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MEDIUM-RANGE LOW FLOW FORECASTS IN THE LOBITH, RIVER RHINE

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Abstract: The aim of this study is to predict low flows 14 days in advance using a data-driven model. First, we apply correlation analysis to select appropriate temporal scales of pre-selected inputs that are precipitation, potential evapotranspiration, discharge, groundwater, snow height and lake levels. The forecasted rainfall has also been used as model input to forecast low flows in the River Rhine at Lobith. The correlation analysis analysis between low flows and basin indicators show stronger correlations for the Alpine sub-basins than the rainfed sub-basins. The Middle and Lower Rhine are downstream channel areas and they do not contribute to the discharge. Therefore, they are excluded from the entire analysis. The low flow predictions for the Alpine sub-basins and the Mosel are reasonable during the validation period, whereas the ANN for Lobith shows low performance for a different test period. The results for the training and the validation period are more encouraging than the test period for Lobith, i.e. Nash-Sutcliffe (NS) efficiency of 0.75 and 0.73 respectively.

Keywords: Low flows, River Rhine, ANN, forecast model

Ren Nehri'ndeki Düşük Debilerin Önceden Kestirimi İçin Model Geliştirilmesi

Öz: Bu çalışmada hedeflenen Ren nehrinin düşük debilerini kara kutu modeli yardımıyla iki hafta önceden tahmin etmektir. Modele eklenecek tanımlayıcı değişkenler korelasyon analizi ile seçildi. Model girdileri seçildikten sonra model geçmiş gözlemlerle kalibre edildi. Ardından bir iklim modeli tarafından tahmin edilmiş yağış verisi hidrolojik modelimize girdi olarak eklendi. Kar yağışının etkin olduğu üst havzalarda düşük debiler ile havza karakteristik verileri (yağış, buharlaşma ve göl seviyesi gibi) arasında yüksek korelasyon değerleri bulunurken yağmurun hakim olduğu aşağı havzalarda korelasyon katsayıları 0.57 ile 0.68 arasında değişmektedir. Benzetim başarımları Doğu Alp havzası için 0.96 NS (1.0 en yüksek değerdir), Batı Alp havzası için 0.83 ve Moselle için 0.77 dir. Lobith çıkış noktası için kalibrasyon ve doğrulama dönemlerindeki tahmin başarımları 0.75 NS civarında olup sonraki çalısmalar için cesaret vericidir.

Anahtar Kelimeler: Düşük debi, River Rhine, yapay sinir ağları, tahmin modeli

1. INTRODUCTION

The people prefer to settle close to the freshwater resources and mostly live in cities along the rivers (Moyle and Leidy, 1992). The River Rhine basin accommodates a dense population i.e. nearly 60 million people (Huisman et al., 2000). The water of the River Rhine is used for different purposes such as river navigation, industrial cooling water, agricultural irrigation, barrier for salinization, recreation and also drinking water for the Netherlands (Heezik, 2008; Tielrooij, 2000). Low flows may have severe effects for the river users. Especially the longer

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period of low flows can cause water shortages for agriculture causing sharp drop in the agricultural harvest and total revenue. The low water levels in the channels have also a negative effect for navigation and the cooling water (Rutten et al., 2008). During low flows the navigation depth is different and the vessels can no longer carry full load. Then the cost per unit for the shipment increases sharply. The power companies can suffer with less water in the river as they have to stop if the the water temperature dangerous for river habitat based on environemtal flow requirements (Rutten et al., 2008). In this study we are interested in predicting low flows two-week in advance using a multi component data-driven model to anticipate above mentioned river problems. A lead time of 14 days can provide time to elaborate the water allocation (De Bruijn et al., 2006).

In general hydrological models are key elements to understand streamflow dynamics in any river. There are mainly three types of models: data-driven, conceptual, physically based distributed models (Danandeh Mehr and Demirel, 2016; Evans and Schreider, 2002). In general the models should meet two criteria. First, they should forecast the discharge properly and secondy it has to include physical basin indicators. Both help to understand governing physical processes and subsequaently simulate the discharge (Demirel et al., 2013). The main objective is to find a proper hydrological forecast model which has good performances during low flows. The causes of low flows and the timing of low flows are both important for hydrologists and basin residents. Rijkswaterstaat (Dutch state water works) usually issues drought warnings for the Netherlands in the spring and summer. They use low flow indicators such as the amount of Alpine snow and the storage in the Alpine lakes and relate these low flow indicators to Lobith. For this purpose we use low flow correlation to examine relationship between each low flow indicator and the sub-basin low flows (Demirel et al., 2013). We analyze the correlation using different lag and temporal resolution. Our approach is different than the one applied by Rijkswaterstaat especially it differs in temporal and spatial resolutions. For the type and variability of diffenrent indicators the use of Artificial Neural Network type models (ANN model) is a good option. ANN models can quickly learn to ignore irrelevant inputs and can deal with input data without knowing exactly the process of what is happening (Southall et al., 1995). A major disadvantage of ANNs is the difficulty of physical interpretation of model structure and parameters since it is a black box model where the interactions inside the model have no physical meaning or interpretation (Benítez et al., 1997). The added value of this study is combining different relevant low flow indicators in an ANN model to forecast low flows at Lobith station. This model could give insight in the longer lead time of 14 days.

2. STUDY AREA AND DATA

a. Study Area

Lobith is the entrance point of The River Rhine to the Netherlands. The Rhine River starts from upstream areas in Switzerland and passes through Liechtenstein, small parts of Italy and Austria, France, Luxembourg, Germany, and a small part of Belgium (Grabs et al., 1997). Figure 1 shows the sub-basins of the Rhine basin. During the late summer the discharge at Lobith consist of 70% of Alpine water (Grabs et al., 1997).

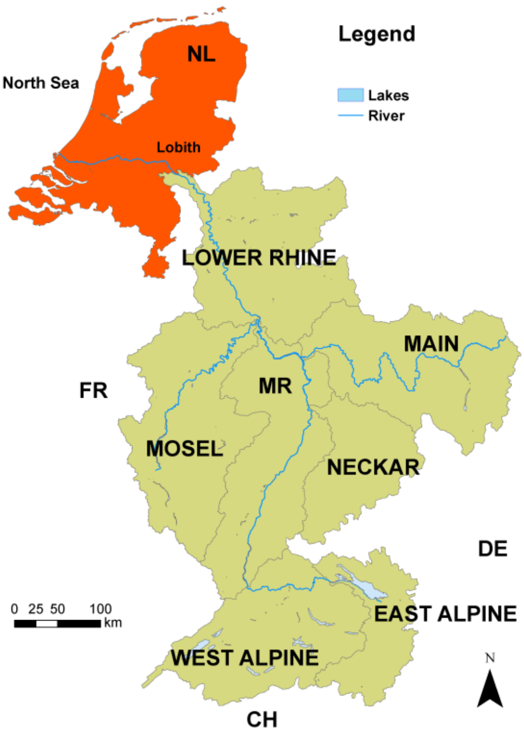

Figure 1:
The River Rhine and seven sub-basins.

b. Data

Table **1** shows summary of the input data i.e. precipitation (P), potential evapotranspiration (PET), groundwater level (G), snow levels (S) and lake levels (L). The two Alpine sub-basins have 6 indicators and the 5 rainfed sub-basins have 4 indicators. Together the number of ANN input is 32.

Table 1 Data summary and collection sources

Data	**Abbreviation**	**Spatial Resolution**	**Number of stations**	**Period**	**Temporal Resolution**	**Source**
Streamflow	Q	Point	172	1974-2008	Daily	GRDC
Precipitation	P	Sub-basins	134	1951-2006	Daily	BfG
Evapotranspiration	E	Sub-basins	134	1950-2006	Daily	BfG
Groundwater	G	Point	1402	1986-2009	Weekly, monthly	BAFU, German states
Snow	S	Point	40	1978-2008	Daily, monthly	SLF
Lake levels	L	Point	11	1978-2008	Daily	BAFU

3. METHODS

a. Correlation analysis

In this sutyd we apply correlation analysis to determine the appropriate lag and temporal resolution of the model inputs to predict two-week ahead low flows. Here the lag time shows the response time of the basin including concentration time and travel time whereas the temporal resolution represents the amount of water entering or leaving the basin (Demirel et al., 2013). For example 50 m^3/s indicates a large amount of water for a stream.

The correlation analysis gives the linear dependency between a sub-basin low flow indicator and the produced discharge of a sub-basin. When the flow is below the threshold at Lobith (LFT) the day is counted as a low flow day. The LFT is the discharge which has been exceeded in 75% of the time (Demirel et al., 2013). The discharge of a sub-basin needs time to travel towards Lobith. During low flows the West Alpine discharge takes around 7 days to reach Lobith after it has passed the West Alpine outlet at Untersiggenthal. This daily travel time is based on an average velocity of 1 m/s. For the East Alpine discharge the travel time is also around 7 days. For the Neckar this is 5 days, for the Main this is around 4 days and for the Mosel around 3 days. So this means the lead time needed for a sub-basin is the forecast time of 14 days at Lobith minus the travel time to a sub-basin outlet.

The correlation analysis between the flow at the subbasin outlet and a indicator start with three daily data series (indicator, daily discharge record at Lobith and the sub-basin discharge). In this study the overlapping data between 1989 and 2006 will be used. For this period a low flow threshold will be determined. This is the discharge which will be exceeded in 75% of the time (Q75 Lobith). The three-day average discharge below this threshold is labeled as low flow days at Lobith. This flow is a composition of the discharge of the sub-basins. The low flow days at Lobith, corrected with the travel time, determine the low flow days at the basin outlet. The three days discharge at the sub-basin outlet is ready for the correlation study. The daily indicator data has for every combination of the lag and temporal resolution. For each combination the correlation could be calculated.

b. Implementation of the ANN model for Lobith

The input layer of ANN model has neurons for every input series, whereas the output layer has a single output layer and in between there is a hidden layer where the transfer functions are used. The number of neurons is a crucial to design the interactions in the model. When the number of neurons is higher then the complexity of the model is higher as well. In this study the ANN model is calibrated (trained) using 1 to 5 neurons in the hidden layer. The ANN model of used for low flows at Lobith has a similar structure to the model of the individual basins. The only different part is the input information. The modeled discharges for five sub-basins are the input instead of the low flow indicators and the short time precipitation. The output node is the predicted low flows at Lobith (Figure 2).

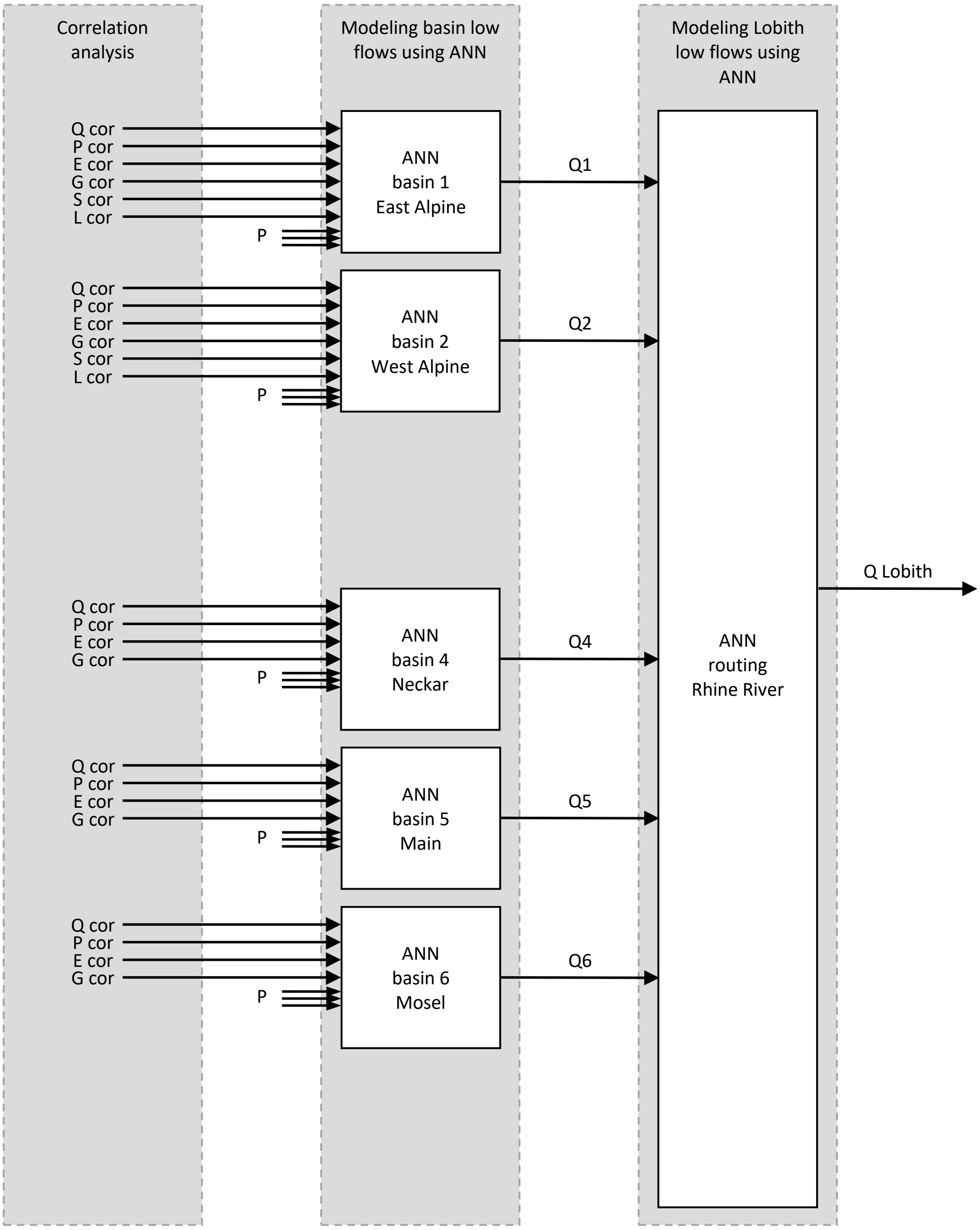

Figure 2:
Schematization of the model setup

4. RESULTS

a. Appropriate input scales for the ANN models

The utility of correlation analysis is to find the optimum lag and temporal resolution for low flow indicators and to select proper inputs for the ANN models. Figure 3 shows one of the correlation results for one of the sub-basins (East Alpine). Based on this figure, the correlation between daily low flows and observed discharge is 0.9 for a 7 day lag-time and 3 weekly observed streamflow.

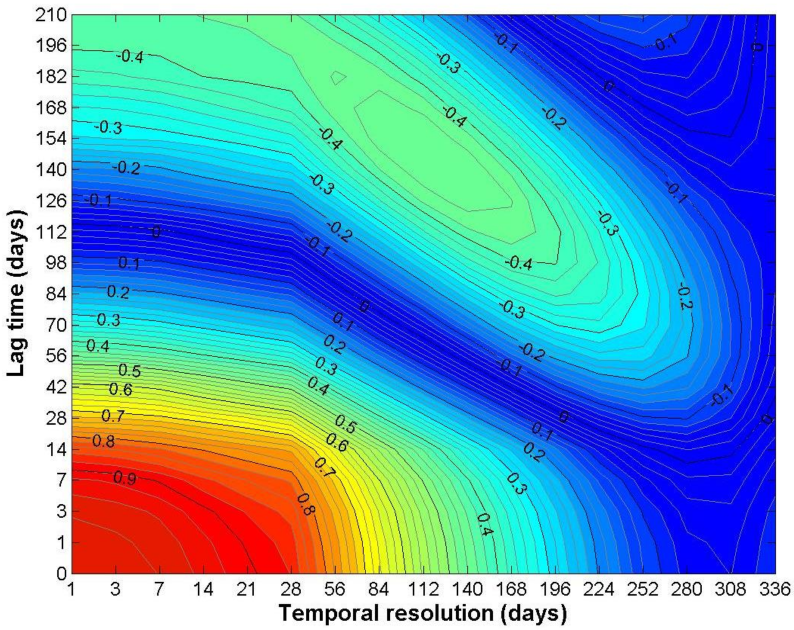

Figure 3:
Correlation between the low flows and the observed discharge in the East Alpine sub-basin for different lags and temporal resolutions

The discharge of the East Alpine and the lake level have high correlations around 0.95. These indicators are probably good indicators for the basin discharge. The highest corelation for low flows and evatranspiration is around 0.68. All other relations are less significant. The precipitation does not show high correlation for short precipitation amounts. For the Neckar sub-basin, there is a corelation between discharge today and the rainfall six days before. The appropriate lead time for the Neckar is found to be nine days.

The discharge in the Middle Rhine and the Lower Rhine are not appropriate from hydrological processes aspect since they are the channel parts rather than a sub-basin so that these basins are not included in the Lobith model (Bouwma, 2011). The lag and temporal resolution for the West Alpine sub-basin are longer showing the memory of large storages of snow and lakes.

b. Predicted low flows in the sub-basins

Figure 4 shows the discharge for the year 2005 based on the lowest mean squared error for the test phase. The plot of the year 2005 below gives a good insight in the performances of the ANN model for that particular basin.

c. Predicted low flows at Lobith outlet

Figure 5 shows that the modeled low flows at Lobith are not encouraging. The results for test phase show only a NS performance of 0.32 and a correlation of 0.71. However, the performance for the training and the validation periods are reasonable. The correlation values are respectively 0.87 and 0.86 and the NS values are 0.75 and 0.72. The observed and simulated low flow hydrographraphs are presented in Figure 5.

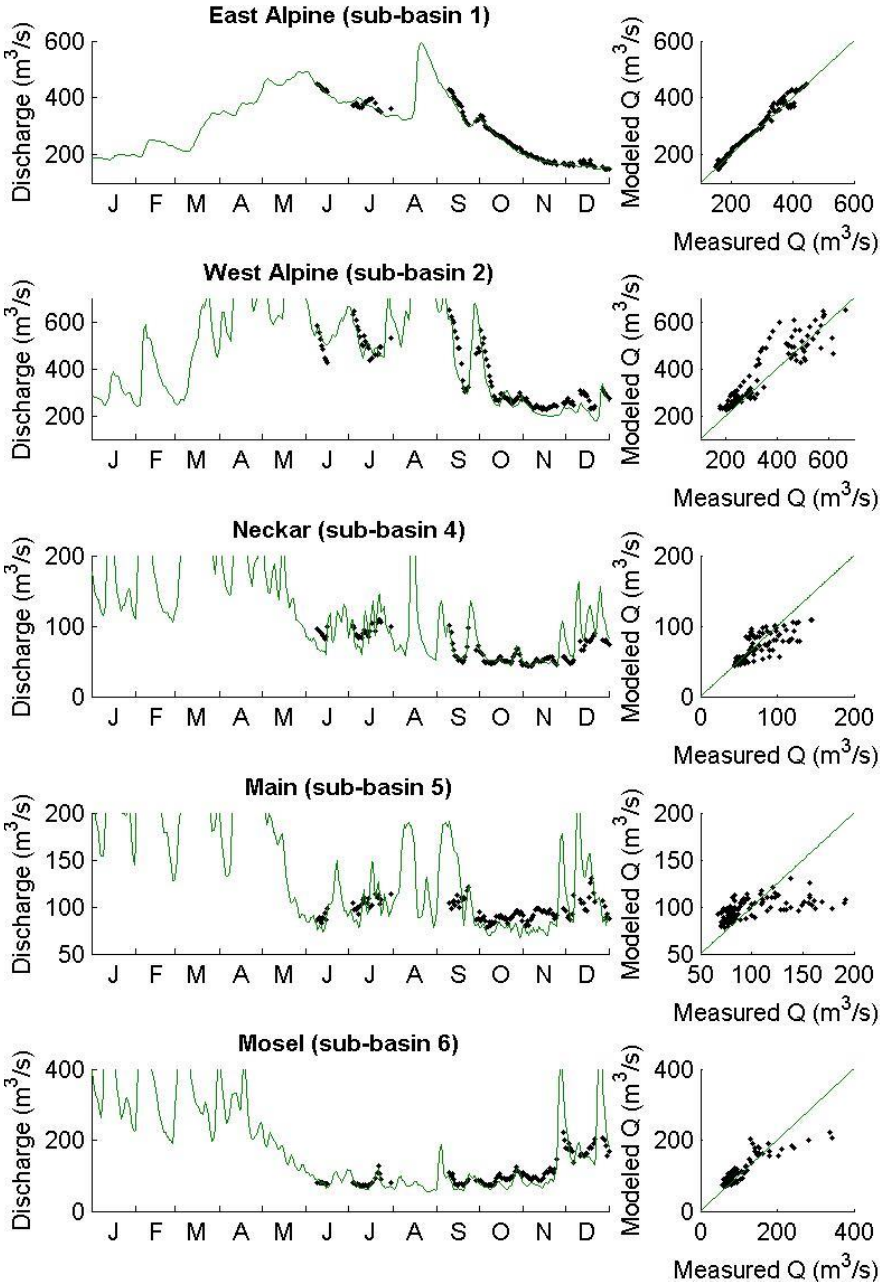

Figure 4:
Observed and simulated discharge (left column) and Q-Q plot (right column) for the modelled five sub-basins test period (year 2005)

5. DISCUSSION

The ANN model for Lobith uses the output discharge of five of the seven modeled subbasins. As mentioned previously, the discharges of two sub-basins that are the Middle Rhine and the Lower Rhine are not taken into account in our modeling framework. The correlations between low flows and indicators in the Lower Rhine are very poor. All rivers have more or less the same land cover and soil characteristics. The travel time to Lobith for different basins is in the same order of magnitude. The forecasted precipitation is an important indicator for the low flows 14 days in advance. The precipitation showers are intensive and have substantial local impacts. The model performance could be improved; however the simulation with 10 days in advance precipitation forecasts has a large uncertainty. The main aim of this study is not on calibration methods, but rather on the testing ANNs for low flow forecasting in the Rhine basin.

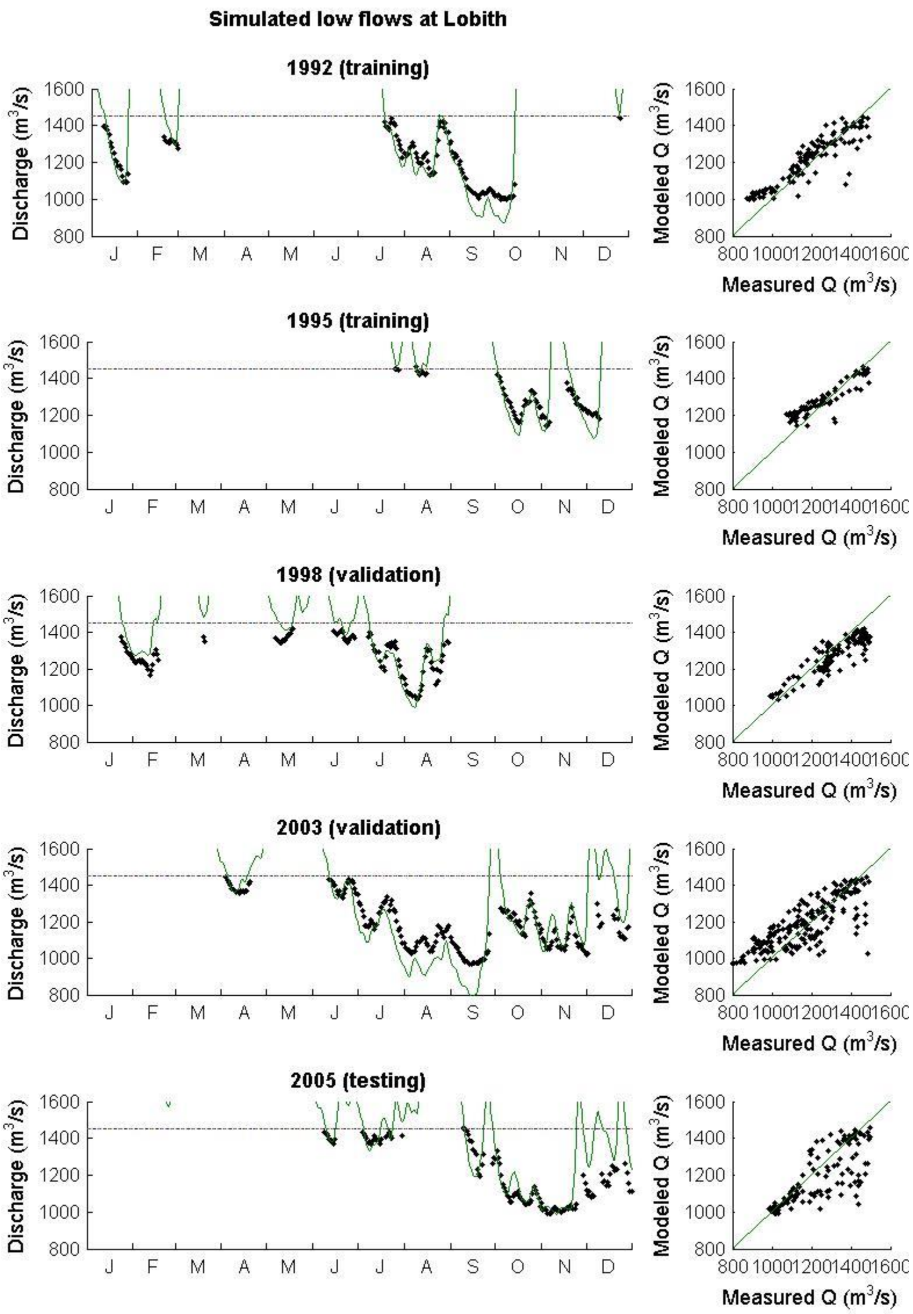

Figure 5:
Observed and simulated discharge (left column) and Q-Q plots (right column) for Lobith

The ANN input data has major influence on the training. The lack of information could lead to a bad training. This became clear for the rainfed sub-basins. The modeled discharge did not react on changes of parameters, because a crucial input process was missing. The forecasted rainfall was implemented, but without considering the efficient lags and temporal resolutions. The MSE error is the default objective function inside MATLAB. Other error functions are not developed. So a MATLAB user is obligated to use MSE or program a new objective function itself. The adaptation to a new objective function causes also that the adaptation for the network weights should be considered. Another objective function could be successful. ANN performance could increase by rescaling measured data (Dawson and Wilby, 2001). Measured data could be transformed with any function. After the ANN training the modeled discharge is still rescaled. The real modeled discharge could be calculated to reverse the rescaling. The used transfer functions are also default functions. The changes towards other functions could have impact on the performance (Dawson and Wilby, 2001). The next step for this study is to implement actual forecasted data. The performance of the modeled discharges is probably overestimated. The training of the ANN models is with perfect forecasted rainfall. However the rainfall is not perfectly forecasted. The rainfall forecast has an uncertainty range, which could be added in the simulation by multiple simulations. The ECMWF generates multiple rainfall scenarios for the coming period. These different rainfall scenarios of the ECMWF could be used for the input of the ANN simulation, which lead to a multiple discharge output. These discharges create a discharge range.

6. CONCLUSIONS

In this study low flow indicators, appropriate ANN input scales and the low flow model performance are assessed. Correlation analysis is used to estimate appropriate lag time and temporal resolution of model inputs. The Alpine sub-basins have the strongest correlations between the historical discharge, lake levels and the low flows. Also, the historical discharge, the snow height and the lake levels are the best indicators for West Alpine. The indicators in the rainfall-dominated basins are less pronounced than Alpine basins. The perfect forecasted precipitation (observed) shows a strong relation between the precipitation and the basin discharge. The Middle Rhine and the Lower Rhine have discharge inlets. The produced discharge inside these basins is difficult to assess, because of the travel time and dispersion affect the produced discharge. The ANNs for the Alpine sub-basins has shown good results. The low flow indicators and the perfect future precipitation are the ANN input. The network transfers the input data to reliable output. The Nash-Sutcliffe Efficiency of the modeled discharge for the Alpine basins is 0.96 for the East Alpine basin and 0.83 for the West Alpine basin in the test phase. This is from the fact that there is the large amount of water storage available in the basins. The Neckar, the Main and the Mosel basin have weaker performances than the Alpine basins. The Nash- Sutcliffe Efficiencies for these sub-basins are 0.48, 0.23 and 0.77 respectively. The Mosel is the only good performing non-Alpine sub-basin. Forecasting low flows at Lobith is a difficult task. The results demonstrate a poor performance with ANN. The Nash-Sutcliffe efficiency for the three days moving average discharge and 14 days in advance is only around 0.32 for the test phase. Newly emerging algortihms like genetic programing (Danandeh Mehr and Kahya, 2017) can be applied to improve the predictive skills.

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REFERENCES

1. Benítez, J.M., Castro, J.L., Requena, I., 1997. *Are artificial neural networks black boxes?* IEEE Trans. Neural Networks 8, 1156–1164. doi:10.1109/72.623216

2. Bouwma, P., 2011. Low flow forecasts for the Rhine at Lobith 14 days ahead A correlation analysis and an artificial neural network study. University of Twente, Enschede (MSc thesis: http://essay.utwente.nl/61075/).

3. Danandeh Mehr, A., Demirel, M.C., 2016. *On the Calibration of Multigene Genetic Programming to Simulate Low Flows in the Moselle River*. Uludag University Journal of The Faculty of Engineering 21, 365–365. doi:10.17482/uumfd.278107

4. Danandeh Mehr, A., Kahya, E., 2017. *A Pareto-optimal moving average multigene genetic programming model for daily streamflow prediction*. J. Hydrol. 549, 603–615. doi:10.1016/j.jhydrol.2017.04.045

5. Dawson, C.W., Wilby, R.L., 2001. *Hydrological modelling using artificial neural networks*. Prog. Phys. Geogr. 25, 80–108. doi:10.1177/030913330102500104

6. De Bruijn, K.M., Passchier, R., De Bruin, K., Passchier, R., 2006. Predicting low-flows in the Rhine River. WL | Delft Hydraulics, Delft, The Netherlands.

7. Demirel, M.C., Booij, M.J., Hoekstra, A.Y., 2013. *Identification of appropriate lags and temporal resolutions for low flow indicators in the River Rhine to forecast low flows with different lead times*. Hydrol. Process. 27, 2742–2758. doi:10.1002/hyp.9402

8. Evans, J., Schreider, S., 2002. *Hydrological impacts of climate change on inflows to Perth, Australia*. Clim. Change 55, 361–393. doi:10.1023/A:1020588416541

9. Grabs, W., Daamen, K., de Montmollin, F., 1997. *Impact of Climate Change on Hydrological Regimes and Water Resources Management in the Rhine Basin (CHR-report I-16)*. CHR/KHR, Lelystad.

10. Heezik, A. V., 2008. Strijd om de rivieren: 200 jaar rivierenbeleid in Nederland of de opkomst en ondergang van het streven naar de normale rivier.

11. Huisman, P., De Jong, J., Wieriks, K., 2000. *Transboundary cooperation in shared river basins: experiences from the Rhine, Meuse and North Sea*. Water Policy 2, 83–97. doi:10.1016/S1366-7017(99)00023-9

12. Moyle, P.B., Leidy, R.A., 1992. *Loss of biodiversity in aquatic ecosystems: evidence from fish faunas*, Conservation Biology. doi:10.1007/978-1-4684-6426-9_6

13. Rutten, M.M., van de Giesen, N., Baptist, M., Icke, J., Uijttewaal, W., 2008. *Seasonal forecast of cooling water problems in the River Rhine*. Hydrol. Process. 22, 1037–1045. doi:10.1002/hyp.6988

14. Southall, H.L., Simmers, J.A., O'Donnell, T.H., 1995. *Direction finding in phased arrays with a neural network beamformer*. IEEE Trans. Antennas Propag. 43, 1369–1374. doi:10.1109/8.475924

15. Tielrooij, F., 2000. Waterbeleid voor de 21e eeuw: geef water de ruimte en de aandacht die het verdient.