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Interactive Comment

Interactive comment on "Multi-step-ahead predictor design for effective long-term forecast of hydrological signals using a novel wavelet-NN hybrid model" *by* J.-S. Yang et al.

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Dear referee #1,

Thank you for reviewing our manuscript. We appreciate all your invaluable suggestions and comments. We have modified the manuscript accordingly, and detailed corrections and explanations are listed below point by point. We believe that by presenting and publishing the interim results other scientist can apply the findings and discussions can be started to further develop the new methods.

Comment 1: Please give the expansion of the CDW-NN in the abstract.

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√ We have explained the CDW-NN in the abstract that "... a novel wavelet-NN hybrid model CDW-NN, combining Continuous and Discrete Wavelet Transforms (CWT and DWT) and Neural Networks (NN), ...".

Comment 2: Page 9248, line 24, Figure 2 should be read as Figure 5.

√ We have corrected all the four places of mistakes in writing in paragraph 1 of Section 3.2, i.e. Fig. 2(a), Fig. 2(b), Fig. 2(c) and Fig. 2(d) have been replaced with Fig. 5(a), Fig. 5(b), Fig. 5(c) and Fig. 5(d).

Comment 3: What is the average changing periodicity. Please explain it more detail.

√ For the old manuscript, in paragraph 2 of Section 3.2 we gave the "average changing periodicity (T)" a simple explanation that "obtained by calculating and averaging the day numbers of each two neighboring high and low river stage periods". Following the referee's suggestion, we have added a more detailed explanation, that "... the average changing periodicity (T) of river stage time series, i.e. the average cycle days between each two time domains with positive wavelet coefficients, was 15 days obtained by calculating and averaging the day numbers of each two neighboring high and low river stage periods.".

Comment 4: Page 9249 line 6 28 years should be read as 28 days.

√ We have corrected this mistake in writing in paragraph 2 of Section 3.2, i.e. "28 years" has been replaced with "28 days".

Comment 5: Using correlation coefficient, R in the model accuracy evaluation can mislead. To prevent this situation, the use of squared errors is recommended. Please evaluate your results by RËĘ2 or Nash-Sutcliffe sufficiency score.

√ Following the referee's suggestion, we have modified the manuscript, i.e. utilizing R square instead of R to select the DWT components and to evaluate model performances. The R values in both Table 1 and Table 2 have been replaced with R square values. Forecast performances among different models have been evaluated by analyzing R2, RMSE and MAE.

Comment 6: The methodology explained for multistep long lead forecasting is confusing. They used CWT to determine significant cycles (12 days and 23 days). These values are used as lag-time to predict future water levels. Then this process is called CW-NN or CW-NF. In my opinion this is not a hybrid model and should not be named in this way. In fact this is a simple NN or NF model that used lagged inputs.

$\surd$ Following this suggestion, we have corrected the confusing speaking of "hybrid models" for the CW- models in the text. In our manuscript, we have established 12 types of models, which can be classified as four major types, CDW-, CW-, DW- and pure models. The CDW- and DW- models can be called hybrid models because new model inputs (TD series) obtained by DWT are used, that CDW- models use 15-day and 28-day lagged new TD as inputs and DW- models use 1-day and 2-day lagged new TD as inputs. While, strictly speaking, the CW- models, which use 15-day and 28-day lagged original data as inputs, can not be called hybrid models, just as the referee's comment.

Comment 7: When we look at Table 1, it is seen that there is no significant differences in correlation coefficients between S and TD. So why do you need decompose S series instead of using the original series. The correlations between S and lagged S are already same.

$\surd$ According to the referee's comment, to eliminate some possible confusion, we have given some expansion of the results analysis about Table 1 in paragraph 2 of Section 3.3. In Section 3.3, the new series TD was obtained by adding 3 DWT components. Generally, the new series might show a little low correlation with S because the other 8 components were filtered. However, results showed that the lagged new series (TD) showed a similar and even slightly higher correlation than the lagged original series with St, which indicated that the new TD series kept the main information of the original signal dynamics in spite of the filtering of much other weak correlated information by DWT. Therefore, our purpose is to prove the new TD series can keep the main information of the original signal. The advantage of the selection of TD as new inputs depends on the prominent ability in filtering weak correlated details and noisy dynamics from original signal in the modeling and forecasting processes. It doesn't depend on the comparison of correlation coefficients between TD and S.

Comment 8: In Table 2, I have seen any improvement of results by CDW over NF, ANN, and LR. Also the scores of hybrid CDW is very low which is not within the acceptable limits.

$\surd$ As we know, there are two kinds of multi-step ahead forecasts. The key difference between these two kinds is the selection of model inputs in the forecasting process. The first kind is using the previous days' original (observed) data as model inputs in each forecast step. The second kind is using the previous days' predicted data as model inputs in each forecast step. The different forecast performances and corresponding mechanisms of these two kinds of long-term forecasting have been published by us in Journal of Hydrology (Yu, S.P., Yang, J.S., Liu, G.M.: A novel discussion on two long-term forecast mechanisms for hydro-meteorological signals using hybrid wavelet-NN model. J. Hydrol. 497, 189-197, 2013). According to the reference, the fist kind forecast (namely a "seeming" long-term forecast) generally generates an abnormally and totally high and similar performance. While the second kind forecast (namely a "true" long-term forecast) generally generates an overall poor performance because of the error accumulation in each forecast step during a long-term forecast process. The 1096-day long-term forecasts by different models in this manuscript belong to the second kind forecast. The overall relatively poor performances of all models in Table 2 are caused by the error accumulations from 74 steps (CDW- and CW- models) and 1096 steps (DW- and pure models). However, the prominent advantage of CDW-NF model, comparing other models, has been revealed. Since there is no effective method yet to improve the forecast accuracy of the "true" long-term forecast, it is one of our main purposes that finding some innovative and valuable approaches to increase the "true" long-term forecast performance. Although the R2 of CDW-NF forecasting in the end of the 1096-day forecast process is relatively low, we have found some other advantage of CDW-NF by further studying its forecast performance during the continuous 1096-day forecasting steps (see Fig. 7).

Comment 9: As far as I understand from Figure 7, the correlation coefficient results is for whole period. To reflect the unbiased conditions, the results should be for testing period.

$\surd$ The forecast performances of 12 types of models in Figure 7 are absolutely obtained from the testing period. In the manuscript, we used 10 years of rive stage data covering 1998-2007, i.e. 3652 days, to train and establish the optimal models. The remaining 3 years of river stage data covering 2008-2010, i.e. 1096 days in Fig. 7, were used to test the models. As was mentioned in the explanation of Comment 8, the model forecasting in our case is a kind of "true" long-term forecast, i.e. using the previous days' predicted data as model inputs in each forecast step to forecast each 1096-day river stage. According to results of Fig. 7, we try to reveal the different forecast performances of 12 types of models in a short-term forecasting, a mid-term forecasting and a long-term forecasting.

Comment 10: Since the manuscript related to continuous wavelet application The authors can give references to Ozger et al (2012) who used continuous wavelet decomposition with neuro-fuzzy approach in their study. Ozger, M., Mishra, A. K.; and Singh, V. P. 2012. Long Lead Time Drought Forecasting Using a Wavelet and Fuzzy Logic Combination Model: A Case Study in Texas, Journal of Hydrometeorology, 13 (1), 284-297.

$\surd$ Following the referee's suggestion, we have read this important reference carefully and added it to the References part in our manuscript.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 10, 9239, 2013.