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

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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

- Requires the formulation of a probabilistic model

\[ p(y) = f(p(x), p(u), \omega) + p(\omega) \]
Operational Probabilistic Forecasts

- Generated with Ensemble Streamflow Prediction (ESP)

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

DeChant and Moradkhani (2011)
Ensemble Data Assimilation

\[
p(x_{t+1} | Y_{t+1}) = \frac{p(y_{t+1} | x_{t+1}) p(x_{t+1} | Y_t)}{\int_{x_{t+1}} p(y_{t+1} | x_{t+1}) p(x_{t+1} | Y_t) dx_{t+1}}
\]

The Forecast (prior distribution) \[ p(x_{t+1} | Y_t) \]

Observation \[ p(y_{t+1} | x_{t+1}) \]

Discrete representation of continuous random state variable, \( x_{t+1} \)

\( x_t \rightarrow x_{t+1} \)

Moradkhani et al. (2012)
MA is a linear weighted average of model ensembles.

**Deterministic**

- Combines single-value forecasts.

\[
M_{\text{ave}} = W_1 \cdot M_1 + W_2 \cdot M_2 + \ldots + W_k \cdot M_k
\]

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

**Probabilistic**

- Combines PDF of forecasts:

\[
f_{\text{ave}} = W_1 \cdot f(M_1) + W_2 \cdot f(M_2) + \ldots + W_k \cdot f(M_k)
\]

- Example: Bayesian Model Averaging

Madadgar and Moradkhani (2014)
Bayesian Model Averaging

Model 1

Model 2

Model 3

Flow

Time

Flow

Time

Flow

Time

Bayesian Model Averaging

Weighted Average

× W3

× W2

× W1

Prior

Posterior

∑
Combining PF-SBC with ESP

Observed Forcing

Resampled Historical Forcing

Predictive Uncertainty

Traditional ESP

ESP with PF-SBC

Spin-Up/Data Assimilation

Ensemble Streamflow Prediction

Spin-Up Start

Forecast Start

Forecast End

Bayesian Model Averaging

Combining PF-SBC with ESP
Combination of DA, Multi-modeling and ESP

Run DA for model $M_1$ over spin up period
Run DA for model $M_2$ over spin up period
Run DA for model $M_3$ over spin up period
... Run DA for model $M_K$ over spin up period

Streamflow during spin-up

Calculate model weights according to PF-SBC

$p(M_k | y_{1:t})$

Run ESP initialized with all $M_1$ states
Run ESP initialized with all $M_2$ states
Run ESP initialized with all $M_3$ states
... Run ESP initialized with all $M_K$ states

Weight each trace with $w_{1,i,y,t}$
Weight each trace with $w_{2,i,y,t}$
Weight each trace with $w_{3,i,y,t}$
... Weight each trace with $w_{K,i,y,t}$

Combine all traces into single ensemble with their respective weights

$p(\tilde{y}_t | x_{1:N,t}, u_{i:y,t-1}, M_{1:k}, y_{1:t}) \approx \sum_{y=1}^{Y} \sum_{i=1}^{N} \sum_{k=1}^{K} \delta(\tilde{y}_t - M_k(x_{i,t}, u_{y,t}, \theta, \alpha)) w_{k,i,y,t}$
Modeling Cases

- 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
Operational Data Assimilation

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
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
Ensemble Simulation for SWE before and after DA
Clackamas River Basin
Streamflow Forecast Before DA

“Johnson Creek”

Before DA

Ensemble Forecast - Open Loop (without Data Assimilation)

Discharge (CFS)

12-01-1970 12:00:00  02-01-1971 12:00:00  04-03-1971 12:00:00  06-01-1971 12:00:00  08-03-1971 12:00:00

Open Loop
Observation
Streamflow Forecast after DA  “Johnson Creek”

Ensemble Forecast with Data Assimilation

% Improvement

RMSE

%15
Streamflow Forecast before/after DA
“Johnson Creek”

Discharge (cfs)


Open Loop (No Data Assimilation)
Data Assimilation
Observation
• 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

**PRMS Input**
- Control file at T
- Parameter file
- Initial condition file at T-1

**PRMS Output**
- Selected states (streamflow, soil moisture, etc.) file at T
- Forcing data file at T

**Particle Filter Module**
- Resampling
- Updated particles

**USGS-PRMS Process**

**Color**
- 01
- 02
- 03
- 04
- 05
- 06
- 07
- 08
- 09

**PRMS Input**
- Control file at T+1
- Parameter file

**PRMS Output**
- Initial condition file at T
- Forcing data file at T+1

**Time Steps**
- T
- T+1

**Map**
- 146 Gauges
- 7739 Hru
- WA, OR, CA, NY, MT, ID, UT, WY
- KGE: < 0, 0 - 0.2, 0.2 - 0.5, 0.5 - 0.7, 0.7 - 1
Madadgar and Moradkhani (2013)
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.
References:


