FORECASTING WATER LEVELS AT THE YANGTZE RIVER WITH NEURAL NETWORKS

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With 4 figures and 5 tables
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Summary: In the last ten years, the application of neural network models has become an emerging field of research in the field of hydrology. In the present study, three different neural network models, namely the Multilayer Perceptron (MLP), the Jordan net, and the Elman net were used for forecasting water levels at Cuntan station, located at the Yangtze River's upper reaches. The performances of the neural network models were compared with each other and with the results of a multiple linear regression (MLR) model. As input variables for the models, not only were precipitation data and antecedent water levels implemented, but also two climatic variables which are usually left out in the field of neural network modeling: evaporation and snow data. Before the models were adopted, the optimal lead time between the input variables and the model output was determined by means of a cross-correlation analysis. The highly significant correlation between the model input and output already indicated a highly linear relationship. Accordingly, the MLR model showed the best performance, even though the results of the other models are only slightly worse. The good capability of the Jordan net in forecasting high water levels should be investigated further. In predicting water levels in general, the integrated snow data improved the performance of the different models only marginally. However, the integration of evaporation data definitely improved the modeling results.

Zusammenfassung: In den vergangenen zehn Jahren hat die Anwendung neuronaler Netze in der Hydrologie zunehmend an Bedeutung gewonnen. In der vorliegenden Studie wurden drei verschiedene neuronale Netzwerkmodelle, namentlich das Multilayer Perzeptron, das Jordan- und das Elman-Netz, eingesetzt, um die Wasserstände an der hydrologischen Station Cuntan (Yangtze-Oberlauf) zu simulieren. Die erzielte Modellgüte der unterschiedlichen Netztypen wurde sowohl untereinander als auch mit den Ergebnissen eines multiplen linearen Regressionsmodells verglichen. Als Eingangsvariablen wurden über die für neuronale Netzwerkmodelle üblichen Eingangsvariablen Niederschlag und Wasserstände der vorherigen Zeitschritte hinaus Verdunstungs- und Schneedaten integriert. Bevor die Modelle eingesetzt wurden, wurde mittels einer Kreuzkorrelationsanalyse der optimale Zeitabstand zwischen den Eingangvariablen und der Modellausgabe berechnet. Die Ergebnisse dieser Korrelationsanalyse zeigen eine hochsignifikante Korrelation und weisen damit auf eine lineare Relation hin. Aufgrund dieser linearen Relation zeigt das multiple lineare Regressionsmodel das beste Resultat, auch wenn die Ergebnisse der anderen Modelle nur als geringfügig schlechter einzuordnen sind. Die gute Leistungsfähigkeit des Jordan-Netzes bei der Simulation der hohen Wasserstände sollte in zukünftigen Studien vertieft untersucht werden. Bei der Simulation sämtlicher Wasserstände konnte durch die Integration der Schneedaten lediglich eine marginale Verbesserung der Modellgüte erzielt werden; mit der Implementierung der Verdunstungsdaten hingegen wurde eine deutlichere Verbesserung erreicht.

Keywords: Cross-correlation analysis, neural network analysis, multiple linear regression analysis, water level, China, Yangtze

1 Introduction

During the last decades, large parts of the Yangtze River basin have been hit by disastrous floods. In the second half of the 20th century extreme floods occurred in 1954, 1981, 1991, 1995, 1996 and 1998, causing the death of almost 40,000 persons (Jiang 2000). These flooding disasters can be distinguished into two main types (Zhao 1999): flooding which affects only a smaller region as in 1981, 1991, 1995 and 1996; and flooding which hits most parts of a river basin as in 1954 and 1998. The first type is caused by local rainstorms, whereas the second type is produced by regional rainstorms which affect tributaries of the upper, middle and lower reaches, as well as the main river at the same time.

In general, floods at the Yangtze River are natural events and have been recorded long before man interfered with the hydrological cycle (Gemmer 2004). The main source of floods in the Yangtze River basin is long-lasting precipitation during the

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summer months mainly determined by the strength of the monsoon circulation. In years with a weak summer monsoon, low wind speeds cause a quasi-stagnation of the so-called "Meiyu" rain belt in the Yangtze River basin, leading to an increased flood risk (Domrös and Peng 1988).

As can be seen above, four of the six heaviest flooding disasters during the second half of the 20th century occurred in the 1990s. Several studies dealing with analyses of precipitation data from the Yangtze River basin for this period point towards a concentration of summer precipitation within a shorter period of time (Becker et al. 2003, 2006; Gemmer 2004). In addition to a significantly decreasing evaporation in that region caused by decreasing wind speed as well as decreasing radiation (Wang et al. 2007), this has led to an aggravation of the flood risk since the 1990s. Beside these climatic impacts, there are also human interventions aggravating the flood situation: soil erosion along the Yangtze River's upper reaches mainly caused by inappropriate land use, the regulation of the river course and wetland reclamation (King et al. 2001).

Especially the Yangtze River's middle and lower reaches are extremely susceptible to floods, which among other reasons is due to the flat relief. However, damages caused by floods are not limited to these regions, but have also been reported from the Sichuan basin, a plane region in the Yangtze River's upper reaches (Gemmer 2000; Hartmann 2002). During the second half of the 20th century, the 1981-flood caused the most damages here. This region, upstream of the Three Gorges Dam, was of interest in the context of this study.

The main aim of the present study was to predict the water level of the Yangtze River for the hydrological station Cuntan, which is located about 10 kilometers downstream of the inflow of the Jialingjiang by Chongqing city at 106°36'E, 29°37'N, 165 m a.s.l. (Fig. 1). Hence, it is located in the flood prone area of the Sichuan basin. The runoff measured at Cuntan station is used as a key variable for predicting the inflow into the Three Gorges Reservoir by the Bureau of Hydrology, Changjiang Water Resources Commission Wuhan (Chen et al. 2004). This points towards the relevance of an accurate prediction of the water level at this station. Figure 2 shows the relationship between water level and runoff at Cuntan station.

Due to the fact that deterministic models need a very high amount of data, which is difficult to obtain and to handle, especially for a drainage area of that size (866,600 km^2), the authors decided to use a stochastic approach. In the last 10 years, the application of neural networks in hydrological modeling has become an emerging field of research. Various studies mostly dealing with the prediction of runoff proved the potential of neural network models for this purpose (e.g. Antar et al. 2006; Cigizoglu 2003; Dibike and Solomatine 2001). However, there still is a need for more inter-model comparisons and rigorous assessment of neural network solutions versus traditional hydrological methods (Dawson and Wilby 2001) including deterministic as well as stochastic approaches. Therefore, in the present study three different neural network models were applied for forecasting water levels: the multilayer perceptron (MLP), the Jordan net, and the Elman net. The performances of the neural network models were compared with each other and also with the outcomes of a multiple linear regression (MLR) model.

Predicting water levels at the Yangtze River was the last step carried out in the context of the project "Teleconnections and their relevance for precipitation patterns in China: time series analyses as a base for an improved flood management in the Yangtze River basin," funded by the German Research Foundation (DFG). During this project, analyses of the climatic variability of different climatic factors as well as medium and long-term predictions of precipitation were undertaken (Becker et al. 2007, 2008; Hartmann et al. 2008a, 2008b; Wang et al. 2007; Zhang et al. 2007). The last step was to analyze the relation between rainfall and water levels in the Yangtze River basin and, through this, to extend the prewarning time for a flood.

2 Data

All data series used in the present study consist of daily averages or totals and cover the period from January 1, 1961 to December 31, 2000.

We started our analyses using precipitation time series of 41 climate stations located upstream of Cuntan hydrological station, either along the Yangtze River or along its tributaries, as potential input variables (predictors) for the models.

The data were provided by the National Climatic Centre (NCC) of the China Meteorological Administration (CMA), Beijing, P.R. China. The homogeneity of the precipitation data was confirmed in a previous study by Becker et al. (2008). The location of the climate stations is shown in figure 1.

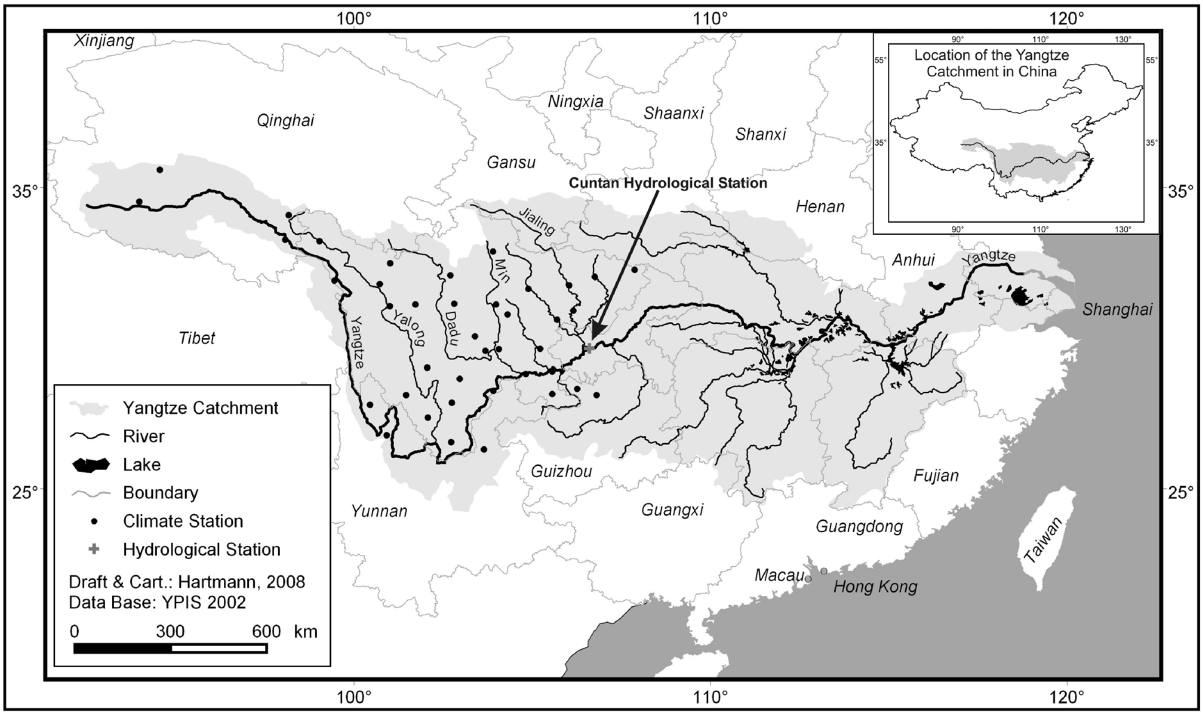

Fig. 1: Location of the 41 climate stations and the hydrological station Cuntan

In addition, we integrated two further climatic variables as predictors into the models, which are usually left out in the field of neural network modeling; these are evaporation and snow water equivalent. Even though it is common knowledge that both are key variables in the water cycle, there are only very few studies in which they were used as input for neural network analyses. An example for using evaporation data for forecasting runoff by neural networks is a study by Dibike and Solomatine (2001). Snow data were implemented for predicting runoff by Nilsson et al. (2006).

Due to difficulties in assessing observational data of evaporation and snow we used potential evaporation rate and water equivalent of snow depth from NCEP/NCAR Reanalysis 1 (Kistler et al. 2001), provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA from their Web site at http://www.cdc.noaa.gov. The location of the grid cells of potential evaporation rate (PER) and of water equivalent of snow depth (WESD), which were selected for this study, can be taken from figure 3.

The output variable of our analyses was water level from Cuntan station located at the upper reaches of the Yangtze River. The hydrological data (water level and runoff, the latter only used in figure 2) was provided by the Changjiang Water Ressources Commission. The hydrological time series were plotted and visually controlled for outliers; no corrections were necessary. As proven in several studies (Dibike and Solomatine 2001; Dawson et al. 2002; Minns and Hall 2004), the use of previous output variables (in this case, previous water level values) as part of the input pattern, usually improves the performance of a neural network model. Therefore, antecedent water levels at Cuntan station were also used as input variables.

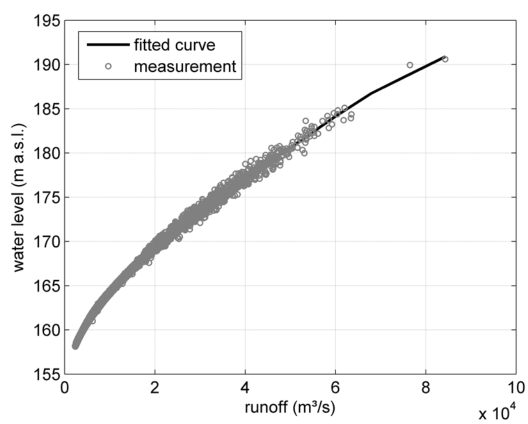

Fig. 2: Relationship between water level and runoff at the hydrological station Cuntan

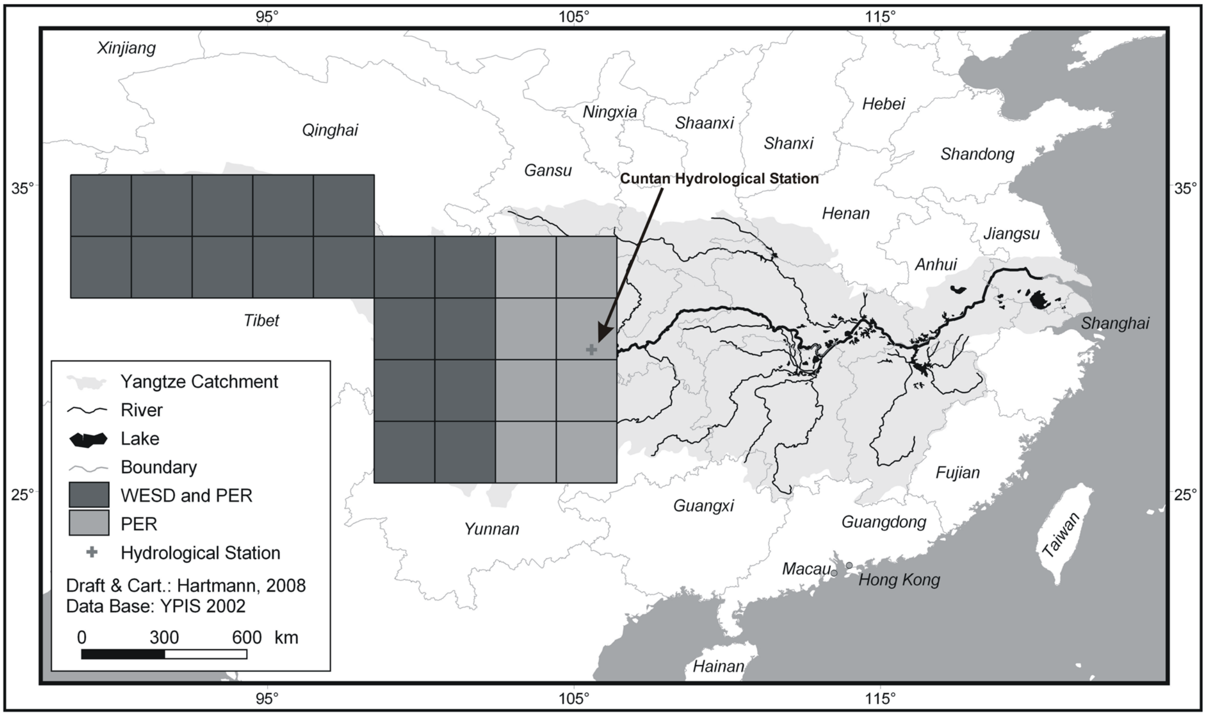

Fig. 3: Location of the selected grid cells of potential evaporation rate (PER) and water equivalent of snow depth (WESD)

3 Methodology

In order to reduce the number of input variables while retaining most of the information contained in the original data set, a principal component analysis (PCA) was carried out on the 26 grid cells of PER. The central idea of PCA is to reduce the dimensionality of a data set which consists of a large number of correlated variables, while retaining as much of the variance of the data set as possible. This is achieved by a transformation to a new set of variables, the so-called principal components (PCs), that are uncorrelated and ordered so that the first few retain most of the variance present in all of the original variables (Jolliffe 1986). Like in Hartmann et al. (2008a) a varimax rotation of the PCs was applied. "Varimax" stands for "variance maximizing"; "varimax rotation" means that the criterion for the rotation is to maximize the variance of the PC, while minimizing the variance around this PC (STATSOFT 2007).

Subsequently, the values of the 18 grid cells of WESD were summed up to one time series.

In order to determine the optimal lead time between the input variables and the model output, cross-correlation coefficients between all of the input variables and the output variable were calculated. According to Long et al. (2006), a lead time of about 4 weeks for the precipitation series recorded in western China was expected. Therefore lead times between 0 and 40 days were tested.

Further data preprocessing included standardizing the time series, which were used as input variables. The time series were rescaled to the interval [0.1, 0.9] to enable the modeling of extreme events occurring outside the range of the training data (Dawson and Wilby 2001). Then, the data was split into three data sets: one for training (80% of the data), one for cross validation (10% of the data), and one for testing (10% of the data). As the terms "cross validation" and "testing" are used differently in various studies, the use of these terms is defined in the following.

In this study, the term "cross validation" describes the procedure of avoiding overfitting by determining when the network has been trained as well as possible. The cross validation data set is used by the network during training. At regular intervals, during training the training data set, the network performance is tested on the cross validation set. During this testing, the performance of the network on the cross validation set is saved and compared to past values. If the network is starting to overtrain on the training data, the cross validation performance will begin to degrade and the training procedure will be stopped (Principe et al. 2005). This definition of "cross validation" was also used, e.g. by Coulibaly et al. (2000), Kang et al. (2006) and Senthil Kumar et al. (2005). Instead of "cross validation", Dawson and Wilby (2001) and Dawson et al. (2002) used the term "testing"; in ASCE (2000) this procedure was named "cross training".

We use the term "testing" for evaluating the chosen model against independent data, as was done in various other studies, such as Backhaus et al. (2003), Principe et al. (2005), and Cigizoglu (2003). What is meant by "testing" in this study, was sometimes expressed by the term "validation" (ASCE 2000; Dawson and Wilby 2001; Dawson et al. 2002) in the field of hydrology.

The training data set covers the time periods from 1961 to 1967, 1970 to 1977, 1980 to 1987, 1990 to 1997, and the year 2000. For the cross validation data set, the following years were selected: 1969, 1979, 1989, and 1999. The test data set consists of the years 1968, 1978, 1988, and 1998. It was one aim to test the model performance for the year 1998, which is known for its severe flooding in the Yangtze River basin. Even though the water level at Cuntan station did not reach an extreme value in that year, it would have been extremely beneficial if it had been forecast accurately.

The authors decided to use neural network models for predicting water levels at Cuntan station due to the fact that these enable the modeling of even nonlinear relationships. This decision was also due to the positive results gained by the application of neural networks in the field of hydrological modeling (e.g. Antar et al. 2006; Cigizoglu 2003; Dibike and Solomatine 2001). Neural networks are parallel computing structures of processing elements (neurons), which are interconnected by a network similar to the human brain (Hsieh and Tang 1998). Three different neural network models were used in this study: the MLP, the Jordan net, and the Elman net. The performances of the neural network models were compared with each other as well as with the outcomes of a MLR model. Two of the neural network models, namely the Jordan and Elman nets, have been rarely used in the field of hydrology until now. Therefore, the authors were interested in evaluating their performances.

At first, a conventional MLP neural network design was applied, which is overwhelmingly favoured in the field of hydrology (Minns and Hall 2004). A MLP is a so-called "feed-forward" neural network because all information flows in one direction. The neurons of one layer are connected with the neurons of the following layer without feedback (Teschl and Randeu 2006). The weights adjustment was performed by the error backpropagation learning algorithm: weights are modified to reduce the error occurrence between actual and desired network outputs backward from the output layer to the input layer (Backhaus et al. 2003).

Then, the Jordan and Elman networks were used to forecast the water levels at Cuntan station. Both networks extend the MLP with context units, which are neurons that remember past activity (Principe et al. 2005).

Until now, the Jordan net has been applied in the field of hydrology in only one study (Varoonchotikul 2003). The Jordan net belongs to the partial recurrent networks, which stand for a net in which connections between neurons feed backwards through the network as well as forwards (Dawson and Wilby 2001). The Jordan net makes use of its output from the output layer to train the network by feeding this, via the context units, back to the hidden layer (Geith 2006). Due to the fact that the modifiable connections are all feed-forward, it was possible to carry out the weights adjustment by the error backpropagation learning algorithm as described above (Varoonchotikul 2003).

Like the Jordan net, the Elman net belongs to the partial recurrent networks. In the case of the Elman net, however, the hidden layer is not only connected to the output layer, but also to the context units. The output of these context units is also inputted to the hidden layer (Cruse 2006). Again, the weights adjustment was performed by the error backpropagation learning algorithm.

The architecture of a neural network is often determined by a "trial and error" approach. In this study, the number of hidden neurons is in a first step determined based on the following formula given by Han et al. (2007):

$$\textit{number of hidden neurons} = (\textit{number of input neurons} + \textit{number of output neurons}) * \frac{2}{3} \quad (1)$$

Thus, at first the performances of the different neural networks with 1 hidden layer and 32 neurons were evaluated. Secondly, further trials with less and more neurons were conducted, which outperformed the 32 neurons architecture. For the MLP and the Elman net, 16 neurons architectures were most successful; and for the Jordan net, a 20 neurons architecture showed the best performance. Thirdly, the performance of two hidden layers was tested for all the neural network models; however, no improvement was achieved. Thus, for the MLP and the Elman net, one hidden layer and 16 neurons were used; and one hidden layer and 20 neurons were used for the Jordan net.

Finally, a multiple linear regression analysis was carried out and the performance of this analysis was compared with the results from the neural network models.

When evaluating hydrological model skill, it is important to apply multiple error measures due to different sensitivities (Dawson and Wilby 2001, 2004). In this study, the performance of the different models was assessed, calculating the coefficient of determination r^2 (Dawson and Wilby 2001), the root mean squared error RMSE (Dawson et al. 2002), and the maximum absolute error MAE (Dawson and Wilby 2001) (see equations 2, 3, 4 respectively):

$$r^2 = \left[\frac{\sum_{i=1}^{n}(Q_i - \overline{Q})(\hat{Q}_i - \widetilde{Q})}{\sqrt{\sum_{i=1}^{n}(Q_i - \overline{Q})^2 \sum_{i=1}^{n}(\hat{Q}_i - \widetilde{Q})^2}} \right]^2 \qquad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{n}} \qquad (3)$$

$$MAE = \frac{\sum_{i=1}^{n}\left|Q_i - \hat{Q}_i\right|}{n} \qquad (4)$$

where Q_i are the $\boldsymbol{n}$ observed flows, $\overline{Q}$ is the mean of the observed flows, $\widetilde{Q}$ are the $\boldsymbol{n}$ modeled flows and $\hat{Q}_i$ is the mean of the modeled flows.

4 Results

4.1 Principal component analysis

The first three rotated PCs explain altogether 80.2% of the total variance of the PER. Almost 68% of the total variance is explained by the first two rotated PCs. More detailed information is given in table 1. Instead of the 26 time series of PER extracted from the grid cells, the first three rotated PC scores were used as input variables for the models.

Table 1: Percentages of variance explained by the first three rotated principal components (PCs) of potential evaporation rate

no. PCs	variance (%)	cumulative variance (%)
1	35.503	35.503
2	31.745	67.248
3	12.984	80.231

4.2 Cross-correlation analysis

The results from a cross-correlation analysis between the 41 precipitation time series from climate stations along the Yangtze River's upper reaches and water level at Cuntan station show a highly significant correlation with a lead time of more than 20 days for the climate stations located in the western Yangtze River basin (Tab. 2). The precipitation time series recorded at these stations are perfectly suited for a prediction up to 4 weeks in advance. The stations located along the Yalong River are also well suited for forecasting water levels at Cuntan station: the precipitation series recorded at the Yalong's upper reaches show a lead time of 28 days reducing to 13 days at its lower reaches. The precipitation series from all stations located east of the Yalong subbasin are far less suitable for a prediction several days ahead. All of these series show the highest correlation with a lead time of 0 days. This is easy to understand for climate stations which are located in the surrounding area of Cuntan station, such as the climate station in Chongqing. However, it is remarkable that the precipitation series from all the stations along the Daduhe and the Minjiang (Fig. 1), even though some of them are located in a distance of more than 700 km to Cuntan station, show the highest correlation coefficients for a lead time of 0 days and lower coefficients for the following days. A shorter lead time would probably improve the modeling results, as the correlation is decreasing with an increase of the time lag. However, a shorter lead time would limit the effectiveness of forecasting, especially of flood forecasting. The prewarning time should be as long as possible and, therefore, we decided to implement these variables with the smallest lead time used for the other variables (8 days also used for the precipitation series recorded at station 566840) and not with a shorter one.

Table 2: Correlation coefficients and lead time between the input variables and observed water levels

	water level at Cuntan	lead time (in days)
precipitation at station 529080	0.341144762	28
precipitation at station 560040	0.34003522	28
precipitation at station 560290	0.376949779	28
precipitation at station 560340	0.366051103	28
precipitation at station 560380	0.385310392	28
precipitation at station 561440	0.389259388	21
precipitation at station 561460	0.337415959	16
precipitation at station 561520	0.382144679	23
precipitation at station 561670	0.361121175	14
precipitation at station 561720	0.33807216	8
precipitation at station 561780	0.309645678	8
precipitation at station 561820	0.280388451	8
precipitation at station 561880	0.231793952	8
precipitation at station 561960	0.212221586	8
precipitation at station 562510	0.380773134	14
precipitation at station 562870	0.250333042	8
precipitation at station 562940	0.239573904	8
precipitation at station 563850	0.282112538	8
precipitation at station 563860	0.216809994	8
precipitation at station 564590	0.395052876	13
precipitation at station 564620	0.385261903	13
precipitation at station 564750	0.32683727	8
precipitation at station 564850	0.259137675	8
precipitation at station 564920	0.217523803	8
precipitation at station 565430	0.315674122	16
precipitation at station 565650	0.357991832	8
precipitation at station 565710	0.296671749	13
precipitation at station 566510	0.366188397	16
precipitation at station 566710	0.307176003	13
precipitation at station 566840	0.26687519	8
precipitation at station 572370	0.200322393	8
precipitation at station 573060	0.187983928	8
precipitation at station 573130	0.179870787	8
precipitation at station 574050	0.193171183	8
precipitation at station 574110	0.187794676	8
precipitation at station 575040	0.20521343	8
precipitation at station 575160	0.185519676	8
precipitation at station 576020	0.19402136	8
precipitation at station 576060	0.207358222	8
precipitation at station 576080	0.188463728	8
precipitation at station 576140	0.200598774	8
potential evaporation rate principal component (PC)1	0.679490611	28
potential evaporation rate PC2	-0.30191028	28
potential evaporation rate PC3	0.147839727	28
water equivalent of snow depth	-0.547433978	27
antecedent water level at Cuntan	0.874343601	8

The PC scores of PER show a highly significant correlation with a self-evidently longer lead time, which is determined at 28 days. As WESD shows a higher (negative) correlation with a lead time of 27 days, the variable was chosen to be integrated into the models with that lead time. The negative correlation is due to high amounts of WESD in winter and low or 0 values in summer, whereas the water level show peaks in summer and minima in winter. Due to the above named reasons, the last input variable, antecedent water levels at Cuntan station, was also implemented into the models with a lead time of 8 days.

Table 2 gives an overview of the correlation coefficients and lead time between the input variables and the observed water levels.

4.3 Neural network and multiple linear regression models

Table 3 provides a summary of the modeling results for the testing, training, and cross validation periods achieved by the application of the different models. It can be concluded that the results of the different models are similar. Regarding all the performance measures, the MLR shows the best result, closely followed by the results of the MLP and the Elman models. The Jordan net takes up the fourth position, when evaluated with the used error measures. Concerning the factor of determination r^2, the testing period demonstrates the best result compared with the performances of the different models during the training and cross validation periods. However, the RMSE and the MAE are smaller for the latter periods indicating that, overall, the results for the different periods are similar in terms of quality.

A comparison of the measured and modeled water levels for the test years 1968, 1978, 1988 and 1998 is presented graphically in figure 4. The MLP (Fig. 4a) performs very well during medium water levels in spring and autumn, well during low water levels in winter, and quite well in summer if the water level is not too high. It performs poor in modeling high water levels like in the summer of 1968 or in the summer of 1998. However, the Jordan net (Fig. 4b) performed a good simulation of the high water levels in all years. Nevertheless, especially the low water levels of January, February, and March 1978 were simulated incorrectly; they were clearly lower than simulated. The Elman net (Fig. 4c) performs similar to the MLP, demonstrating the same shortcomings in simulating the high water levels. The best performance was

Table 3: Performance comparison of the different models for the a) testing, b) training, and c) cross validation period

a)

TESTING	r^2	RMSE (m)	MAE (m)
MLP	0.8548	2.16	1.35
Jordan net	0.8391	2.27	1.55
Elman net	0.8548	2.17	1.39
MLR	0.8611	2.09	1.26

b)

TRAINING	r^2	RMSE (m)	MAE (m)
MLP	0.8207	2.07	1.31
Jordan net	0.7892	2.25	1.49
Elman net	0.8162	2.10	1.35
MLR	0.8250	2.05	1.25

c)

CROSS VALIDATION	r^2	RMSE (m)	MAE (m)
MLP	0.8478	1.91	1.30
Jordan net	0.8162	2.12	1.57
Elman net	0.8433	1.94	1.38
MLR	0.8485	1.90	1.28

achieved by using the MLR model (Fig. 4d). This model simulates low, medium and high water levels close to reality.

Sensitivity analyses, which were carried out for all the neural network models, point towards the importance of PER as input variable for simulating water levels at Cuntan station. The implemented WESD seems to be less relevant. A consecutive test of the model performance excluding PER (Tab. 4) and WESD data (Tab. 5) confirmed this outcome. Leaving out the PER data led to a deterioration of performance by a decrease of r^2 on an average of 0.025, and an increase of the RMSE and MAE of about 0.15 m. Leaving out the WESD data caused a decrease of r^2 by an average of only 0.008, and an increase of the RMSE and MAE of 0.05 m and 0.03 m, respectively. Analogous to the neural network models, leaving out PER data led to a worse result than leaving out the WESD data for the MLR model. When the WESD data was left out, the outcome was hardly affected.

5 Discussion and conclusions

In the last ten years, neural networks have become a widely accepted tool in the field of hydrological modeling. The majority of studies deal with the application of neural networks for rainfall-runoff modeling (e.g. Antar et al. 2006; Cigizoglu et al.

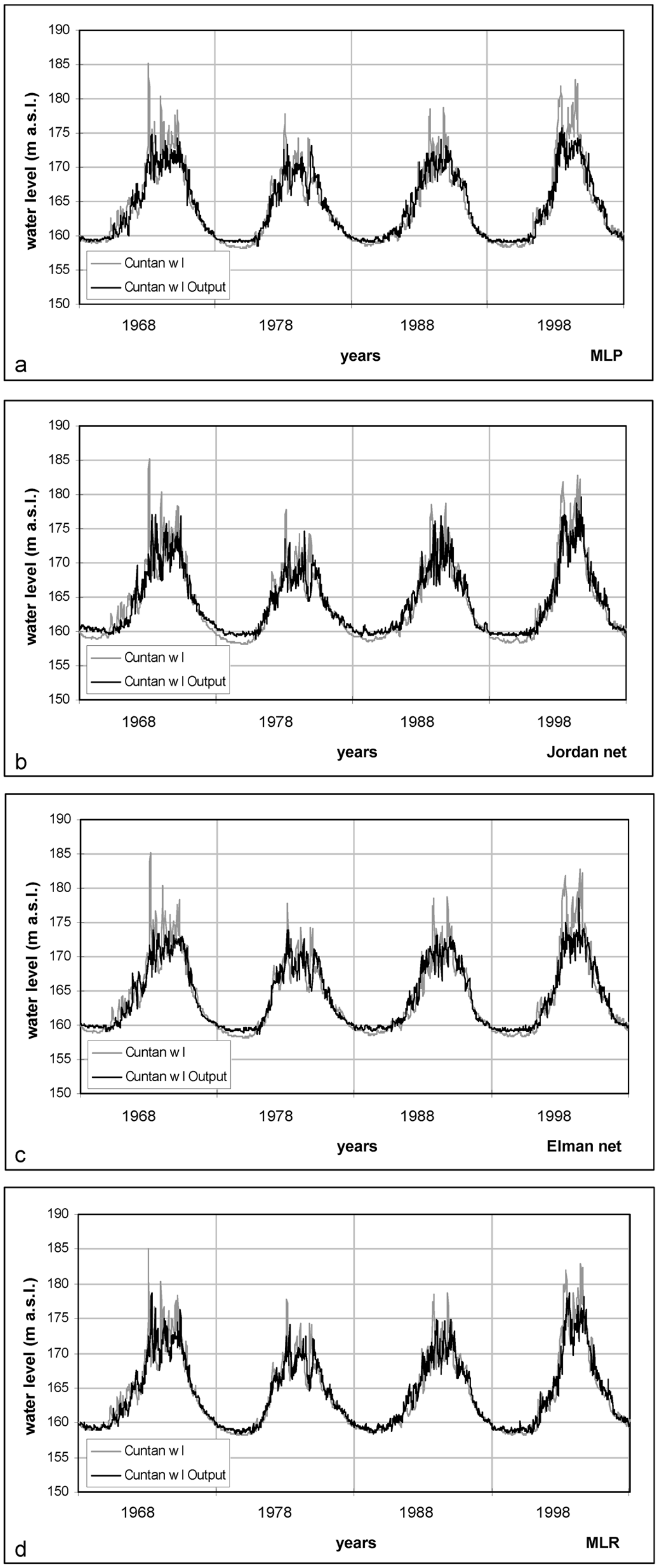

Fig. 4: Measured (in gray) and predicted (in black) water levels for the test years 1968, 1978, 1988 and 1999: a) for the Multi-layer Perceptron (MLP), b) for the Jordan net, c) for the Elman net, d) for the multiple linear regression (MLR) model

Table 4: Performance comparison of the different models without the implementation of potential evaporation rate (PER) for the a) testing, b) training, and c) cross validation period

a)

TESTING	r^2	RMSE (m)	MAE (m)
MLP	0.8386	2.28	1.48
Jordan net	0.8042	2.48	1.75
Elman net	0.8224	2.37	1.64
MLR	0.8509	2.15	1.35

b)

TRAINING	r^2	RMSE (m)	MAE (m)
MLP	0.8142	2.11	1.37
Jordan net	0.7693	2.35	1.61
Elman net	0.7819	2.28	1.55
MLR	0.8137	2.11	1.33

c)

CROSS VALIDATION	r^2	RMSE (m)	MAE (m)
MLP	0.8373	1.97	1.37
Jordan net	0.7778	2.33	1.76
Elman net	0.8132	2.13	1.55
MLR	0.8428	1.94	1.34

2007; DAWSON et al. 2002; DIBIKE and SOLOMATINE 2001; SENTHIL KUMAR et al. 2005). Neural networks have also been used for forecasting water levels (ALVISI et al. 2006; BUSTAMI et al. 2006; CHAU and CHENG 2002; PHIEN and KHA 2003). However, the number of studies dealing with this topic is rather limited.

In the majority of cases, neural networks show a very good performance, often outperforming other models (ANTAR et al. 2006; CIGIZOGLU 2003; DAWSON et al. 2002; DIBIKE and SOLOMATINE 2001). ANTAR et al. (2006) showed that the application of a MLP for simulating rainfall-runoff processes at the Blue Nile was more successful than the application of a distributed physically based model. DIBIKE and SOLOMATINE (2001) compared the performances of two neural network models (MLP and radial basis function net) with a conceptual rainfall-runoff model; the neural network models were slightly better in forecasting the runoff of the Apure River (Venezuela). In CIGIZOGLU (2003), a MLP outperforms a multiple nonlinear regression model by forecasting runoff of three rivers in Turkey.

However, there are also studies in which regression models show similar or even slightly better results than neural network models. HSIEH et al. (2003) carried out seasonal predictions of the Columbia River streamflow at Donalds (Canada). The results achieved by applying feed-forward neural networks were essentially identical to the results of a MLR model. PHIEN and KHA (2003) forecast water levels for three stations along the Red River (Vietnam). The outcome of this study is that the MLR models perform slightly better than the applied multilayer feed-forward neural network with backpropagation algorithm.

In DAWSON et al. (2002), artificial neural networks were applied for runoff forecasting at the Yangtze River, about 600 km downstream of Cuntan station. They identified the two applied neural networks (MLP and radial basis function net) as the most successful models. However, the application of a stepwise MLR model showed a result that is only slightly worse than that of the neural network models.

Like in the above cited study of PHIEN and KHA (2003), in the present study, the MLR model performance is slightly better than the performances of the neural network models. Even though the performance measures of the different models are similar (Tab. 3), the diagrams comparing the modeled and measured water levels for the test years (Fig. 4) illustrate this result. Whereas the MLR model simulates low, medium and high water levels close to reality, the MLP and the Elman net illustrate shortcomings mainly in forecasting high water levels, and the Jordan net in forecasting low water levels.

The authors conclude that there is a strong linear relationship between the input variables and water level at Cuntan station. This is also indicated by the highly significant correlation between input and output variables, which can be taken from table 2. According to this strong linear relation, the MLR model shows the best result in forecasting water levels at Cuntan station.

It is quite problematic to put this result into a wider context, as the number of studies comparing the results of neural network models with the outcomes of regression analyses is rather limited. As can be seen above, the results obtained by such a comparison furthermore differ regionally. Concerning regional setting and methods, the study corresponding most with the present one is the above mentioned by DAWSON et al. (2002). The deviation from our result might be attributed to the period of analysis. In DAWSON et al. (2002) only data from June to mid-August for the period from 1991 to 1993 were used. In the Yangtze River basin, the highest rainfall is generally recorded during these months, and therefore these months are often accompanied by flood events, six during their study period. It is obvious that the relevance of influential factors during the

Table 5: Performance comparison of the different models without the implementation of water equivalent of snow depth (WESD) for the a) testing, b) training, and c) cross validation period

a)

TESTING	r^2	RMSE (m)	MAE (m)
MLP	0.8484	2.25	1.39
Jordan net	0.8337	2.32	1.55
Elman net	0.8308	2.32	1.52
MLR	0.8607	2.09	1.27

b)

TRAINING	r^2	RMSE (m)	MAE (m)
MLP	0.8166	2.10	1.31
Jordan net	0.7867	2.26	1.49
Elman net	0.8078	2.14	1.40
MLR	0.8249	2.05	1.25

c)

CROSS VALIDATION	r^2	RMSE (m)	MAE (m)
MLP	0.8463	1.91	1.31
Jordan net	0.8157	2.12	1.51
Elman net	0.8279	2.05	1.50
MLR	0.8485	1.90	1.29

summer precipitation maxima is significantly different from observations that include the entire year. Consequently, methods suitable for one approach might be less suitable for another approach.

All in all, the application of a MLR model enables an accurate prediction of the water level at Cuntan station 8 days in advance. In addition to this main result, some further conclusions can be drawn: the Jordan net, rarely used in the field of hydrology until now, shows a good capability in forecasting high water levels. As the prediction of high water levels is of special interest for flood risk management, this should be investigated in future studies.

It can also be concluded that the additional implementation of evaporation and snow data, usually left out in the field of neural network modeling, generally improved the model performance. Whereas the integrated WESD data improved the performance of all the models only marginally, the implementation of the PER data definitely improved the modeling results.

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References

Alvisi, S.; Mascellani, G.; Franchini, M. and Bárdossy, A. (2006): Water level forecasting through fuzzy logic and artificial neural network approaches. In: Hydrology and Earth System Sciences 10, 1–17.

Antar, M. A.; Elassiouti, I. and Allam, M. N. (2006): Rainfall-runoff modelling using artificial neural networks techinque: a Blue Nile catchment case study. In: Hydrological Processes 20, 1201–1216.

ASCE (American Society of Civil Engineers) (2000): Artificial Neural Networks in Hydrology I: Preliminary Concepts. In: Journal of Hydrologic Engineering 5, 115–123.

Backhaus, K.; Erichson, B.; Plinke, W. and Weiber, R. (2003): Multivariate Analysemethoden. Berlin, Heidelberg.

Becker, S.; Gemmer, M. and Jiang, T. (2003): Observed and interpolated precipitation trends and variability in the Yangtze catchment area. In: Journal of Lake Sciences 15, 123–130.

– (2006): Spatiotemporal analysis of precipitation trends in the Yangtze River catchment. In: Stochastic Environmental Research and Risk Assessment (SERRA) 20, 435–444.

Becker, S.; Hartmann, H.; Coulibaly, M.; Zhang, Q. and Jiang, T. (2007): Quasi periodicities of extreme precipitation events in the Yangtze River Basin, China. In: Theoretical and Applied Climatology. Published online 28 December 2007.

Becker, S.; Hartmann, H.; Zhang, Q.; Jiang, T. and Wu, Y. (2008): Cyclicity analysis of precipitation regimes in the Yangtze River Basin, China. In: International Journal of Climatology 28, 579–588.

Bustami, R. A.; Bessaih, N. and Muhammad, M. S. (2006): Artificial neural network for daily water level estimation. In: Engineering e-Transaction 1, 7–12.

Chau, K. W. and Cheng, C. T. (2002): Real-time prediction of water stage with artificial neural network approach. In: McKay, B. and Slaney, J. (eds.): AI 2002: advances in artificial intelligence. Berlin, Heidelberg, 715.

Chen, G.; Cheng, H.; Zou, B. and Ge, S. (2004): Flood forecasting technologies applied in the Changjiiang River Basin. Proceedings of the Workshop on Flood Prevention and Control on the Yangtze River (FOCYR). January 9–12. Wuhan. http://kepler.ia.ac.cn/seminars/FOCYR/fullpaper/ChenGuiya.pdf (07.08.2008).

Cigizoglu, H. K. (2003): Estimation, forecasting and extrapolation of river flows by artificial neural networks. In: Hydrological Sciences-Journal 48, 349–361.

Cigizoglu, H. K.; Aşkin, P.; Öztürk, A.; Gürbüz, A.; Ayhan, Ö.; Yildiz, M. and Ucar, I. (2007): Artificial neural network models in rainfall-runoff modelling of Turkish Rivers. Proceedings of the International Congress on River Basin Management. March 22–24. Antalya. http://www.dsi.gov.tr/english/congress2007/chapter_4/118.pdf (07.08.2008).

Coulibaly, P.; Anctil, F. and Bobée, B. (2000): Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. In: Journal of Hydrology 230, 244–257.

Cruse, H. (2006): Neural networks as cybernetic systems – Part II. In: Brains, Minds and Media 2, bmm290. http://www.brains-minds-media.org/archive/290 (07.08.2008).

Dawson, C. W. and Wilby, R. L. (2001): Hydrological modelling using artificial neural networks. In: Progress in Physical Geography 25, 80-108.

– (2004): Single network modelling solutions. In: Abrahart, R. J.; Kneale, P. E. and See, L. M. (eds.): Neural Networks for Hydrological Modelling. London, 39–59.

Dawson, C. W.; Harpham, C.; Wilby, R. L. and Chen, Y. (2002): Evaluation of artificial neural network techniques for flow forecasting in the River Yangtze, China. In: Hydrology and Earth System Sciences 6, 619–626.

Dibike, Y. B. and Solomatine, D. P. (2001): River flow forecasting using artificial neural networks. In: Physics and Chemistry of the Earth (B) 26, 1–7.

Domrös, M. and Peng, G. (1988): The Climate of China. Berlin, Heidelberg.

Geith, A. (2006): Künstliche neuronale Netze zur Missbrauchserkennung in Mobilfunknetzen auf Basis von Verbindungsdaten. Diploma Thesis. Vienna. http://michael.hahsler.net/stud/done/geith/geith_dipl.pdf (07.08.2008).

Gemmer, M. (2000): Hochwasserschutz und Landnutzungsänderungen am Yangtze-Mittellauf, VR China: Satellitenbilddokumentierte Entwicklung der Metropole Wuhan und des Jingjiang-Hochwasserrückhaltebeckens als Beispiel für die wachsende Bedeutung und limitierte Umsetzbarkeit einer bestehenden Hochwasserschutzplanung. Unpublished Diploma Thesis. Giessen.

– (2004): Decision support for flood risk management at the Yangtze River by GIS/RS-based flood damage estimation. Aachen.

Han, D.; Kwong, T. and Li, S. (2007): Uncertainties in real-time flood forecasting with neural networks. In: Hydrological Processes 21, 223-228.

Hartmann, H. (2002): Das Drei-Schluchten-Projekt und sein Einfluss auf die Hochwassersituation am Mittellauf des Yangtze. Diploma Thesis. Giessen. http://geb.uni-giessen.de/geb/volltexte/2004/1514/pdf/HartmannHeike-2004-04-28.pdf (07.08.2008).

Hartmann, H.; Becker, S. and King, L. (2008a): Predicting summer rainfall in the Yangtze River basin with neural networks. In: International Journal of Climatology 28, 925–936.

– (2008b): Quasi-periodicities in Chinese precipitation time series. In: Theoretical and Applied Climatology 92, 155–163.

Hsieh, W. W. and Tang, B. (1998): Applying neural network models to prediction and data analysis in meteorology and oceanography. In: Bulletin of the American Meteorological Society 79, 1855–1870.

Hsieh, W. W.; Yuval; Li, J.; Shabbar, A. and Smith, S. (2003): Seasonal prediction with error estimation of Columbia River streamflow in British Columbia. In: Journal of Water Resources Planning and Management 129, 146-149.

Jiang, T. (2000): Analysis of flood hazards in the Yangtze River Valley and strategies for sustainable flood risk management. Aachen.

Jolliffe, I. T. (1986): Principal component analysis. New York.

Kang, M. S.; Kang, M. G.; Park, S. W.; Lee, J. J. and Yoo, K. H. (2006): Application of grey model and artificial neural networks to flood forecasting. In: Journal of the American Water Resources Association 42, 473–486.

King, L.; Gemmer, M. and Wang, R. (2001): Hochwasserschutz und Landnutzung am Yangtze. In: Geographische Rundschau 53, 28–34.

Kistler, R.; Kalnay, E.; Collins, W.; Saha, S.; White, G.; Woollen, J.; Chelliah, M.; Ebisuzaki, W.; Kanamitsu, M.; Kousky, V.; van den Dool, H.; Jenne, R. and Fiorino, M. (2001): The NCEP_NCAR 50-year reanalysis: monthly means CD-ROM and documentation. In: Bulletin of the American Meteorological Society 82, 247–267.

Long, T.; Woo, M. and Thorne, R. (2006): Monthly streamflow simulation for Upper Changjiang basin above the Three Gorges, China. Proceedings of the 2nd GWSP Asia Network Workshop on Hydrological Sciences for Managing Water Resources in the Asian Developing World. June 8–10. Guangzhou.

http://www.chikyu.ac.jp/USE/GWSP/proceedings/second/new technologies in hydrological practices.pdf (07.08.2008).

Minns, A. W. and Hall, M. J. (2004): Rainfall-runoff modelling. In: Abrahart, R. J.; Kneale, P. E. and See, L. M. (eds.): Neural networks for hydrological modelling. London, 157-175.

Nilsson, P.; Uvo, C. B. and Berndtsson, R. (2006): Monthly runoff simulation: Comparing and combining conceptual and neural network models. In: Journal of Hydrology 321, 344–363.

Phien, H. N. and Kha, N. D. A. (2003): Flood forecasting for the upper reach of the Red River Basin, North Vietnam. In: Water SA 29, 267–272.

Principe, J.; Lefebvre, C.; Lynn, G.; Fancourt, C. and Wooten, D. (2005): NeuroSolutions – Documentation. Gainesville.

Senthil Kumar, A. R.; Sudheer, K. P.; Jain, S. K. and Agarwal, P. K. (2005): Rainfall-runoff modelling using artificial neural networks: comparison of network types. In: Hydrological Processes 6, 1277–1291.

STATSOFT INC. (2007): Electronic Statistics Textbook. Tulsa. http://www.statsoft.com/textbook/stathome.html (07.08.2008).

Teschl, R. and Randeu, W. L. (2006): A neural network model for short term river flow prediction. In: Natural Hazards and Earth System Sciences 6, 629–635.

Varoonchotikul, P. (2003): Flood forecasting using artificial neural networks. Lisse.

Wang, Y.; Jiang, T.; Bothe, O. and Fraedrich, K. (2007): Changes in pan evaporation and reference evapotranspiration in the Yangtze River basin. In: Theoretical and Applied Climatology 90, 13–23.

YPIS (2002): Yangtze Project Information System. Unpublished Information System. Giessen.

Zhang, Z.; Fraedrich, K.; Jiang, T. and Zhang, J. (2007): Projection of future precipitation extremes in the Yangtze River Basin for 2001–2050. In: Advances in Climate Change Research 3, 340–344. (in Chinese, English abstract).

Zhao, M. (1999): Analysis of the 1998 Yangtse River flood and consideration of flood control strategy. Proceedings of the '99 International Symposium on Flood Control. November 11–13. Beijing.

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