

Interactive comment on “Modeling Error Learning based Post-Processor Framework for Hydrologic Models Accuracy Improvement” by Rui Wu et al.

Rui Wu et al.

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Dear Dr. Bethanna Jackson,

Thank you for your comments. We have carefully reviewed the comments and have revised the manuscript accordingly. Our responses are given in a point-by-point manner below. Changes to the manuscript are shown in bold.

â We acknowledged Dr. Paul Miller’s constructive comments in the paper with the following text: “We really appreciate valuable comments from all the reviewers, especially Dr. Paul Miller for his constructive comments.”

â Thank you for pointing out Dr. Paul Miller’s last comment. To clarify our ideas from both computer science and hydrologic science, we added the following paragraphs in

the Discussion Section: “ As model driving forces, the data input is heavily relied upon in physical-based hydrologic models. On physical bases, the meteorologic input is modeled with water flow storage and path within the earth system. The streamflow, as demonstrated in this research, is one of the examples. During this process, all numerical models simplify physical processes to some degree, either spatial-wise, such as hydrologic response unit, or temporal-wise, such as summer leaf index. Such conceptualization and simplification compose a static numerical modeling environment that cannot capture all environmental stressors, such as in the meteorological inputs. This is long-time stressing issues in hydrologic science.

To capture the environmental stressors, such as meteorological changing trend, land cover variation, vegetation growth, we can use different hydrologic models or add additional physical-based algorithms to capture the specific processes and correct bias from missing representations. However, with a mix of stressor, it is hard to distinguish the causes of biases and remove/mitigate these biases, from data input, parameters or model structures. Machine learning techniques fill this gap.

Instead of switching to another model better capturing data input, according to our experiment results, the proposed machine learning techniques help update a hydrologic model to characterize input data bias as a plug-in in our proposed framework. It can sense data trend and compensate hydrologic model predictions with the window selection method. The effect is similar to have multiple hydrologic models for different input data biases.

Machine learning in this application attempts to use relevant input data to reproduce hydrologic behavior, i.e., flow hydrograph as close to observed as possible. The overall difference in observed and modeled hydrograph is categorized as an error. In hydrologic literature, it has been recognized that this difference can be due to uncertainty in input and output data, bias in model parameterization, and issues with model structure. With the current machine learning approaches, it is not possible to disentangle and attribute total error to multiple sources such as input data, model parameters, and model

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structure. Moreover, machine learning approaches cannot provide physical reasoning for this error. This is a recognized issue in hydrology and an active area of research. Since no prior model structure is provided to machine learning approach - it learns model structure and parameters from input data and observed output- it can be stated that contribution of model structure and parameters towards total error is relatively small compared to bias or uncertainty in model input. The separation of data into training and testing samples provides a safeguard against overfitting the model. However, issue of disentangling error and attributing it to multiple sources remains unresolved in this work. Future research should focus on this issue.”

Sincerely, Rui Wu, Lei Yang, Chao Chen, Sajjad Ahmad, Sergiu M. Dascalu, and Frederick C. Harris, Jr.

Interactive comment on Geosci. Model Dev. Discuss., <https://doi.org/10.5194/gmd-2018-136>, 2018.

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