Reply to CC2' comments

Legend

Reviewers' comments

Authors' responses

Direct quotes from the revised manuscript

The paper couples the Copula-based hydrological uncertainty processor with the Bayesian model averaging method to quantify and reduce uncertainty in flood forecasting upstream of the Three Gorges Reservoir in the Yangtze River basin, China. The topic is timely and the paper is technically sound. The paper could benefit from additional clarification in some sections.

Response: We deeply appreciate your constructive comments and the time you spent on reviewing the paper. We have accepted all the revision comments. Point-by-point replies to the comments or suggestions made can be found below.

1. Line 9: The full name of "CHUP-BMA" needs to be given the first time it is mentioned.

Response: The corresponding content has modified to "This study proposed the CHUP-BMA method by introducing a copula-based HUP in the framework of BMA to bypass the need for normal quantile transformation of the HUP-BMA method".

2. Lines 68-70: The description here is not clear to me, e.g. why the BMA ignores the constraint of initial conditions. Further explanation of the reason and how the HUP-BMA mentioned later can obtain the posterior distribution function of the observed flow is suggested in the Introduction section.

Response: It can be shown from Raftery et al. (2005) that the conditional distribution of the member ($Q_{f,i}$) in the BMA is assumed to follow the normal distribution with expectation $\mu_i = a_i+b_i \cdot Q_{f,i}$ (a_i and b_i are the bias correction coefficients) and variance σ_i, which implies that the conditional distribution is only related to the member's forecasted flow and is not affected by the observed flow at the start of the forecast. Therefore, it is not reasonable to produce the same posterior distribution when the forecast results are the same at different moments. The corresponding content has been modified as follows:

However, most studies ignore an essential issue: the BMA does not consider the constraint of initial conditions (i.e., observed flow at the start of the forecast). It can be shown from Raftery et al. (2005) that the conditional distribution of the member ($Q_{f,i}$) in the BMA is assumed to follow the normal distribution with expectation $\mu_i = a_i + b_i \cdot Q_{f,i}$ (a_i and b_i are the bias correction coefficients) and variance σ_i, which implies that the conditional distribution is only related to the member's forecasted flow and is not affected by the observed flow at the start of the forecast. It is not reasonable to produce the same posterior distribution when the forecast results are the same at different moments. The hydrological uncertainty processor (HUP) can obtain the posterior distribution function of the actual value under the condition of the forecast value and the observed flow at the start of the forecast based on Bayesian principles and the assumption of perfect rainfall forecasting (Krzysztofowicz and Kelly, 2000). Darbandsari and Coulibaly (2021) firstly constructed the conditional distribution of the observed flow under the conditions of the member forecasted flow and the observed flow at the start of the forecast and used the BMA method to weight the conditional distribution of all members to obtain the final posterior distribution, which is called the HUP-BMA method. Their results showed that the HUP-BMA method outperforms the HUP method and improves the BMA method in short-term probabilistic forecasting. In addition, the derivability of the posterior distribution for the ensemble members is theoretically enhanced, the heteroskedasticity of the ensemble members is considered, and the interpretability and logical rationality of the BMA method are improved.

3. Lines 85-86: It seems that this work is motivated by the copula-based HUP method in Liu et al. I suggest giving a brief description of this method and how it is used to improve forecast accuracy here.

Response: A modification has been made to the article as follows:

Liu et al. (2016) adopted the copula to derive the conditional distribution of the observed flow under the conditions of the forecasted flow, which avoids the assumption that the flow series obeys a normal distribution in the HUP and relaxes the application limitation. The study shows that the CHUP can improve the probabilistic forecasting performance of the HUP method.

4. Line 87: I suggest presenting the objectives and research steps one by one. For example, the novelty of this work can be introduced in the previous paragraph, along with the shortcomings of

current methods, and then the implementation of the proposed method in streamflow forecasting can be briefly introduced.

Response: The corresponding content has been modified as follows:

The main innovations and research steps are shown as follows: (1) A novel CHUP-BMA method is proposed for the first time by coupling CHUP into BMA, which not only solves the problem of the flow series obeying the assumption of normal distribution in HUP-BMA, but also considers the constraints of the initial condition of the forecast. (2) An ensemble forecast containing eight members is constructed by combining two types of forecast precipitation, two long short-term memory (LSTM) models, i.e., the recursive encoder-decoder structure-based LSTM-RED model and the feature-temporal dual attention-based DA-LSTM-RED model, and two objective functions of model calibration. (3) The ensemble forecast performance of the proposed method is analyzed and discussed in comparison to the HUP-BMA benchmark method in terms of the deterministic and probabilistic forecast. The interval basin between Xiangjiaba Dam and the Three Gorges Dam is selected as case study

5. Section 3.2: It seems that the model structure uncertainty in this study is considered by using two forecast models with LSTM-RED structure. why not using two different types of models (e.g., ANN-based vs. tree-based or physical-based vs. data-driven models)?

Response: It has been demonstrated in many studies that LSTM models have relatively better forecasting performance than ANN, tree-based models, and physical mechanism models (Kratzert et al., 2018; Hu et al., 2018; Han & Morrison, 2021; Zhang et al., 2022; Hayder et al., 2023). Meanwhile, in the interval basin between Xiangjiaba and TGR dam-site, the physical mechanism model usually is very complex and has low forecasting accuracy. This study is a further research based on Cui et al. (2023), which demonstrated that the DA-LSTM-RED model structure improved by the dual-attention mechanism resulted in a substantial improvement in forecast accuracy relative to the LSTM-RED model. Therefore, this study uses two advanced LSTM-RED and DA-LSTM-RED models for flood forecasting and focuses on the uncertainties associated with these two models.

Reference:

Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M.: Rainfall–runoff modelling using

Long Short-Term Memory (LSTM) networks, Hydrol. Earth Syst. Sci., 22, 6005–6022, https://doi.org/10.5194/hess-22-6005-2018, 2018.

Hu, C., Wu, Q., Li, H., Jian, S., Li, N., & Lou, Z. Deep learning with a long short-term memory networks approach for rainfall-runoff simulation[J]. Water, 10(11): 1543, https://doi.org/10.3390/w10111543, 2018.

Han, H., & Morrison, R. R. Data-driven approaches for runoff prediction using distributed data[J]. Stoch. Environ. Res. Risk. Assess., 1-19. https://doi.org/10.1007/s00477-021-01993-3, 2021.

Zhang, Y., Ragettli, S., Molnar, P., Fink, O., & Peleg, N. Generalization of an Encoder-Decoder LSTM model for flood prediction in ungauged catchments[J]. J. Hydrol., 614: 128577. https://doi.org/10.1016/j.jhydrol.2022.128577,2022.

Hayder, I. M., Al-Amiedy, T. A., Ghaban, W., Saeed, F., Nasser, M., Al-Ali, G. A., & Younis, H. A. An Intelligent Early Flood Forecasting and Prediction Leveraging Machine and Deep Learning Algorithms with Advanced Alert System. Processes, 11(2), 481. https://doi.org/10.3390/pr11020481, 2023.

Cui, Z., Guo, S., Zhou, Y., Wang, J. Exploration of dual-attention mechanism-based deep learning for multi-step-ahead flood probabilistic forecasting. J. Hydrol., 622, 129688. https://doi.org/10.1016/j.jhydrol.2023.129688, 2023.

6. Also, what is the purpose of using MAE and MSE as prediction evaluation metrics in this work? These two metrics are similar to each other. In order to account for model parameter uncertainty, it seems more appropriate to use three apparently different evaluation metrics, such as Nash-Sutcliffe efficiency, mean absolute error (MAE), and relative error of total discharge (RE).

Response: In this paper, we have trained the model parameters using different loss functions. The indicator MAE focus on different points, while the MAE focus on the magnitude of the error mean, and the MSE is sensitive to outliers with large errors. As a result, the model can be guided to produce varying parameters to account for parameter uncertainty. We make the following changes in the article:

For example, the mean absolute error function focuses on the magnitude of the error mean. The mean square error function usually is sensitive to outliers with large errors, which may make the model parameters with different objective functions produce forecast results with different focus points (Duan et al., 2007).

7. Some reference to the first mentioned methods is suggested, e.g. the reference to the "Adam method" is suggested in line 283.

Response: We make the following changes:

The model is trained by the Adam method (Kingma& Ba, 2014).

Additional references:

Kingma D P, Ba J. Adam: A method for stochastic optimization[J]. arXiv preprint arXiv:1412.6980, https://doi.org/10.48550/arXiv.1412.6980, 2014.