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 a benchmark model and more explanations to the revised manuscript, and modified some tables and figures. 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 submitted a revised version that addresses some, but not all, of the concerns raised in the initial review. The manuscript still lacks the critical analysis of LSTM correction mechanisms that was requested in the first review. This represents a gap in understanding how the proposed EDL model actually functions as a hybrid physics-ML system.

As indicated in Section 3.2.1, two benchmark models are presented: the LSTM model and the XAJ model. While the authors claim in lines 368-369 that " The purpose of this model is to demonstrate the contribution of the XAJRNN layer in the EDL model", a careful examination of the underlying logic reveals a fundamental flaw. Since the primary difference between the EDL model and the XAJ model lies in the LSTM component, comparing EDL against XAJ essentially analyzes the role of the LSTM layer, not the XAJRNN layer as claimed. Conversely, comparing EDL to LSTM would properly demonstrate the contribution of the XAJRNN component.

Moreover, this comparison framework requires first establishing whether XAJRNN outputs differ from XAJ outputs—something that could be verified by extracting and analyzing the Q values directly from the XAJRNN layer. Such analysis would reveal how the XAJRNN functions when combined with an LSTM post-processing layer and how it differs from the directly calibrated XAJ model. Additionally, this study could compare the EDL model with an offline post-processed approach (i.e., using XAJ model outputs as inputs to a separately trained LSTM). This comparison would help readers better understand the value of the online integration of XAJRNN with the post-processing LSTM module.

In summary, the central question is whether the proposed coupling between physical and ML components provides genuine synergistic benefits or merely represents a sophisticated form of post-processing. This distinction is crucial for understanding the true value of hybrid physics-ML models. Such analysis would elevate this work from a performance comparison to a deeper investigation of physics-ML coupling mechanisms and distinguish it from previous similar research.

Response: We sincerely thank the reviewer for the constructive comments and for highlighting the importance of analyzing the correction mechanism in hybrid physics–ML models. We agree that our previous revision did not sufficiently address this aspect, and we have carefully revised the manuscript to include a more detailed analysis.

We acknowledge the reviewer's observation that comparing EDL with XAJ primarily reflects the role of the LSTM layer, whereas comparing EDL with LSTM better illustrates the contribution of the XAJRNN. We have clarified this logic in the revised manuscript:

Lines 361-363: The first benchmark model is the ordinary XAJ model, which also takes areal mean rainfall and evaporation as input to illustrate the role of the XAJRNN layer in the EDL model.

Lines 372-373: The purpose of LSTM model is to compare the contribution of XAJRNN layer to the simulation performance in the EDL model.

Following the reviewer's suggestion, we have extracted the Q values from the XAJRNN layer and analyzed them against the calibrated XAJ outputs. This analysis has revealed how XAJRNN layer operated when integrated with the LSTM post-processing module and how it differed from a conventional XAJ model.

Lines 413-422: Furthermore, as noted in Section 3.1.2, the XAJRNN layer within the EDL model can directly output simulated outflow (*Q*). To evaluate its performance, we extracted the runoff from the XAJRNN layer and compared it against observed streamflow in these two basins. The results are described as follows: in the Lushui River basin, the training period yielded *NSE*=0.92, *RE*=4.02%, *RMSE*=74.69 m^3/s, while the testing period yielded *NSE*=0.90, *RE*=10.87%, *RMSE*=86.98 m^3/s. In the Qingjiang River basin, the training period achieved *NSE*=0.89, *RE*=3.84%, *RMSE*=172.64 m^3/s, and the testing period *NSE*=0.86, *RE*=-7.17%, *RMSE*=198.74 m^3/s. Compared with the XAJ model, the runoff simulated by the XAJRNN layer shows overall improvement. However, its accuracy still falls short of the full EDL model. These findings confirm that while the XAJRNN layer has advantages over the standard XAJ model, integrating it with the LSTM layer could improve simulation accuracy.

We fully agree that comparing the EDL model with an offline post-processed approach (i.e., using XAJ model outputs as inputs to a separately trained LSTM) would help readers better understand the value of the online integration of XAJRNN with the post-processing LSTM module. We have added a benchmark model (XAJ-LSTM). And subsequent content has been added to compare the performance of the XAJ-LSTM model and the EDL model.

Lines 378-384: The third benchmark model is the XAJ-LSTM hybrid model. This model utilizes the simulated discharge generated by the ordinary XAJ model as its primary input, augmented by observed areal mean rainfall and pan evaporation data. The final output of this model is the simulated flow discharge. Similarly, the training process and hyperparameter configurations for the XAJ-LSTM model are kept consistent with those used in the two previous benchmark models. The purpose of this benchmark model is to demonstrate the superior performance of the proposed EDL model in comparison to using the LSTM layers solely for hydrological post-processing.

Line 434:

Table 2: Comparative analysis of model simulation accuracy evaluation metrics.

Basin	Model	Training period			Test period		
		NSE	RE (%)	RMSE (m^3/s)	NSE	RE (%)	RMSE (m^3/s)
Lushui River	EDL	0.98	1.59	34.11	0.98	-2.69	43.71
	XAJ	0.86	-26.07	93.83	0.90	-18.50	89.60
	LSTM	0.97	-1.90	44.87	0.96	-0.61	54.27
	XAJ-LSTM	0.93	4.24	70.90	0.92	19.06	73.54
Qingjiang River	EDL	0.95	1.10	104.09	0.92	-8.74	167.94
	XAJ	0.85	5.91	182.05	0.85	-7.92	231.17
	LSTM	0.90	-4.16	147.89	0.93	-6.19	155.71
	XAJ-LSTM	0.88	1.56	164.52	0.86	-11.80	227.62

In the revised Discussion section of the manuscript, we have analyzed whether the coupling between the proposed physical and machine learning components provides genuine synergistic benefits from a parameter optimization perspective:

Lines 575-584: Since the parameter adjustments of the hydrological and DL models are conducted independently, the resulting parameter combination is often suboptimal, thereby constraining simulation accuracy. A comparison between the EDL model and the XAJ-LSTM model highlights this issue. The XAJ-LSTM model, which uses the outputs of the traditional XAJ model as inputs and is trained independently, shows some improvement over the XAJ model but still underperforms compared with the EDL model. By contrast, the proposed EDL model integrates hydrological and DL components within a unified framework, enabling synchronized training and joint parameter optimization. This online strategy not only eliminates the parameter mismatch inherent in conventional post-processing methods but also ensures that both hydrological and DL parameters are optimized simultaneously, leading to generate synergistic benefits.