Paper ID: hess-2021-596 (A deep learning technique-based data-driven model for accurate and rapid flood predictions in temporal and spatial dimensions)

Dear Dr. Dimitri Solomatine,

We greatly appreciate the additional comments to improve the revised manuscript. We have addressed all the reviewers' comments in the resubmitted version and the point-by-point responses are provided in the Response Letters to each reviewer. The detailed changes have been highlighted in the Annotated Version. We sincerely hope that you and the reviewers will find the revised version more scientifically clear and robust. We look forward to hearing from you soon.

Thank you for your time and efforts on our manuscript again.

Sincerely Yours,

Dr. Qianqian Zhou
On behalf of all authors
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Response to Editor

Comment 1

"I have now finally both reviews - but based on the comments of both referees I have to kindly ask you for an additional revision. This is a "minor revision". I would like to ask to give special attention to the comments made by Referee 1. I am citing:

"(1)...after reading the manuscript again, it is still unclear what are the input data for the LSTM flood prediction model presented in the manuscript. More specifically, I could not find in the document that DEM is one of the input data along with the rainfall event (see Figure 3). This seems to me a little bit odd, as far as I can understand without the DEM, i.e. without providing the terrain features as input data, the proposed LSTM flood prediction model would struggle, if not impossible, to be applicable to case studies (catchments) other than the one used for training. This is a STRONG problem the authors do not clearly explain. In order to make the scientific development presented meaningful and trustful, this aspect needs, in my opinion, to be clarified.

(2) As the authors mention, the key for successful data-driven simulations is the number and variety of the data used for training the LSTM (and other data-driven models). In the manuscript, very little information is provided about the data set used for training. How many simulations? how different were the simulations? ...

Based on the two points raised above, which for me are critical, I suggest the authors to attempt an additional revision.""

Response: Thanks for the comments to better clarify the methodology. In the revised version, we have provided additional details to explain 1) LSTM methodology and input data requirement, 2) the number and variety of input data. Both comments have been properly addressed, please find more details in the Response Letter to Referee 1.

Comment 2

"Further, this referee points out that it is important to address these two comments in a meaningful way, especially the first comment. I agree with this opinion. Please share your

thoughts and provide explanations about the possibilities of using the trained data-driven model(s) for other catchments."

Response: We have better explained the use of transfer learning technique in adapting the trained model for other catchments. The method proposed in this paper is a compromise between prediction accuracy, computational efficiency and adaptability, which can achieve excellent flood prediction results. More details can be found in the Response Letter to Referee 1.

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Response to Reviewer 1

Comment 1

"*I acknowledge the substantial revisions the authors conducted in the original version of the manuscript. Most of the reviewers' comments were adequately addressed.*"

Response: We greatly thank your helpful suggestions to improve the paper and acknowledgment of our efforts in the first revision.

Comment 2

"However, after reading the manuscript again, it is still unclear what are the input data for the LSTM flood prediction model presented in the manuscript. More specifically, I could not find in the document that DEM is one of the input data along with the rainfall event (see Figure 3). This seems to me a little bit odd, as far as I can understand without the DEM, i.e. the terrain features, the proposed LSTM flood prediction model would struggle, if not impossible, to be applicable to other case studies (catchments) other than the one used for training."

Response: We agree that the terrain features are a key factor in implementing flood prediction tasks. Besides, other catchment hydrological properties (e.g., land use, area and imperviousness) and network parameters (pipeline distribution and capacity) also have essential impacts on flood conditions. When designing the method, we actually considered the impacts of all influencing factors in the network training, but without specifying/demanding them in the model input. Instead, we used the mapping relationships between rainfall and flood depth to reflect the impact of these factors on flood through the established LSTM, i.e., regression model. We will clarify this by the following points:

(1) The site information contains a vast amount of data. Although computer technology has made significant progress recently, deep learning algorithms still face significant challenges in processing high-dimensional data. Such data can significantly decrease the prediction efficiency of the algorithm, particularly when applied to large-scale areas. This will affect/harm the real-time performance of the prediction model.

(2) Neural network technology involves learning and creating a mapping relationship between input and output data. In this study, the input data is rainfall intensity, and the output is flood depth. As mentioned previously, the depth of rainfall is influenced by e.g., terrain features, catchment hydrological factors, network parameters. The function of neural network is to establish the relationship between the input, these implicit influence conditions and the output. The results of this study demonstrate that LSTM can accurately establish the above relationships. As a result, the method proposed took into account the impact of terrain features and other influencing factors in the network model.

(3) We understand the reviewer's concern on the applicability of the model, as it appears that the model established is only applicable to the investigated site. The problem can be solved by using transfer learning technology to implement flood prediction for new sites. Data of the new site is used to fine-tune the LSTM model obtained from the old site (more details can be found in the Methodology－2.3.3 Transfer learning (TL)). The results of our testing site showed that the LSTM could quickly adapt to the prediction task in the new site, and the transferred LSTM performed accurate flood predictions. Especially when dealing with large-scale site information, the transfer learning method requires less time, lower resource cost, and delivers better real-time performance.

To summarize, this paper proposes a flood prediction model based on three key aspects: 1) mitigating the impacts of high-dimensional site feature data on the efficiency of the prediction model; 2) establishing an accurate prediction model using only rainfall intensity and flood depth data, while leveraging the nonlinear mapping characteristics of input, site features and output based on the LSTM network; 3) employing transfer learning technology to achieve the prediction task in new sites. As such, the method proposed in this paper represents a compromise solution that takes into account prediction efficiency, accuracy, and adaptability.

Comment 3

"As the authors mention, the key for successful data-driven simulations is the number and variety of the data used for training the LSTM (and other data-driven models). In the manuscript, very little information is provided about the data set used for training. How many simulations? how different were the simulations? ..."

Response: We have provided more details on the input data. Specifically, two types of datasets were established: (1) maxH dataset, i.e., the maximum flood depth: there were in total 90 rainfall events adopted, with return periods ranging from 1 to 100 years and rainfall duration of 2, 4 or 6 hours, respectively. Meanwhile, three types of rain peak position coefficients were tested, including 0.3, 0.5 and 0.7. That means there were 90 simulations from the physical model. The details on the return period, rainfall duration and peak position of the input rainfall events are provided in the attached Figure 1; (2) time series dataset: we adopted 11 rainfall events and recorded the flooded water depths every 10 minutes for the entire case study under each rainfall. As for the training process of the network, 90% of the rain intensities were used as training samples, and 10% as testing samples. In addition, 170 Bayesian optimizations were performed to identify the optimal network structure, which achieved the best prediction error after 385 training iterations.

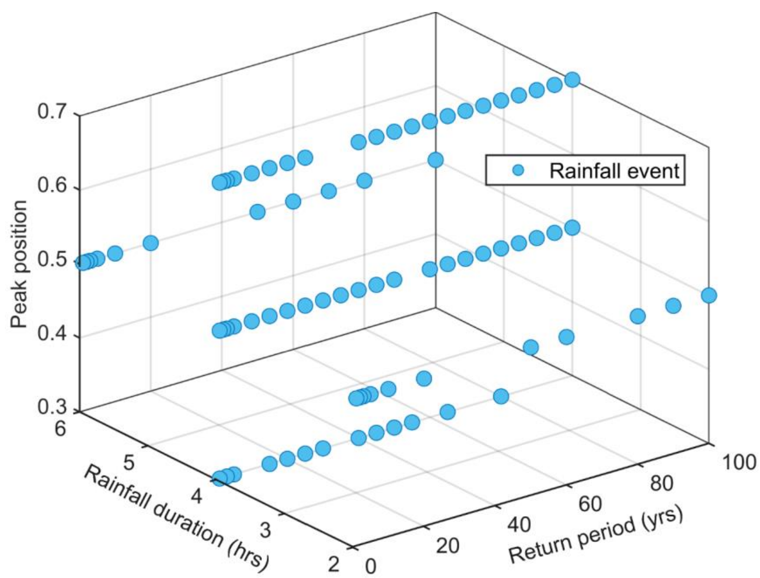

Figure 1: Details of simulated rainfall events.

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Response to Reviewer 3

Comment 1

"*LSTM is well-documented in literature in dealing with time series predictions. Obviously, this work's novelty is that the authors applied LSTM to a spatial and temporal forecasting task. My major concern is that the authors failed to elaborate well enough on how they transformed the spatial forecasting tasks so that LSTM can handle them. For instance, does the model output grided predictions, such as water depths, for the 27,183 grid points in the study area all at once? If so, how? Or, does it predict water depth for those grid points one at a time? Or, does it only predict at a few locations and then some extrapolation algorithms were used to obtain the flood map for the entire area?*"

Response: Thanks for the comments. In this paper, the output of LSTM is the water depth of all grid points all at once. A regression algorithm is used for the LSTM model. Specifically, the input rainfall intensity is processed through multiple LSTM layers and activation layers, and finally, a regression layer outputs the water depth of the 27,183 grid points for the entire area. A regression case (https://doi.org/10.1016/j.ijfatigue.2022.106812) has demonstrated the superior performance of the regression layer. In other words, the process is akin to a fitting process, in which different rainfall intensities are matched nonlinearly to the water depth of grid points. The number of output grids can be set during LSTM modeling so that the output grid can be specified for different sites.

Comment 2

"Lines 100-106: Normally, we don't put results in the introduction section. As the opening sentence of this paragraph states, you should focus only on why you are doing this, how you plan to do this (in brief), and how your work is going to close some of the gaps in the literature. You can keep most of your writings in this paragraph as they are and simply remove those results."

Response: We agree with the reviewer and have removed the relevant text.

Comment 3

"Figures 1 and 2: Consider adding a scale bar for those two study areas."

Response: Both figures have been revised as suggested.

Comment 4

"*Line 142: Maximum water depth about what? As you indicated in Line 372, there are 27,183 grid points on your map. Do you create a maximum water depth record for each of those grid points? Do you aggregate them following some algorithms? Or do you only utilize water depth at certain locations, such as those manholes? The same question is also here for your output. Does your LSTM output a 2D map directedly? Does it predict the flood depth for grid points one at a time? Does it only predict the depths for a few points then some interpolation methods were used to expand from the scattered predictions to the entire* study area?"

Response: Sorry for the confusion. As explained previously (Comment 1), the maximum water depth is for the entire area (i.e., 27,183 grid points). LSTM outputs a 2D map directly, which describes the water depth of all grid points all at once. We have better clarified this information in the revised version.

Comment 5

"*Figure 3: What is the unit of T here? I assume it should be [year] as indicated by the caption of Figure 3. In the hydro-science research field, some of the most widely used return periods include 2-, 10-, 50-, 100-, 200-, and 500-yr. Therefore, I was wondering about the case where T=90. You should consider explaining why there is such a case with a return period of 90 years somewhere between lines 140 and 144 where you introduce your data. This could be how you determined those return periods for each rainfall event if you manually compute those statistics or a brief introduction about how your reference source (if the rainfall data are obtained from any existing data sources) assigned those rainfall events with various return periods*"

Response: The reviewer is right that the unit of T is [year] and we have added the information in the revised caption. Moreover, we agree with the reviewer about the choice of the representative return periods, and have added more information on the rainfall events, and revised Figure 3 by providing a case with a return period of 100 years (instead of the 90 years).