# EVALUATING THE POTENTIAL FOR CHARACTERIZING RIVER DEPTH FROM SWOT MEASUREMENTS: A CASE STUDY FOR THE OHIO RIVER

**Yeosang Yoon**[*], PhD student
**Michael Durand**[**], Research Scientist
**Carolyn J. Merry**[*], Professor
[*] Department of Civil and Environmental Engineering and Geodetic Science
The Ohio State University
Columbus, OH 43210
yoon.203@osu.edu
merry1.@osu.edu

[**] Byrd Polar Research Center
The Ohio State University
Columbus, OH 43210
durand.8@osu.edu

## ABSTRACT

This paper presents the methods for estimating river depths to evaluate the potential for characterizing river depth from the Surface Water and Ocean Topography (SWOT) satellite observations. The SWOT mission is a swath mapping radar altimeter that will measure inland water surface elevation (WSE). Since the SWOT satellite will be launched during the 2013-2016 time frame, we generated synthetic SWOT WSE measurements for the entire Ohio River Basin. To do this, we simulated the true hydraulics parameters using LISFLOOD-FP hydrodynamic model and corrupted the results by adding spatially-correlated height errors based on SWOT instrument design. The Ensemble Kalman filter (EnKF) with SWOT WSE measurements and LISFLOOD-FP model as its dynamic core was used to estimate the river depths. The experiments showed that the filter was able to recover the water depths from WSE measurements with 0.7m mean accuracy, which is 39.7% less than the prior RMSE.

**Keywords**: SWOT, hydraulic modeling, river depth and discharge, EnKF, data assimilation

## INTRODUCTION

The energy and water cycle play a critical role in climate variability and climate change. Climate has a strong influence on aspects of the global water cycle on which society and nature depend. Rivers, especially river discharge, which is part of the global water cycle, is crucial for understanding Earth system science process (Alsdorf *et al*., 2007; Smith and Pavelsky, 2008). River discharge has traditionally been estimated by measurements of stream velocity and cross-sectional area. However, the observations of river discharge globally are generally sparse, except for a few developed countries. For instance, although the Amazon River is one of the largest rivers in the world, the few river gauging stations are located mainly along the mainstream (LeFavour and Alsdorf, 2005; Smith and Pavelsky, 2008). Furthermore, many countries do not share their hydrologic data, depending on the political and economic situation of a country. The global gauging networks are also in decline (Shiklomanov *et al*., 2002). Over the past decade, researchers have been trying to better extract river discharge using remote sensing techniques to complement the existing in situ gage networks (LeFavour and Alsdorf, 2005; Alsdorf *et al*., 2007; Smith and Pavelsky, 2008).

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). The SWOT mission will provide measurements of water storage changes in terrestrial surface water bodies globally. The SWOT WSE estimates will also provide a source of information for characterizing river discharge at the global scale. The SWOT mission was selected by the National Research Council decadal survey committee for launch during the 2013-2016 time frame (NRC, 2007).

However, because the SWOT satellite will measure changing elevations of the water surface, not true depth to river bottom, the "true" river discharge cannot be estimated without ancillary data, namely the river channel bathymetry. We thus have measurements of water elevation and need to estimate water depths and discharge or bathymetry. This is the exact inverse of normal hydraulic modeling, where we use discharge and river bathymetry to calculate water elevation. Therefore, the SWOT WSE data will need to be processed using additional techniques (*i.e.,* inverse problems) to retrieve river depths. Data assimilation schemes, which are essentially solutions to inverse problems, can be used to estimate variables that are not directly observed from space. Although the sophistication of data assimilation schemes varies, the methods have been used extensively in earth science areas, including atmospheric and ocean sciences (Swinbank *et al*., 2003; Reichle, 2008) and in hydrologic remote sensing (Andreadis *et al.*, 2007; Durand *et al*., 2008).

In this paper, the methods for estimating river depths to evaluate the potential for characterizing river depth from the SWOT satellite observations. To do this, our methods proceed as follows: (1) simulate the mainstream of the Ohio River using the hydrodynamic model, LISFLOOD-FP, to produce hydraulic parameters, which used as a general input to river depth estimation method; (2) estimate river depths by solving the inverse problem; and (3) demonstrate the potential accuracy of depths estimates.

## BACKGROUND

### The SWOT Hydrology Virtual Mission

The SWOT hydrology Virtual Mission (VM) has provided data to illustrate assimilation schemes for characterizing discharge using simulated SWOT measurements. For instance, several VM studies have been performed to estimate river depths and discharge using an ensemble-based data assimilation framework. Andreadis et al. (2007) and Clark et al. (2008) performed river depth and discharge estimation using the assimilation of the water surface elevation data, which is simulated by the Variable Infiltration Capacity (VIC, Liang et al., 1994) and LISFLOOD-FP models (Bates and De Roo, 2000). Durand et al. (2008) demonstrated an ensemble-based data assimilation method for estimating bathymetric depth from WSE measurements and LISFLOOD-FP. In this paper, we built on and enhanced this work to demonstrate estimation of river bathymetry within an assimilation scheme.

### Inverse Problems

Traditional hydraulics models predict WSE and slope given discharge and channel bathymetry, whereas SWOT will measure WSE with the goal of estimating river discharge. Thus, estimation of river discharge from SWOT measurements is a classic inverse problem, which has been intensively studied in ground water modeling. Yeh (1986) reviewed the typical parameter identification models in the groundwater hydrology area, as well as the inverse problem method to determine the parameters. McLaughlin (1996) shows how the methods of function analysis are used to develop a general groundwater inverse problem. Carrera *et al*. (2005) reviewed the process steps of the current state of the inverse modeling methods to find a standard strategy for aquifer characterization. As stated earlier, various statistical methods for solving the inverse problem have been applied to Earth system science areas. For example, the Ensemble Kalman Filter (EnKF) is a variant of the traditional Kalman filter, and is flexible in its treatment of errors in model dynamics and parameters (Evensen, 2004; Evensen, 2009). The method has been implemented for hydrologic remote sensing observations (Andreadis *et al*., 2007; Durand *et al*., 2008). In this paper, we utilize a data assimilation based on the EnKF framework to provide a solution to the inverse problem to estimate discharge from SWOT measurements.

## DATA RESOURCES AND STUDY SITE

### Study Site

Our study area is the Ohio River Basin; the Ohio River flows from Pittsburgh, PA, to the Mississippi River at Cairo, IL (Figure 1). The river is approximately 1,579 km long and drains an area of 528,357 $km^2$. The annual average flow is 7,500 $m^3s^{-1}$ (Lee *et al*, 2003). For this study, we chose 11 major and 7 minor tributaries to include in the model; the 11 major and 7 minor tributaries represent a total of 474,211$km^2$ (89.8%) of the Ohio River Basin drainage area (Table 1). The remaining 10.2% of the drainage area is drained by rivers that are not gaged.

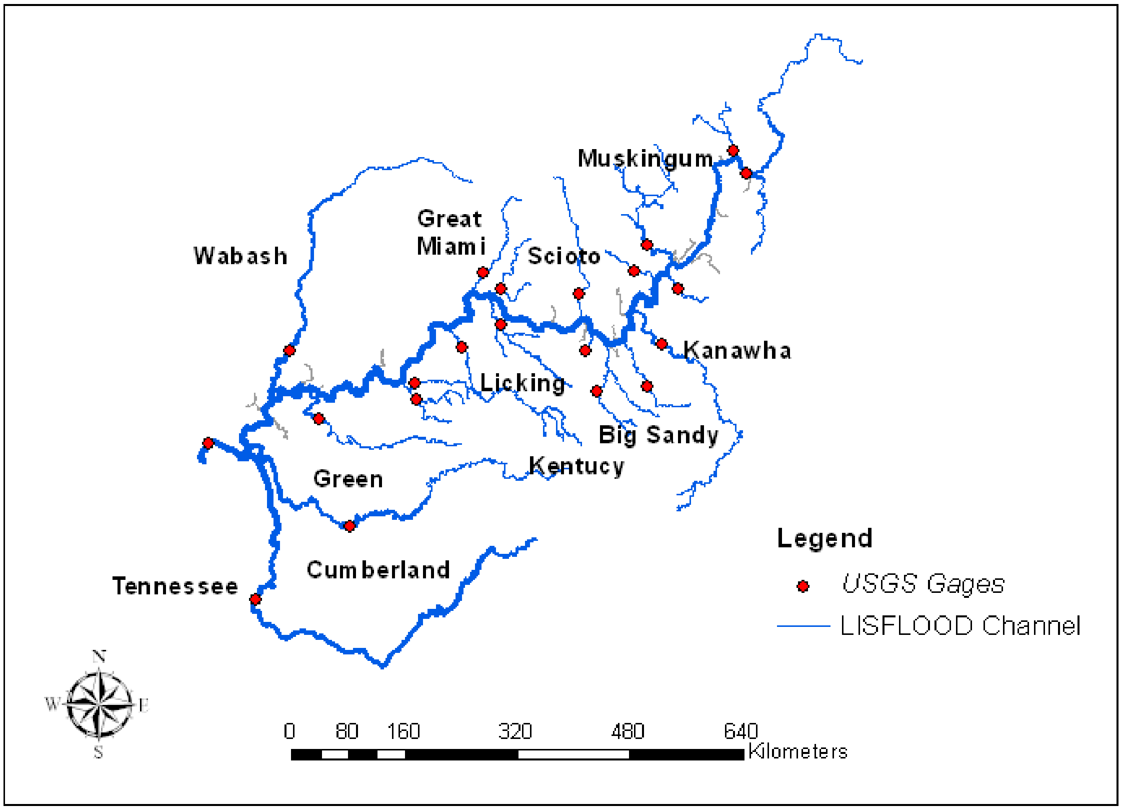


**Figure 1.** A map of the Ohio River Basin, including 11 major tributaries and 7 minor tributaries, used in the model. Drainage area size of each tributary is shown by the relative thickness of the blue lines. The USGS gages used for boundary conditions are shown.

### Data

To obtain realistic river depths and discharge from the model, accurate bathymetry data are needed. We utilized bathymetry from the U.S. Army Corps of Engineers (ACE) for this study. The USGS stream gage network data are used as boundary condition dataset.

## HYDRODYNAMICS MODEL

We used the LISFLOOD-FP hydrodynamics model to simulate "true" hydraulic parameters such as, the river depths and discharge (Bates and De Roo, 2000). The model uses a two-dimensional diffusion wave representation of floodplain flow and a one-dimensional approach to simulate river channel flow. The LISFLOOD-FP model requires as its input estimates of the river centerlines, channel bed elevation along the centerline, and channel width are needed, as well as upstream boundary discharge data of tributaries and downstream water depths on the mainstream.

The Ohio River points layer, which was obtained by ACE, and HydroSHEDS dataset were used to provide estimates of the river centerline. HydroSHEDS dataset was derived from the Shuttle Radar Topography Mission (SRTM) at 15 arc-second resolution. Stream centerlines was manually created from the dataset with approximately 750m spatial resolution, and represented as a series of sequential location points. The channel bed elevation, width, and roughness were derived from ACE dataset.

The diffusion wave model of LISFLOOD-FP requires upstream boundary discharge of each tributaries and downstream water depth on the mainstream for boundary condition. In this study, we used USGS gages network to provide the depth and discharge boundary conditions from January 1, 2005 to June 30, 2005. The location of each gage used as boundary condition is shown in Figure 1. From Table 1, the gages represent between 50% and 99% of the drainage area of each tributaries. As a whole, the gages represent a total of 392,717.3km$^2$, which is approximately 74.3% of the Ohio River Basin drainage area. To account for the remaining 25.7% of the drainage area, we increased the discharge based on the 30 years (from 1979 to 2008) average discharge and drainage area of each tributary by scaling the discharge based on a power law fit between the discharge and drainage area:

$$Q_{gage} = bA_{gage}^{c} \qquad Q_{all} = bA_{all}^{c} \tag{1}$$

From equation (1):

$$f = \frac{Q_{all}}{Q_{gage}} = (\frac{A_{all}}{A_{gage}})^{c} \tag{2}$$

$$Q_{upscaling} = f \times Q_{gage} \tag{3}$$

where $Q_{gage}$ and $Q_{all}$ are respectively discharge at drainage area from gage and entire region of each tributary; $A_{gage}$ and $A_{all}$ are respectively drainage area from gage and entire region of tributary; f is upscaling factor.

**Table 1**. Drainage area of each 11 major (bold tributary name) and 7 minor tributaries included in the model. The information from USGS used as a boundary condition for each tributary.

| Tributary Name | Drainage Area (km$^2$) | USGS Gauge ID | Drainage Area (km$^2$) from gage | Percent covered by gauge |
|---|---|---|---|---|
| Beaver River | 8106.7 | 03107500 | 8044.5 | 99.2% |
| **Muskingum River** | 20823.5 | 03150000 | 19222.9 | 92.3% |
| Little Kanawha River | 6008.8 | 03155000 | 3926.4 | 65.3% |
| Hocking River | 3082.1 | 03159500 | 2442.4 | 79.2% |
| **Kanawha River** | 31597.9 | 03198000 | 27060.2 | 85.6% |
| Guyandotte River | 4325.3 | 03203600 | 2157.5 | 49.9% |
| **Big Sandy River** | 11085.1 | 03212500 | 5552.9 | 50.1% |
| Little Sandy River | 1875.2 | 03216500 | 1036.0 | 55.2% |
| **Scioto River** | 16860.8 | 03237020 | 15115.2 | 89.6% |
| Little Miami River | 4325.3 | 03245500 | 3115.8 | 72.0% |
| **Licking River** | 9505.3 | 03253500 | 8547.0 | 89.9% |
| **Great Miami River** | 13985.9 | 03274000 | 9401.7 | 67.2% |
| **Kentucky River** | 18052.2 | 03290500 | 16006.1 | 88.7% |
| Salt River | 7485.1 | 03298500 | 3100.2 | 41.4% |
| **Green River** | 23905.6 | 03320000 | 19595.9 | 82.0% |
| **Wabash River** | 85728.6 | 03377500 | 74164.3 | 86.5% |
| **Cumberland River** | 46412.6 | 034315005 | 33307.2 | 71.8% |
| **Tennessee River** | 105956.4 | 03593500 | 85832.2 | 81.0% |
| Sum | **474211.3***  | | **392717.3*** | 82.8% |
| Ohio River Basin | 528202.18 | | | |

* The area includes at upstream drainage area on the mainstream.

## DATA ASSIMILATION

To estimate the river depths, the combined parameter and state estimation problem with the EnKF will be applied Evensen, 2004; Evensen, 2009). For this approach, the river water height is treated as the model state variable, and channel bathymetry is treated as uncertain model parameters. The data assimilation scheme involves three steps: (1) characterize the "open-loop" or "prior" state, which is a first-guess of the true states from perturbed inputs, which is generated from appropriate error models; (2) calculate posterior estimates of dynamic river depths using the EnKF with prior state and synthetic SWOT WSE observations; and (3) evaluate the estimates of river depths against the "truth" data set, derived from the LISFLOOD-FP model, relative to the open-loop estimates.

## Ensemble Generation

The prior ensemble stochastically characterizes the relationship between WSE, channel bathymetry and other model inputs. In this study, only errors in bathymetry were represented. 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. This procedure resulted in an ensemble of 20 possible bathymetries for LISFLOOD-FP model.

### Synthetic SWOT Measurements

As mentioned before, SWOT will launch during the 2013-2016 time frame. Therefore, we represent the SWOT measurement $h_{SWOT}$ as the true WSE plus measurement error *v*. The true WSE obtained from LISFLOOD-FP simulation results and *v* assumed a normal distribution with zero mean, and standard deviation $\sigma_v$. In this study, we make the very conservative assumption that SWOT spatial resolution in both along-track and cross-track will be approximately 50m. Height accuracies of SWOT measurement also assumed as 0.5m for individual pixel (Alsdorf *et al.*, 2007). Thus, *v* can be modeled as

$$v = N\left(0, \frac{1}{\sqrt{n_{obs}}}\sigma_v\right) \qquad (4)$$

where $n_{obs}$ is the number of SWOT pixel that would be contained within a LISFLOOD-FP model pixel.

## EnKF

To calculate posterior estimates of dynamic river depths, we used the EnKF update, which is given by:

$$\begin{bmatrix} y_k \\ z_k \end{bmatrix}^+ = \begin{bmatrix} y_k \\ z_k \end{bmatrix}^- + K(h_{SWOT} + w_k - H\begin{bmatrix} y_k \\ z_k \end{bmatrix}^-) \qquad (5)$$

$$K = [(\rho \circ C_{xx})H'][H(\rho \circ C_{xx})H' + C_v]^{-1}$$

where y and z are vectors of water depths and bathymetry, respectively, with length n, for each replicate k=1, 2,..$n_k$, where $n_k$ is the ensemble size ($n_k$ is 20). The - and + superscripts denote the prior and posterior estimates, respectively; the vector $h_{SWOT}$ is the observed WSE with length n; $w_k$ is a randomly-generated mean zero normal variable with standard deviation $\sigma_v$; H is the forward operator; K is Kalman gain, which is calculated by localizing the sample covariance $C_{xx}$ from ensemble with correlation matrix ρ [see Gaspari and Cohn 1999, their Eq. (4.10)]; and $C_v$ is the assumed error covariance of the WSE measurement, which calculated as the product of the scalar $\sigma_v^2$ and the n dimensional identity matrix; thus we assume that measurement error variance is constant in space and time, which is valid as first-order approximation.

# RESULTS

## LISFLOOD-FP Model Evaluation

To verify that the LISFLOOD-FP model setup for estimating true river depths and discharge is producing reasonable results, we compared the discharge at the downstream model outlet with the discharge observed at the USGS gages. Figure 2 shows estimates of river discharge at the downstream model outlet. The model discharge clearly matches the observed discharge with an absolute relative mean error of 6.05% and a correlation coefficient of 0.93. Discharge for both the model and gage ranges from 2,000 $m^3sec^{-1}$ to 30,000 $m^3sec^{-1}$. From the agreement between the modeled and observed flow, we concluded that the model is adequate to investigate the proposed method to estimate river depths and discharge.

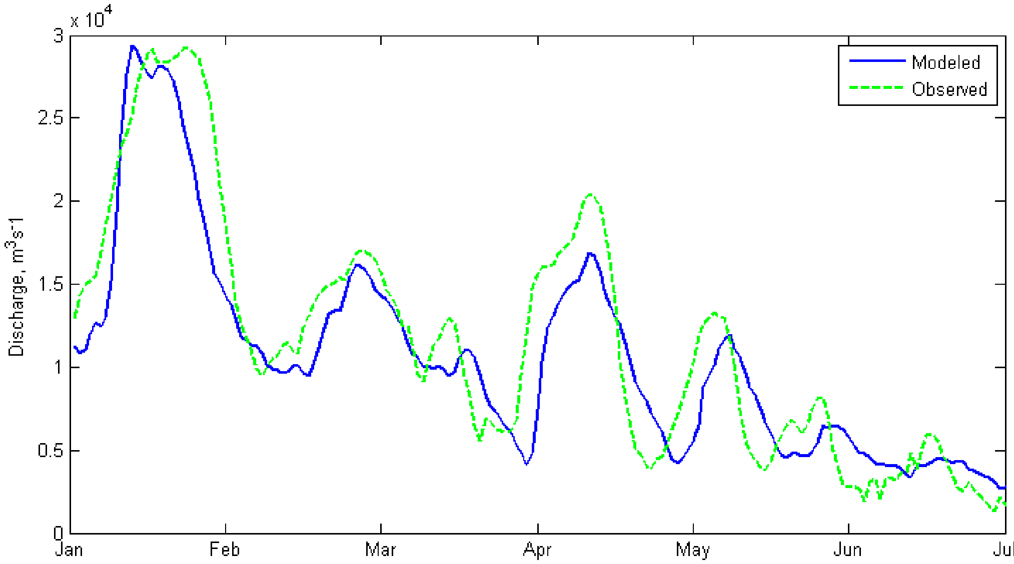


**Figure 2**. LISFOOD-FP modeled discharge at downstream model outlet is shown (blue) as well as the discharge from the USGS gage (green).

## Estimating Depth

The LISFLOOD-FP model was integrated for each ensemble member and its output is shown in Figure 3. In Figure 3, we are showing ensemble outputs for 14 days, from February 22, 2005 to March 7, 2005. The discharge variations in 3(a) are due to variations in the routing of the flow due to the differences in the bathymetry across the ensemble. The water depth variations in 3(b) are due to the bathymetric differences at the model outlet.

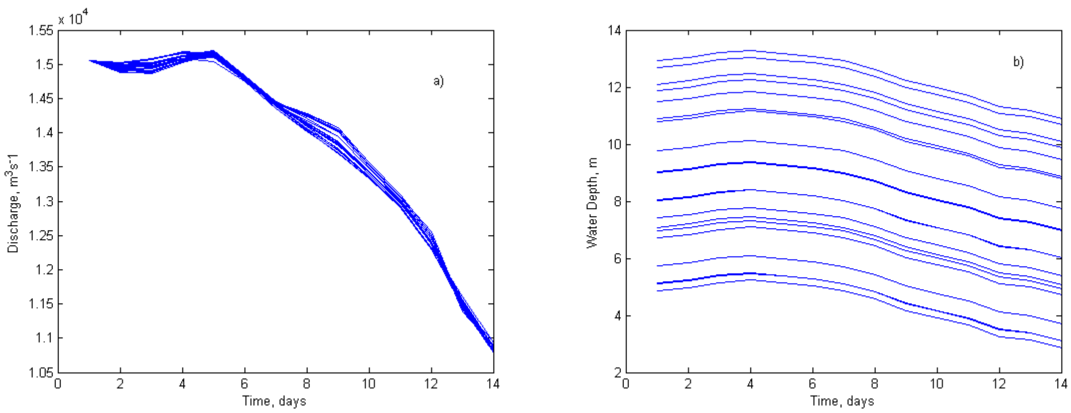


**Figure 3.** LISFLOOD-FP model is shown for 14 days for the 20 ensemble members of model runs: (a) discharge and (b) water depth at the downstream model outlet.

To improve the accuracy of the method, we applied the update using three observations, which are February 25, 2005 (peak flow), March 2, 2005 (medium flow) and March 7, 2005 (low flow) respectively. Figure 4 shows the prior and posterior water depth estimates on March 7, 2005, as well as truth. From the inspection, the posterior bathymetry was similar to the truth, while prior estimates do not correspond well with the true bathymetry. The reach-average RMSE for the prior and posterior estimate shown was 1.3 m and 0.68 m, respectively. Thus, the EnKF reduces the absolute value of the posterior mean error by 48.3%. The RMSE of prior and posterior water depth estimates on February 25, 2005 is 1.0 m and 0.73 m, respectively. The RMSE of prior and posterior water depth estimates on March 2, 2005 is 1.2 m and 0.70 m, respectively. Overall, the experiments showed that the filter was able to recover the water depths from assimilating SWOT WSE measurements with 0.7m mean accuracy, which is 39.7% less than the prior RMSE.

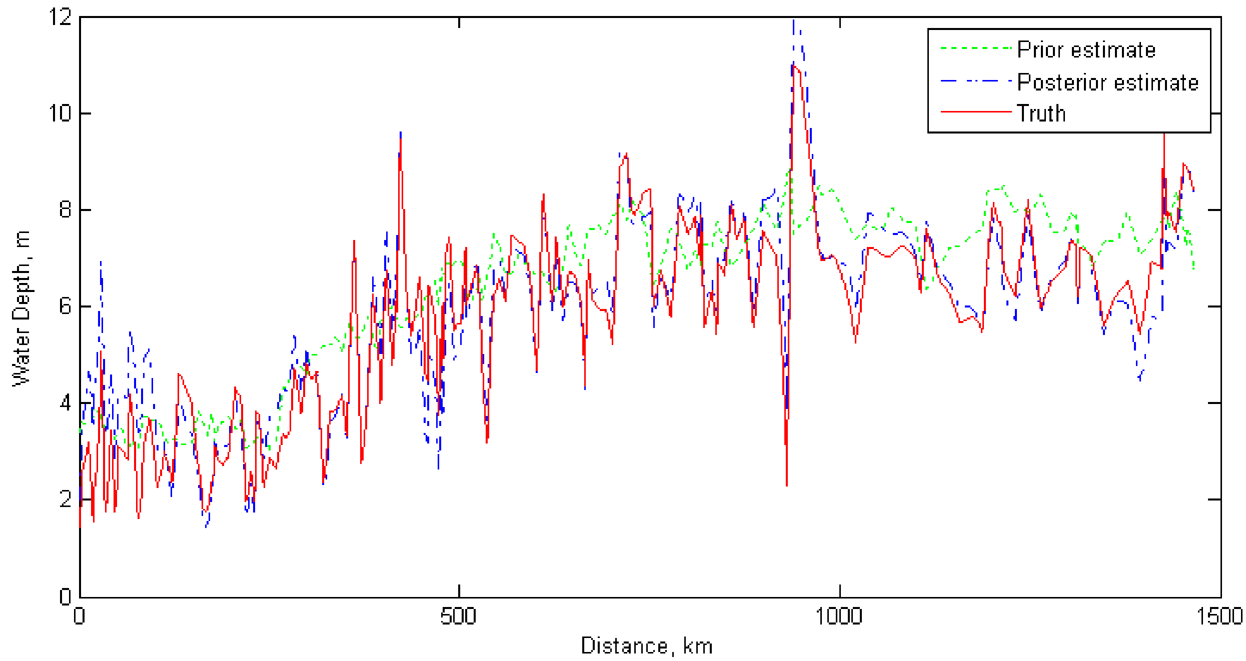


**Figure 4.** The prior (green) and posterior (blue) water depth estimates on March 7, 2005 were shown, as well as truth (red).

## CONCLUSIONS

In this paper, we presented a method to evaluate the potential for characterizing river depths from the SWOT WSE measurements. Synthetic SWOT WSE measurements were generated using random height errors and true hydraulic parameters, which were simulated for the entire Ohio River Basin using the LISFLOOD-FP hydrodynamic model. The model accurately reproduced the true discharge with an absolute relative mean error of 6.05% and a correlation coefficient of 0.93, from which we conclude that the model is sufficiently accurate for the purpose of evaluating the assimilation scheme. The EnKF data assimilation technique was applied to estimate the river depths. The filter simulation showed that the true river depths were able to be recovered by assimilating synthetic SWOT WSE measurements; the posterior river depth was estimated with a 0.7m mean accuracy, which is 39.7% less than the prior RMSE.

Although this study shows that 39.7% accuracy improvement in river depths using assimilation of the SWOT WSE measurements into the LISFLOOD-FP model, the accuracy can be improved by using several additional works: (1) Here we have only assimilated three observations. Presumably, as the number of observations assimilated increases, the error will be reduced. (2) Increasing the ensemble size has the potential to improve accuracy. (3) Perform the EnKF analysis separately for river segments in between tributaries. We will address these in future work. Furthermore, in this paper, we only assumed errors in bathymetry. In the future, we will need to investigate other characteristics (e.g., channel roughness) and evaluate their sensitivity.

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