On behalf of my co-authors, we are very grateful to your affirmative recommendation on the manuscript (Manuscript Number: EGUSPHERE-2023-2710) submitted to ‘Hydrology and Earth System Sciences’.

We highly appreciate your insightful comments. We have carefully read the reviewers report, and we have made corrections in the revised manuscript accordingly. Here are our responses to each of the questions in the reviewers’ report, which are reproduced in italics. The newly added text has been marked in blue.

Response to reviewer #1:

1. *The authors have used a hybrid deep-learning model to attempt to predict rainfall. While the paper is scientifically sound and quite in-depth, I can't see it as a good article for HESS because the focus is just so strongly on the Deep-Learning infrastructure. This is already evident in the Introduction which is clearly written with an audience in mind that is up-to-date with the terminology and typical issues that come with deep-learning models, whereas there is very little attention for the real-world practical problems this model is trying to solve (the abstract mentions urban runoff issues which are never mentioned anywhere in the main body, for instance). This would be fine for a journal that focuses on that particular research area, but the typical HESS reader (or at the very least, myself) will be completely lost in the methodology section.*

We noted your concern about the manuscript’s focus on deep learning models. In fact, this focus is consistent with the fact that deep learning is increasingly used in hydrological research and we aim to bridge the knowledge gap for readers who are not familiar with deep learning models. We believe that by framing the deep learning approach as a powerful tool for addressing a hydrological challenge, i.e. nowcasting, the paper becomes more attractive to a wider readership. Precipitation is so difficult to predict that one-step-ahead prediction cannot be considered to be outside of the practical problems of the real world. The following paragraph has been included to explain its suitability for HESS.

Given the growing usage of deep learning in hydrological research, it is important to bridge the knowledge gap for readers who are not familiar with deep learning models. The pedagogical aspect of our work has the potential to contribute to the hydrology community by providing a deeper understanding of the application of deep learning models and multifractals technique in short-term rainfall prediction that remains a fundamental problem of hydrology starting with one-step-ahead prediction.

2. *It's way too detailed in explaining the core mathematical concepts behind the model (once again, scientifically absolutely good work, but not for a hydrology-focused journal), whereas the section discussing the used dataset for validation purposes (section 3.1) is barely 10 lines long and doesn't contain any information about the type of data collected (is it radar, tipping bucket, time-integrated, point measurements, etc etc).*

We greatly simplified the mathematical presentation, e.g., we removed two paragraphs in the introduction that describe the detailed implementation and concepts of the hybrid model. We also simplified the description about double trace moment technique in section 2.3.

We provide some information on the dataset we used for training in section 3.1, e.g.:

Two rainfall time series with daily and hourly resolutions in Champs-sur-Marne ($48.8425^{\circ}N$, $2.5886^{\circ}E$) were collected from MERRA-2 (Modern-Era Retrospective analysis for Research and Applications, Version 2) precipitation dataset that is produced by NASA's Global Modeling and Assimilation Office (GMAO), refer to The POWER Project (https://power.larc.nasa.gov). The corrected MERRA-2 precipitation dataset is a reanalysis product that integrates various observational data types (like radar, tipping bucket gauges, and satellite) through sophisticated data assimilation techniques into a climate model.

We also clarify that the role of the training set is less stringent than believed at first glance and therefore the transportability of the model is much greater: One could worry about the model's applicability beyond the chosen study area , i.e. its transportability, because the model only has to be trained once. In principle, a new dataset from different regions or time periods can be fed directly into the well-trained model without repeating the training process to obtain the prediction on the new dataset.

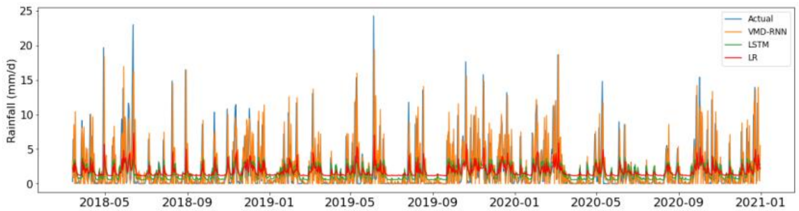
3. *That aside, the outcomes of the study are also a bit disappointing from a practical point of view. The authors acknowledge that their chosen study area has a fairly typical rain pattern, which makes me wonder whether this means such a model can't be applied anywhere else without specifically training it for that area - which would defeat the purpose of using a model, in my opinion.*

We have just provided an answer to this concern

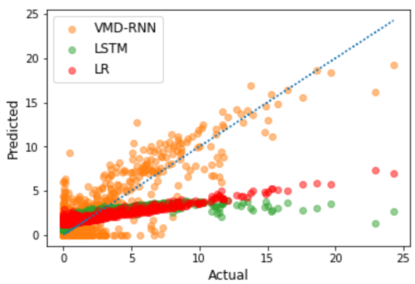
Secondly, and perhaps most importantly: the authors conclude that with the used lead time (1 time step) the applicability of the model is severely limited for prediction purposes, nor can it handle the stochastic nature of rainfall variability all too well. A conclusion on my end would be then that it's not any better than just interpolating observational data...

We noted your opinion about the limited attention to real-world practical problems. However, we already pointed out that precipitation is so difficult to predict that one-step-ahead prediction cannot be considered outside the practical problems of the real world. We believe that this point of view would be supported by urban water managers. Furthermore, the study presented in this manuscript serves as a kind of pedagogical example, acting as a starting point for further research that can extend to longer lead-time nowcasting. As we described in the future works, multi-step-ahead rainfall prediction is currently under investigation, and the model combined multifractals with deep learning is being developed to analyse and monitor the variability of forecast rainfall time series.

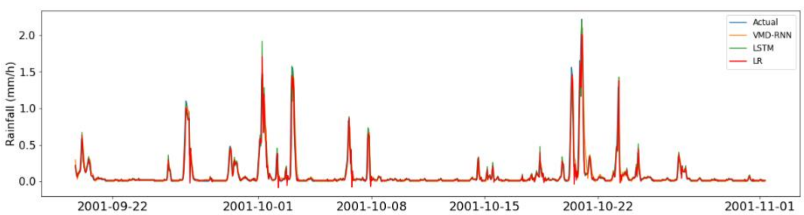
To clarify that our deep learning prediction cannot be considered as similar to a linear interpolation we have introduced the traditional linear regression method as one of baseline methods in the Section 4. Figures 8 and 9 for daily resolution, and Figures 11 and 12 for hourly resolution have updated to include the results of the linear regression method, which do not fit deep learning prediction. We include below copies of Figs 8-12.



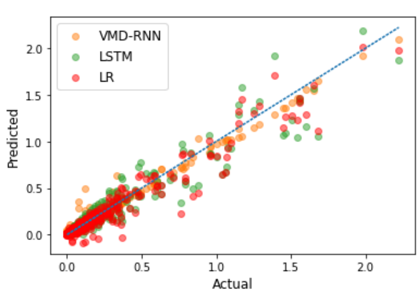
Figures 8: Predicted and actual daily time series in the testing set



Figures 9: The comparison between predicted and actual daily rainfall values



Figures 11: Predicted and actual hourly time series in the testing set



Figures 12: The comparison between predicted and actual hourly rainfall values

Response to reviewer #2:

1. *Lines 47 and 48: "However, these pure variant models are…preprocessing." Please consider citing some previous studies to support your statement.*

We agree on the importance of backing up our statements by citing previous studies and emphasise the originality of our contributions since they aim to overcome current limitations by employing the combination of DL with Decomposition. Therefore, five references (Liu et al., 2020; Huang et al., 2021; Zhang et al., 2021; Lv and Wang, 2022; Ruan et al., 2022) have been cited to support the statement.

2. *The second to last and third to last paragraphs in the Introduction section should be in the Method section. They went into details about either a model or an evaluation index, rather than focusing on the context and motivation of this study.*

The suggestion regarding the placement of two paragraphs, currently in the Introduction, is duly taken into account. They were initially positioned in the Introduction because these two paragraphs describe how our work differs from others' studies and clarify the contribution of our work. The three following paragraphs havereplaced the two original paragraphs to explain the purpose and motivation of this study.

The inherent variability of rainfall typically results in limited prediction performance for single RNN-variant models. In response to this situation, the integrated forecasting paradigms have been widely employed to improve the precision and robustness of time series forecasting. The hybrid VMD-RNN model is based on the fundamental concept of considering the dominant characteristics of VMD in decomposing nonlinear time series and the beneficial performance of variant RNN models in predicting complex sequential problems.

The main purpose of this study is to provide a reliable one-step-ahead rainfall prediction. In order to achieve this objective, it is essential to fully extract the underlying patterns of rainfall time series. An additional crucial point is to develop prediction models with a satisfactory level of accuracy. According to the aforementioned two factors, this study implements a hybrid approach known as VMD-RNN, which combines different RNN-variant models with VMD decomposition for predicting rainfall time series.

The effectiveness and reliability of the employed VMD-RNN approach are extensively validated by applying this method to forecast the following step's rainfall in both daily and hourly resolution. Furthermore, a comparison study is carried out to further demonstrate the superiority of the adopted VMD-RNN model, in comparison to the baseline method, pure LSTM model without decomposition. In addition, the UM technique is used to confirm the ability of the predicted time series to accurately describe rainfall variability.

3. *I suggest that the authors elaborate on their motivation and clarify the contribution of this work. Based on the current introduction, the model is not new, and the dataset is not new. It's okay if this work is focused on applying a method to a dataset and this application has not been documented in previous research. But you will need to justify your decision with appropriate citations. For instance, why is that application important? It could be because of limitations from previous approaches or the good performance of some new approaches, and so on. You just need to justify this work by elaborating why it is important.*

We appreciate your suggestion to elaborate more on the motivation and contribution of our work. As replied to the second comment, we improved the introduction section by providing a more comprehensive description to emphasize the importance of our work, e.g., the number of decomposition levels in the process of VMD is determined by analyzing the power spectral density of the corresponding last sub-sequence.

As responded to the second comment, the advantages and the purposes of combining RNN models with variational mode decomposition and multifractals have been explained in the three new paragraphs in the Introduction section.

4. *Maybe I missed something, but why do you need steps 3 and 4? I suggest that the authors explain why they want to generate sub-sequences on combined sequences with both training and non-training sequences and then clip to get the non-training ones instead of generating the non-training sub-sequences using directly the non-training original sequences.*

We thank you for bringing up this point. Steps 3 and 4 are included in our method due to the fact that directly decomposing the non-training original sequences will result in the leakage of future data from the testing set. Because rainfall time series is observed daily or hourly, the decomposition process is repeated with daily or hourly rainfall data of the next step appended. This approach can mitigate the risk of exposing future data during the decomposition of non-training time series. The following paragraph has been added to clarify the methodology.

To minimize the possibility of exposing future data during the decomposition of non-training time series, a precautionary approach (Step 3 and Step 4) has been implemented. This approach differs from the direct way of decomposing the testing time series using VMD. The non-training data was added to the training set in a sequential manner to create a new time series, and the amount of new generated time series was equal to the number of non-training data points. The VMD technique was thereafter used to decompose the aforementioned new time series into several sub-sequences. Subsequently, the final data point of each newly generated sub-sequence was retrieved and designated as non-training data, which was then used to build validation and testing samples.

5. *Sub-section 3.3 open sources. The title of this sub-section is weird to me. Maybe consider using titles like Model Settings and Implementation*

The comment about the title of subsection 3.3 is taken into account. The subsection primarily introduces the open-source software used in this study. The suggested title ‘Model Settings and Implementation’ seems to be in the good direction, despite we do not implement a model in the classical sense, but set together different open-access software. The title has been changed to ‘Open-source software’

6. *Result analysis. Since for each testing sub-sequence several RNN models were used and only the best result was kept for result aggregation, it will be really helpful to add a summary table showing the result of each RNN model on each sub-sequence. This will not only allow readers to understand how the eventual result was aggregated but will also bring insights into which model is the best, and so on.*

We totally agreed with your suggestion to add summary tables showing the results of each RNN model on each sub-sequence. Table 2 and Table 3 have been included in the section 3.2.3 to improve the clarity and interpretability of our results. Two tables show the MAE and RMSE results of the optimal RNN-variant model with first, second and third hidden layers for predicting first sub-sequence (IMF1). Then, Table 4 succinctly presents the ideal models with optimal parameters for other sub-sequences, which were obtained by the same way as IMF1.

Table 2. Results of the VMD-RNN model with one hidden layer for IMF1 predicting

Model type	Numbers of input	Model structure	MAE	RMSE	Model type	Numbers of input	Model structure	MAE	RMSE
		32	0.246	0.496			32	0.144	0.380
	5	64	0.157	0.396		**5**	64	0.150	0.387
		128	0.188	0.433			**128**	**0.136**	**0.369**
		32	0.144	0.380			32	0.142	0.377
LSTM	10	64	0.144	0.380	**GRU**	10	64	0.171	0.413
		128	0.174	0.417			128	0.190	0.436
		32	0.190	0.435			32	0.144	0.379
	15	64	0.176	0.420		15	64	0.163	0.404
		128	0.160	0.400			128	0.154	0.392
		32	0.178	0.422			32	0.137	0.370
	5	64	0.160	0.400		5	64	0.168	0.409
		128	0.239	0.489			128	0.192	0.438
		32	0.158	0.397			32	0.161	0.401
BiLSTM	10	64	0.234	0.484	BiGRU	10	64	0.156	0.395
		128	0.185	0.431			128	0.162	0.403
		32	0.138	0.371			32	0.155	0.393
	15	64	0.183	0.428		15	64	0.171	0.414
		128	0.198	0.445			128	0.185	0.430

Table 3. Results of the optimal model with second and third hidden layers for IMF1 predicting

Model type	Model structure	MAE	RMSE
	128-32	0.139	0.373
	128-64	0.157	0.396
	128-128	**0.128**	**0.358**
GRU	128-128-32	0.152	0.39
	128-128-64	0.157	0.396
	128-128-128	0.17	0.142

Table 4. Variant RNN models of IMF1-IMF8

VMD component	Model type	Numbers of input	Model structure
IMF1	GRU	5	128-128
IMF2	BiLSTM	15	64
IMF3	BiGRU	15	64-64-64
IMF4	LSTM	10	64
IMF5	LSTM	10	64-64-64
IMF6	BiLSTM	15	64
IMF7	BiLSTM	10	128-128
IMF8	BiGRU	15	32-32

7. *I feel that the Result section is not very well elaborated. So far there are only results but no discussion, which damaged the value of this study. How will readers benefit from reading this paper? To me what's more important is the insights behind specific results. For instance, why are some models better than others? In what circumstances? What insights can I gain regarding model selection and tuning after reading this work? etc. I suggest the authors add more in-depth discussions (please also refer to my 6th comment) to improve the quality of this section.*

We also agree with your feedback on the Result section. We therefore strived to provide in-depth discussions to explain the significance of our model and the contribution of our work in the field of hydrology. The following discussion has been added to further explain the results.

The hybrid VMD-RNN model, which integrates VMD decomposition and several RNN-variant models, showed a powerful ability to predict the next step's rainfall time series at both daily and hourly resolution. In order to further verify the effectiveness of the hybrid VMD-RNN approach, two baseline methods (the pure LSTM model without decomposition and the linear regression model) were also tested with the same daily and hourly rainfall time series. The hybrid VMD-RNN model and the baseline method were compared to highlight the necessity of VMD decomposition and every RNN-variant model for accurate rainfall prediction.

In terms of the regression results of daily time series, the hybrid VMD-RNN model outperforms the baseline methods in regards to the prediction of rainfall values. The findings obtained from Table 5 indicate the superiority of the used hybrid approach in daily rainfall regression, as evidenced by the lower values of MAE, RMSE, and MAPE. In addition, the scatter plot in Figure 9 shows that the baseline models consistently underestimate the intensity of rainfall, resulting in misjudgement and delayed responses to potential flood disasters. For hourly rainfall time series, the prediction performance of VMD-RNN is comparable to that of the pure LSTM model, without demonstrating substantial advantages of decomposition, which can be attributed to the small values of hourly time series.

According to the results of multifractal analysis, the UM parameters obtained from the time series predicted by VMD-RNN exhibit a higher degree of similarity to the actual time series, in comparison to the parameters from the time series predicted by LSTM without decomposition, specifically for daily time series. The values of C_1 calculated from predicted time series are lower, which is due to the fact that predicted time series tend to produce very small values rather than indicating the absence of rainfall. However, in the case of hourly time series, the UM results quantitatively suggest that the predictive performance of the VMD-RNN model is similar to that of the pure LSTM model, without explicitly showing the advantages of decomposition.