

Hydrol. Earth Syst. Sci. Discuss., referee comment RC2
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Comment on hess-2021-596

Anonymous Referee #2

Referee comment on "A deep learning technique-based data-driven model for accurate and rapid flood predictions in temporal and spatial dimensions" by Qianqian Zhou et al., Hydrol. Earth Syst. Sci. Discuss., <https://doi.org/10.5194/hess-2021-596-RC2>, 2022

The author used the rainfall as the input to generate simulated flood inundation maps. The paper is well organized, and the LSTM model and Bayesian optimization method appears to be correct and effective. However, there are three major issues. First, the summary of the earlier work needed improvement. There are many related papers using data-driven approach to generate flood maps, however the authors do not include them in the introduction. Second, a research may be regarded as a novel study if it resolves a problem or constraint in earlier studies. However, the LSTM is a new neural network layer that can perform better than ANN or linear regression models, and this manuscript does not appear to have demonstrated its novelty. Lastly, this manuscript lacked baseline models and results, which prevented me from knowing how much better the LSTM model is than a simple average baseline, linear regression model, or an ANN model.

Details:

1. Method section 2.2. If my understand is correct, all the flood maps are simulated by your physically-based model. Thus, you are developing a deep learning model as a surrogate model of your Mike series models. Such studies have been studied in the past several years using Deep Learning models (see the following papers). If the main difference between your study and theirs is the use of LSTM other than a fully connect layer, this is not novel enough.

Berkhahn, S., Fuchs, L., & Neuweiler, I. (2019). An ensemble neural network model for real-time prediction of urban floods. *Journal of hydrology*, 575, 743-754.

Lin, Q., Leandro, J., Wu, W., Bholá, P., & Disse, M. (2020). Prediction of maximum flood inundation extents with resilient backpropagation neural network: case study of

Kulmbach. *Frontiers in Earth Science*, 8, 332.

2. What is the color in Figure 6a represents? Can you provide more details about this figure? It seems like the increase of the number of optimizations does not decrease the error much.

3. Are your figures 9 and 10 captions correct? And, is your legend correct for Figure 10? The base color Cyan should represents 0 on your Y-axis, but the legend shows it is 0.5 relative error.

4. Can you provide results from several baseline models to justify your model performance is good? Some sample baselines could be: 1, models such as ANN as Berkhahn, S., Fuchs, L., & Neuweiler, I. (2019) did (deep learning model using only FC layers other than LSTM). 2, a Lasso or Ridge Regression (or machine learning models) for each point with the overall rainfall as input, water depth as output. 3, an average/median flood map of the training dataset (a.k.a. simple average, see the link below). Without these baselines, your results in Figure 8a and 8b cannot prove much -- we know your model is good, but we don't know how good your model comparing to other simple linear models or simple average of training sets.

<https://otexts.com/fpp2/simple-methods.html>