Data assimilation of soil moisture and snow water equivalent into hydrologic model of an urban basin.

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Introduction

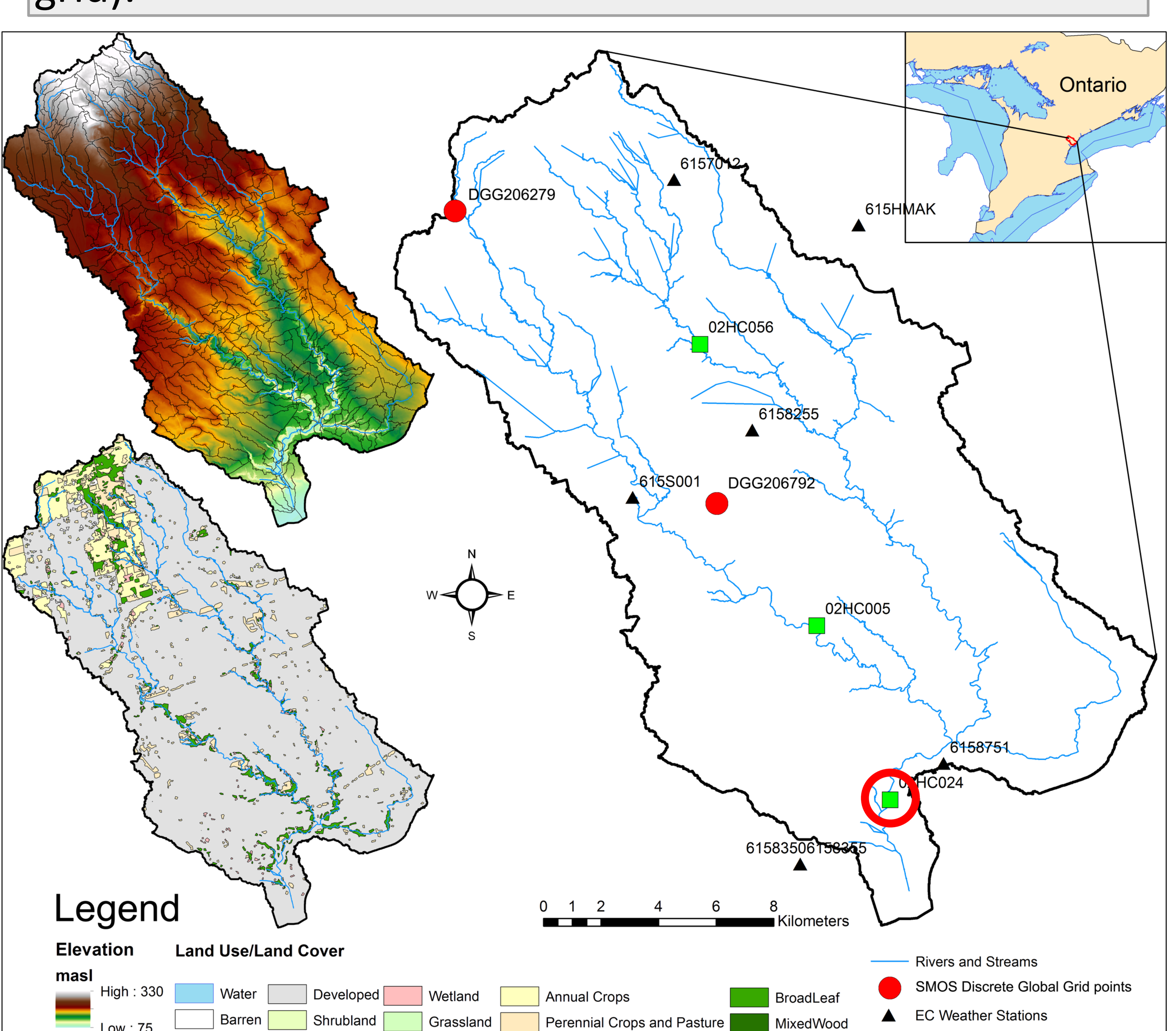
Both Soil Moisture (SM) and snow have major roles in the water cycle. Data assimilation (DA) can be used to integrate data into hydrologic models while accounting for their uncertainties [1].

Using the Ensemble Kalman Filter (EnKF), SM and Snow Water Equivalent (SWE) data will be integrated in to the Sacramento Soil Moisture Accounting (SAC-SMA) Model. These analyses will examine the impact that different assimilation schemes have on hydrologic modeling and forecasting in an urban basin.

Study Area and Data

Don River watershed covers municipalities of Toronto, York, Markham, Richmond Hill, and Vaughan. The area of the watershed is 358 km^2. Length of major tributaries range from 9–43 km and they have an average monthly streamflow of 4 m^3/s [2].

Data used for these analysis include daily streamflow from Water Survey of Canada HYDATA database (02HC024), historical weather data from Environment and Climate Change Canada, the Soil Moisture and Ocean Salinity (SMOS) Level 2 SM data (15km grid), and the Snow Data Assimilation System (SNODAS) SWE (1km grid).



Method

SAC-SMA Hydrologic Model:

- Lumped conceptual rainfall-runoff model.
- Five storages used to represent the water accumulation in the catchment. Degree day snow routine.
- Calibrated using Particle Swarm Optimization (PSO).
- Forecast run from 1 to 14 days using 'perfect' forcing data.

Data Processing:

- SMOS data filtered based on probability of radio frequency interference and data quality index then bias-corrected using CDF matching [7].
- SNODAS snowdepth was validated against ECCC snowdepth, bias-corrected using CDF matching and the CDF matching function was then applied to the SNODAS SWE to get a pseudo-bias-corrected SWE data set.

Ensemble Kalman Filter (EnKF)

- Uses randomly generated ensemble members to estimate the PDF of state variables [3-5].
- Here used to assimilate different combinations of streamflow, SM, and SWE data for state and parameter updating.
- Ensemble mean used as best estimate when comparing performances.
- Formulated as [6]: $x_t^{i+} = x_t^{i-} + K_t\left(y_t^i - \hat{y}_t^i\right)$,

Where:

x_t^{i+} is the ith updated ensemble state variable at time t,
x_t^{i-} is the ith ensemble state variable at time t,
y_t^i is the ith member of perturbed observations at time t,
$\hat{y}_t^i$ is the ith predictive variable at time t,
K_t is the Kalman gain, $K_t = \Sigma_t^{xy}[\Sigma_t^{yy} + \Sigma_t^{y}]$,
Σ_t^{yy} is the error covariance matrix of the prediction $\hat{y}_t^i$,
Σ_t^{xy} is the cross covariance of x_t^{i-} and $\hat{y}_t^i$,
Σ_t^{y} is the variance of y_t^i.

Results

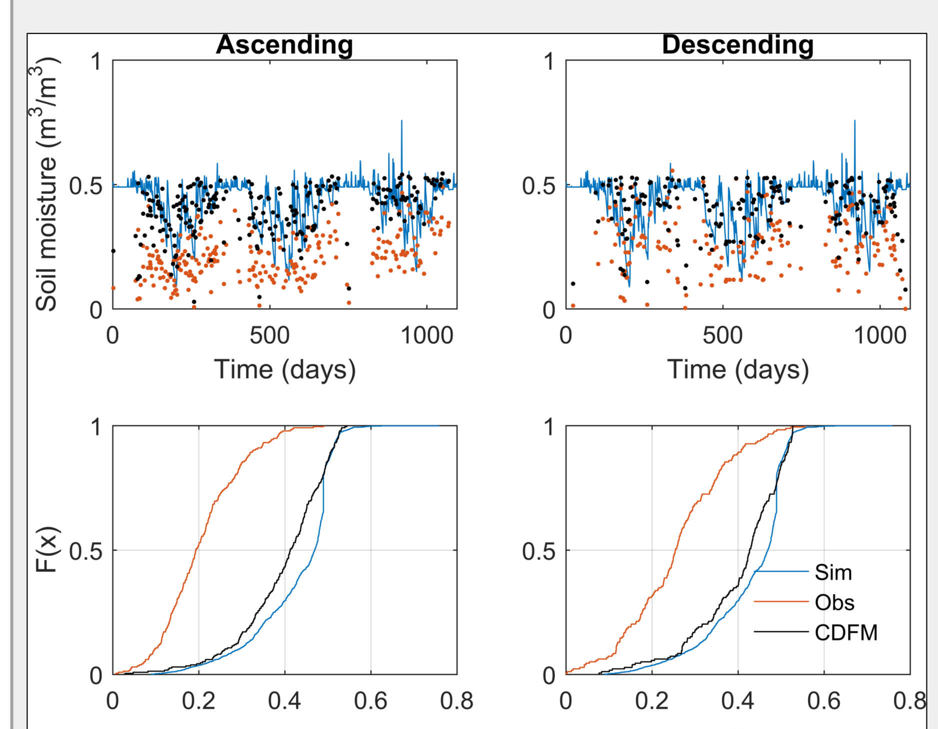


Figure 1: Bias corrected SM using CDF matching [7]. SMOS L2 SM data was matched to SAC-SMA SM (UZTWS+UZFWS)/(UZTWM+UZFWM) to reduce the chance of systematic errors.

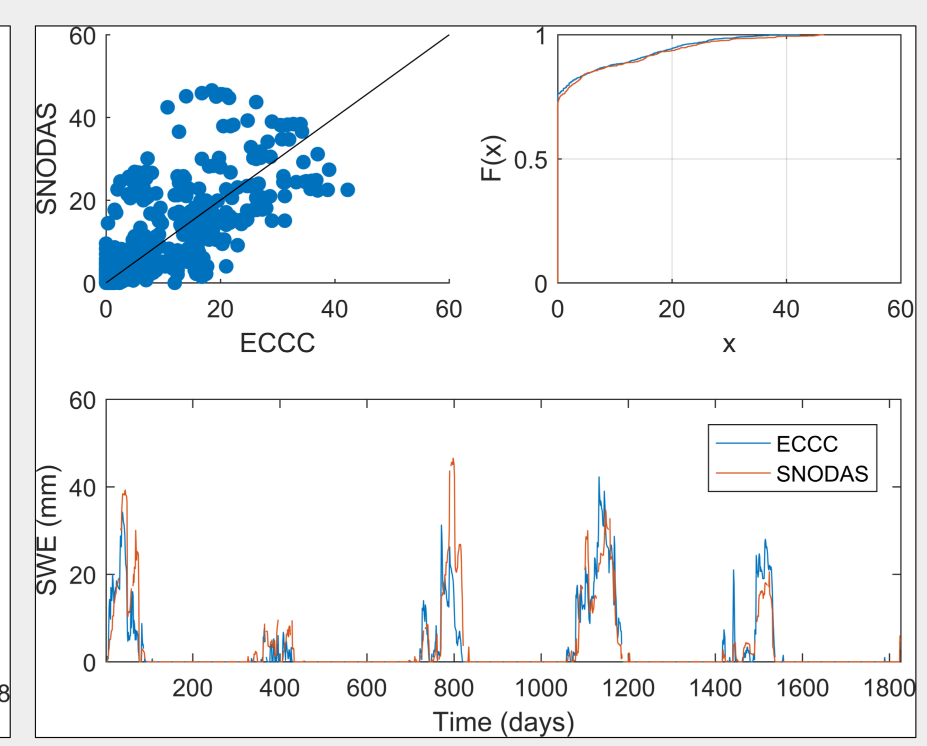


Figure 2: Corrected SNODAS SWE compared with ECCC SWE (snow depth/10).

Table 1: Performance of SAC-SMA model of Don River basin under different assimilations schemes compared with open loop simulation. Using PSO, the calibration period was 2001-2010, and validation was 2011-2013.

SCHEME	NSE	RMSE	BIAS
OL – CAL	0.60	0.86	-0.04
OL – VAL	0.63	0.93	-0.06
Q	0.80	0.68	-0.11
SM	0.44	1.14	-0.15
SMSWE sd*	0.34	1.16	-0.14
SMSWE ec**	0.42	1.16	-0.15
SWE sd	0.17	1.17	-0.10
SWE ec	0.43	1.16	-0.19
***Q-Q	0.53	1.15	-0.01
Q-SM	0.82	0.68	0.09
Q-SMSWE sd	0.83	0.66	0.02
Q-SMSWE ec	0.82	0.66	0.00
Q-SWE sd	0.81	0.63	0.05
Q-SWE ec	0.84	0.62	-0.02

*SNODAS, **ECCC, ***Q- indicates parameters were updated using streamflow.

Table 2: Raw and Bias corrected SNODAS SWE Performance

	NSE	RMSE	BIAS
SWE	-5	17.39	6.76
SWE Corr.	0.63	4.31	0.32

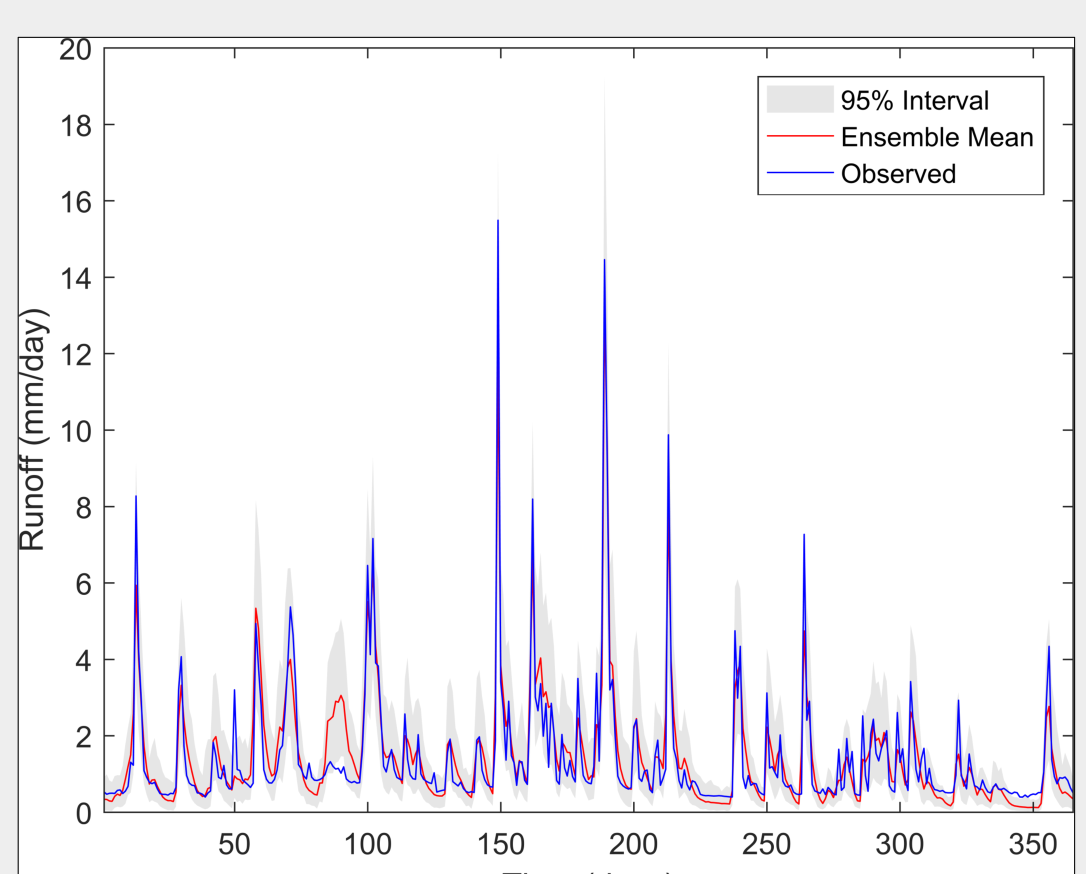


Figure 3: 2013 simulation results from assimilating streamflow to update model parameters and SM and SWE to update model states. From Q-SMSWE sd scheme listed in Table 1.

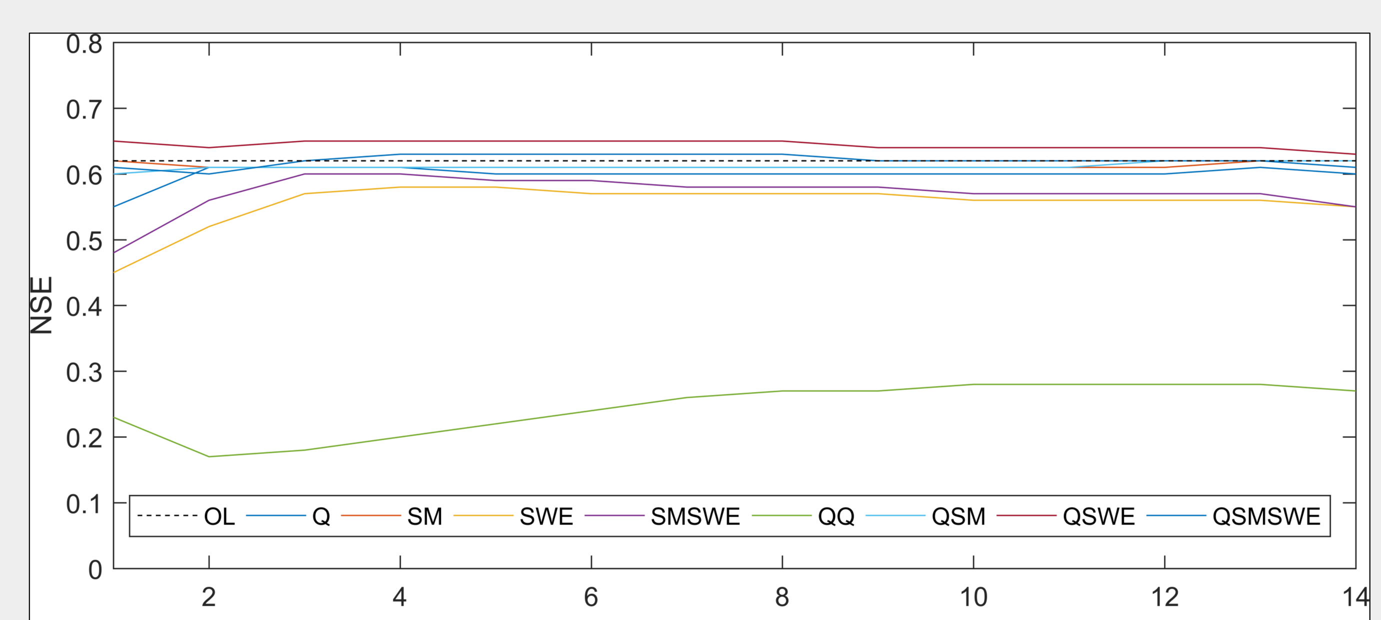


Figure 4: Forecast results for 1 to 14 day lead time for different assimilations schemes. For the forecasts, only the SNODAS SWE was tested. The forecasts were performed using 2013 data. The open loop performance is shown for reference.

Discussion

In general, the state and parameter updating DA schemes had better performance for both simulation and forecasts. Under state updating, a large difference is seen in the performance when using ECCC over SNODAS SWE data, however, when updating parameters and states this difference was negligible.

Despite the improvements gained from DA, the peak flows were not always correctly represented by the ensemble mean. However, they were still captured by the ensemble (Figure 3).

The forecast performances for each assimilation scheme, except the Q-Q scheme, were fairly similar to the open loop, with the Q-SWE and Q-SMSWE schemes performing marginally better. One explanation of this is due to the forcing data used, as it was just the historical values and not an actual forecast product.

Summary and Future Work

The analyses found the Q-SMSWE and Q-SWE assimilation schemes have the better performances for both simulation and forecasts. Indicating that after some pre-processing the SMOS L2 SM and SNODAS SWE data products can be used for assimilated and provide improved performances. To determine how robust these results are, future work will include:

- Using different hydrologic models
- Transitioning into distributed models of basin
- Using hourly time scale
- Using forecast data sets instead of 'perfect' forecast
- Examining different DA methods

References

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