Surface Soil Moisture Assimilation with SWAT

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August 4, 2010
Seoul, Korea

- Importance of soil moisture (SM) in hydrology, agriculture, meteorology and environmental studies

- Why surface soil moisture data assimilation?
  - Limitations of field measurements and remote sensing data
    - Temporal and spatial limitation (field measurement)
    - Shallow sensing depth and large grid size (remote sensing)
  - Data assimilation: better prediction of SM **profile** by combining observed **surface** SM data and hydrologic models


Research Objectives

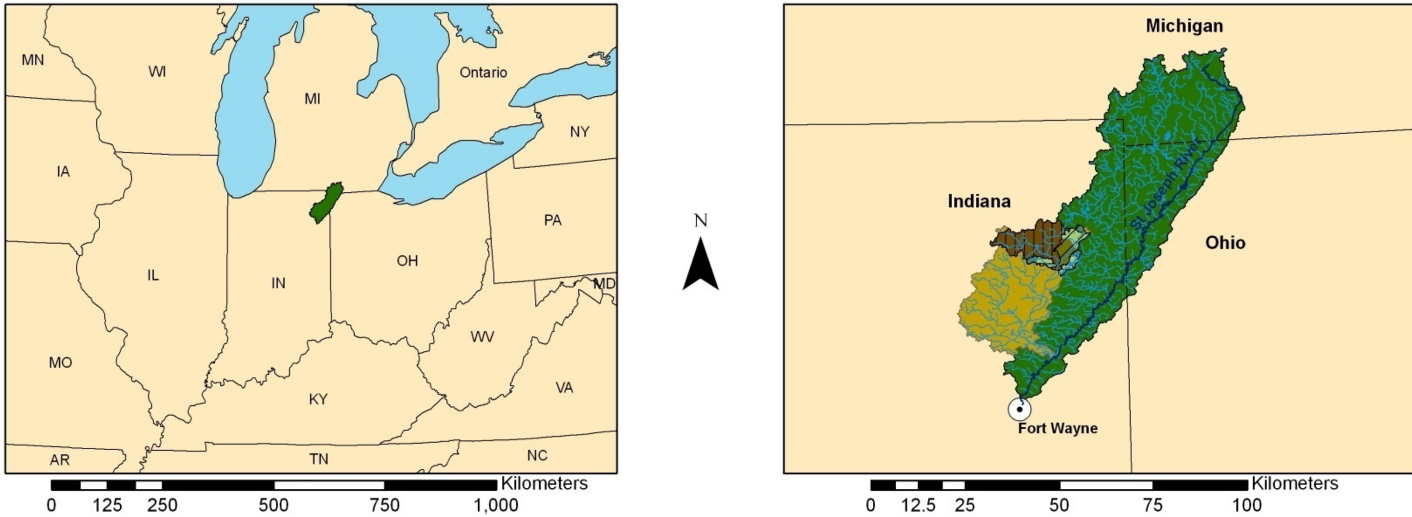
- Application of data assimilation techniques to a **watershed scale hydrologic model** to improve soil water content

  → SWAT + Ensemble Kalman Filter (EnKF)

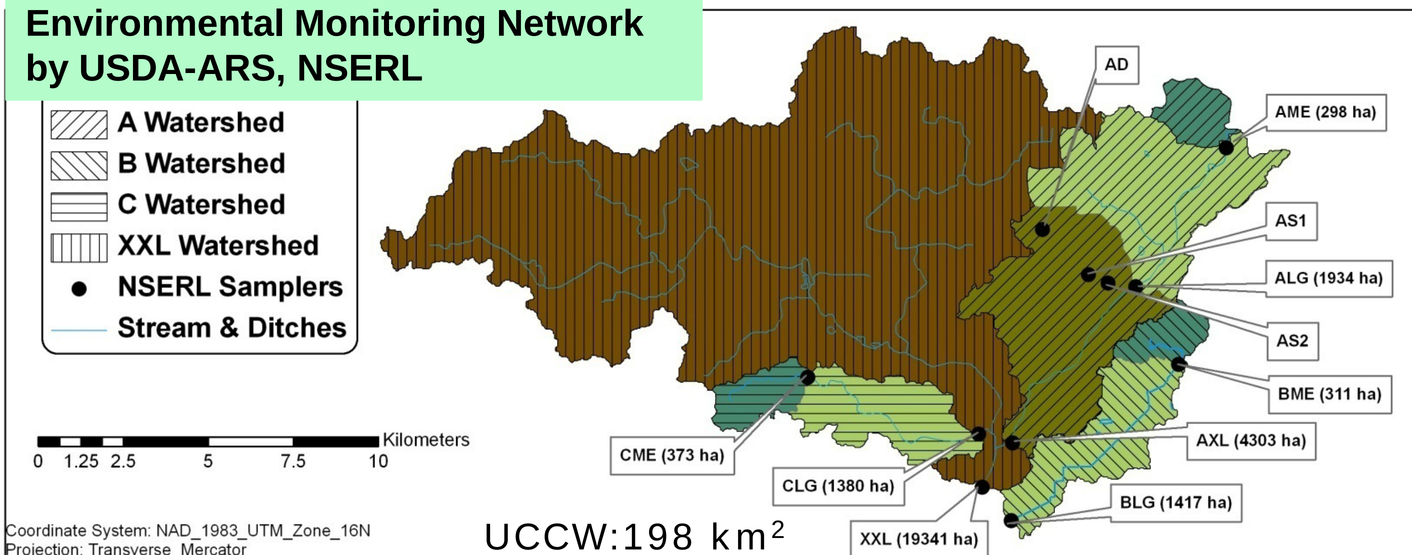
- To investigate how near surface SM assimilation affects runoff and **streamflow prediction** through **synthetic** experiment

- To investigate how the spatial variability of inputs affect the potential capability of data assimilation (DA) techniques

Upper Cedar Creek Watershed, IN



Environmental Monitoring Network by USDA-ARS, NSERL



UCCW:198 km^2

Previous Research

- 1D point-scale soil moisture profile estimation (AS1 and AS2)
- Application of two DA methods (EnKF and direct insertion) into the **Root Zone Water Quality Model** with field measured surface SM

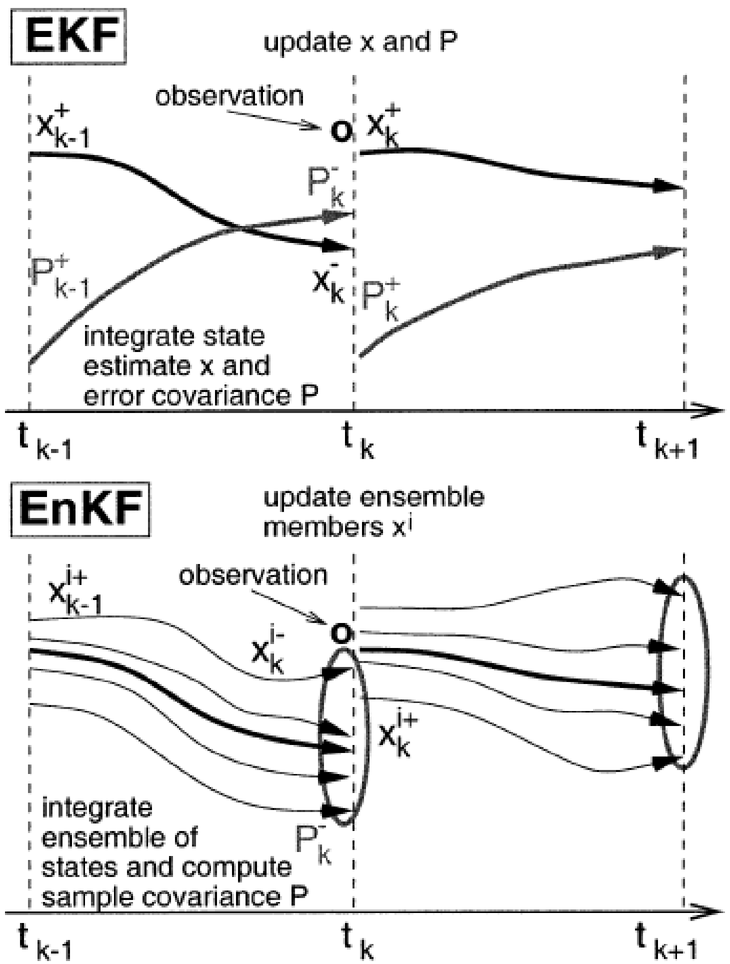
Comparison of simulation results (simulation period : April to October, 2007)

Site	Depth (cm)	W/O assimilation			Direct Insertion			EnKF		
		R	RMSE	MBE	R	RMSE	MBE	R	RMSE	MBE
AS2	5	0.6904	0.0908	0.0782	0.8913	0.0491	0.0418	0.9038	0.037	0.0279
	20	0.32	0.0495	0.0241	0.573	0.0311	0.0045	0.6119	0.0286	-0.0054
	40	0.1087	0.0725	0.0559	0.3362	0.0541	0.0407	0.3827	0.0461	0.0335
	60	0.4124	0.0333	0.0217	0.46	0.031	0.0194	0.4847	0.0279	0.0148

➢ Daily assimilation of surface soil moisture improved soil moisture estimation in the upper dynamic layers (5 and 20cm depth) while less certain improvement in the deep layers (40cm and 60cm depth)

➡ **Watershed scale** application of the EnKF with a (semi-) distributed model (SWAT)

Data assimilation – Ensemble Kalman Filter



(Source: *Reichle et al.* 2002)

◆ Nonlinear System model

$$x_{k+1} = f_k(x_k) + w_k$$

$$y_k = H_k x_k + v_k$$

w_k : Process noise, P(w)~ (0, Q)

v_k : Measurement noise, P(v)~(0,R)

y_k : Measurement

* Error Covariance Matrix: $P = \overline{(x-\bar{x})(x-\bar{x})^T} \cong P_e$

Forecast step

$$x_k^{i-} = f_{k-1}(x_{k-1}^{i+}) + w_{k-1}^i \qquad i = 1, \cdots, N$$

$$P_k^- = \frac{1}{N-1} D_k D_k^T \qquad D_k = \left[(x_k^{1-} - x_k^-), \cdots, (x_k^{N-} - x_k^-)\right]$$

$$x_k^- = \frac{1}{N}\sum_{i=1}^{N} x_k^{i-}$$

Update step

$$x_k^{i+} = x_k^{i-} + K_k\left[y_k - H_k x_k^{i-} + v_k^i\right]$$

$$K_k = P_k^- H_k^T \left[H_k P_k^- H_k^T + R_k\right]^{-1}$$

Why synthetic experiment?

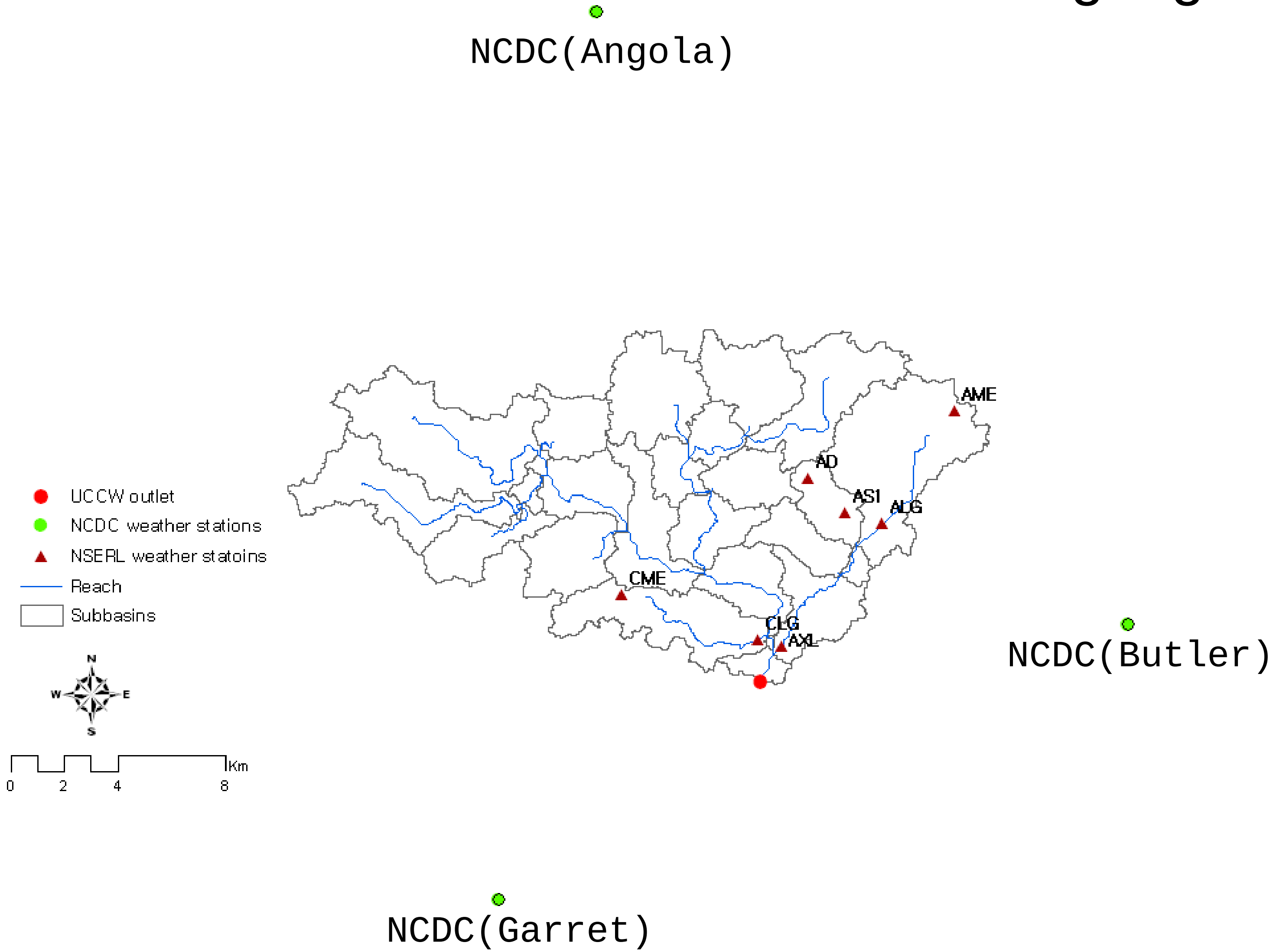
- SWAT: HRU based semi distributed model
- Coarse resolution of currently available remote sensed soil moisture data
- Uncertainties due to model and observation are known
  → Better understanding on the effect of DA

Experiment set up

True state	"prior" (no assimilation)	EnKF
• Rainfall data from NCDC and NSERL raingauge network	• Rainfall data only from NCDC • Intentionally poor initial condition	• Same set up as "prior" • Updated soil water content using the observed surface soil moisture (~5cm)

Our imperfect knowledge of the true system

Rainfall gauge stations

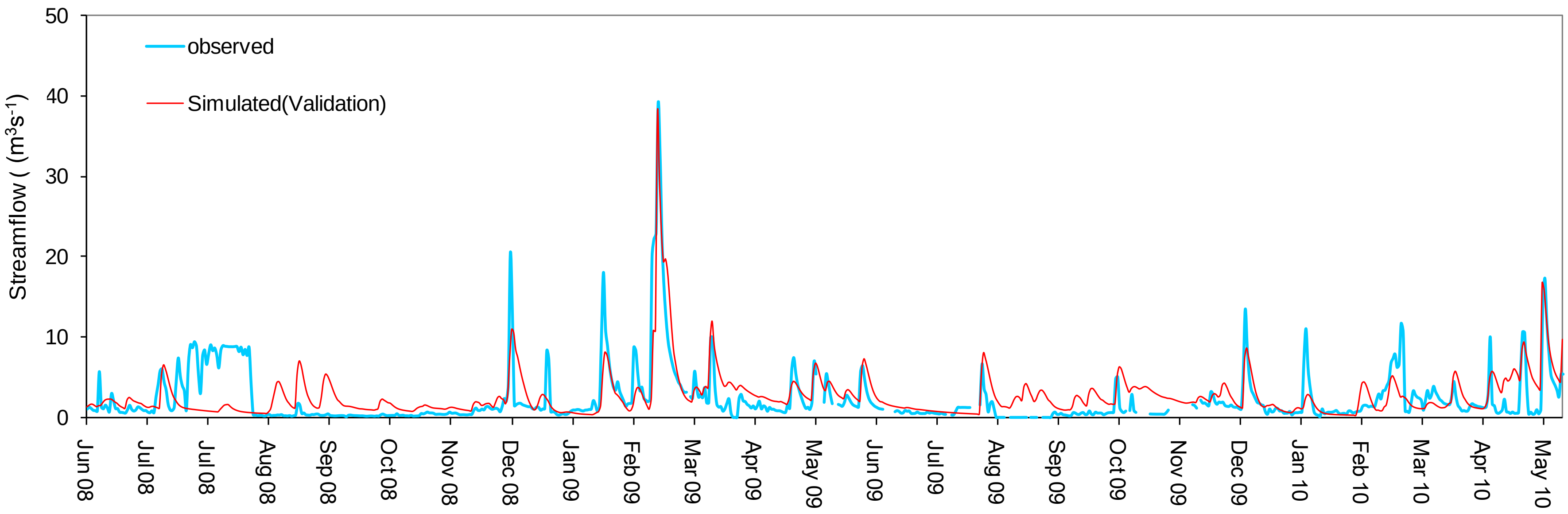


True state preparation

- Data source
  - DEM: 30m
  - Soil: SSURGO database
  - Landuse : NLCD2001
- Watershed delineation & HRU creation using ArcSWAT
  - 25 subbasins
  - Total 206 HRUs
- Model calibration using measured streamflow
  - Warm-up period (April 2003 – April 2006)
  - Calibration period (May 2006 – May 2008)
  - **Validation period (June 2008 – May 2010)**
  - Calibrated 18 parameters based on sensitivity analysis and literature
    (Cn2, Esco, Surlag, Timp, Ch_K2, Sol_Awc, Blai, Alpha_Bf, Sol_Z, Rchrg_Dp, Smtmp, Epco, Ch_N2, Revapmn, Slope, Sol_Alb, Canmx, Sol_K)

True state preparation (contd.)

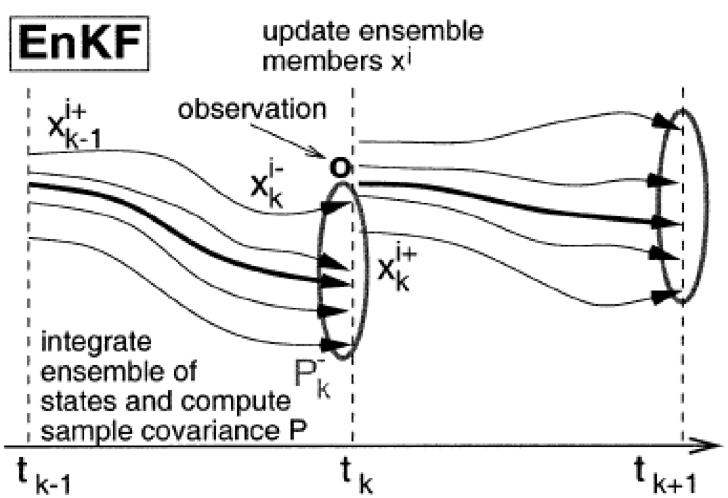
	R^2	R_{NS}^2
Calibration (May 2006 – May 2008)	0.46	0.44
Validation (June 2008 – May 2010)	0.42	0.37



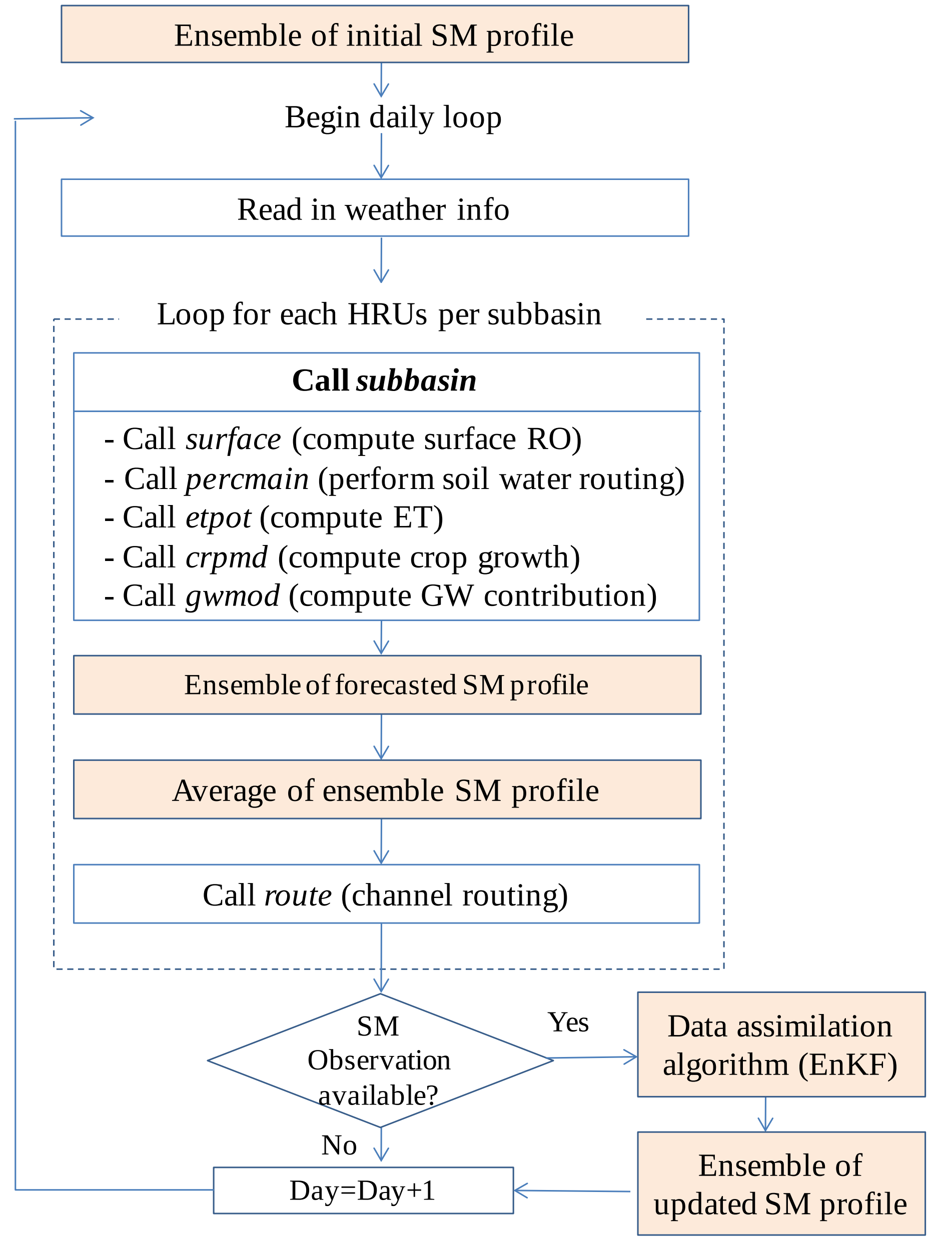
Methodology

Implementation of the EnKF with the SWAT

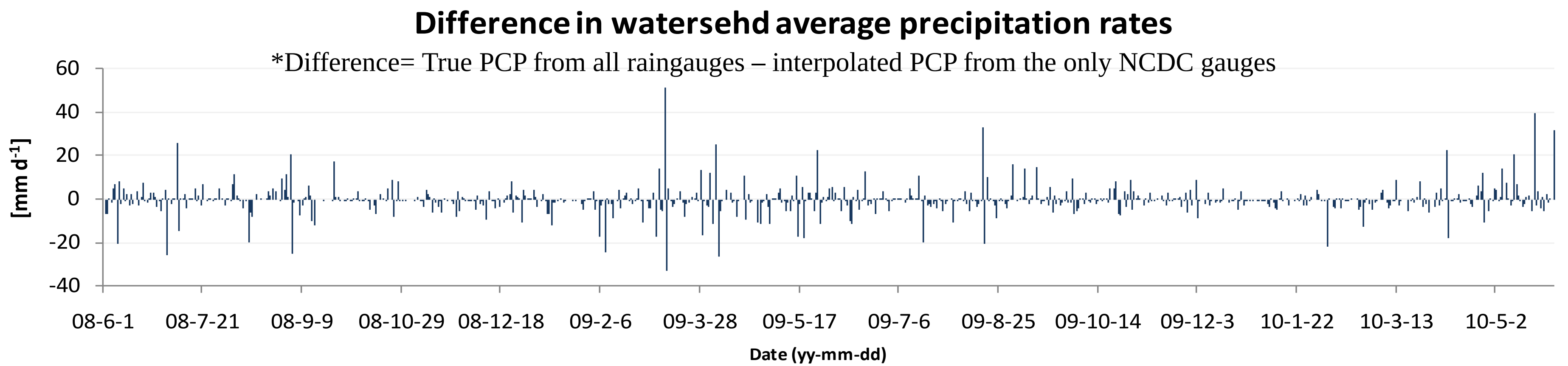
- Daily update
- Ensemble size: 50
- Observed data for the 1st layer (~5cm) generated from the true simulation by adding observation error (0.007)

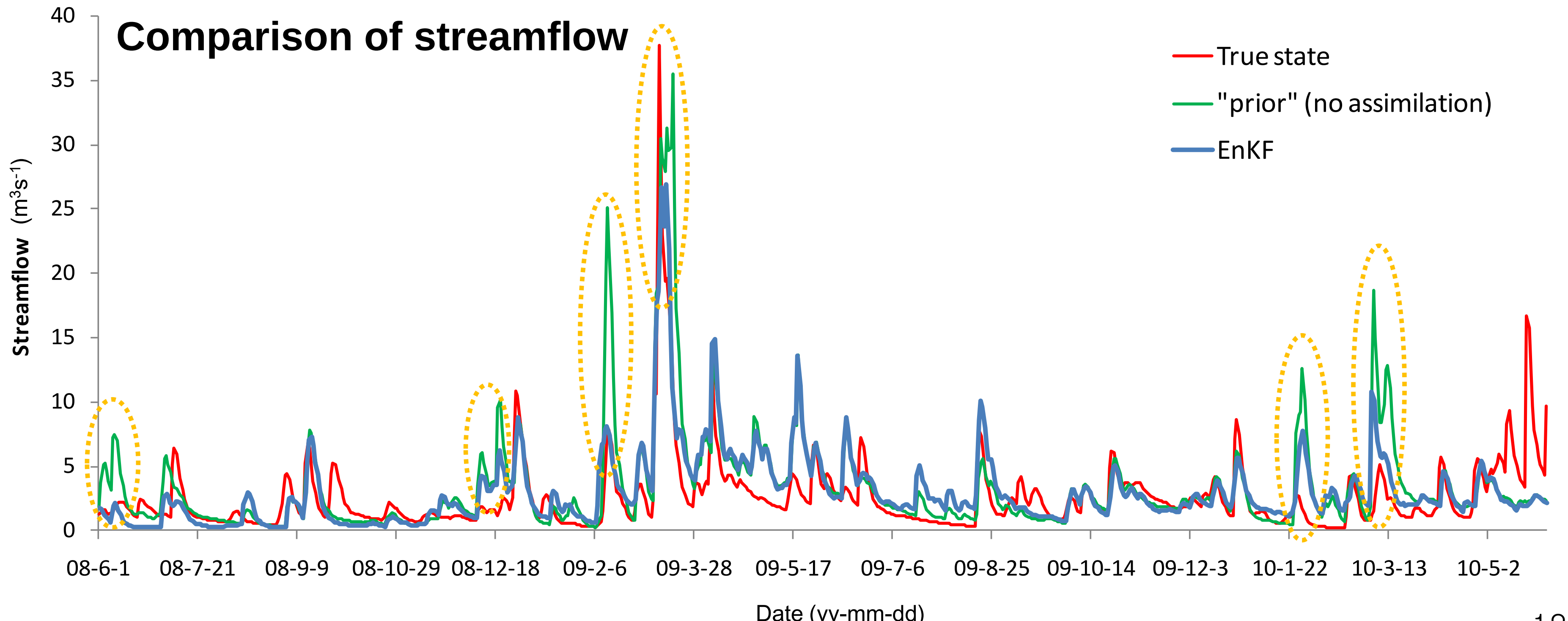


(Source: *Reichle et al.* 2002)



Preliminary Results

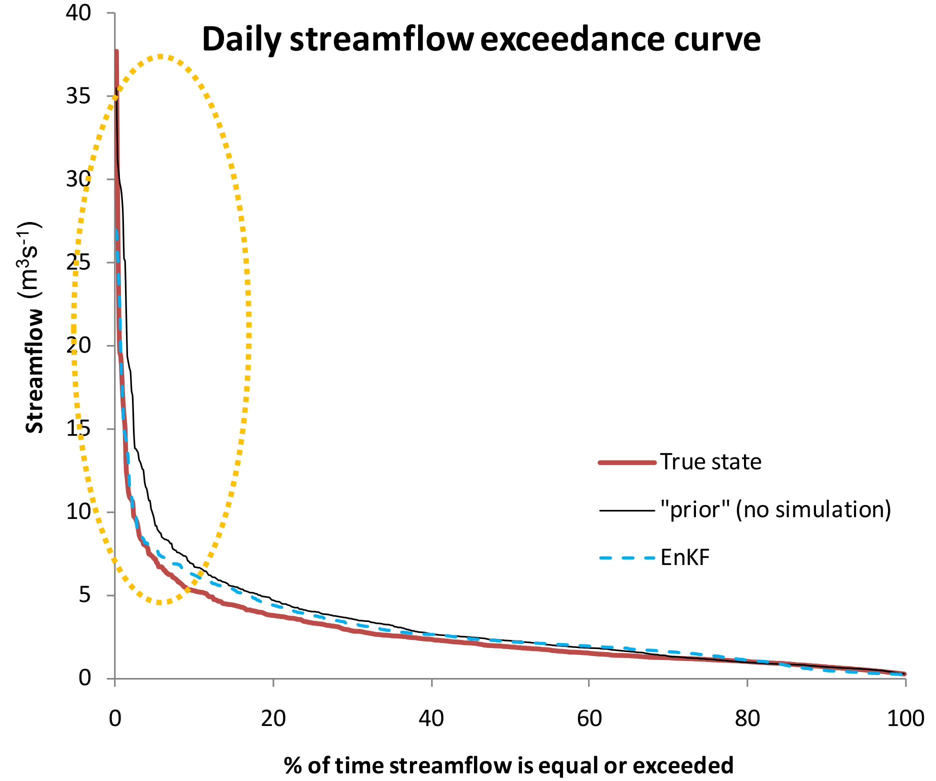




Preliminary Results

Statistical results

	R^2	R_{NS}^2
"prior" (no assimilation)	0.447	-0.118
EnKF	0.514	0.407



- Better representation of soil water contents through surface soil moisture assimilation can improve rainfall-runoff modeling
- Effective especially for improving the overestimated streamflow due to the wrong high rainfall

- Inaccurate simulation results due to the limited knowledge on the forcing data can be improved partially by updating surface soil moisture condition (EnKF data assimilation)

Future works

- To investigate how the surface soil moisture assimilation affects each hydrologic components and water balance (Total water content in the soil, ET, lateral flow etc.)
- To explore how to use currently available remote sensing (soil moisture) data for HRU-based SWAT model for data assimilation
- To examine better assimilation approaches (e.g. assimilating streamflow observation)

Reference

- Reichle, R. H., Walker, J. P., Koster, R. D., and Houser, P. R. (2002). "Extended versus Ensemble Kalman Filtering for Land Data Assimilation." In: *Journal of Hydrometeorology*, American Meteorological Society, 728.

Thank you !

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