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DISCUSSIONS

The results presented here are preliminary investigations to the assimilation of SWOT water surface elevations product into a large-scale hydrological model. This study focused on the correction of a critical river parameter, the river Manning coefficient.

For all simulations, the Manning coefficient distribution is set to be constant in time. For each grid cell, one value of the Manning coefficient is used for the entire simulation. However, in reality, it is commonly accepted that this parameter could vary in time, depending on the seasonal cycle or also some extreme hydrological event such as large flooding events, which can even modify the bathymetry itself **[R#1-m#19]**. The results showed that, for this OSSE, the data assimilation is able to converge quite quickly towards the true value. For example, for the left-bank tributaries zones, namely zones 4 and 5, in every experiment, the associated control variable converges toward the true value in only one assimilation cycle. Then, in a real-case experiment, we could expect to retrieve the temporal variations of the Manning coefficient from one assimilation cycle to another. The good performances of the assimilation platform are mainly related to the fact that, in the ISBA-CTRIP model, the water depth diagnostic variables are sensitive to the Manning coefficient (Emery et al., 2016). Thus, when simulated water depth are not that sensitive to the Manning coefficient (e.g. right-bank tributary zones during the low flow season), the data assimilation performances slightly degrade. These results are specific to the ISBA-CTRIP model. To apply the same method to another model and even another region, one need to first study the sensitivity of the (other) model to the (other) study region.

Secondly, the study investigates the potential of assimilating water surface anomalies instead of direct water surface elevations. The use of water surface anomalies is driven by the need to avoid potential bias between the control and the observed variables. Indeed, a bias will likely be introduced from a discrepancy between the elevation of the river bed in the model and in the observations with respect to a reference surface such as a geoid or an ellipsoid (see Figure 4). Under the assumption that the water variations are the same between the model and the observations, the use of anomalies as observed variables should prevent this bias from affecting the results.

Another likely bathymetry error corresponds to error on the river bankful depth, the river width and more generally, representativeness errors due to the use of a simplified bathymetry **[R#2-M#2]**. This type of error was artificially introduced by perturbing the model bankful depth in PE3. Specifically to ISBA-CTRIP, the river bankful depth controls when the model floods, which has a direct impact on the water depth dynamics. Therefore, background anomalies and observed anomalies may present different dynamics where either the observed variables flood while the model variables do not or inversely. The experiment PE3 illustrated the effect of this bias on the variations of Manning coefficients. Instead of being maintained at the true value, their value slightly varies around the true values to account for the difference in dynamics between the model and the observations. However, one could expect even more variations in the updated control variables around the true value if more and different errors in the bathymetry exist (which will likely happen with more realistic experiments) **[R#2-M#2]**.

Furthermore, real-case experiment may suffer from another type of bias originating from errors in the atmospheric forcing and in the surface and sub-surface runoff provided by the LSM (i.e. ISBA). Both control the amount of water entering the river system. A basic idea to attenuate this issue would be to consider their uncertainties when generating the background ensemble **[R#1-m#11]**. This approach may become limited when the errors in the forcing are very large and may lead to unrealistic, even non-physical, updated Manning coefficient values. Besides, when correcting the model's parameters, we only re-distribute the water volume within the basin while such type of errors could actually require adding/withdrawing water in/from the system. Therefore, the potential solution would be to include such forcing or LSM variables in the control vector or, to update variables closer to the observations, including CTRIP's state variables such as the water storage. This would change the current framework to a dual state-parameter estimation approach **[R#1-M#1][R#1-m#18]**.

Noting this, there may be an additional advantage in assimilating water anomalies instead of the direct water depths. Comparing the Kalman gain between the PE1 experiment (that assimilated direct water depths) and the PE2/PE3 experiments (that assimilated water anomalies), the gain magnitude for the water anomalies is lower than the water depth gain magnitude. This is to be expected as the Kalman gain is stochastically estimated from an ensemble of model runs and the magnitude of the simulated water anomalies is lower than the simulated water depth magnitude. The consequence of this lower gain is the correction applied to the control variable is also lower. If the convergence toward the true value takes more than one assimilation cycle, the divergence from it in the presence of bias is also diminished.

Beyond the bias issues, real-data assimilation configuration will raise the question of the unknown true parameter value, if it exists. First, there will be no true estimates of the control variables to compare the assimilated simulations to. The assimilation will be evaluated against the observed variables directly. Then, with real data, model structure error will be introduced. To our knowledge, the model structure error is still a challenging error to estimate and most data assimilation studies assume no model structure error. However, when using ensemble-based model, a possibility to deal with such structure error is to enrich the background ensemble by considering more uncertainties from variables that are not necessarily in the control vector (including errors in the forcing or parameters from both the LSM and the RRM). The capacity of such ensemble to tackle model structure error can be tested using synthetic observations based on a different hydrological model **[R#2-M#2]**.

Additionally, the real SWOT data will have a finer resolution than the synthetic SWOT data currently used. Still, the coarser resolution observations are found to provide information to constraint the model and improve the value of the spatially-varying Manning coefficients. Then, when moving to real-data assimilation experiments, we can consider averaging the fine-scale SWOT product over a coarse grid cell corresponding to an ISBA-CTRIP cell so that the resolution of the observations and the model matches.

Ultimately, going towards more realistic experiments also implies more realistic representation of the observation errors. The current study uses a simple white noise model to define the observation errors. But more complex errors should be expected for the real SWOT product. Some correlated errors along the swath should be expected due to the instrument but also to motion of the satellite and delays due the propagation of the electromagnetic waves in the ionosphere and atmosphere. Nevertheless, as part of the mission science requirements, the sum of all errors should not exceed 10 cm when the measured data is averaged over 1 km^2. There should also be additional errors affecting the observations that can be described as "detectability errors" such as "dark water", "layover" and "false positive". "Dark water" pixels will result in missing data and will not be included in the assimilation; "layover" pixels will have a higher vertical error due to surrounding vegetation and topography, but should also be flagged (Biancamaria et al., 2016). Eventually, "false positive" pixels (i.e. pixels classified as water, whereas they correspond to land) will be the most complicated to anticipate. With these additional errors taken into account in the assimilation framework, one could expect a slower convergence of the control variables. Note that these aspects of the measurement errors are related to water surface elevations products **[R#1-m#12]**.