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Article

Estimation of Missing Streamflow Data Using Anfis Models and Determination of the Number of Datasets for Anfis: The Case of Yeşilırmak River

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Abstract: Good data analysis is required for the optimal design of water resources projects. However, data are not regularly collected due to material or technical reasons, which results in incomplete-data problems. Available data and data length are of great importance to solve those problems. Various studies have been conducted on missing data treatment. This study used data from the flow observation stations on Yeşilırmak River in Turkey. In the first part of the study, models were generated and compared in order to complete missing data using ANFIS, multiple regression and Normal Ratio Method. In the second part of the study, the minimum number of data required for ANFIS models was determined using the optimum ANFIS model. Of all methods compared in this study, ANFIS models yielded the most accurate results. A 10-year training set was also found to be sufficient as a data set.

Keywords: anfis, missing data, multiple regression, normal ratio method, Yeşilırmak

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1. Introduction

Both the growing population and the rapidly developing industrialization lead to an increased demand for water. The limited availability of resources results in a number of problems in meeting the demand. Exploitation of unused water resources or using existing water resources in an optimum way can be a solution to these problems. Optimal utilization of available water resources, in particular, requires a good analysis of data. Due to the small number of stations in project areas or insufficient data length, some studies have been undertaken to generate new data using existing measurement stations [1]. These hydrological studies have mainly focused on precipitation [2], evaporation [3] and river flows [4].

Studies on missing data treatment generally address data correlation [5,6], back-propagation (BP) neural network using Artificial Intelligence [7], ANFIS models [8,9] and models using artificial neural networks (ANN) [10,11]. In addition, Fuzzy studies [12], in which modeling is based on pure expert knowledge, are also important. Some studies on missing data treatment using ANFIS are the completion of missing flow data of the Middle Euphrates basin [13], completion of missing precipitation data in Serbia [14] and Malaysia [15], and completion of missing flow data and modelling of sediment transport of Terengganu River, Malaysia [16] and Gediz River, Turkey [17].

This study investigated the monthly data of the stations of Yeşilirmak River in the North of Turkey. In the first part of the study, multiple regression tests based on interstation correlations were performed. In the second part of the study, an optimum data completion model was selected using ANFIS. In the last part of the study, the number of data required for a correct prediction was searched and the minimum number of data required for reliable estimates was discussed.

2. Materials and Methods

The first part of this section of the study will present information and statistics on Yeşilırmak River and its stations. The second part will provide information on the classical method, multiple regression method and ANFIS used in the study.

2.1. Yeşilırmak River and Stations

The Yeşilırmak basin, one of the 25 basins in Turkey, is located between latitudes 39° 30' and 41° 21' and longitudes 34° 40' and 39° 48' (Figure 1). The basin is named after Yeşılırmak River. The main river channel of the basin is 519 km in length. The main tributaries of Yeşilırmak River are Kelkit, Çekerek, Çorum, Çat and Tersakan streams. Estimated to be about 3,8 million ha, Yeşilırmak basin is the third largest basin in Turkey [18,19].

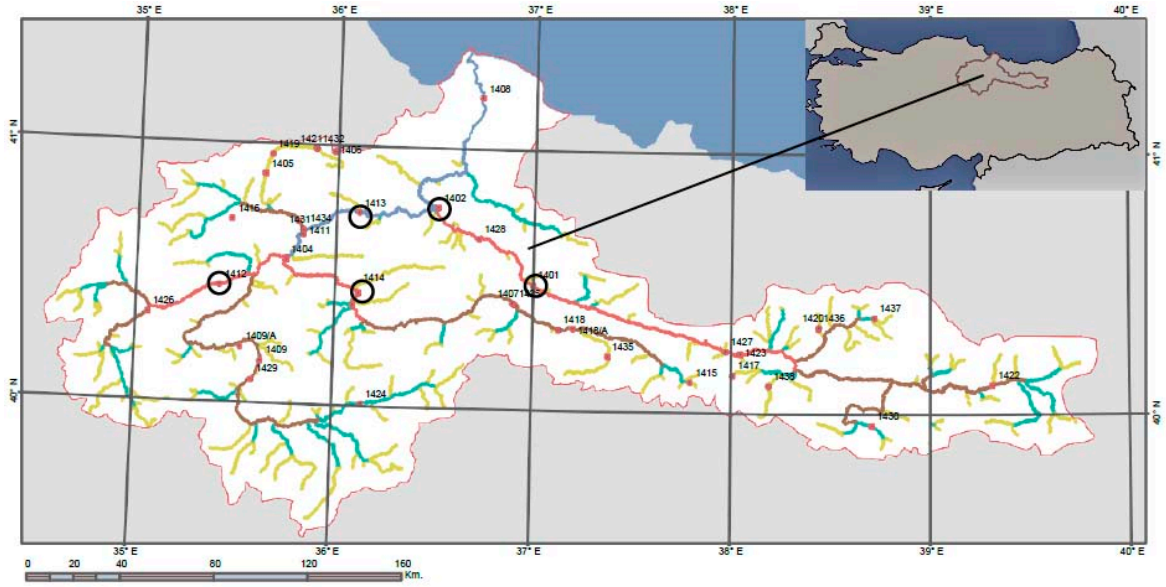


Figure 1. Site location map of Yeşilırmak Basin

Stations No 1401, 1402, 1412, 1413 and 1414 of Yeşilırmak River were used in the study. Table 1 shows the statistics of the stations. Table 2 summarizes the correlation between the stations.

Table 1. Statistical analysis of data from stations

	1401	***1402***	***1412***	***1413***	***1414***
Y-coordinate	40°28′42′′	40°46′18′′	40°27′06′′	40°44′40′′	40°26′03′′
X-coordinate	36°59′56′′	36°30′45′′	35°25′03′′	36°06′43′′	36°07′05′′
Precipitation Area (km²)	10048.8	33904.0	3668.8	21667.2	5409.2
Altitude	375	190	530	301	510
Mean	71.96	150.01	7.35	63.88	25.68
Standard Error	3.07	5.17	0.37	2.34	0.84
Median	35.45	102.50	4.21	45.30	19.65
Standard Deviation	83.65	136.11	8.65	54.95	19.71

Kurtosis	4.27	2.81	6.10	3.41	4.79
Skewness	2.06	1.66	2.24	1.70	1.81
Max	5.23	13.50	0.02	2.47	2.46
Min	548.00	791.00	59.10	350.00	139.00
Number of Data	744	692	536	552	546
Confidence Interval (95,0%)	6.02	10.16	0.73	4.59	1.66

Table 2. Correlation between data from stations

Stations	*1401*	*1402*	*1412*	*1413*	*1414*
1401	1				
1402	0.909	1			
1412	0.516	0.784	1		
1413	0.702	0.926	0.885	1	
1414	0.539	0.565	0.432	0.518	1

2.2. Missing Data Treatment Using Normal Ratio Method

In this method, each input data is divided by its annual average value, and these values are multiplied by the average of the station (average of data) whose missing data are to be completed. All input values obtained in the last stage of the calculation are summed, and divided by the number of inputs so that the missing data are completed [16].

$$Q_e = (Q_1 * \frac{Q_{e(ort)}}{Q_{1(ort)}} + Q_2 * \frac{Q_{e(ort)}}{Q_{2(ort)}} + \cdots + Q_n * \frac{Q_{e(ort)}}{Q_{n(ort)}})/n \quad (1)$$

where Q is the flow rate and n is the number of input stations.

2.3. Multiple Regression Analysis

Multiple regression analysis is a statistical method for determining the mathematical dimension of the relationship between variables affecting each other. The value to be estimated using the equation formulated based on multiple regression analysis is written in the form of a function of values affecting it [21].

$$Y = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + U \quad (2)$$

where Y is the dependent (estimated) variable, X is the independent (explanatory) variable, β is the regression coefficient, k is the number of input parameters and U is the error term.

Multiple linear regression analysis can be used when data are normally distributed, the relationship between independent variables and dependent variable is linear, and error variance for each independent variable is constant [22].

2.4. ANFIS (Artificial Neural Network Fuzzy Inference Systems)

Developed by Jang in [22], ANFIS is a modeling method that combines Fuzzy Logic and YSA models. Different from Fuzzy Logic, ANFIS is based on the use of data for the automatic acquisition of rules. ANFIS structure uses artificial neural networks' learning ability and fuzzy logic inference, and therefore, it is more successful than when artificial neural networks model or fuzzy logic is used alone. When input and output values are known, ANFIS determines all possible rules or allows them to be generated using input and output values (Figure 2). ANFIS structure consists of five layers: fuzzification layer, rule layer, normalization layer, defuzzification layer and summation layer (Figure 3). The first and fourth layers are adaptable [23,24].

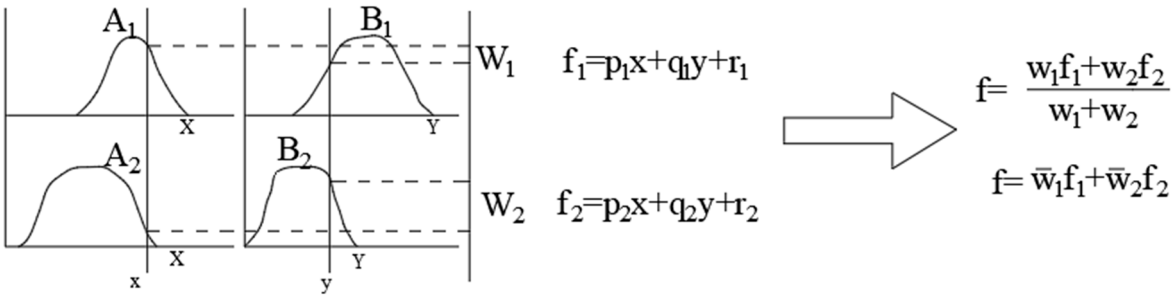


Figure 2. Fuzzy inference system

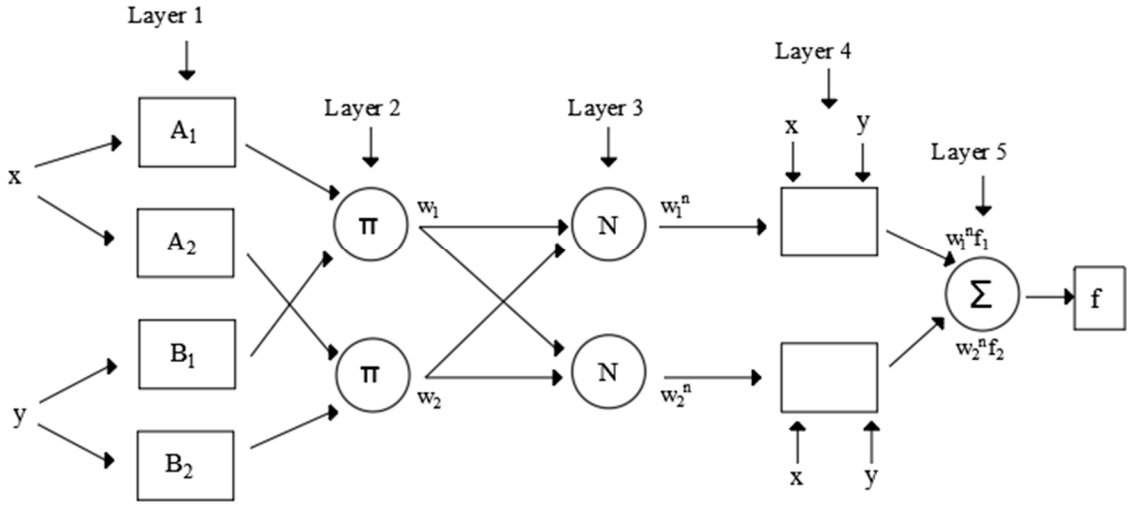


Figure 3. ANFIS architecture

3. Results

Models were developed using Yeşilırmak River data for the estimation of missing data of stations 1402 and 1413. Two-input-one-output models and four-input-one-output models were developed to complete the missing data of station 1402. The two-input-one-output models were used as the output of station 1402. Stations 1413 and 1401 connected to station 1402 on the left- and right-hand sides, respectively, were used to estimate station 1402. In addition to these stations, stations 1412 and 1414 connected to station 1413 on the left- and right-hand sides, respectively, were used to estimate station 1413 in the four-input-one-output models. A two-input-one-output model was developed, and stations 1414 and 1412 were used for the estimation of missing data of station 1413. In the models developed for stations 1402 and 1413, classical and multiple regression models were constructed and compared as well as the ANFIS method. In the last part of the study, the minimum number of data required to reach the correct result using ANFIS models was obtained.

3.1. First Data Set Models

The aim of these models was to complete the missing data of station 1402. For this, the data of stations 1413 and 1401 were used. Of 540 data, the first 400 were used for training and the remaining for testing. In addition to ANFIS models generated by changing the number of sets of input parameters, classical method and the multiple regression model were used to compare the results (Table 3).

The equation of the classical method is:

$$X_{1402} = (2{,}072 * X_{1401} + 2{,}215 * X_{1413})/2 \quad (1)$$

The equation of the multiple regression model is:

$$X_{1402} = 0{,}896 * X_{1401} + 1{,}178 * X_{1413} + 5{,}37 \quad (2)$$

Table 3. Training and testing data results of models developed for the first data set

		Training Data		Testing Data	
Models		R^2	Mean Squared Error %	R^2	Mean Squared Error %
ANFIS Models	3-3	0.976	11.73	0.977	17.36
	4-4	0.977	11.66	0.978	17.38
	5-5	**0.983**	**10.99**	**0.979**	17.55

	6-6	0.980	11.13	0.978	**16.60**
	7-7	0.979	11.12	0.961	17.00
	8-8	**0.983**	11.09	0.959	17.12
Normal Ratio Method		0,970	11.79	0.955	18.85
Multiple Regression		0,972	13.54	0.960	18.62

The results of this part of the study show that ANFIS models are not superior to the classical and multiple regression models but that all ANFIS models yield better results than the other two methods. The models in which each input has 5 subsets are the optimum models. The speed of the training phase of the model is also noteworthy. The comparison of the values obtained from the optimum ANFIS model with the observed values shows that the errors of both the minimum and maximum flow values are very few (Figure 4).

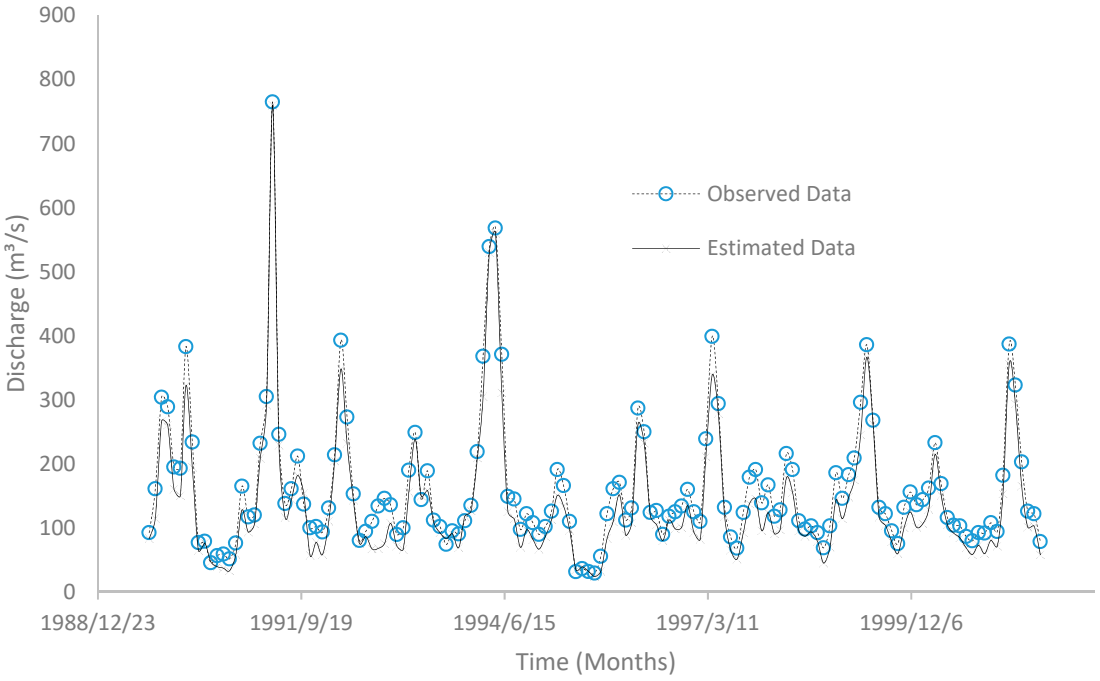


Figure 4. Comparison of observed data and estimated data of Anfis (5-5) model test data for the first data set

3.2. Second Data Set Models

These models also aimed to complete the missing data of station 1402. To achieve this, the data of stations 1412 and 1414 as well as those of 1413 and 1401 were used. Of 504 data, the first 405 were used for training and the remaining for testing. In addition to ANFIS models generated by changing the number of sets of input parameters, classical method and multiple regression model were used to compare the results (Table 4).

The equation of the classical method is:

$$X_{1402} = (2{,}107 * X_{1401} + 19{,}53 * X_{1412} + 2{,}26 * X_{1413} + 5{,}44 * X_{1414})/4 \quad (3)$$

The equation of the multiple regression model is:

$$X_{1402} = 0{,}921 * X_{1401} + 1{,}036 * X_{1412} + 1{,}090 * X_{1413} - 0{,}251 * X_{1414} + 11{,}071 \quad (4)$$

Table 4. Training and testing data results of models developed for the second data set

		Training Data		Testing Data	
Models		R^2	Mean Squared Error %	R^2	Mean Squared Error %
ANFIS Models	3-3-3-3	0.933	28.96	0.916	26.92
	4-4-4-4	0.986	11.27	0.919	16.94
	5-5-5-5	**0.991**	10.30	0.918	18.14
	6-6-6-6	**0.991**	**9.85**	0.919	19.09
Normal Ratio Method		0.873	33.79	0.863	28.61
Multiple Regressions		0.976	18.26	**0.975**	**16.73**

The results show that ANFIS models provide more accurate results than the classical model and worse results than multiple regression models. The models with 4 inputs are quite slow, especially when the number of subsets of inputs is greater than 5. The models with an increasing number of inputs are much slower than multiple regression models. The comparison of the values of the optimum ANFIS model with the observed values shows that although the largest error is at the minimum flow values, this error is quite small at the maximum flow values (Figure 5).

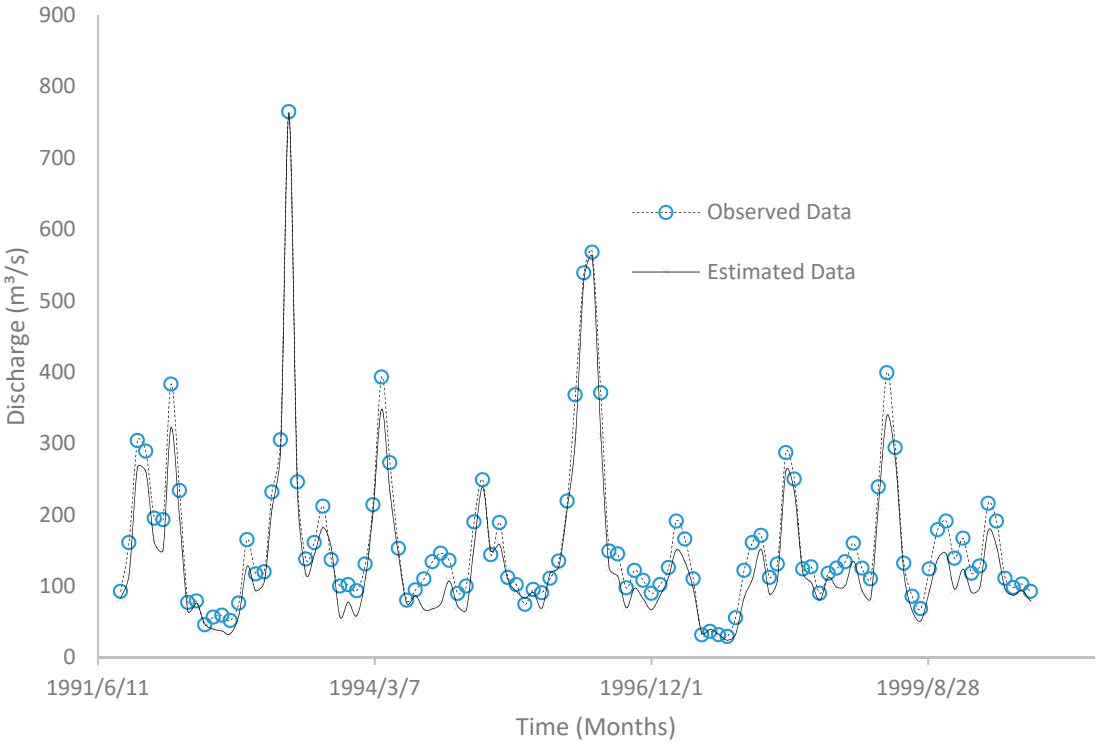


Figure 5. Comparison of observed data and estimated data of Anfis (5-5) model test data for the second data set

3.3. Third Data Set Models

The aim of these models was to complete the missing data of station 1413. For this, the data of stations 1412 and 1414 were used. Of 504 data, the first 405 were used for training and the remaining for testing. The results were compared using the classical method and multiple regression model as well as ANFIS models generated by changing the number of sets of input parameters (Table 5).

The equation of the classical method is:

$$X_{1413} = (2{,}407 * X_{1414} + 8{,}641 * X_{1412})/2 \quad (5)$$

The equation of the multiple regression model is:

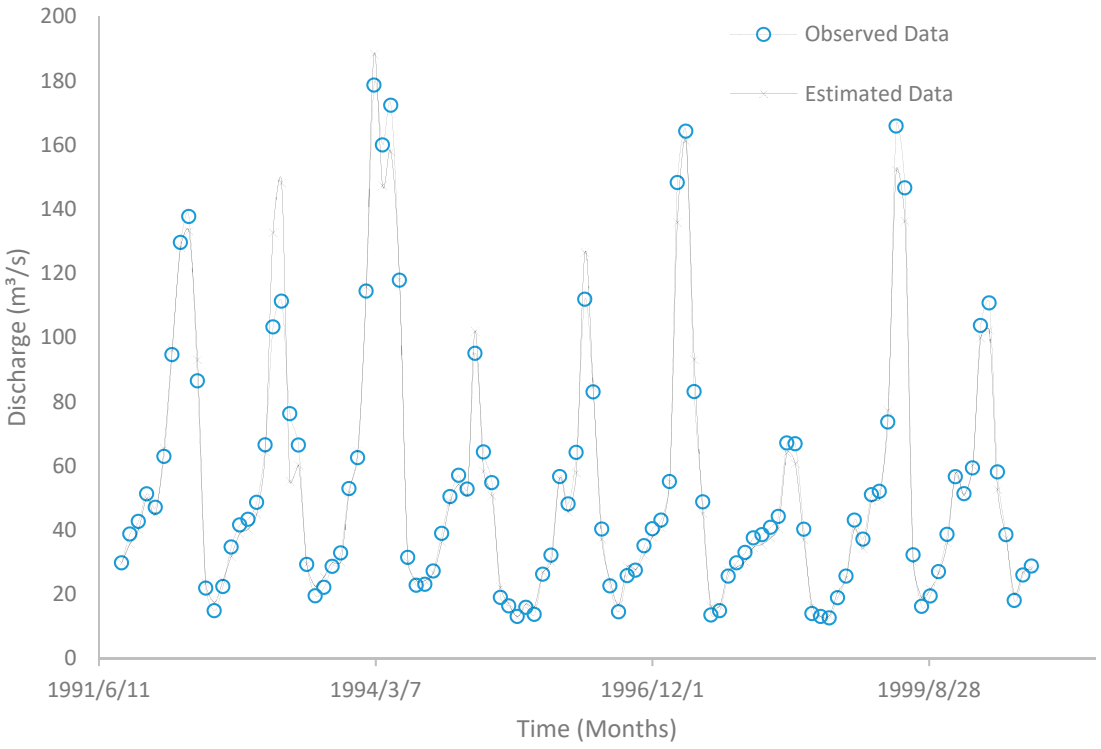
$$X_{1413} = 0{,}404 * X_{1414} + 4{,}904 * X_{1412} + 17{,}576 \quad (6)$$

167 **Table 5**. Training and testing data results of models developed for the third data set

		Training Data		Testing Data	
Models		R^2	Mean Squared Error %	R^2	Mean Squared Error %
ANFIS Models	3-3	0.890	20.29	0.865	23.24
	4-4	0.892	19.35	0.872	22.93
	5-5	**0.881**	**18.64**	**0.879**	**22.56**
	6-6	0.865	19.88	0.854	23.07
Normal Ratio Method		0.764	27.41	0.694	36.60
Multiple Regressions		0.905	34.26	0.757	46.74

168

169 The results show that ANFIS models provide more accurate results than the classical and
170 multiple regression models. Although the results are not as good as those in the first data set, they
171 remain within acceptable error limits. The models in which each input has 5 subsets are the optimum
172 models. The comparison of the values of the optimum ANFIS model with the observed values shows
173 that the errors of both the minimum and maximum flow values are very few (Figure 6).



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175 **Figure 6**. Comparison of observed data and estimated data of Anfis (5-5) model test data for the third data set

176 3.4. Determining the Minimum Number of Data for Anfis Model Training

177 This part of the study attempted to obtain the minimum number of data required for a reliable
178 ANFIS model training. The model with a 5-5 set of the first data set (the optimum modelling) were
179 the model of choice for this purpose. The models were trained using a 10-year data set and the
180 procedure was repeated year by year. The evaluation of the results is summarized in Table 4.

181 **Table 6.** Regression and error values for the number of data used for ANFIS model training

	Training Data		**Testing Data**	
Veri sayısı	R^2	Mean Squared Error %	R^2	Mean Squared Error %
1 - year	0,999	0,74	0,036	169,27
2 - year	0,993	13,42	0,071	118,02
3 - year	0,992	16,79	0,139	111,06
4 - year	0,985	21,38	0,198	36,91
5 - year	0,980	22,39	0,628	30,44
6 - year	0,981	21,23	0,738	21,92
7 - year	0,982	19,77	0,803	20,12
8 - year	0,983	18,76	0,844	17,77
9 - year	0,984	16,88	0,898	17,74
10-year	0,985	12,27	0,967	17,65
33-year	0,983	10,99	0,979	17,55

182

183 The number of data used for ANFIS model training does not affect the regression coefficient of
184 the training data very much (Table 6). However, the regression results obtained during the testing of
185 the models show that the results of the 10-year data set and model are very similar to those of the 33-
186 year data and training (Figure 7). The error values show that the 8-year data set is sufficient for
187 training (Figure 8). In conclusion, a 10-year data set may be sufficient for Anfis model training.

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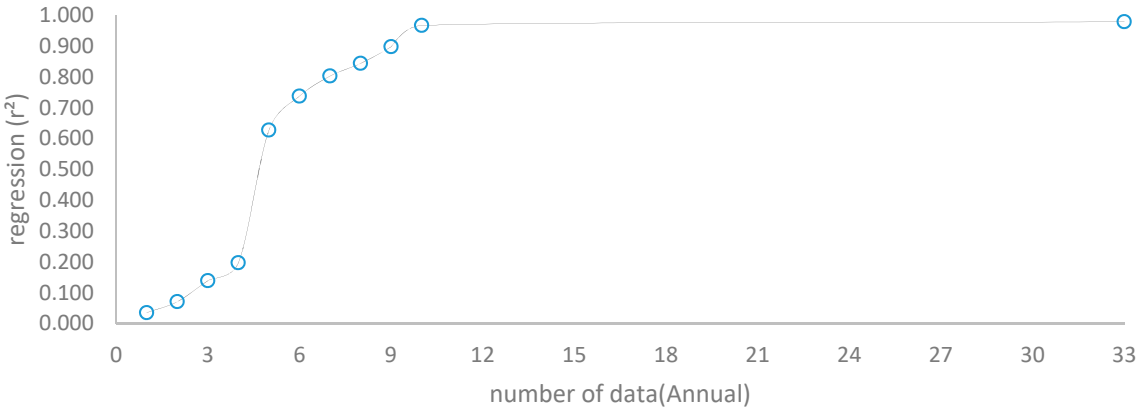

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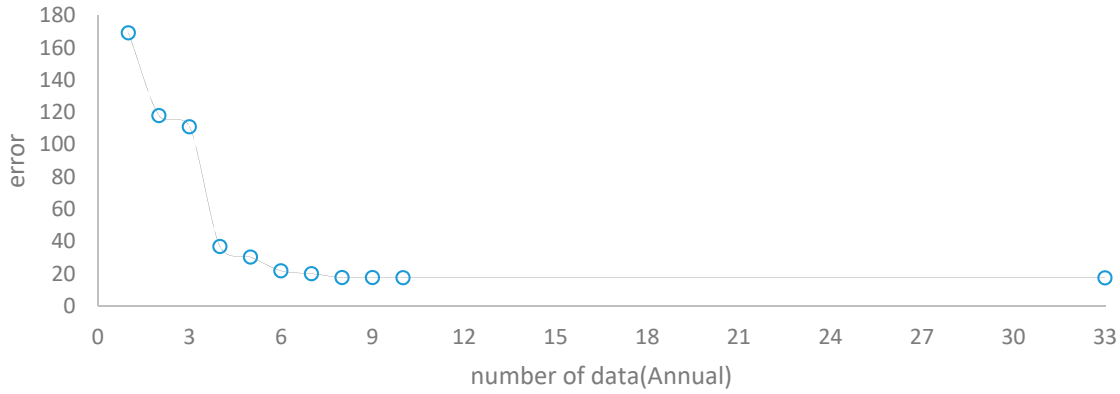
189 **Figure 7.** Regression values for the number of data used for ANFIS model training



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191 **Figure 8.** Error values for the number of data used for ANFIS model training

192 **4. Conclusions**

193 It is not always possible to collect long and coordinated data to optimally use water resources
194 projects. The aim of this study was to develop ANFIS models for stations on Yeşilırmak River in order
195 to solve this problem and improve the existing methods. Another aim of the study was to investigate
196 how the number of input parameters and amount of data affect ANFIS models. For this purpose, 3
197 different data sets were analyzed.
198 Results show that besides classical and regression models, ANFIS models can be used to
199 complete missing flow data. ANFIS models yield very accurate results especially when the number
200 of input parameters is small. However, multiple regression models yield better results than ANFIS
201 models when the number of input parameters is large. In addition, it takes ANFIS models longer to
202 achieve results when the number of input parameters increases. Lastly, at least a 10-year data is
203 required for a reliable ANFIS model training phase.
204 In conclusion, the ANFIS modelling yield accurate results and therefore can be used to complete
205 missing data when the number of input parameters is small and data set is older than 10 years.
206 It is not always possible to collect long and coordinated data to optimally use water resources
207 projects. The aim of this study was to develop ANFIS models for stations on Yeşilırmak River in order

to solve this problem and improve the existing methods. Another aim of the study was to investigate how the number of input parameters and amount of data affect ANFIS models. For this purpose, 3 different data sets were analyzed.

Results show that besides classical and regression models, ANFIS models can be used to complete missing flow data. ANFIS models yield very accurate results especially when the number of input parameters is small. However, multiple regression models yield better results than ANFIS models when the number of input parameters is large. In addition, it takes ANFIS models longer to achieve results when the number of input parameters increases. Lastly, at least a 10-year data is required for a reliable ANFIS model training phase.

In conclusion, the ANFIS modelling yield accurate results and therefore can be used to complete missing data when the number of input parameters is small and data set is older than 10 years.

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

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