Low flow forecasts for the Rhine at Lobith 14 days ahead

A correlation analysis and an artificial neural network study

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List of abbreviations

ANN model	Artificial Neural Network model
C	Correlation
E	Evatranspiration
ECMWF	European Centre for Medium-range Weather Forecasts
G	Groundwater storage
L	Lake level
LFT	Low Flow Threshold
MAE	Mean Absolute Error
MATLAB	The computer program used for the calculations, modeling and plotting
NSE	Nash Sutcliffe Efficiency
P	Precipitation
Q	Discharge
Q75	The discharge which will be exceeded in 75 percent of the time
S	Snow package storage

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Summary

The River Rhine has periods of low flows during the year. Low flows may cause difficulties for water demand. Insight in low flows could help to understand the discharge behavior and reduce damage. The main objective of this study is to forecast the discharge at Lobith 14 days ahead during low flow conditions using an Artificial Neural Network (ANN) model. In this study a correlation analysis is carried out, and ANN models are developed and applied to simulate the sub-basin discharges and the Rhine discharge at Lobith.

The Rhine basin upstream of Lobith is divers and therefore, it is sub-divided into seven sub-basins. The sub-basins are East Alpine, West Alpine, Middle Rhine, Neckar, Main, Mosel and Lower Rhine. For all sub-basins an overlapping period of 16 years of daily data series is available. These data series include information about the discharge, precipitation, evapotranspiration, groundwater storage, snow depths and lake levels.

The correlation analysis is performed to determine the linear relation between the discharge at the outlet of each sub-basin during low flows and a single low flow indicator. The outcomes of the correlation analysis and forecasted rainfall have been used to define the input for the ANN per sub-basin to simulate low flows. Finally, low flows at Lobith are simulated using an ANN model and the simulated discharges of five sub-basins.

The results of the correlation analysis show good correlations for the Alpine sub-basins (East Alpine: 0.98 and West Alpine: 0.81), but relatively low correlations for the rainfed sub-basins (Neckar: 0.67, Main: 0.57 and Mosel: 0.68). The correlations for the Middle and Lower Rhine are unreliable, because of poor discharge data. The simulated low flows per sub-basin resulted in good Nash-Sutcliffe Efficiencies (NSE) for the Alpine sub-basins and the Mosel for the test phase (East Alpine: 0.96, West Alpine: 0.83 and Mosel: 0.77). The Neckar and the Main have a NSE of just 0.48 and 0.23. The independent test phase of the ANN for Lobith shows a low performance, namely a NSE of 0.32. The results for the training and the validation period are much better with a NSE for Lobith of 0.75 and 0.73 respectively.

The results should be interpreted taking into account that perfect weather forecasts for rainfall have been used to train the ANNs. And discharges of the sub-basins Middle Rhine and Lower Rhine have been neglected. Discrepancy of rainfall in the Middle Rhine and Lower Rhine sub-basins in perspective to the other rainfed sub-basins will cause a rise of the actual discharge at Lobith. However this will not be seen in the simulation at Lobith, because of these basins will be left out of the input.

The performance at Lobith is poor. However the correlations and simulated discharges for the Alpine basins are very good and during low flows 70 percent of the flow at Lobith originates from the Alps. This indicates the potential of using ANN models for forecasting low flows with a lead time of 14 days. Future work should focus on improving and refining the input data and ANN modeling in order to improve the low flow forecasts at Lobith.

1 Introduction

1.1 Background

A human consists of two thirds of water and it is dependent of fresh water. So the majority of the world's population lives nearby rivers and lakes to fulfill the fresh water need. The people live mostly in cities which lay along waterways (Moyle and Leidy, 1992). Around 60 million people live in the Rhine basin (Huisman et al., 2000).

Because of the large amount of inhabitants of the River Rhine basin, the dependence on the river is high and will cause claims on its water. The River Rhine is used for multiple purposes (Tielrooij, 2000) like navigation, cooling water for industry, irrigation water for agriculture, defense against salinization, support nature, residing, recreation, and as a source for drinking water for the Netherlands (Heezik, 2008).

Low flows have consequences for the users. A period of low flows causes water shortages for the agriculture, so the harvest is lower and the income of the agriculture decreases. The lower discharges have also a negative effect for navigation and for the cooling water supply (Rutten et al., 2008). During low flows the navigation depth is no longer guaranteed, so vessels could no longer carry full load. The costs per unit for the shipment will increase. The power companies use river water for cooling purposes. During the summer this cooling function is harder, because of two reasons. First the amount of river water is low during the summer. Secondly the temperature of the river water is higher. Because of a restriction in the maximum temperature of river water, the cooling capacity is limited (Rutten et al., 2008).

The discharge of the Rhine is also crucial for the Dutch fresh water supply. River water is used for drinking water. The IJsselmeer is an important fresh water basin in the northern part of the Netherlands. The basin is filled by the IJssel River, which is a downstream branch of the Rhine. During droughts the water of the IJsselmeer could be used for the supply of the surrounding areas.

Another problem that is affected by low flows is the salt intrusion in vertical and in horizontal direction. The salty groundwater layer lays only a few meters under the surface level near the coast. In periods of droughts the fresh water pressure from above decreases, so the environment could be affected by the salty groundwater. The other way salt intrusion is a problem are the transitions between fresh and brackish surface water. For example, the sluices of IJmuiden require an amount of fresh water to protect the inland water quality. Also the river mouth requires a huge amount of fresh water to protect the environmental quality and sometimes also the fresh water supply in the coastal regions (Oude Essink, 2001).

For a lot of these harmed sectors it would be useful to have a better understanding of the low flows. An early estimation of the low flow could help the management. If the estimation of the low flows has a good quality, the sectors could act on a possible low flow in time (Rutten et al., 2008).

In the Netherlands the river flows could be steered well (Schielen et al., 2007). When during low flow periods rainfall events occur in the Alps and Germany, there will be a raise of the discharge (Landelijke Commissie Waterverdeling, 2011). This quantity of water could be allocated in the Netherlands. Insight in the quantity and the timing is than of major importance. A lead time of 14 days provides time to discuss the water allocation.

Low flow forecasts are important for many users. For navigation short-term forecasts about a week or two weeks ahead are required. For industries, recreation, and other users long-term indications of low flows would be useful (De Bruin and Passchier, 2006).

Hydrological rainfall-runoff models could help to understand low flows behavior of a river. There are three types of models, which could be categorized as conceptual, physically based and data-driven models (Evans and Schreider, 2002). Each category includes many models and each model could be adapted to a study area. For example HBV and TOPMODEL are conceptual models (Seibert, 1999). The HBV model has been applied to the Rhine River basin for a schematization with 134 sub-basins. This system includes a hydraulic model (SOBEK) for the routing of the simulated discharges to Lobith (Van de Langemheen et al., 2002). Te Linde used FEWS RHINE for low flow modeling. The outcomes were poor, even for forecasts with a short lead time. Examples of data driven models are the Artificial Neural Network model (ANN) and Model Trees (Solomatine and Dulal, 2010). An example of a physically based discharge model within GIS is the LISFLOOD model (De Roo et al., 2001). A disadvantage of this model type is the amount of data and computer capacity (De Roo et al., 2001).

The model which will be used should fulfill two major criteria. First it should forecast the discharge properly and secondly it has to include low flow indicators. The second function helps to understand the discharge behavior better. The main objective is to find a proper hydrological forecast model which has good performances during low flows. The reason why low flows appear and when they appear are of the same importance. Hydrologists would like to understand what is happening (De Vos and Rientjes, 2008).

There are already signals why low flows appear. Rijkswaterstaat usually issues drought warnings for the Netherlands in the spring and summer. They use indicators such as the amount of Alpine snow and the storage in the Alpine lakes. Rijkswaterstaat connect these low flow indicators to a Lobith discharge (Landelijke Commissie Waterverdeling, 2011). Also a connection is created between the behavior of low flows and indicators.

For this purpose the low flow correlation is a good method to detect a connection between indicator and the sub-basin discharge (Demirel et al., 2011). By analyzing the correlation using different lag and temporal resolution it is possible to create a low flow parameter (Demirel et al., 2011). These parameters are comparable as the parameters mentioned by Rijkswaterstaat, but the parameters of this study could differ in temporal and spatial resolution.

The appropriate lag and temporal resolution of the indicators will depend on the basin characteristics and lead time. The use of a specific lag and a temporal resolution for the indicators cause that many indicators do not fit in most models any longer. The appropriate lag and temporal resolution will differ for each indicator. So it is hard to combine these indicators into one model. Therefore the number of appropriate models decrease. To deal with the variability of indicators an Artificial Neural Network model (ANN model) is a good option.

ANN models can learn to ignore irrelevant inputs (Southall et al., 1995). A strong point of ANNs is that they could deal with input data without knowing exactly of what is happening (Southall et al., 1995). A huge disadvantage of ANNs is that they are hard to interpret. An ANN is a black box model where the interactions inside the model have no physical meaning or interpretation (Benitez et al., 1997). So possibly it is good to interpolate, but is hard to extrapolate results. Therefore it is important that the ANN generates good outcomes.

The added value of this study is that low flow indicators are combined in an ANN model to forecast low flows at Lobith. The development of a 14 days ahead forecast model could give insight in the longer lead time with also using an ANN model. If the modeling process is understood, the ANN approach could be improved further. So this study is a setup for future research, so a new study could start at a higher level.

1.2 Research objective and central questions

The main objective is to forecast the discharge at Lobith 14 days ahead during low flow conditions with an Artificial Neural Network model.

As discussed before it is hard to choose a model in advance. However the use of low flow indicators and the performances of model types in the past help to make a decision. ANN is a promising modeling technique and it can include the identified indicators.

The model will be run without the seasonal weather forecasts or other forecasted data for checking the low flow performances. The time was limiting this implementation. Perfect forecasted data will be used instead of real forecasted data. The comparison between modeled and measured discharge will only be carried out during during low flows when the discharge at Lobith is below a threshold. This is because a model could not be accurate for all objective functions (Madsen, 2000). Therefore a threshold will be implemented, which defines low flows and will be used in the objective functions. This threshold helps the model to train an objective function for low flows effectively (Madsen, 2000).

The forecasted discharge could be very uncertain, caused by many aspects. Two main reasons for a difference between the observed and simulated low flows can be:

- Measurement errors – At Lobith and at other gauging stations the discharge is measured over a long period of time. These measurements have an unknown uncertainty range. For this study these uncertainties will be assumed negligible.
- Stationarity – The sub-basins and the river change in time. The historic discharge data series have a length of more than over a one hundred year. Other data series are longer than a few decades. For this study the overlapping data between 1989 and 2006 will be used.Even in this time the river and the sub-basins might have changed, but these changes will be neglected in the models, so this study assumes a stationary situation.

This study includes the following steps. First the indicators will be determined. With this information the ANN model could be set-up and the model training and validation could start. The final part is to draw conclusions and reflect on the study. The research questions are listed below.

- Question 1 - What are the indicators for low flows at Lobith and have to be part of the ANN model?
- Question 2 - What performance can be achieved in estimating low flows at the five sub-basin outlets and at Lobith using ANN?

1.3 Research approach and outline

This study consists of three steps which lead to the forecasted low flows at Lobith. The first step is the correlation analysis. The analysis is about the relation between low flow indicators and the discharges of the sub-basins during low flows. The results of the correlation analysis are part of answering research question 1. The second step includes the ANN modeling for the sub-basins. The inputs of the models are based on the results of the correlation analysis and the outputs of the models are the sub-basin discharges. These modeled sub-basin discharges are the input for the ANN model for the discharge at Lobith. These ANN models and resulting performances will help to answer research questions 2 and 3.

Chapter 2 is about the Rhine basin upstream of Lobith and the available data. The Rhine basin is diverse and needs to be divided into smaller sub-basins. Chapter 3 includes the model framework. The implementation of the correlation analysis and the ANN models will be discussed stepwise. Chapter 4 contains the results of the three modeling steps. The chapter starts with the appropriate input for the ANN models as a result of the correlation analysis. Then the forecasted discharges for the five sub-basins and the forecasted discharge at Lobith will be described. Chapter 5 is about the discussion of the consequences of the model choices and the results. Chapter 6 combines the findings of the study into conclusions and recommendations.

2 Study area and data

2.1 Study area

The River Rhine enters the Netherlands at Lobith. The Rhine River discharge at the Dutch-German border originates from upstream areas in Switzerland, Liechtenstein, small parts of Italy and Austria, France, Luxembourg, Germany, and a small part of Belgium (Grabs et al., 1997). In this section the upstream basin will be split into seven sub-basins, because the area is too divers to aggregate all processes into one major basin (Demirel et al., 2011).

Figure 1 shows the sub-division of the Rhine basin. The river Rhine originates in the Alps. During the late summer the discharge at Lobith consist of 70 percent of Alpine water (Grabs et al., 1997). The Alpine regions have major stores, for example large lakes, snows packages and glaciers (Grabs et al., 1997). The division in the Alps is based on the location of the major Lake Constance (or: Bodensee) (Demirel et al., 2011). This lake has a large buffer function (Grabs et al., 1997). The upstream part has been named East Alpine. The rest of the Alpine area is West Alpine (Demirel et al., 2011). The river Aare covers the largest area of West Alpine.

The non-Alpine region has been split into five regions (Middle Rhine, Neckar, Main, Mosel and Lower Rhine). The Middle Rhine and the Lower Rhine are combinations of smaller sub-basins and have a discharge inlet. The Neckar, Main and Mosel are sub-basins without an inlet. All five sub-basins are rainfall-dominated sub-basins. The sub-division of the Rhine basin upstream of Lobith has been taken from Demirel et al. (2011).

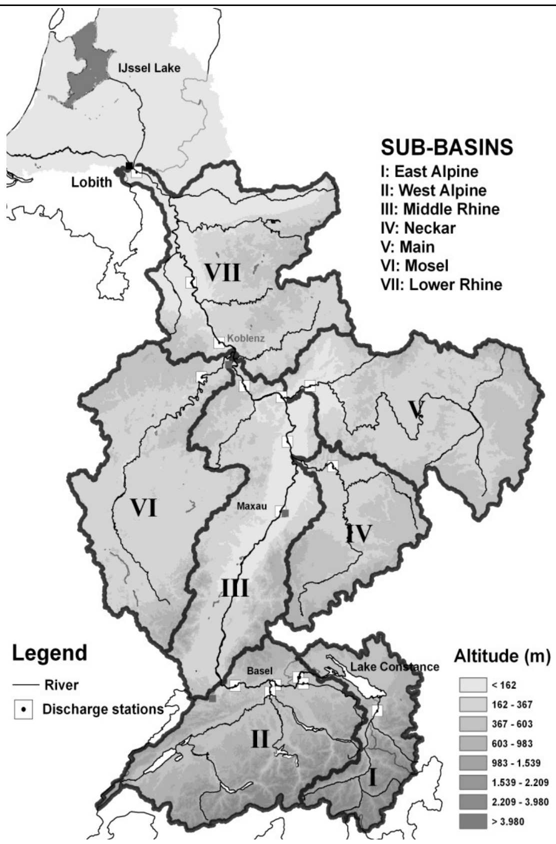


Figure 1 - Sub-divisions of the Rhine River basin upstream of Lobith

2.2 Data collection and availability

For the 32 indicators in the seven sub-basins there is an overlap of 16 years of data. These 32 indicators are specified in Table 1. The two Alpine sub-basins have 6 indicators and the 5 rainfed sub-basins have 4 indicators. Together it is 32. Table 1 shows the sources of the data. Table 2 contains the start date and the end date of the data availability of each indicator. In this table the time period used for the study becomes visible with the dark blue color.

Table 1 - Data resources

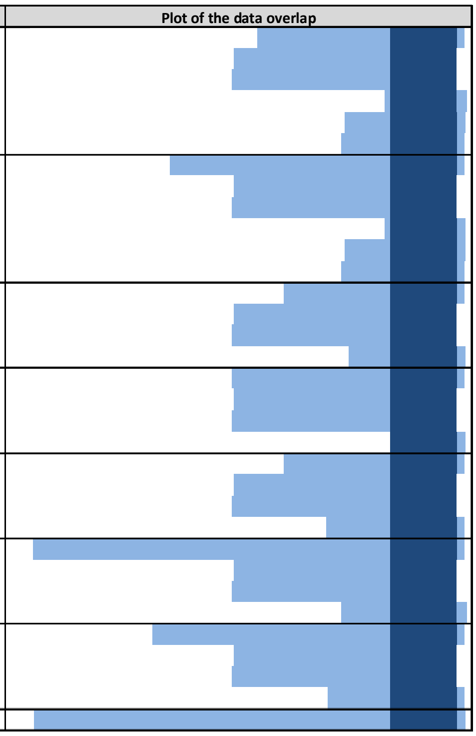
Data	Index	Spatial resolution	Number of stations or sub-basins	Period	Temporal resolution	Source
Discharge	Q	Point	172	1974-2008	Daily	GRDC-Koblenz
Precipitation	P	Sub-basins	134	1951-2006	Daily	BfG-Koblenz
Evatranspiration	ET	Sub-basins	134	1950-2006	Daily	BfG-Koblenz
Groundwater levels	G	Point	1402	1986-2009	Weekly, monthly	German states and BAFU.ch
Snow	S	Point	40	1978-2008	Daily, monthly	SLF.ch
Lake levels	L	Point	11	1978-2008	Daily	BAFU.ch

Table 2 - Data availability

	Start	End
Total length	1900-11-01	2009-10-07
Overlapping length	**1990-06-28**	**2006-12-31**

Basin	Indicator	Start	End
Basin 1 East Alpine	Q	1957-01-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1989-01-02	2009-07-20
	S	1978-12-23	2009-03-31
	L	1978-01-01	2008-12-31
Basin 2 West Alpine	Q	1935-01-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1989-01-02	2009-07-01
	S	1978-12-23	2009-03-31
	L	1978-01-01	2008-12-31
Basin 3 Middle Rhine	Q	1963-11-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1980-01-07	2009-04-27
Basin 4 Neckar	Q	1950-11-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1990-06-28	2009-04-21
Basin 5 Main	Q	1963-11-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1974-06-15	2009-02-15
Basin 6 Mosel	Q	1900-11-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1978-02-08	2009-10-07
Basin 7 Lower Rhine	Q	1930-11-01	2008-12-31
	P	1951-01-01	2006-12-31
	E	1950-11-01	2006-12-31
	G	1974-08-05	2009-02-23
Lobith	Q	1901-01-01	2009-06-18

Plot of the data overlap



= No data available

= Data overlap

=Data available

3 Methods

3.1 Modeling framework and modeling objectives

The low flows at Lobith using ANN could not be modeled into one single step. The Rhine basin is too divers and this requires a division into sub-basins (section 2.1). The basin is well gauged and a long daily record is available (section 2.2). A correlation analysis is a good method to determine low flow indicators (Demirel et al., 2011). An ANN model could deal well with irregular input and has a good performance (chapter 1). This study has a three step approach to model low flows at Lobith (Figure 2).

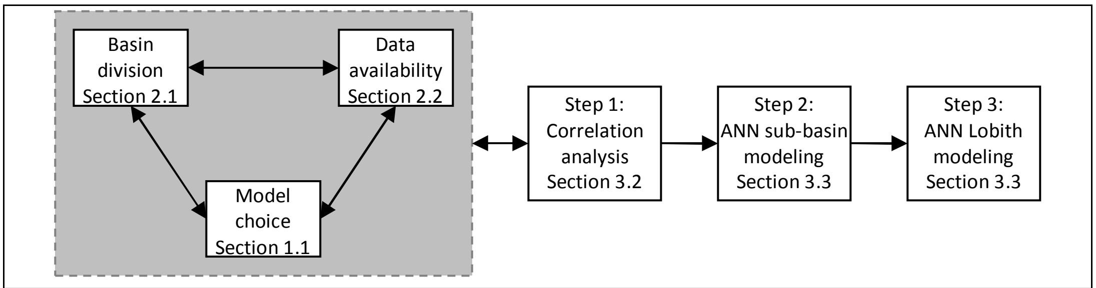


Figure 2 - The schematization of the modeling

Modeling objective for the correlation analysis (step 1)

First the number of input data will be reduced by using the results of the correlation analysis (section 3.2), because a large number of inputs will lead to a insufficient training and the training will not converged to the optimum (Dawson and Wilby, 2001). The modeling objective is to analyze the linear relation between sub-basin indicators and sub-basin flows based on low flows at Lobith. The linear relation is a good method to select appropriate data for the simulation of low flows (Demirel et al., 2011). The discharges at the sub-basin outlet will be linked to a low flow travel time to Lobith. If a low flow day has been measured at Lobith, this day corresponds to the sub-basin discharge a specific days before. These sub-basin discharge has been used in the low flow analysis.

Modeling objective for the sub-basins (step 2)

The modeling objective is to simulate the discharge at the outlet of sub-basin based on low flows at Lobith using an ANN model and using relevant input from the correlation analysis. The output of the correlation is the input for the first ANN which describes the sub-basin flows (section 3.3).

Modeling objective for Lobith (step 3)

The modeling objective is to simulate the low flows at Lobith using an ANN model and using simulated discharges from the sub-basin modeling (section 3.3).

3.2 Correlation analysis

ANN models need as little input as possible to minimize the calculation time (Dawson and Wilby, 2001). The input information should be reduced. A correlation analysis is a relative simple way to analyze relations between inputs and outputs. And to reduce the number of inputs to the ANN (Demirel et al., 2011). The combined inputs have a hydrological meaning (Demirel et al., 2011). The correlation between an indicator and the sub-basin outflow will be determined as follows:

$$C = \frac{\sum(Q_i - Q_{mean})(I_i - I_{mean})}{\sqrt{\sum(Q_i - Q_{mean})^2 \sum(I_i - I_{mean})^2}} \quad (1)$$

In this formula is Q_i the sub-basin discharge for each time step; Q_{mean} is the average of the sub-basin discharges; I_i is the indicator value for each time step; and I_{mean} is the average indicator value.

In the correlation analysis is a set of combinations for the lag and temporal resolution will be tested. The lag time holds information on the response time of the basin including concentration time and travel time whereas the temporal resolution holds information on the scale of the water volume entering or leaving the system (Demirel et al., 2011). The lag and temporal resolution summarizes the indicator data to one input for each time step. The plot of Figure 3 shows the conceptual working of the lag and temporal resolution.

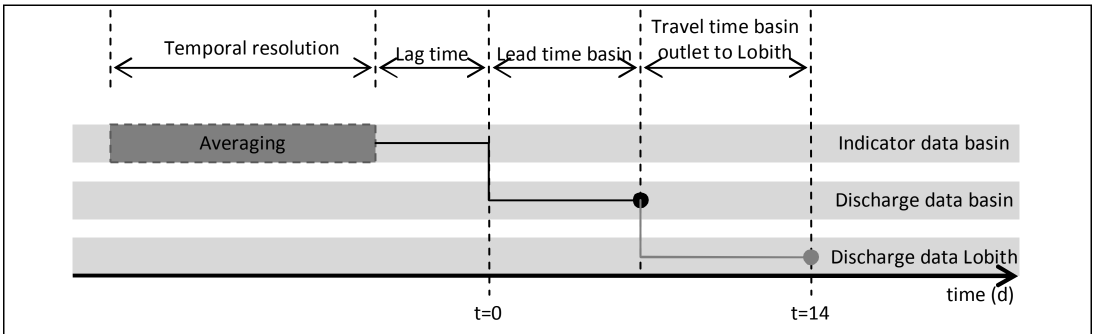


Figure 3 - Explanation of the support and lag time

This correlation analysis is about the linear dependency between a sub-basin low flow indicator and the produced discharge of a sub-basin. The selection of a low flow day in s sub-basin depends on the measured discharge at Lobith. When the flow is below the low flow threshold at Lobith (LFT), the day counts as a low flow day. The LFT is the discharge which has been exceeded in 75 percent of the time. The discharge of a sub-basin needs time to travel towards Lobith. In reality the travel time of a discharge wave between the sub-basin outlet and Lobith is not fixed, but in this study the travel time from the sub-basin outlets to Lobith are fixed parameters, because ANN for Lobith requires a continuous daily input. During low flows the West Alpine discharge needs around 7 days to reach Lobith after it has passed the West Alpine outlet at Untersiggenthal. This daily rounded 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.

Table 3 - Low flow travel times and the lead time inside the sub-basins

Basin [-]	Outlet [-]	Rheinkilometer [km]	Distance to Lobith* [km]	Travel time** [days]	Lead time*** [days]
Basin 1 - East Alpine	Neuhausen	49	813	9	5
Basin 2 - West Alpine	Untersiggenthal	102	760	9	5
Basin 4 - Neckar	Rockenau	428	434	5	9
Basin 5 - Main	Frankfurt Osthafen	497	365	4	10
Basin 6 - Mosel	Cochem	592	270	3	11

* Lobith is located 862 kilometer downstream of Lake Constanz (= Rheinkilometer 0).
**The travel time is the rounded time in days that the discharge needs during low flows to travel between the basin outlet and Lobith based on an average speed of 1 m/s.
The used travel times were determined by the distance on the road. These distances underestimates the actual distances for the Alpine basins with 2 days.
** The forecast time inside a basin based on the 14 days ahead discharge at Lobith minus the travel

The sub-basin lead times could be found in table Table 3. The conceptual approach for the correlation analysis is shown in Figure 4. The correlation analysis between the flow at the sub-basin 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 percent of the time (Q75 Lobith). The three days discharge below this threshold will be marked 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. This will result in a table with correlation and could be visualized as a plot.

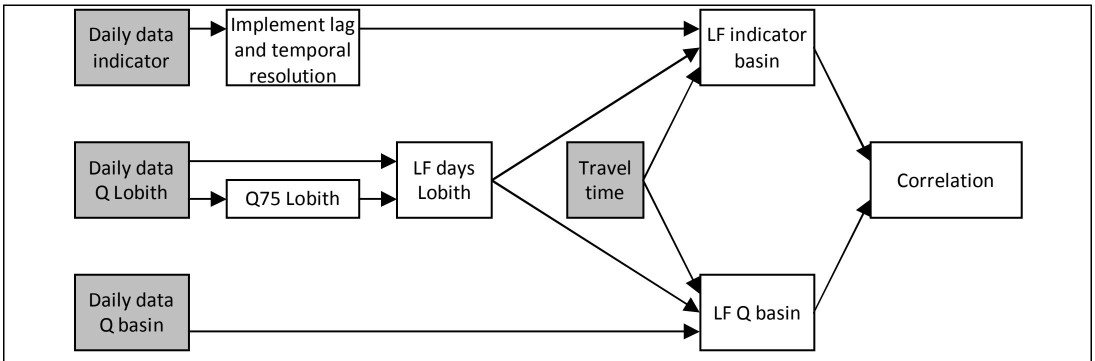


Figure 4 - The approach to calculate the correlation

3.3 Implementation of ANN models for Rhine sub-basins

The first set of artificial neural network models are the models for the sub-basin discharges. The basin discharge has been linked with the low flow days at Lobith. The schematization of the ANN model (Figure 5) contains the topics inside this section.

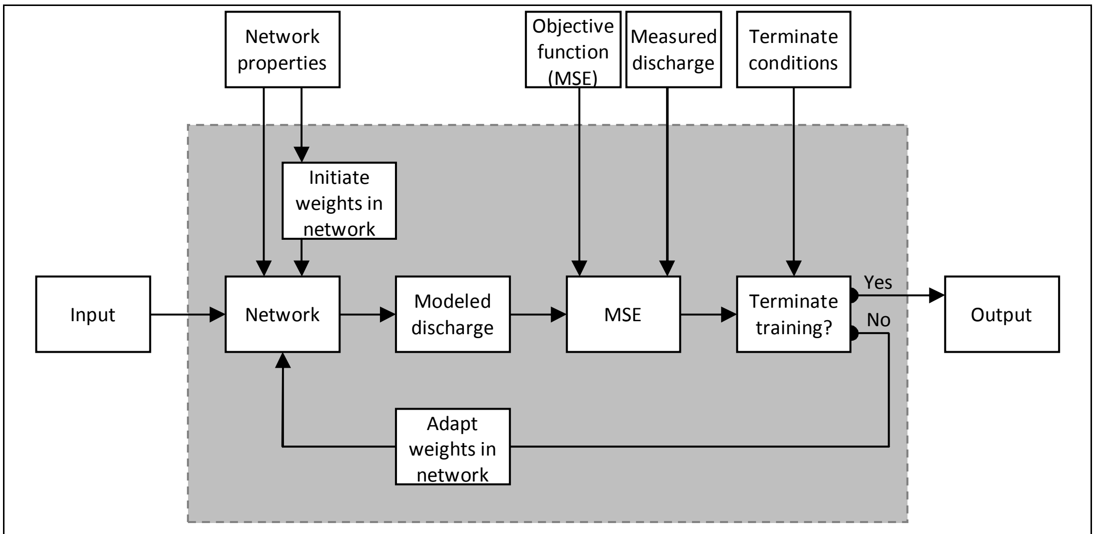


Figure 5 - Artificial Neural Network approach

Input

The amount of input neurons has been reduced based on the correlation analysis. Each low flow indicator is one input. This means that the input data vary from four to six input neurons. Nevertheless, this information is too limited, so the short time rainfall is also part of the input. Each day has its own input neuron. The input data set is split into three time periods, a training, validation and testing set. this will be into a training, a validation and a testing set. The distribution in data length between the parts are respectively 0.5, 0.3 and 0.2, based on Srinivasulu et al. (Srinivasulu and Jain, 2006). The validation period is not a totally independent set. The testing phase is the only independent period.

Network

The network of an ANN model has the ability to transform input data to one output. For a physically related problem as the discharge of an area three layers are enough (Shamseldin, 1997). In the figure below (Figure 6) these three layers are visible. The input layer has neurons for each input. The output layer is one single output, the produced discharge in a basin. In between is one hidden layer. The number of neurons has influence on the interaction in the model. When the number of neurons increase, then the number of parameters will increase as well. In this study the ANN model will be trained for 1 to 5 neurons in the hidden layer. The output neuron in a network has a number of incoming lines with information. For example end-node N2.1 information originates from each input and it has a bias. The blue lines represent these connections. Each line has a weight factor. And the inputs for the end-node N3.1 are rescaled. For layer 1 to layer 2 the inputs are rescaled with the tansig formula. And for layer 2 to layer 3 the inputs (neurons 2.i) are rescaled with the purelin formula.

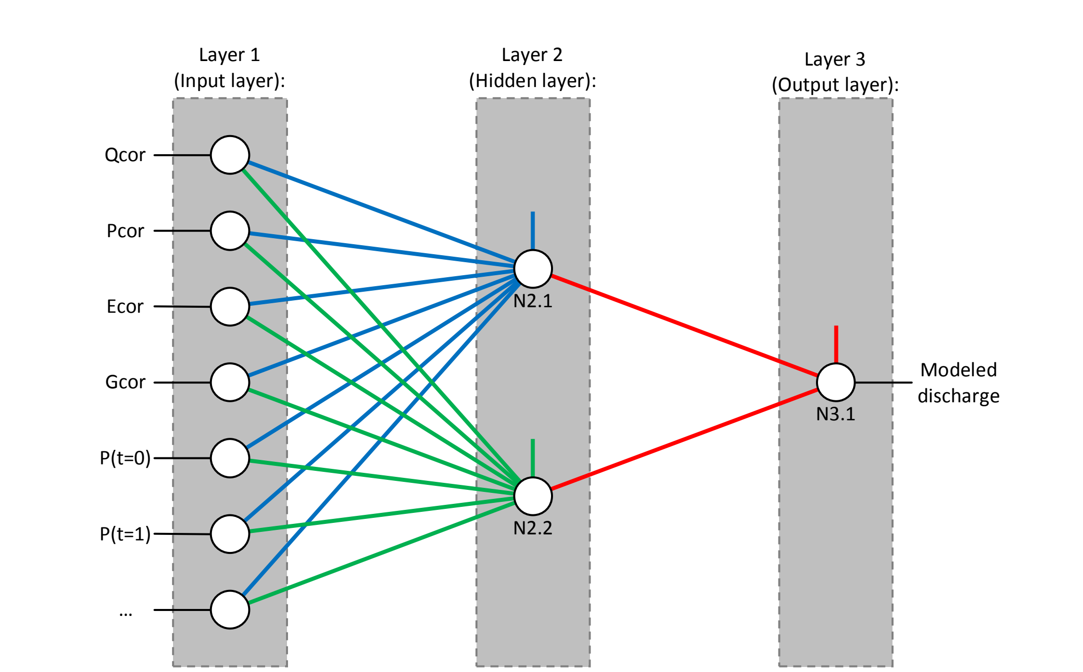


Figure 6 - ANN network with 3 layers

Calibration objective functions

In this study four objective functions will be used. The mean squared error (MSE) is the objective function for the training and a standard function inside MATLAB for ANN training. Other used functions are the correlation (C), mean absolute error (MAE) and the Nash-Sutcliffe Efficiency (NSE). The correlation function is a good way to check the improvement of the ANN results compared to the correlation analysis. The NSE value is a typical hydrological objective function. The MAE is an extra objective function to check the performances. The four objective functions are given in equations 1-4.

$$MSE = \frac{\sum(Q_i - M_i)^2}{n} \qquad (2)$$

$$NSE = 1 - \frac{\sum Q_i - M_i}{\sum Q_i - Q_{mean}} \qquad (3)$$

$$MAE = \frac{\sum Q_i - M_i}{n} \qquad (4)$$

In these objective functions is Q_i the measured discharge during low flows; M_i is the simulated discharge; n is the number of measurements; Q_{mean} is the mean of the measured low flows.

The aim of the model is to minimize the error, which depends on the modeled discharge and the observed discharge. For the Middle-Rhine and the Lower-Rhine no proper discharge data exist, because both basins have discharge inlets. Because of that it is not possible to obtain reliable basin discharges and so the ANN training becomes unreliable as well. The West Alpine area has also an inlet of the East Alpine. But by using the discharge data series of the Aare, the inlet is no longer a problem. The Aare covers a large area of the West Alpine (71 percent). So the modeled discharge of the West Alpine sub-basin would be an underestimation of the real produced discharge. But the timing and the behavior of the basin will probably be simulated well, so it has almost no negative influence for the discharge simulation at Lobith.

Termination

In the ANN model there is a looping. Each loop the model adapts parameters to optimize the performance of the model. Nevertheless, the model would not reach the minimum error by running it infinitely. The model could be trapped in a local minimum (Krishna et al., 2011). Termination rules prevent the model for unnecessary long runs and will protect the calculation capacity (Mokhtarzade and Valadan Zoej, 2007, Paulo Davim et al., 2008). If only one rule has been fulfilled, than the training stops. However, if not one termination rule has been accomplished, the training will continue and have a new loop. The used termination rules are listed below:

- Maximum number of epochs/loops – The maximum number of epochs is also not an important termination parameter. Just like the maximum calculation time the number of epochs is set to a number which is not limiting the training. For this training this is 100 epochs.
- Maximum calculation time – If the calculation takes too long, the training will be terminated. The calculation time is not an important termination parameter. Therefore it is set to a high value, so the calculation time is not the limiting factor. The maximum calculation time is set at 200 seconds.
- Satisfying performance – If the value of the objective function become below the satisfying performance, the training will be terminated. The satisfying performance is not an important parameters. Therefore it is set to a low value, so the satisfying performance is not the limiting factor. The satisfying performance is set to 0.0001.
- The minimum improvement of the objective function – The training stops when the improvement is too little. This means that the error will be compared with the loop before. When the improvement is little, this means that the solution is around a (global) optimum. If the improvement of the objective function is below 0.0001, then the training will be terminated.
- The adaption of the weights (mu) – The weights of the network will be corrected each loop. The mu is a factor for the size of the corrections. For this property the default values for the minimum and maximum have been copied.
- Maximum number of validation deteriorations – During the training the error will be reduced for the training set. To check if the improvement has a global behavior, the objective function will be tested on the validation data. The maximum number of validation deteriorations terminates the training when there is no validation improvement. The maximum number of validation deteriorations is set to 1. So, if the weights and biases are adapted to improve the training set, the improve will be checked for the validation set. If there is no improvement for the validation set, the training will be terminated immediately.

Number of runs

The number of initializations per basin is 5000. The network will only be varied for the number of neurons in the hidden layer. The network will be initialized and trained for 1 to 5 neurons in the hidden layer for each number of neurons in the hidden layer the model will be initialized a thousand times. This high number of initializations and trainings have been used to increase the chance to find the global optimum.

ANN training

The number of inputs and the network properties define the network. However the connections have no initial weights. To start the training, the weights should have a value. In the initialization all the weights get values and afterwards the training could start.

The weights in the network generate a modeled discharge based on the input. These modeled discharge differ from the measured discharge. The objective function values the error. In the terminate phase the results of the loop will be tested. If there is no reason for termination, the weights in the network will be adapted and the process starts all over again, except the initialization, this has been replaced by the adapting the weights in the network.

Implementation of the ANN model for Lobith

The ANN model of low flows at Lobith is almost similar to the model of the individual basins. The only parts that differs 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 low flow at Lobith. The schematization is shown in Figure 7. The training of the model is based on the same settings as for the ANN for the sub-basins.

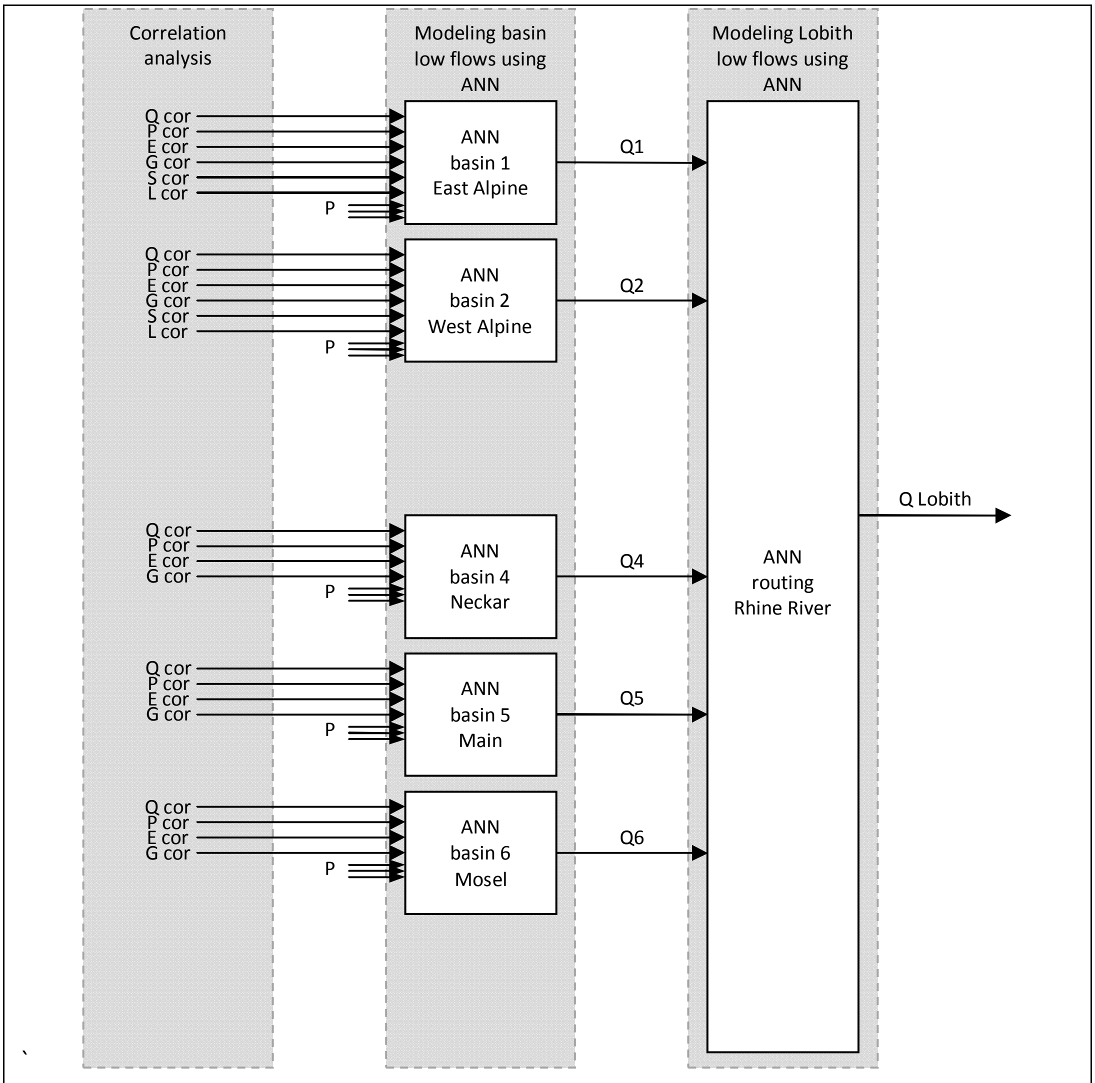


Figure 7 - Modeling setup

4 Results

4.1 Appropriate inputs for the ANN models

The function of the correlation analysis is to detect the optimum lag and temporal resolution for low flow indicators and to find proper input for the ANN models. Grids with the correlation value are the main result. These grids will be formed by the temporal resolution (horizontal axis), the lag (vertical axis) and the correlation value (contour lines). Figure 8 shows an example of a grid plot. Each point in the grid corresponds with a temporal resolution on the horizontal axis and with a lag time on the vertical axis. The value in a point is the correlation. All grid plots of each indicator are presented in Appendix 2. Table 4 contains the maximum correlation per basin indicator and corresponding lags en temporal resolutions. The results of Table 4 have been visualized in Appendix 1.

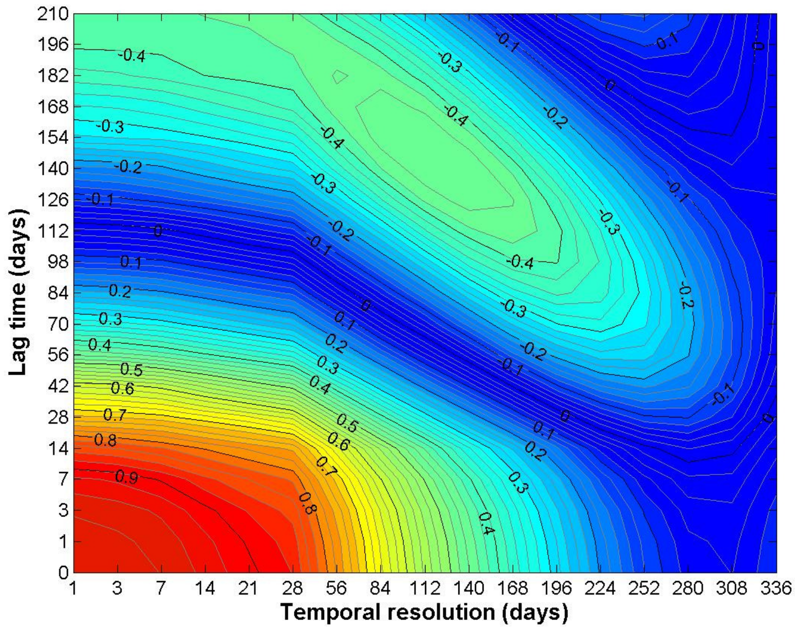


Figure 8 - Correlation plot for the low flows of the East Alpine sub-basin and the historic discharge

The Alpine basins have good correlations. For the East Alpine the discharge and the lake level have correlations higher than 0.95. These indicators will probably explain well the basin discharge behavior. Moreover 70 percent of the low flows originates from the Alpine sub-basins (Grabs et al., 1997). So if the Alpine sub-basins correlate well, the forecasted discharge at Lobith could be high as well.

The other 30 percent of the Lobith low flows originates from the other five rainfall-dominated basins. These correlations are not so strong as the Alpine indicators. The highest relation is for low flows and evatranspiration and is 0.68. All other relations are less strong.

Nevertheless there are interesting parts in the correlation plots of the precipitation. The precipitation has no high correlations for short precipitation in the past. However in the period between the present and the moment the water is released at the sub-basin outlet (lead time) there is a relation. For the Neckar there is a relation between discharge and the rainfall six days before. The lead time for the Neckar is 9 days, so this relation is not visible in the correlation plot of Figure 21 in Appendix 2. The interesting lag and temporal resolution in the precipitation plot is an addition to the ANN input. The short time precipitation contains no global information about low flows, but it has a strong influence.

Table 4 - Lag and temporal resolution for the maximum correlations

Correlation analysis results								Input ANN	
Basin Number	Basin Name	Indicator Number	Indicator Name	Cor -	Lag time Days	Support Days		Lag time Day	Support Days
1	EA	1	Q	0,98	0	1		0	1
1	EA	2	P	0,69	0	56		0	56
1	EA	3	E	-0,73	112	168	→	*0*	*21*
1	EA	4	G	-0,38	210	140		210	140
1	EA	5	S	0,63	112	112		112	112
1	EA	6	L	0,96	0	1		0	1
2	WA	1	Q	0,81	0	1		0	1
2	WA	2	P	0,53	0	21		0	21
2	WA	3	E	-0,75	98	168	→	*0*	*21*
2	WA	4	G	0,58	0	1		0	1
2	WA	5	S	-0,63	210	224	→	*112*	*112*
2	WA	6	L	0,72	0	1		0	1
3	MR	1	Q	0,51	0	21	X	No proper target	
3	MR	2	P	0,36	0	196	X	No proper target	
3	MR	3	E	-0,54	0	56	X	No proper target	
3	MR	4	G	0,45	0	1	X	No proper target	
4	Neckar	1	Q	0,67	0	21		0	21
4	Neckar	2	P	0,28	98	168		98	168
4	Neckar	3	E	-0,60	3	140		3	140
4	Neckar	4	G	0,38	0	1		0	1
5	Main	1	Q	0,57	0	1		0	1
5	Main	2	P	0,38	196	308	→	*0*	*56*
5	Main	3	E	-0,48	0	168		0	168
5	Main	4	G	0,46	0	1		0	1
6	Mosel	1	Q	0,63	0	21		0	21
6	Mosel	2	P	0,35	14	168		14	168
6	Mosel	3	E	0,68	182	56	→	*0*	*56*
6	Mosel	4	G	0,59	0	1		0	1
7	LR	1	Q	0,29	0	14	X	No proper target	
7	LR	2	P	0,18	0	14	X	No proper target	
7	LR	3	E	0,18	14	336	X	No proper target	
7	LR	4	G	0,20	0	1	X	No proper target	

The results could not be implemented directly into the ANN. The results of the Middle Rhine and the Lower Rhine are not proper, because the generated discharge record is not reliable. Therefore those basins are not included in the model. For the other basin indicators some lag and temporal resolution have been decreased to have a more physical relationship (Table 4). The lag and temporal resolution for the West Alpine sub-basin are 210 and 224 days. This high values does not represent the snowfall in winter. However the combination a lag time of 112 days and a temporal resolution of also 112 day has almost the same correlation and it has a more logical physical relations. Also the evatranspiration will be corrected. After these corrections the data are ready for the ANN model.

4.2 Forecasted discharges for five sub-basins

The results of the sub-basin modeling are discussed in this section. Figure 9 shows the discharge for the year 2005 based on the lowest MSE of the test phase. The plot of the year 2005 gives a good insight in the performances of the ANN model for that particular basin. Table 5 summarize the basin performances by means of the four objective functions.

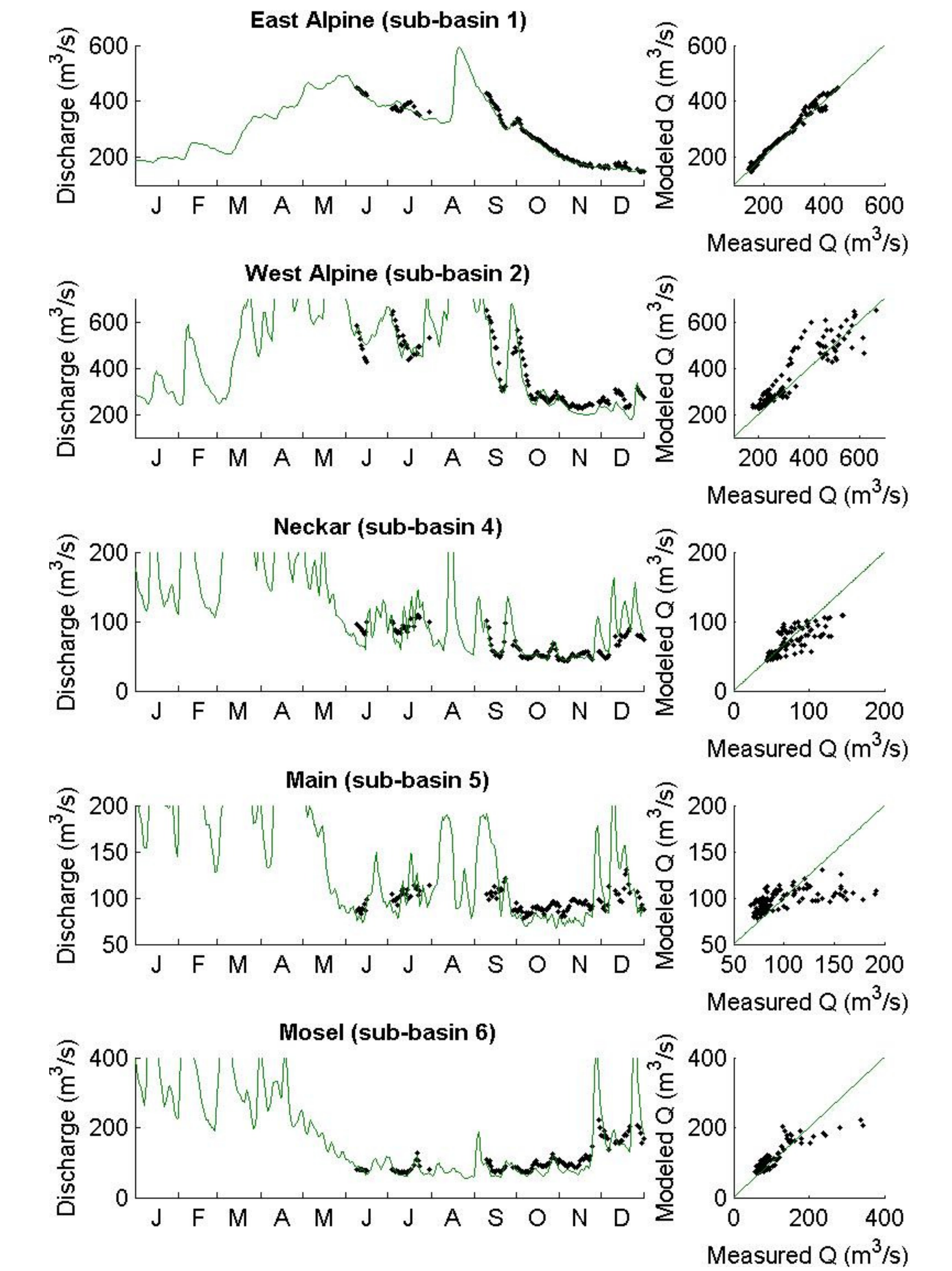


Figure 9 - Simulated discharges and scatter plots of the sub-basins in 2005 (test period)

Table 5 - The performances of the ANNs per sub-basin and per objective function

Values of objective functions in best run			Basin 1 EA	Basin 2 WA	Basin 4 Neckar	Basin 5 Main	Basin 6 Mosel	
	C	Training	0.99	0.96	0.87	0.85	0.90	
		Validation	0.98	0.85	0.87	0.68	0.93	
		Test	0.99	0.93	0.70	0.51	0.89	
	MSE	Training	151	1374	169	445	590	
		Validation	316	2948	157	300	423	
		Test	**250**	**2508**	**240**	**490**	**843**	*
	NS	Training	0.98	0.92	0.76	0.57	0.81	
		Validation	0.96	0.72	0.61	0.26	0.83	
		Test	0.96	0.83	0.48	0.23	0.77	
	MAE	Training	9.4	27.0	9.5	13.8	17.1	
		Validation	11.9	42.0	9.7	14.3	15.5	
		Test	12.5	37.4	11.6	16.9	20.1	

* Best ANN run selected for the minimum value of the MSE in the test phase

The modeled low flows of the two Alpine basins fits very well with the observed discharges. The forecasted discharge follows the shape of the measured discharge. The observations of the Alpine regions coincide with the simulated low flows. The NSE for East Alpine is 0.96 and for West Alpine 0.83 in the test phase.

The other three basins show more mixed performances. The Main River has the lowest Nash-Sutcliffe Efficiency (NSE) of 0.23. The Neckar River has a NSE of 0.48. The best modeled rainfall-dominated river is the Mosel River. The NSE is 0.77. The Middle Rhine and the Lower Rhine are excluded of the sub-basin low flows. So only the Mosel sub-basin of the rainfed area is well functioning. For the other four sub-basin the simulated discharges are poor.

The forecasted precipitation is important for the sub-basins, because without the short time rainfall the ANN model produces very poor results. The simulated discharge is a horizontal line in time or a discharge curve with only a few regimes. The low flow indicators do not include information on fast discharge changes. The addition of forecasted rainfall helps ANN to train to much better results. However the ANN model uses the perfect rainfall, so this causes an overestimation of the actual performance of the model.

4.3 Forecasted discharge at Lobith

The results of the forecasted discharge at Lobith are given in Table 6. The modeled low flows at Lobith are poor. The training and the validation period has a good performance. The correlation values are respectively 0.87 and 0.86 and the NSE values are 0.75 and 0.72. However the results for test phase shows only a NSE performance of 0.32 and a correlation of 0.71. The graphs are presented in Figure 10.

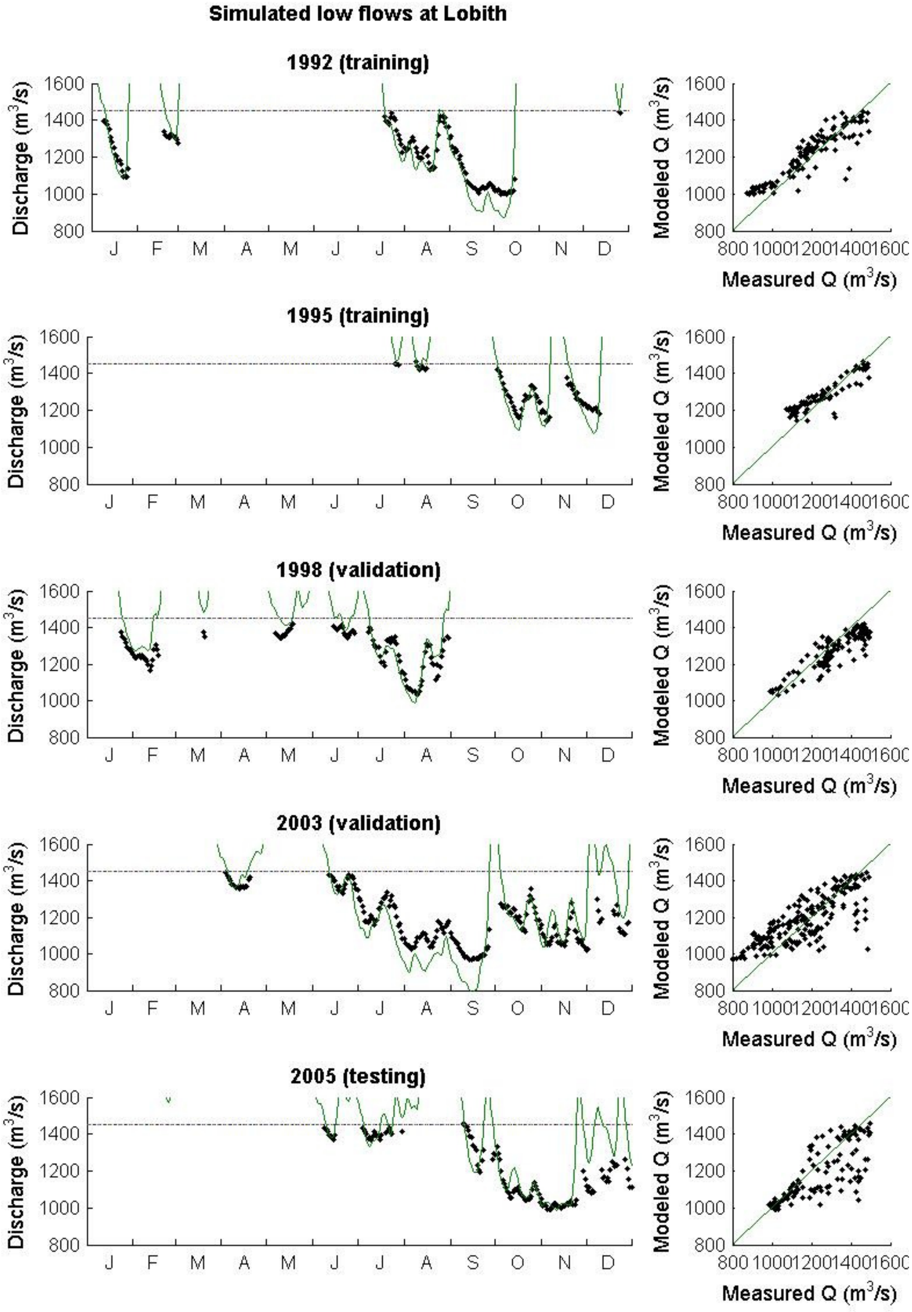


Figure 10 - Simulated discharges and scatter plots at Lobith

The model error for the sub-basin flows is part of the input of the ANN for Lobith. The ANN for Lobith does not take the error into account, but the Lobith model trains the sub-basin outputs as perfect input. This is a benefit when there is a systematic error in the sub-basin output. If the sub-basin output has a random error, the performances of the test phase could be much lower.

Another approach for Lobith could affect the performance in the test phase. The measured discharges could replace the simulated discharge in the Artificial Neural Network model. The training performances increase dramatically. The training correlation is above 0.95, the validation is 0.90 and the correlation in the test period is 0.87. The network is a product of the training. A simulation causes the modeled discharge at Lobith by using these network properties and the modeled discharges per basin. This approach of training with measured discharges and replace these by simulated sub-basin discharges leads to lower training and validation performances, but the test phase generates better results.

The human intervention the river could also affect the discharge measurements. Part of the discharge could be used for irrigation (Grabs et al., 1997). Also discharges could be influenced by weirs (Grabs et al., 1997).

Table 6 – The performance of the ANN at Lobith

			Lobith	
Values of objective functions in best run	C	Training	0.87	
		Validation	0.86	
		Test	0.71	
	MSE	Training	5441	
		Validation	9079	
		Test	**13839**	*
	NS	Training	0.75	
		Validation	0.72	
		Test	0.32	
	MAE	Training	59.2	
		Validation	75.1	
		Test	87.4	

* Best ANN run selected for the minimum value of the MSE in the test phase

5 Discussion

Perfect weather forecast

The performances of the ANN models are higher than the actual 14 days ahead low flow forecasts could be. The forecasted rainfall during validation and the test period is perfectly forecasted, because they are measurements and not forecasts. The real forecasted rainfall with uncertainty will cause a lower performance.

The future precipitation has a perfect quality. The forecasted rainfall for the time period up to 14 days ahead are also measurements. The rainfall forecasts are less precise. It is not possible to foresee where heavy rainfall events will appear multiple days ahead.

The European Centre for the Medium-range Weather Forecasts (ECMWF) has already data available for the daily precipitation. The data consist a few scenarios how the weather could develop. These scenarios are a result of small changes in the initial conditions.

Neglect sub-basins

The input of the ANN for Lobith is the modeled discharge of five of the seven modeled sub-basins. The discharges of the Middle Rhine and the Lower Rhine are not taken into account since the net outflow per basin is unclear. Both basins have inlets and that creates poor net discharge records per basin. But the timing between the inlet and the outlet depends on the discharge level, so the time lag between those points is not constant. There could be also some storage inside a sub-basin. The outcomes of the correlation analysis for the Lower Rhine are very poor. The outcomes for the Middle Rhine are better, but unreliable.

The quality of an ANN model is that it can deal with missing information (Ishibuchi et al., 1995). Similar basins cover the missing areas. For the Middle Rhine and the Lower Rhine this means that the Main, the Neckar and the Mosel are representative. All rivers have more or less the same spatial characteristics. The timing towards Lobith is in the same order of magnitude. Only there is no travel time between the Lower Rhine outlet and Lobith.

The future precipitation is a strong indicator for the low flows 14 days ahead. The precipitation showers are intensive and have local impact. When there are intensive rainfall showers in the Middle Rhine and the Lower Rhine and not in the other rainfall-dominated rivers, there is no reaction of the modeled discharge at Lobith. The modeled discharge at Lobith depends not on the processes in those two sub-basins. An option is to extend the input data for the ANN model for Lobith with processes of the Lower Rhine and the Middle Rhine. This could improve the quality of the ANN. This possibility has not been investigated, because of the jump between training and simulation. The training could be improved, however the simulation with 10 days ahead precipitation forecasts has a large uncertainty. This will probably result in a better training, but not in a better simulation.

During low flows the Alpine discharge of the Rhine River is about 70 percent of the flow at Lobith (Grabs et al., 1997). The contribution of the sub-basins the Middle Rhine and the Lower Rhine is only a part of the remaining 30 percent. The uncertainty in the future rainfall is large. The replacement of these sub-basins with same characteristics seems justified.

6 Conclusions and recommendations

6.1 Conclusions

In this section the research questions will be answered. The first question is about the low flow indicators and appropriate ANN input. The other is about the low flow modeling of the discharges.

Low flow indicators

However there are strong low flow indicators. These low flow indicators have a strong relation with the basin discharge based on low flows at Lobith. The Alpine sub-basins have the strongest correlations between the historic discharge and the flow, and between the level of Lake Constance and the flow. The discharge, the snow package and the lakes are the best indicators for West Alpine. The indicators for the rainfall-dominated basins are less strong. The perfect forecasted precipitation shows a strong relation between the precipitation and the basin discharge.

The Middle Rhine and the Lower Rhine have discharge inlets. Therefore the produced discharge of a basin is difficult to calculate, because of the travel time and dispersion affect the produced discharge. Therefore the indicators of these sub-basins are unreliable, so results of the indicator analysis could not be implemented in the ANN model.

Modeled low flows

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 because of the large amount of available water inside the basins (Grabs et al., 1997). 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. The Mosel is the only good performing non-Alpine sub-basin. The reason for this fact remains unclear.

The modeled discharge at Lobith is poor. Although 70 percent originates from the Alpine sub-basins and those sub-basins have good performances, the modeling performances at Lobith are poor.

Discharge at Lobith

The low flows at Lobith are difficult to forecast. The results demonstrate a poor performance with ANN. The Nash-Sutcliffe efficiency for the three days discharge 14 days ahead is only 0.32 for the test phase.

6.2 Recommendations

In chapter 5 the limitations of the performance of ANN, together with the simulation of the network with real discharge data and the routing have been discussed. In this chapter there will be suggestions to improve these aspects. This suggestions could increase the performances of the ANNs and the functionality of the low flow forecasts.

The settings of the ANN network influence the outcome (Langella et al., 2010). The number of parameters to investigate are large and most are not investigated. It is therefore not clear what the best ANN settings are.

Improve performance ANN

ANN is a promising method (Srinivasulu and Jain, 2006). However, its optimization is difficult, because of the irregular solution space (Alp and Kerem Cigizoglu, 2007). The focus of this study is not on optimizations, but rather on the global implementation of ANNs for low flow forecasting in the Rhine basin. The ANN performances are relatively low and there is improvement possible. The results require progress to become functional. There are several issues inside the network which could lead to better results. Points to consider are:

- Input data

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.

- Objective function

The MSE error is the default objective function inside MATLAB. Other error function 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.

- Rescaling data

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.

- Transfer functions

The used transfer functions are also default functions. The changes towards other functions could have impact on the performance (Dawson and Wilby, 2001).

Simulate network with real weather forecasts

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.

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Appendices

Appendix 1 - Correlation analysis and the ANN model setup in one figure

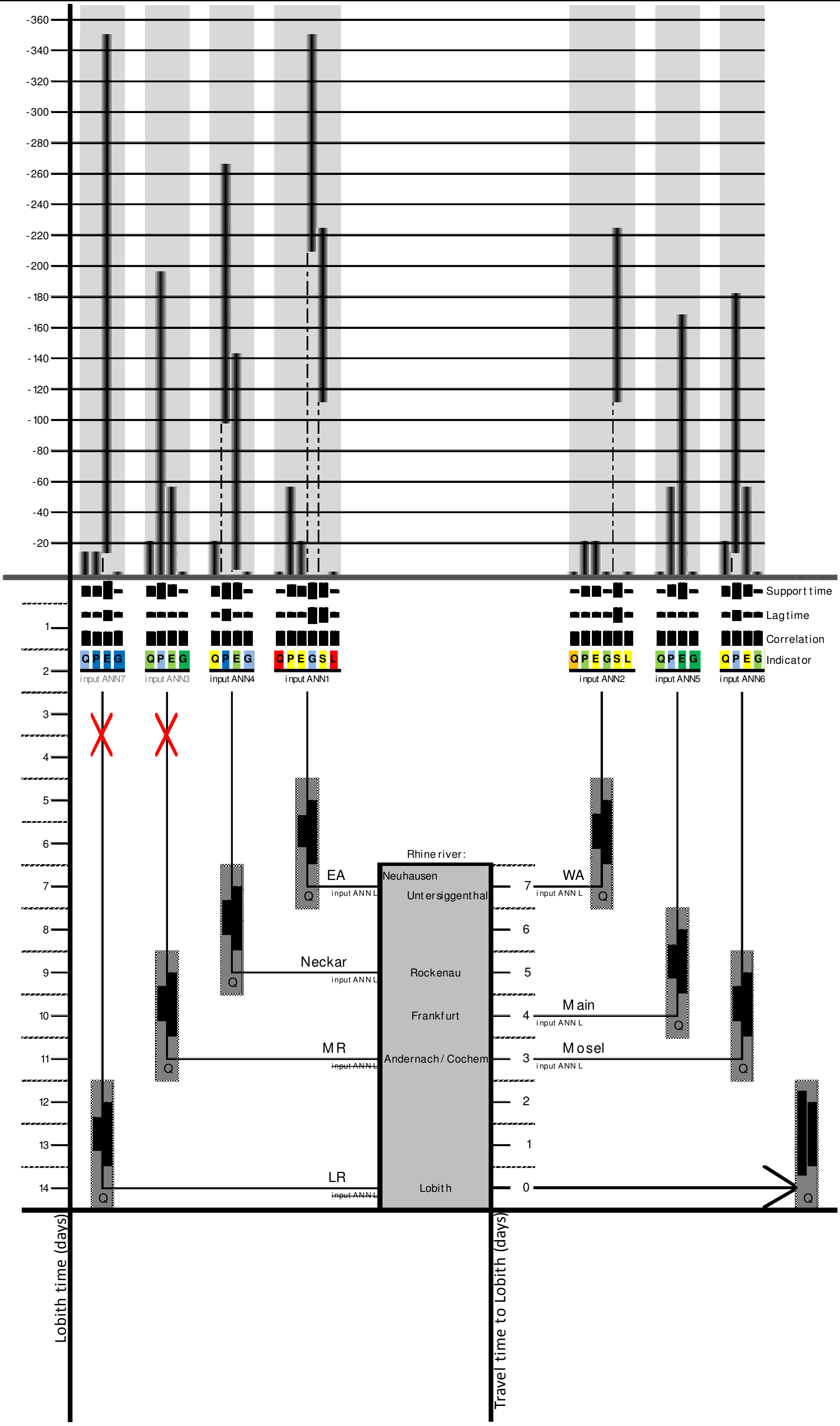

Figure 11 - The correlation results and the method for ANN in one figure

Appendix 2 - Correlation plots

Sub-basin 1 (East Alpine)

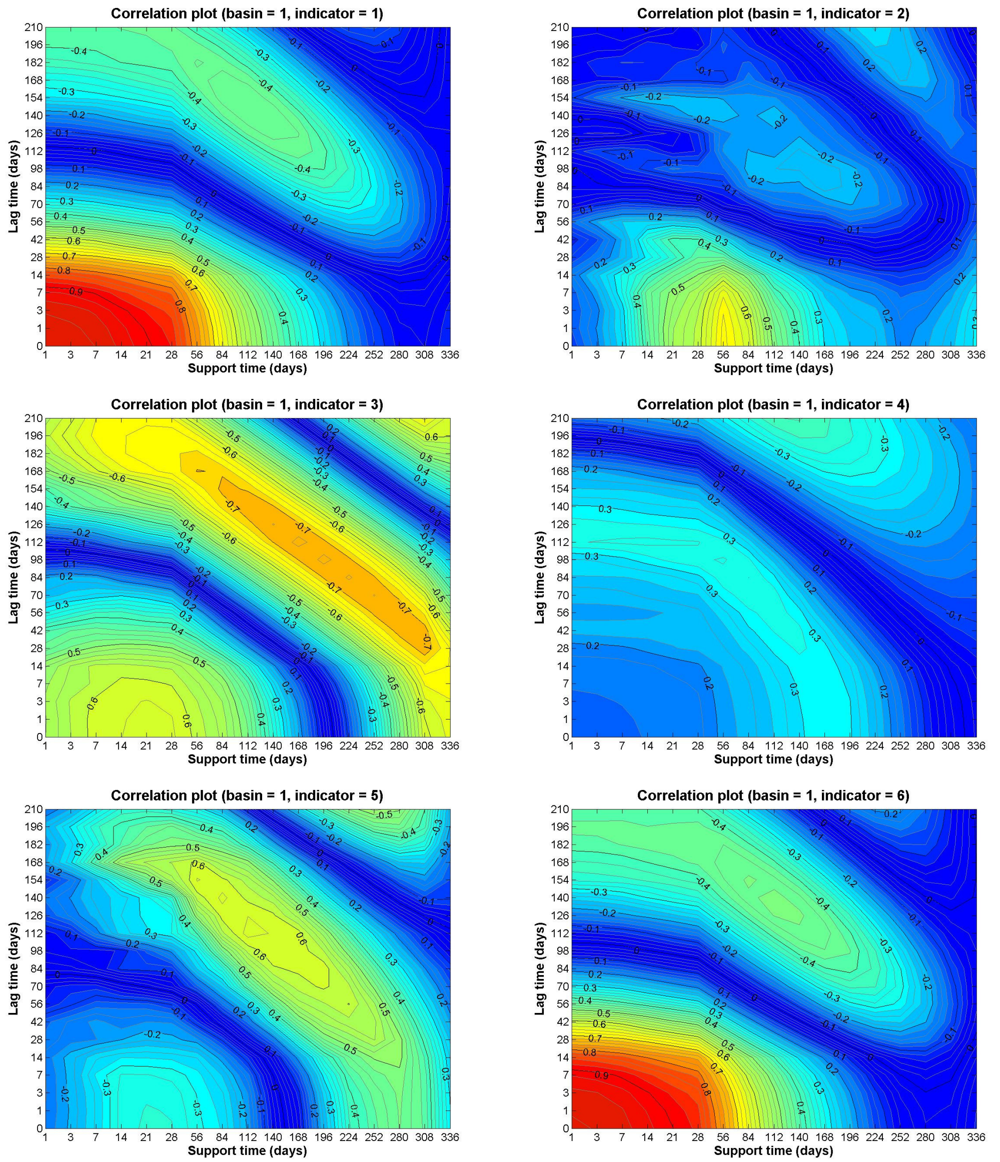

Figure 12 - Correlation plots of sub-basin 1 (East Alpine)

Sub-basin 2 (West Alpine)

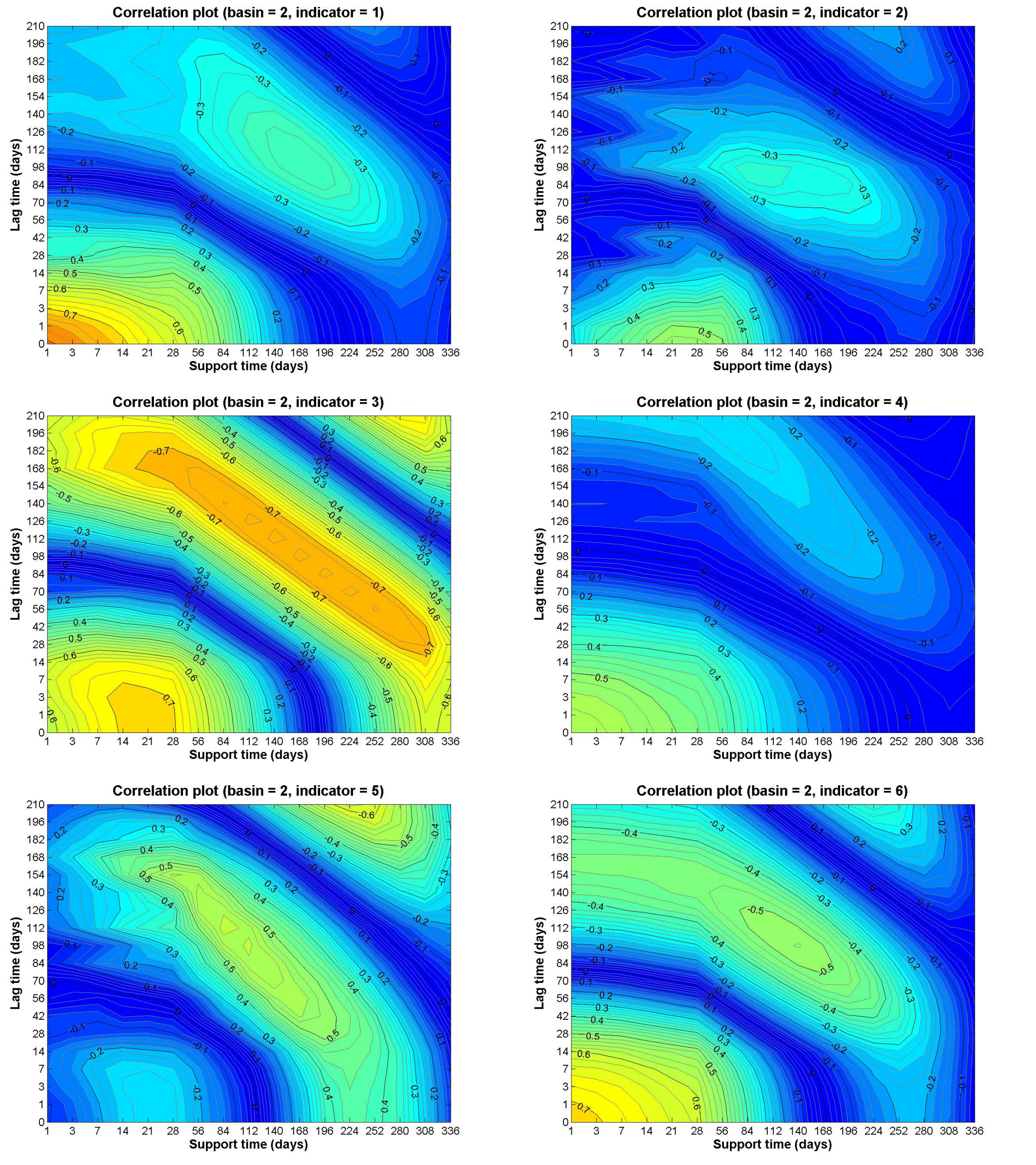

Figure 13 - Correlation plots of sub-basin 2 (West Alpine)

Sub-basin 3 (Middle Rhine)

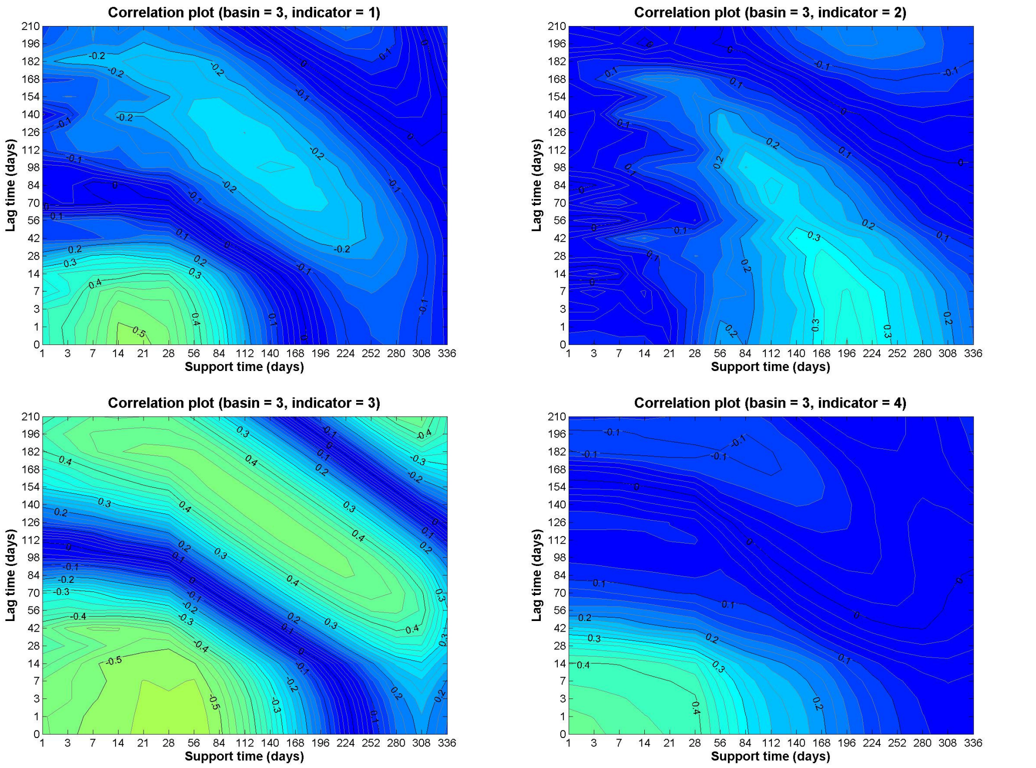

Figure 14 - Correlation plots of sub-basin 3 (Middle Rhine)

Sub-basin 4 (Neckar)

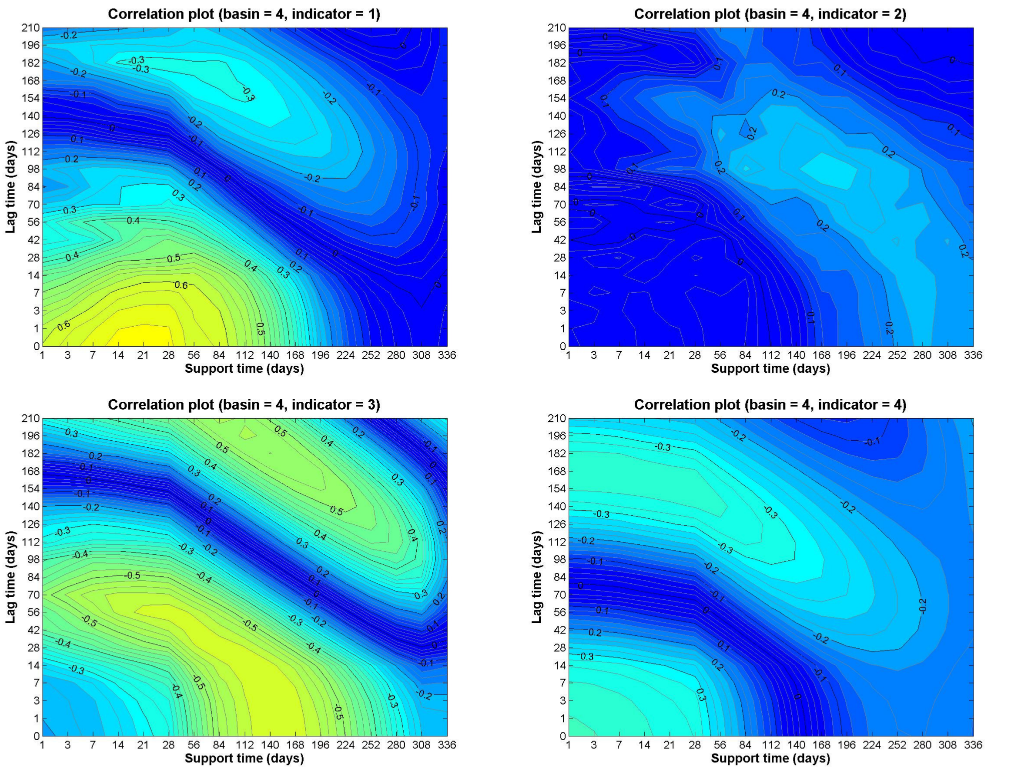

Figure 15 - Correlation plots of sub-basin 4 (Neckar)

Sub-basin 5 (Main)

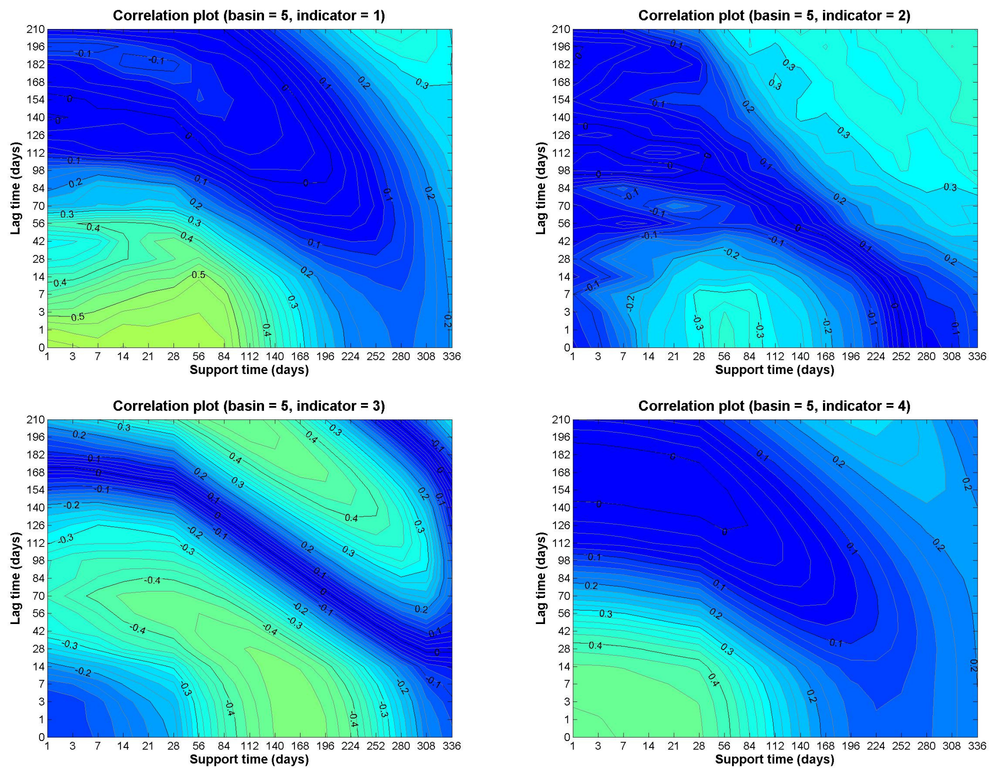

Figure 16 - Correlation plot of sub-basin 5 (Main)

Sub-basin 6 (Mosel)

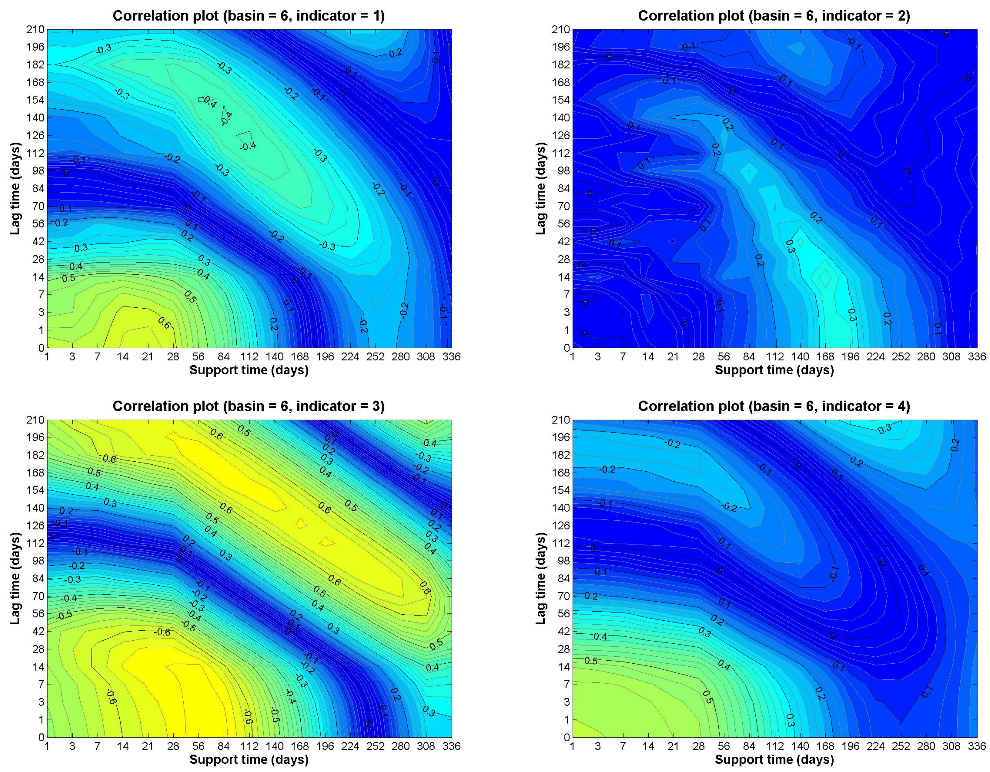

Figure 17 - Correlation plots of sub-basin 6 (Mosel)

Sub-basin 7 (Lower Rhine)

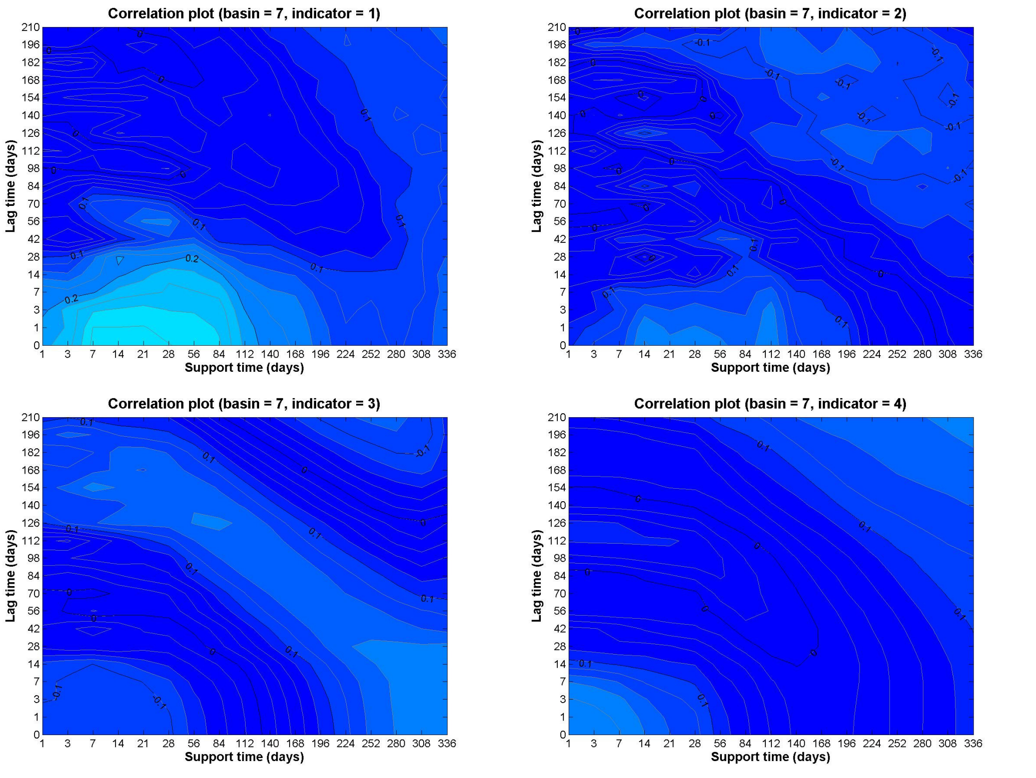

Figure 18 - Correlation plots of sub-basin 7 (Lower Rhine)

Appendix 3 - Results for the sub-basins using ANN

- (a) is the scatter plot for the training, validation and test phase
- (b) is the plot for the discharge in five years showing the simulated low flow (bold points) versus the measured discharge during the year (green line).

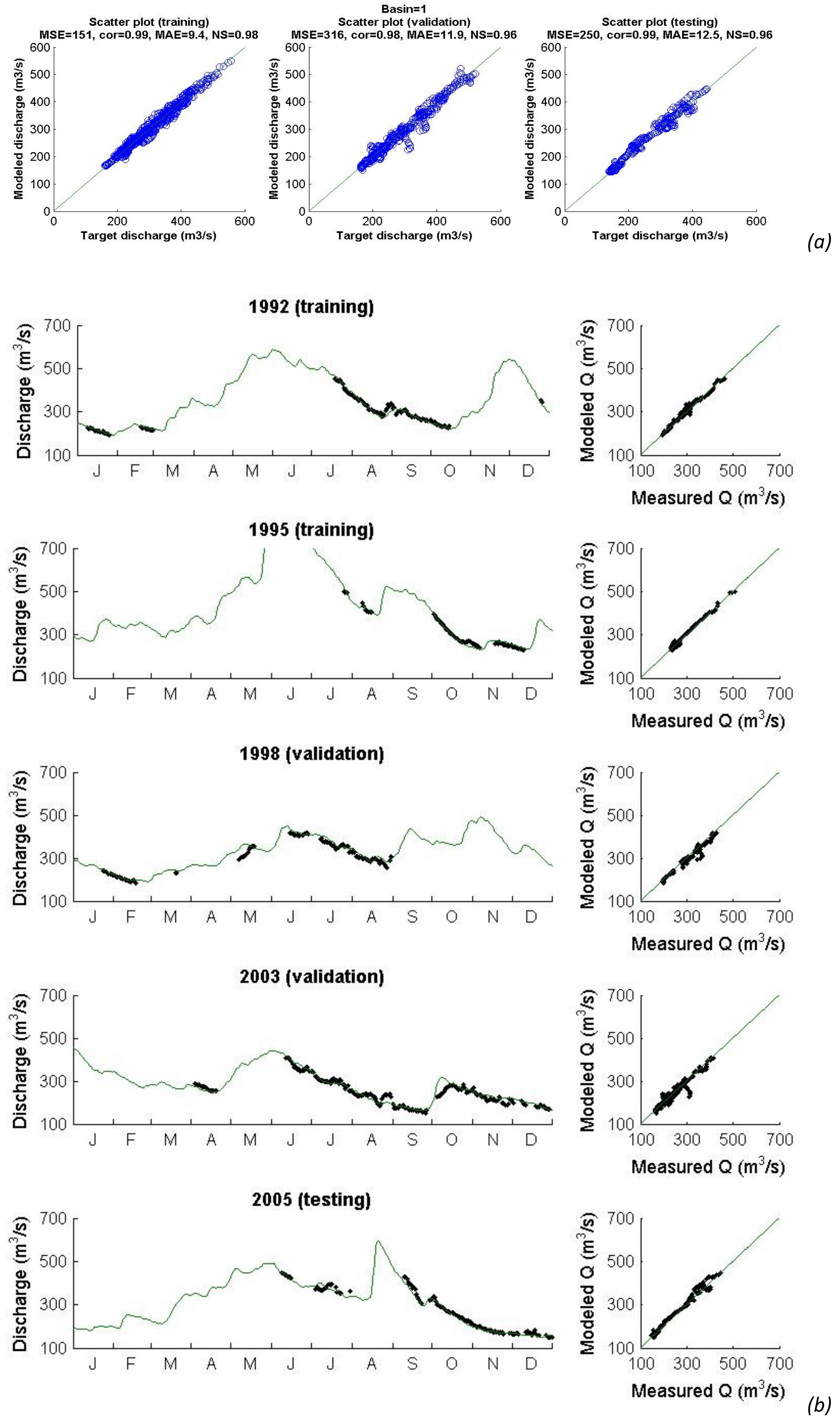

Figure 19 - Plots sub-basin 1 (East Alpine)

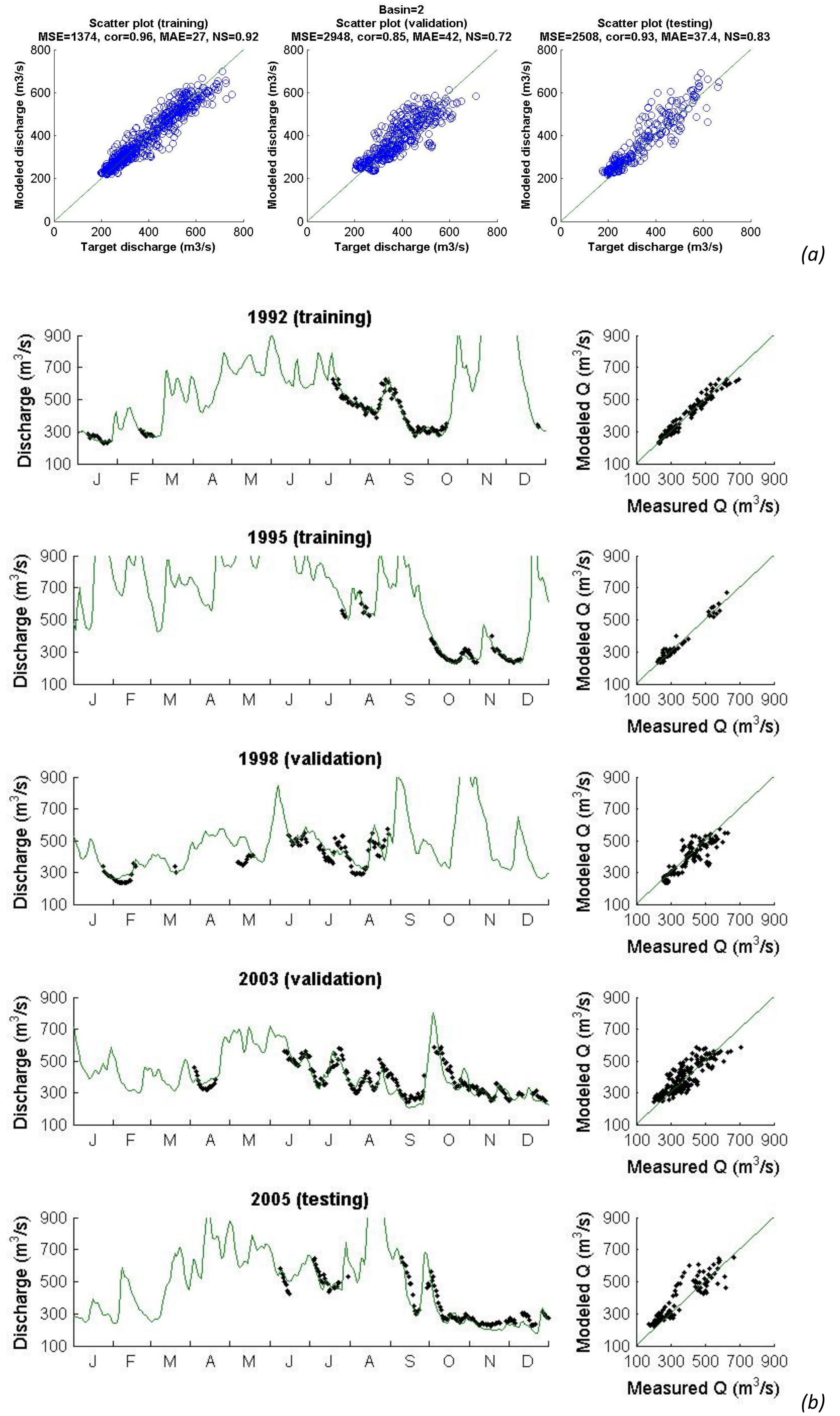

Figure 20 - Plots sub-basin 2 (West Alpine)

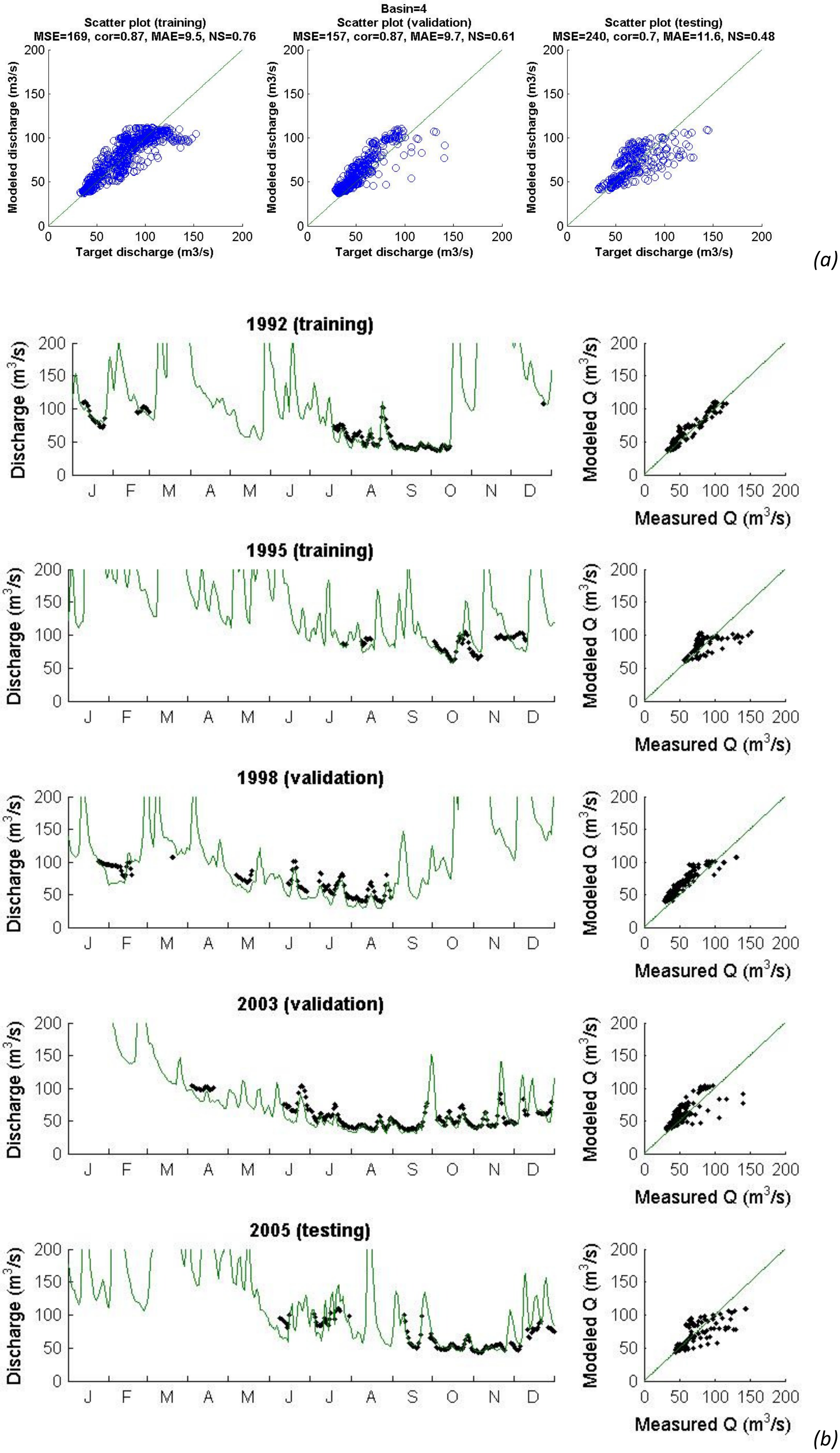

Figure 21 - Plots sub-basin 4 (Neckar)

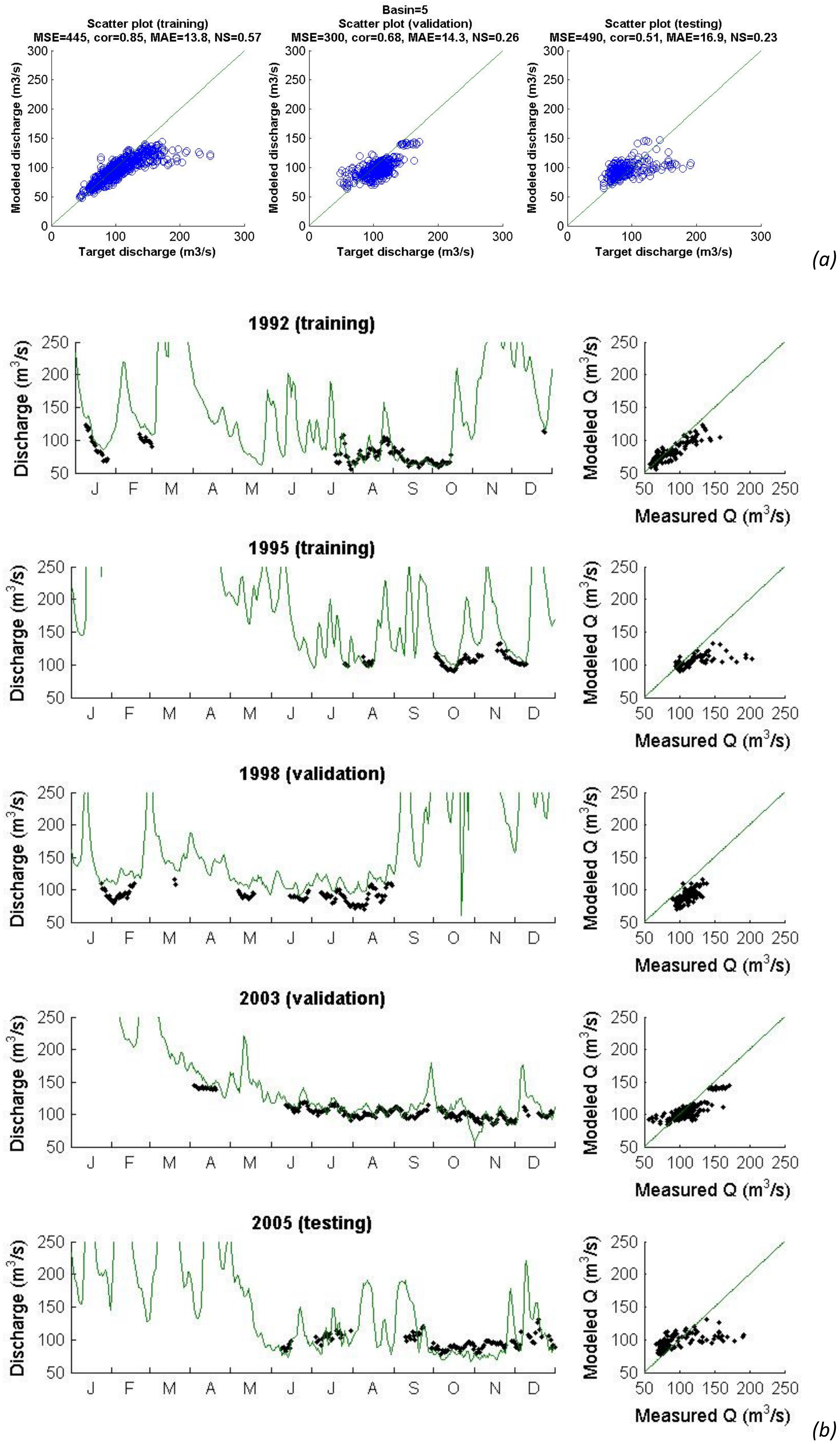

Figure 22 - Plots sub-basin 5 (Main)

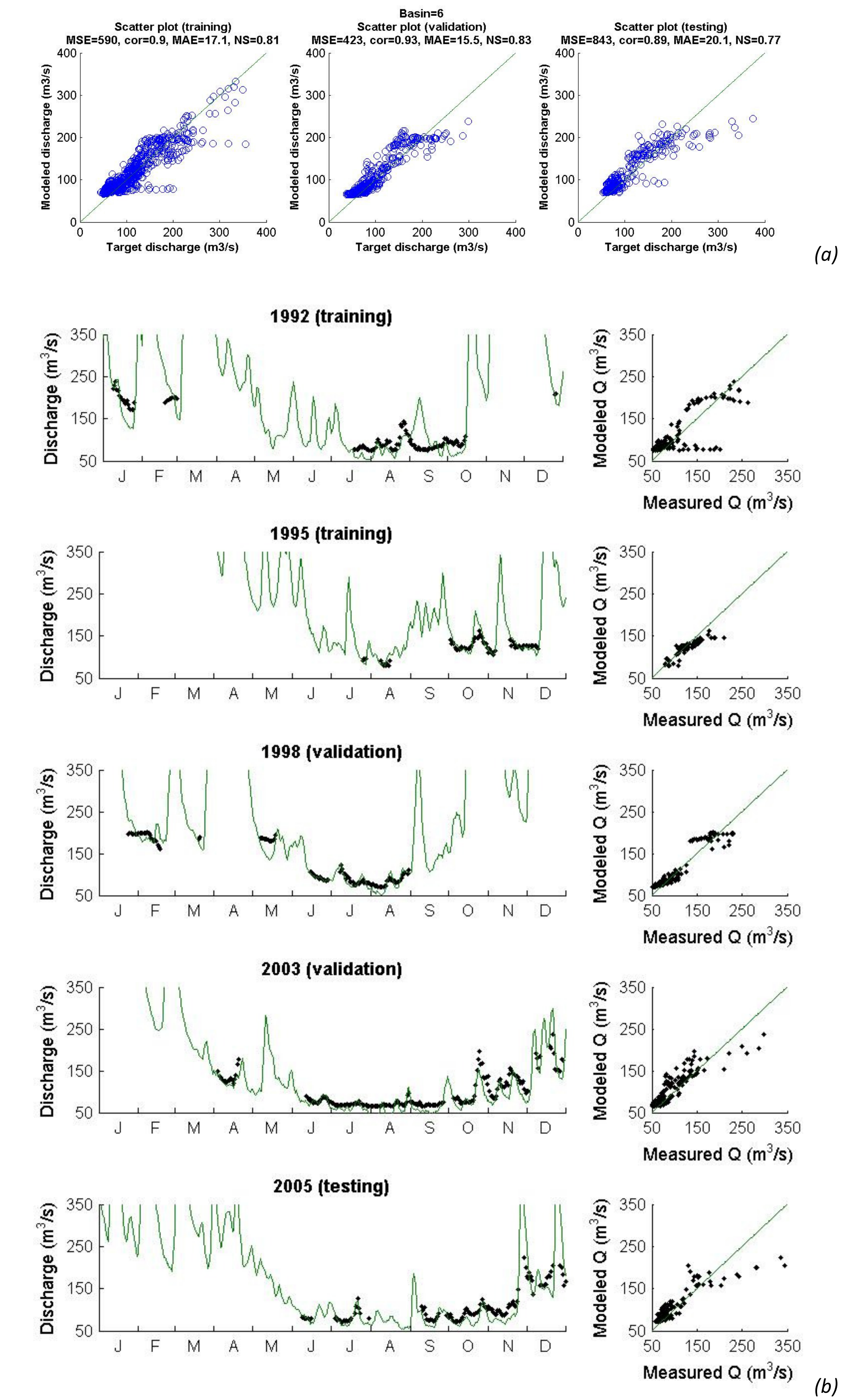

Figure 23 - Plots sub-basin 6 (Mosel)

Appendix 4 - Results for Lobith using ANN

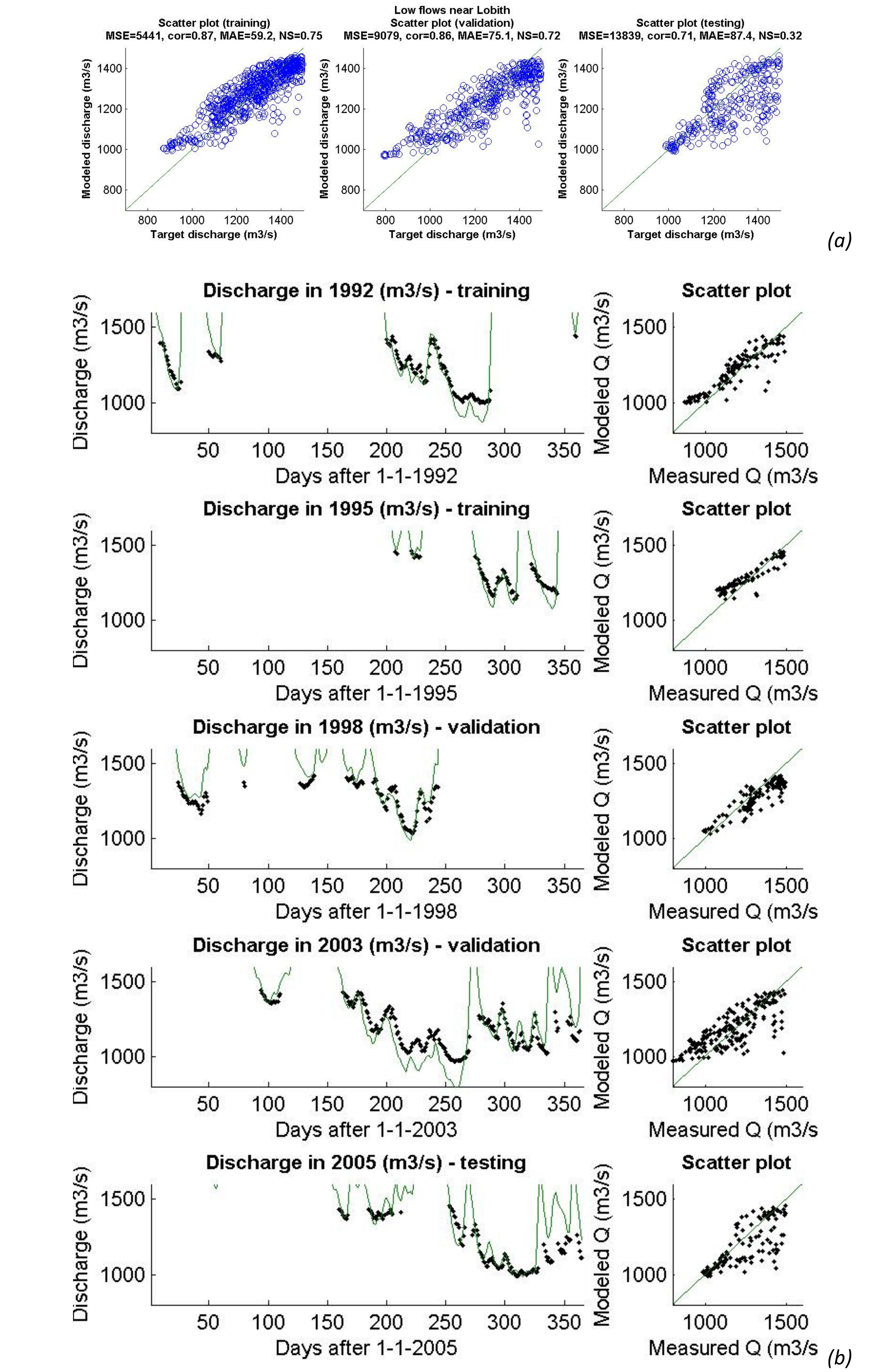

Figure 24 - Plots for Lobith