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Research Article

Estimation of the Monthly Average Flows of the Kızılırmak River Using Fuzzy Logic Approach

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Abstract

River flow values are used in the design and operation of hydraulic structures. Determining the correct flow value is important in terms of controlling water movements in the operation of hydraulic structures, irrigation of agricultural lands, hydroelectric production, environmental protection and flood control. In the literature, different methods are used to predict possible river flows using the available data. The fuzzy logic approach is a kind of intelligent system method used in solving problems involving uncertainty. The method has been widely used in the modeling of hydrological data for 2000's. In this study, the fuzzy logic method was applied to estimate the flow data of Yamula Station on the Kızılırmak River in the Kızılırmak basin, one of the largest basins in Turkey. In addition to these flow station data, the monthly average temperature and monthly total precipitation data of the Kayseri meteorology station, which affects the station flows, were also used for modeling. Three different models were created for the flow estimates. In these models, temperature and precipitation data were selected as input values and river flow data were chosen as output values. In the models, 1982-2012 data of the stations were used. Model output data were tested with data set of 2013, 2014 and 2015. As a result of the research, it was seen that the fuzzy logic approach gave appropriate results when both temperature and precipitation data were used as inputs. Thus, it has been concluded that fuzzy logic model can be used in project flow estimations in the design of water resources projects planned on the Kızılırmak river.

Keywords: Fuzzy logic, Precipitation, River flow, Temperature

Bulanık Mantık Yaklaşımı Kullanılarak Kızılırmak Nehri Aylık Ortalama Akımlarının Tahmini

Öz

Hidrolik yapılarının projelendirilmesi ve işletmesinde akarsu akım değerleri kullanılmaktadır. Doğru akım değerinin belirlenmesi, hidrolik yapıların işletilmesinde, tarım arazilerinin sulanması, hidroelektrik üretimi, çevre koruması ve taşkın kontrolü açılarından önemlidir. Literatürde eldeki veriler kullanılarak olması muhtemel nehir akımlarının tahmin edilmesi için farklı yöntemler kullanılmaktadır. Bulanık mantık yaklaşımı, belirsizlik içeren problemlerin çözümünde kullanılan bir tür akıllı sistem yöntemidir. Yöntem son yıllarda hidrolojik verilerin modellenmesinde yaygın olarak kullanılmaktadır. Bu çalışmada, bulanık mantık yöntemi, Türkiye' nin en büyük havzalarından birisi olan Kızılırmak havzasındaki Kızılırmak Nehri üzerinde bulunan Yamula İstasyonuna ait akım verilerinin tahmin edilmesi için uygulanmıştır. Bu akım istasyonu verileri yanında, istasyona etki eden Kayseri meteoroloji istasyonuna ait aylık ortalama sıcaklık ve aylık toplam yağış verileri de modelleme için kullanılmıştır. Akım tahminleri için üç farklı model oluşturulmuştur. Bu modellerde girdi değeri olarak sıcaklık, yağış verileri, nehir akım değerleri ise çıktı olarak seçilmiştir. Modellerde, istasyonlara ait 1982-2012 verileri kullanılmıştır. Model çıktı verileri ve 2013, 2014 ve 2015 yıllarına ait veriler ile test edilmiştir. Sonuç olarak, bulanık mantık yönteminin hem sıcaklık hem de yağış verilerinin girdi olarak kullanıldığında sağlıklı sonuçlar verdiği görülmüştür.

Anahtar Kelimeler: Bulanık mantık, Nehir akım, Sıcaklık, Yağış.

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1. Introduction

Water is very important for human life. Hydraulic structures are required to take advantage of the water. These structures include domestic, industrial, agricultural and recreational use. The quality and quantity of these structures are directly proportional to the quality of human life. As it is known, water is not always available in the desired quantity and quality in the world. On the contrary, in some cases, there may be an undesirable amount of water such as flooding. Especially when the water is in an uncontrollable amount for a short time, it causes loss of human life and great damage to real estates. Solving these problems is related to the effective management of water resources. For this, the water structures to be built on these resources should be planned correctly. Meteorological and hydrological data are needed in studies conducted for this purpose (Tosunoğlu et al., 2017).

From a broader perspective, the flow value of a river is used in flood prevention projects, water sharing models and measures to be taken during drought. Flow rates of streams that have been accurately measured and predicted to be in the future are also very important in lake level calculations. Sudden changes in the lake level adversely affect the use of residential areas, agricultural areas and transportation networks around the lake. For this reason, in order to detect level changes in advance, the relationship between meteorological data and flow should be determined well. For these reasons, estimating the flow data of a stream using the available meteorological data gains importance especially in the design of water resources where flow measurement is difficult for various reasons.

Since the events affecting hydrology consist of many parameters, suitable models cannot be created with classical methods (key curve, linear regression). Since these parameters are random, they can be independent of each other. Since it is difficult to determine the relationship between parameters, simple, time-consuming and economical methods have been developed. In hydrological studies, methods such as Fuzzy Logic (BM), Artificial Neural Networks (ANN), adaptive neural fuzzy system (ANFIS) can be used. Fuzzy logic control, which is one of them, gives much more accurate and efficient results. The difference between Fuzzy Logic models and other models is that they are trained by expert opinion. Models created by taking the opinions of experts are compared with experimental or mathematical results and their accuracy is determined. The output logic of this method is based on the clustering system being more flexible. The truth or falsity of any event can be accepted within the framework of certain weights (Dodangeh et al., 2021).

There are many researches of fuzzy logic method is used in river flow estimation in literature. Some of these are as follows:

Liong et al. developed a fuzzy flood model for water level estimation in the Dhaka (Bangladesh) region. The research results were tested with the artificial neural network results. As a result, it was seen that the fuzzy approach was successful in this region. (Liong et al., 2000). In the study conducted at stations in Taiwan, the flow data of another station was estimated with a model created by combining Fuzzy Logic and ANN (Chang et al, 2001). In study of Ertunga and Duckstein, a fuzzy conceptual rainfall-runoff study was performed to address the parameter uncertainties of the experimental watersheds data in USA rainfall-runoff models. The utility of fuzzy logic in the decision maker's CRR model sensitivity and uncertainty was proven. (Ertunga, C.Ö., & Duckstein, 2001). Mahabir et al. used FL in estimating the UN seasonal flow. A rule-based UN forecasting model was applied to the watershed. This model was tested with the neighboring Middle Creek watershed. They found that the BM method gave better results than the classical methods (Mahabir et al., 2003). Bisht and Jangid developed ANFIS and Linear Multiple Regression (MLR) methods for flow estimation in rivers. They observed that ANN models and Fuzzy Logic models are applicable for flow prediction in rivers. (Bisht and Jangid 2011). Jayawardena et al. used the fuzzy logic model to estimate daily and 6-hour discharges in 4 rivers in 3 countries with contrasting climatic, geographic and land use characteristics. In the first application, daily upstream precipitation and flow data were used for two tropical rivers in Sri Lanka. The second application was for another tropical river in Fiji. In the third application, daily upstream and tributary discharges in a temperate-climate river in China were used to estimate downstream discharges using a clustered TAF type fuzzy inference system. According to the research results, the methods are robust and the results are in reasonable agreement with the observations (Jayawardena et al, 2014). Sun and Trevor applied the QFLM-ANFIS) and MLR methods to calculate the maximum water level in rivers. There is a problem of ice breaking in this region. Therefore, the river ice breaking dataused for model comparisons. As a result of the research, it was seen that QFLM was suitable for the pre-screening model in the flood risk calculation. In hydrological practice, ANFIS and MLR have proven to be estimation and backup tools. (Sun and Travor, 2015). Jia et al applied a fuzzy logic-based method combined with GIS in river evacuation models. The test of the model was checked with the data of the city of Bordeaux. As a result, it was predicted that the evacuation need maps created by the fuzzy method could be used in crisis management (Jia et al , 2016). Anusree and Varhese estimated the daily flow from the watershed outlet of the Karuvannur (Thrissur) river. For this purpose, they used multiple nonlinear regression (MNLR) method, ANN method and ANFIS methods. They created the combinations from different precipitation-flow and different time data. Models were evaluated with RMSE and Nash-Sutcliffe coefficients. As a result, it was observed that the daily flow estimation of the ANFIS model gave more reliable estimations than the ANN and MNLR methods (Anusree and Varhese 2016). Bardzadeh et al combined Wavelet Multiple Resolution Analysis and the ANFIS model to develop the WNF model. They received monthly flow estimates from Australia's Ellen Brook River and Railway Parade stations in Western. They then combined the wavelet coefficients with the neuro-fuzzy model. The models were developed in the next step based on the Takagi-Sugeno-Kang Fuzzy Inference System. The mean square error and the Nash-Sutcliffe coefficients were chosen as performance. At the end of the studies, they observed that the ANFIS model and WNF models gave better results, especially in long-term predictions (Bardzadeh et al., 2018). In other study, MLR, ANN and WD were used for flow prediction in the East River basin, China. While the cover model showed similar performance in 1-day-ahead flow prediction, W-MLR and W-ANN performed better in 5-day-ahead prediction (Zhang at al., 2018). Dawood et. get. studied the effects of climate parameters on river discharge using a fuzzy logic approach. They used precipitation, temperature, snowfall and discharge (runoff) data for possible climate change scenarios. They estimated climate change detections in uncertain situations with a fuzzy logic rule-based model. As a study area, they took the Swat River Basin in Pakistan. They set a total of fifty-three rules for fuzzy analysis. After fuzzy modeling, they confirmed an extremely close and high climatic trend relationship between discharge, temperature, precipitation and snowfall from the integrated analysis (Dawood et.al, 2021). Patel and Chitnis used water quality data in their study. evaluated. In this study, a fuzzy approach was used to derive a water quality model. The results showed that the role of regulations for industrialization also played an important role by comparing the monsoon effect and the water quality model of the Ahmedabad city water quality on the Sabarmati river quality (Patel and Chitnis, 2022).

In this paper, monthly average flow estimations were made with fuzzy logic method Mamdani deduction method. As data, flow data of Yamula flow station on Kızılırmak River and climate data of Kayseri Station were used. This study discusses the applicability of the fuzzy logic model of flows to be used in Kızılırmak basin modeling and water resources projects studies and reveals the differences. In this respect, it differs from similar studies in the literatüre.

2. Material and Method

2.1. Material

The Kızılırmak river was chosen as the study area in this article (Figure 1). For this purpose, the river flow values of the Yamula Stream Observation Station (E15A001) in the Yamula Sub-Basin located within the boundaries of the Kızılırmak basin and the monthly average temperature and total precipitation data of the Kayseri station (17196) operated by the General Directorate of Meteorology were used (MGM, 2022).

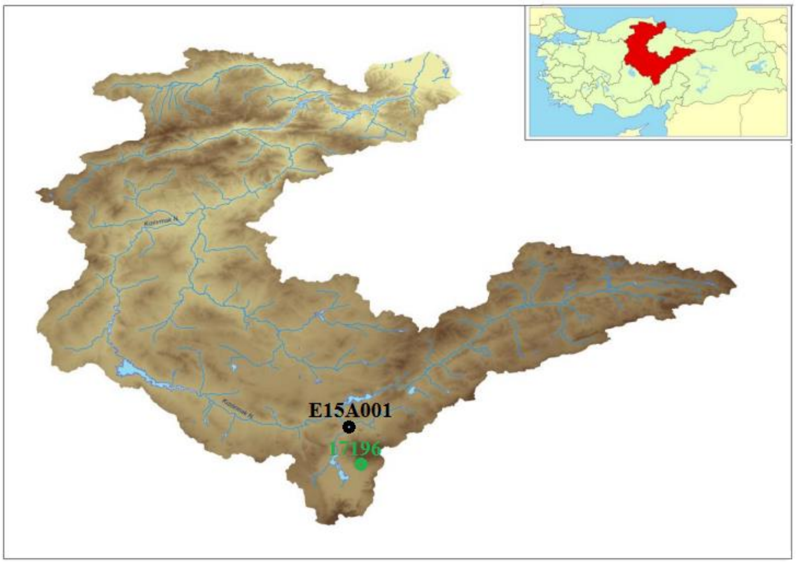

Figure 1. Kızılırmak Basin and stations

The Kızılırmak Basin has a precipitation area of 82 221 km2, which is approximately 10.49% of Turkey's surface area. Within the boundaries of the Kızılırmak Basin, which covers some parts of the Central Anatolia, Black Sea and Eastern Anatolia Regions; Ankara, Çankırı, Yozgat, Çorum, Kırıkkale, Kırşehir, Nevşehir, Kayseri, Sivas, Samsun, Sinop, Kastamonu, Aksaray, Niğde, Tokat, Erzincan, Amasya and Konya provinces are all or part of it. Drainage area of the basin is 82 221 km2, annual average precipitation is 435.60 mm/m2, annual average yield: 2.4 l/s/km2, Average annual flow: 6.12 km3. Kızılırmak, which is the longest of Turkey's rivers with a length of 1263 km, originates from Kızıldağ in İmranlı District of Sivas Province and empties its waters into the Black Sea.

In the study, monthly average flow data of Yamula Station was chosen as the output fuzzy set. The drainage area of Yamula station is 26972.65, the average flow height is 136 mm, and its height is 995 m. Monthly average temperature and monthly total precipitation data of Kayseri station were chosen as input value. The precipitation height of this meteorological station is 394.73 mm/year, its polygonal area is 2445.01 km^2 and its height is 1094m. Kayseri station was chosen to represent the Yamula station because it remains within the polygonal area (SYGM, 2022).

According to the station data, the average temperature was 10.7 °C, the average highest temperature was 18.1 °C and the average lowest temperature was 3 °C. Average monthly temperature values of Kayseri Station were shown in figure 2.

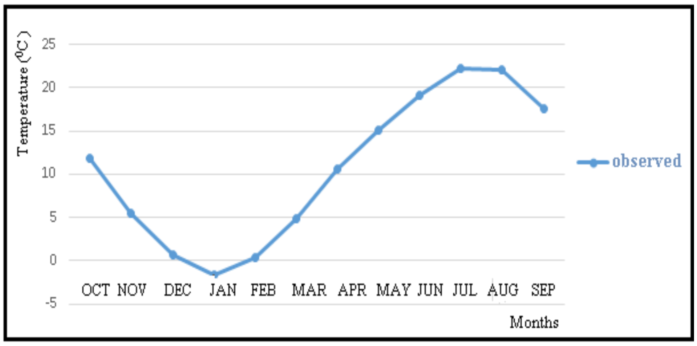

Figure 2. Average monthly temperature values of Kayseri Station

According to the station data, the monthly average of the highest total precipitation amount (May) was 51.7 (mm), and the average of the lowest monthly total precipitation amount (August) was 8.9 (mm). Average monthly precipitation heights were shown in figure 3.

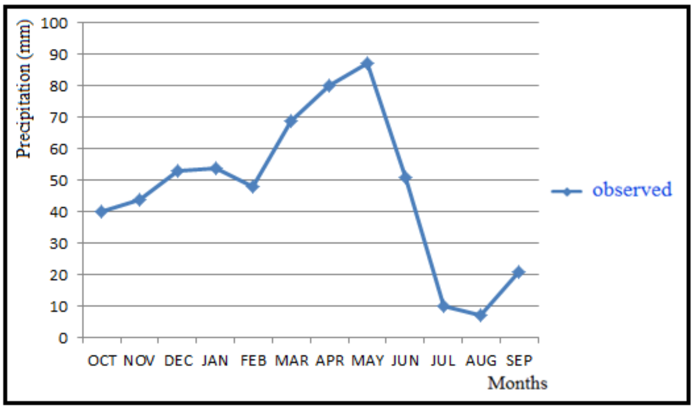

Figure 3. Average monthly precipitation heights of Kayseri Station

The presence of any snowmelt process that causes runoff at the stations was not found in the researches. For this reason, precipitation data, which is effective in the formation of flow in the study area, were used as input. In addition, it has been determined that there are flow losses due to evaporation in the region where the continental climate is effective. Therefore, temperature values are used.

he homogeneity condition of our precipitation data was already reported by Arıkan and Kahya (2019). The authors are also advised to do the same for other data.

2.2. Method

Zadeh defined the multi-valued logic value set in the range [0,1] and named this theory as Fuzzy Logic Theory (Zadeh, 1965). The basis of the concept of fuzzy logic is the principle of gradual belonging to clusters instead of strict boundaries. Fuzzy logic proposes a transition state between opposing expressions such as 0 and 1, true and false. This allows some events to be handled with invaluable logic. The main difference of this method from classical systems is that it does not have to create a mathematical model. For the desired output, only the input values are edited. With the mechanism of fuzzy control, it is in parallel with the control ability of an expert. That is, it is similar to humans that machines use fuzzy logic and fuzzy set operations. Artificial neural networks and fuzzy logic, neuro-fuzzy and neural fuzzy systems, or genetic-fuzzy systems have emerged from this compatibility of fuzzy logic. Thus, intelligent systems have started to make rapid progress (Jang et al, 1996).

There are two cases where fuzzy logic differs from classical methods. In this method, people's opinions and value judgments are included in the event that the analyzed case is too complex and there is insufficient information. The method also gives positive results in situations that require human judgment, insights and decision (Şen and Altunkaynak, 2006).

In fuzzy logic modeling, fuzzification, creation, evaluation and collection of rule bases, clarification processes follow each other. The fuzzy system process is modeled as in Figure 4.

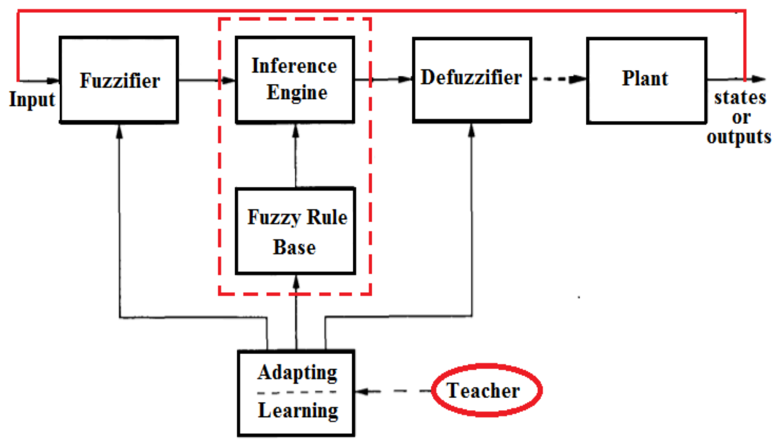

Figure 4. Fuzzy Inference System (Jung at al., 1995).

In fuzzy systems, input and output values are used linguistically. These values can be numerical or verbal. It should be noted that in real systems, these values are exact, not fuzzy. In order to eliminate this disadvantage, a turbidizer is added to the input of the system and a clarifier to the output. The fuzzifier converts the exact values in the input to fuzzy values. The defuzzifier, on the other hand, converts the fuzzy values at the output to precise values. The task of the output unit is to collect the output values with the help of fuzzy inference engine. (Büyükkaracığan, 2022).

In the fuzzy rule-based system, the Mamdani method is the most widely accepted analysis method. Since Mamdanide is manually trained, it gives very realistic values. Sub membership functions are created with input and output values. By using if/and, it is tried to estimate the output values close to the measurement data. Manual training techniques customize membership functions so that we can best model fuzzy system data. Mamdani is a method of obtaining net outputs with fuzzy inputs. This approach is suitable for situations with little data and for verbal statements about the problem (Mamdani, 1974). In contrast, the Takagi-Sugeno approach requires only numerical data and does not work with verbal data. For this reason, Takagi Sugeno approach is a data-based method and gives better results when digital input-output data are provided (Takagi and Sugeno, 1985).

The Mamdani deduction method is simpler and easier to apply than other fuzzy models. This approach is effective in dealing with nonlinear and dynamic behaviors. This model can achieve the desired goals and has a preferable model. Mamdani model can show its legibility and understandabilityto the users (Chai et al, 2009). For these reasons, the Mamdani deductive method is preferred to be intuitive in this study.

A range value is determined for each linguistic variable according to the number of linguistic variables and range values determined during the fuzzification process. While this determined range is expressed graphically, blurring structures are used. Gaussian blur was used in the study.

In this study, three different models were created for monthly average river flow estimation. In the first model, only the temperature variable, in the second model only the precipitation variable, in the last model, the temperature and precipitation variables together were determined as the input set, the flow data were determined as the output set and Mamdani type was used (Figure 5).

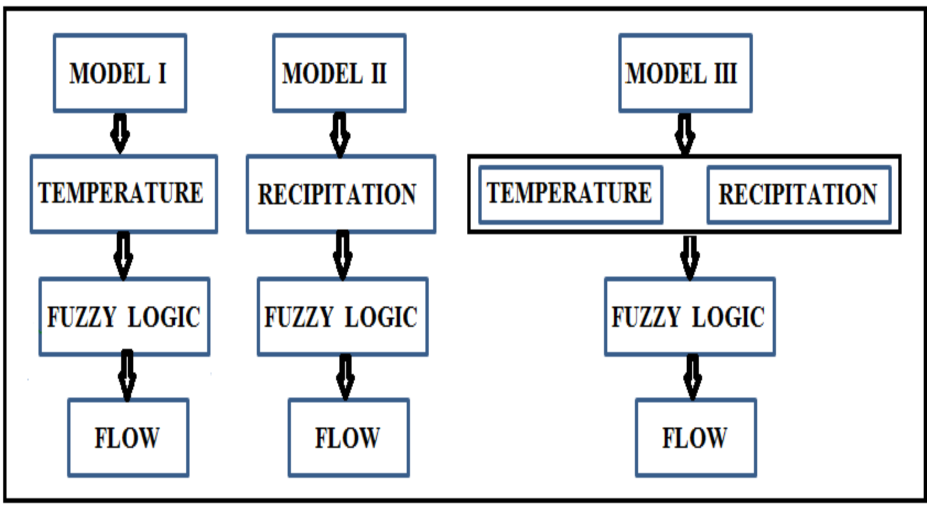

Figure 5. Fuzzy Logic Models

In the first model, 10 Gaussian membership functions were established for the temperature data selected as the input variable and varying in the range of -20, +40 ºC. 5 Gaussian type membership functions are written for the flow data, which has an output variable and varies in the range of 0-120 m3/s. Taking into account the average values that will reflect the character of each month, 10 rules have been created.

In the second model, 10 gaussian membership functions were written for the monthly total precipitation data and 10 rules were defined. Although the precipitation values for each month are close to each other, different membership functions have been created. Separate rules are also written for the months of February, March, April and May, which have the highest average precipitation and flow amount. Since the rules are written over the average values that will reflect the character of the months, the margin of error is high in the model that reflects the character of the months below the average.

In the third model, precipitation and temperature data are taken as input and flow data as output. Thus, the problems experienced in the case of measuring the same precipitation or temperature in months with different characteristics are minimized.

The generated Fuzzy Model was run in Matlab program and monthly average flow data for 2013, 2014 and 2015 were estimated. Root mean error (RME) and coefficient of determination (R^2) values were used to evaluate the performances of the models.

3. Results and Discussion

Flow data for the years 2013, 2014 and 2015 were estimated using the models created by examining the flows of the Yamula Flow Observation Station on the Kızılırmak River in the Kızılırmak Basin and the temperature-precipitation values of the Kayseri Meteorological Observation Station, between 1992 and 2012.

Figure 6 shows the estimation results and measurement values obtained from the first model with only temperature data as input. As a result of measuring the temperature value, which was written as a rule to measure the performance of the model, in October 2013, the model estimated the flow value very close to its real value. As a result of the calculation, the RME value was found to be 1.42 m^3/s, and the R^2 value was 0.94.

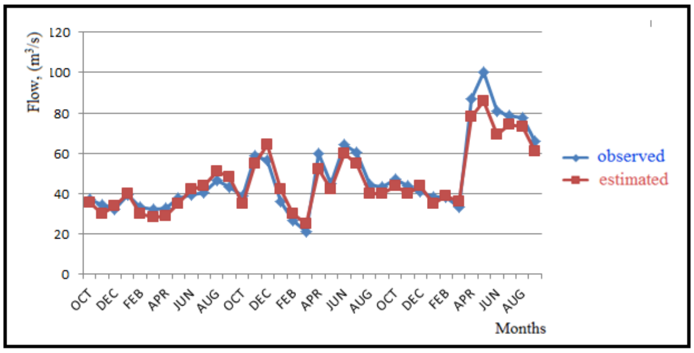

Figure 6. Flow estimation results based on temperature data

The estimation results and measurement values obtained from the second model, whose only precipitation data was selected as input, were shown in Figure 7.

When the data of the past years are examined, frost events due to low temperatures in winter months pose a problem in writing the rules between precipitation and flow in these months. Although the temperature and precipitation values that can be seen in other months are measured in November-March and April, it was observed that the flow value is relatively high. In the model, the RME value was found to be 3.2 m^3/s, and the R^2 value was 0.82.

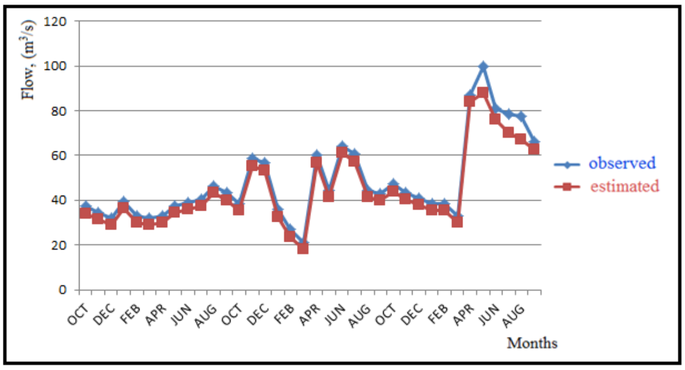

Figure 7. Flow estimation results based on precipitation data

Figure 8 shows the estimation results and measurement values obtained from the last model, where both temperature and precipitation data were selected as inputs. Taking temperature and precipitation as inputs at the same time prevented the problems experienced in models 1 and 2 and reduced the amount of errors, so the RME value was calculated as 0.27 m3/s and the R2 value as 0.96.

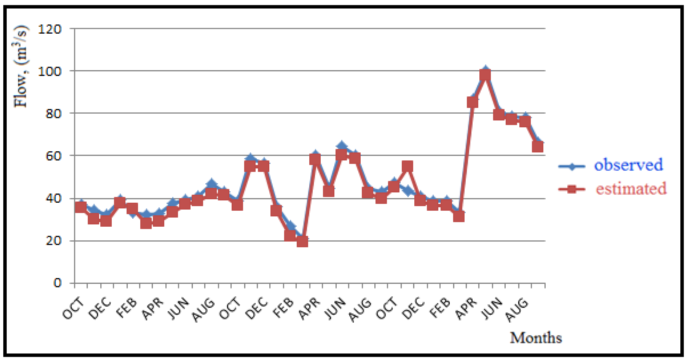

Figure 8. Flow estimation results based on temperature - precipitation data

When the results obtained in the three models are evaluated together, 2014 was the year in which the fluctuation between the measurement and prediction values in the second model was experienced the most. The biggest difference between the estimated and measurement flow values in the first model was determined in April with a value of 1.587 m^3/s, in March with a value of 0.515 m^3/s in the second model and in March as 0.18 m3/s in the third model.

Observation values and forecast results for 2015 and their differences was also shown.Table1. As can be seen from the Table 1 that values, statistically, the observation and prediction values show compatibility within the confidence limit.

Table 1. Observed and estimation results for 2015 for each model.

Data	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JULY	AUG	SEP
MODEL I (Temperature-Flow)												
Observed	37.2	34.4	32.0	39.4	33.2	32.1	32.9	37.5	39.1	40.6	46,5	43.2
Estimated	35.2	29.8	33.8	40.6	30,2	28.4	29.2	34.9	42.2	34.9	51.1	48.4
Err	2,0	4,6	1,8	1,2	3,0	3,7	3,7	2,6	3,1	5,7	4,6	5,2
MODEL II (Precipitation-Flow)												
Observed	37.2	34.4	32.0	39.4	33.2	32.1	32.9	37.5	39.1	40.6	46,5	43.2
Estimated	34,1	31,3	28,9	36,3	30,1	23,2	34,4	36,0	36,5	43,4	40,9	38,9
Err	3,1	3,1	3,1	3,1	3,1	8,9	-1,5	1,5	2,6	-2,8	5,6	4,3
MODEL III (Temperature / Precipitation-Flow)												
Observed	37.2	34.4	32.0	39.4	33.2	32.1	32.9	37.5	39.1	40.6	46,5	43.2
Estimated	36,3	30,8	29,4	37,9	34,1	29,6	33,4	38,0	38,4	38,7	42,9	41,6
Err	0,9	3,6	2,6	1,5	0,9	2,5	0,5	0,5	0,7	1,9	3,6	1,6

4. Conclusions and Recommendations

In this study, the application of the Mamdani type of fuzzy logic model was carried out to create the forecast model of monthly average river flow data based on meteorological data.

The irregular behavior of natural events requires pre-processing to meet these conditions before modelling. The fuzzy logic model is used simply to model all natural phenomena without requiring any preprocessing. There are three different models created for this purpose. The performances of the models were measured relative to each other. In the MODEL I only temperature, in the MODEL II only precipitation, in the third model both are selected as inputs. When the results were examined, it was seen that the third model had better results than the other two models. Thus, with the MODEL III, it is possible to use it in estimating missing data in the event that no measurement can be made in the river.

In forecasting flow values in a river, there are numerous volumes of research works focused on the relation between flow and well known large-scale atmospheric oscillations to improve the forecasts regardless of the methods used. In this context, among others, Şarlak et al. (2009) showed a notable potential of critical drought forecast in relation to North Atlantic Oscillation in Göksu river and Karabörk and Kahya (2009) documented the forecast potential of various hydrological and climate variables in Türkiye. Therefore, it is worthwhile to include such circulation indexes in the set-up of fuzzy logic approaches in order to increase accuracy of model outcomes.

In addition, the use of other hydrometeological data such as snowfall, evaporation and humidity can be used to increase the sensitivity of the model and reduce the margin of error. Thanks to the prepared model, it will be possible to complete the missing data in the event that measurements cannot be made in any month or year due to climatic conditions, transportation difficulties, technical problems and malfunctions.

As a result, it has been seen that the fuzzy logic model will be appropriate for the estimation of the flow rates, which will be taken into account in the design of any hydraulic structure planned to be built on the Kızılırmak river.

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