# Estimating bathymetry and river depth in the Ohio River using simultaneous state-parameter estimation with an Ensemble Kalman filter

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## ABSTRACT

In spite of the critical role of river discharge in land surface hydrology, knowledge about river discharge globally is relatively poor, due to the sparse spatial distribution of river gages. The upcoming Surface Water and Ocean Topography (SWOT) mission can be used to complement the in situ gage network. SWOT is a swath mapping radar interferometer that will measure water surface elevation (WSE), both temporally and spatially. However, because SWOT will measure WSE, not the true depth to the river bottom, the river discharge cannot be estimated without ancillary data, namely the river channel bathymetry. We have measurements of WSE and need to estimate water depth or bathymetry and discharge. We focus on retrieving river depth for estimating river discharge from SWOT measurements. Since SWOT will be launched during the 2019-2020 time frame, we generated synthetic SWOT WSE measurements for the main stem of the Ohio River. For the measurements, we simulated the true hydraulic parameters using the LISFLOOD-FP hydrodynamic model and corrupted the results by adding height errors based on the SWOT instrument design. The ensemble Kalman filter (EnKF) was used to estimate the river depths, given the SWOT WSE measurements and WSE predictions by LISFLOOD-FP. We modelled errors in river discharge in the LISFLOOD-FP boundary conditions by coupling LISFLOOD-FP with the Variable Infiltration Capacity (VIC) model, and introduced errors into the VIC precipitation forcing. Errors in channel bathymetry were modelled using an exponential correlation function with a spatial correlation length of 100 km. The experiments showed that the EnKF update was able to recover the bathymetry from WSE measurements with 0.52 m reach-average accuracy, which is 67.8% less than the initial guess. The experiments also confirmed the usefulness of a multi-temporal data set for retrieving bathymetry.

## STUDY SITE

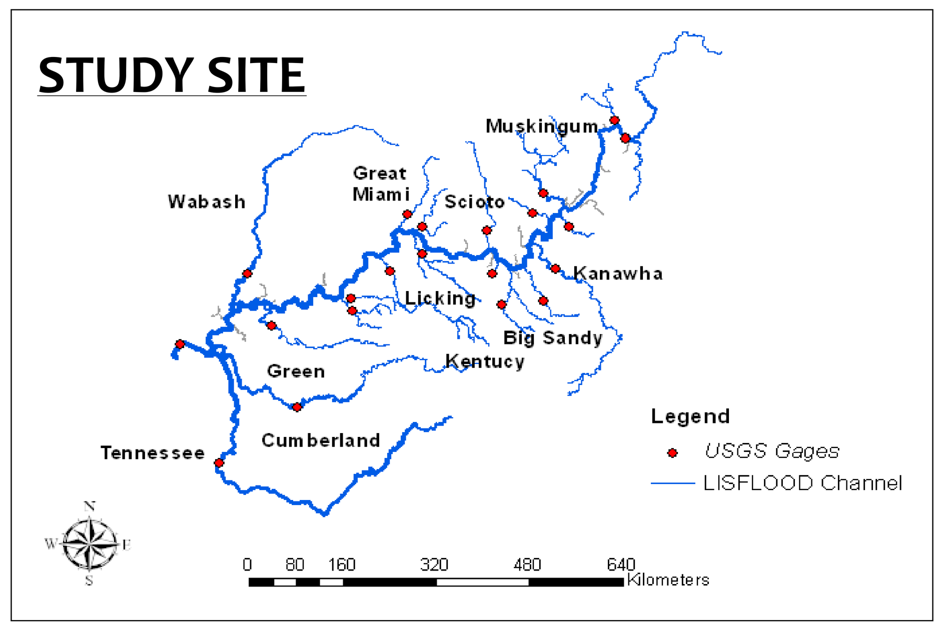
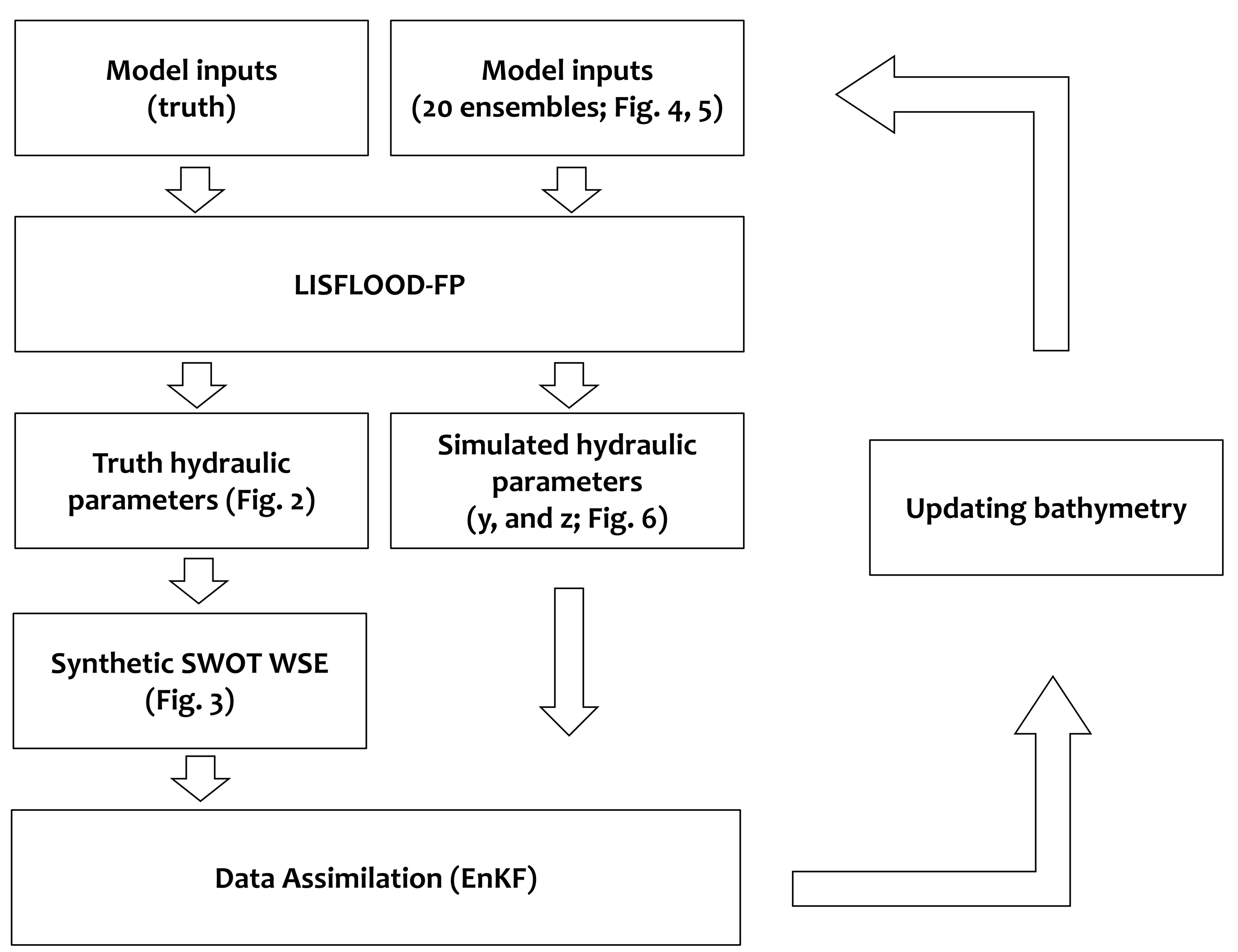



**Figure 1.** A map of the Ohio River Basin, including 11 major tributaries and 7 minor tributaries, used in the model. Drainage area size of each tributary is shown by the relative thickness of the blue lines. The USGS gages used for boundary conditions are shown.

## APPROACH




## Hydraulic parameters - truth

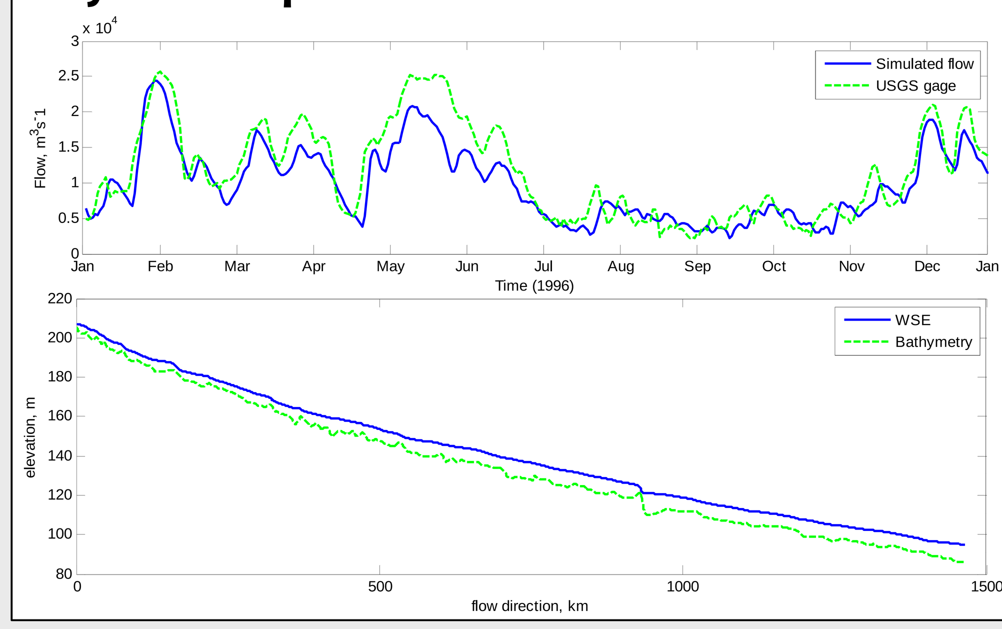



**Figure 2.** True hydraulic parameters of the Ohio River (Jan. 1 – Dec. 31, 1996) were simulated using the LISFLOOD-FP model (Bates and De Roo, 2000) with USGS observed flows and bathymetry estimated from the U.S. Army Corps of Engineers data. Modeled discharge at the downstream model outlet is shown (blue), as well as the discharge from the USGS gage (green) (top). The estimates of the bathymetry and WSE are shown (bottom). The data were used to generate synthetic SWOT data and to evaluate results.

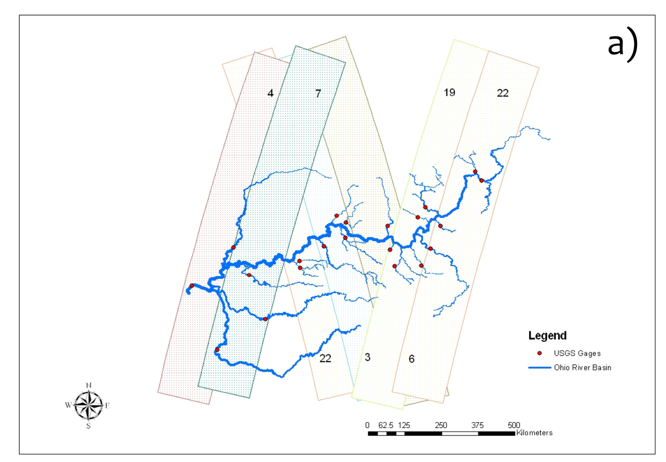
## Synthetic SWOT WSE measurements

Conservative assumptions for the SWOT observation (Alsdorf *et al.*, 2007 )

- Spatial resolution: **50 m** (both along-track and cross-track)
- Height accuracies: **0.5 m** (for individual pixels)

$$WSE_{SWOT} = WSE_{LISFLOOD} + h_{error} \qquad h_{error} = N\left(0, \frac{1}{\sqrt{n_{obs}}}\sigma_v\right)$$

**SWOT spatiotemporal sampling**



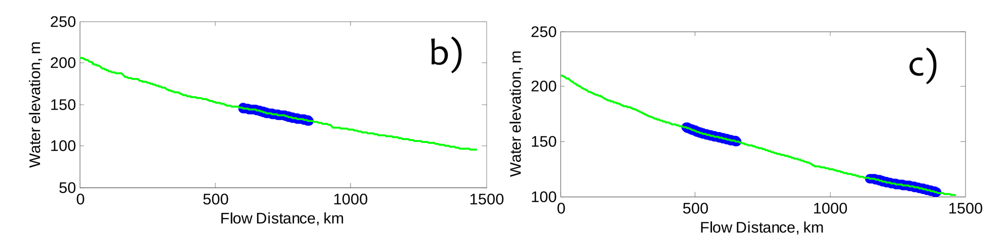




**Figure 3.** The SWOT coverage of the Ohio River Basin; representative SWOT measurement swaths from 22-day and 78° orbit inclinations are shown (a); examples of the synthetic SWOT height observations (blue circles) and true water elevations simulated by LISFLOOD-FP (green line) (b and c).

## Initial guess for unknown parameters

Assumptions for the model include:

- Unknown parameters: **Bathymetry (z) and Discharge (Q)**
- Known parameters: Channel width (w) and WSE (h) from SWOT and roughness (n) from ancillary data

**Bathymetry**

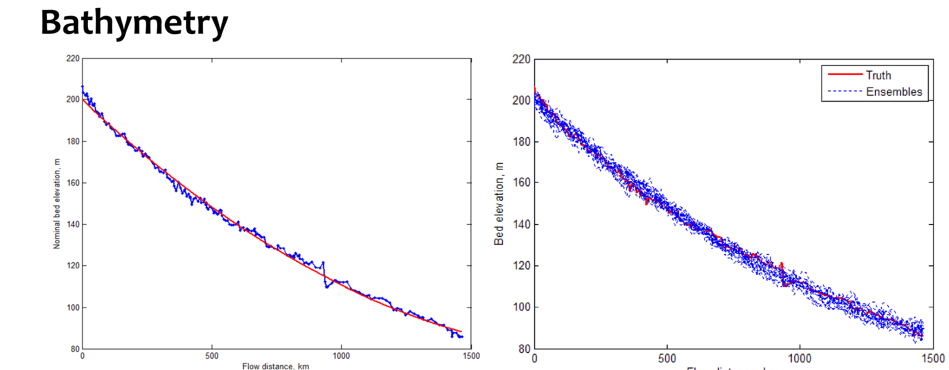



**Figure 4.** Ensembles of 20 possible bathymetries are shown. We modeled bathymetry errors as being spatially-correlated, following an exponential correlation function with a correlation length of 100 km. Errors were modeled as being additive, with zero mean, and a standard deviation of 2.5 m.

**Boundary discharges**

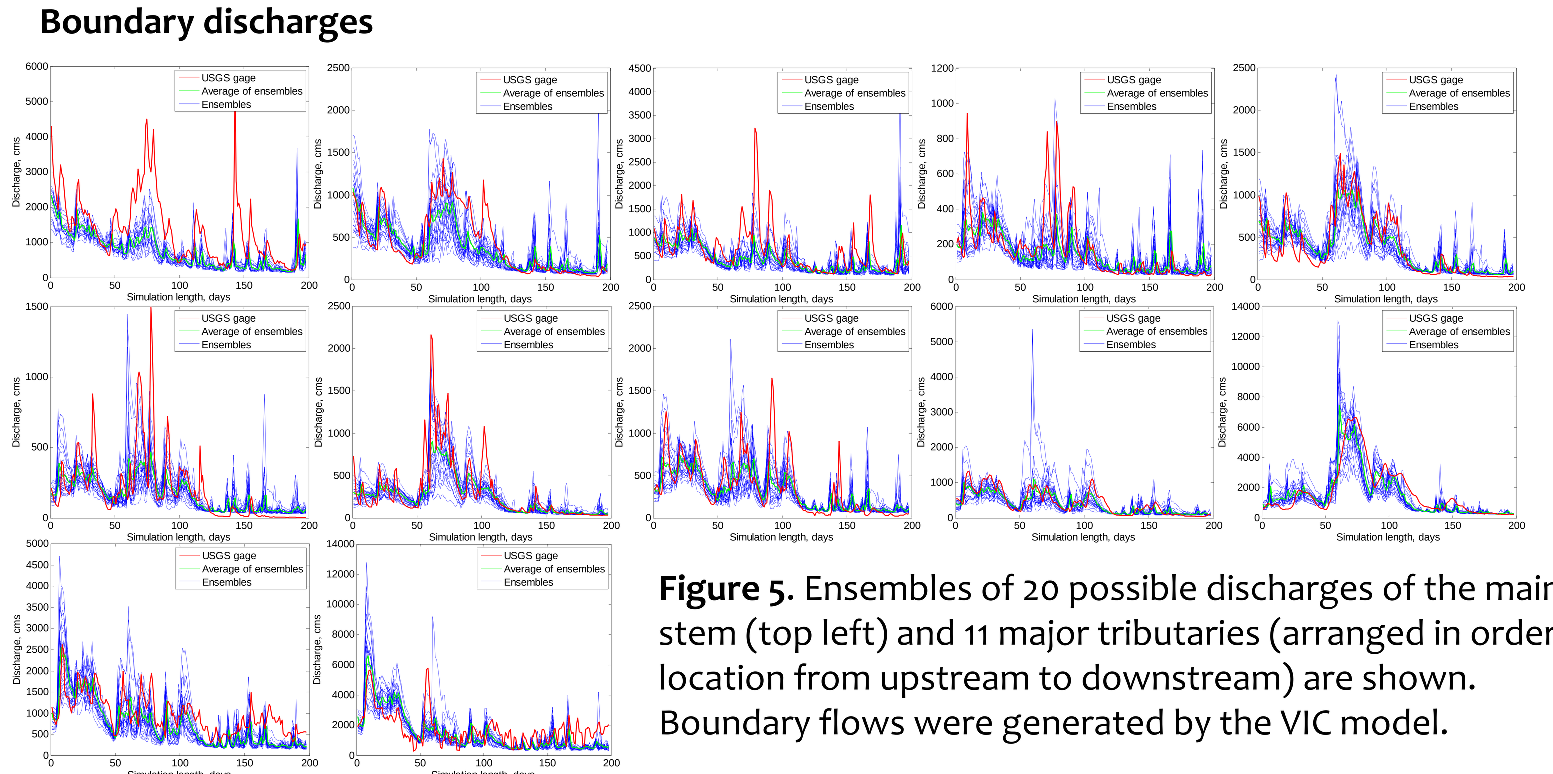
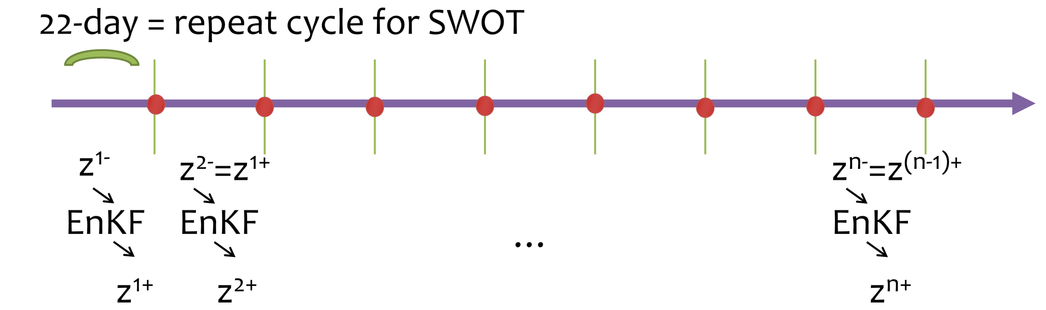



**Figure 5.** Ensembles of 20 possible discharges of the main stem (top left) and 11 major tributaries (arranged in order of location from upstream to downstream) are shown. Boundary flows were generated by the VIC model.

## Spatiotemporal Ensemble Kalman Filter

Assumptions for EnKF:

- **Bathymetry** does **not change** within relatively short periods
  -> Update bathymetry for next data assimilation




$$\begin{bmatrix} y_c \\ z \end{bmatrix}^{t_{i+1}} = \begin{bmatrix} y_c \\ z \end{bmatrix}^{t_i} + K\left(h_{SWOT} - H\begin{bmatrix} y_c \\ z \end{bmatrix}^{t_i}\right) \qquad K = \left[(\rho \circ C_{xx})H^T\right]\left[H(\rho \circ C_{xx})H^T + C_v\right]^{-1}$$

$t$ = 1, 2, … , n cycle; 1 cycle = 22 days

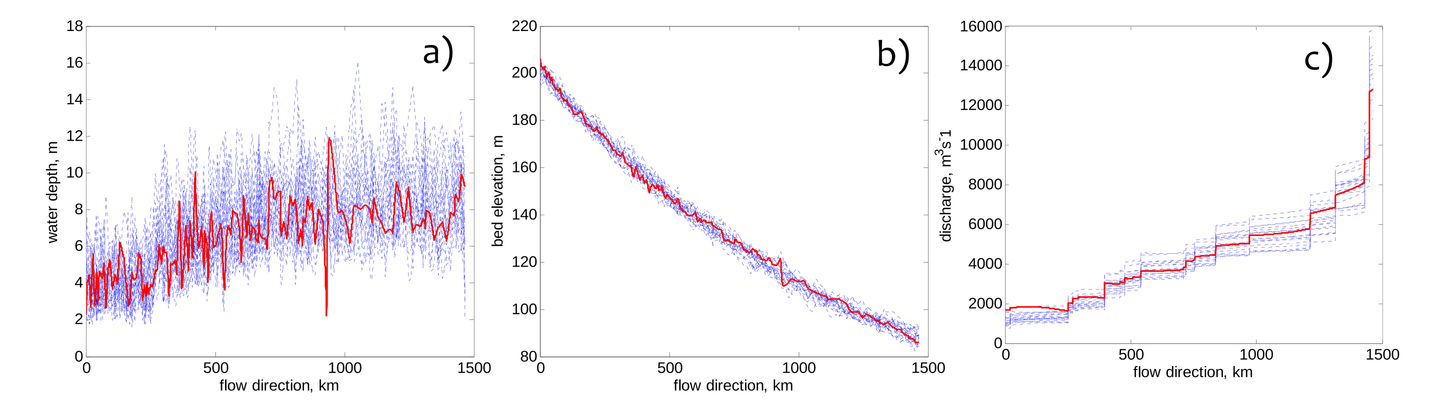



**Figure 6.** Initial inputs for EnKF; ensembles (blue) of 20 possible water depths (a), bathymetries (b), and flows on day 3 (c) are shown as well as the true one (red).

## RESULTS

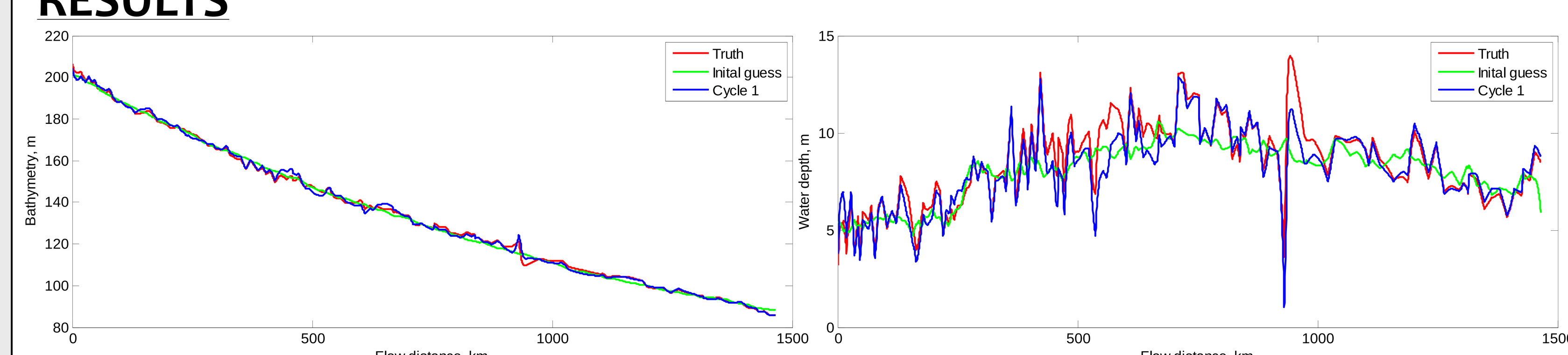



**Figure 7.** Initial estimates of bathymetry and water depth (day 3) are shown. After filtering, the estimates of bathymetry and water depth clearly improve their pattern and accuracy (19.8% and 38.3%, respectively).

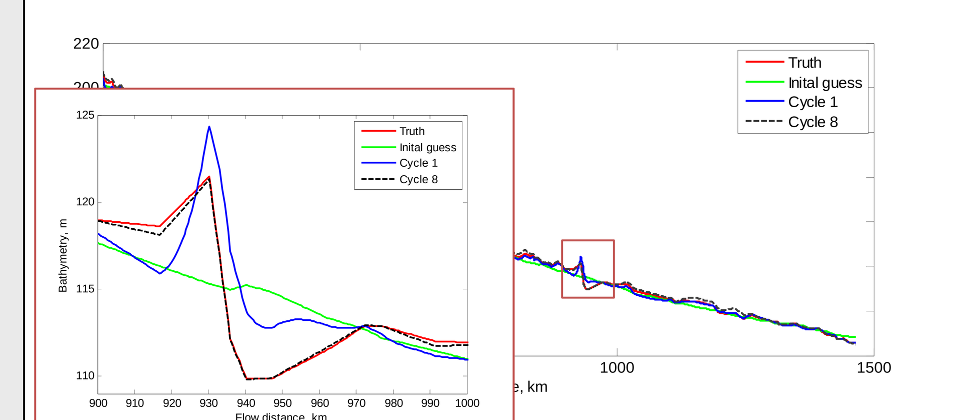



**Figure 8.** Graphs show the EnKF update results (bathymetry) of each cycle. After performing each EnKF update, the errors were clearly reduced.

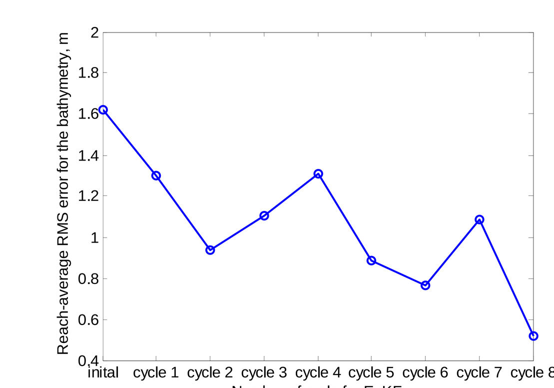



**Figure 9.** Graph shows the reach-average RMS error of each cycle after the EnKF processing. The error after 8 cycles of processing is 0.52 m, which improves the accuracy by 67.8% compared to the initial bathymetry.

## CONCLUSIONS

- As the time series (cycle) becomes longer, the accuracy of the bathymetry estimate improves.
- The errors of the bathymetry estimate increase, depending on the bias of the boundary inflows.
- Future work will investigate methods to reduce the effect of the bias of the boundary inflows.

## REFERENCES

Alsdorf, D.E., E. Rodriguez, and D.P. Lettenmaier, 2007. Measuring surface water from space, *Reviews of Geophysics.*, 45, RG2002, doi: 10.1029/2006RG000197.

Bates, P.D., and A.P.J. De Roo, 2000. A simple raster-based model for flood inundation simulation, *Journal of Hydrology*, 236(1-2): 54-77.

Evensen, G., 2009. The ensemble Kalman filter for combined state and parameter estimation, *IEEE Control Systems Magazine*, 29(3): 82-104.