Response letter of hess-2020-19-RC2

Dear Anonymous Referee #2,

Please find the responses to the comments.

Comments made by the reviewer were highly insightful. They allowed us to greatly improve the quality of the manuscript. We described the response to the comments.

Each comment made by the reviewers is written in *italic* font. We numbered each comment as (n.m) in which n is the reviewer number and m is the comment number. In the revised manuscript, changes are highlighted in yellow.

We trust that the revisions and responses are sufficient for our manuscript to be published in *Hydrology and Earth System Sciences*

Responses to the comments of Referee #2

This paper presents a study of data assimilation based on a conceptual sociohydrologic model. The authors used the SIRPF method to assimilate human-flood interaction data based on the flood risk model developed by Di Baldassarre et al. (2013). The manuscript is well-written and the study topic is of interest to the audience of HESS. I have the following comments that I hope the authors could address in their revision. Specific comments:

(2.1) Lines 251-252: The authors should be clear about the time scale of the model, which I assume is annual. The human-flood interactions will be different at different time scales. Also, in the time series figures, the authors should make clear statement about the annual time step.

→ This point was indeed unclear in the original version of the paper. We chose the annual time step. We have clarified this point in the model section of the revised paper.

"The timestep was set to annual."

This point has also been clarified in the caption of figures.

(2.2) In the Results section, the authors provided interpretations of the experiment results.It would be helpful if the study can include some validation of the method. For example, the authors could apply their proposed method in a realistic case study.

→ Thank you very much for this comment. We performed the real-data experiment using the data collected by Ciullo et al. (2017). The results have already been shown in the other Authors' comment. We have also attached it below as the proposal of the revision.

"**3.2. Real-data experiment**

In addition to the OSSEs, we performed the real-world experiment in the city of Rome, Italy. Ciullo et al. (2017) collected real-world data and calibrated their flood risk model. Using the data collected by Ciullo et al. (2017), we performed the data assimilation experiment. It should be noted that the flood risk model of Ciullo et al. (2017) is different from our model (i.e. Di Baldassarre et al. 2013), although they are conceptually similar.

All the data were collected from Figure 1 of Ciullo et al. (2017) by WebPlotDigitizer (https://automeris.io/WebPlotDigitizer/). The observed high water level of Tiber River was used as input forcing data (W). The levee height (H) and population (G) were used as the observation data to be assimilated into the flood risk model. In Ciullo et al. (2017), population values within the Tiber's floodplain were normalized by the theoretical maximum Tiber's floodplain population which is estimated to the range between 10^6 and 2×10^6. Since our flood risk model needs the population values (not normalized values), we multiplied 1.5×10^6 and the normalized values shown in Figure 1 of Ciullo et al. (2017) to obtain population in the floodplain.

We added lognormal multiplicative noise to the observed high water level as we did in the OSSEs. The observation errors of levee height and population were set to 10% and 25% of the observed values, respectively. Since Ciullo et al. (2017) showed the large uncertainty in the estimation of the theoretical maximum population (see above), it is reasonable to assume that the estimation of population values also has relatively large uncertainty.

As the second and third OSSEs, we have 4 unknown parameters in this real-world experiment. We used the same settings of parameters as the OSSEs, which are shown in Table 1, except for ξ_H, proportion of additional high water level due to levee heightening. In this real-world experiment, we set $\xi_H = 0$ because the observed high water level includes the effects of levee heightening. This treatment is consistent to Ciullo et al. (2017) (see their Table 2).

The initial conditions of H and M were set to 0. The initial conditions of D were obtained from the uniform distribution between 1000 and 5000. The initial conditions of G were obtained from the uniform distribution between 1500 and 50000.

4.2. Real-data experiment

Figure 12 shows the timeseries of the model variables calculated by 5000 ensembles with no data assimilation. The 5000-ensemble simulation reveals the two bifurcated social systems. One builds a high levee and maintains a course of stable economic growth. The other one has no levee and its economy is damaged by severe floods many times (ensemble mean shown in Figure 12b implies that there are many ensemble members with zero levee height).

In reality, the city of Rome constructed the levee responding to the severe flood occurred on 28 December 1870. After the construction of this levee, no major flood losses occurred, allowing the steady and undisturbed growth. Figure 13 indicates that our SIRPF successfully constrains the trajectory of the ensemble simulation to the real-world (i.e. high levee and stable economic growth) by assimilating the real data of H and G. Figure S8 shows the SIRPF-estimated unknown parameters. Our SIRPF suggests lower γ_E than the initial ensemble mean to promote the levee construction with lower costs. Lower κ_T is also obtained because the assimilated real data show no decay of levee from 1874 to 2009. Compared with the OSSE experiment 2, the large uncertainty in estimated parameters remains at the final timestep due to the limited number of assimilated observations. In contrast to the OSSEs, our observation network has the uneven temporal distribution. Figure 13 clearly indicates that our SIRPF is robust to these intermittent observations whose intervals temporally change.

We analyzed the impacts of the individual observation types (i.e. H and G) on the simulation skill as we did in the OSSEs. Figure 14 indicates that our SIRPF realistically simulates the socio-hydrologic dynamics in the city of Rome and provides the similar estimated state variables shown in Figure 13 by assimilating only population data. As we found in the OSSEs, observations of the size of the human settlement G are informative to effectively constrain the flood risk model. The dynamics of the parameter estimation is similar to the case in which data of both G and H are assimilated (Figure S9).

On the other hand, assimilating only levee height data cannot provide the similar results to those shown above. Figure 15 shows the timeseries of the model variables by the data assimilation experiment in which we assimilated the observation data of H only. Observations of the levee height cannot effectively constrain D, G, and M compared with the observations of G. This finding is consistent to the OSSEs. The uncertainty in estimated parameters becomes larger when we omit to assimilate observations of G (Figure S10). Although the impact of levee height data is limited compared with population data, it is promising that we can estimate the socio-hydrologic dynamics to some extent only from the levee height data whose distribution is temporally sparse.

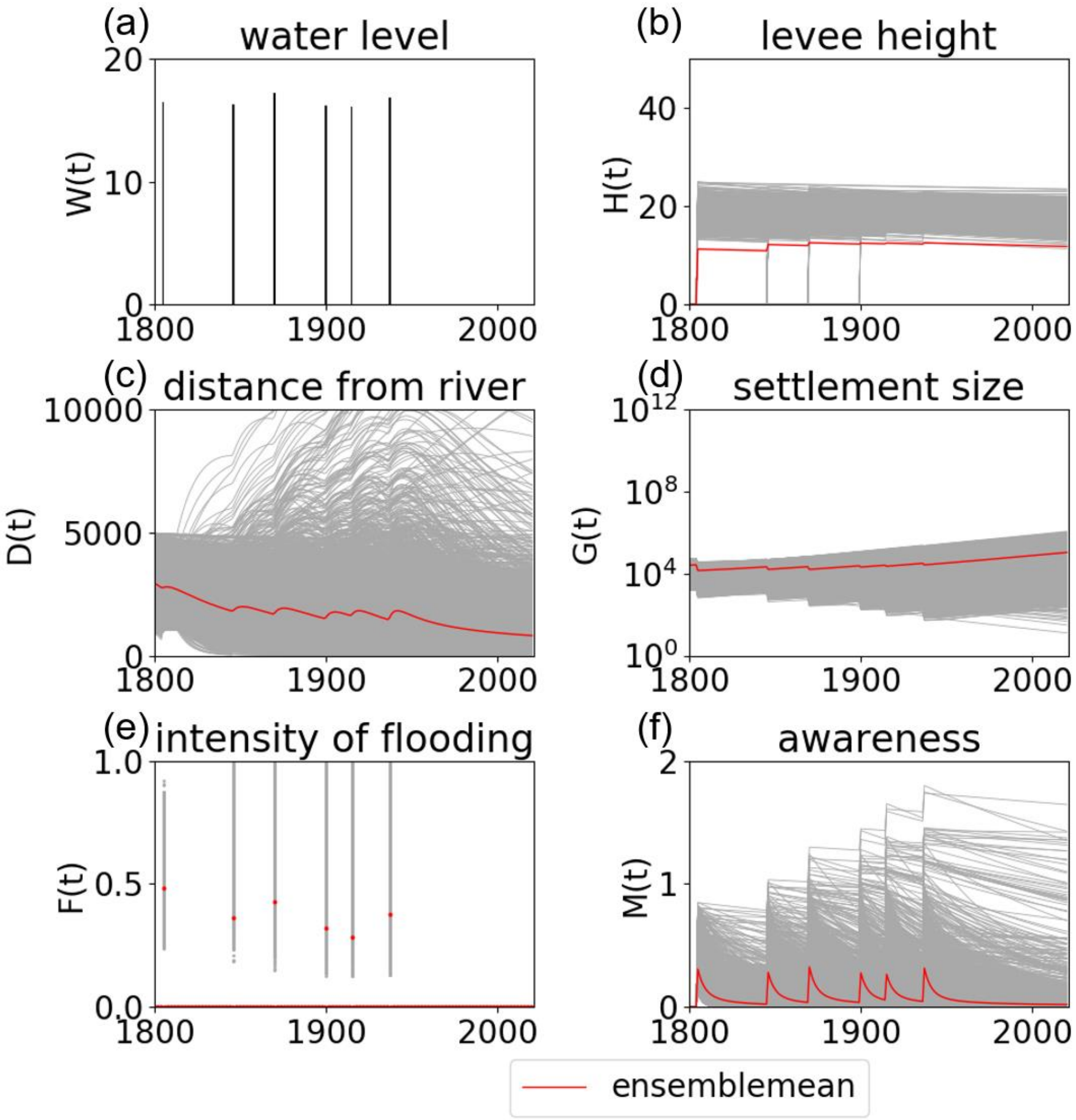

Figure 12. Timeseries of (a) high water level W(t), (b) the flood protection level (or levee height) H(t), (c) the distance of the center of mass of the human settlement from the river D(t), (d) the size of the human settlement G(t), (e) the intensity of flooding events F(t), and (f) the social awareness of the flood risk M(t) simulated by 5000 ensembles with uncertain high water levels and no data assimilation in the real-world experiment in the city of Rome. The time step is annual. Grey, and red lines are the ensemble members and their mean, respectively.

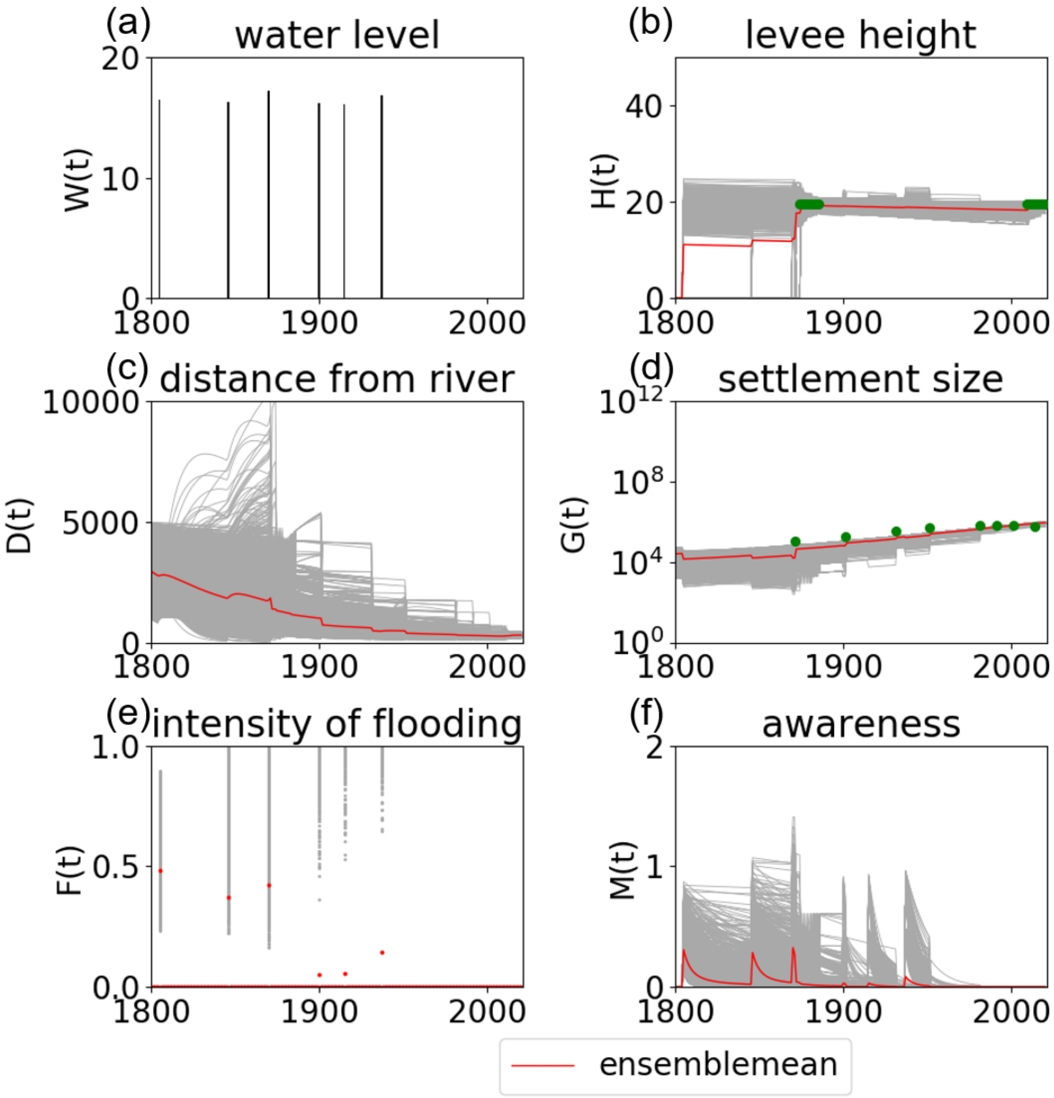

Figure 13. Timeseries of (a) high water level W(t), (b) the flood protection level (or levee height) H(t), (c) the distance of the center of mass of the human settlement from the river D(t), (d) the size of the human settlement G(t), (e) the intensity of flooding events F(t), and (f) the social awareness of the flood risk M(t) simulated by the data assimilation experiment in which the real-world observations of G and H (green dots) are assimilated into the model with 5000 ensembles in the real-world experiment in the city of Rome. The time step is annual. Grey, and red lines are the ensemble members and their mean, respectively.

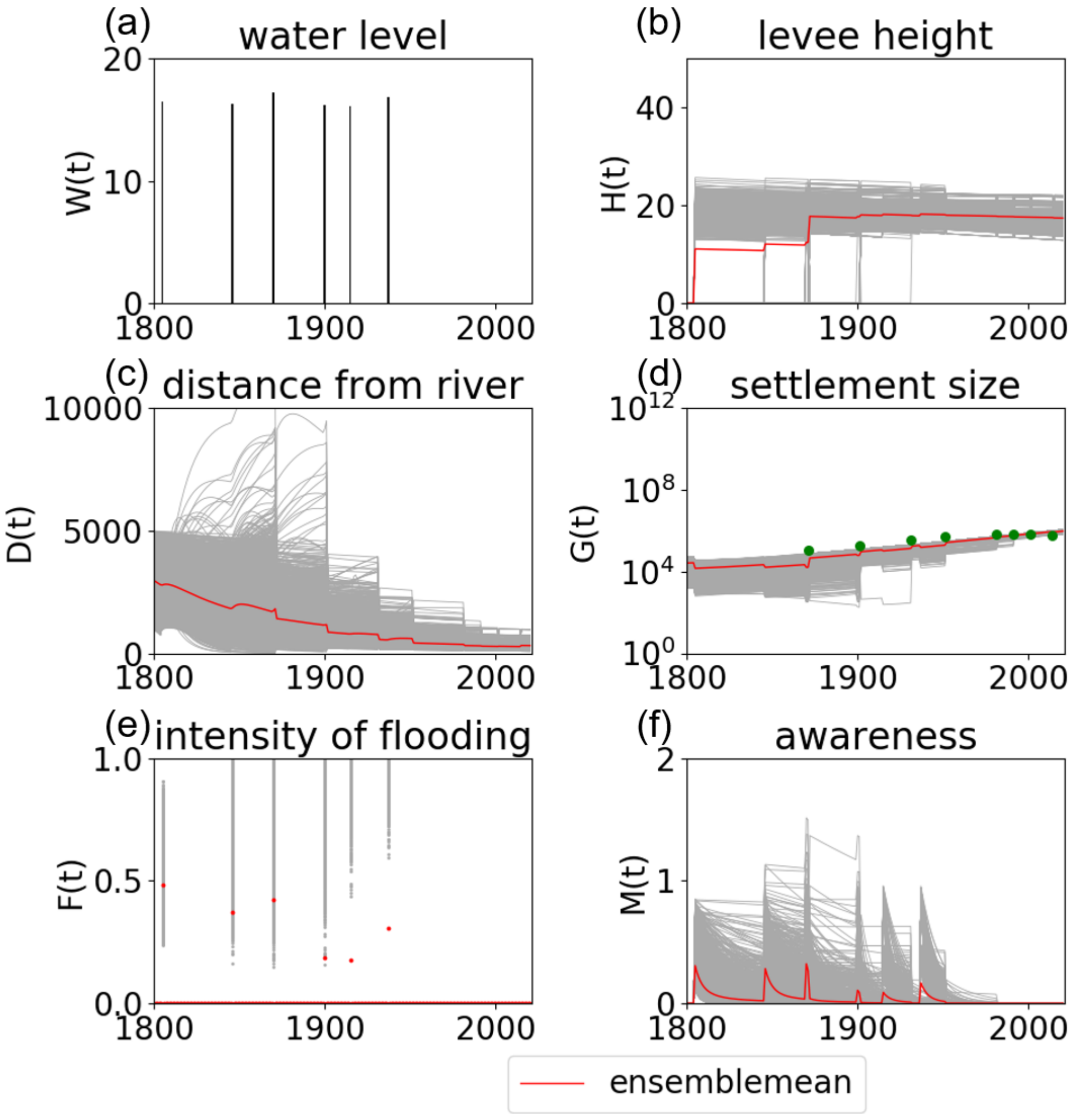

Figure 14. Same as Figure 13 but only real data of G are assimilated.

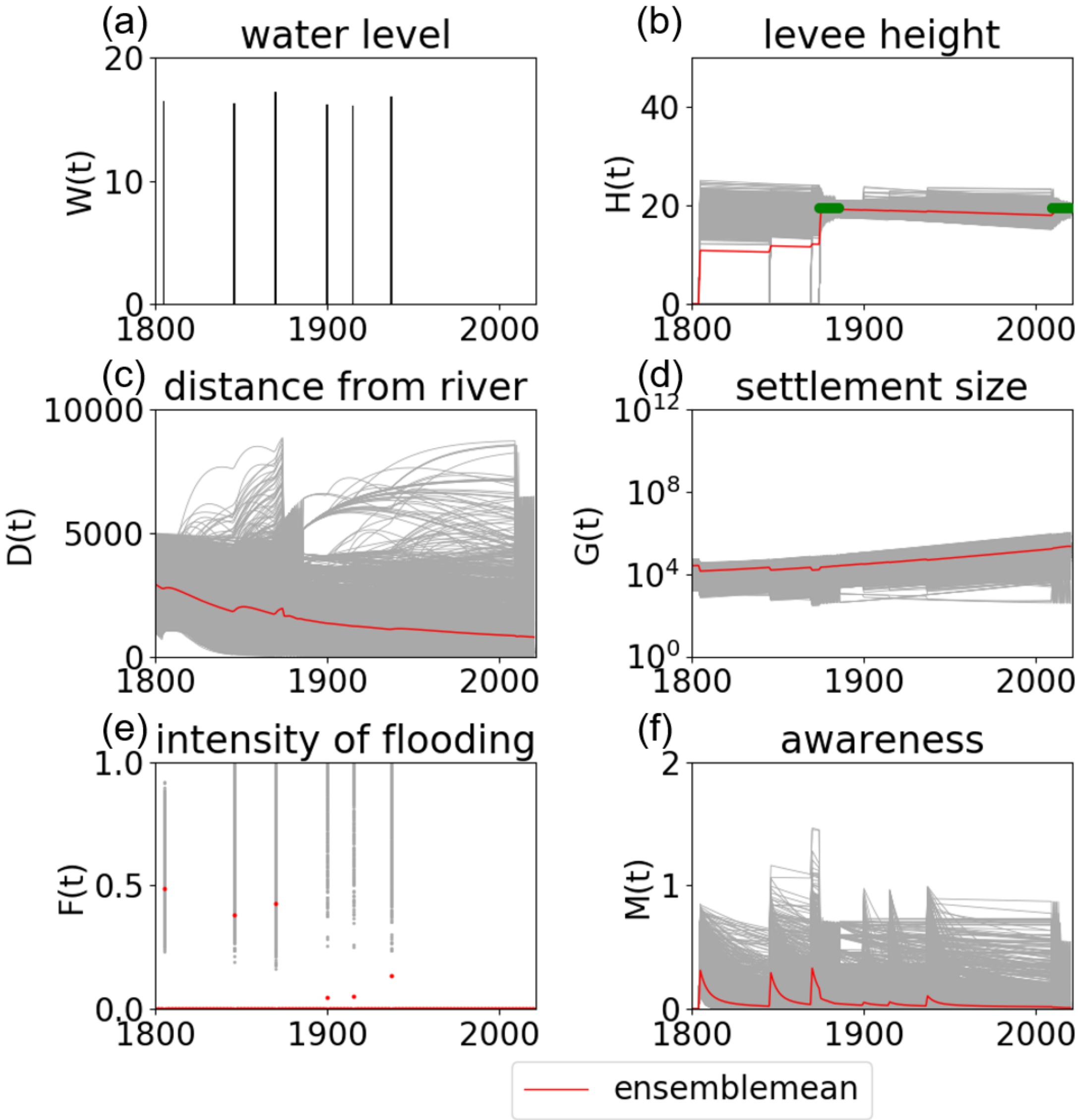

Figure 15. Same as Figure 13 but only real data of H are assimilated.

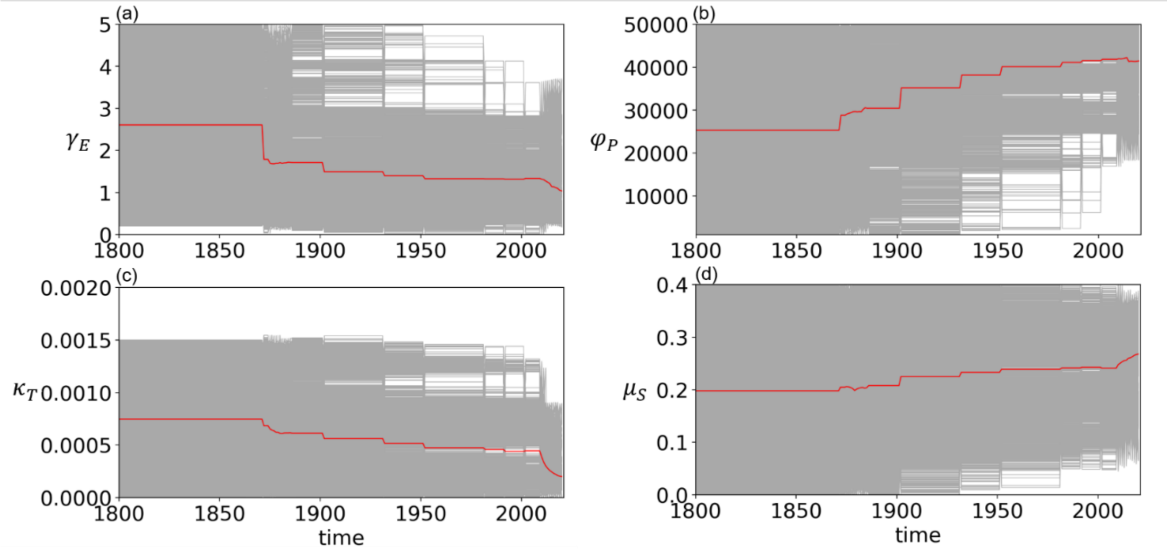

Figure S8. Timeseries of (a) the cost of levee raising γ_E, (b) the rate by which new properties can be built φ_P, (c) the rate of decay of levees κ_T, (d) memory loss rate μ_S estimated by the data assimilation of observations of G and H with 5000 ensembles in the real-world experiment in the city of Rome. The timestep is annual. Grey and red lines are the ensemble members and their mean, respectively.

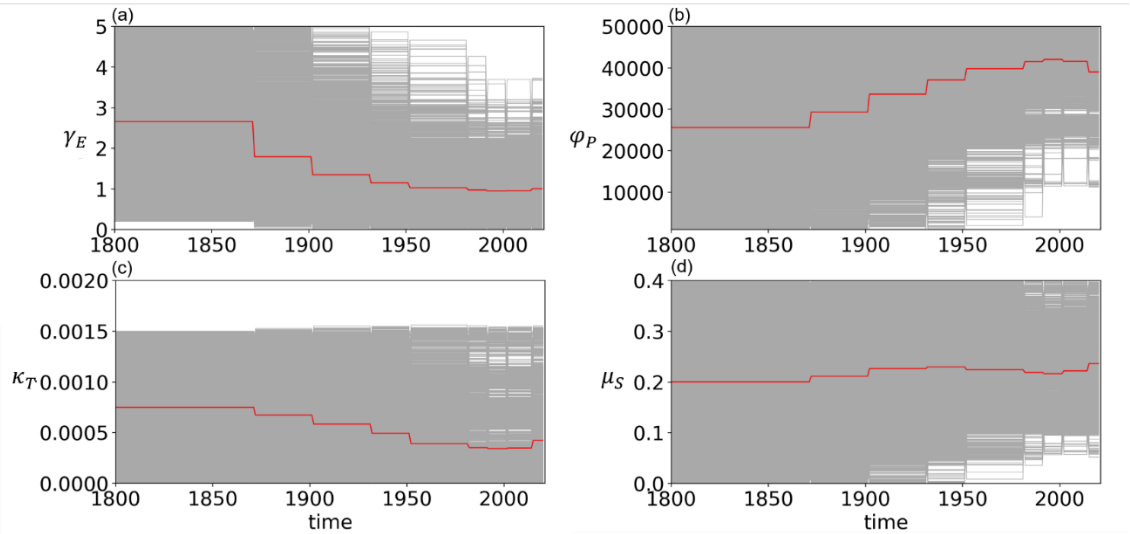

Figure S9. Same as Figure S8 but only real data of G are assimilated.

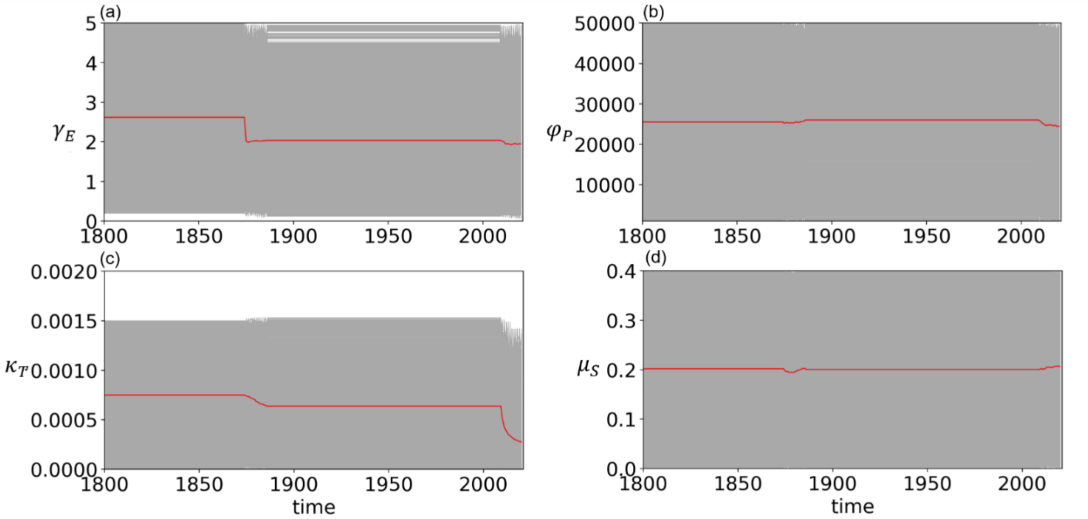

Figure S10. Same as Figure S8 but only real data of H are assimilated."

(2.3) Section 4.3, the discussion about the experiment 3 results is too general. The study could include more temporally changing variables in experiment 3 (the cost of levee raising, the rate of new properties, and the decay rate of levees), since they are all changing with time in reality.

→ Thank you for this comment. We could include more temporally changing parameters as the referee indicated. In the revised version of the paper, we have included the rate by which new properties can be built, φ_P, as a time-variant parameter. We have modified the manuscript as follows:

"Specifically, the rate by which new properties can be built, φ_P, and the memory loss rate, μ_S, were temporally varied in the experiment 3:

$$\varphi_P(t) = \begin{cases} 5000\ (t < 250) \\ 5000 + (t - 250) \times \frac{40000-5000}{500}\ (250 \le t < 750) \\ 40000\ (750 \le t) \end{cases} \quad (24)$$

$$\mu_S(t) = \begin{cases} 0.01\ (t < 250) \\ 0.01 + (t - 250) \times \frac{0.10-0.01}{500}\ (250 \le t < 750) \\ 0.10\ (750 \le t) \end{cases} \quad (25)$$

In the data assimilation experiment, we assumed that the dynamics of φ_P and μ_S was unknown, and we integrated the flood risk model with time-invariant φ_P and μ_S."

"In addition to the experiment 2, two of the unknown parameters (φ_P and μ_S) temporally vary in the synthetic truth of the experiment 3. We found that a larger spread of φ_P is required to stably track the time-variant synthetic true φ_P so that we increased s_0 in equation (18) from 0.05 to 0.5 only for φ_P in this experiment 3. Figure 10 and Table 4 indicate that despite the error in the model's description, our SIRPF can greatly improve the simulation of the flood risk model.

Please note that the synthetic truth shown in Figure 10 is different from that of the previous experiments especially for D and M. Figures 11b and 11d indicate that we can accurately estimate the time-variant parameters (φ_P and μ_S) as well as the other time-invariant parameters (Figures 11a and 11c). This result is promising since we cannot expect the perfect description of the socio-hydrologic model in the real-world applications. We also performed the sensitivity test on observation types, observation intervals, and ensemble sizes, which results in the same conclusions as the experiment 2 (not shown)."

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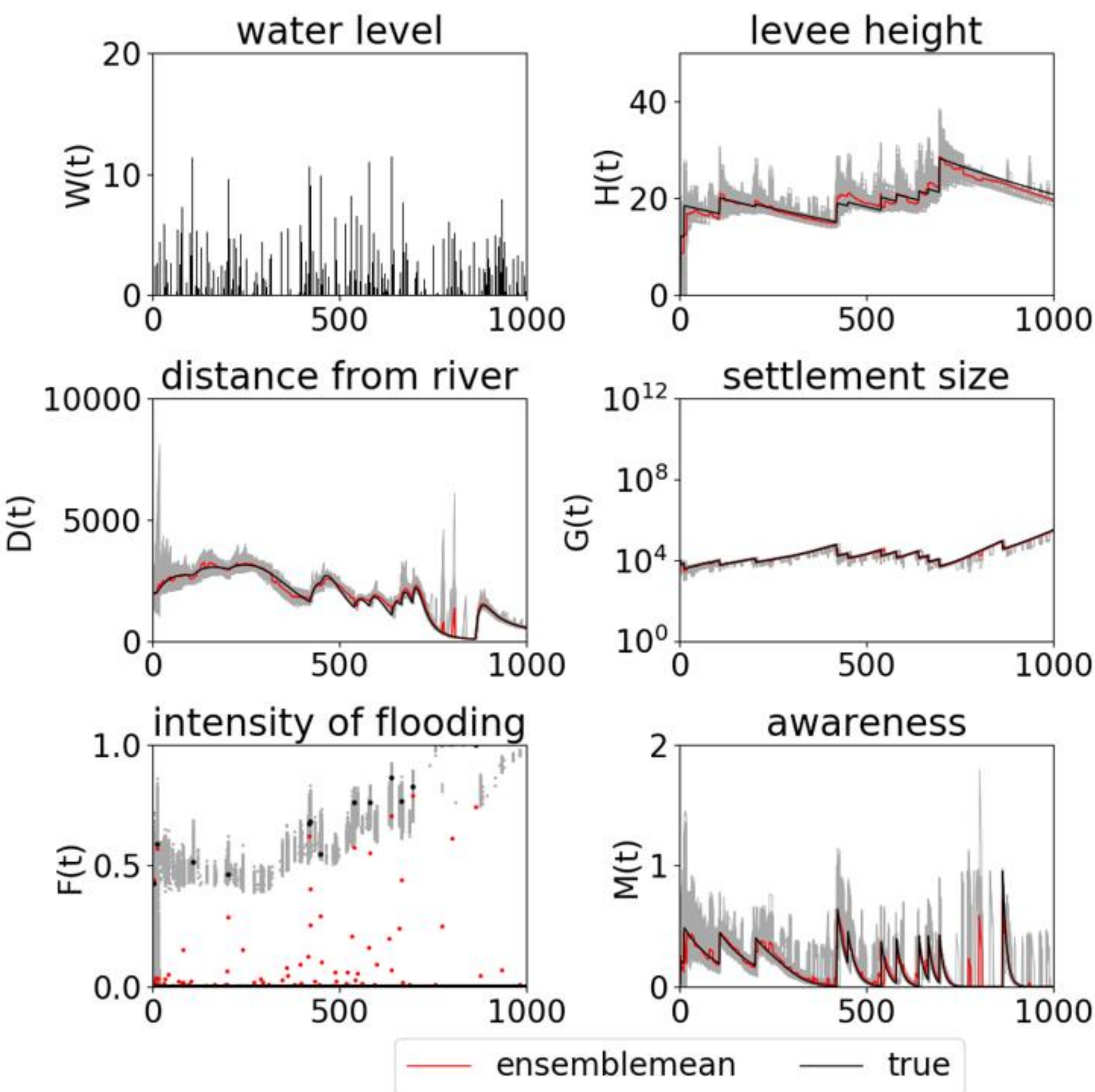

Figure 10. Timeseries of (a) high water level W(t), (b) the flood protection level (or levee height) H(t), (c) the distance of the center of mass of the human settlement from the river D(t), (d) the

size of the human settlement G(t), (e) the intensity of flooding events F(t), and (f) the social awareness of the flood risk M(t) simulated by the data assimilation experiment in which the observations of F, G, D, H, and M are assimilated into the model every 10 years with 5000 ensembles in the experiment 3 (see section 3.1.3). The time step is annual. Grey, red, and black lines are the ensemble members, their mean, and the synthetic truth, respectively.

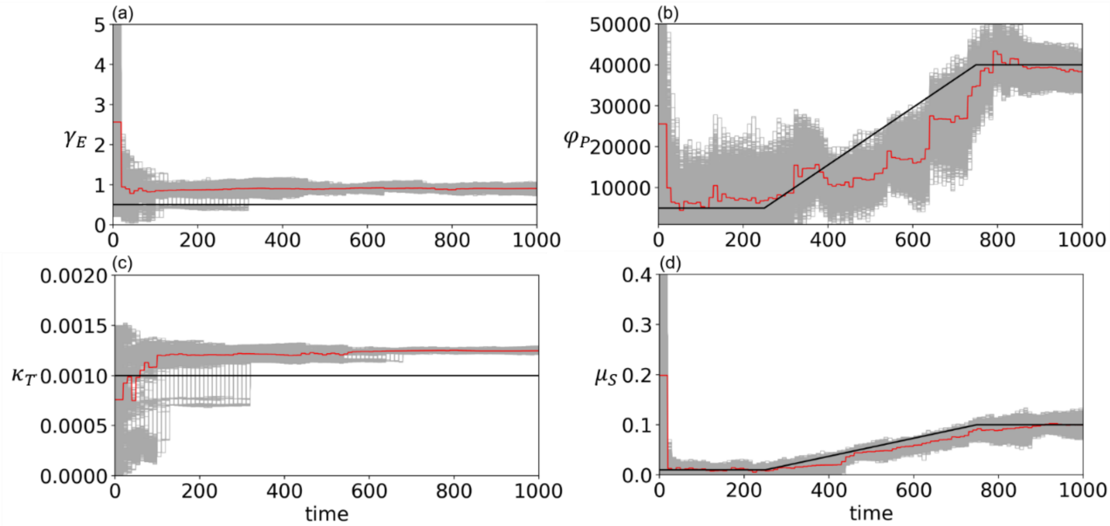

Figure 11. Timeseries of (a) the cost of levee raising γ_E, (b) the rate by which new properties can be built φ_P, (c) the rate of decay of levees κ_T, (d) memory loss rate μ_S estimated by the data assimilation of all observations (F, G, D, H, and M) with 5000 ensembles every 10 years in the experiment 3 (see section 3.1.3). The time step is annual. Grey, red, and black lines are the ensemble members, their mean, and the synthetic truth, respectively."

The other two parameters, the cost of levee raising and the decay rate of levees, were still kept constant in the synthetic truth. This is because the temporal change in these two parameters has small impacts on the state variables, which make it difficult to sequentially estimate the temporal change of the parameters. The cost of levee raising mainly affects the state variables in the early stage of the simulation and the change in the decay rate of levees has much smaller impacts than the uncertainty of high water level. This point was indeed unclear in the original version of the paper although it should be mentioned as the limitation. In the revised version of the paper, we have included this point as follows:

"The cost of levee raising γ_E affects the state variables of the flood risk model mainly in the initial early years and the gradual change of the rate of decay of levees κ_T has few impacts on the state variables. Therefore, we found that it is difficult to track the temporal change of these two parameters."

As we discuss in the response to the comment from the referee #1 (comment (1.3)), the problem setting of the parameter estimation strongly depends on the case and purpose of the study. We believe that our current problem setting is one of the reasonable examples without the significant loss of generality. The referee mentioned that all parameters may be time-variant. Although we can agree with it, if all parameters of the model can be time-variant, the model provides no reasonable constraints of the trajectory of the state variables. In this case, we doubt that it is beneficial to use the model to analyze the socio-hydrologic phenomena. Therefore, we believe that it is reasonable to assume some of the parameters are known and only a few parameters are time-variant. Please also see the discussion with the referee #1 attached below.

(1.3) 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.

→ The referee mentioned that only 1 parameter were considered in the third experiments. Please note that we actually considered all 4 parameters and one of the 4 parameters were assumed to be time-variant. As the response to the comment from the referee #2, we will include one more parameter as time-variant parameters in the revised version of the paper, if we are allowed to revise. Please see our response to the comment (2.3) of the referee #2.

We believe that the selection of the targeted parameters in socio-hydrologic data assimilation will depend on the case and purpose of the study. The problem setting adopted in this study can be recognized as one of the reasonable examples without the significant loss of generality. Here we explain how to select those parameters as a reasonable example of socio-hydrologic data assimilation. First, it is unlikely that the parameters related to F in equation (1) are much more inaccurate than the other parameters. They are mainly determined by the topography and we believe the process described in equation (1) can be replaced by the more accurate hydrodynamic models. Second, we selected four unknown parameters one by one from four equations of economy, politics, technology, and social to discuss how each state variable's observation affects the parameter space. Third, our 4 unknown parameters, their initial uncertainties, and the uncertainty in the high water level make our problem difficult enough to demonstrate the potential of data assimilation in the socio-hydrologic domain. Figure 5 indicates that we can get no useful information of the socio-hydrologic processes with this specified uncertainty. Although the referee may think that the number of unknown parameters is too small, we believe that our problem gives enough uncertainty to demonstrate the potential of data assimilation. Fourth, we successfully applied this setting to the real-world case in the city of Rome so that our specified initial uncertainty is reasonably good. We have added some sentences to explain this point in the revised version of the paper.

> "We selected these unknown parameters one by one from four equations of economy, politics, technology, and social to discuss how each state variable's observation affects the estimation of parameters across these four equations (see section 2.1). We have no unknown parameters related to F (equation (1)) since it is unlikely that the parameters in equation (1) are much more inaccurate than the other parameters. The parameters related to flood are mainly determined by the topography of the flood plain so that the process described in equation (1) can be replaced by more accurate hydrodynamic models in the real-world case study. The initial parameter variables were assumed to be distributed in the bounded uniform distributions whose ranges were found in Table 1. The uncertainty of the simulation induced by these parameters' uncertainty is large enough to demonstrate the potential of data assimilation to minimize the simulation's uncertainty (see Results)."

The referee suggested to changing the structure of the paper in the latter part of this comment. We would like to keep the structure of the original paper because in the current structure, the problem setting gets harder and approaches to the real-world problem (and eventually arrive at the real-data experiment). We believe that the referee's concerns have been addressed by out responses to the comments. Please see our responses to the comments (1.1) (real-data experiment), (1.2) (observation error) and (1.4) (temporally uneven observation). We believe the change in the structure of the paper is not absolutely necessary to meet the referee's requirements. We have decided not to change this aspect of the paper.