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Prediction of maximum annual flood discharges using artificial neural network approaches

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Research paper

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Prediction of maximum annual flood discharges using artificial neural network approaches

The applicability of artificial neural network (ANN) approaches for estimation of maximum annual flows is investigated in the paper. The performance of three neural network models is compared: multi layer perceptron neural networks (MLP_NN), generalized feed forward neural networks (GFF_NN), and principal component analysis with neural networks (PCA_NN). The proposed approaches were applied to 33 stream-gauging stations. It was found that the optimal 3-hidden layered PCA_NN method was more appropriate than the optimal MLP_NN and GFF_NN models for the estimation of maximum annual flows.

Key words:

artificial neural networks, principal component analysis, maximum annual flows

Prethodno priopćenje

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Predviđanje maksimalnih godišnjih poplavnih protoka primjenom umjetnih neuronskih mreža

U radu se istražuje primjenjivost pristupa umjetnih neuronskih mreža (ANN) za određivanje maksimalnih godišnjih protoka. Uspoređuje se učinkovitost triju modela neuronskih mreža: višeslojne perceptronske neuronske mreže (MLP_NN), generalizirane neuronske mreže usmjerene prema naprijed (GFF_NN) i analiza osnovnih komponenata pomoću neuronskih mreža (PCA_NN). Predloženi pristupi primijenjeni su na 33 vodomjerne. Utvrđeno je da je optimalna metoda PCA_NN s tri skrivena sloja prikladnija za određivanje maksimalnih godišnjih protoka od optimalnih modela MLP_NN i GFF_NN.

Ključne riječi:

umjetne neuronske mreže, analiza osnovnih komponenata, maksimalni godišnji protoci

Vorherige Mitteilung

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Vorhersage der maximalen jährlichen Hochwasserflüsse durch Anwendung künstlicher neuronaler Netze

In der Abhandlung wird die Anwendbarkeit des Ansatzes neuronaler Netze (ANN) zur Bestimmung maximaler jährlicher Durchflüsse untersucht. Verglichen wird die Leistung dreier neuronaler Netzmodelle: mehrlagige perceptron-neuronale Netze (MLP_NN), generalisierte vorwärtsgerichtete neuronale Netze (GFF_NN) und Analyse der Hauptkomponenten mithilfe des neuronalen Netzes (PCA_NN). Die vorgeschlagenen Ansätze wurden bei 33 Wassermessstationen angewendet. Es wurde festgestellt, dass die optimale PCA_NN-Methode mit drei verborgenen Schichten zur Bestimmung der maximalen jährlichen Durchflussraten besser geeignet ist, als die optimalen MLP_NN- und GFF_NN-Modelle.

Schlüsselwörter:

künstliche neuronale Netze, Analyse der Hauptkomponenten, maximale jährliche Durchflüsse

1. Introduction

In Turkey, flooding is a highly important natural hazard, second only to earthquakes. Flood damage has been extremely severe over the past 100 years and has caused great human casualties and economic losses. Many floodplains are currently highly populated and industrialized. On the other hand, there is often only a limited presence or total absence of the recorded annual maximum discharge data at the site of interest. Many annual flood series are also too short for accurate estimation of devastating floods. Therefore, the use of regional information to estimate flood discharges at sites with little or no available data has become increasingly important for the flood control and planning of hydraulics structures, especially in Turkey.

A number of techniques for the estimation of flood discharges have been developed over years. These techniques can be divided into three categories: parameter estimation techniques, regression techniques, and artificial intelligence techniques. Major developments in the estimation of flood discharges were made based on the regional frequency analysis according to the idea of probability weighted moments introduced by Greenwood [1] and the theory of L moments proposed by Hosking [2]. L moments, certain linear combinations of probability weighted moments, can be defined as the measures of location, scale and shape of probability distributions, and form the principal for an extensive theory of the description, identification and estimation of the distributions. The approach of L moments in regional frequency analysis has been applied successfully in a number of studies in Southern Africa [3], the UK [4], India [5], Canada [6], China [7], Egypt [8], Iran [9], Malaysia [10], Italy [11, 12], Kenya [13], and Turkey [14-16].

Spatial variations in frequency analysis are closely related to the variations of regional meteorological and physiographic factors. Therefore, regression models are frequently used to make estimates of flow statistics. Different quantile estimation studies based on regression models [17-22] have clearly indicated that regression based methods of flood regionalization are reliable for flood discharge estimation using variables dependent on site characteristics at ungauged sites.

Most hydrological processes are highly nonlinear, variable in time, and spatially distributed. ANN have a flexible mathematical structure that can identify complex nonlinear relationships between inputs and outputs without predefined knowledge of the underlying physical processes involved in the transformation [23]. In recent years, artificial neural networks (ANN) have been successfully used to directly map complicated nonlinear relations. ANN have proven to be an efficient alternative to traditional methods for modelling qualitative and quantitative water resource variables [24-26], and it has numerous applications in hydrology. In the study by Shu and Burn [27], it was used for index flood and flood

quantile estimation. The application to selected catchments in the United Kingdom (UK) shows that the ANN model performs better than multiple linear regression methods. ANN models are also thought to be beneficial and applicable, especially in problems whose procedures are difficult to define using physical equations [23]. Aziz et al. [28] examined the utility of the ANN based regional flood frequency analysis (RFFA) method and compared the performances of the ANN-based RFFA models with regression analysis. They found that the ANN-based RFFA model performed better than other models with regression analysis. Seckin et al. [29] developed ANN, linear and nonlinear models as alternatives to L-moments method for estimation of flood peaks of various return periods. They showed that the estimator productivity of the ANN multi-layer perceptrons model led to a much better performance than others. Anilan et al. [16] investigated feasibility of the L-moments based ANN method in predicting flood discharges using the data set of the Eastern Black Sea Basin (EBSB). The applied ANN model outperformed the regression models, which shows that the ANN is more appropriate for flood discharge estimation at ungauged sites.

This paper compares the applicability of three ANN models for the estimation of flood discharges using the data set of EBSB. The performance of each method is evaluated by the mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE) and relative error (RE) values.

2. Study area and data used

The Black Sea coast receives the greatest amount of rainfall and is the only region in Turkey that receives rainfall throughout the year. The Eastern Black Sea Basin (EBSB) is located on the North Eastern coast of Turkey, as shown in Figure 1. The basin is surrounded by the Eastern Black Sea Mountains in the south and Black Sea in the north. The total basin area is 24,077 km², yielding 14.9 km³ of water with an average 19.5 lt/sn/km² yield, [30]. The EBSB averages nearly 1 100 mm rainfall annually, this value can reach 2 300 mm near the Rize Province [31]. The strata of the region are generally made of impermeable or semi permeable volcanic rocks, which prevent the rainfall from percolation and force the water to flow as runoff [30]. Flood discharge estimation is essential for the region since it has a great potential risk against floods due to its hydrologic and topographic characteristics. This study involves two basic types of data:

- streamflow data (the annual maximum flood peaks)
- basin characteristics data (physiographical, meteorological, and hydrological data).

The stream-gauging stations in Turkey are operated by the General Directorate of State Hydraulic Works (DSI) [32]. A total of 53 stations were initially selected, which then reduced to 38 due to the deficiencies in streamflow data like

Table 1. Catchment independent variables used in some previous studies

Authors	Independent variables adopted
Jingyi i Hall (2004)	A, R, S, E, main stream length, geological feature index, plantation cover index
Shu i Burn (2004)	A, R, soil drainage type
Leclerc et al. (2007)	A, R, gauging station latitude, gauging station longitude, mean air temperature
Palmen i Weeks (2011)	A, R, S, I, D, river length, sediment area, plantation area, evapotranspiration
Malekinezhad et al. (2011)	R, Length of main waterway, compactness coefficient, mean annual temperature
Haddad et al. (2012)	A, R, I, D, mean annual evapotranspiration,
Aziz et al. (2013)	A, R, S, I, evapotranspiration,
Seckin et al. (2013)	A, E, latitude, longitude, return period
This paper (2014)	A, R, S, E, D, return periods

*A - drainage area, R - mean annual rainfall, S - stream slope, E - elevation, I - rainfall intensity, D - stream density

corresponding to each flood discharge were calculated using the log normal distribution, as the best-fit distribution of the region. Seckin et al. [29] state that the relationship between $\ln(Q)$ and the independent variables is more significant compared to Q as the dependent variable. Thus $\ln(Q)$ values were used as a dependent variable in this study.

3. ANN approaches

Artificial neural networks (ANNs) are flexible mathematical structures that are capable of identifying complex non-linear relationships or patterns between input and output data sets, and can estimate output values based on training and learning processes. The main differences between the various types of ANNs are arrangement of neurodes (network architecture) and the many ways to determine the weights (w) and functions for inputs (x) and neurodes (training) [36].

3.1. Multi layer perceptron neural networks (MLP_NN)

Multilayer perceptrons (MLP_NN) have been applied successfully in many different problems since the advent of the error backpropagation learning algorithm (BP). The main advantage of MLP_NN is that they are easy to handle and can approximate any input/output map [37, 38]. MLP_NN consist of one or more hidden layers and their computation nodes are correspondingly called hidden neurons of the hidden units. In general, intervening between the external input and the network output is the function of hidden neurons. The network is able to extract higher order statistics when one or more hidden layers are added to the system. If the size of the input layer is large, this ability of hidden neurons is especially valuable. MLP_NN is trained by leading a particular input to a special target output. The weights are calibrated based on a comparison of the output and the target, until the network output matches the target [39-41].

3.2. Generalized feed forward neural networks (GFF_NN)

Generalized feed forward neural networks (GF_NN) are a generalization of the FF_NN consisting of several hidden layers of generalized neurons, and an output layer of generalized, sigmoidal or linear neurons [42]. Because GF_NN presents a larger number of connections, this type of network can generally be trained more quickly than the non-generalized MLP_NNs [43]. By adapting the weights, the neural network works towards an optimal solution based on a measurement of its performance [44].

3.3. Principal component analysis with neural networks (PCA_NN)

The major analytical object of PCA is to reduce dimensions of the observed information, compiled in a data set, preserving the original data variability [45]. The PCA transforms the original variables into new, uncorrelated variables (axes), called principal components, which are linear combinations of the original variables [46]. A principal component (PC) can be expressed as:

$$Z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + \dots + a_{im}x_{mj} \quad (1)$$

where z is the component score, a is the component loading, x is the measured value of variable, i is the component number, j is the sample number, and m is the total number of variables [47].

3.4. Neural networks training algorithms

Two different ANNs training algorithms, namely Back Propagation and Conjugate Gradient (CG) were used in the present study. This was done with a view to see which algorithm produces better results for the application under

consideration [48]. The algorithms used in the study are briefly introduced below.

3.4.1. Back propagation algorithm

The BP is the learning algorithm that is most widely used in neural networks, while also being one of the most powerful algorithms. The BP was developed by Rumelhart et al. [49]. The objective of the BP algorithm is to find optimal weights to generate an output vector as close as possible to the output vector target values with the selected accuracy. Following the calculated error value between the computed and actual output, the algorithm back propagates to the layers. The weights are subsequently updated depending on their contribution to the error function [48, 50]. A more detailed information about this algorithm can be found in Kisi and Uncuoglu [48], Nacar et al. [51], and in any ANN text books.

3.4.2. Conjugate gradient

This technique differs from the error BP in gradient calculations and subsequent corrections to weights and bias [52, 53]. Here a search direction is computed at each training iteration k and the error function $f(X)$ is minimized along with the use of a line search. The gradient descent does not move down the error gradient as in the foregoing back propagation method but along a direction that is conjugate to the previous step. The change in gradient is thus taken as orthogonal to the previous step with the advantage that the function minimization, carried out in each step, is fully preserved because of the lack of any interference from the subsequent steps. Details about these well-known algorithms can be found in Thirumalaiah and Deo and Kisi [54, 55].

3.5. Training process

The main objective of this section is to develop an ANN model with three different neural network models and two different training algorithms that estimates the flood discharges using the data set of EBSB. When designing an ANN architecture, it is important to choose a proper network size. Although the ANN can have more than one hidden layer, theoretical works have shown that a single hidden layer is enough for an ANN to approximate any complex nonlinear function [56, 57]. However, not only single hidden layer models but also two hidden layer models have been tried in this study. Each layer is fully connected to the next, but no connections exist between neurons in the same layer. The first and third layers contain the input and output data, respectively. The numbers of hidden layer neurons were found using the simple trial-and-error method from three to nine in all applications. The connections between the input layer and the middle or hidden layer contain weights, which are usually determined through training of the system. The hidden layer sums the weighted inputs and uses the transfer function to create an output value. The transfer function is a relationship between the internal activation level of the neuron (called activation function) and the outputs [36]. Two different transfer functions, i.e. tangent hyperbolic and sigmoid functions, are used in hidden and output layers for this study. Pourhaghi et al. [58] used the tangent axon and the sigmoid axon functions for predicting the input flows by ANN. Fayed and Abdelbary [59] also showed that the application of sigmoid axon is more efficient for hydrological forecasting by ANN. In this study, the tangent axon and the sigmoid axon functions and their combinations were investigated in hidden and output layers for identifying their performance. The learning and momentum rates for BP algorithm were taken as 1 and 0.7, respectively. The available data set (909 observations) was

Table 2. Input and output data used in the analysis

Data set	Statistic	Return period, T [yeat]	Drainage area, A [km ²]	Stream density, SD [km/km ²]	Stream slope, S [m/km]	Elevation, E [m]	Mean annual rainfall, R [mm]	Ln Q (discharge) [m ³ /s]
Training	Min	1.013	83.3	192.6	0.022	17	208.556	2.272
	Mean	5.829	637.102	267.675	0.051	467.673	1166.3	4.303
	Max	501.971	3132.8	446.3	0.084	1150	3332.2	6.594
Testing	Min	1.022	258.6	167.2	0.029	90	414.6	2.912
	Mean	4.619	441.364	241.096	0.043	345.925	774.88	4.234
	Max	63.099	576.8	284	0.058	530	1343.8	5.198
Validation	Min	1.007	162.7	237.7	0.031	78	434.339	3.281
	Mean	5.134	544.779	266.178	0.049	252.646	1139.9	4.571
	Max	83.394	834.9	328.5	0.064	400	2443.488	6.223

divided into three subsets: training (668), validation (108), and test (133). All the variables were selected randomly independently of stations, in total, about 73 % of the data is used for training, 12% for validation, and 15% for test. The minimum, average, and maximum values of the data set are presented in Table 2.

Neural networks generally show improved performance with normalized data. The use of original data as input to neural network may cause a convergence problem [16]. All the data sets were therefore, transformed into values between 0.1 and 0.9 as:

$$\text{Normalized value} = \left[\frac{\text{Raw value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}} \right] \times (0.9 - 0.1) + 0.1 \quad (2)$$

The model behaviour, development and validation steps, were evaluated by calculating statistical parameters RMSE, RE, MAE and MSE, as shown in equations (3) to (6) respectively:

$$\text{RMSE} = \left[\frac{1}{N} \sum_{i=1}^N (\text{Ln}(Q)_{\text{observed}} - \text{Ln}(Q)_{\text{predicted}})^2 \right]^{1/2} \quad (3)$$

$$\text{RE} = \frac{\sum_{i=1}^n \left(\frac{\text{Ln}(Q)_{\text{observed}} - \text{Ln}(Q)_{\text{predicted}}}{\text{Ln}(Q)_{\text{observed}}} \right)}{N} \times 100 \quad (4)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N \left| \text{Ln}(Q)_{\text{observed}} - \text{Ln}(Q)_{\text{predicted}} \right| \quad (5)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (\text{Ln}(Q)_{\text{observed}} - \text{Ln}(Q)_{\text{predicted}})^2 \quad (6)$$

4. Results and discussion

Three neural network methods were examined using the annual peak flows of 33 SGS in order to predict flood

discharges for ungauged catchments. MLP_NN, GFF_NN and PCA_NN methods were adapted to the data of six independent variables and LnQ. As explained in the training process, the data sets were divided into training, validation, and test data sets for all ANN models applied. As shown in Table 3, hidden layers with the number of different processing elements were applied for each of the three types of ANN method with sigmoid axon and tangent hyperbolic axon transfer functions. BP and CG learning algorithms were examined by determining the MSE, RMSE, MAE, and RE values for both validation and test data.

Each of the three methods for different processing elements (PE) led to significant changes in error values of training algorithms. Models with CG algorithm for each method had usually lower error values than models with BP algorithm, as shown in tables 3 and 4. The lowest RMSE value for the validation data set amounted to 0.21, as determined according to the PCA_NN method and CG algorithm using the three hidden layer model. In addition, the lowest RMSE for the test data set amounted to 0.30, again as determined with the PCA_NN method and CG algorithm.

The type of transfer function also has a great effect on the performance of the ANN model. The performed analysis results show that the sigmoid axon transfer function performed better than tangent axon. Calculated errors for the validation data set of the models set up with the sigmoid axon transfer function provided lower values than the values for the tangent hyperbolic axon transfer function in each of the three methods. The error values of the models set up with the sigmoid axon transfer function for the test data set were again lower than the models with the tangent hyperbolic axon transfer function in GFF_NN and PCA_NN methods as shown in Table 4.

Table 3. Error values of MLP_NN, GFF_NN and PCA_NN for different processing elements, transfer functions and learning algorithms for validation data set

Model	Error	3PE				6PE				9PE			
		THYP		SIG		THYP		SIG		THYP		SIG	
		BP	CG	BP	CG	BP	CG	BP	CG	BP	CG	BP	CG
MLP_NN	RMSE	0.29	0.28	0.39	0.26	0.34	0.42	0.39	0.31	0.39	0.30	0.39	0.30
GFF_NN		0.36	0.29	0.42	0.30	0.49	0.35	0.41	0.31	0.38	0.36	0.41	0.31
PCA_NN		0.28	0.28	0.39	0.21	0.29	0.34	0.44	0.30	0.39	0.36	0.39	0.30
MLP_NN	MSE	0.08	0.08	0.15	0.07	0.11	0.18	0.15	0.09	0.15	0.09	0.16	0.09
GFF_NN		0.13	0.08	0.17	0.09	0.24	0.12	0.17	0.09	0.15	0.13	0.17	0.10
PCA_NN		0.08	0.08	0.15	0.04	0.09	0.12	0.19	0.09	0.16	0.13	0.16	0.09
MLP_NN	MAE	0.23	0.21	0.30	0.21	0.28	0.33	0.30	0.24	0.31	0.21	0.30	0.24
GFF_NN		0.30	0.23	0.32	0.21	0.39	0.28	0.31	0.25	0.30	0.27	0.31	0.25
PCA_NN		0.22	0.23	0.30	0.17	0.23	0.28	0.34	0.24	0.32	0.29	0.30	0.22
MLP_NN	RE	5.55	5.06	7.24	5.09	6.72	8.17	7.22	5.91	7.38	5.15	7.26	5.73
GFF_NN		7.16	5.66	7.56	5.17	9.85	6.67	7.55	6.08	7.08	6.72	7.56	6.00
PCA_NN		5.31	5.45	7.17	4.05	5.65	6.75	8.25	5.74	7.54	7.00	7.27	5.54

Table 4. Error values of MLP_NN, GFF_NN and PCA_NN for different processing elements, transfer functions and learning algorithms for testing data set

Model	Error	3PE				6PE				9PE			
		THYP		SIG		THYP		SIG		THYP		SIG	
		BP	CG	BP	CG	BP	CG	BP	CG	BP	CG	BP	CG
MLP_NN	RMSE	0.59	0.35	0.51	0.47	0.57	0.47	0.50	0.49	0.47	0.39	0.50	0.46
GFF_NN		0.52	0.64	0.52	0.46	0.55	0.46	0.46	0.45	0.69	0.41	0.52	0.44
PCA_NN		0.74	0.59	0.50	0.30	0.61	0.57	1.43	0.56	0.52	0.47	0.52	0.48
MLP_NN	MSE	0.35	0.12	0.26	0.22	0.32	0.22	0.25	0.24	0.22	0.15	0.25	0.22
GFF_NN		0.27	0.41	0.27	0.21	0.31	0.21	0.21	0.20	0.48	0.17	0.27	0.19
PCA_NN		0.55	0.34	0.25	0.09	0.37	0.32	2.04	0.31	0.27	0.22	0.28	0.23
MLP_NN	MAE	0.48	0.30	0.38	0.38	0.46	0.35	0.38	0.36	0.36	0.32	0.38	0.36
GFF_NN		0.39	0.52	0.39	0.35	0.44	0.35	0.35	0.35	0.56	0.33	0.39	0.33
PCA_NN		0.63	0.46	0.38	0.25	0.52	0.44	1.35	0.41	0.39	0.36	0.39	0.36
MLP_NN	RE	10.85	6.61	8.38	8.20	10.26	7.68	8.34	8.12	7.92	6.91	8.29	7.98
GFF_NN		8.58	11.70	8.37	7.95	9.52	7.70	7.70	7.79	11.70	7.22	8.35	7.36
PCA_NN		14.17	10.25	8.32	5.46	11.31	9.87	28.73	8.84	8.50	7.89	8.37	8.29

The influence of varying the number of hidden layers was examined to achieve the best performance of the utilized ANN models. Models with 1 and 2 hidden layers were tested. The analysis results shown in Tables 3 and

4 reveal that the one hidden layer ANN model has the best performance. When the number of hidden neurons increased, the performance of the network model decreased.

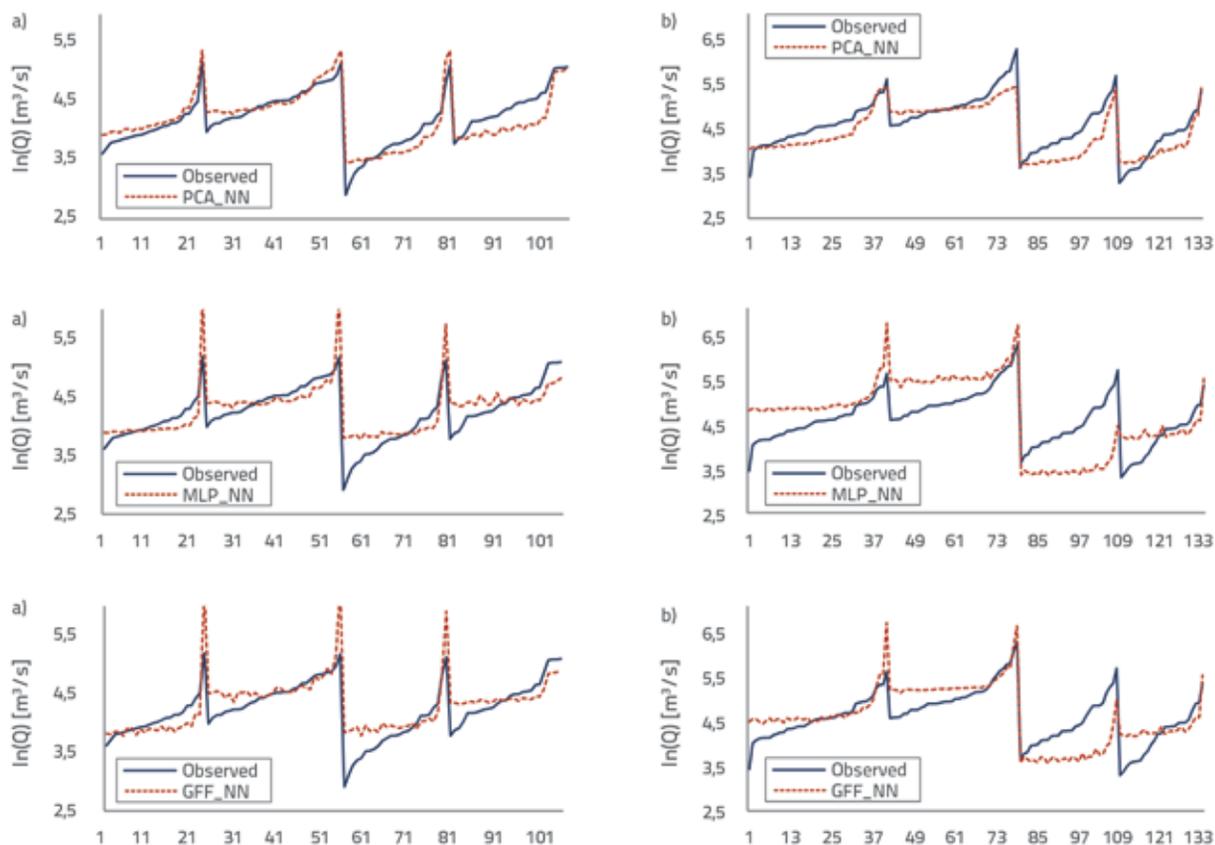


Figure 3. Observed and calculated flood discharges by PCA_NN, MLP_NN, and GFF_NN models for: a) validation; b) test

The best model was obtained using conjugate gradient learning algorithm and sigmoid axon transfer function with the 1 hidden neuron layer, learning rate 1 and momentum constant 0.7 PCA_NN model (providing lowest MSE: 0.04, RMSE: 0.21, MAE: 0.17, RE: 4.05 for validation data set, lowest MSE: 0.09, RMSE: 0.30, MAE: 0.25, RE: 5.46 for test data set). Figure 3 shows the test and validation data set analysis results using the MLP_NN, GFF_NN and PCA_NN models. Figure 4 illustrates scatter plots of the observed and calculated flood discharges by MLP_NN, GFF_NN and PCA_NN models for both validation and test data sets. It is clear that the optimum model exhibits the minimum error values, as explained above. Flood discharges for different return periods can be calculated with this optimum PCA_NN model for EBSB. RMSE values of the PCA_NN models having different number of principal components (PC) are presented in tables 5 and 6, respectively. The accuracy of the model did not improve by an increased number of hidden layers. Error values of the models for the test and validation data sets decreased with an increase in PC number, as shown in tables 5 and 6. The lowest error value was obtained from the model in which 6 PC used.

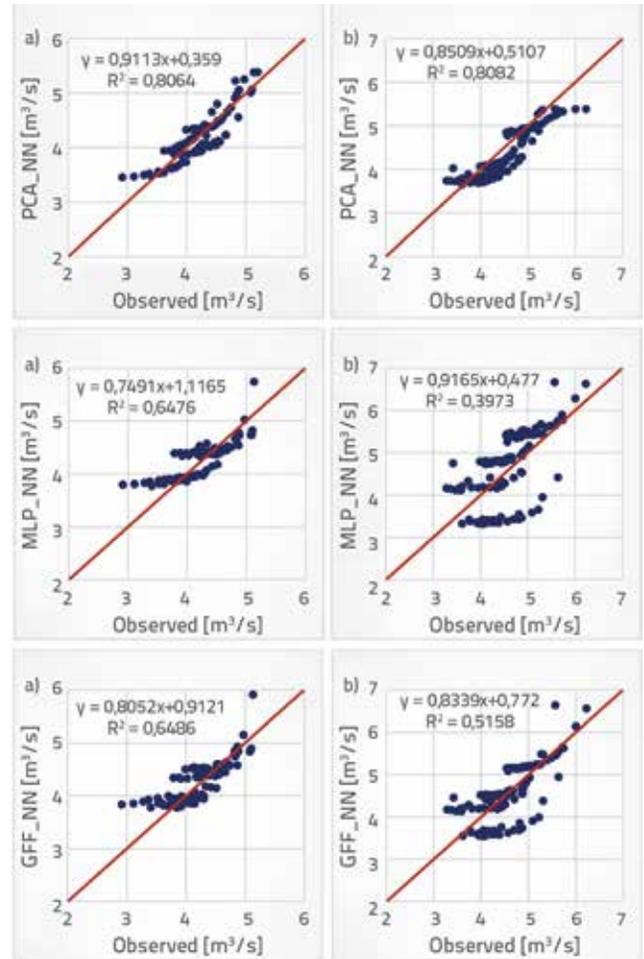


Figure 4. Comparison of observed and computed results by PCA_NN, MLP_NN, and GFF_NN models for: a) validation; b) test

Table 5. RMSE values of PCA_NN with different PC for validation data set

Basic component	3PE				6PE				9PE			
	Tanj. akson.		Sigm. akson.		Tanj. akson.		Sigm. akson.		Tanj. akson.		Sigm. akson.	
	BP	CG										
2 PC	0.45	0.46	0.46	0.46	0.44	0.40	0.46	0.45	0.44	0.44	0.45	0.45
3 PC	0.44	0.45	0.46	0.46	0.47	0.45	0.45	0.45	0.44	0.42	0.45	0.45
4 PC	0.42	0.40	0.44	0.37	0.41	0.34	0.44	0.37	0.42	0.42	0.43	0.38
5 PC	0.36	0.36	0.45	0.39	0.39	0.39	0.43	0.39	0.39	0.38	0.43	0.40
6 PC	0.28	0.28	0.39	0.21	0.29	0.34	0.44	0.30	0.39	0.36	0.39	0.30

Table 6. RMSE values of PCA_NN with different PC for test data set

Basic component	3PE				6PE				9PE			
	Tanj. akson.		Sigm. akson.		Tanj. akson.		Sigm. akson.		Tanj. akson.		Sigm. akson.	
	BP	CG										
2 PC	0.64	0.62	0.64	0.65	0.61	0.56	0.65	0.67	0.60	0.60	0.64	0.64
3 PC	0.54	0.62	0.65	0.66	0.57	0.62	0.64	0.62	0.57	0.52	0.65	0.63
4 PC	0.51	0.61	0.54	0.60	0.58	0.61	0.53	0.64	0.56	0.53	0.53	0.56
5 PC	0.65	0.73	0.57	0.54	0.52	0.71	0.54	0.54	0.57	0.63	0.53	0.55
6 PC	0.74	0.59	0.50	0.30	0.61	0.57	1.43	0.56	0.52	0.47	0.52	0.48

5. Conclusions

The estimation of flood discharges is an important issue in hydrology and water resources engineering. The use of regional information to estimate flood discharges at sites with little or no observed data has become increasingly important for the flood control and planning of hydraulic structures, especially in Turkey.

A number of independent variables related to catchment meteorological and hydrologic characteristics were tested and six of them were found to be the most appropriate. These were the drainage area, main stream slope, elevation, stream density, mean annual rainfall, and return periods. Models were developed with these parameters by using three different ANN approaches. MLP_NN, GFF_NN and PCA_NN models were applied to previously recorded annual maximum flow data of the EBSB in Turkey. Out of the three methods, the best results were obtained from PCA_NN. Additionally, the error values in the models of CG algorithm were lower when compared to BP algorithm. Of the two transfer functions used in the models, the sigmoid axon transfer function had influence on the falling of the error values. The best results for the both validation and test data sets were obtained from the 3-hidden layered PCA_NN

method trained with CG algorithm using sigmoid axon transfer function. The lowest error value was derived from the model in which 6 basic components were used. The results showed the feasibility and applicability of these models.

It can be concluded from the study conducted in this paper that the best model for predicting flood discharge includes the following parameters:

- Sigmoid axon transfer function
- One hidden layer with 3 PEs
- Epoch value of 10 000
- Momentum and learning rate values of 0.7 and 1, respectively.

The optimum model can be applied for flood quantile estimation in EBSB and the results can be further developed for different hydrologically and physically similar basins in Turkey. This study will help the authorities to use valuable knowledge about flood peak discharges of the basin for any return periods when hydraulic structures and settlements projects are at the design stage. Thus, the results of this study may help decrease the risk of failure for water structures and reduce severe environmental consequences by flooding in the basin. The findings from this research can be used in the development of regional flood estimation techniques for other basins.

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