

Reply on RC1

Roberto Bentivoglio et al.

Author comment on "Deep Learning Methods for Flood Mapping: A Review of Existing Applications and Future Research Directions" by Roberto Bentivoglio et al., Hydrol. Earth Syst. Sci. Discuss., <https://doi.org/10.5194/hess-2021-614-AC1>, 2022

Reply to anonymous Reviewer #1

We thank the Reviewer for reading our paper and providing comments for its improvement. Here we provide answers to the issues raised along with details on the amendments to the original manuscript to be featured in the revision. Unless otherwise specified, reported line numbers refer to the updated version.

It was difficult to see the justification for the need of this research. The literature review is poor. The paper needs to clearly state what are the problems with the existing works (these types of approaches) and what problem(s) this particularly paper was going to address. Without this clearly problem statement readers would have difficulty to see the merit of this paper. The author only lists some references, I did not find the problem with the exist method. The problem of the existing method is not clear. The author should show us deep analysis about the gap between existing method.

We have restated the justification of this research in the introduction (lines 61-65): "The existing reviews mainly focused on the temporal variability of floods, especially concerning rainfall-runoff modeling, covering only a few instances of flood mapping applications. But the spatial evolution of flood events is extremely important to determine affected areas, plan mitigation measures and inform response strategies. Yet, there are no comprehensive overviews and analyses of DL in flood mapping to facilitate flood researchers and practitioners. The aim of this review is thus to advance the emerging field of DL-based flood mapping by surveying the state-of-the-art, identifying outstanding research gaps, and proposing fruitful research directions."

We report some problems with the existing methods throughout Section 3, and we dedicated Section 4 "Knowledge gaps" to summarise those we believe are the major ones, common to all reviewed papers. In particular, we highlight:

- The lack of "general" DL models that can work across multiple case scenarios. Our review shows that models are usually deployed for single case studies, which greatly limits their applicability.
- Existing DL models are not suitable for modelling complex interactions with the natural and built environments; this hinders their operational use for all types of applications.
- The focus so far has been only on developing deterministic models, while flood management requires accounting for uncertainties in outcomes and probabilistic

predictions.

- Further efforts should be directed in developing DL models for flood risk or real-time flood warning applications or tackling problems related to data availability.

We argue that the community should address these problems by transferring recent fundamental advancements in DL to flood mapping. These advancements mainly include mesh-based neural networks, such as Graph Neural Networks and Fourier Neural Operators, as well as Probabilistic Deep Learning. The future research directions in Section 5 of the paper substantiate these suggestions and provide insights on how to apply these methods to improve flood mapping.

While we believe that the paper's justification and contributions are sufficiently clear, we tried our best to improve it during the revision process. As suggested by the Reviewer, we modified the manuscript to further clarify its merits and purpose.

2i¼ □ A Review of flood mapping or Deep Learning? This is confused for me.

As stated in the title of the paper, this review concerns deep learning methods for flood mapping. We evaluate the efforts of the community concerning the design and implementation of deep learning methods for flood mapping. Therefore, the manuscript explores the intersection between these two areas, as stated in lines 66-69 of the original manuscript: "45 papers are analysed considering two main parallel yet intertwined directions. On the one hand, we focused on the flood management application, spatial scale of study, and type of flood. On the other hand, we examined the deep learning model, type of training data, and performance with respect to alternative methods. This strategy provides insights from a flood management perspective and concurrently facilitates reflection on how to successfully apply DL models."

3) The flowchart of the method should be insert.

We thank the Reviewer for the suggestion. We have now added a flow chart (Fig. 3) to explain our methodology better.

4) There were very few discussions of previous studies.

Thank you for raising this point. While some specific discussions on individual studies have been included throughout Section 3, we opted for a concise, yet meaningful, contribution of the reviewed papers to respect also the length limitations. Common to successful review papers of the field (e.g., Maier, 2013), we preferred to report observations that are valid across multiple studies, especially when outlining the knowledge gaps and proposing future research directions. That said, as suggested by the reviewer, we included further insights from individual studies throughout Section 3 of our paper to enrich the overall narrative.

Here follow some examples we included in the revised manuscript:

Lines 434-437 "Most CNN models show noticeable improvements with respect to traditional threshold methods, such as the Normalized Difference Water Index (NDWI) and

automatic threshold model (ATM) (e.g., Wieland and Martinis, 2019; Isikdogan et al., 2017; Nemni et al., 2020), and with respect to machine learning models such as random forest (RF) and support vector machine (SVM)."

Lines 461-464 "However, Wang et al. (2020b) and Liu et al. (2021) show that 1D-CNNs, which perform convolution on the input features for each domain's cell, are not suited for this problem, as they do not properly leverage any inductive bias. Some works showed that deep belief networks (DBN), an unsupervised variation of MLPs, could outperform standard MLPs in flood susceptibility mapping (e.g., Shirzadi et al., 2020; Pham et al., 2021)."

Lines 516-517 "Hu et al. (2019) and Jacquier et al. (2021) use a LSTM and a MLP, respectively, in combination with a reduced order modelling framework."

Other comment:

Figure: The resolution of figure should be improved.

Thanks for the suggestion. We improved the font sizes and resolutions of all figures.

Reference

There are a lot of latest article should be updated.

We thank the Reviewer for pointing out this very important detail. By refining the search procedure described in Section 3.1, we retrieved 13 more very recent papers which are now included in the review. The complete list of added papers is shown in the references below.

References:

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Added references:

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Syifa, M., Park, S. J., Achmad, A. R., Lee, C.-W., and Eom, J.: Flood mapping using remote sensing imagery and artificial intelligence techniques: a case study in Brumadinho, Brazil, *Journal of Coastal Research*, 90, 197–204, 2019.

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Yokoya, N., Yamanoi, K., He, W., Baier, G., Adriano, B., Miura, H., and Oishi, S.: Breaking limits of remote sensing by deep learning from simulated data for flood and debris-flow mapping, *IEEE Transactions on Geoscience and Remote Sensing*, 2020.

Xie, S., Wu, W., Mooser, S., Wang, Q., Nathan, R., and Huang, Y.: Artificial neural network based hybrid modeling approach for flood inundation modeling, *Journal of Hydrology*, 592, 125–605, 2021.