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Assimilating SWOT Water Surface Elevations into the WRF-Hydro Modeling System in Alaska using HydroDART

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1. Background

- Surface Water Ocean Topography (SWOT) mission (Rodriguez 2016; Biancamaria et al. 2016)
  - 2021 launch
  - Wide-swath (120 km), bistatic, Ka-band (36 GHz) radar interferometer
  - 10 m spatial resolution
  - Global measurements of channel water surface elevation (WSE) for rivers with widths greater than 50-100 meters
- Weather Research and Forecasting (Skamarock et al, 2008) hydrological extension package (WRF-Hydro) (Gochis et al. 2018)
  - High-resolution hydrologic routing and streamflow modeling framework
  - Couples column land surface, terrain routing, and channel routing modules (Figure 1)
  - Acts as the basis of the NOAA National Water Model (NWM; OWP 2018)

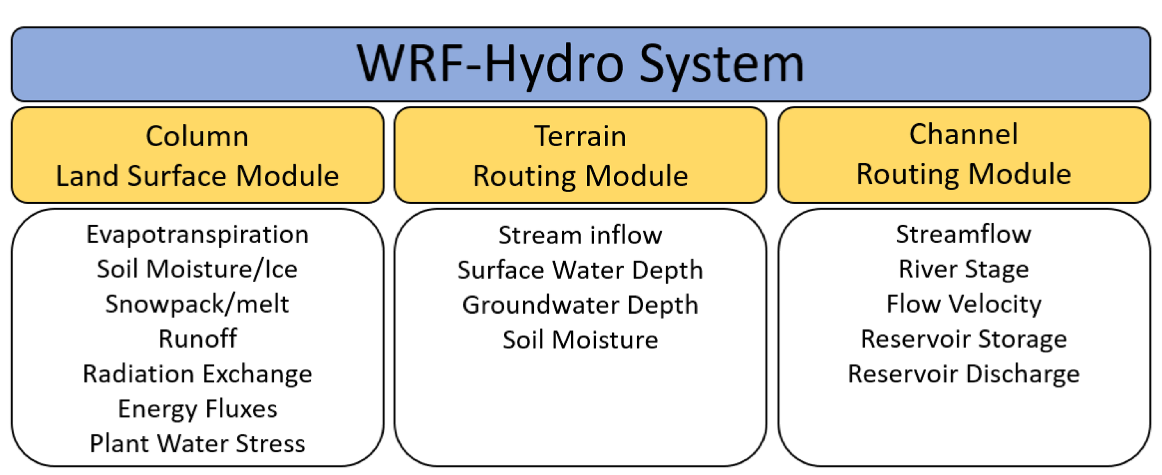

Figure 1. WRF-Hydro modules and output variables (NCAR 2018)

- HydroDART (McCreight et al. 2018)
  - Data assimilation system built on National Center for Atmospheric Research (NCAR) Data Assimilation Research Testbed (DART; Anderson et al. 2009)
  - For offline implementation of WRF-Hydro

2. Motivation

- In situ stream gauges are spatially limited networks are declining globally (Pavelsky et al., 2014)
- Lack of data assimilation in operational hydrologic forecast systems limits forecast accuracy and skill (Liu et al., 2012)
- SWOT mission will provide high spatial coverage of stream observations at spatial resolutions ideal for assimilating into hydrologic models to improve model initialization

3. Model Configuration

- WRF-Hydro coupled with 1-km resolution Noah Land Surface Model with Multi-Parameterization options (Noah-MP)(Niu et al. 2011)
- Regridded, 2 arc-second National Elevation Dataset (NED)(USGS 2017) for WRF-Hydro subsurface flow, overland flow, and diffusive wave channel routing
- Global Land Data Assimilation System Version 2 (GLDAS-2; Rodell et al. 2004) meteorological forcing (0.25° spatial resolution)
- Fraternal twin experiment (i.e., observation system simulation experiment) consisting of control and corrupted simulations (Figure 2)
- Control ("nature") run (100-m WRF-Hydro simulation)
  - Calibrated against USGS stream gauges Mar 2011 – Mar 2014 for parameters shown in Table 1
  - 8-year model spin-up (Mar 2009 – Mar 2017)
  - Control simulation is assumed to be free of errors and representative of true state
  - Used to derive virtual gauges (Section 4)
- Corrupted run (uncalibrated 250-m WRF-Hydro simulation)
  - 4-year model spin-up (Mar 2013 – Mar 2017)
  - Virtual gauge observations assimilated into WRF-Hydro channel routing module using HydroDART Ensemble Kalman Filter (EnKF; Evensen 1994)
  - 80 ensemble members for EnKF created by randomly varying calibration parameters within valid parameter ranges (Table 1)
  - Validated against control run

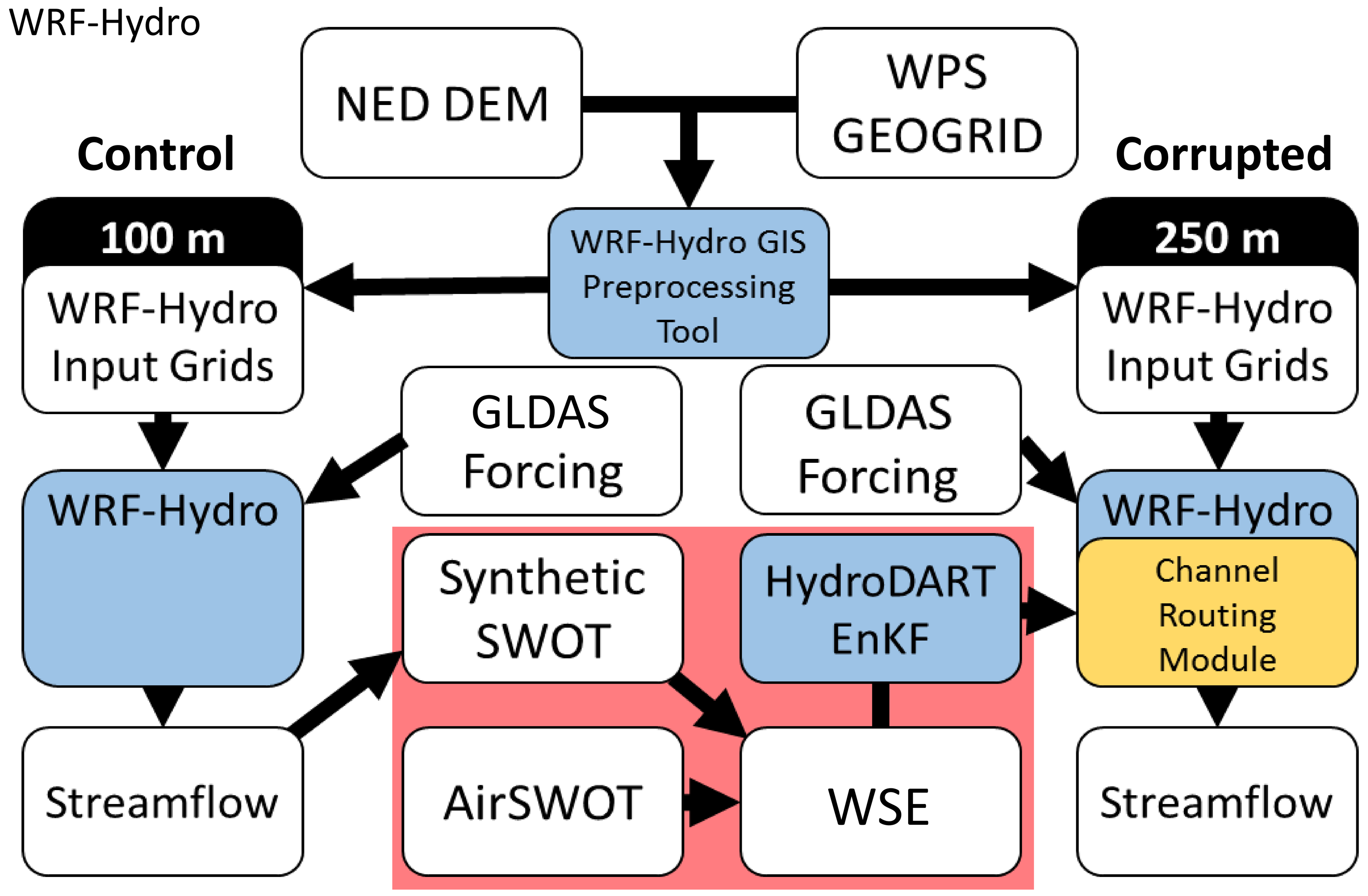

Figure 2. Fraternal twin experiment workflow. Blue boxes indicate models, processing tools, or data assimilation systems, whereas white boxes indicate datasets and model inputs/outputs. The data assimilation portion of the experiment is indicated by the red box.

4. Generating Virtual Gauges

- Synthetic SWOT WSE generated following Biancamaria et al. (2016) (Figure 3)
- SWOT orbit was simulated for Mar 2013 – Oct 2017
- At each SWOT overpass, the WSE was calculated for every channel point within SWOT swath extent and with stream order ≥4 (rough estimate for rivers with widths greater than 100 m)
- Randomly generated noise (σ=0.25 m) was added to calculated WSE to mimic SWOT instrument error
- To create virtual gauge for approximately each channel reach, domain was split into 0.1° lat/lon grid
- A single WSE point was randomly selected within each grid box and designated as the virtual gauge
- The virtual gauge is then assimilated into the 250-m corrupted run using HydroDART

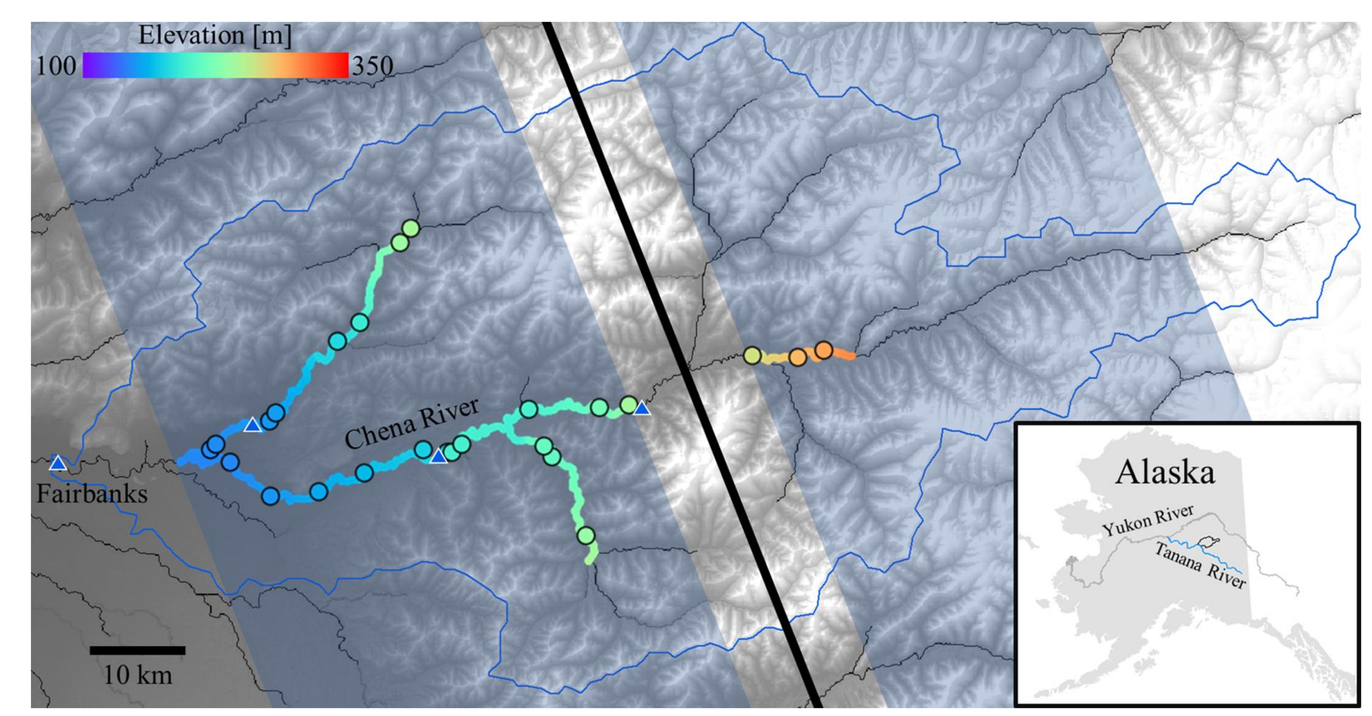

Figure 3. WRF-Hydro-derived synthetic SWOT elevations (colorbar) for the Chena River watershed (outlined in blue) for a simulated SWOT overpass (swath shaded in blue; nadir track shown by the thick black line). Randomly sampled virtual gauges (colored circles outlined in black), current USGS stream gauge sites (blue triangles), and terrain (grayscale; NED DEM) are also shown.

Parameter	Initial Value	Calibrated Value	Min Value	Max Value
Clapp-Hornberger B exponent (soil moisture)	1	1.563	0.4	1.9
Soil moisture maximum	1	0.903	0.8	1.2
Saturated soil conductivity	1	9.140	0.2	10
Soil infiltration	0.6	0.121	0.1	4
Soil drainage	0.1	0.767	0.1	1
Retention depth	1	5.333	0.1	10
Saturated soil lateral conductivity	1000	184.9	10	10000
GW max depth	25	176.1	10	250
GW exponent	1.75	4.062	1	8
Canopy wind (ET)	1	1.931	0.5	2
Max carboxylation 25°C	1	1.378	0.6	1.4
Ball-Berry conductance relationship slope	1	1.390	0.6	1.4
Snowmelt Parameter	2	1.370	0.5	3.5

Table 1. Parameters used during calibration, with the values used in the control run listed under "Calibrated Value".

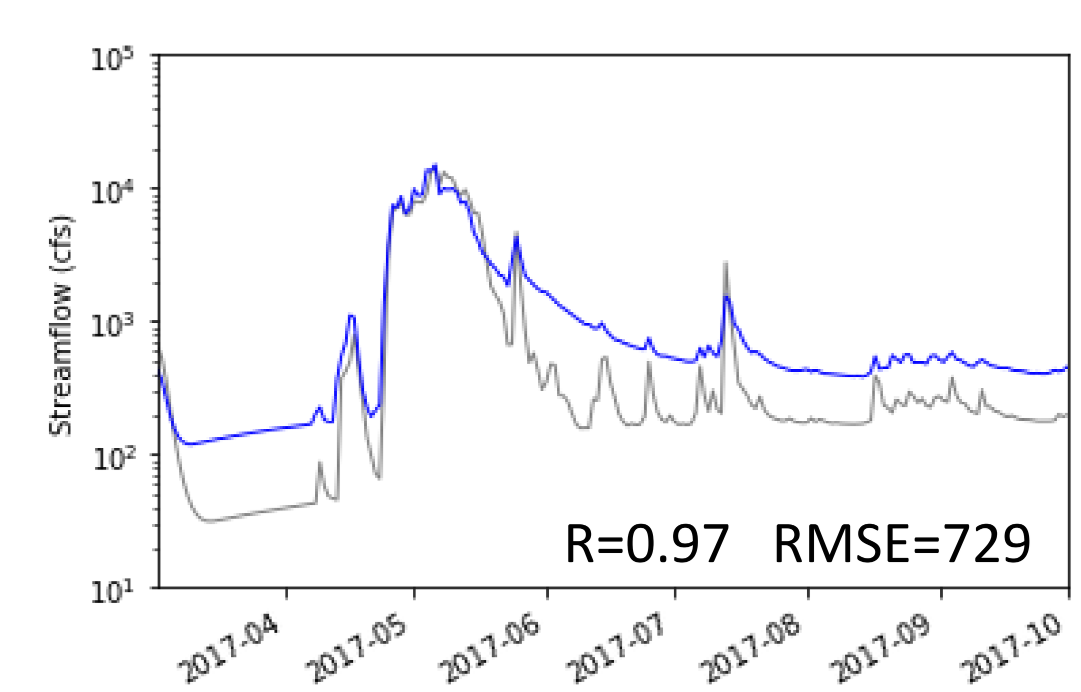

Figure 4. Chena River hydrographs for the fraternal twin experiment control run (gray) and corrupted run without SWOT data assimilation (blue). Results for the corrupted run with SWOT data assimilation are forthcoming.

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5. Results

- The corrupted run overestimates streamflow compared to the control run (truth) (Figure 4)
- High correlation indicates the model captures the timing of individual precipitation events well, but magnitude of the long-term baseflow is overestimated
- Results for the corrupted run with synthetic SWOT data assimilation are forthcoming
- It is expected that the corrupted run will more closely match the control run when the virtual gauges are assimilated into WRF-Hydro

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