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Interactive comment

Interactive comment on "Using Long Short-Term Memory networks to connect water table depth anomalies to precipitation anomalies over Europe" *by* Yueling Ma et al.

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Dear Anonymous Referee 1,

Hereby the authors of the revised paper hess-2020-382 take the opportunity to thank you for the useful comments and suggestions for improving our manuscript.

Please find below our responses to each of your comments. Your comments are marked in ***black italic***, and our responses are provided in regular font.

Authors used the LSTM network to forecast water table depth in Europe and analyzed the effects of local elements, which is very interesting. Comments are shown as follows:

Thank you for the positive feedback.

1. Line 63-64: The most obvious advantage of ANNs is not using learnable parameters. Some basic machine learning models, such as MLP, can also adapt weights and bias.

Yes, this is true. The MLP (Multilayer perceptron) is a type of feedforward network, belonging to ANNs, so probably you meant models such as linear regression.

The aim of Line 63-64 is not to express that using learnable parameters is the largest advantage of ANNs, but to give the reader a brief overview of how ANNs work (i.e., "adapting learnable parameters on the links between neurons") and what they can achieve (i.e., "give an appropriate input-output mapping based on observed data even for complex nonlinear relationships"). We will rephrase this part in the revised version for clarity.

2. It is suggested that the authors should describe the relationship between ANN and RNN before introducing the details of RNN. The same problem occurs in the introduction of LSTM. The limitation of RNN is not introduced first.

Thanks for pointing out the structural inconsistency.

RNNs are a type of ANNs designed for sequential data analysis, outperforming feed-forward networks in handling the relationship between sequences. LSTM networks belong to RNNs, capable to better exploit the long-term relationship between sequences than standard RNNs.

We agree and will modify the relevant content in the introduction section.

3. Line 71. Lots of research should be cited related to RNN rather than ANN here.

We cited many references related to feedforward networks and their variants (i.e., ANNs) in Line 71 to demonstrate the popularity of their application in groundwater level modeling, and then highlighted the advantage of using RNNs compared to feedforward networks. Further, the reader can find a considerable amount of research related to RNNs from the cited papers in the reference section. However, we agree that considering some more references specifically related to RNNs might be beneficial for the manuscript. Therefore, we will add some additional references in the respective paragraph.

4. Line 129. Why did the authors say they have the same architecture of hidden

neurons as Gers et al. (2000) but without the detailed introduction of Gers et al. (2000) or the architecture?

Gers et al. (2000) is one of the pioneer papers on LSTM networks. We gave a short introduction about the structure of hidden neurons in Line 131-132, and illustrated all the components of a hidden neuron in Fig.2. Moreover, we provided the reader with the pseudocode of the LSTM network displayed in Fig.2 to help the reader understand how data is transferred in a LSTM hidden neuron. Therefore, we think the current information regarding the structure of a LSTM hidden neuron should be sufficient. Detailed information such as the functions of each component in the hidden neuron might be too technical for the reader, and the one who is interested in the detail is referred to Gers et al. (2000).

5. In equation (3), some representation should be shown as subscript

We will modify them.

6. Line 194. TSMP should be written in full name when it shows for the first time.

We will modify it.

7. The website of data access should be shown in this paper.

Could you please specify which data you are referring to? If you meant the TSMP-G2A data set, we have provided the corresponding DOI in “Code and data availability” in Line 423, which guides the reader to the data set.

8. Figure 5 shows the result of the training dataset. The good performance of the training dataset cannot prove that the model is good. It is suggested that the test dataset should be used to show the result of the model.

We agree that the model cannot be proved to be good based on its training performance. That is why we reported the model performance for both the training dataset and the test dataset. In Fig.5, we provide the comparisons between the water table depth anomaly maps not only in 2003 (i.e., in the training period) but also in 2015 (i.e., in the test period). We will extend the figure caption accordingly.

9. Line 311. It is confusing that the authors say Figure 6 is based on the categories in Table 3, but the categories seem to base on Table 1 in Figure 6.

Table 1 mainly describes the climatologic information of our study regions (i.e., the PRUDENCE regions), and Table 3 presents the value ranges of the categories. For example, we categorized the selected pixels in each PRUDENCE region into two categories of yearly averaged snow water equivalent based on the value ranges in Table 3, and calculated the average and standard deviation of R^2 and RMSE for each category in each region to obtain Fig.6d. We will rephrase the related section for clarity.

10. When C3 is shown, it only means that the training process of the model has some problems and needs to be modified further.

As we applied the same structure of the networks at individual pixels, we wanted to identify the climatologic characteristics of a pixel where the proposed LSTM networks failed to learn from the training set, and thus, we conducted analyses presented in Fig.8 and 9. According to the results in Fig.8, nearly all the pixels with network performance of type C3 are located in a deep aquifer (i.e., yearly averaged water table depth > 10 m), constituting locations where the relationship of pr_a and wtd_a is not that strong. In these cases, further information (e.g., soil moisture anomaly) may help improving deep aquifer predictions.

11. Line 365. What is the standard of the selection of Pixels 1-3?

We randomly selected pixels that satisfied the representative climatologic characteristics of C1, C2 and C3 given in Line 354-358 and Fig.8, and conducted cross wavelet transform at those locations to verify our hypothesis that there was a time-varying pattern between pr_a and wtd_a at several pixels over the European continent. Here, we only showed Pixels 1-3 and Pixels 4-6 (in Appendix C) as representative examples.