SWOT APPLICATIONS FOR WRF-HYDRO MODELING IN ALASKA

Nicholas Elmer and Christopher Hain
NASA Marshall Space Flight Center, Huntsville, Alabama, USA

James McCreight and David Gochis
National Center for Atmospheric Research, Boulder, Colorado, USA

ABSTRACT

The Surface Water Ocean Topography (SWOT) mission, launching next year, will provide high-spatial resolution measurements of terrestrial surface water, including global rivers with widths greater than 50-100 m. SWOT measurements are naturally suited for stream hydrology, and many previous studies have worked to quantify the impact of SWOT observations on the modeling of channel flow. This work highlights the application of SWOT for WRF-Hydro modeling in Alaska for data assimilation and model calibration to support ongoing National Oceanic and Atmospheric Administration (NOAA) National Water Model development. Results demonstrate the effectiveness of using SWOT discharge estimates to calibrate WRF-Hydro in ungauged basins, and quantifies the impact of SWOT data assimilation on WRF-Hydro performance.

Index Terms— SWOT, WRF-Hydro, National Water Model, Hydrology, Alaska

1. INTRODUCTION

Traditionally, in situ gauge networks have been used to monitor stream hydrology, but these networks are spatially limited and on the decline globally due to the lack of funding and need for regular maintenance [1]. Furthermore, very few measurements are available from satellite platforms, since all current satellite missions theoretically capable of measuring river stage using radar and laser nadir altimetry, including the Jason series and the second Ice, Cloud and land Elevation Satellite (IceSAT-2) missions [2, 3, 4], have insufficient spatial and temporal resolutions for adequate sampling of rivers [5, 6]. To fill this observation gap, the Surface Water Ocean Topography (SWOT) mission will launch in 2021 to provide the first global inventory of lakes, wetlands, and rivers [6]. SWOT supports a nadir altimeter and a Ka-band Radar Interferometer (KaRIn) [7]. KaRIn provides high-resolution water surface elevations (WSE) across two 50-km swaths for rivers with widths greater than 50-100 m [1, 6, 8].

Prelaunch, the impact of SWOT observations must be quantified using proxy datasets typically generated using an Observation System Simulation Experiment (OSSE). Previous studies have used proxy SWOT data to demonstrate potential SWOT mission impacts on the modeling of channel flow [9, 10] and reservoir management [11], estimating river bathymetry [12, 13, 14, 15], optimizing hydrologic model parameters [16] and representing SWOT spatial and temporal coverage for complementing existing in situ gauge networks [1].

Hydrologic models, including the National Oceanic and Atmospheric Administration (NOAA) National Water Model (NWM) [17] which is an instantiation of the Weather Research and Forecasting Hydrological extension package (WRF-Hydro) [18], are typically calibrated using in situ gauges. WRF-Hydro is a modeling framework which couples column land surface, terrain routing, and channel routing models. WRF-Hydro is fully-distributed with multi-physics options and multi-scale capabilities, enabling it to represent processes on a wide range of spatial scales [18, 19, 20]. This paper presents a simple method for deriving proxy SWOT WSE using WRF-Hydro. Furthermore, it demonstrates the effectiveness of using proxy SWOT discharge estimates to calibrate WRF-Hydro in ungauged basins, and quantifies the impact of SWOT data assimilation on WRF-Hydro performance.

2. METHODOLOGY

2.1. Model Configuration

This paper focuses on the Chena River watershed within the Tanana River basin near Fairbanks, Alaska. WRF-Hydro was configured for the Chena River watershed with a 1-km resolution Noah-Multiparameterization Land Surface Model (Noah-MP LSM) [21]. The WRF-Hydro terrain routing grid (250m resolution) and channel network were derived from the WRF-Hydro GIS Pre-processing Toolkit v5.1 [22] using the Weather Research and Forecasting (WRF) [23] Preprocessing System geogrid file and the National Elevation Dataset (NED) [24] Digital Elevation Model (DEM) as inputs. Global Land Data Assimilation System (GLDAS) Version 2 [25] meteorological forcing was used during runtime. This study uses WRF-Hydro version 5.0.3 [18], which is the same model version supporting the current NWM configuration [17]. The model configuration and physics parameterizations selected for these case studies mimick those used by the NWM. A key difference is that the diffusive wave gridded channel routing option is used here instead of the Muskingum-Cunge [26] channel routing used by the NWM.

An 80-member ensemble of the 250-m configuration was created by perturbing the thirteen most sensitive WRF-Hydro parameters [27]. For each ensemble member, each sensitive parameter was randomly assigned a value within the valid parameter range using a uniform distribution. A spin-up simulation for the 250-m WRF-Hydro simulation was for a period of eight years (March 2009 - February 2017) and used ensemble-averaged parameter values. The March 2017 restart files from the spin-up simulation were then used to restart each ensemble member beginning March 2014 using the perturbed parameter values. All ensemble members were propagated forward in time to the start of the study period (1 March 2017). The long spin-up period allows better representation of groundwater storage and snowpack and permits each ensemble member to reach equilibrium.

2.2. Generating Proxy SWOT Observations

To generate proxy SWOT data, a simple Observing System Simulation Experiment (OSSE) was used following the methodology in [6]. The OSSE consists of a 100-m resolution WRF-Hydro simulation, similar to the 250-m resolution simulation described in Section 2.1, that acts as the "truth" simulation. The 100-m simulation was calibrated over the Chena River watershed focusing on the thirteen most sensitive WRF-Hydro parameters determined by a sensitivity test. The 100-m model output provides the "truth" geolocation, channel head (*h*), bed elevation (*z*), and discharge (*q*) values used in the OSSE.

The 100-m model output is corrupted with random white noise following a Gaussian distribution (*N*). Proxy WSE (*WSE'*) was derived following the equation:

$$WSE' = z + h + N(0, 25\ cm), \quad (1)$$

where the standard deviation of 25 cm is based on the expected SWOT WSE measurement error for a 100 m x 100 m area [6, 12, 13, 15]. Proxy discharge (*q'*) is based on the equation:

$$q' = q + N(0, 0.35q), \quad (2)$$

where 0.35 is the expected discharge error given by [28].

The WRF-Hydro output was sampled based on the CNES proxy SWOT orbit [29] to obtain proxy SWOT observations of WSE and discharge with appropriate orbit characteristics. First, the cross-track distance of each WRF-Hydro reach from the proxy SWOT orbit at each overpass was calculated. For each pass, only channel points with cross-track distances of 10-60 km (i.e., within the SWOT measurement range) and with a Strahler streamorder greater than or equal to four (used to approximate rivers with widths greater than 50 m) were extracted.

2.3. Calibration and assimilation using proxy SWOT

Calibration of WRF-Hydro to mimic ungauged basins was performed by comparing the modeled streamflow at the watershed outlet for each ensemble member to the proxy

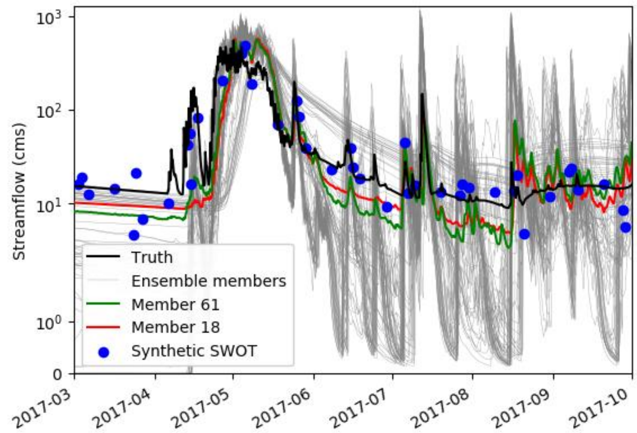

Figure 1. Chena River hydrographs for the truth discharge (black), ensemble members (gray), proxy SWOT discharge estimates containing expected measurement errors (blue), and the two ensemble members that best match with observations and truth (red, green).

SWOT discharge estimates at the watershed outlet for the period of March 2017-September 2017. The mean between the Nash-Sutcliffe Efficiency (NSE) [30] and the logarithmic NSE served as the metric for comparison, and hereafter referred to as the mean weighted NSE. The parameter values for the ensemble member with the highest mean weighted NSE were then selected as the calibrated values for the watershed.

For the data assimilation experiment, the 250-m resolution 80-member ensemble was used to calculate error statistics. For the period of March 2017-September 2017, proxy SWOT WSE were assimilated into the WRF-Hydro channel routing module using HydroDART, a data assimilation system built around the Data Assimilation Research Testbed (DART) [31] for the offline implementation of WRF-Hydro [32].

3. RESULTS AND DISCUSSION

3.1. Model Calibration in Ungauged Basins

Figure 1 compares the truth discharge and proxy SWOT discharge estimates with the ensemble member simulated discharge. The truth values are shown in black, from which the proxy SWOT discharge estimates (blue dots) were derived using the OSSE. The mean weighted NSE was calculated between each ensemble member (gray lines) and both the truth discharge and the proxy SWOT discharge, with results shown in Figure 2. The use of proxy SWOT discharge in calibration selects the same ensemble members (members 61 and 18) that have the highest mean weighted NSE with respect to the truth, indicating that SWOT discharge estimates are an effective means for calibrating WRF-Hydro in ungauged basins at high-latitudes.

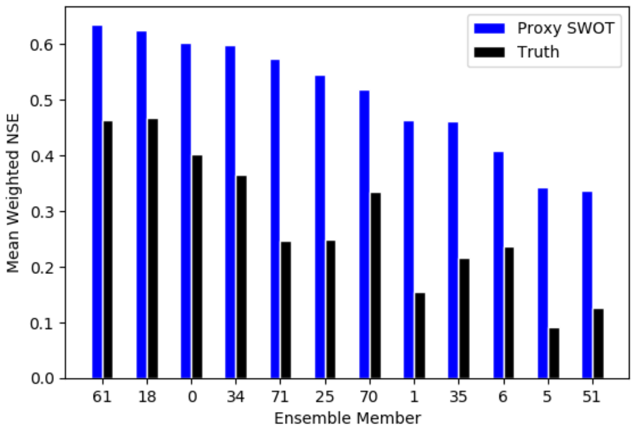

Figure 3. Mean weighted NSE for the twelve, best-match ensemble members when compared against synthetic SWOT discharge (blue) and truth (black) for the Chena River watershed.

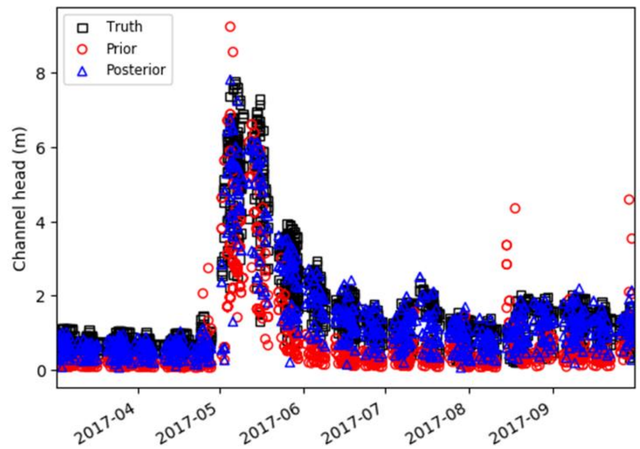

Figure 2. Scatterplot showing truth (black), prior ensemble mean (red), and posterior ensemble mean (blue) for every channel point where assimilation was performed.

3.2. Data Assimilation

Figure 3 demonstrates the utility of SWOT data assimilation to improve streamflow prediction. The Pearson correlation between the truth and the prior ensemble mean is 0.781, but increased to 0.893 for the posterior ensemble mean following assimilation and analysis. Similarly, the root mean squared error (RMSE) between the truth and the ensemble mean decreased from 1.283 m prior to assimilation to 0.664 m for the posterior ensemble mean. Figure 3 also demonstrates how assimilation removes the errant hydrograph peaks shown in the prior ensemble mean scatterplot during May, August, and September, to better match the truth.

4. CONCLUSIONS

As demonstrated by the results shown in Section 3, SWOT has the potential to improve WRF-Hydro calibration in ungauged basins and streamflow prediction through data assimilation. Results for larger Alaskan basins, including the Tanana River upstream of Nenana and the Susitna River, are forthcoming and will provide broader insight into potential SWOT impacts in Alaska for hydrologic modeling applications.

Future work will incorporate the CNES SWOT Hydrology Simulator [33] to provide more realistic proxy SWOT observations, and replace the use of stream order to estimate river width with actual river width derived from the NARWidth [34] dataset. Additionally, the potential for SWOT to be used for model calibration at mid- and low-latitudes will also be examined.

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