Response to RC1: 'Comment on egusphere-2024-3355', Anonymous Referee #1

We want to thank the referee for the detailed evaluation of our paper. In this document, we answer the questions, comments and suggestions given. We will address those comments individually. For clarity, the original comments posted by the referee are written in blue.

The paper addresses the challenge of predicting sub-daily forecasts. In such cases, sub-daily inputs are utilized to achieve optimal performance. However, when longer dependencies are present, processing this data at a sub-daily resolution can be quite time-consuming, as both sub-daily and monthly information may be required.

The authors introduce a simple and innovative approach to handle both short and long dependencies using the same LSTM model. They demonstrate that LSTM can effectively manage data with different frequencies by incorporating a label that indicates the data frequency, without sacrificing performance. Additionally, they show that LSTM can accommodate varying numbers of inputs at different frequencies by including an embedding layer before the LSTM.

These findings apply to any forecasting problem involving multiple time dependencies, suggesting that the proposed approach could have widespread utility.

The paper is well-written, with clear results, and I believe it should be accepted with minor comments.

We thank the referee for the well-structured summary of our paper.

Minor comments:

Line 25-26: I believe that one year is insufficient to capture groundwater behavior due to the longer residence times in these systems. Even in snowmelt-dominated catchments, additional memory may be necessary if snow accumulates between years. If you wish to retain this sentence, you must include a reference to support this assertion or refrain from mentioning specific processes.

Response: Thank you for the suggestion. We agree that groundwater processes might have residence times longer than a year. For snow-dominated catchments, Kratzert et al. (2019) show an example of a snow influence basin, where they demonstrated that the output of the LSTM during the snowmelt period considers input up to 150 days prior. Therefore even though in some basins multiannual snow accumulation might play a role, in most cases one year of data might be enough. We propose to modify the sentence as such:

> *By spanning a full year of data, this approach allows the LSTM model to capture long-term seasonal processes, such as snowmelt (Kratzert et al., 2019).*

Line 98: It would be helpful to provide a brief explanation of the example before presenting any values. For example, Why are you using 351?

Response: In line 98, our idea is to explain the architecture with a concrete example, to make it easier to understand. We used the same values as the ones used during the actual experiments to increase consistency, however, the values in the example could be arbitrary. The value of 351 timesteps at daily resolution and 336 at hourly resolution were taken from Gauch et al. (2021), where they used hyperparameter tuning to determine them. We will add this explanation to a revised version of the manuscript.

Line 106-107: This section indicates that the value of 351 is arbitrary and that any other value could be used. If this is the case, does it imply that this value is a hyperparameter? How should it be estimated? Additionally, how do you determine the duration when dealing with hourly, daily, and monthly periods?

Response: Yes exactly, this is a hyperparameter. Given the computation cost of training the models, the hyperparameter tuning step can be highly time-consuming. Gauch et al. (2021) applied a grid search method, which could also be applied here. Another option is to use surrogate-assisted optimization, however, this method is more complex, and one has to build a high-fidelity surrogate model, which can become a topic of its own.

For the hourly-daily-weekly experiment, we maintained the one-year sequence length and we also processed the last 14 days in hourly resolution. The cut between the amount of data that was processed weekly and daily was done somehow arbitrarily.

Line 159: You mentioned that the median KGE was similar, but what about the entire distribution (CDF)? If there are no significant differences, you could include the figure in the appendix. Did you consider extending the sequence beyond one year, particularly since you can now process longer sequences with reduced computational costs?

Response: Thank you for the suggestion. We will add a figure with the full distribution in a revised version of the manuscript.

About including sequence length longer than a year, this would depend on the type of application one is interested in. However, it is important to clarify that if one is interested in certain processes that might require longer lookback periods, the experiments should be designed accordingly. In our case, we are using a variation of the mean squared error loss function to train our model, which implicitly prioritizes high flows. These high flows are usually explained well enough with a lookup period of one year. If one is interested in groundwater processes that might require multi-annual lookback periods, the loss function and selection of the training points should reflect this. Otherwise, even with longer lookback periods, the model would not be able to utilize the additional information.

Therefore, we agree that the MF-LSTM architecture opens up the possibility of extending the sequence lengths without incurring on a prohibited computational cost. However, depending on the objective of the experiment, other factors should also be considered.

Final remarks

We would like to thank the referee for the overall positive evaluation of our manuscript and hope we could address the questions raised in a satisfactory manner.

References

- Gauch, M., Kratzert, F., Klotz, D., Nearing, G., Lin, J., and Hochreiter, S.: Rainfall–runoff prediction at multiple timescales with a single Long Short-Term Memory network, Hydrology and Earth System Sciences, 25, 2045–2062, https://doi.org/10.5194/hess-25-2045-2021, 2021.

- Kratzert, F., Herrnegger, M., Klotz, D., Hochreiter, S., & Klambauer, G. (2019). NeuralHydrology -- Interpreting LSTMs in Hydrology. *arXiv*. https://doi.org/10.48550/arXiv.1903.07903