Estimating Bathymetry and River Depth from SWOT Measurements with Ensemble Kalman Filter

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Abstract

The upcoming Surface Water and Ocean Topography (SWOT) mission is a swath mapping radar interferometer that will measure water surface elevation (WSE) and its temporal variability (*dh/dt*) and spatial variability (*dh/dx*). However, because the SWOT satellite will measure changing elevations of the water surface, not the true depth to 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. In this paper, we focus on retrieving bathymetry for estimating river discharge from SWOT measurements. Since the SWOT satellite 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 hydraulics parameters using the LISFLOOD-FP hydrodynamic model and corrupted the results by adding spatially-correlated height errors based on the SWOT instrument design. The Ensemble Kalman Filter (EnKF) was used to estimate the bathymetry, given the SWOT WSE measurements and WSE predictions by the LISFLOOD-FP. The experiments showed that the EnKF update was able to recover the bathymetry from WSE measurements with 0.16 m reach-average accuracy, which is 89.9% less than the initial guess. The experiments also confirmed the usefulness of a multi-temporal data set for retrieving bathymetry.

SWOT Mission

The SWOT mission, which is wide-swath interferometric altimetry data, will provide mesoscale oceanography data and inland water surface elevation (WSE) data (*i.e.*, river, lakes, wetland, and reservoirs). A joint project between NASA and CNES, the SWOT mission has a planned launch date of 2019.

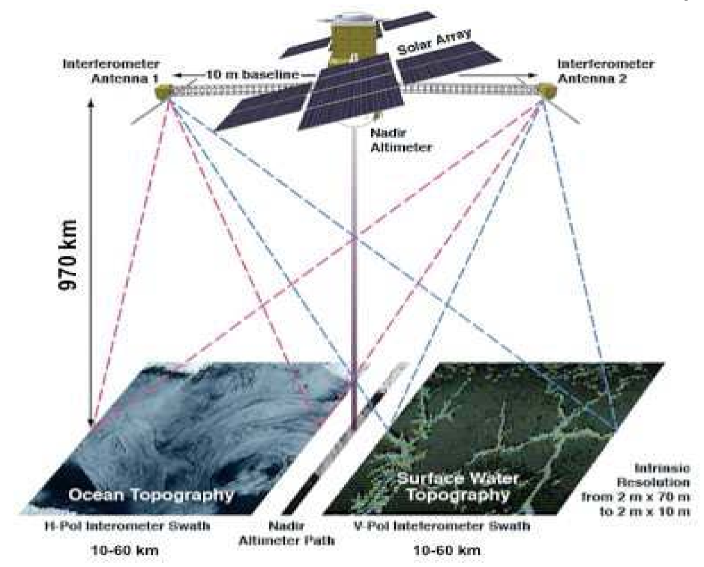


Figure 1. The core technology for SWOT is a Ka-band Radar INterferometer (KaRIN), a near-nadir viewing, 120 km wide swath-based instrument that uses interferometric SAR processing of the returned radar pulses to yield single-look 5 m azimuth and 10 to 70 m range resolution, with a worst-case elevation accuracy of approximately 50 cm for 50 m pixels.

Methods

1. Simulate true hydraulic parameters using Hydrodynamic model

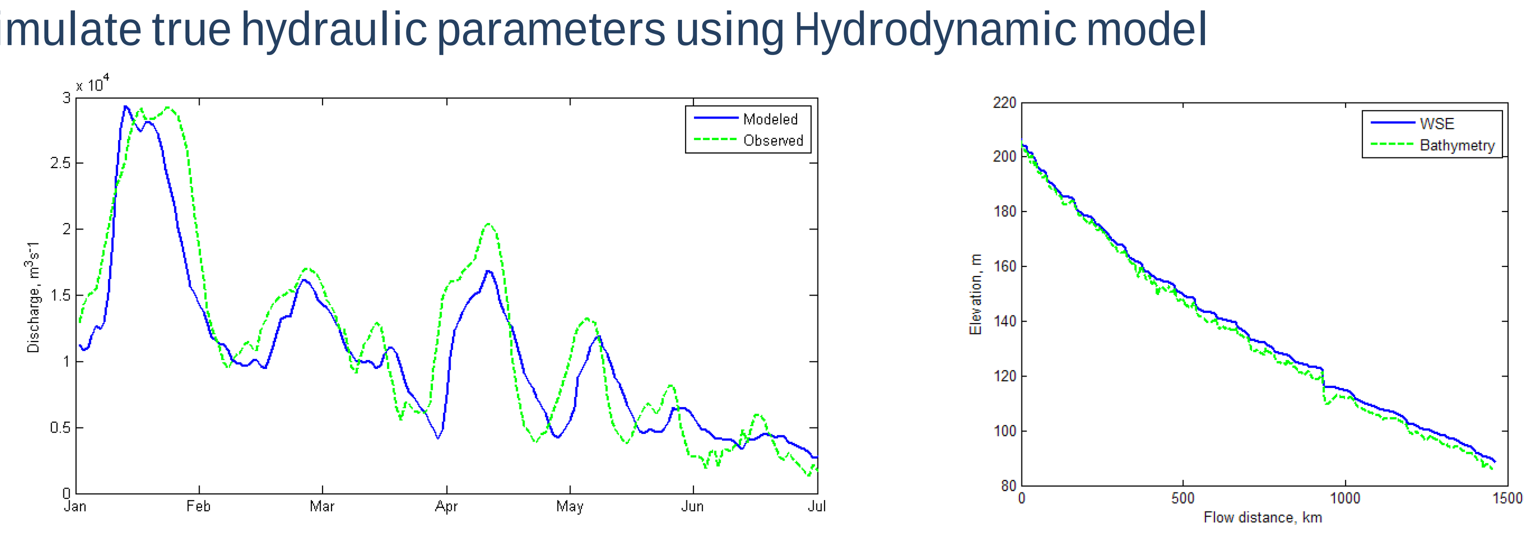
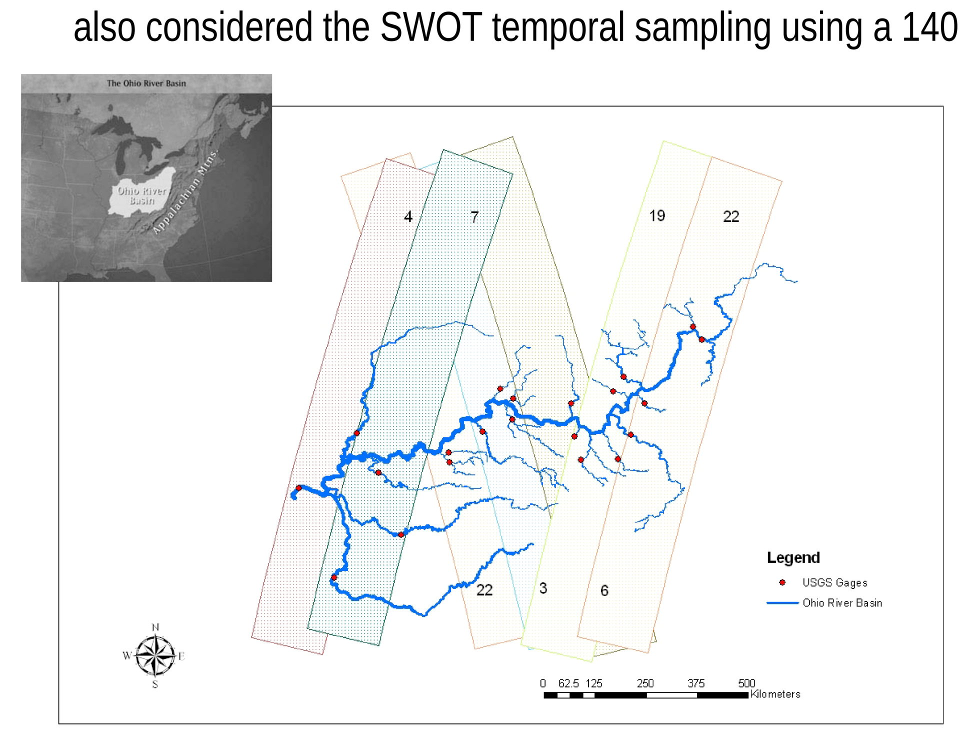


Figure 2. True hydraulic parameters of the Ohio River (January 1 - June 30, 2005) were simulated using the LISFLOOD-FP model (Bates and De Roo, 2000). Modeled discharge at the downstream model outlet is shown (blue), as well as the discharge from the USGS gage (green) (left). The estimates of the bathymetry and WSE are shown (right). The model discharge clearly matches the observed discharge with an absolute relative mean error of 6.05% and a correlation coefficient of 0.93. The data were used to generate synthetic SWOT data and to evaluate results.

2. Generate synthetic SWOT WSE measurements

The SWOT WSE measurements were calculated as the sum of the true WSE (see Figure 2) and random height errors based on the SWOT instrument design. In this study, we make the very conservation assumption that the SWOT spatial resolution in both along-track and cross-track will be approximately 50 m. Height accuracies of the SWOT measurement were also assumed as 0.5 m for an individual pixel (Alsdorf *et al.*, 2007). In addition, we also considered the SWOT temporal sampling using a 140 km swath for a 78° orbit inclination (Figure 3).



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

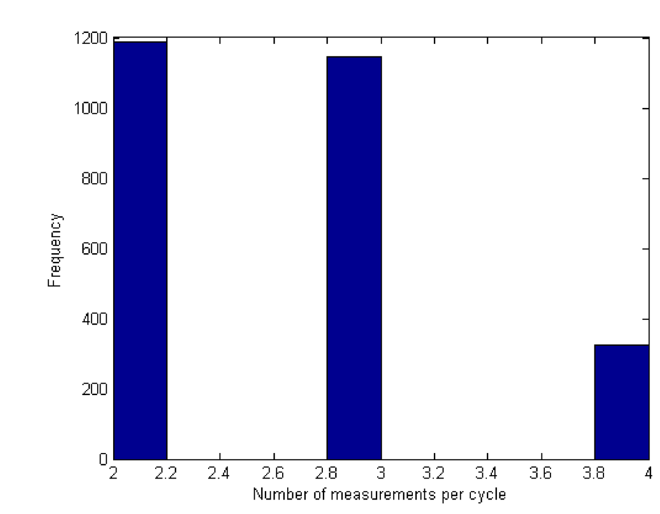


Figure 3. Representative SWOT measurements swaths from 22 days and 78° orbit inclination are shown.

Figure 4. The number of times each of the 2657 model pixels is measured in 22 days (main stem of the Ohio River) with a 78° orbit inclination is shown.

3. Ensemble Kalman Filter (EnKF)

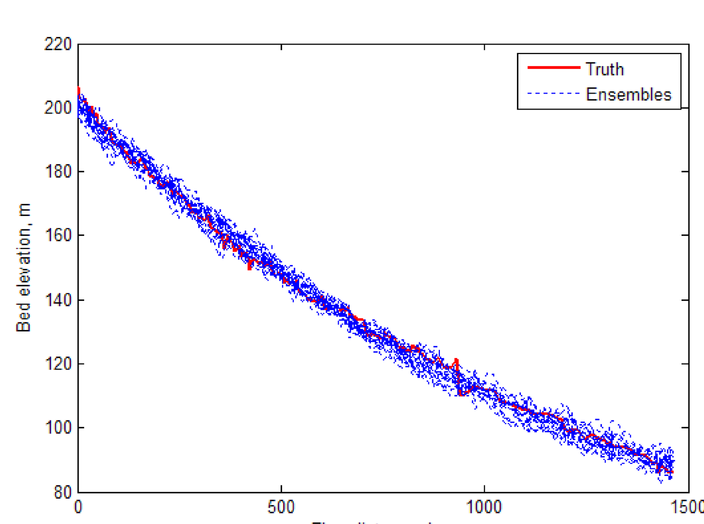
Assumptions for the EnKF include:

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

3.1. Initial guess for unknown parameters

3.1.1. Bathymetry

Figure 5. 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.



3.1.2. Discharge

For the flow, we estimated the true coefficients of the power law relationship between discharge and WSE. We then corrupted the results by adding 10% random noise. Based on these simulated coefficients, we generated the 20 possible discharges of each tributary.

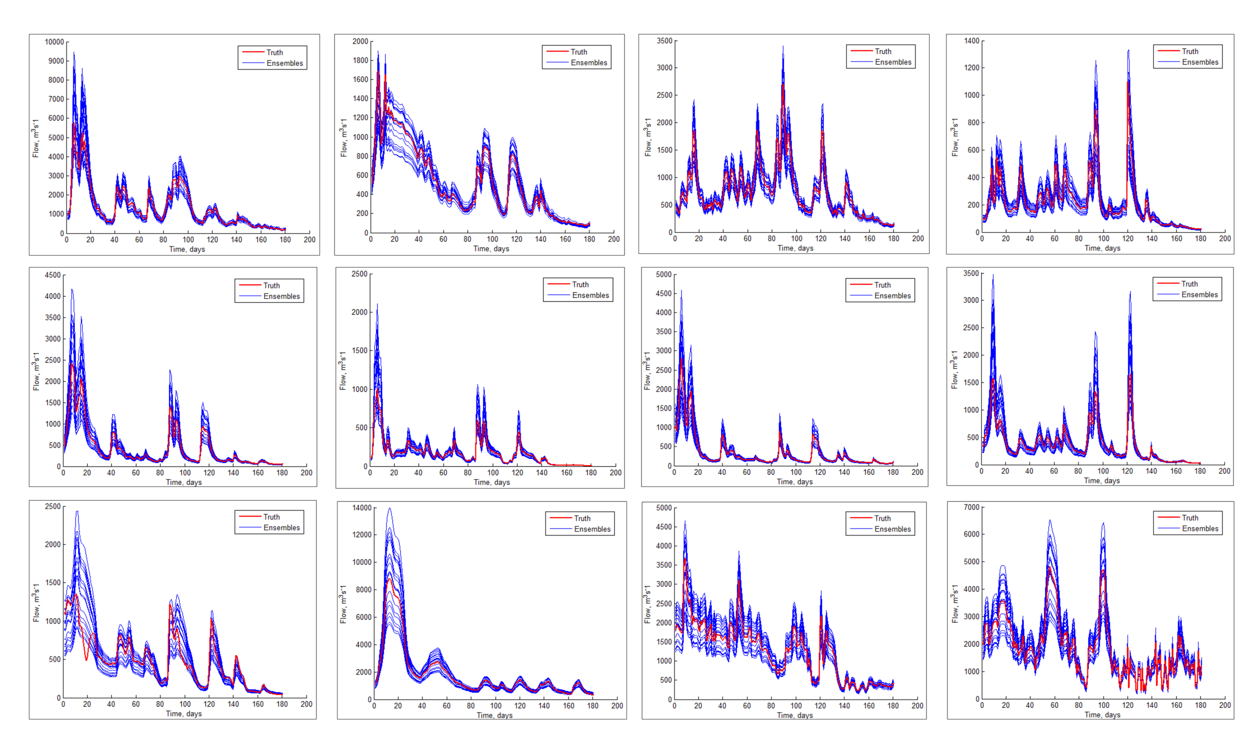


Figure 6. Ensembles of 20 possible discharges of main (top left) and 11 major tributaries (arranged in order of location from upstream to downstream) are shown.

3.2. Simultaneous state-parameter estimation with EnKF

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

Results

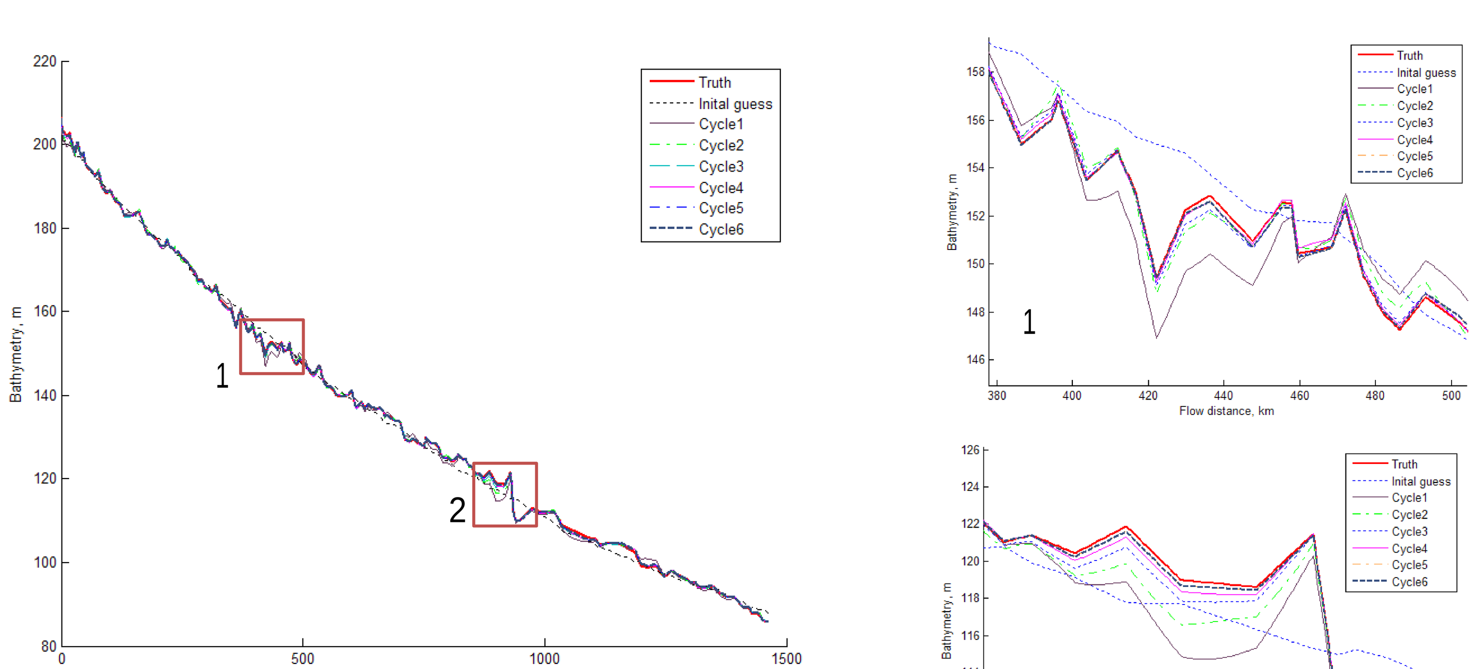


Figure 7. Graphs show the EnKF update results (bathymetry) of each cycle (1 cycle = 22 days). After performing each EnKF update, the errors were clearly reduced.

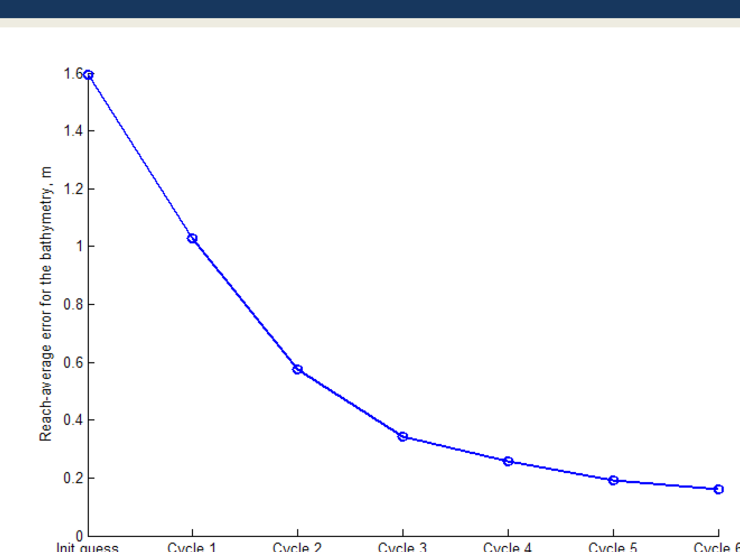


Figure 8. Graph shows the reach-average error of each cycle after the EnKF processing. The errors were reduced at each EnKF update and converged to approximately 0.16 m.

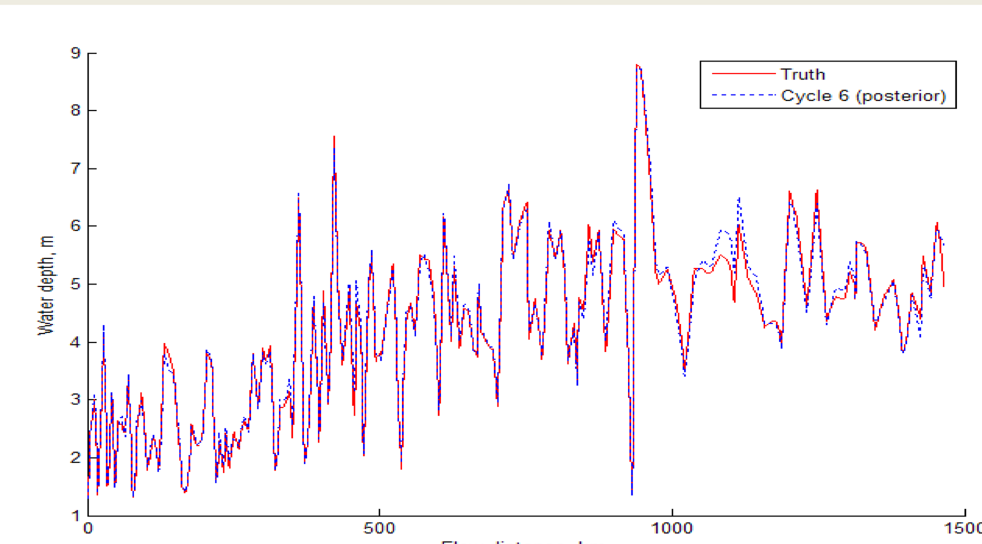


Figure 9. Posterior (blue) water depth estimates on April 2, 2005 are shown, as well as the truth (red). The reach-average error for the posterior estimates was 0.19 m.

References

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