Contributions to Geophysics and Geodesy Vol. 42/4, 2012 (295–311)

Application of Artificial Neural Networks for estimating index floods

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Abstract: This article presents an application of Artificial Neural Networks (ANNs) and multiple regression models for estimating mean annual maximum discharge (index flood) at ungauged sites. Both approaches were tested for 145 small basins in Slovakia in areas ranging from 20 to 300 km^2. Using the objective clustering method, the catchments were divided into ten homogeneous pooling groups; for each pooling group, mutually independent predictors (catchment characteristics) were selected for both models. The neural network was applied as a simple multilayer perceptron with one hidden layer and with a back propagation learning algorithm. Hyperbolic tangents were used as an activation function in the hidden layer. Estimating index floods by the multiple regression models were based on deriving relationships between the index floods and catchment predictors. The efficiencies of both approaches were tested by the Nash-Sutcliffe and a correlation coefficients. The results showed the comparative applicability of both models with slightly better results for the index floods achieved using the ANNs methodology.

Key words: index flood, catchment predictors, Artificial Neural Networks (ANNs), multiple regression models

1. Introduction

The estimation of design floods or flood peak statistics for the purposes of flood control is obviously difficult at ungauged sites without flood peak data *(Pekárová et al., 2012)*. Such estimates are often provided on the basis of transferring analogous data from sites that are hydrologically similar in terms of their catchment areas, rainfall and soil types *(Dawson et al., 2006)*.

The growing number of gauging stations in small basins with longer

doi: 10.2478/v10126-012-0014-7

records made it possible to test how some of the new concepts of regional homogeneity and regional flood frequency analysis reported in the literature (e.g. *Acreman and Sinclair, 1986; Zrinji and Burn, 1994; Meigh et al., 1997; Hosking and Wallis, 1997* and *FEH, 1999*) perform also in the specific conditions of Slovakia. Summaries of the results of these efforts were published e.g. in *Kohnová and Szolgay (2002), Kohnová et al. (2006), Solín (2008),* or *Pekár et al. (2012).*

The index flood method proposed by *Dalrymple (1960)* was one of the first approaches for estimating regional floods and belongs among the simplest procedures which have been used for a long time in hydrological practice. The key assumption in the index flood method is that the distribution of floods at different sites in a region is the same except for a scale or index flood parameter, which reflects the rainfall and runoff characteristics of each region. This method consists of identifying geographically homogeneous regions and determining a regional standardised flood frequency curve. The index flood may be the mean or median of maximum floods, although any other location parameter of the frequency distribution may also be used *(Hosking and Wallis, 1991).*

In this case, regional quantile estimates at a given site for a given return period T, Q_T can be obtained as

$$Q_T = \mu_i q_T, \qquad (1)$$

where q_T is the quantile estimate from the regional distribution for a given return period, and μ_i is the mean flow at the site.

Artificial Neural Networks (ANNs) represent a mathematical model inspired by the structure and functions of biological neural networks. They consist of an interconnected group of artificial neurons and provide information using a connectionist approach to the computation. Artificial neural networks started, like other components of artificial intelligence, with the advancement of computers. The first mathematical model of artificial neural networks was introduced by *McCulloch and Pitts (1943)*, and in 1957, Rosenblatt developed a perceptron, which is a generalization of McCulloch and Pitts's neuron model of *Volná (2002).* A calibration algorithm for training artificial networks of sufficient sizes and complexities was developed by *Rumelhart and McClelland (1986).* Since that time research of ANNs has expanded, and a number of training algorithms and different network types have evolved. Nowadays, ANNs are used as an alternative modeling tool in many research fields. They can model any relationships between a series of independent and dependent variables without defining the physical relationship between them; therefore, they are often applied for modelling highly nonlinear processes. The physical processes modeled by ANNs are encoded in the network, and the weights are not revealed to the user *(Chatfield, 1993)*.

In hydrology, ANNs have been applied within the field of rainfall-runoff modeling *(Rajurkar et al., 2004; Elshorbagy and Simonovic, 2000; Tokar and Markus, 2000; Fernando and Jayawardena, 1998)*, stream flow forecasting *(Aqil et al., 2007; Moradkhani et al., 2004; Anctil et al., 2004; Zealand et al., 1999)*, and in groundwater modeling *(Garcia and Shigidi, 2006)*. A simple multi-layer architecture of the neural networks was tested for short-term flow forecasting in *Anctil et al. (2004)*. *Ayalew et al. (2007)* applied a simple multi-layer network for a 6-hour forecast of flooding on the Omo River in southern Ethiopia. In *Dawson et al. (2006)*, an estimation of the annual flood flows and flood index (median average maximum flow) using regression models and ANNs was provided for 850 basins across the UK.

Those studies confirm that artificial neural networks can work just as well as other mathematical models and, in some cases, with even better results. Compared to physically – based mathematical models, the advantage of artificial neural networks is the fact that they can simulate processes without the incorporation of physical laws in the mathematical form. On the other hand, neural networks are often susceptible to overtraining, which occurs when a training data set reduces error and increases the errors of the test data set. This happens especially when a large number of layers and neurons in the hidden layers are used *Volná (2002)*.

The aim of this article is to show the possibility of deriving the values of mean annual maximum discharges (index floods) using ANNs at ungauged catchments. Based on selected catchment predictors, 145 small and medium-sized basins in Slovakia were grouped in to 10 homogeneous pooling groups. ANNs were applied in these pooling groups to estimate the values of the index floods from a range of catchment descriptors. The artificial neural network was constructed as a multilayer neural network with forward signal propagation. For a comparison, the values of the index floods were also estimated by multiple regressions between the index floods and catchment predictors. The efficiency of both approaches was tested by the Nash-Sutcliffe and Pearson correlation coefficients.

2. Data

The input data consisted of the flood and catchment characteristics of 145 small and medium-sized basins in Slovakia with catchment areas ranging from 20 to 300 km^2 and an observation period of at least 20 years.

To derive the index flood values which in our case represent the mean annual maximum discharges at individual gauging stations the annual maximum discharges from the whole observation period in all the stations were collected and statistically analyzed. Subsequently, the following set of geographical and climatic catchment characteristics was derived in the GIS environment and tested for the regional analysis:

A – catchment area [km^2],
N – gauge datum [m a.s.l.],
O – the mean aspect [-],
SH – the catchment shape coefficient [-],
SI – the soil infiltration index [-],
P_{100} – maximum annual rainfall total [mm] with a return period of 100 years,
SR – the average slope of the main river [%],
SC – the average catchment slope [%],
HG – the hydrogeological index reflecting the permeability of the subsoil [-],
FA – forested area [%],
T – the average annual air temperature [°C],
R – the average specific runoff for the period 1931-1980 [$l.s^{-1}\ km^{-2}$],
P – the average annual precipitation from the period 1931-1980 [mm],
q_{max} – the value of the index flood [$m^3\ s^{-1}\ km^{-2}$].

The hydrogeological index was calculated using the following equation:

$$HG = 1n + 2s + 3v + 4w, \tag{2}$$

where:
n, s, v, w are the categories of the permeability (transmission) of the rocks in the catchment:

n – is the low permeability,
s – is the medium high permeability,
v – is the high permeability,
w – is the very high permeability.

The HG values vary from 100 for the low to 400 for the high subsoil permeability.

3. Deriving homogeneous pooling groups

In the hydrologic literature, numerous techniques have been proposed to identify homogeneous pooling groups for regional flood frequency analysis. *Hosking and Wallis (1997)* recommends using methods that rely only on physiographic site characteristics. In this study we employed a cluster analysis to pool the catchments into homogeneous groups, where the physiographic attributes of the basins and climatic characteristics act as pooling variables. In accordance with *Hartigan (1975)*, k-means clustering with Euclidean metrics with the same weight assigned to each characteristic was adopted in the clustering process.

Subsequently, at-site flood characteristics were used to independently test the homogeneity of the pooled catchments. The measure proposed by *Hosking and Wallis (1997)*, which is based on L-moment ratios for testing the homogeneity of the pooling groups, was applied here. It compares the site variations in the sample values *L-Cv* (coefficient of variation) with the expected variation for a homogeneous pooling group. The method fits a four-parameter kappa distribution to the regional average *L-Cv* ratios. The estimated kappa distribution is used to generate 500 homogeneous pooling groups with population parameters equal to the regional average sample *L-Cv* ratios. The properties of the simulated homogeneous pooling group are compared to the sample *L-Cv* ratios as

$$H = \frac{(V - \mu_V)}{\sigma_V}, \tag{3}$$

where μ_V is the mean of the simulated V values, and σ_V is the standard deviation of the simulated V values. For the sample and simulated pooling groups, respectively, V is calculated as

$$V = \left\{ \frac{\sum_{i=1}^{N} n_i (t^{(i)} - t^R)^2}{\sum_{i=1}^{N} n_i} \right\}^{1/2}, \tag{4}$$

where N is the number of sites; n_i is the record length at the site I; $t^{(i)}$ is the sample L-Cv at site I; and t^R is the regional average sample L-Cv. Following Hosking and Wallis, the pooling groups were usually classified as acceptably homogeneous if ($H < 1$), possibly heterogeneous ($1 < H < 2$) and heterogeneous ($2 < H$).

Various combinations of the physiographic catchment characteristics were tested to pool the catchments into homogeneous pooling groups. Only combinations with a small degree of correlation (a Pearson's correlation coefficient of less than 0.3) between the selected catchment characteristics were used. Finally, the following combination of site attributes yielded the most acceptable results:
A – catchment area [km^2],
HG – hydrogeological index reflecting the permeability of the subsoil [-],
FA – forested area [%],
P – the long-term average annual precipitation from the period 1931–1980 [mm].

Table 1. Values of the Hosking-Wallis homogeneity measures (H) for the derived pooling groups

Pooling group	**No. of basins**	**H**	**Degree of homogeneity**
1	18	1.64	possibly heterogeneous
2	17	1.67	possibly heterogeneous
3	10	1.25	possibly heterogeneous
4	7	1.26	possibly heterogeneous
5	17	1.75	possibly heterogeneous
6	12	0.15	acceptably homogeneous
7	7	0.39	acceptably homogeneous
8	19	1.86	possibly heterogeneous
9	12	1.41	possibly heterogeneous
10	26	1.75	possibly heterogeneous

This combination of site attributes resulted in 10 pooling groups, all of which were homogeneous according to Hosking's H homogeneity measure. Table 1 presents the values of the homogeneity measures and the number of catchments belonging to each pooling group. The gauging stations in all the catchments and selected pooling groups are illustrated in Fig. 1.

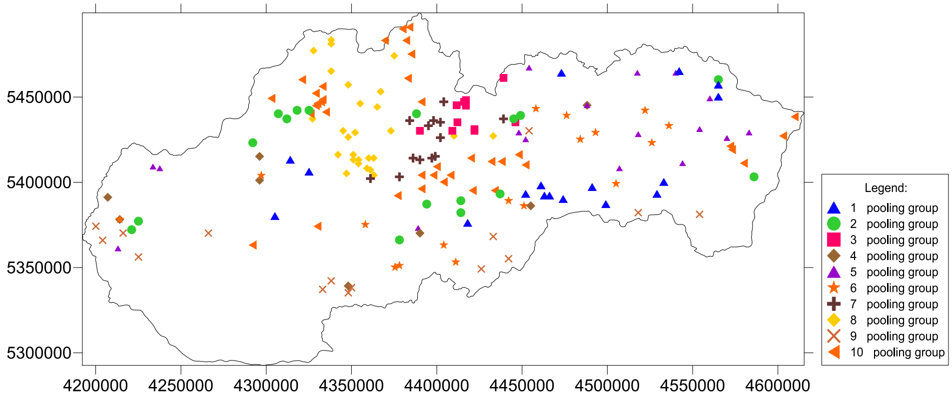


Fig. 1. Location of the analysed catchments and their distribution in 10 pooling groups.

4. Estimation of the index flood in the homogeneous pooling groups

4.1. Selection of mutually independent catchment predictors

After the regionalization of the basins into homogeneous pooling groups, the input data for the ANNs and the multiple regression models were selected. The mean annual maximum specific discharge (q_{max}) was considered as the index flood. The input data (predictors) for each pooling group were chosen from the catchment's characteristics based on their relatively high correlation with the output (index flood) and the small degree of mutual correlation between each other.

Table 2 shows the Pearson correlation matrix for the basin characteristics in the 18 catchments of pooling group 1, in which the selected input data for both models were the soil infiltration index SI, forested area FA and specific runoff R. The predictors selected for all the pooling groups are shown in Table 3.

Table 2. The Pearson correlation matrix for pooling group 1

	N	O	SH	SI	P_{100}	SR	HG	FA	SC	T	R	P	qmax
N	1.00												
O	-0.37	1.00											
SH	0.06	-0.18	1.00										
SI	-0.02	-0.21	0.12	1.00									
P_{100}	0.45	-0.70	-0.06	0.43	1.00								
SR	0.35	0.20	0.25	0.36	0.19	1.00							
HG	-0.33	0.39	-0.37	0.11	-0.24	-0.31	1.00						
FA	-0.20	0.36	0.41	0.35	-0.15	0.53	-0.24	1.00					
SC	0.23	-0.18	0.07	0.64	0.55	0.45	-0.33	0.48	1.00				
T	-0.66	0.19	0.21	-0.43	-0.64	-0.55	0.24	-0.16	-0.75	1.00			
R	0.44	-0.50	0.11	0.07	0.54	0.03	-0.59	-0.14	0.48	-0.50	1.00		
P	0.33	-0.61	0.20	0.34	0.54	0.04	-0.53	0.10	0.67	-0.50	0.82	1.00	
qmax	0.06	-0.15	0.18	-0.60	-0.26	-0.35	-0.36	-0.42	-0.44	0.36	0.41	0.08	1.00

Table 3. Predictors selected for the 10 pooling groups

Predictors	1	2	3	4	5	6	7	8	9	10
SI	X		X		X	X	X			
P_{100}		X	X	X						
SR								X	X	X
HG		X	X		X	X		X		X
FA	X			X		X				X
T			X	X			X	X		
R	X				X				X	

4.2. Estimations of index flood using ANNs

The most commonly used neural network is a type of multilayer perceptron (MLP) network, which represents a forward type of ANN with a teacher (known patterns). Signals are forwarded from the input neurons (terminals) to the output; a network of this type has no feedback between the layers or neurons in the same layer. Inputs are repeatedly submitted to the neural network; they are then transformed by the network weights and the activation function of the neurons in the hidden layers. Any error in the output of the network is calculated as a difference between the output in the last layer and the known patterns. Subsequently, on the basis of that error, the network weights are re-repaired; the most commonly used algorithm is the back-propagation algorithm *(Rumelhart et al., 1986)*. Designing the topology (architecture) of ANNs does not have any clear rules; it is mainly based on a series of calculations and experiments. The number of hidden layers and the number of neurons in each layer determine the ability of a network to approximate nonlinear processes and to select the complexity of the modeled process *(Taufer et al., 2006)*.

The neurosolutions 5.0 simulator was applied to create a neural network. This simulator enables the design of any neural network architecture; in our case it contained one hidden layer with various amounts of hidden neurons. The activation function was a hyperbolic tangent with a range of values (−1, 1). The input data to the network were normed by linear scaling in a range of values (−0.9, 0.9). A simplified diagram of the neural network is shown in Fig. 2.

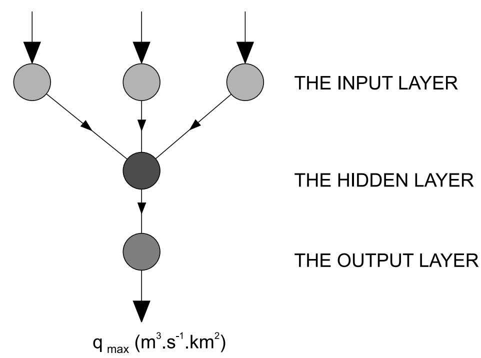


Fig. 2. Simplified scheme of the neural network.

Due to the fact that the different regional types contained relatively little input data for training and testing, the network was highly susceptible to overtraining. In the process of training the ANNs, the backward propagation of error method was applied. After a certain number of iterations, a network error is calculated by the equation:

$$E(t) = \frac{1}{2}\sum_{i}\left(d_i^t - y_i^t\right)^2, \tag{5}$$

where
d_i^t – is the estimated value (sample of ANNs) in iteration t,
y_i^t – is the value calculated by the neural network in iteration t,

i – the number of catchments in a pooling group,
t – number of iterations.
The weights w_1, $w_2 \ldots w_n$ are corrected based on this error.

Each pooling group was trained separately, using training data selected from all the catchments in this group, except for the data from one catchment, which entered into the model as test data (an unknown value for the network). Thus all the catchments for each regional category were gradually tested (the jack-knife method).

The number of neurons in the hidden layer and the number of epochs used in training the ANN are shown in Table 4.

Table 4. The number of neurons and epochs in the hidden layer for each pooling group

Pooling group	Number of neurons	Number of epochs	Number of catchments
1	1	1000	18
2	13	1000	17
3	1	1000	10
4	14	1000	7
5	1	1000	17
6	3	1000	12
7	19	1000	7
8	3	1000	19
9	5	1000	12
10	21	1000	26

For a comparison of the results achieved by the neural network, a multiple regression model was derived for each homogeneous pooling group, which was based on the following equation:

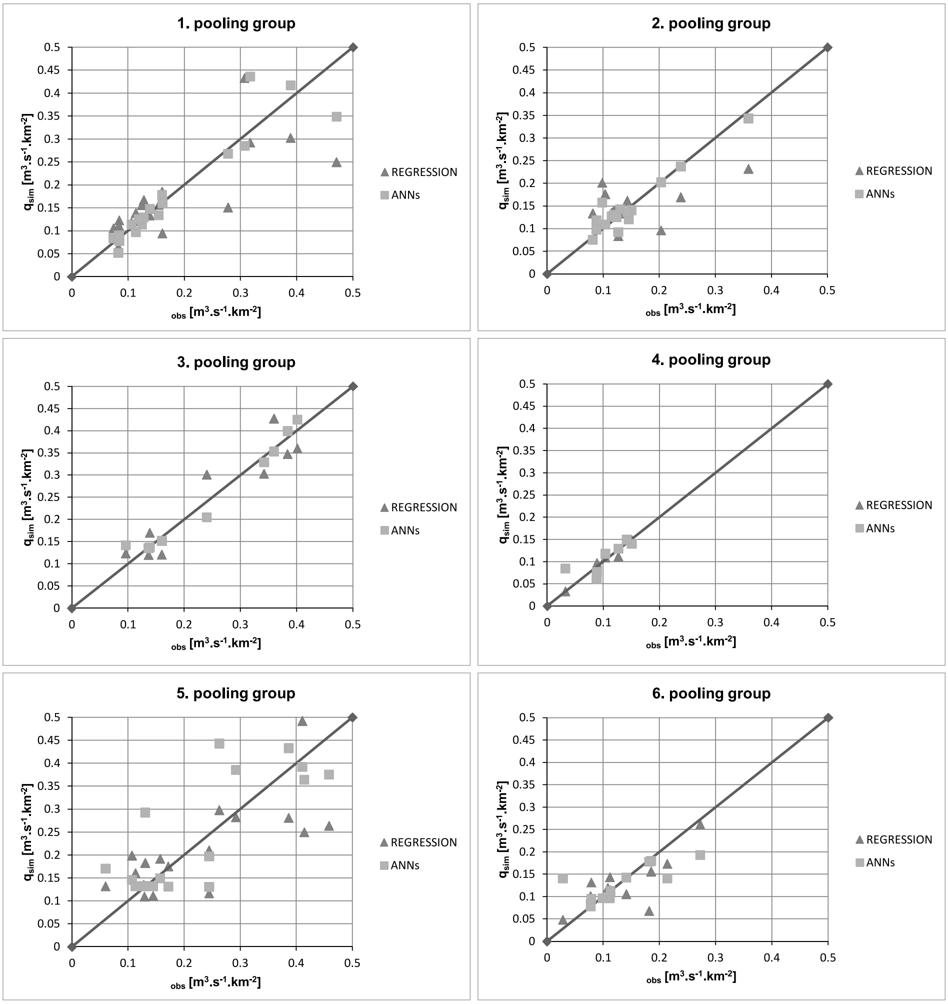
$$q_{\max} = k \cdot A^a \cdot B^b \cdot C^c \ldots, \qquad (6)$$

where
k, a, b, c – are regional parameters,
A, B, C – are predictors (selected climatic and physiographic catchment characteristics).

5. Results and conclusion

The results of the ANN simulations expressed by comparing the simulated and observed values of the index floods for the different pooling groups are shown in Fig. 3.

The performance between the observed and simulated values of the index



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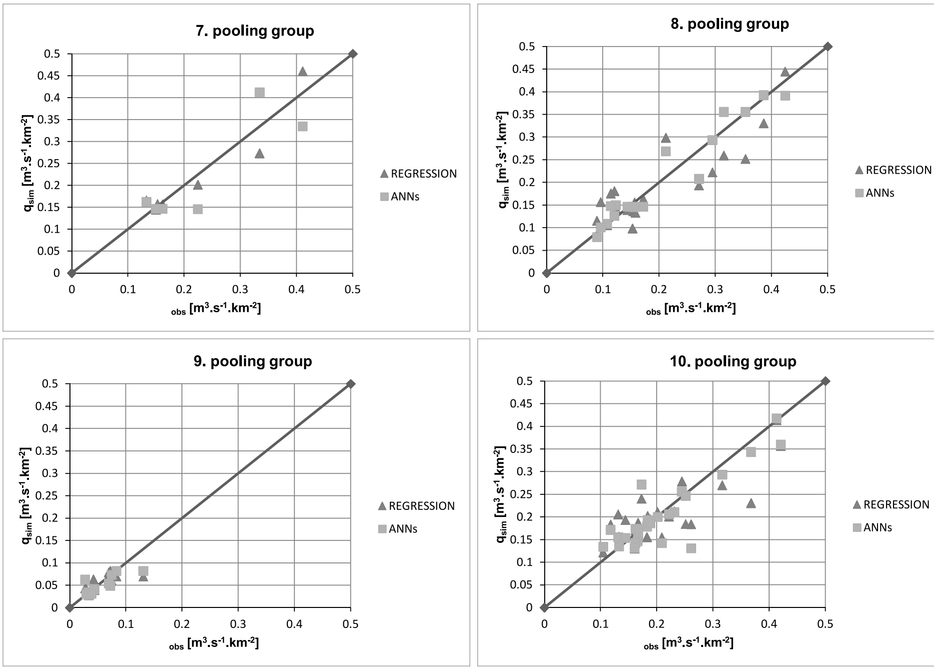

Fig. 3. Comparison of the observed and simulated index floods for the individual pooling groups.

floods was evaluated by the Nash-Sutcliffe (NS) and Pearson correlation coefficients.

The Nash-Sutcliffe coefficient (also called the "coefficient of determination R^2") is a frequently used measure of the differences between the values predicted by a model and the values actually observed. The better value is one closer to unity:

$$NS = 1 - \frac{\sum_{i=1}^{n}(M_i - P)^2}{\sum_{i=1}^{n}(M_i - \bar{M}_i)^2}, \tag{7}$$

where:
n – number of patterns,
M – observed value,
P – simulated value,
$\bar{M}$ – average of the measured values.

The correlation often measured by the correlation coefficient r indicates the strength and direction of a linear relationship between two variables (the model's output and observed values). The correlation is +1 in the case of a perfectly increasing linear relationship and −1 in the case of a decreasing linear relationship, and the values in between indicate the degree of the linear relationship between the simulated values and observations. A correlation coefficient of 0 means there is no linear relationship between the variables:

$$r = \frac{\sum_{i=1}^{n}(M_i - \bar{M})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(M_i - \bar{M})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}}, \tag{8}$$

where
n – number of patterns,
M – observed value,
P – simulated value,
$\bar{M}$ – average of the observed values,
$\bar{P}$ – average of the simulated values.

Comparison of the efficiency of both approaches in estimating index floods is shown in Table 5 and Figs. 4 a, b.

The neural network achieved best results in estimating the index floods for pooling group 8, where the coefficient of r was 0.966 and the NS was

Table 5. Comparison of the r and NS coefficients for the individual pooling groups

	ANNs		**Multiplicative regression**	
Pooling group	**r**	**NS**	**r**	**NS**
1	0.93	0.86	0.76	0.57
2	0.92	0.78	0.81	0.49
3	0.88	0.72	0.97	0.93
4	0.99	0.98	0.97	0.95
5	0.79	0.56	0.73	0.51
6	0.74	0.51	0.77	0.57
7	0.99	0.92	0.95	0.89
8	0.96	0.93	0.86	0.74
9	0.78	0.56	0.72	0.49
10	0.98	0.94	0.82	0.66

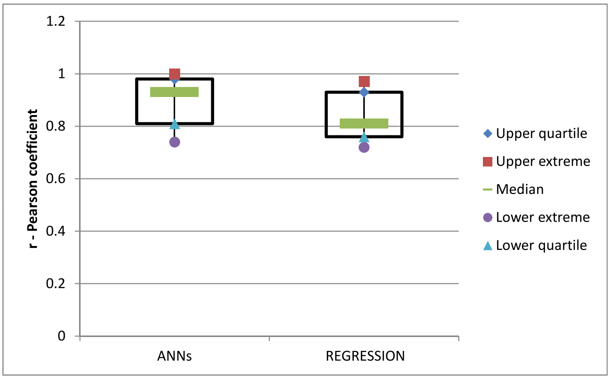

Fig. 4a. Comparison of the Pearson correlation coefficients r for ANNs and multiple regression models.

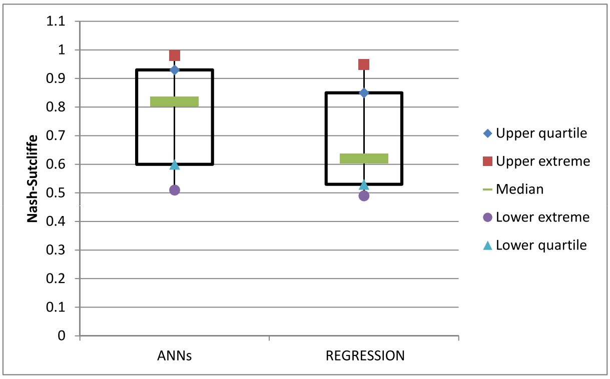

Fig. 4b. Comparison of the NS coefficients for ANNs and multiple regression models.

0.935. The worst results from the ANN models were achieved in pooling group 9, where the value of the coefficient r was only 0.786 and the value of NS was 0.561. The multiple regression models had the best estimates for pooling group 3, where the coefficient r reached a value of 0.968 and an NS of 0.934. From an overall evaluation of the efficiencies of the models in the box-plots in Fig. 4, it is evident that the higher median of the NS and r coefficients, and the fewer differences between their minimal and maximal values were achieved by the neural networks. This confirmed that the results achieved by the neural network were slightly better than the results achieved by the multiplicative regression models. The main requirement for successfully estimating index floods using ANNs is to divide the catchments into homogeneous pooling groups and choose suitable catchment predictors for the network. Therefore, an appropriate architecture and training network was constructed separately for each pooling group. Because there were relatively small data sets in the different pooling groups (from 7 to 26 catchments), the jack-knife method was used for estimating the index flood in the individual catchments. Generally, the results proved that ANNs can reproduce theory index flood with a comparable (or even better) degree of accuracy than those obtained by multiplicative regression models and can be used to estimate the values of index floods for ungauged catchments.

Acknowledgments. This work was supported by the Agency for Research and Development under Contract No. APVV-0496-10 and by the VEGA Agency 1/0908/11. The authors thank the agencies for their research support.

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