HEPEX

a community of research and practice to advance hydrologic ensemble prediction

Ensemble for Better Hydrological Forecasts

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Accounting for Combined Effects of Initial Condition and Model Uncertainty in Seasonal Forecasting Through Data Assimilation

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Uncertainties in Hydrologic Modeling

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1) Meteorological forcing

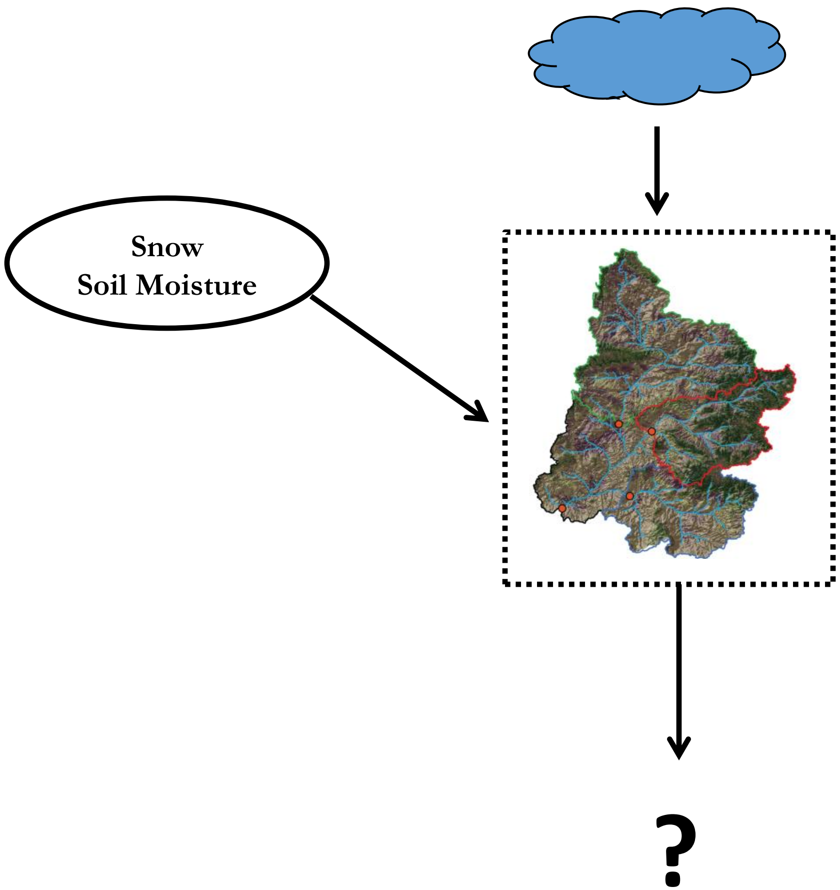
- Earth's chaotic atmosphere makes forecasting unreliable at extended lead times

2) Initial condition (states)

- Land surface hydrological conditions are highly variable spatially (e.g., snow and soil moisture)

3) Hydrologic model

- Hydrologic models are simplifications to land surface processes



Quantifying Uncertainty

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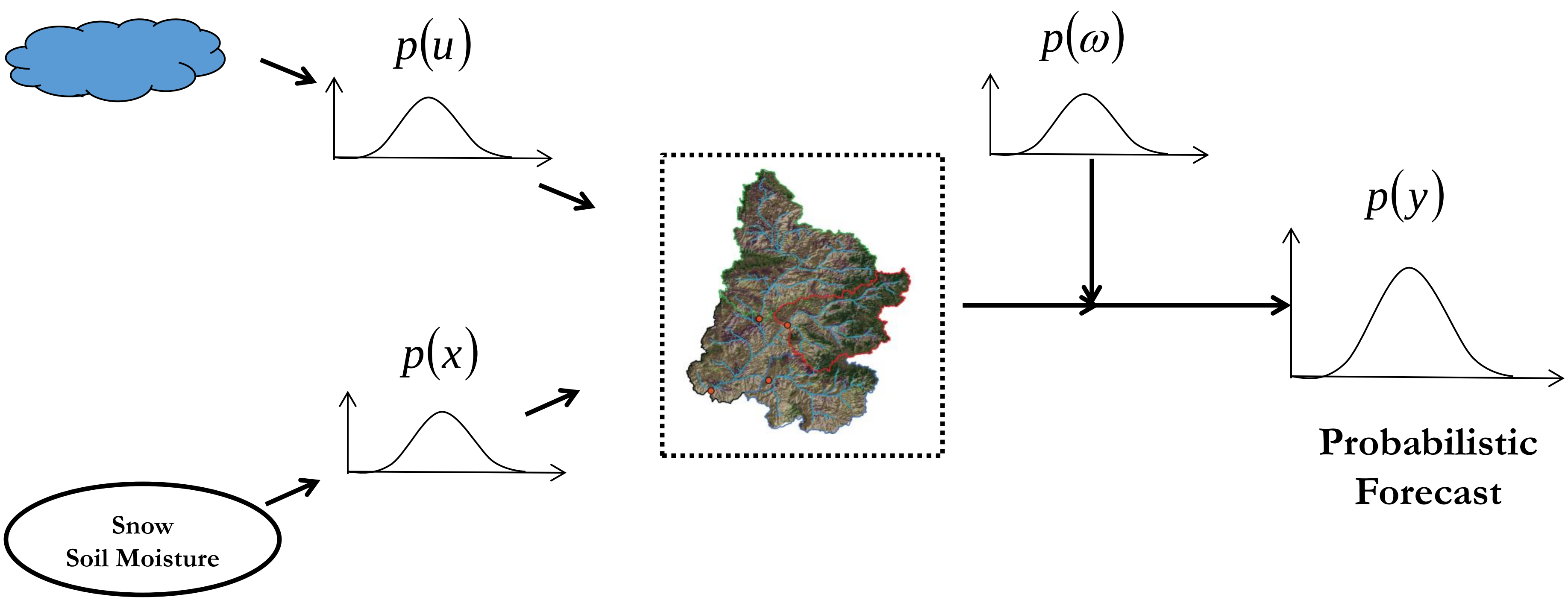
- Requires the formulation of a probabilistic model

$$p(y) = f(p(x), p(u), q) + p(w)$$



Operational Probabilistic Forecasts

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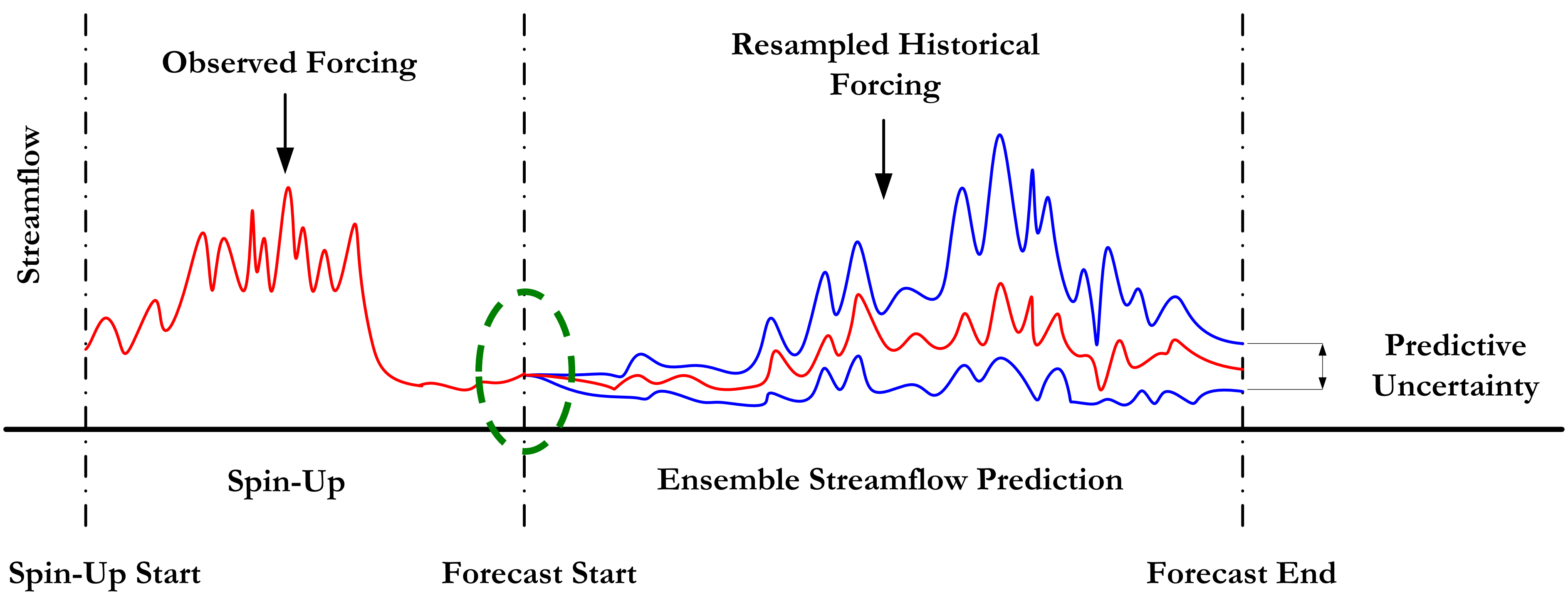
- Generated with Ensemble Streamflow Prediction (ESP)

- This ignores initial state and model uncertainty
  - **Ensemble Data Assimilation**

DeChant and Moradkhani (2011)



Ensemble Data Assimilation

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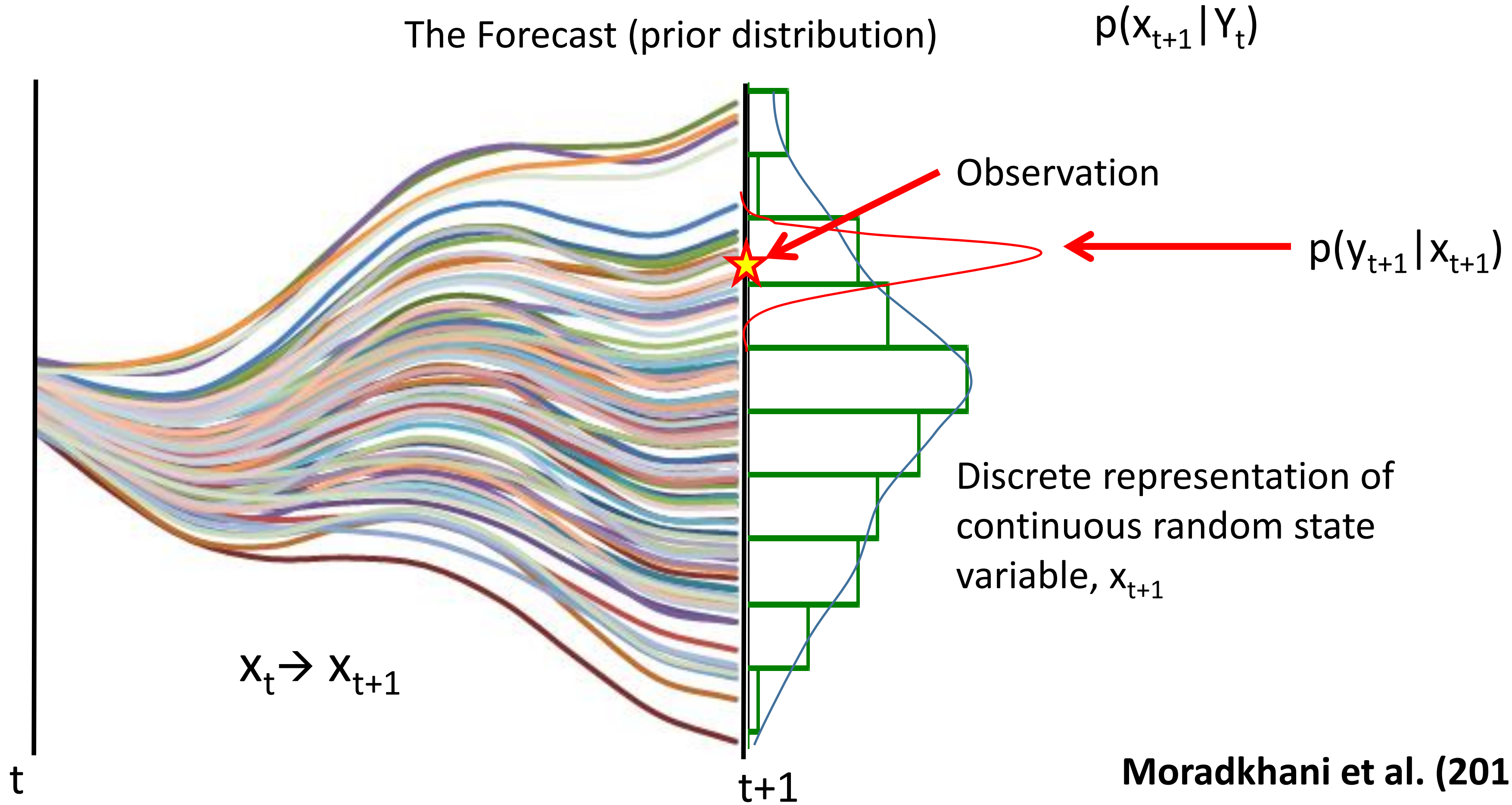
$$p(x_{t+1} \mid Y_{t+1}) = \frac{p(y_{t+1} \mid x_{t+1})\, p(x_{t+1} \mid Y_t)}{\int_{x_{t+1}} p(y_{t+1} \mid x_{t+1})\, p(x_{t+1} \mid Y_t)\, dx_{t+1}}$$



Moradkhani et al. (2012)

Model Averaging

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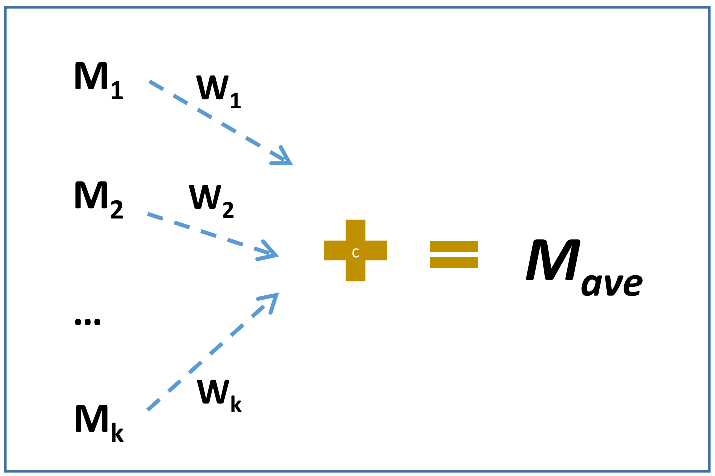
MA is a linear weighted average of model ensembles.

Deterministic

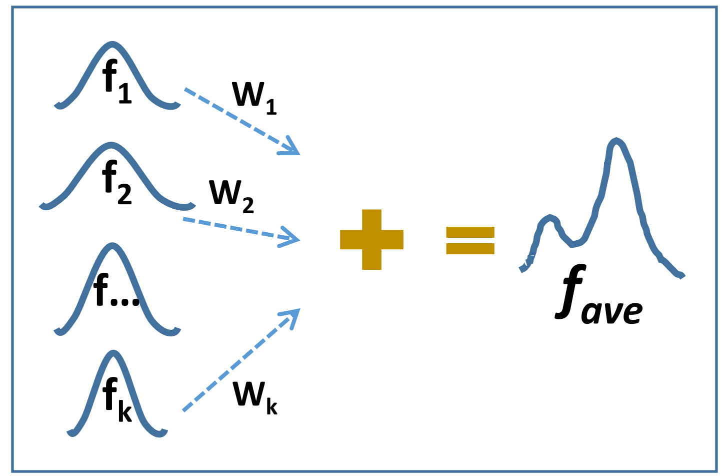


➢ Combines single-value forecasts.

$$M_{ave} = W_1.M_1 + W_2.M_2 + \ldots + W_k.M_k$$

- Examples: Equal weights, Bates-Granger averaging , AIC and BIC-based model averaging.

Probabilistic



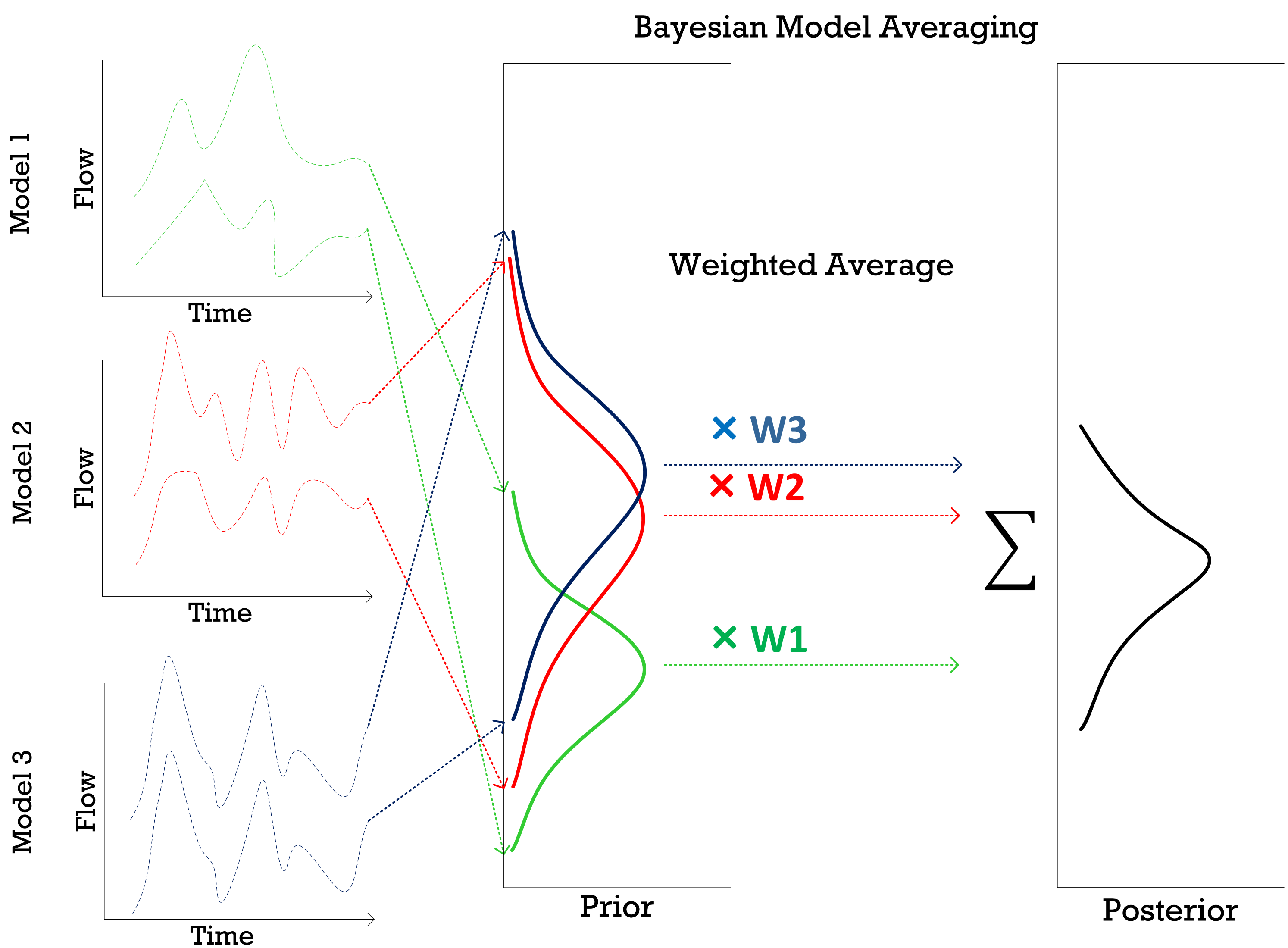
➢ Combines PDF of forecasts:

$$f_{ave} = W_1.f(M_1) + W_2.f(M_2) + \ldots + W_k.f(M_k)$$

– Example: Bayesian Model Averaging

Madadgar and Moradkhani (2014)

Bayesian Model Averaging



Combining PF-SBC with ESP

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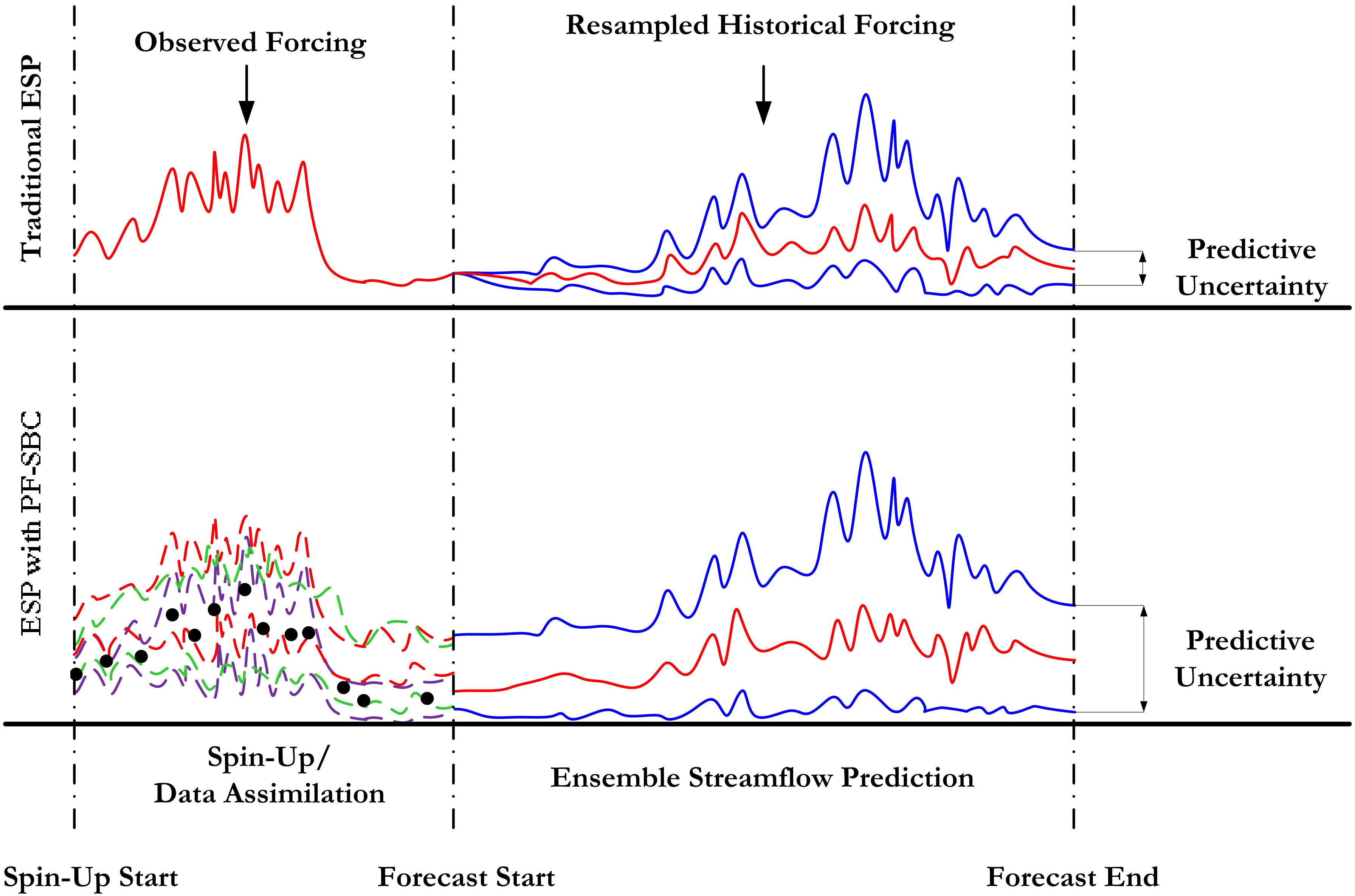
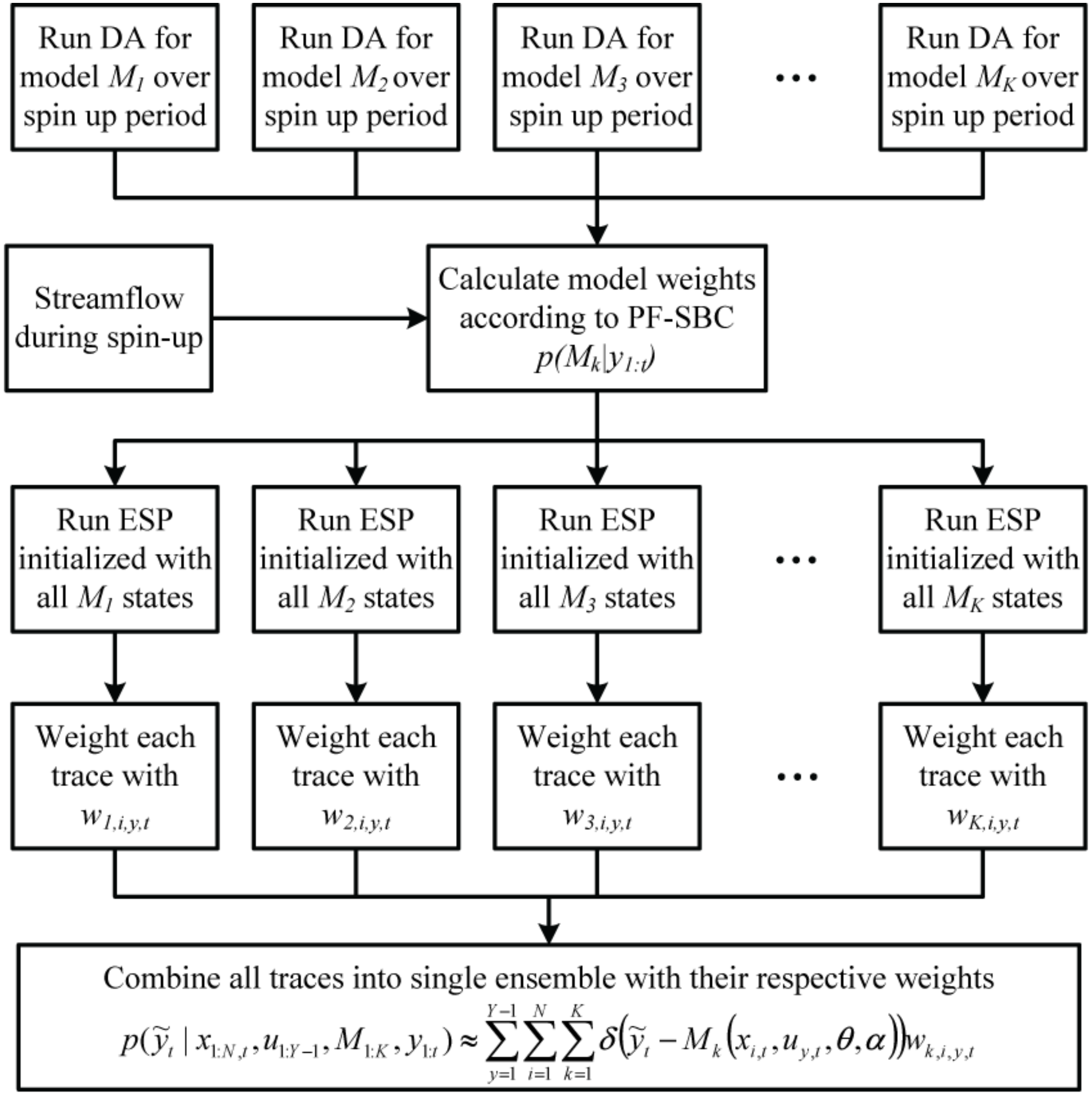
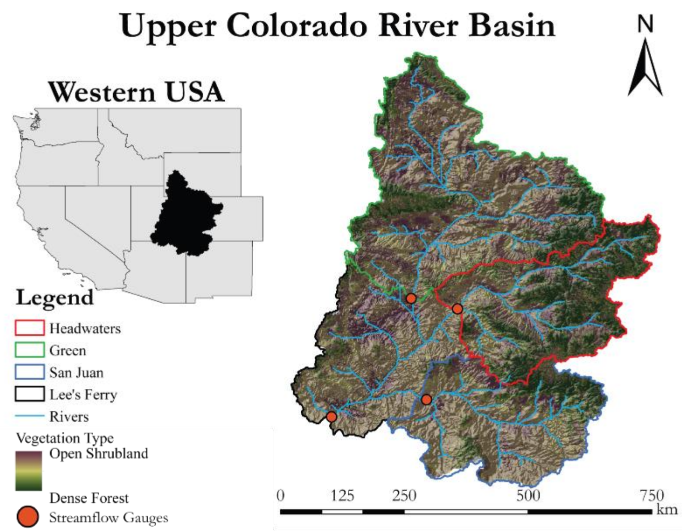


Combination of DA, Multi-modeling and ESP





DeChant and Moradkhani (2014)

Modeling Cases

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- Two Models
  1) Variable Infiltration Capacity (VIC)
     - Physically-based distributed model

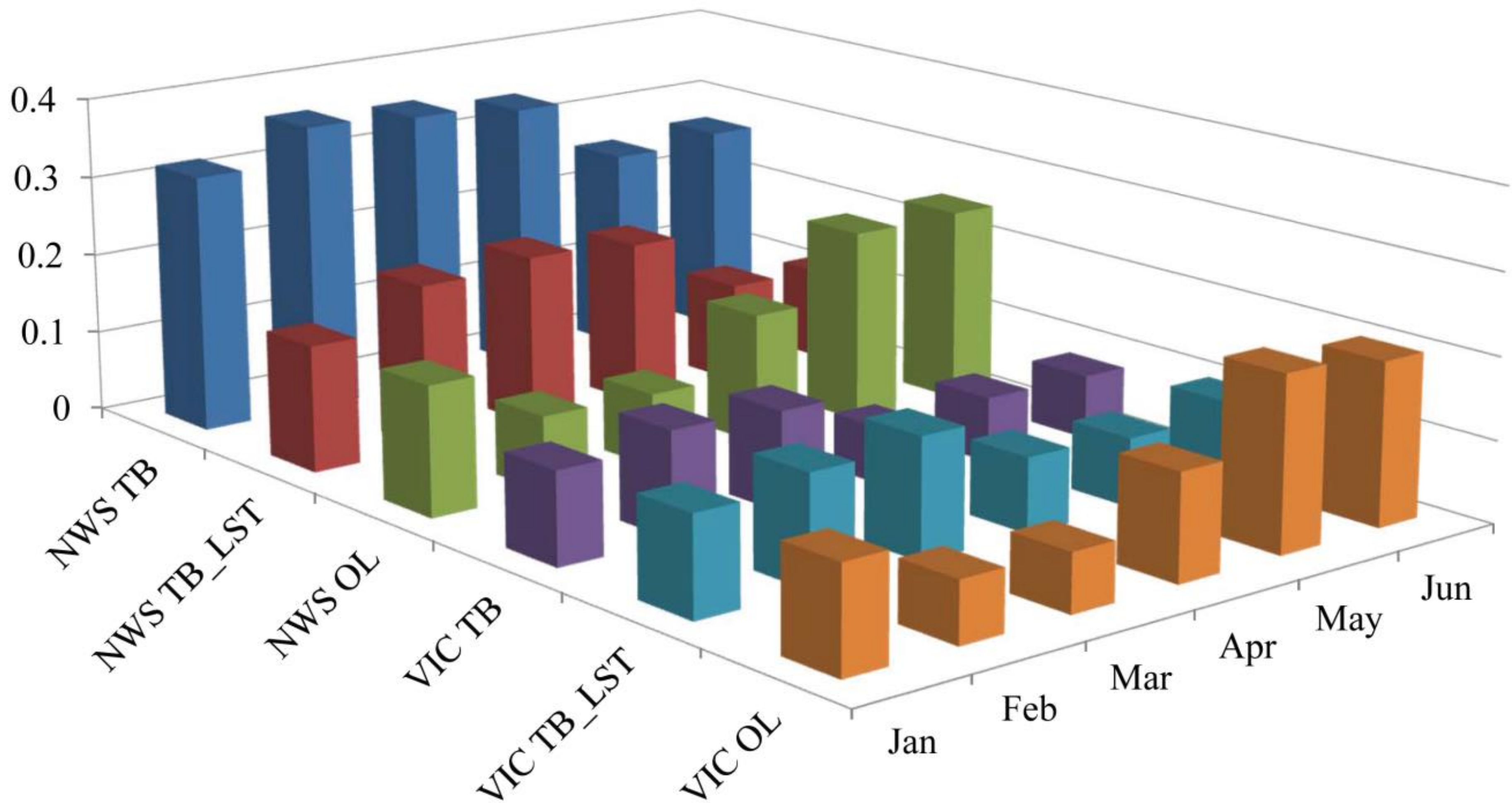
  2) Coupled SNOW-17 and Sacramento models (NWS)
     - Conceptual semi-distributed models

- Three cases for forecast spin-up
  1) Open Loop (no assimilation)

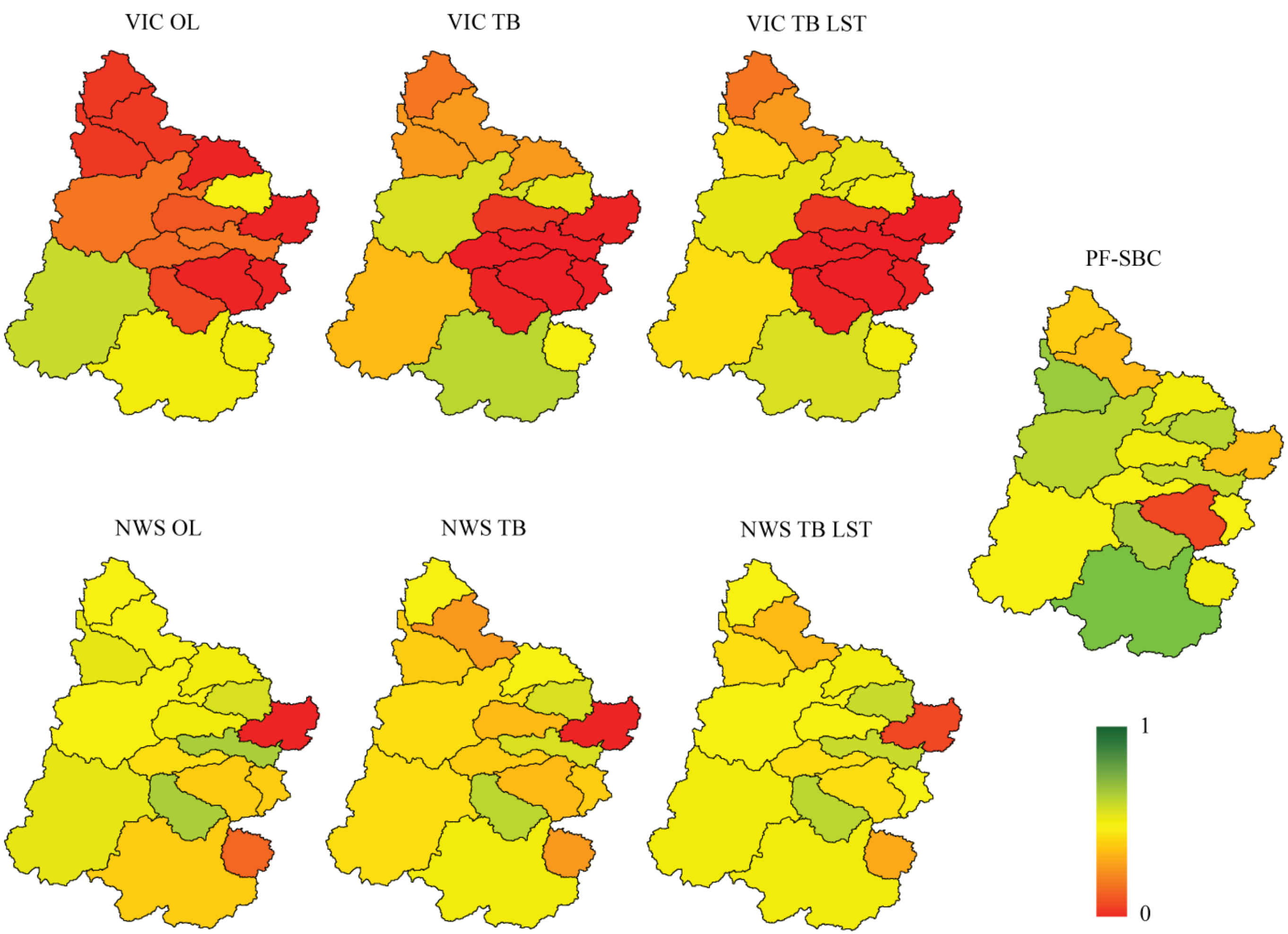
  2) Passive Microwave Brightness Temperature (TB)

  3) Land Surface Temperature (LST) with TB

Weights or Importance of Each Model



Reliability of volumetric streamflow forecasts



Multi-remotely sensed Data Assimilation. PF-SBC is showing combined data assimilation and Multi-Modeling

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Implement data assimilation within FEWS framework

- Build a system that allows for implementation with any model connected to FEWS (even models that will be connected in the future)
- Make the system flexible, allowing users to adjust the application of data assimilation (lumped vs distributed, multiple data sources, complex timing of observation time-series ...)
- Utilize existing FEWS-CHPS functionalities to simplify the data assimilation program

Challenges for DA in FEWS/CHPS

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- The general FEWS workflow system is not conducive to DA
  - Entire time series are sent to models
  - Lots of I/O – computationally expensive
- Balance of computational demand, flexibility of framework and minimization of coding
  - Depending on where the DA algorithm is placed, the computational demand, model flexibility and amount of coding necessary will be effected
- Opted for significant coding in the pursuit of system flexibility with minimal computational cost
  - Required software development to create a data assimilation model driver (DADriver)

Simulation without/with DA

No Data Assimilation

- OHDFewsAdapter ships data for model runs one at a time
- Each model's driver performs simulation over the whole time series
- OHDFewsAdapter imports output data from single model

Data Assimilation

- OHDFewsAdapter ships data for multiple model runs
- DADriver only gives data required to run driver to the next observation
- OHDFewsAdapter imports data from all models involved in DA simultaneously

Data Assimilation within FEWS/CHPS Over the Pacific Northwest US

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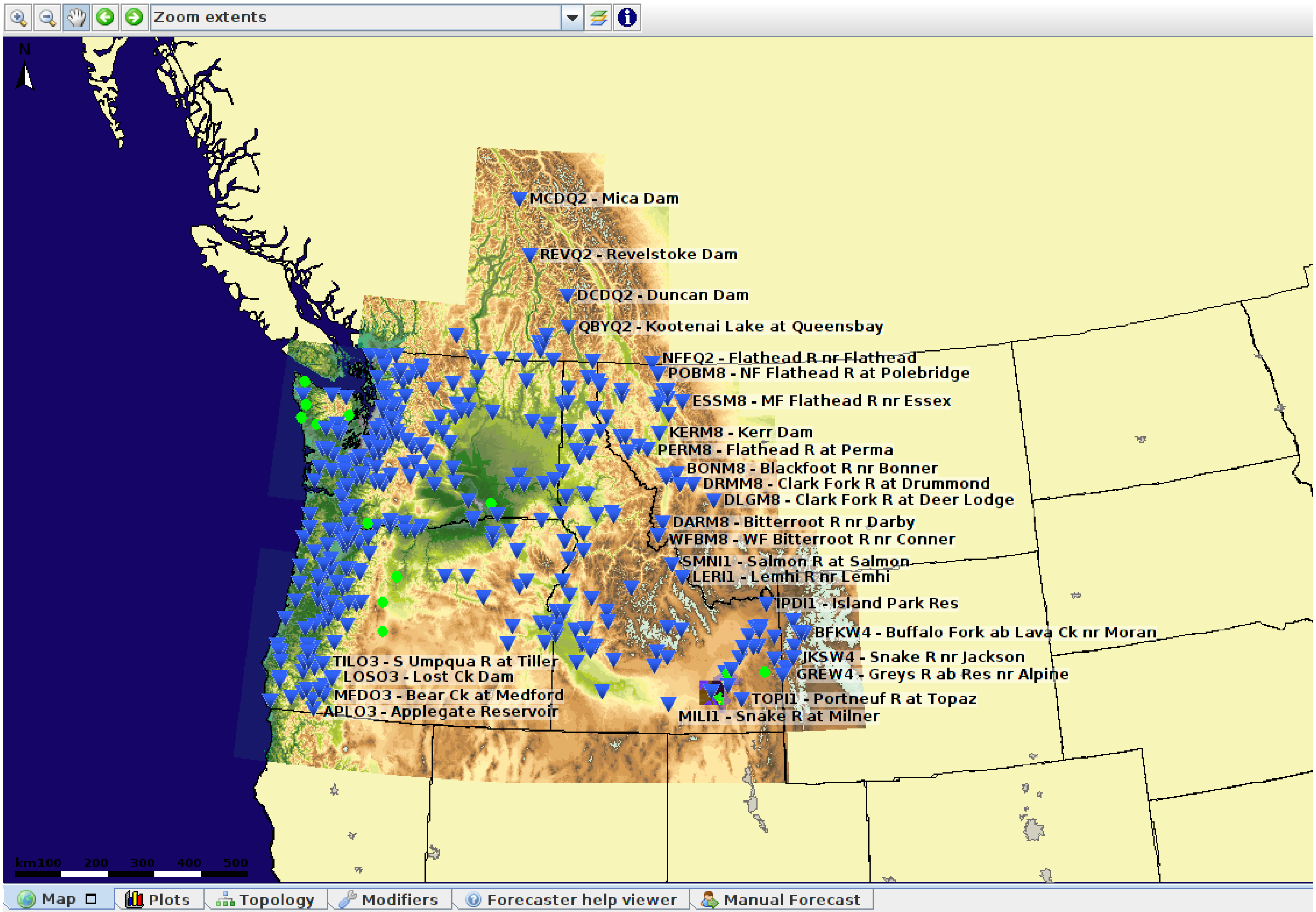
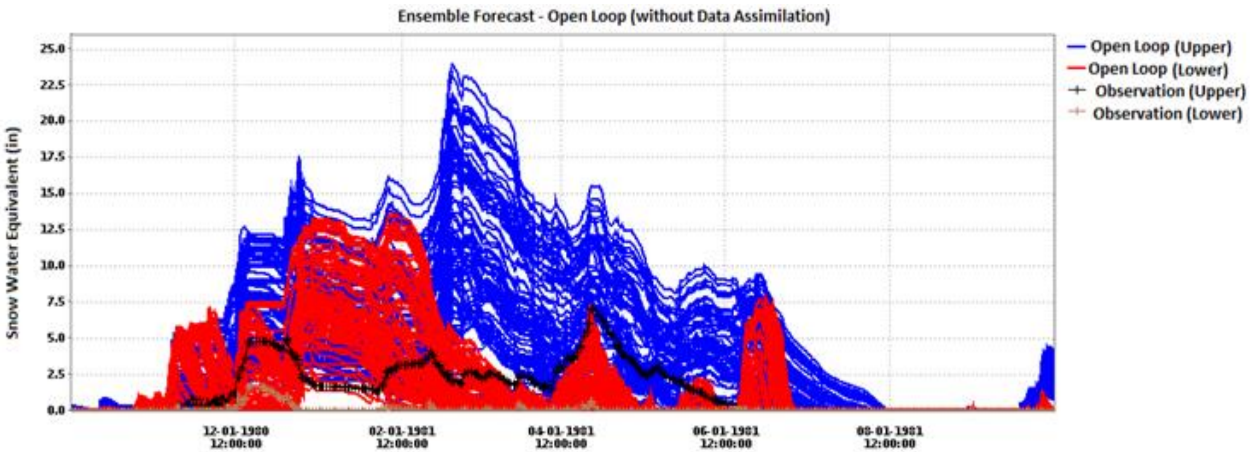
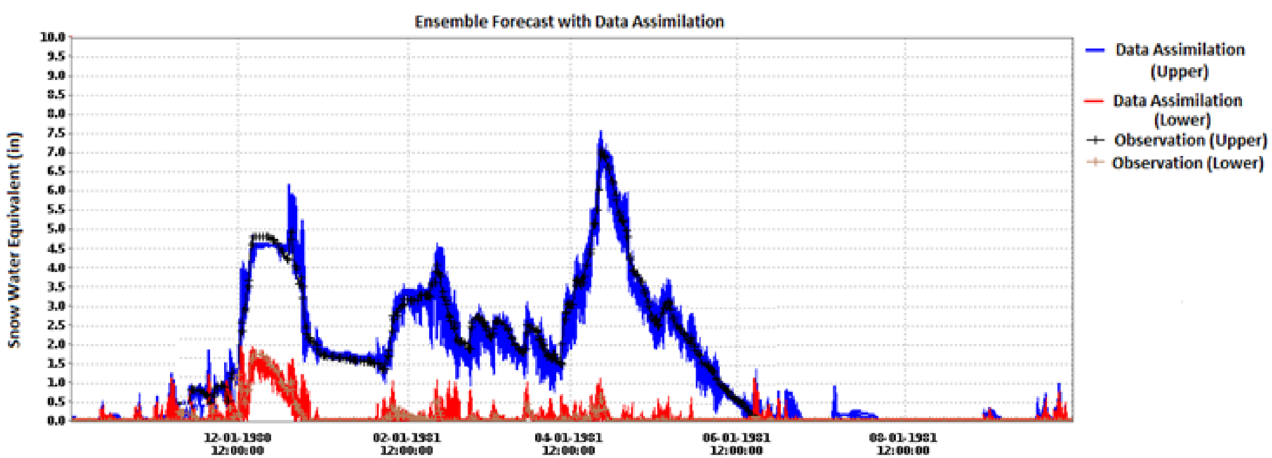
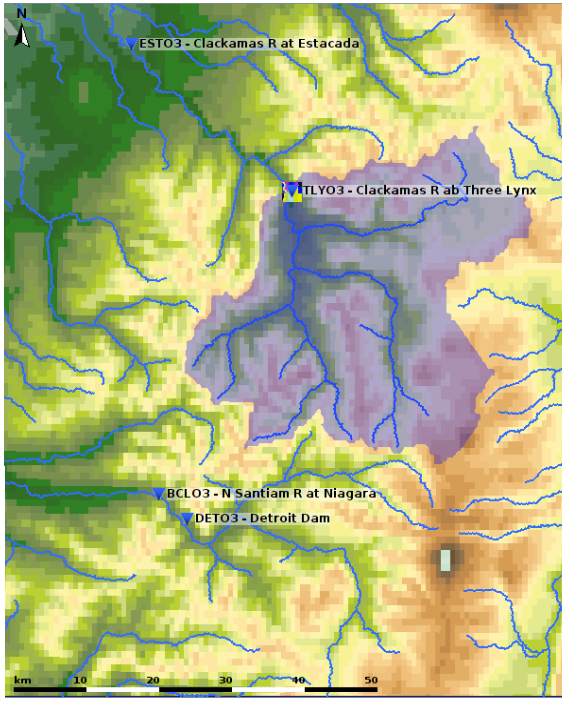


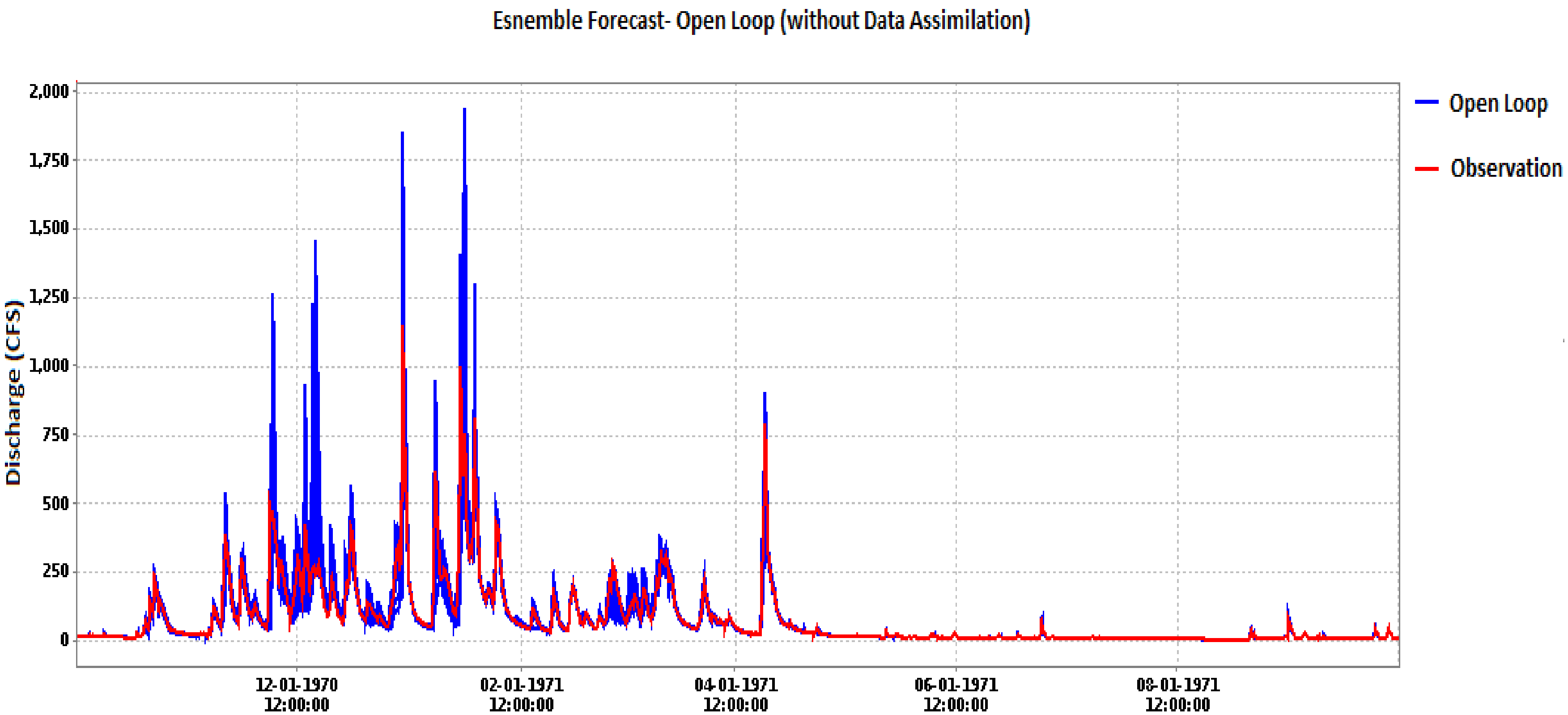
Ensemble Simulation for SWE before and after DA
Clackamas River Basin



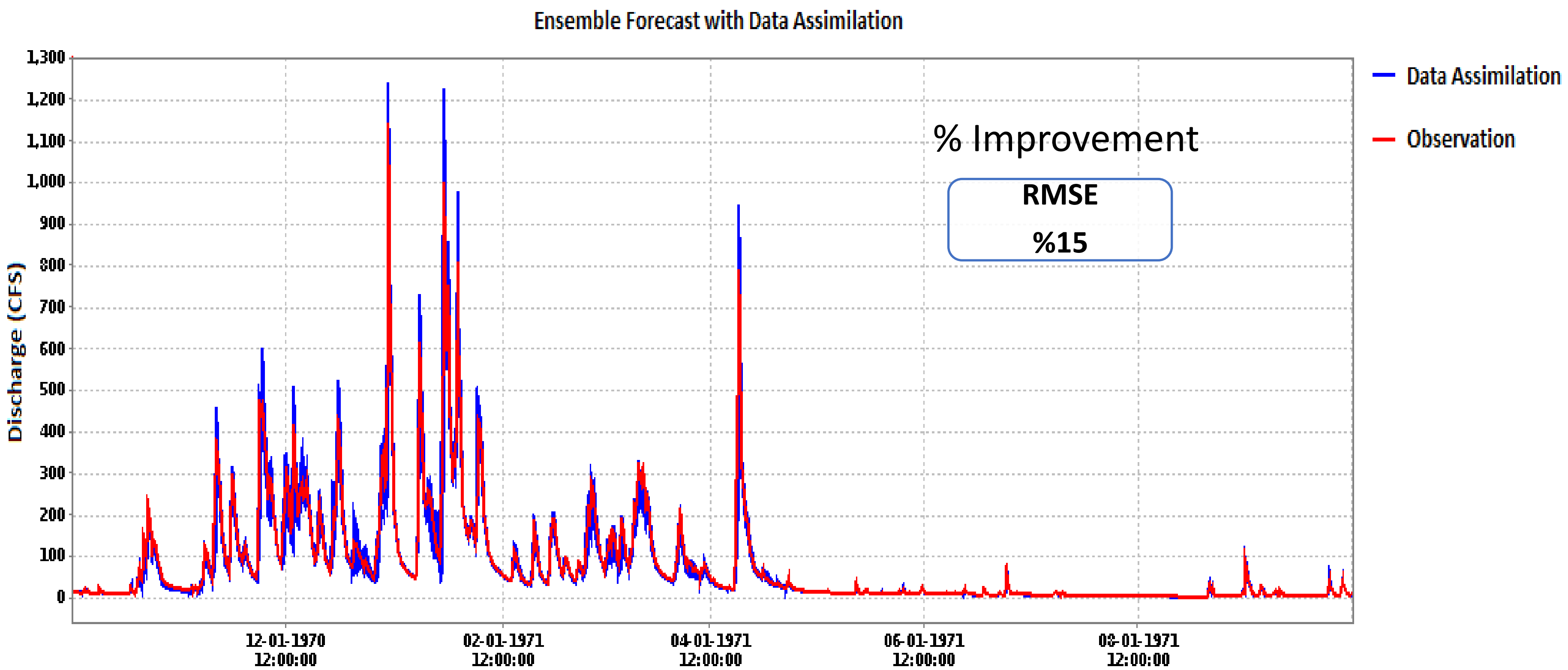




Before DA


Esnemble Forecast- Open Loop (without Data Assimilation)
Discharge (CFS)
2,000
1,750
1,500
1,250
1,000
750
500
250
0
12-01-1970 12:00:00
02-01-1971 12:00:00
04-01-1971 12:00:00
06-01-1971 12:00:00
08-01-1971 12:00:00
Open Loop
Observation

Streamflow Forecast after DA "Johnson Creek"



Streamflow Forecast before/after DA
"Johnson Creek"

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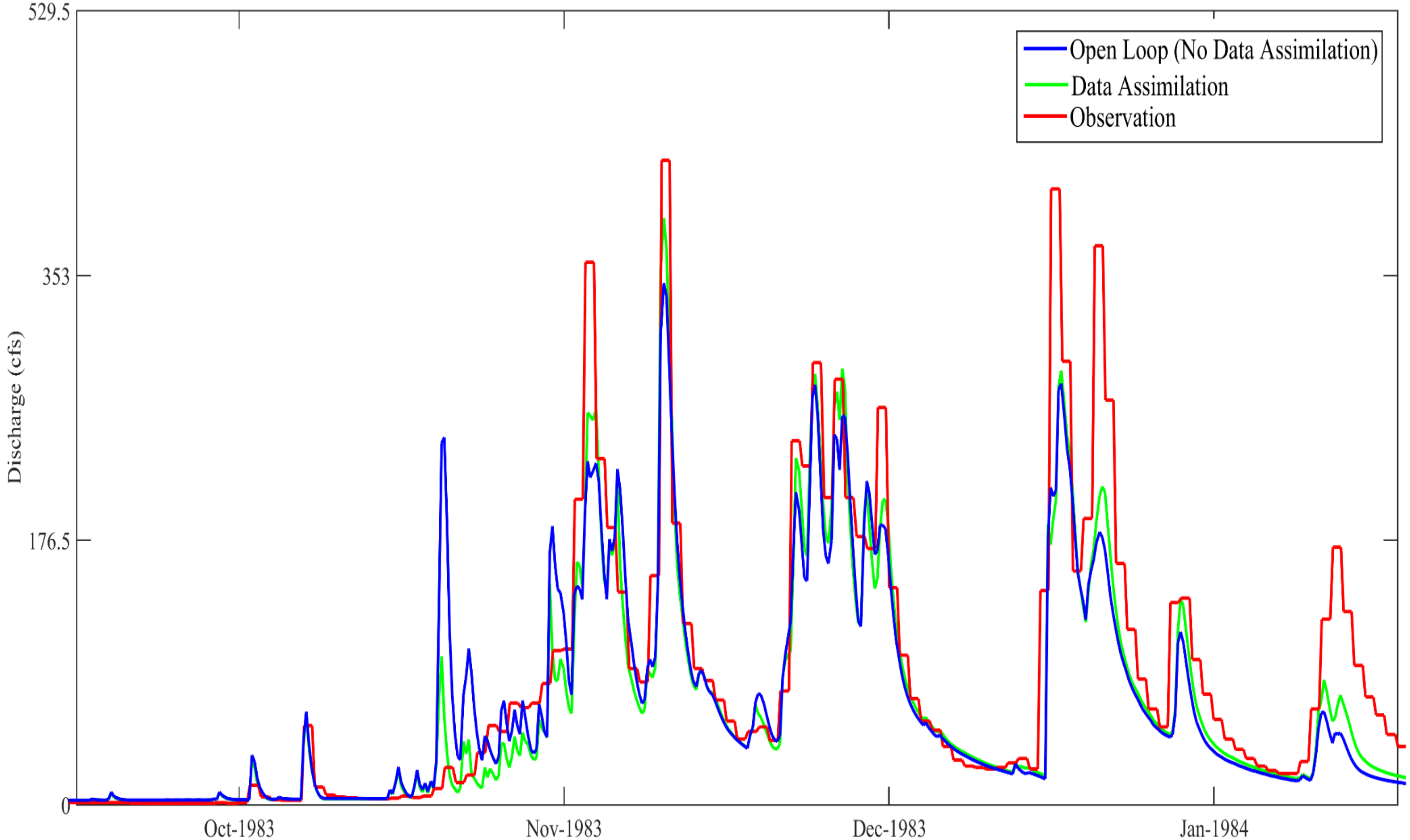

Pacific Northwest Drought

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- The proposed method was verified with two drought events in 2013 and 2015 in Pacific Northwest (PNW).
- In 2013 spring (A-M-J), drought was declared for 9 counties in the southern Idaho. After 3 months, drought emergency was issued for 19 counties.
- In 2015 winter (J-F-M), PNW received historically low snowpack. Washington and Oregon governor declared state drought emergence in 2015 spring.
- Seasonal drought forecasting for the two drought events were applied using the proposed method.

Data Assimilation System for initializing the Drought Forecast

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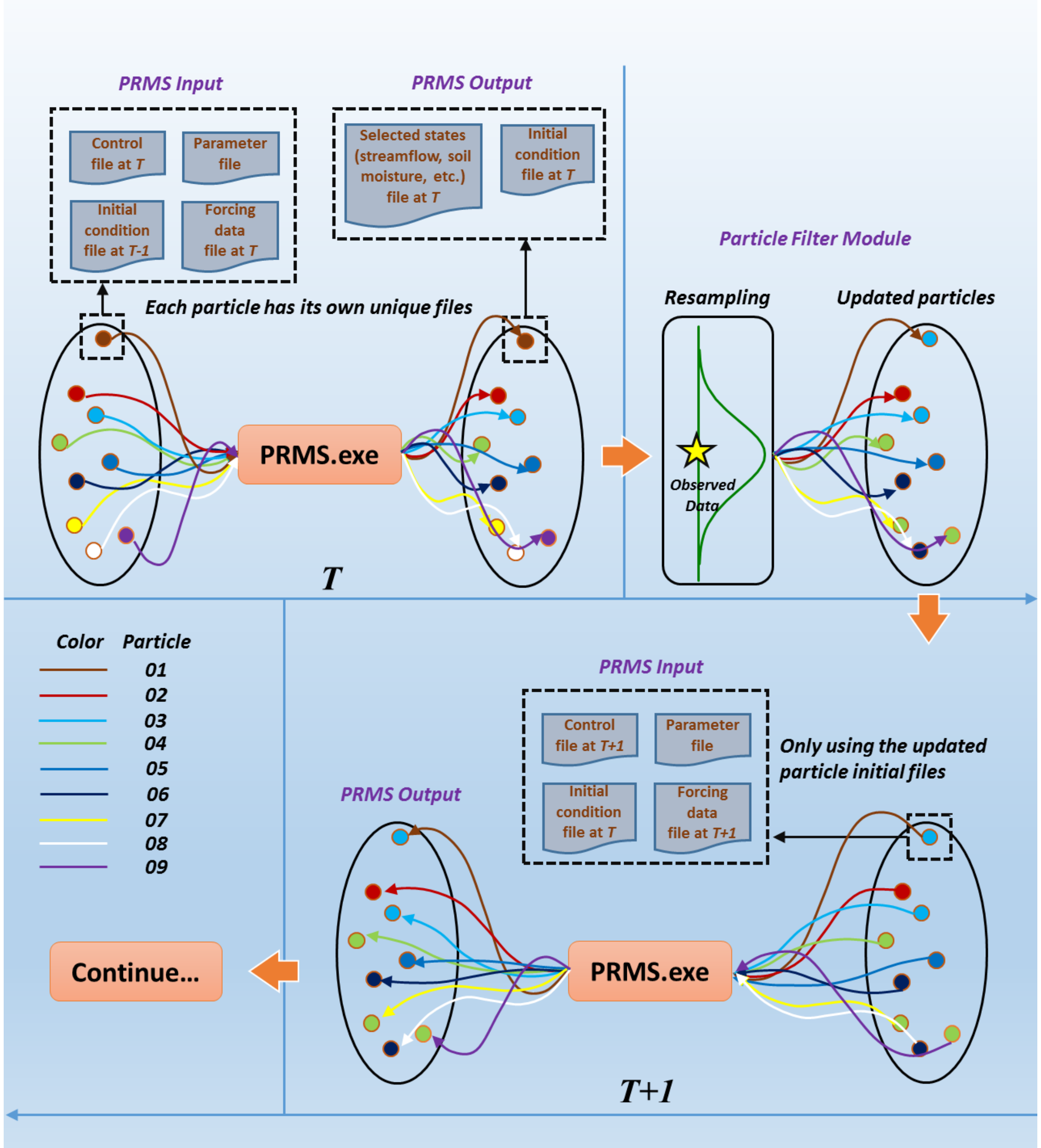
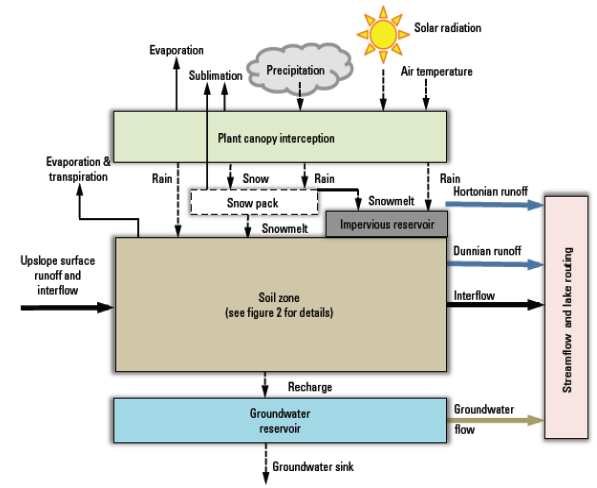
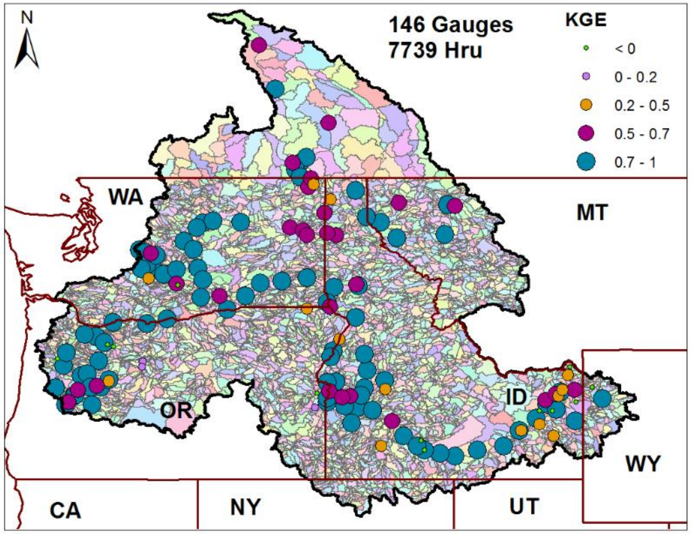




USGS-PRMS Process



Probability of Summer Drought | Spring Drought

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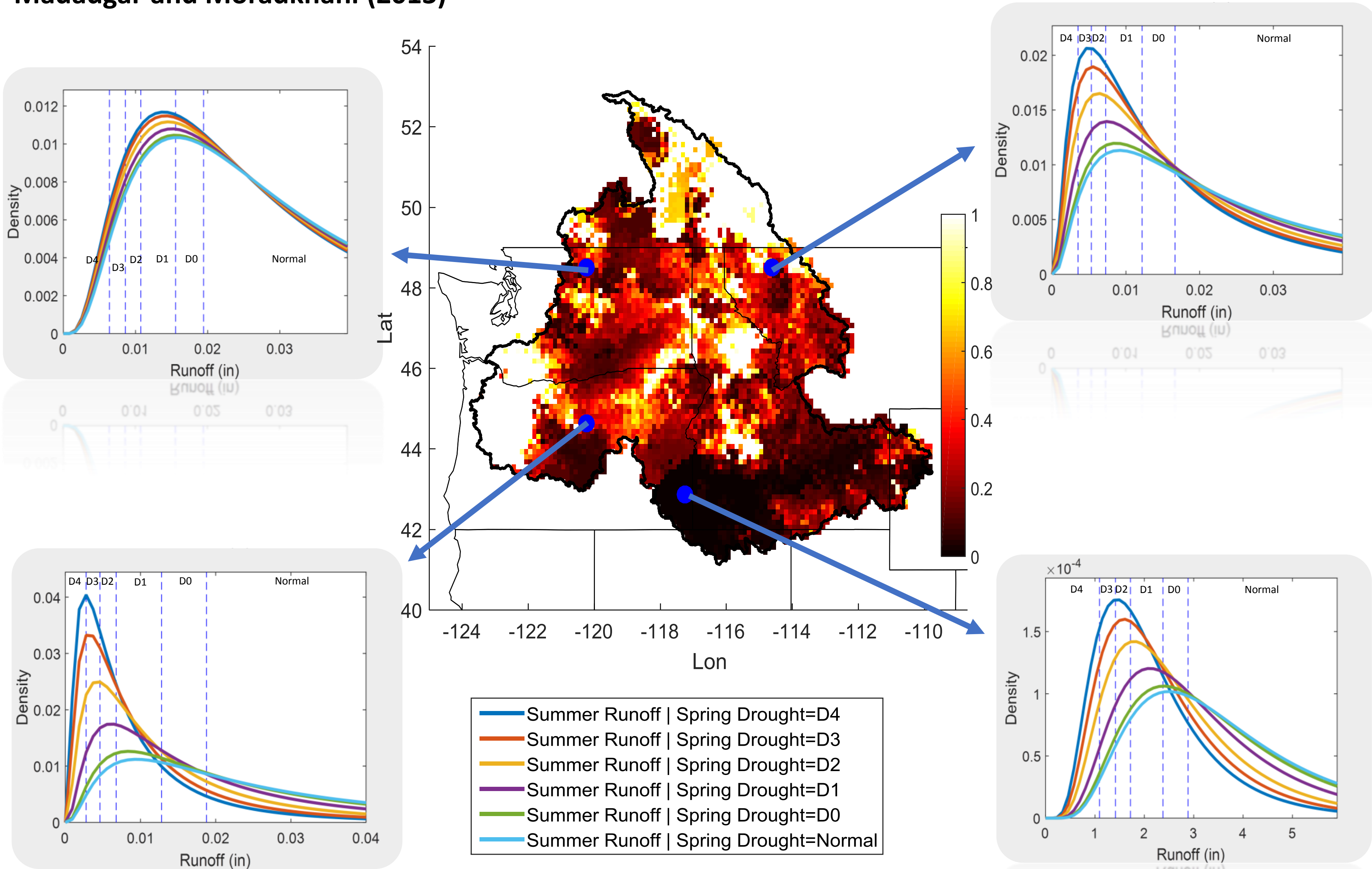
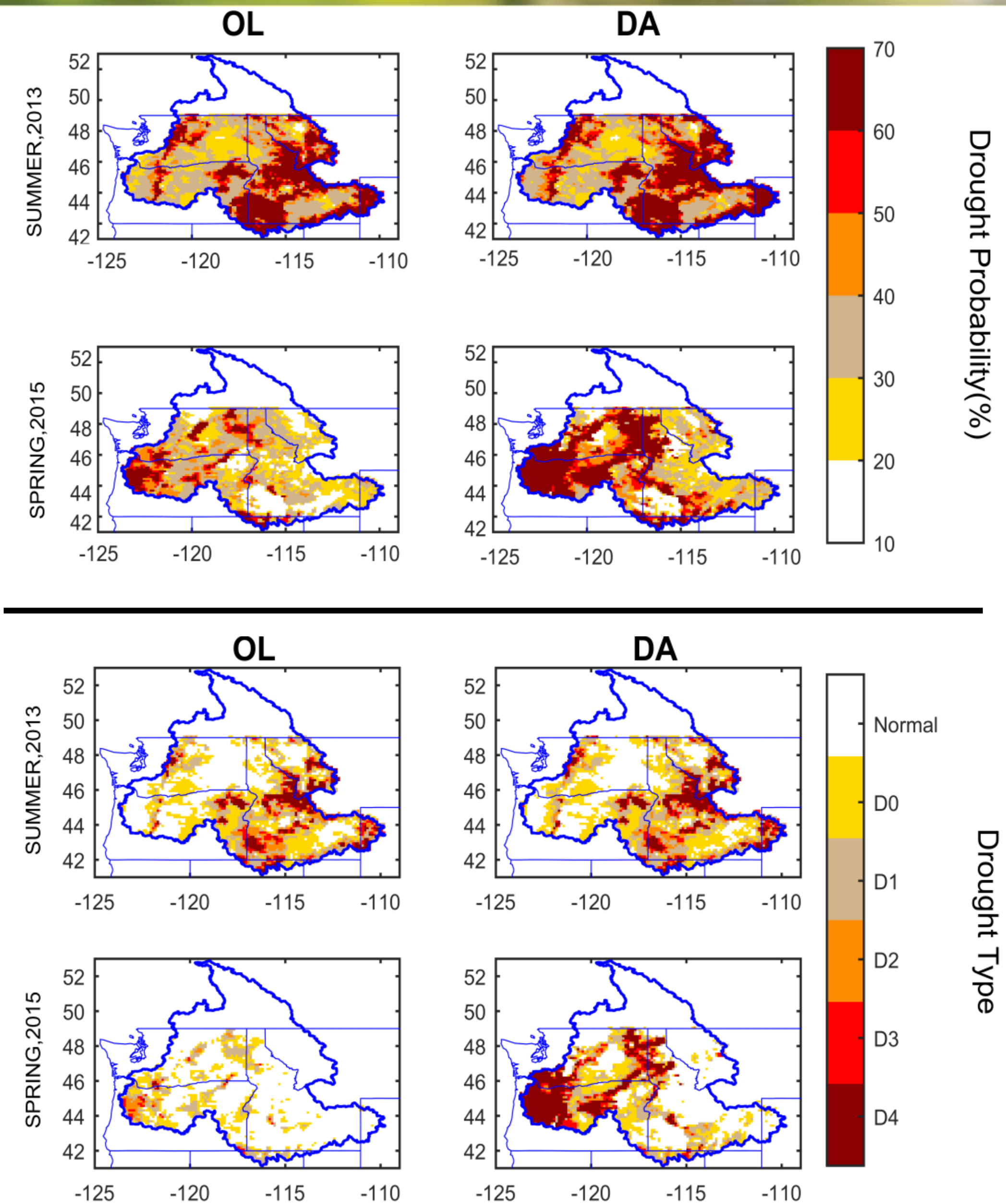
Madadgar and Moradkhani (2013)



Seasonal Drought Forecasting Results



- The results demonstrate the benefit of the proposed probabilistic forecasting system to aid the stakeholders for drought preparation and declaration, 3 to 6 months in advance

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References:

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