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[GMDD]

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

Rui Wu et al.

raywu1990@nevada.unr.edu

Received and published: 16 August 2018

Dear Dr. Kerkweg,

Thank you for your comments. We have changed our title into "MELPF Version 1: Modeling Error Learning based Post-ProcessorFramework for Hydrologic Models Accuracy Improvement" and referred to our proposed framework with the name "MELPF" in the paper.

We have also introduced version number and how to access the two hydrologic models in Section 4 "Discussion". Please check the attached PDF file for more details and let us know if these are enough. Thanks again for the feedback.

Best regards, Rui

Please also note the supplement to this comment:
https://www.geosci-model-dev-discuss.net/gmd-2018-136/gmd-2018-136-AC1-supplement.pdf

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

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

Rui Wu et al.

raywu1990@nevada.unr.edu

Received and published: 11 September 2018

Dear Dr. Kerkweg, Thank you so much for your suggestions. We have added model download web-links in the "Code and Data availability" section. Best regards, Rui

Please also note the supplement to this comment:
https://www.geosci-model-dev-discuss.net/gmd-2018-136/gmd-2018-136-AC2-supplement.pdf

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

Rui Wu et al.

raywu1990@nevada.unr.edu

Received and published: 14 May 2019

Dear Dr. William Paul Miller,

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 in this paper.

Review: On page 7, the authors note that the uncalibrated models with default values are compared with the calibrated cases from traditional calibration and post-processor methods. To what extent do the default values impact the results of this study? Are the default values relatively close to the traditionally calibrated values, or are they significantly different? -Response: Thanks for the comment. A physical hydrologic model

usually cannot generate good results with default values. In the paper, we have two examples that show default values produce inaccurate results by comparing Table 1 Calibrated Original PRMS vs. Table 2 Uncalibrated Original PRMS and Table 3 Calibrated Original HEC-HMS vs. Table 4 Uncalibrated Original HEC-HMS. To further explain our ideas, we added the following sentences in the Discussion section: "A physical hydrologic model usually cannot generate good results with default values and requires calibration (Chen30et al., 2015b; Hay et al., 2006; Hay and Umemoto, 2007b). In the paper, we have two examples that show default values produce inaccurate results. With the same model and study area, Table 1 Calibrated Original PRMS results are much more accurate than Table 2 Uncalibrated Original PRMS based on performance evaluation indices. Similarly, Table 3 Calibrated Original HEC-HMS results are much better than Table 4 Uncalibrated Original HEC-HMS. Numerical experiments have corroborated the superior performance of the proposed method, compared with traditional methods with different default values."

Review: Do the default values accurately, or inaccurately, physically represent the system being modeled. I think it's important for the authors to discuss how the default values in the models studied here impact the results presented. -Response: We appreciate the comment. This is a great point. To clarify our ideas, we added the following sentences in the Discussion section: "There may be various types of default parameters used in a physical hydrologic model for development efficiency. Parameters can be classified as sensitive and insensitive, or model execution related and process algorithm related. Apart from the model execution related parameters and other insensitive parameters, the process algorithm related sensitive parameters are typically critical to model development, which greatly affect the model's performance. Default values can well follow physical laws and be contained in the corresponding computation algorithms, but not necessarily capture the regional hydrologic characteristics at a study site. Capturing such site-specific features is the process of calibration. As such, the differences between uncalibrated - default set- models and calibrated models are determined by the significance of sensitive parameters in affecting the modeling perfor-

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mance."

Review: Are the authors able to attribute errors identified through their Modeling Error Learning algorithm to any model biases that are physically based? For example, is there a particular streamflow behavior or weather pattern that is not accurately captured in the HEC-HMS or PRMS models due to a limitation into how a physical process is modeled or represented in those models? -Response: Thank you for the comment. The proposed method is data-driven and not only designed for physically based models. It is tested with physical hydrologic models. We have done experiments and found that if the errors of hydrologic models are correlated with model inputs, our proposed method will work. We have mentioned this point in the abstract. To further clarify the idea, the following paragraph is added to Section 4 Discussion: "The proposed method is not designed specifically for physically based models. We tested the proposed methods with physical hydrologic models and would like to exam it with other types of models in the future. In our opinion, the proposed method works because it can find hydrologic model limitations, such as improve modeling peak values, based on the patterns of model errors."

Review: If there is no attributable physical reason for the errors identified through the learning algorithm, is it really appropriate to be making those changes; that is, are we getting the right (or more accurate) answer for the wrong reason? The modeling Error Learning algorithm may be just identifying a limitation of the model. -Response: Thank you for pointing this out. Yes, our proposed method is based on the limitations of a hydrologic model. The limitations of HEC-HMS and PRMS models are that these two models cannot model peak values. Figure 2 is an example to show that a hydrologic model's error is much higher if there is a peak. To clarify our idea, the following paragraph is added to Section 4 Discussion: "In this paper, model limitations mean peak values. For example, if a hydrologic parameter changes massively within a short period, i.e., peak values, a physical hydrologic model may not be able to characterize the trend. Figure 2 is an example that shows a physical hydrologic model has a higher

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error rate when there is a peak. Our proposed method identifies the limitations of a physical hydrologic model based on errors and their correlation with model inputs. If there is such a connection between model errors and inputs, it means the hydrologic model does not characterize the relation between inputs and outputs well enough. To fix the issue, we leverage machine learning techniques and propose a novel method to find out data patterns in this paper." Sincerely, Rui Wu, Lei Yang, Chao Chen, Sajjad Ahmad, Sergiu M. Dascalu, and Frederick C. Harris, Jr.

Please also note the supplement to this comment:
https://www.geosci-model-dev-discuss.net/gmd-2018-136/gmd-2018-136-AC4-supplement.pdf

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

Rui Wu et al.

raywu1990@nevada.unr.edu

Received and published: 18 June 2019

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.

âŮŔ 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."

âŮŔ 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.