Ensemble-based Streamflow Data Assimilation for an Operational Distributed Hydrologic Model

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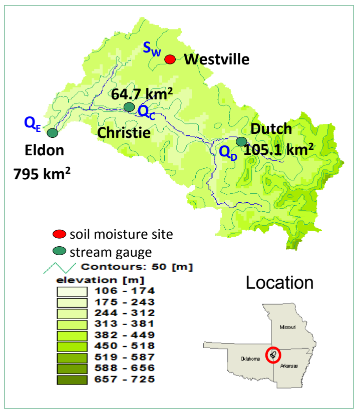
Introduction

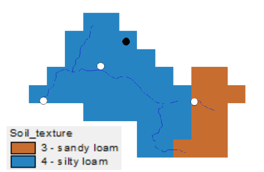
- Applying advanced data assimilation techniques to distributed modeling holds great potential for improving operational streamflow forecasting, particularly in light of increasing computing power and the availability of remotely sensed data with high spatial and temporal resolutions.
- The objectives of this work are to
  1) Integrate an ensemble-based data assimilation framework (i.e. Ensemble Kalman Filter (EnKF)) within the National Weather Service (NWS) Hydrology Lab's Research Distributed Hydrologic Model (HL-RDHM);
  2) Assess the performance of this ensemble framework in estimating flows as compared to observed flows, flows derived from stand alone HL-RDHM and from a deterministic DA technique (i.e. four dimensional variational data assimilation (4DVAR)).

Study Area



Left: Eldon basin (ELDO2)
- elevation map (50m resolution)
- main channel network
- soil moisture gauge
- streamflow gauges

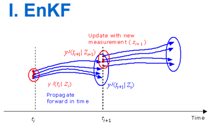
Below: ELDO2 soil map



Dataset: hourly gridded precipitation & hourly outlet flow (2000/6/21-2005/9/30)

Methodology

I. EnKF



Step 1: Propagation

$y_i(t) = A[\alpha_i, u_i(t), t]$;

$y_i(t = t_0) = y_{0_i}$

Step 2: Updating

$y_j^+ = y_j^- + K[z + \varepsilon_j - M_j(y_j^-)]$

$K = C_{yz}[C_{zz} + C_\varepsilon]^{-1}$

$j = 1, 2, \ldots, N$

Z: Flow measurement

y: Model states

N: Ensemble size

II. 4DVAR

Step 1: Create adjoint model (from Tapenade (http://tapenade.inria.fr:8080/tapendade/index.jsp))

Step 2: Minimize

$$
\begin{aligned}
J_k = & \frac{1}{2}[\mathbf{Z}_q - \mathbf{H}_{qq}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)]^T \mathbf{R}_{qq}^{-1}[\mathbf{Z}_q - \mathbf{H}_{qq}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)] \\
& + \frac{1}{2}[\mathbf{Z}_\theta - \mathbf{H}_{\theta\theta}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)]^T \mathbf{R}_{\theta\theta}^{-1}[\mathbf{Z}_\theta - \mathbf{H}_{\theta\theta}(\mathbf{X}_{s,k-l}, \mathbf{X}_p, \mathbf{X}_e)] \\
& + \frac{1}{2}[\mathbf{Z}_p - \mathbf{H}_{pp}\mathbf{X}_p]^T \mathbf{R}_{pp}^{-1}[\mathbf{Z}_p - \mathbf{H}_{pp}\mathbf{X}_p] \\
& + \frac{1}{2}[\mathbf{Z}_e - \mathbf{H}_{ee}\mathbf{X}_e]^T \mathbf{R}_{ee}^{-1}[\mathbf{Z}_e - \mathbf{H}_{ee}\mathbf{X}_e] \\
& + \frac{1}{2}[\mathbf{Z}_b - \mathbf{H}_{bb}\mathbf{X}_{s,k-l}]^T \mathbf{R}_{bb}^{-1}[\mathbf{Z}_b - \mathbf{H}_{bb}\mathbf{X}_{s,k-l}]
\end{aligned}
$$

Z_q: flow measurement

Z_θ: soil moisture meas.

Z_p: precipitation data

Z_e: potential evaporation (PE) data

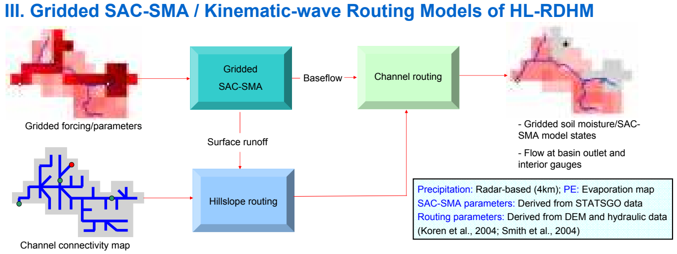
Z_b: initial model soil moisture state

$\textit{subject to } \mathbf{X}_{s,j} = \mathbf{F}(\mathbf{X}_{s,j-1}, \mathbf{X}_{p,j}, \mathbf{X}_{e,j}),\ j = k-l+1, \ldots, k$ Abide by the model dynamics

$X_{s,i}^{\min} \le X_{s,k,i} \le X_{s,i}^{\max},\ j = k-l, \ldots, k;\ i = 1, \ldots, 6$ Model states (X_j) in feasible ranges

Methodology (cont.)

III. Gridded SAC-SMA / Kinematic-wave Routing Models of HL-RDHM



Precipitation: Radar-based (4km); PE: Evaporation map
SAC-SMA parameters: Derived from STATSGO data
Routing parameters: Derived from DEM and hydraulic data
(Koren et al., 2004; Smith et al., 2004)

IV. Experimental Design

a) Focus

Biggest four events of the dataset
- 1st: June 21-23, 2000 (Q_{peak} = 1549 cms)
- 2nd: April 22-26, 2004 (Q_{peak} = 1255 cms)
- 3rd: April 6-12, 2002 (Q_{peak} = 445 cms)
- 4th: Dec.15-21, 2001 (Q_{peak} = 368 cms)

b) Error models
- EnKF:
  Precipitation uncertainty: log-normal
  Flow measurement error: Gaussian
  (covariance depends on flow magnitudes)
- 4DVAR:
  Standard setting of Lee et al., 2010

c) Sensitivity test (1st event)

Baseline setting (BS):
- Precipitation uncertainty variance (C_{vp}): 0.5mm²
- Flow measurement error variance (C_{vq}): $(Q_t/60)^2$
- Ensemble size (N): 50

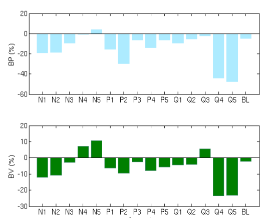
Scenarios
- N1-N5: N = 10,25,75,100,150 (C_{vp}, C_{vq} unchanged)
- P1-P5: C_{vp} = 0.1,0.25,0.36,1,1.5 (C_{vq}, N unchanged)
- Q1-Q5: Cvq = $(Qt/100)^2$, $(Qt/80)^2$, $(Qt/40)^2$, $(Qt/20)^2$, $(Qt/10)^2$ (C_{vp}, N unchanged)

d) Flow simulation

Evaluation metrics: bias in peak (BP), bias in volume (BV), timing error (TE)

Results

I. Sensitivity test



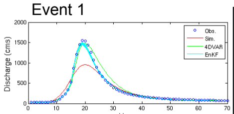
Left: Percent bias in simulated peak flow (BP) for the baseline and 15 sensitivity test scenarios. When N > 50, its impact on peak flow estimate is not significant; when uncertainty in precipitation (C_{vp}) is small and errors in flow observations (C_{vq}) are large, the filter tends to underestimate the peaks by a larger amount, indicating that proper error setting is needed to enable satisfactory filter performance.

* Timing error (TE) only observed for scenarios N1 and Q5 (1 hour), suggesting that small N and large C_{vq} leads to TE

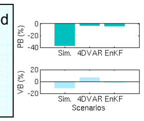
Above: Percent bias of total flow volume (BV). With increasing N, the bias changes gradually from negative to positive values; the sensitivity to errors in precipitation and flow observations shows a similar pattern to that of BP.

* The EnKF is configured with the setting of Baseline scenario and applied in flow simulation.

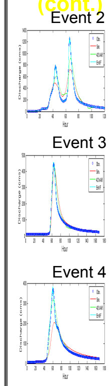
II. Flow simulation



Left: HL-RDHM, 4DVAR, and EnKF-simulated flows of Event 1. Both 4DVAR and EnKF outperform the original model. EnKF under-catches the peak. Right: Bias in peak and volume. EnKF performs the best.



Results (cont.)



Right: TE of model-simulated, 4DVAR and EnKF derived flow for four events. EnKF estimates have no TE for the first three events. For Event 4, EnKF and 4DVAR estimates have comparable ...

Summary

- Increasing ensemble size for EnKF does not necessarily lead to flow estimates with less bias in both the peak and volume
- ...

Ongoing / Future work

- Investigating the capability of the ...

References

Koren, V., S. Reed, M. Smith, Z. Zhang, ... Seo, 2004. Hydrology laboratory research modeling system (HL-RMS) of the US national weather service, Journal of Hydrology, 291, 297-318.

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