Response to the second round comments of the second reviewer (RC2) on the paper: "*Integrated hydrodynamic and machine learning models for compound flooding prediction in a data-scarce estuarine delta*"

We want to thank again the reviewer2 for taking the time to re-review our paper. Their comment has been beneficial and helped us to improve the article. In what follows, the reviewer's comments are presented in italic type and my response in roman type.

General Comments

The authors should include a limitation section/subsection highlighting all the potential errors that the authors faced when developing this model so that other research may build upon this. Currently, the model's limitations are all over the manuscript, but it will benefit the reader if they are all summarized in a section. For example, the following are some limitations collected through the manuscript

• The authors assumed that channel runoff volume would not affect the hydrodynamics of the river due to its small volume compared to the riverine volume.

• The authors assume that within 10 months, all the possible compound flood scenarios occurred.

• Lack of drainage system in the hydrodynamic model for the urban region of the domain.

• The accuracy of the machine learning model depends on the accuracy of the hydrodynamic model.

Response:

The suggestion has been followed. We added the following subsection in the manuscript:

2.6. Model limitations

During the development process, we encountered potential errors that could be highlighted as model limitations. Firstly, we assumed that channel runoff volume would not affect the hydrodynamics of the river due to its small volume compared to the riverine volume. The average daily discharge of the Kapuas River and the Landak River during the simulation is about 4,137 m3/s and 406 m3/s. At the same time, the total daily runoff of all channels which enter the hydrodynamic model domain in the KRD is about 32 m^3/s. The runoff contributes only about 0.7% of the total inlets in the hydrodynamic simulations; therefore, we assumed it is insignificant.

Secondly, we assumed that all the possible compound flood scenarios would occur within ten months. Since we already set some extreme values in the predictor parameters during the time, we assumed that all possible causes that drive compound flooding in the domain are represented. However, this assumption may not be accurate.

Next, we only imposed the runoffs as inlets on the river banks in the hydrodynamic model domain. Hence, the model did not capture the hydrodynamic processes in the channels within the city. It means that the inundation processes in Pontianak were still not well represented. The model still lacks drainage systems for the urban region.

Moreover, the accuracy of the machine learning model depends on the hydrodynamic model's accuracy. The more accurate the hydrodynamic model in predicting observational floods, the better the machine learning model will perform. Therefore, we need to tune the hydrodynamic model as accurately as possible.

Furthermore, since the rainfall impact on river water level is minor compared to other parameters, the model could not optimally capture urban flooding due to excessive rainfall. Based on the field observation, the city is shortly inundated if rain falls excessively for a few hours. This inundation could be due to the poor quality of the urban drainage system. Unfortunately, this phenomenon is not directly captured by the water level observation located within the river. The increase in the river water level due to the heavy rain is minor.

Lastly, the model relies on the predicted input parameters such as weather parameters and river discharges to predict the future water level. Consequently, the more biased the predictors, the higher the uncertainty in the water-level prediction. Therefore, observational data as input parameters are needed to reduce the uncertainty and create a more robust model. "

Specific Comments

"A new paradigm that combines deterministic and machine learning components has been proposed and implemented to tackle data and computational limitations in environmental modeling (Krasnopolsky and Fox-Rabinovitz, 2006; Goldstein and Coco, 2015). However, to the best of our knowledge, no previous modeling frameworks have developed a deterministic model to train a machine learning model for compound flooding studies. As a common practice, compound flood modeling typically uses the coupling of two or more hydrodynamic, hydraulic, or hydrological models (Hsiao et al., 2021; Santiago-Collazo et al., 2021; Ikeuchi et al., 2017). The coupling could be one-way, two-way, or dynamic coupling. Another approach is deep learning and data fusion (Muñoz et al., 2021), and data assimilation (Muñoz et al., 2022)."

What type of environmental modeling did the authors refer to? There are many examples, such as subsurface flow, pollutant transport, etc. Please give examples within the same sentence.

Response:

The suggestion has been followed. We edited and added examples within the sentence become:

"A new paradigm that combines deterministic and machine learning components has been proposed to tackle data and computational limitations in environmental modeling, such as hybrid climate models (Krasnopolsky and Fox-Rabinovitz, 2006) and an ML model for 2D surface water catchment problems (Maxwell et al., 2021)."

2.3 Hydrodynamic model setup and calibration

In how many locations did the authors impose the runoff in the model? It only refers to "some channels entering the domain", but it is important to specify the amount as a minimum and preferably show their locations on a map.

Response:

The suggestion has been followed. We showed the locations in Figure 4 (Just added to the manuscript). Then, we added the information in the sentence.

"We also imposed runoff, obtained by converting rainfall over the Kapuas Kecil River catchment area as an inlet water flux at 15 channels entering the domain (Fig. 4)."

The value of 0.32 given in parenthesis when talking about the correlation between the SWAT model and the observation is unclear. Is this 0.32 referring to r-squared value, RMSE, etc.? Be more specific in the manuscript text.

Response:

The value of 0.32 referred to the Pearson correlation coefficient (*r*). Therefore, we edited the sentence become:

"Unfortunately, during the tuning of the SWAT+ model, the correlation between the model's output (runoff) and the observation data is still low (Pearson correlation coefficient = 0.32)."

The location of the upstream riverine boundary condition is missing details. For example, how far away was this boundary from the coast? In any compound flood model, the upstream riverine boundary condition should be inland enough that any water level variation due to tides is negligible. Thus, only riverine forces are the ones driving the flow downstream. The authors should mention in the manuscript text that the distance from these locations' coasts is minimal.

Response:

The suggestion has been followed. We added detailed information about discharges by inserting the below sentences (blue text) in the second paragraph of subsection 2.3:

"The hydrodynamic model simulation is forced by wind and atmospheric pressure from ECMWF (Hersbach et al., 2020), and tides from TPXO (Egbert and Erofeeva, 2002). As upstream boundary conditions, we imposed discharge from the Kapuas River and the Landak River. The discharge data were retrieved from the Global Flood Monitoring System (GFMS) (Wu et al., 2014) at about 70 km and 40 km from the river mouth (Fig. 4). Since the GFMS calculates the flow using Integrated Multi-Satellite Retrievals for GPM (IMERG) precipitation information as input, the coastal processes do not affect the model output (predicted river flow)."

The authors claim that the channel runoff volume is much less than the river discharge. How much less is it? It needs to be quantified in the manuscript.

Response:

The suggestion has been followed. We described the comparison between total daily runoffs and discharges in the new subsection (2.6 Model limitations) as follows:

"The average daily discharge of the Kapuas River and the Landak River during the simulation is about 4,137 m3/s and 406 m3/s. At the same time, the total daily runoff of all channels which enter the hydrodynamic model domain in the KRD is about 32 m3/s. The runoff contributes only about 0.7% of the total inlets in the hydrodynamic simulations; therefore, we assumed it is insignificant."

RMSE and NSE acronyms are not defined before their appearance in this new subsection. I strongly recommend the authors create a small subsection describing the performance criteria used to verify the model. In this way, the authors could properly define each metric (e.g., NSE, R2, RMSE), including the equations used.

Response:

The suggestion has been followed. We created a new subsection to describe the performance criteria which used (2.3. Metrics for model performance evaluation).

The authors mentioned that they sampled 6,000 points from their predicted water levels but did not mention how it was sampled. Did the authors use a random sampling technique or a probabilistic distribution to select these 6,000 points? Please specify this in the manuscript text.

Response:

We use a random sampling technique to obtain the sampled points. We added this additional information within the associated sentence in the manuscript (blue text):

"Then, we selected 6,000 sample points of the predicted water levels at Pontianak with their associated input dataset using a random sampling technique."

Add the proper citation to reference the GFMS rather than the URL in the text.

Response:

The suggestion has been followed. We added citation for GFMS.

Response to comments on Line 92-93

The authors should include the response to the reviewer in the manuscript text with respect to the coupling details between SWAT and SLIM

Response:

The suggestion has been followed. We inserted the below sentences (blue text) in the paragraph:

"We also imposed runoff, obtained by converting rainfall over the Kapuas Kecil River catchment area as an inlet water flux at some channels entering the domain. The runoff of every channel was calculated from rainfall data using SWAT+ (Bieger et al., 2017), which considered the pressure, the humidity, and other weather parameter input. Here, we use one-way coupling, where the SWAT+ model runs first and independently. The SWAT+ model only produces the flow of channels that enter the river stream within the KRD. Then, we used these channel outlets as boundary conditions for the SLIM model. Unfortunately, during the tuning of the SWAT model, the correlation between the model's output (runoff) and the observation data is still low (NSE = 0.32). However, we decided to use the output as the channels' inlet boundary condition in the hydrodynamic model because the channel runoff volume is much less than the river discharge. Therefore, we assumed that it does not significantly affect the hydrodynamics of the river."

Response to comments on Line 93-95

The authors should include the figure in response to the reviewer on the manuscript since it gives a better perspective of the hydrologic processes in the study area.

Response:

The suggestion has been followed. We included the below figure in the manuscript.

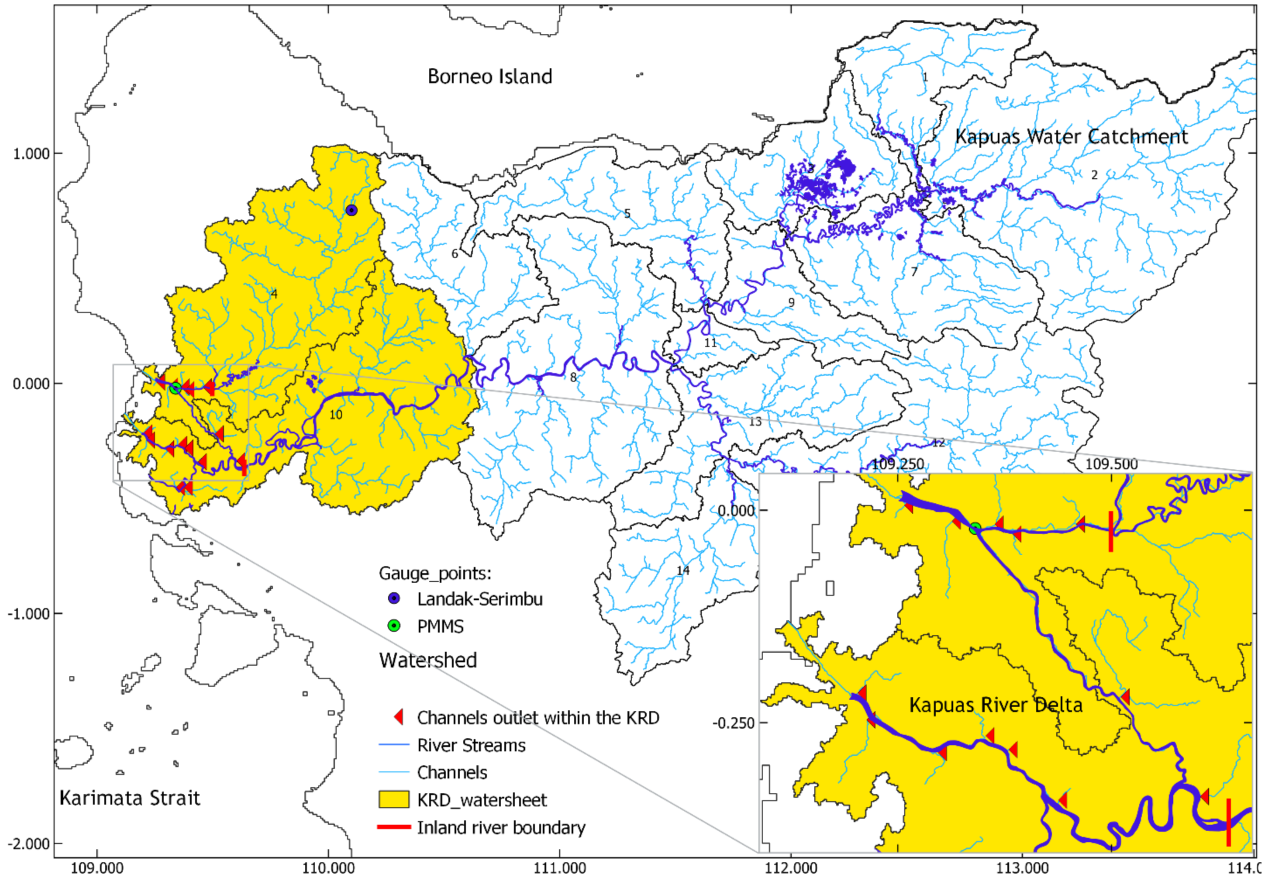

Figure 4: The Kapuas River watershed and its sub-basins. Since the discharges of the Kapuas River are retrieved at the middle stream, only two sub-basins are considered for the SWAT+ model (yellow area). The runoffs (channel outlets of the SWAT+ model that enter the river stream within the KRD) are set as inlets for the hydrodynamic model domain.

References

Bieger, K., Arnold, J. G., Rathjens, H., White, M. J., Bosch, D. D., Allen, P. M., Volk, M., and Srinivasan, R.: Introduction to SWAT+, a Completely Restructured Version of the Soil and Water Assessment Tool, J. Am. Water Resour. Assoc., 53, 115–130, https://doi.org/10.1111/1752-1688.12482, 2017.

Egbert, G. D. and Erofeeva, S. Y.: Efficient inverse modeling of barotropic ocean tides, J. Atmos. Ocean. Technol., 19, 183–204, 2002.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.: The ERA5 global reanalysis, Q. J. R. Meteorol. Soc., 146, 1999–2049, https://doi.org/10.1002/qj.3803, 2020.

Krasnopolsky, V. M. and Fox-Rabinovitz, M. S.: A new synergetic paradigm in environmental numerical modeling: Hybrid models combining deterministic and machine learning components, Ecol. Modell., 191, 5–18, https://doi.org/10.1016/J.ECOLMODEL.2005.08.009, 2006.

Maxwell, R. M., Condon, L. E., and Melchior, P.: A Physics-Informed, Machine Learning Emulator of a 2D Surface Water Model: What Temporal Networks and Simulation-Based Inference Can Help Us Learn about Hydrologic Processes, Water 2021, Vol. 13, Page 3633, 13, 3633, https://doi.org/10.3390/W13243633, 2021.

Wu, H., Adler, R. F., Tian, Y., Huffman, G. J., Li, H., and Wang, J.: Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model, Water Resour. Res., 50, 2693–2717, https://doi.org/10.1002/2013WR014710, 2014.