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Prospects for river discharge and depth estimation through assimilation of swath-altimetry into a raster-based hydrodynamics model

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[1] Surface water elevation profiles for a reach of the Ohio River were produced by the Jet Propulsion Laboratory Instrument Simulator to represent satellite measurements representative of those that would be observed by a wide swath altimeter being considered jointly by U.S. and European space agencies. The Ensemble Kalman filter with a river hydrodynamics model as its dynamical core was used to assimilate the water elevation synthetic observations, and to estimate river discharge. The filter was able to recover water depth and discharge, reducing the discharge RMSE from 23.2% to 10.0% over an 84-day simulation period, relative to a simulation without assimilation. An autoregressive error model was instrumental in correcting boundary inflows, and increasing the persistence of error reductions between times of observations. The nominal 8-day satellite overpass produced discharge relative errors of 10.0%, while 16-day and 32-day overpass frequencies resulted in errors of 12.1% and 16.9% respectively. **Citation:** Andreadis, K. M., E. A. Clark, D. P. Lettenmaier, and D. E. Alsdorf (2007), Prospects for river discharge and depth estimation through assimilation of swath-altimetry into a raster-based hydrodynamics model, *Geophys. Res. Lett.*, *34*, L10403, doi:10.1029/2007GL029721.

1. Introduction

[2] Humans use 54% of accessible global runoff for withdrawals, consumption, and instream flow needs [*Postel et al.*, 1996]. Nonetheless, estimates of river discharge globally are highly uncertain due to limitations of in-situ observations, especially in the developing world and in sparsely populated high latitude regions. River discharge and lake and reservoir storage have traditionally been derived from stage (elevation) measurements; but networks of such stream gauges are in decline globally [*Stakstad*, 1999].

[3] Recent advances in satellite technology, particularly the development of synthetic aperture radar, have the potential to produce accurate estimates of surface water storage in complex systems such as wetlands [*Alsdorf et al.*, 2007]. By simultaneously measuring inundated area and its surface elevation, altimetry imagery ("swath altimetry") would enable hydrologists to estimate variations in water storage (changes in water volume) in ways that are not possible using stream gauges [*Alsdorf and Lettenmaier*, 2003]. Although these estimates would be valuable in their own right, for many scientific and practical applications, estimates of discharge are required. Furthermore, satellite platforms with polar or inclined (as contrasted with geostationary) orbits cannot produce spatially contiguous or temporally continuous surface fields. Therefore, if swath altimetry observations are to be a viable source of data for inland waters, strategies which extend satellite observations in time and space will be required. On the other hand, hydrodynamic models can simulate spatially and temporally continuous discharge, but they are susceptible to errors in forcing data and other error sources, and work best if they are periodically re-initialized with observations.

[4] Data assimilation provides a framework to merge satellite observations and hydrodynamic model predictions to estimate river discharge in a way that accounts for both model and observation errors [*McLaughlin*, 1995]. The objective of this paper is to evaluate such a system, which combines the spatial and temporal continuity of a hydrodynamic model with satellite swath altimetry measurements to produce streamflow estimates. The basis for our evaluation is a proposed joint European-U.S. satellite mission, WatER (Water Elevation Recovery) [*Alsdorf et al.*, 2007]. The satellite would host a near-nadir viewing, 120 km wide, swath altimeter that uses two Ka-band synthetic aperture radar (SAR) antennae at opposite ends of a 10 m boom to measure water surface elevations. Interferometric SAR processing of the returned pulses would yield a 5 m azimuth and 10 m to 70 m range resolution, with elevation accuracy of ±50 cm for 10 m sized pixels [*Alsdorf et al.*, 2007]. A key attribute of swath altimetry (which distinguishes it from a series of current and past altimeters that have been used primarily for observations of the open ocean) is that it produces spatial fields of surface water elevation rather than transects.

2. Methods

2.1. Experimental Design

[5] We use an identical twin experiment, in which observations are synthetically generated using a "parent" model which is corrupted by noise, and then assimilated into a dynamical core which uses the same parent model (identical twin). The "truth" simulation is produced using the LISFLOOD-FP river hydrodynamics model of *Bates and de Roo* [2000]. The model is then integrated for the same

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time period, April 1 to June 23, 1995 (84 days), with error-corrupted estimates of discharge at the upstream boundary of the 50 km study reach of the Ohio River (near Martin's Ferry, Ohio, with a drainage area of ~60,000 km^2), and of lateral inflows. The boundary discharges are produced using the grid-based Variable Infiltration Capacity (VIC) model [*Liang et al.*, 1994]. The resulting simulation corresponds to the ''first guess'' or open-loop simulation. The data assimilation system, the core of which is also LISFLOOD-FP, ingests the synthetic observations, using the same boundary and lateral inflows as the open-loop simulation.

[6] For purposes of this study, the ''truth'' model does not attempt to represent precisely the real system, but only a hypothetical system which is similar to the above noted reach of the Ohio River. For this reason, neither the boundary discharges nor channel characteristics (width and roughness) are intended to represent observations, but only to approximate the real system.

2.2. Data Assimilation Algorithm

[7] The assimilation technique used in this study is the Ensemble Kalman filter (EnKF) [*Evensen*, 1994], which is a variant of the traditional Kalman filter (KF) [*Gelb*, 1974]. The standard KF provides the optimal solution for a system with linear model and measurement dynamics, and explicitly propagates a prediction error covariance matrix. However, estimation of this error covariance can be computationally infeasible, a problem which the EnKF overcomes by estimating the error covariance information required to update the model states from a (simulated) ensemble of model states. The latter are comprised of water depth and discharge, while the measurement vector contains the satellite water surface elevations. Here we use a square root implementation of the analysis scheme for the EnKF [*Evensen*, 2004] that avoids the perturbation of measurements and allows for the low-rank representation of the observation error covariance matrix. This EnKF algorithm solves the full problem with low computational cost, and without the approximations imposed by the standard EnKF implementation.

2.3. Hydrodynamics Model

[8] LISFLOOD-FP is a two-dimensional hydrodynamics model that is designed to estimate floodplain inundation over complex topography [*Bates and de Roo*, 2000]. LISFLOOD-FP couples two modeling approaches: one-dimensional finite difference solution to a kinematic wave approximation for channel flow, and a two-dimensional diffusion wave representation of floodplain flow. The solution of the latter is simplified by decoupling the x- and y- components of the flow [*Horritt and Bates*, 2001]. Inputs to the model include slopes and elevations of the domain derived from the Shuttle Radar Topography Mission (SRTM) 1 arc-sec DEM, channel characteristics (width and roughness) taken from the National Hydrography Dataset, and upstream and lateral inflow discharge hydrographs. We chose a spatially uniform Manning's coefficient for the channel and floodplain, 0.03 and 0.042 respectively. In order to reduce computational demands and random errors associated with the DEM, LISFLOOD-FP was run at a spatial resolution of 270 m; and a time step of 20 s. Boundary inflows were produced using VIC, implemented at a 3-hourly time step as described by *Maurer et al.* [2002].

2.4. Ensemble Generation

[9] Both the open-loop and filter simulations represent model uncertainties through an ensemble of model states, where each ensemble corresponds to a different realization of the precipitation forcing fields that drove the VIC model which produced the boundary discharges. Model uncertainty can emanate from errors in forcings (boundary inflows) and model parameters/formulation (e.g. Manning's coefficient). Generally the ensemble of model states is generated by treating model forcings and/or parameters as stochastic variables. In this study, we only represent the first type of error, that is, errors in the upstream and lateral boundary inflows. To do so, the VIC simulations of upstream and lateral boundary conditions were corrupted with log-normally distributed multiplicative errors (coefficient of variation taken as 25%) in precipitation, with an exponential correlation function used to describe spatial variability, following [*Nijssen and Lettenmaier*, 2004]. In addition, an artificial negative bias of 25% was introduced to the VIC-simulated upstream boundary discharge, so that the open-loop water surface level (WSL) errors would be sufficiently larger in comparison to the satellite observation errors. This procedure resulted in an ensemble of 20 boundary inflow hydrographs.

2.5. Satellite Measurements

[10] Synthetic WSL fields were produced from the ''truth'' LISFLOOD-FP simulation. The simulated WSLs were then sampled using the JPL Instrument Simulator [*Rodriguez and Moller*, 2004]. The Instrument Simulator generates sample satellite water surface elevation swaths (images) by adding noise to a spatial sub-sample of the simulated WSL fields. This procedure reflects the instrument errors and spatial resolution, as well as the path of the proposed satellite orbit. Based on analysis of the synthetic measurements, the measurement errors can be represented as spatially uncorrelated and following a Gaussian distribution with zero mean and standard deviation of about 5 cm. This standard deviation corresponds to the 0.5 m accuracy for 10 m sized pixels that was mentioned above, but since errors decrease exponentially with spatial aggregation, at the LISFLOOD-FP model resolution of 270 m, the standard deviation of errors is about 5 cm.

3. Results

[11] The evaluation of the data assimilation system was based on comparison of three estimates. The first was the open-loop estimate (the mean of the ensemble without assimilation of WSL). The second was the filter estimate (the mean of the ensemble with assimilation of the synthetic WSL observations). The third was the ''truth'' simulation, based on running LISFLOOD-FP with error-free boundary forcings.

3.1. Water Depth

[12] The main experiment involves the assimilation of synthetic WSL observations into a (boundary forcing) corrupted LISFLOOD-FP simulation, with an ensemble size of 20 members and observation standard deviation in WSL

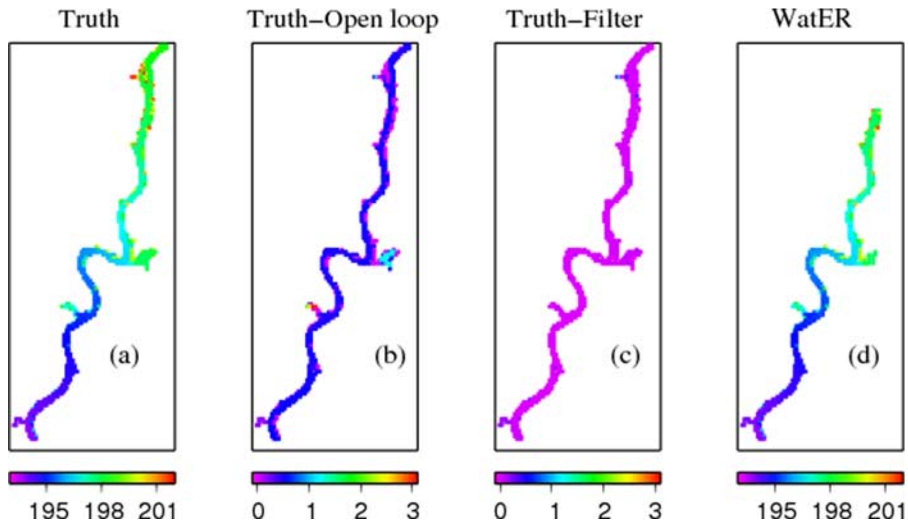

Figure 1. Spatial snapshots of WSL (in meters) for (a) the Truth simulation; (b) differences of Open-loop and (c) Filter WSL simulations from the truth; and (d) the satellite observation WSL image assimilated at the timestep shown (28 April 1995, 06:00). The satellite image is an overlay of the left and right viewing angles, with coverage limited by the orbits used in the instrument simulator.

of 5 cm. The simulated satellite overpass frequency for the domain was 8 days. As expected, at times when satellite observations are available, the assimilation is very effective at correcting the model water depth estimate to the "true" value. Figure 1 shows spatial snapshots of WSL for the three different simulations and the synthetic observation image for a specific time step. The open-loop water depth is lower than the "true" water depth, both along the channel (especially downstream) and on parts of the floodplain. This difference is attributable mostly to the imposed bias on the upstream boundary inflows. The almost perfect match between the true and filter WSL is attributable to the fact that the statistics of the EnKF observation error are the same as those used to generate the synthetic observations. The average (over the reach) RMSE of water depth for the open-loop simulation is 56.0 cm, vs 21.6 cm for the filter simulation. In addition, the EnKF reduces the error in the simulated inundated area by 5.4% (mean difference in flooded area is 14.6% and 9.2%, for the open-loop and filter simulations respectively).

[13] The EnKF updates water depth and discharge each time a satellite observation is available. The updated water depth is then used as an "initial condition" to LISFLOOD-FP, which produces discharge estimates until the next observation becomes available. Clearly, the effect of the assimilation will be limited by the persistence of the initial condition. In channels where boundary conditions almost fully govern the flow regime, the time window of model skill improvement due to assimilation of the observations can be expected to be short. In addition, after each update the model attempts to match the prescribed boundary conditions and at the same time retain the "correct" water depth, leading to errors that propagate downstream with time. One approach to resolve this issue is to use an error forecast model to update the upstream boundary inflow between observation times. A similar approach was taken by *Madsen and Skotner* [2005], who used a filtering algorithm combined with an error forecast model to update model estimates at measurement locations.

[14] The error forecast model is an AR(1) (autoregressive) model, that essentially regresses the current value of a time series against the value at the previous time step, where the lagged difference of upstream discharge is an exogenous variable, i.e. $Q_{err,t} = AQ_{err,t-1} + B\epsilon_t + C(Q_t - Q_{t-1})$, where Q_{err} is the upstream boundary discharge error, Q is the model upstream discharge, and ϵ is a zero mean, unit variance random number. The parameters A, B, C are estimated from a Nelder-Mead search algorithm that minimizes the squared difference between the AR-predicted and the filter-predicted upstream discharge error, at each observation time in an off-line simulation.

3.2. Discharge

[15] The EnKF updates model discharge across the spatial domain as well as water depth at the observation times. The filter estimate is much closer to the true channel discharge than the open-loop simulation, which results from the improvement in water depth prediction. The time-averaged RMSE of channel discharge is 161.5 m^3/s for the open-loop simulation (23.2% relative error), and 76.3 m^3/s for the filter simulation (10.0% relative error), demonstrat-

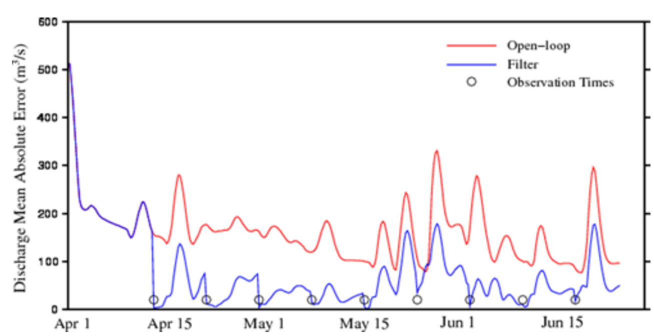

Figure 2. Spatially averaged mean absolute error of channel discharge for the Open-loop (red line) and Filter (blue line) simulations. The black circles indicate assimilation times (~8 days).

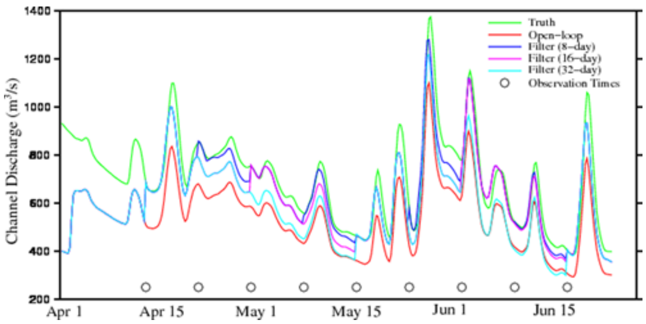

Figure 3. Time series of model-predicted discharge at the downstream edge of the channel from different simulations. These include the Truth, Open-loop, and the Filter with 8-, 16-, and 32-day assimilation frequency.

ing the positive effects of assimilation. It is clear that, during observation times the assimilation is able to correct model-predicted water depth and discharge for the errors introduced by inaccurate boundary inflows, through use of satellite WSL fields.

[16] Figure 2 shows the spatially averaged absolute error of channel discharge estimation for the open-loop and filter simulations, along with the assimilation times. It is clear that the discharge error for the filter simulation is greatly reduced at times when a WSL observation is available. At observation times channel discharge errors are reduced by 88.4 m^3/s (15.0%) on average. In addition, the filter channel discharge has a smaller error throughout the simulation, which can be mostly attributed to the use of the boundary inflow correction in the time window between observations, as well as the persistence of the assimilated water depths. The respective time series for water depth exhibits similar behavior (not shown).

3.3. Sensitivity to Observation Frequency

[17] The overpass interval for the proposed satellite is 8 days for the study region, however knowledge of the sensitivity of the results to the assimilation frequency is an important design parameter. We conducted two additional experiments with overpass intervals, of 16 days (designated "filter-16" simulation), and 32 days (designated "filter-32" simulation). Figure 3 shows model-predicted discharge at the downstream boundary of the reach for the truth and open-loop simulations, including the two additional overpass intervals. All filter simulations perform better than the open-loop simulation, with the nominal simulation having moderately smaller error. The channel discharge RMSEs are 89.2 m^3/s (12.1% relative error) and 118.3 m^3/s (16.9% relative error), while the water depth RMSEs are 24.9 cm and 33.3 cm for the "filter-16" and "filter-32" simulations respectively. As expected, the assimilation system performance degrades as the observation frequency becomes sparser. The 8-day satellite overpass frequency provides the best results (76.3 m^3/s RMSE and 10.0% relative error for channel discharge, 21.6 cm RMSE for water depth).

4. Discussion and Conclusions

[18] While a swath altimetry satellite mission would provide WSL information that would have inherent value in and of itself, the ability to estimate river discharge would have tremendous additional value by providing global measurements of river discharge, a major term in the land surface water budget. Such estimates would best be provided through a data assimilation strategy build around a river hydrodynamic model. Through a set of identical twin data assimilation experiments with synthetically generated observations ingested into a LISFLOOD-FP model simulation, using an EnKF, we found that: (1) The filter was able to successfully recover water depth and discharge from a corrupted LISFLOOD-FP simulation by assimilating synthetic WatER WSL observations. (2) Filter simulations showed little sensitivity to assumed observation errors (0 and 25 cm standard deviation) with RMSEs being 22.4 and 26.9 cm (water depth), and 82.1 and 98.7 m^3/s (discharge) respectively. (3) System performance degraded substantially as the assimilation frequency became longer. The proposed 8 day satellite overpass, gave the best overall results relative to 16-day and 32-day observation frequencies (10.0% versus 12.1% and 16.9% discharge relative error).

[19] Although this study shows that improvements in discharge and water depth estimation over a given river reach may be improved by the assimilation of water surface elevation satellite observations into the LISFLOOD-FP model, several additional factors will need to be considered in a real-time implementation of this technique. Most importantly, we assumed that errors in the boundary inflows are the only source of model error. This assumption serves the purpose of this proof-of-concept study, but the effects of errors in channel characteristics (e.g. Manning's n), topography, and model formulation can be important contributors to the model errors, and merit further study.

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