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Estimating the impact of satellite observations on the predictability of large-scale hydraulic models

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ABSTRACT

Large-scale hydraulic models are able to predict flood characteristics, and are being used in forecasting applications. In this work, the potential value of satellite observations to initialize hydraulic forecasts is explored, using the Ensemble Sensitivity method. The impact estimation is based on the Local Ensemble Transform Kalman Filter, allowing for the forecast error reductions to be computed without additional model runs. The experimental design consisted of two configurations of the LISFLOOD-FP model over the Ohio River basin: a baseline simulation represents a "best effort" model using observations for parameters and boundary conditions, whereas the second simulation consists of erroneous parameters and boundary conditions. Results showed that the forecast skill was improved for water heights up to lead times of 11 days (error reductions ranged from 0.2 to 0.6 m/km), while even partial observations of the river contained information for the entire river's water surface profile and allowed forecasting 5 to 7 days ahead. Moreover, water height observations had a negative impact on discharge forecasts for longer lead times although they did improve forecast skill for 1 and 3 days (up to 60 $m^3/s/km$). Lastly, the inundated area forecast errors were reduced overall for all examined lead times. Albeit, when examining a specific flood event the limitations of predictability were revealed suggesting that model errors or inflows were more important than initial conditions.

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1. Introduction

Movement of water through rivers and adjacent floodplains impacts greatly on various ecosystems and the biogeochemical cycle. At times and in many places around the world, high river flow and floodplain inundation poses a serious risk to human population. In developed countries observation networks and hydrodynamic modeling efforts help understand and predict water flow but over large scales, hydrodynamic processes are still poorly understood primarily because of a lack of adequate data and models [1]. In areas where there is a dense river gauging network, channel survey data and fine resolution floodplain topographic data, flood risk mapping as well as flood forecasting is commonly performed using hydraulic models; however in many locations around the world modeling and forecasting efforts are still limited and satellites provide currently one of the only means to infer information about hydrodynamic processes and build reliable models. Data assimilation algorithms can merge observations with models, providing optimal estimates of flood characteristics by taking into account the errors in both models and observations [2]. Forecasting in river hydraulics depends on the projected inflows but also on the accuracy of the initial conditions [3], and therefore data assimilation can benefit forecast skill by improving its initialization. Previous studies have shown that the ingestion of observations into a river hydraulic modeling system have improved its performance both in terms of reanalysis [e.g. 4,5] and forecasting [e.g. 6–8]. Nevertheless, there is a need to quantify the impact of any assimilated observations on forecasting and more generally on the model fidelity and value of the observational system (e.g. measurement network).

The impact of the assimilated observations can be estimated via data-exclusion experiments, wherein part of the observations are not used and the results (i.e. forecast skill) are then compared with the experiment that used the entire set of available observations [e.g. 9]. Langland and Baker [10] developed a technique to estimate the impact of observations using the adjoint of the forecast model, i.e. without the need to re-run the model for each observation subset. The adjoint-based method allowed the quantification of the observation impact separately according to observed variable, sensor, and location. Despite these methods being successful at estimating the observation impact, they are limited by the validity of the adjoint models as well as other approximations [11]. Liu and

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Kalnay [12] proposed a method that does not require an adjoint model, but rather uses an ensemble of model forecasts and a version of the Ensemble Kalman Filter. The method, termed Ensemble Sensitivity (ES), yields similar results to the adjoint-based method but proved more robust probably due to the nonlinearities captured by the forecast ensemble.

The objective of this study is to evaluate the impact of satellite observations on the predictability (or forecast skill) of large-scale hydraulic models. The observation impact is assessed by adapting the ES method to a river hydraulic modeling context over a large-scale river basin. Although the observations assimilated are synthetic, they are generated with specific satellite missions (both current and proposed) in mind. The hydrodynamic model that lies at the core of the forecasting system, along with the ES method and the experimental design are described in Section 2. Results are presented in Section 3, while Section 4 provides a summary and discussion of the implications of the work presented.

2. Methods

2.1. Ensemble Sensitivity

In order to evaluate the impact of observations on the forecast accuracy of a large-scale hydraulic model, a cost functional is derived and its sensitivity to the assimilated observations at the forecast initialization time is calculated [10]. Let t_0 be the time when an observation is available and also the initialization time for the forecast. The forecasts produced for time t ($t - t_0$ is equal to the forecast lead time) consist of two model trajectories (Fig. 1), initialized at the observation time t_0 (i.e. benefiting from the assimilation of the observations) and at a time prior to t_0 (labeled t_{-1}) containing no information from the available observations. The corresponding forecast errors are defined as

$$e_{t|0} = \bar{x}^f_{t|0} - \bar{x}^a_t \tag{1}$$

$$e_{t|-1} = \bar{x}^f_{t|-1} - \bar{x}^a_t \tag{2}$$

where $x^f_{t|-1}$ is the forecast without any assimilation, $x^f_{t|0}$ is the forecast with assimilation, and x^a_t is the verification at the forecast time that can be either an actual measurement or the analysis at time t (implicitly assumed to be more accurate than both forecasts).

The cost function that measures the reduction in the forecast error due to the assimilation at time t_0, i.e. the observation impact, is defined as

$$J = \frac{1}{2}\left(e^T_{t|0}e_{t|0} - e^T_{t|-1}e_{t|-1}\right) \tag{3}$$

The cost functional at time t is the difference of the squared forecast errors (L2 norm) between the forecast that is initialized at time t_0 (observation time, i.e. the forecast benefits from the assimilation)

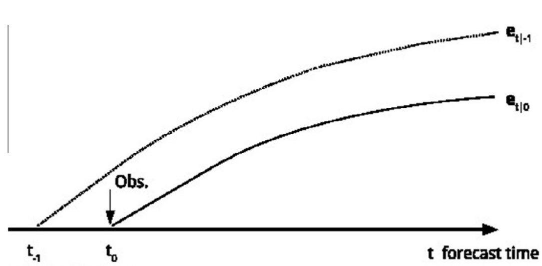

Fig. 1. Schematic of forecast model trajectories with definitions of initialization/assimilation and forecast times (adapted from [10]).

and the forecast that is initialized at t_{-1} (does not benefit from the assimilation of any observation).

Let y^o_0 be the observations at t_0, and define the observation increments as $v_0 = y^o_0 - H(x^f_{0|-1})$. Substituting the definitions of the forecast errors (Eq. (2)) into Eq. (3), the cost functional is rewritten as

$$J = \frac{1}{2}\left(2e_{t|-1} + x^f_{t|0} - x^f_{t|-1}\right)^T\left(x^f_{t|0} - x^f_{t|-1}\right) \tag{4}$$

Utilizing the Local Ensemble Transform Kalman Filter (LETKF) [13] analysis formulation, the rightmost term in Eq. (4) can be rewritten as

$$x^f_{t|0} - x^f_{t|-1} \approx X^f_{t|-1}\widetilde{K}_0 v_0 \tag{5}$$

where $X^f_{t|-1}$ is a matrix containing the forecast ensemble perturbations $\delta x^{f,i}_{t|-1} = x^{f,i}_{t|-1} - \bar{x}^f_{t|-1}$, and $\widetilde{K}_0$ is the Kalman gain matrix (dimensionality of ensemble size × number of observations) given by

$$\widetilde{K}_0 = \left[(n-1)I + \left(HX^b\right)^T R^{-1}\left(HX^b\right)\right]^{-1}\left(HX^f\right)^T R^{-1} \tag{6}$$

where n is the ensemble size, H is the observation operator (i.e. HX^b is a matrix containing the predicted measurements), R is the observation error covariance matrix, X^b is the background state perturbation matrix (state during the assimilation time t_0). Substituting Eq. (5) into Eq. (4), the cost functional that represents the sensitivity of the forecast skill to the observations can be expressed as (see [12,14] for additional details)

$$J = \left\langle v_0, \widetilde{K}^T_0 X^{fT}_{t|-1}(e_{t|-1} + \frac{1}{2}X^f_{t|-1}\widetilde{K}_0 v_0)\right\rangle \tag{7}$$

or

$$J = \left[e_{t|-1} + \frac{1}{2}X^f_{t|-1}\widetilde{K}_0 v_0\right]^T X^f_{t|-1}\widetilde{K}_0 v_0 \tag{8}$$

Each term in Eq. (8) can be calculated from the ensemble of forecasts initialized at time t_{-1}, which avoids the need for generating forecasts after assimilating any observation (i.e. $x^f_{t|0}$). The cost functional can be computed for each time an observation is available and different lead times by selecting the appropriate t and t_0 times for the forecasts and observations.

2.2. Experimental design

The experimental design is based on a fraternal twin synthetic experiment [15], in which a control simulation that produces hydrodynamic states and fluxes such as water surface elevation (WSE) and flood extent is designated as "truth". These "true" fields are then sampled to generate synthetic observations that have the same spatial, temporal and error characteristics as the sensor whose observations are being emulated. Another simulation, the open-loop or first-guess, uses the same model albeit corrupted by errors manifested either from erroneous model forcings (e.g. boundary inflows), model parameters (e.g. channel roughness) or model initialization. The open-loop simulation represents our uncertain knowledge of the "true" hydraulic variables, and are used to initialize the open-loop forecasts that do not benefit from the satellite observations. In contrast, the assimilated forecasts are initialized after the observations have been assimilated into the open-loop model but are forced with the open-loop forecast inflows. The only difference between the open-loop and assimilated forecasts then are the initial conditions, allowing for the evaluation of the observation impact on the forecasts. The evaluation of the forecast skill was done in terms of WSE, discharge and inundated area which are variables that govern flood characteristics. Although the synthetic observations do not correspond to any

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