Summary

This study combines hydrodynamic modeling and machine learning techniques to predict water level in the Kecil-Kapuas River, Indonesia. The authors run 6000 hydrodynamic simulations of synthetic events and create a dataset of model outputs to train multilinear regression, random forest, and support vector machine algorithms. The trained algorithms are then used to predict water level for combinations of riverine, oceanic, and atmospheric forcing. The proposed scheme is validated against three historical flood events observed in Pontianak and suggests that random forest is the most suitable algorithm for predicting compound flooding.

General comments

This study develops a scheme to integrate physically-based and data-driven approaches as proposed in similar studies with either conventional machine learning algorithms (Hosseiny et al., 2020; French et al., 2017; Kabir et al., 2020b) or more advanced deep learning techniques (Kabir et al., 2020a; Muñoz et al., 2021). Yet, the scheme has critical technical flaws and is not well-aligned with the main goal of this study that consists of reducing computation burden for water level prediction in data-scarce regions. At this point, I believe that the manuscript requires major improvements to be considered for publication. Nevertheless, please find below a list of suggestions that can help improve the proposed scheme as well as my concerns that should be addressed and/or clarified.

Specific comments

Title: ‘compound flooding prediction’ certainly draws the reader’s attention, but unfortunately there is no formal analysis in this study suggesting that Pontianak experienced such compound events in the past. Although the introduction elaborates on the mechanisms triggering compound flooding, the authors should conduct preliminary process-based or statistical analyses to confirm this. See for example the works of Kumbier et al., (2018), Valle-Levinson (2020), Ward et al., (2018), Ghanbari et al., (2021) among others.

Abstract: ‘Compound flood’ scenarios should be derived from preliminary statistical analysis that account for the dependence among flood drivers. See for example Serafin et al., (2019), Moftakhari et al., (2019), etc. The abstract should be revised to clearly report the findings of this study. Random forest is used to predict water levels only, yet ‘flooding hazards’ and ‘compound flooding’ are mentioned repeatedly without presenting any flood maps in Pontianak. A very preliminary assessment could be achieved by projecting water level to adjacent areas of the Kapuas-Kecil River in case 2D flood modeling is computationally demanding.

Introduction: Literature review falls short in content and cohesion. The introduction should mention the state-of-the-art techniques for compound flood hazard modeling and assessment. (Bevacqua et al., 2019; Couasnon et al., 2020; Ye et al., 2021; Muñoz et al., 2022).

Material and methods: This section is of major concern since the methodology presented in this study is not technically sound. I agree that developed countries might face challenges to implement hydrodynamic models due to data scarcity and computational resource limitations. Nevertheless, assuming that those countries develop such a model and want to implement the proposed scheme.

Are 6000 simulations really necessary to train machine learning algorithms? Would not it be better to wisely sample a small set of realistic forcing conditions that effectively lead to compound flooding? Although machine learning is a ‘data-hungry’ technique, I consider thousand of hydrodynamic simulations a bit exaggerated. I suggest the authors train the models with a small sample size (e.g., hundred of simulations) and report the results. This can help reduce computation time associated with hydrodynamic simulations. How long does it take to run the 2D-model of the Kapuas-Kecil in a regular desktop computer?

Section 2.2: There is no information regarding model calibration. This is critical as the authors rely on hydrodynamic simulations to train the machine learning algorithms. Referring to a pre-print/unpublished work (Sampurno et al., 2021) for additional details of the model is not acceptable. Please describe the model calibration process in detail.

Section 2.4. Another point of major concern is the calibration of machine learning algorithms. It is no clear whether the authors tuned random forest and support vector machine in the training phase or not. In that regard, the training dataset (e.g., 6000 model outputs with the associated input variables) should have been split into training/validation datasets to conduct hyperparameter tuning and so prevent overfitting issues. Using all model outputs to train the algorithms (as reported here) and relying on default parameter-values is not a wise use of machine learning (e.g., Random requires tuning of the number of trees, sample leaf, sample split, etc.). The authors should conduct a thorough ‘hyperparameter’ tuning as it substantially improves the performance of machine learning algorithms.

Results. “Even though all algorithms perform very well during the training phase, the performances are different during the testing phases”. This is known as overfitting (Ying, 2019) and occurs because random forest and support vector machine are not calibrated/tuned in the training phase.

<u>Technical corrections</u>

L10 and thorough the text: There are odd terms that should be corrected like hydrodynamic modeling instead of ‘water level modeling’.

L28: What is the growth rate in the last decade?

L38: Please elaborate more on non-structural measures. This sentence is not clear.

L40: Which issue? Please explain clearly.

L45-47: ‘Machine learning can enable us…’ How? Please, elaborate more on this. More references are needed discussing the benefits of machine learning for water level prediction and/or flood forecasts.

L96: Please locate Pontianak in Figure 2.

L97: Section 2.3 is very short (4 lines) and should be included in the previous section.

L65: More details of the study area are needed. What is the catchment size, average river flow, tidal regime, rate of local sea level rise at the Kapuas River?

L115: I suggest a more robust statistical analysis to evaluate multicollinearity among the variables (e.g., Variance Inflation Ratio (VIF), see Alipour (2020)). Multicollinearity negatively affects the performance of support vector machine and multilinear regression models. VIF can help reduce the number of predictors.

L155-156: NSE and RMSE might improve after a thorough hyperparameter tuning of the machine learning algorithms.

L158: There are no such inundation scenarios (no flood maps). This should be clarified and better replaced for water level scenarios.

Table 1. What are the criteria to come up with those range of values?

Figure 2. Scale bar and north arrow are missing.

Figure 6. Comparison of predicted and 'simulated' hourly water levels of training data. There are no observed water levels in the training phase.

Figure 8. X-axis is not observation but hydrodynamic simulation.

L295. There are references not included in the main text. See for example Rozum et al., 2020.

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