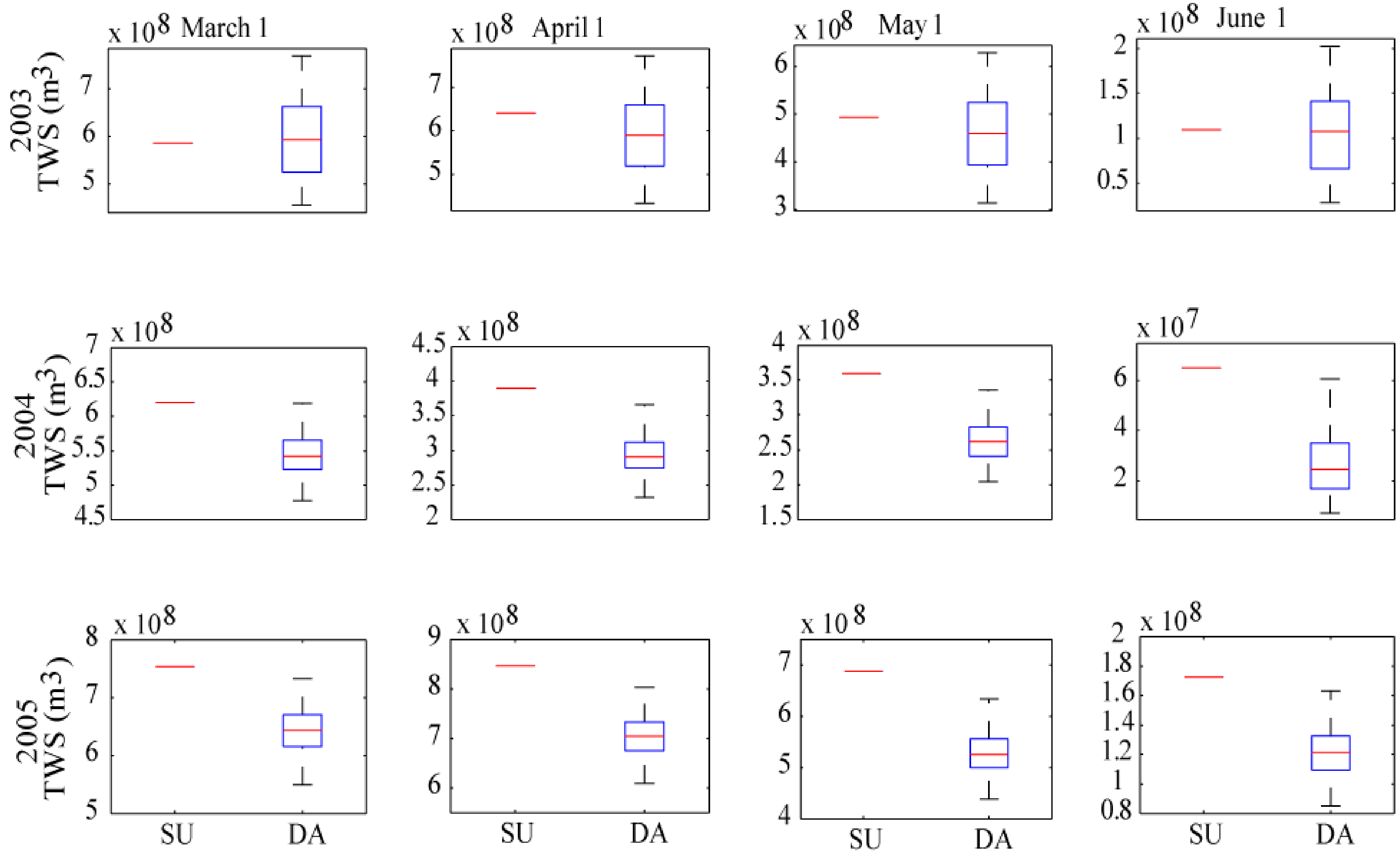


SNOTEL Representativeness

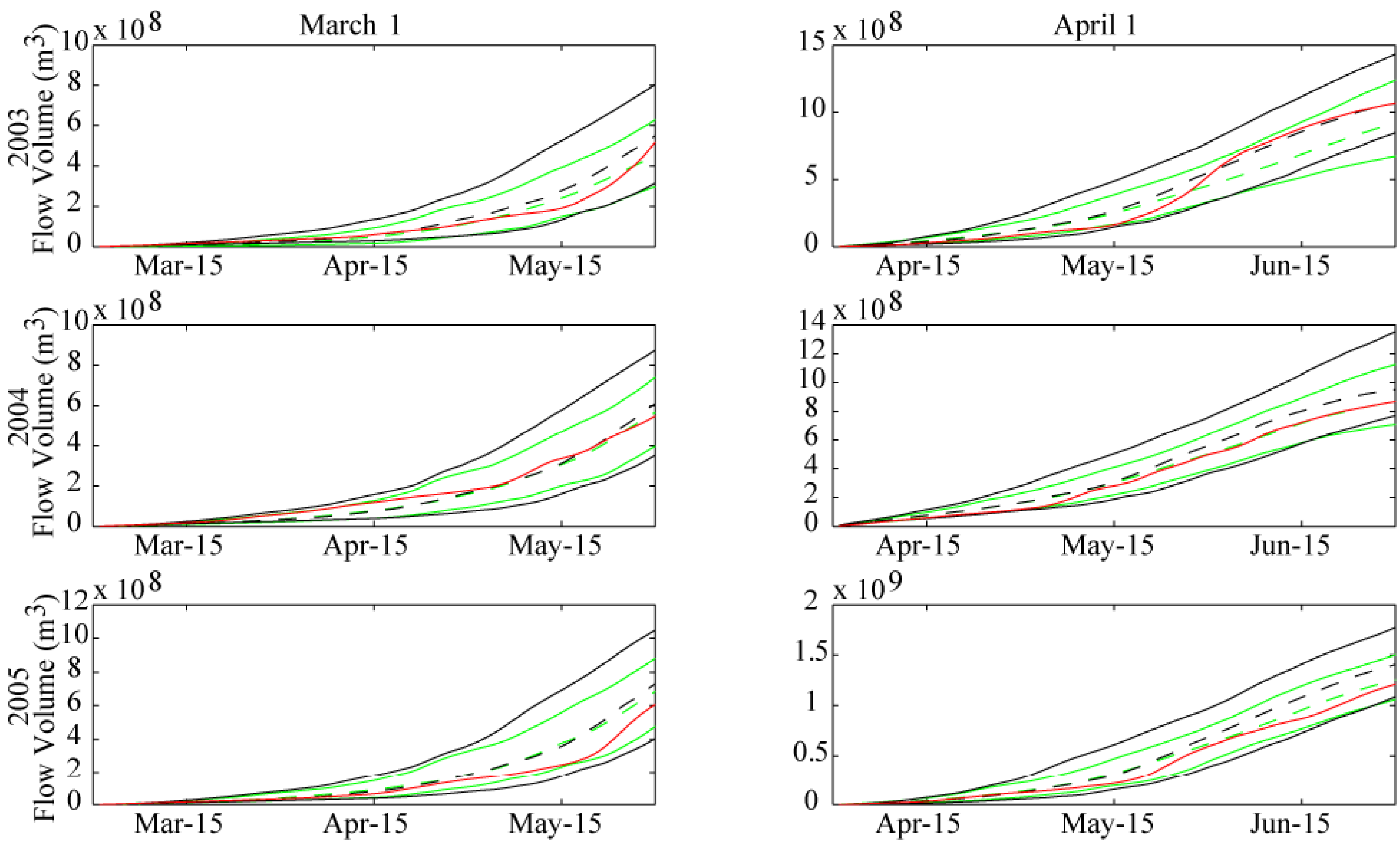
- Model elevations (middle elevation band) between 2800 and 3400 are best represented in terms of elevation
  - Elevation strongly affects the time at which ablation starts
  - Only elevation bands that have similar SNOTEL elevations are expected to achieve accurate assimilation
  - This elevation range typically begins melting late winter and early spring
  - Seasonal predictions beginning on March 1st, April 1st and May 1st are expected to perform the best because of accurate assimilation



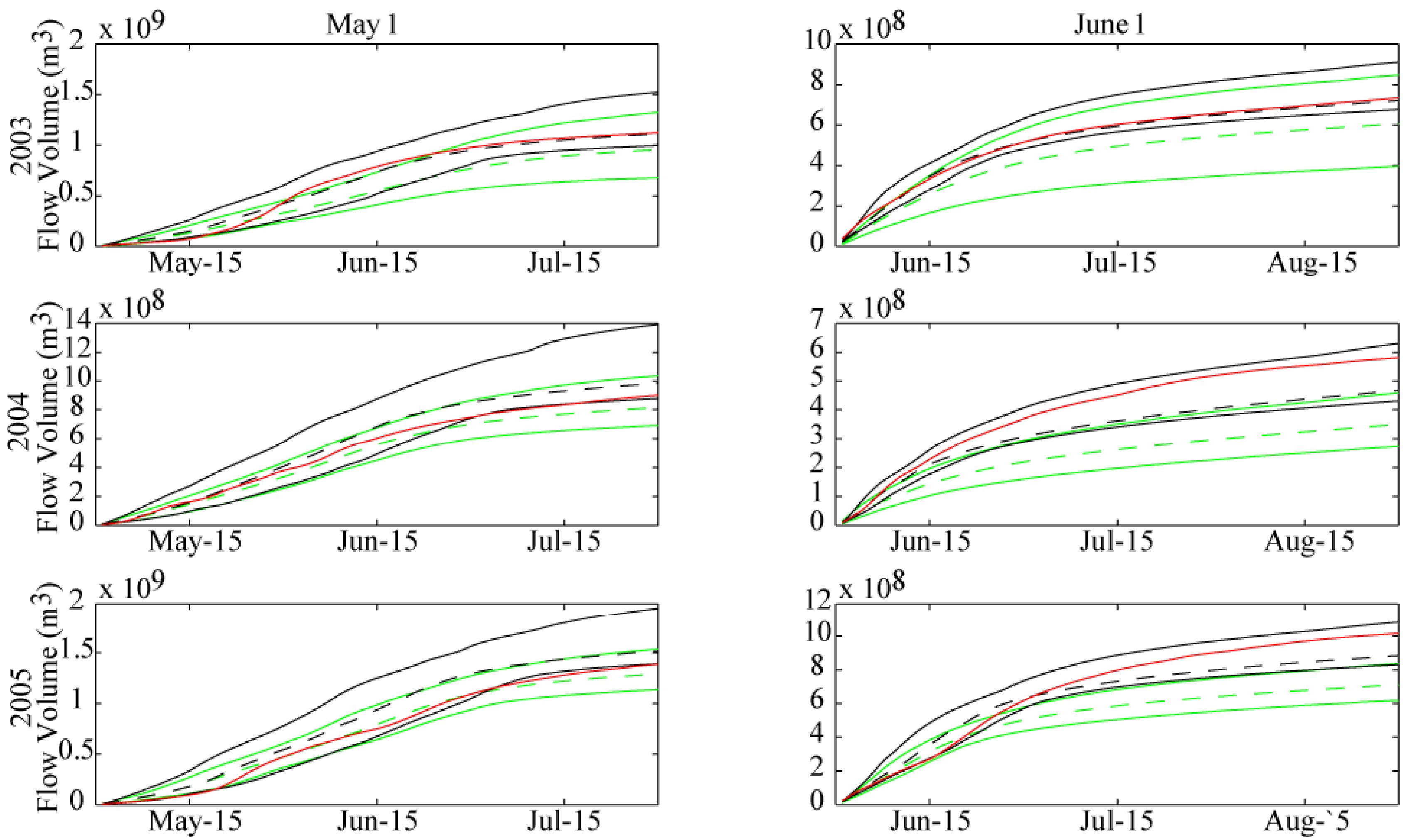
Initial Snow Water Equivalent



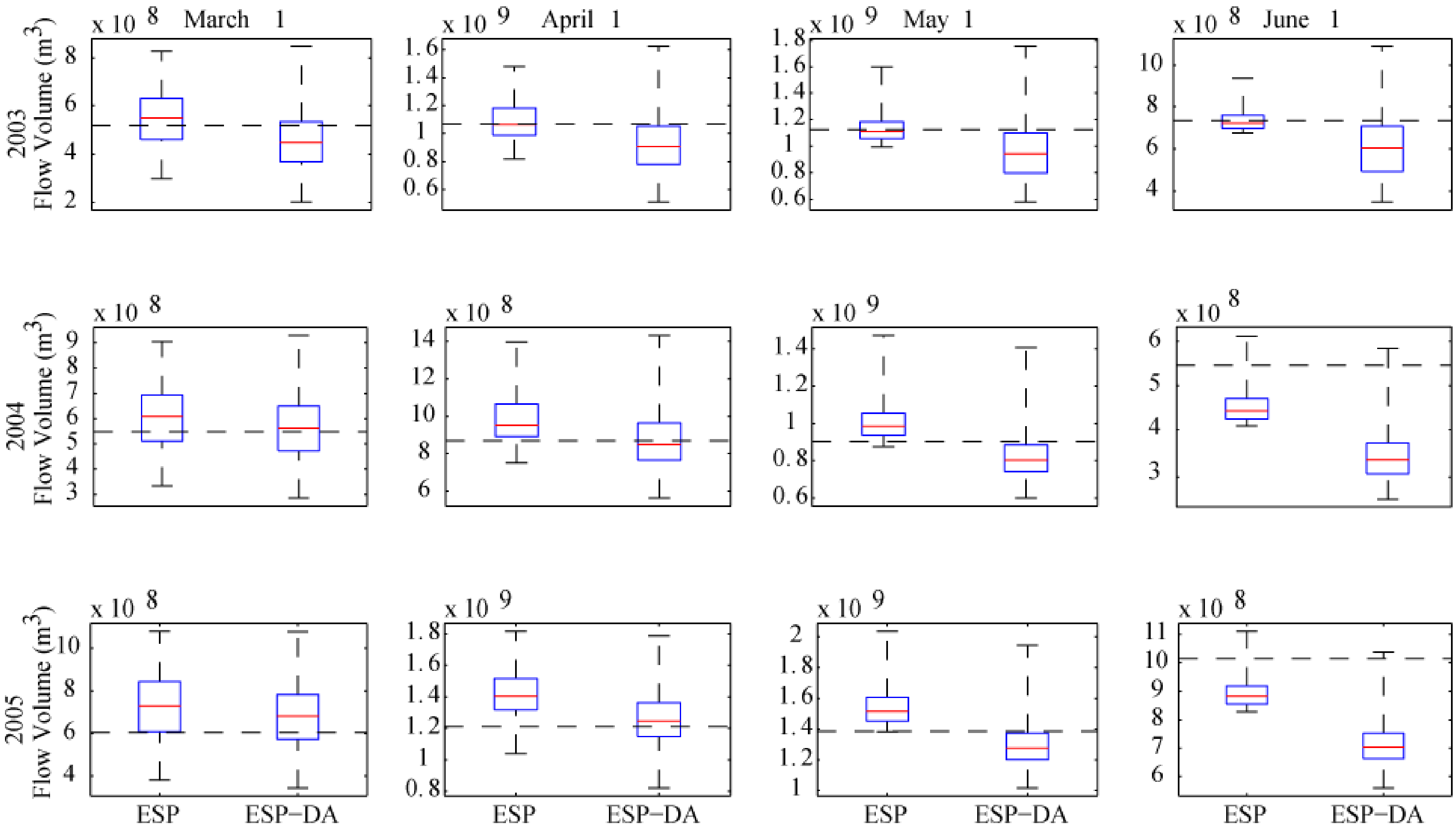
Seasonal Cumulative Prediction



Seasonal Cumulative Prediction



Seasonal Volume Prediction



Probabilistic Verification

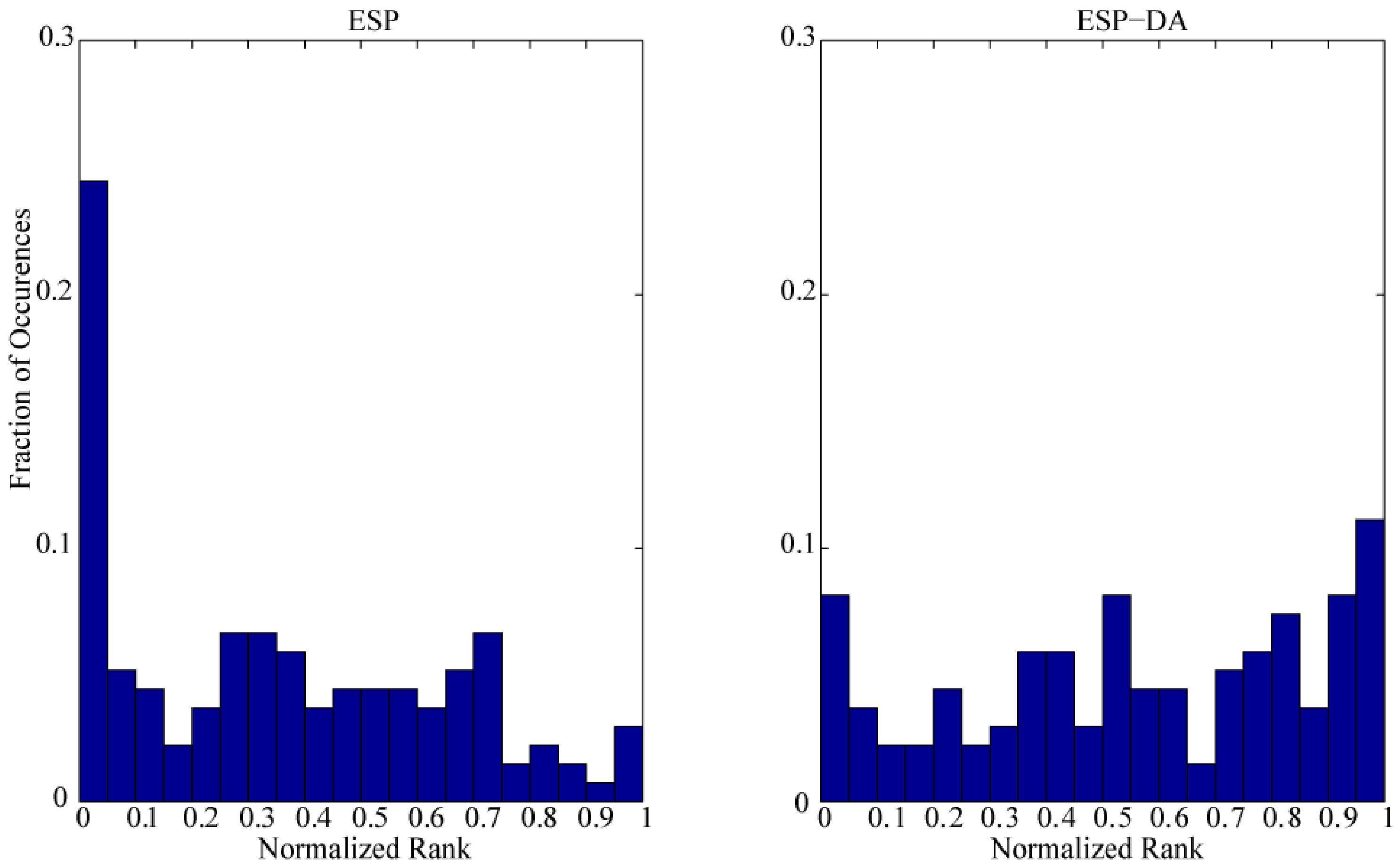
Validation Figures

- Rank histogram
  - A histogram showing the reliability of the ensemble forecast
  - $Rank_n = I\left(y_{i,n} < O_n \text{ and } y_{i+1,n} < O_n\right)$
- Q-Q plot
  - A plot comparing the uniform distribution and predictive accuracy
  - $z_n = \frac{I\left(y_{i,n} < O_n \text{ and } y_{i+1,n} < O_n\right)}{N}$
  - $U_n = \frac{n}{N}$

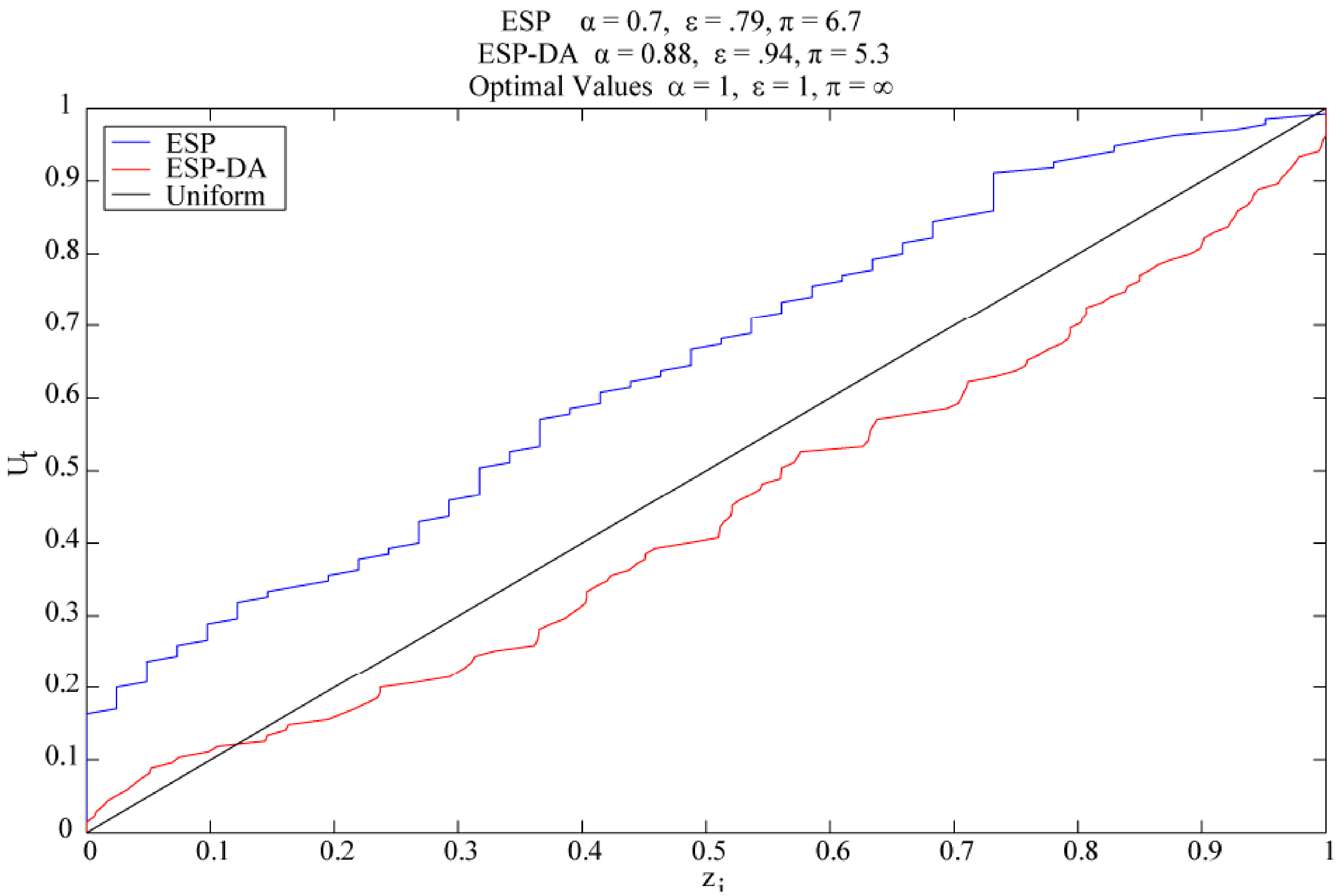
Validation Statistics

- Reliability
  - Measures the accuracy of the ensemble prediction
  - $\alpha = 1 - 2\sum_{n=1}^{N} |z_n - U_n|$
  - $\varepsilon = 1 - \sum_{n=1}^{N} \frac{\varepsilon_n{}'}{N}$
  - $\varepsilon_n' = \begin{cases} 1 \text{ if } z_n = 1 \text{ or } z_n = 0 \\ \quad \text{otherwise } 0 \end{cases}$
- Resolution
  - Measures the precision of the prediction
  - $\pi = \frac{1}{N}\sum_{n=1}^{N} \frac{E[y_n]}{SD[y_n]}$

Rank Histograms



Quantile-Quantile Plot of Seasonal Volumetric Predictions



Quantile of observed

Conclusions

- ✓ Given an accurate assimilation, ESP-DA provides a more reliable seasonal prediction
- ✓ Limitations of ESP-DA are due to lack of accurate SWE observation
- ✓ ESP-DA can easily be coupled with advanced forcing generation techniques to further constrain uncertainty
- ✓ ESP-DA has potential to improve the reliability of operational forecasting

Thanks for your Attention!