Hydrol. Earth Syst. Sci. Discuss.,
https://doi.org/10.5194/hess-2020-19-RC1, 2020

Hydrology and Earth System Sciences
Discussions

Interactive comment on "Socio-hydrologic data assimilation: Analyzing human-flood interactions by model-data integration" *by* Yohei Sawada and Risa Hanazaki

Anonymous Referee #1

Received and published: 21 March 2020

The paper "Socio-hydrologic data assimilation: Analyzing human-flood interactions by model data integration" applied a sequential data assimilation approach to the socio-hydrological model developed by Di Baldassarre et al. (2013) to update model state and estimate the model parameters. While I found the idea of combining data assimilation with socio-hydrological modeling interesting, I believe that there are different shortcomings that prevent the publication of the paper in the present form. I have provided more comments below to help the authors strengthening their paper:

- My main concern is related to the use of synthetic observations to test the hindcast assimilation experiment. On the one hand, it is a standard procedure to use synthetic

experiments to test new approaches and observations. On the other hand, synthetic experiments must be coupled with real-world analysis when observations are available. The authors state: "Although our experiment design was idealized, this study reveals several important findings toward real-world applications" (in the Discussion section). However, authors do not provide any empirical comparison or validation of their approach with real-world applications. Does the model perform better against any real-world criteria? The main reason for integrating observations into a mathematical model is to improve the representation of reality by updating model states, output, parameters or input. If this new modeling approach cannot be applied to a single case study then, what is it the purpose of this study if not just a mere numerical exercise? For example, you could use the same data reported in Barendrecht et al. (2019) to test your assimilation approach.

- The proper estimation of the observational error plays a key role in the assimilation performances (especially in socio-hydrological models in which uncertainty of social observation can be quite high). How is the covariance matrix of the observation error process estimated in this study? Are some observations more reliable than others? Small observational errors can force the updated model closer to the observation, while high observational errors may lead to poor model updates. Are the good results achieved in the experiments due to low observational error with respect to the model error with NoDA? The authors mentioned that M is considered as an observed variable for assimilation purposes. How are the authors planning to estimate the accuracy of flood awareness observations in real-world applications?

- I have some doubts about the setup of the experiments. Why only 4 parameters and 1 parameter are considered in the second and third experiments respectively? Why the authors selected those parameters and not others? This must be explained as the results can be biased by the selection of the parameters. Personally, the way I would structure the experiments (and results) of this study is 1) Uncertain input and uncertain observation (assuming different observation errors); 2) Temporal uneven distribution of observational data (similar to Figure 4); 3) Assimilation strategies (similar to Figure 3); 4) Real-world application. I have already explained the reason behind points 1 and 4. I have included more comments on point 2 below.

- It is mentioned that “our SIRPF can efficiently improve the simulation of the socio-hydrologic state variables using the sparsely distributed data”. I guess the authors refer to the temporal availability of observation and not spatial as the system dynamic model of Di Baldassarre et al. (2013) is lumped. I appreciate that the authors considered the effect of different assimilation updating times. However, I would find more interesting to consider intermittent and uneven temporal distributions of social and hydraulic information. In fact, it can be that flood awareness and other social data are not available regularly available as you assumed in your study. How would the intermittency characteristics of social data affect the model performances?

- Results need to be discussed in a more critical way. For example, why when only G is updated also the other state variables are improved? Also “Observing F, D, and M negatively impacts the estimation of H and observing H does not significantly improve the simulation of D and M”. I found these results counter-intuitive. If a flood occurs, then flood awareness will increase and this will lead to reinforcement of the levee system (as already described in Di Baldassarre et al. (2013), Di Baldassarre et al. (2015), and other related papers). However, you found a negative impact. Why? Levees are built and reinforced to protect urbanized areas from flooding and F should be critical for the estimation of H. In the same way, levee systems (H) can shape human flood awareness and distance from the river (as already described in Di Baldassarre et al. (2013), Di Baldassarre et al. (2015), and many other related papers). So, how can you justify your results? Provide a real-world example in which flooding and flood awareness are not relevant to the reinforcement of a levee system.

- Line 268: “In the first OSSE, we assumed that the model was perfect, and we knew it”. I honestly doubt that the model is perfect and I strongly invite the authors to remove this sentence as conceptually wrong. No model is perfect, in particular socio-hydrological

models that represent complex social interactions as the distance from the river, flood awareness, etc.

- What do you mean with “H is decoupled from the other state variables”?

- Line 298-300. The sentence is unclear and has to be rephrased.

- Line 270: “Our SIRPF estimated only state variables”. Change “estimated” with “updated”.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2020-19, 2020.