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Reply on RC1

Alexander Y. Sun et al.

Author comment on "A graph neural network (GNN) approach to basin-scale river network learning: the role of physics-based connectivity and data fusion" by Alexander Y. Sun et al., Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2022-111-AC1, 2022

Reviewer 1 Comments

This work presents a multistage, physics-guided, graph neural network (GNNs) approach for basin-scale river network learning and stream forecasting. This approach is computationally less demanding than vector-based river network models. I am a hydraulic engineer with some expertise in the modelling of river reaches, including under flood conditions. I have accepted the invitation to review this paper in the hope to be able to provide constructive and useful comments and suggestions to the authors, and in the hope to expand my own knowledge base.

Reply: Thanks for the summary and we really appreciate the careful review and comments from Reviewer 1.

I have enjoyed reading the paper and I have understood the concept of the method, which I find very interesting. I have the impression that the authors master the theme and have made a worthwhile contribution. But I have to admit that I am not sufficiently familiar with the topic to make an authoritative assessment of the quality and originality of the contribution.

Reply: Thank you for the generous comments.

I hope that the following suggestions will be helpful to the authors:

The paper is very technical and probably not very appealing to non-experts in the field of neural network approaches. The authors may want to make an effort to make the paper more appealing to a broader readership.

Reply: We appreciate the comment. In preparing the manuscript, we endeavored to balance between the machine learning (ML) methodology contribution, scientific significance, and readability to elevate the manuscript to a publishable level. This is largely because a large body of peer-reviewed ML articles have already been published. We made multiple efforts to improve the readability of the manuscript, including:

- A general Introduction laying out the background and the need for spatiotemporal

streamflow modeling.

- Figure 1 provides a high-level diagram describing the workflow, including data formulation, training steps, and data fusion. For most readers, this diagram should be sufficient to understand the content and contribution of this work.
- A multi-stage Result section that demonstrates the performance of each stage corresponding to Figure 1.

The methodology part includes several equations to describe how the graph neural net (GNN) works, which may lower readability. However, we argue the level of mathematics and jargons used are comparable to a typical ML paper involving long short-term memory network (LSTM) or convolutional LSTM (Conv-LSTM). For example, both GNN and LSTM use the latent variable extensively to transfer information. In the revision, we carefully revised the Abstract and the text, wherever appropriate, to further ease the readability.

The authors highlight that a major advantage of the graph-neural-network approach over a vector-based river model is the much lower computational demand. I suggest substantiating/quantifying this lower computational demand.

Reply: Accept. The GNN framework presented in this manuscript embraces a "physics-based post-processing" approach, as described around L60-80 in the Introduction. Thus, there are two parts, the training part and the online operation part. The training part uses supervised learning, in which simulated data is required for the model to learn the behavior of the vector-based river model, where the prediction part uses past model outputs and meteorological forcing data to predict future streamflow. It is the latter part that we believe can significantly reduce the running time of vector based model. In the revision, we added the quantification of test time around L406, "The total running time is 5.4 sec wallclock time on the test data."

The model is only demonstrated for one relatively small snow-dominated watershed in the western US. Is this a sufficient basis for claiming general validity of the model in watersheds in other geographical settings.

Reply: Accept. During the revision, we tested the GNN framework on a much larger basin (20,000 km^2 vs. 1800 km^2) in the same Upper Colorado Basin. Results demonstrate that the performance of the GNN framework largely holds without much changes. We report the additional results in the newly added Section 6.

I suppose these suggestions amount for a moderate revision (something in between a minor and a major revision).