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Reply on RC1

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Author comment on "Impact of Spatial Distribution Information of Rainfall in Runoff Simulation Using Deep-Learning Methods" by Yang Wang and Hassan A. Karimi, Hydrol. Earth Syst. Sci. Discuss., <https://doi.org/10.5194/hess-2021-371-AC2>, 2021

Please use this authors' response to this reviewer's comment as the posted text on Friday (Oct 8) was unedited.

Authors' response for Setting

The points you raise here are correct. Traditional hydrological models are physical-based requiring different parameters thus different models for different areas. One advantage of using deep learning models for rainfall runoff simulation is that training data can be drawn from multiple watersheds. This makes the trained models suitable for watersheds in different areas. We think this is also a possible direction to look at in the future. Since in this paper, we compare the effect of inputs with and without spatial information on the performance of the deep learning model, the comparison of individual watersheds provides a more direct indication of the difference in the results.

Most studies apply rainfall and previous discharges with different time steps and combinations as inputs^{1,2}. One of the features of the LSTM model is to find the relationship between sequences. Using the previous runoff as input is to discover the intrinsic relationship of the time series data. From the perspective of a data-driven model, we include the previous runoff in the input as additional information to get a better result. The two data-driven models differ only in whether the input contains spatial information or not. Many factors related to runoff, such as rainfall and temperature, are characterized by uneven spatial distribution. The purpose of this study is also to show the importance of spatial distribution information. As one potential future research direction, instead of runoff we may include topography, evaporation, among other features with spatial distribution information and evaluate the contribution of each to the simulation results.

Authors' response for Method:

CAMELS contains a total of 671 catchments with minimal anthropogenic disturbance in the contiguous United States. For each catchment, CAMELS dataset include: (i) daily cumulative rainfall, (ii) daily minimum air temperature, (iii) daily maximum air temperature, (iv) mean short-wave radiation, and (v) vapor pressure. In our work the daily cumulative rainfall is treated as the catchment mean rainfall data without spatial distribution information for each catchment. CAMELS dataset also includes the average rainfall for each hydrologic response unit of certain catchment. We use the catchment

mean daily cumulative rainfall as the input precipitation with spatial information, and use the combination of average rainfall from each hydrologic response unit in the catchment as the input precipitation with spatial information. For example, as Catchment 1 had a total of 64 hydrologic response units in the dataset, we used a vector of size 64 to represent the rainfall data with spatial distribution information. CAMELS calculates the average rainfall in a catchment by weighting it by the area of each HRU. Our rainfall data with spatial information does not consider weights because we are portraying the distribution of rainfall in the basin by combining rainfall from different HRUs.

Authors' response for Result:

Thank you very much for the suggestion. Each experiment was performed with a different look-back window and look-forward window to test how much the results would change with different data. We think adding some basic statistical test is a good idea.

1. Van, S. P. et al. Deep learning convolutional neural network in rainfall-runoff modelling. *J. Hydroinformatics* 22, 541–561 (2020).
2. Xiang, Z., Yan, J. & Demir, I. A Rainfall-Runoff Model With LSTM-Based Sequence-to-Sequence Learning. *Water Resour. Res.* 56, (2020).