Cover Letter

Dear Editor and Reviewers

This is the resubmitted version of the revised manuscript entitled: An explainable deep learning model based on hydrological principles for flood simulation and forecasting (Manuscript No. EGUSPHERE-2025-279). The paper has been revised along the lines suggested by the reviewers. All the comments are addressed in the new version of our paper. We have added more explanations to the revised manuscript. The changed and added parts of the text (except some language correction) are marked in RED color for easy review.

It would be greatly appreciated if the revised version of the paper can be re-evaluated by the same reviewer who spent available time to provide constructive and professional comments and suggestions, which have led to improvement on the presentation and quality of the paper.

We sincerely hope you will find the revised version of the paper is to your satisfaction. We are, of course, more than happy to further improve the paper upon request.

In the following, we provide point to point response to the comments of the reviewers.

Yours sincerely,

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Response to Reviewers' comments

Legend

Reviewers' comments

Authors' responses

Direct quotes from the revised manuscript

The authors have satisfactorily addressed the comments raised in the previous review round. The manuscript is much improved. I have only a few minor points that require further clarification before the paper can be accepted for publication.

Response: We sincerely appreciate the reviewer's recognition of our revised manuscript. The paper has been improved according to the reviewer's specific comments in the revised version.

Specific Comments:

1. Training Strategy: The study applies the proposed EDL model to different basins. Could the authors please clarify the training strategy used? Specifically, were the model parameters trained jointly using data from all basins simultaneously, or was a separate model trained individually for each basin?

Response: Thank you for your comment. In our study, a separate model was trained for each basin for flood simulation and forecasting. The corresponding clarification has been added to the revised manuscript.

Lines 356-358: In our study, a separate model was trained for each basin for flood simulation and forecasting, whose parameters were directly updated using the standard end-to-end backpropagation approach.

2. Parameter Update Mechanism: The authors state that the parameters in the XAJRNN layer are updated via gradient descent and backpropagation. To be precise, are these parameters updated using a standard, end-to-end backpropagation approach directly? Or is the method more aligned with a differentiable parameter learning (dPL) paradigm, such as the one proposed by Tsai et al. (2021), which is cited in the manuscript?

This clarification is related to point 1. The concern is that if a single set of parameters is optimized via backpropagation for each basin individually, the result is essentially a 'local training' model, similar to traditional calibration. A key benefit of dPL-style approaches is the ability to train 'one model for all basins' (i.e., a regional or global model) by leveraging data from many catchments. Could the authors clarify if their framework is intended to or capable of supporting this more generalizable, multi-basin training approach?

Response: Thank you for your valuable suggestion. As mentioned in our revised manuscript, the model parameters are updated directly using the standard end-to-end backpropagation approach. In our study, a separate set of parameters was optimized for each basin through backpropagation, which essentially results in a "locally training" model, similar to traditional calibration. We have acknowledged this limitation in our study and discussed it. One key advantage of the differentiable parameter learning approach lies in its ability to leverage data from multiple basins to train a single model applicable to all basins (i.e., a regional or global model). Developing our framework to support this more generalizable multi-basin training approach will be an important direction for future research.

3. Conclusion Expansion: The conclusion section is concise. However, I would suggest the authors briefly and explicitly elaborate on the potential limitations of the current study (e.g., whether the current framework can leverage information from multiple basins as discussed in point 2, or if it is limited to single-basin calibration). Moreover, I recommend a slight expansion to touch upon the broader implications of this work or more specific future research directions that stem from the study's findings and its limitations.

Reference:

Tsai, W. P., Feng, D., Pan, M., Beck, H., Lawson, K., Yang, Y., Liu, J., and Shen, C.: From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling, Nat. Commun., 12, 5988, https://doi.org/10.1038/s41467-021-26107-z, 2021.

Response: Thank you for your suggestion. Following your advice, we have revised the Discussion section of the paper to discuss the limitations of this study and outline specific directions for future research, as shown below:

Lines 587-599: This study demonstrates that the proposed EDL model, which tightly integrates physical mechanisms with DL, can effectively improve the accuracy of flood simulation and forecasting. A limitation of the present work is that the model parameters were obtained separately for each basin. Consequently, the current implementation represents a locally trained model that is functionally similar to traditional calibration. Future research should therefore pursue two complementary directions to improve generality and adaptability. One is to develop multi-basin (regional or global) training strategies via differentiable parameter learning, transfer learning, or meta-learning, which can leverage data from many basins to produce a single, generalizable model. Another is to introduce mechanisms for dynamic, input-dependent parameter adaptation so that model parameters can evolve with temporal changes in inputs. Additional promising avenues include explicit uncertainty quantification, tighter coupling between physics and data-driven components, and online-updating for real-time forecasting. Pursuing these directions would increase the model applicability across diverse basins and enhance its potential for scientific discovery.