Acta Scientiarum

http://periodicos.uem.br/ojs
ISSN on-line: 1807-8664
Doi: 10.4025/actascitechnol.v47i1.70976

Determining Runoff Coefficient For Kalecik Basin by Using SMRGT

Fatih Şevgin[1*] and Zeynel Fuat Toprak[2]

[1]Muş Alparslan University, Vocational School of Technical Sciences, 49100, Muş, Turkey. [2]Dicle University, Faculty of Engineering, Department of Civil Engineering, Division of Hydraulics, Diyarbakir, Turkey. *Author for correspondence. E-mail: f.sevgin@alparslan.edu.tr

ABSTRACT. Precipitation causes runoff with significant uncertainty. The rainfall-runoff modeling relationship depends on the runoff coefficient. Many models have been developed with different methods to calculate the runoff coefficient. Black box or fuzzy models can be preferred instead of deterministic methods in uncertain natural events. However, black box methods often do not consider the event's physical aspect. Therefore, in the present study, Simple Membership Functions and Fuzzy Rules Generation Technique (SMRGT) which base on fuzzy logic was preferred in determining the runoff coefficient since it also reflects the physical cause-effect relationship of the event. By this way, both the hydrological event's uncertainty and physical aspects were addressed. Therefore, it can be used for any basin when the limit values of the variables are expanded. Correctly determining fuzzy sets and fuzzy rule bases are essential points to be considered in fuzzy modeling. According to the literature, SMRGT is the best one to use for this purpose. On the other hand, SMRGT is relatively new. Meteorological, geomorphological, and land use-related characteristics were considered for modeling. The Kalecik Basin's runoff coefficient is found as 0.28 which is lesser than the average of Turkey. The model has 2.28% of MARE.

Keywords: Runoff coefficient; fuzzy logic; SMRGT, kalecik basin

Received on January 12, 2024.
Accepted on June 05, 2024.

Introduction

The actuation of the precipitation waters under the effect of gravity is called runoff. Precipitation and runoff are the two main factors shaping the water cycle. Not all precipitation that falls into the basin of a channel can runoff because of infiltration, evaporation, and retention on the earth. The runoff coefficient, which is the rate of runoff, is calculated by dividing the runoff depth by the rainfall depth. There are two different approaches to estimating the runoff coefficient; time (annual, monthly) and event-driven (hydrograph analysis). There are significant differences and challenges in calculating the runoff coefficient between a large and small basin. Because as the basin expands, the number of observation stations becomes insufficient and needs to provide sufficient data on the behavior of the basin. Estimating the runoff coefficient from a model is very challenging. The model depends on many essential variables, such as seasonal distribution of precipitation, precipitation area, precipitation intensity, soil type, infiltration rate, basin parameters, urbanization, water accumulation structures, artificial groundwater recharge, and in-basin water transfers (Pektaş, 2012). However, many variables only sometimes make the model the best. When the variables are reflected in the model, it is necessary to give value to each of the variables (Toprak, 2019).

In the present study, a physics-based model was developed to predict the runoff coefficient of any basin. The model was developed by using the Fuzzy Logic Method. Mamdani's Approach was used as the operator. The Simple Membership Functions and Fuzzy Rules Generation Technique (SMRGT) Method, developed by Toprak (2009), was used to determine membership functions (blurring the inputs and outputs of the model) and to create the fuzzy rule base. SMRGT was preferred over the other methods as it also reflects the physics-cause-effect relationship to the model.

There are many studies in the literature conducted on runoff coefficient calculations. The runoff coefficient, which has an essential role in determining the moisture cycle of the soil, can be considered a critical parameter to monitor the change of soil moisture over time. If this coefficient increases, the soil becomes barren, and the green areas decrease (Savenije, 1996). Especially in previous studies that were conducted on bankfull discharge, the runoff coefficient was reported to be the most crucial parameter. If there is no precipitation, a runoff event does not occur, and the bankfull discharge cannot be determined without determining the runoff coefficient. For this reason, the correct calculation of the runoff coefficient (when floods are examined and the flood runoff is calculated) will help minimize possible damages. However, the data needed for the model in current calculations are obtained by remote sensing technology (Nayak & Jaiswal, 2003). For instance, the ArcGIS Method can calculate hydrological variables in basins with small drainage areas. Therefore, the determination of direct runoff hydrographs can be easily realized with a hydrological model. Akbaş et al. (2018) examined the relationship between precipitation, runoff, and evaporation in the Marmara Sea basin with the data received from General Directorate of Meteorology (Meteoroloji Genel Müdürlüğü, MGM) and General Directorate State Hydraulic Works (Devlet Su İşleri, DSI). The study converted precipitation and evaporation from point data to spatial data using Thiessen Polygons. As a result of their research, they reported that evaporation is the variable that has the most significant effect on the basin and negatively affects the water budget. It was also emphasized that there is a high correlation between precipitation and runoff (Akbaş et al., 2018). It is expected that there is a high correlation between precipitation and runoff, except for basins with permeable but unsaturated soils, as in deserts. In the present study, evaporation was chosen as one of the model inputs because of its significant effect on the basin runoff coefficient.

Cleveland et al. (2006) created a precipitation-runoff model with instant unit hydrograph analysis with about 1600 storm data taken from 91 stations in the USA of Texas. The observed data were appropriate in the model with two different evaluation functions. The model was compared with the Texas Hydrograph and was found to have reliable performance. The Unit Hydrograph Model is the most common model used in basin modeling. However, the nonlinear precipitation runoff relationship is the most significant difficulty in modeling the basin. Some assumptions must be made in such nonlinear systems, and the system must be linearized (Cleveland et al., 2006). As well as the study mentioned above, Mimikou and Rao (1983) and Cleveland et al. (2006) designed a monthly precipitation-runoff model with a nonlinear component over the Aracthos River Basin in Greece. This way, the model had a structure that could be applied to basins with linear and nonlinear precipitation-runoff characteristics. Two parameters, *k*, the degree of the basin characteristic model, and *n*, which controlled the memory of the precipitation runoff process, were used in the model (Mimikou & Rao, 1983). Tsykin (1985) developed a model with simple time series and applied it in Australia to calculate monthly bankfull discharge rates. The coefficient of determination (R2) between the model results and the available data was calculated between 0.90-0.96. However, it must be addressed that the trends of the series must stay the same over time, and the data must be normal, linear and homosedastically distributed to apply Regression Analysis to time series in this and similar studies (Tyskin, 1985). It must also be noted that the high correlation coefficient or the determination coefficient, which is the square of it, indicates that the statistical relationship between the two series is high. It only sometimes indicates that the model is successful. Merz (2006) used the data of 50.000 rainfall-runoff events in 337 basins with areas of 80 to 10000 km2 in Australia to calculate the runoff coefficient hourly. In the present study, which they conducted according to time and space using the data covering the years 1981-2000, they reported that the runoff coefficient depending on the space was weakly correlated with land use and soil type but with a strong correlation with the annual average precipitation height. If there is a time-oriented approach in runoff coefficient calculations, another point to be considered is that this time is relatively short (hours, days). At least six months or annual measures will give more reasonable and realistic results (Merz et al., 2006). Palta et al. (2019) worked on precipitation and runoff with two runoff observation stations in the Göksu Basin and used the Mann-Kendall Trend Analysis. The runoff coefficient of the Hamam station was found to be 43.49%, and the runoff coefficient of the Karahacılı station was 41.28%. Also, it was considered to represent the entire basin, and the runoff coefficient of the Göksu Basin was accepted as 41.28% because Karahacılı station is close to the exit point of the basin. Evaporation is the most crucial reason for the significant loss difference between precipitation and runoff in the basin (Palta et al., 2019).

Parida et al. (2006) estimated semi-arid basins' runoff coefficient using the ANN Model. They calculated the runoff coefficients between 1978 and 2000 by applying the water budget technical model to the Botswana Notware basin. It was found that the increase in the runoff coefficient until 2020 was approximately 1%. Although the study sets an important example, especially for semi-arid basins, including the slope, which is a very important variable and not considered, as well as precipitation, evaporation, temperature, humidity capacity and urbanization in the model will contribute to a more realistic result for the runoff coefficient

(Parida et al., 2006). Because the slope increases the runoff rate and reduces the infiltration and evaporation time. Similar to the black box study of Parida et al. (2006), Sedki et al. (2009) used the Genetic algorithm method to estimate the precipitation-runoff of the Ourika semi-arid basin in Morocco with an area of 503 km^2. Here, the precipitation-runoff values in the previous time were taken as the system's input to predict the runoff in any period. The authors argued that the model predictions were supremely satisfactory. It is necessary to use retrospective datasets only to train black box methods such as ANN and GA. Therefore, using these methods in watersheds with insufficient data must not be expected to yield realistic results. Also, among the disadvantages of these methods, they do not deal with the physics aspect of the event (Sedki et al., 2009). The MIKE 11 NAM model, which is a deterministic approach, was developed by Kumar et al. (2017) and employed it in a runoff simulation for the Arpasub Basin in India. The caliber of the model was made and verified using the discharge data of the Kota Station with an area of 1681.8 km^2. According to these results, it was reported that the model could well define the rainfall-runoff relationship of the basin and predict the daily values of the surface runoff (Kumar et al., 2017).

Materials and methods

In the present study, a model with Simple Membership Functions and a Fuzzy Rules Generation Technique (SMRGT as a simple technique for determining membership functions and fuzzy rule base) was developed to estimate the runoff coefficient of the Kalecik Basin. The method was first proposed by Toprak (2009) (Toprak, 2006). All the details of the technique were included in the present study. Also, there are many articles in the current literature (aside from the main article given above, there are also studies conducted by Toprak et al., 2012; Altaş et al., 2018; Toprak et al., 2017; Yalaz et al., 2016) and studies presented as papers in scientific meetings (Toprak, 2018; Toprak, 2017; Toprak et al., 2012; Altaş et al., 2018; Gunal & Mehdi, 2023; Toprak et al., 2013a; Toprak et al., 2013b). Because of its easy applicability and very realistic results, it was adopted in a short time after entering the literature and used in postgraduate thesis studies in many different disciplines (Altaş, 2018).

Although SMRGT was employed as a method in the studies mentioned above, each application area was different. For example, Altaş et al. used the SMRGT Method for the modeling of water surface profiles in open channel flows, in other words, in the field of hydraulics (Altaş et al., 2018). The first application in environmental science was made by Gunal & Mehdi. (2023) (Gunal & Mehdi, 2023). Aside from these, Toprak (2009) conducted the first study in the field of hydraulics on the dimensioning of open channels. Toprak et al. (2013) used it to calculate losses and leaks in drinking water network lines, in other words, in environmental sciences (Toprak et al., 2013). The study Yalaz et al. (2016) used fuzzy linear regression in the analysis of Fuzzy time-dependent data, in other words, in the field of mathematics (Yalaz et al., 2016). Yalaz et al., (2016) also used it in the field of mathematics in fuzzy linear regression analysis (Yalaz et al., 2016). Toprak et al. (2017) mentioned both the advantages and disadvantages of the method and its practical applications (Toprak et al., 2017). Unes et al. (2020) reported that this method gives more reasonable results when compared to other methods in river runoff estimation (Üneş et al., 2020). Ustun et al. (2020) used it to determine the estimation of the radiation from the sun (Üstün et al., 2020). Güven (2020) used it to estimate the revenues of the Istanbul Bosporus bridges in his master’s thesis (Güven, 2020). The most important advantage of the method is that it detects both the Fuzzy Rule (FRs) base and Membership Functions (MFs) at the same time with a straightforward technique (Toprak, 2009).

According to the fuzzy SMRGT method;

1. Firstly, the decision is made for the current event's dependent and independent variables. Dependent variables are taken as input, and independent variables are taken as output (Toprak et al., 2017).

2. All variables must have a specific limit range, and their minimum and maximum values must be known. Xmin and Xmax values must be chosen based on an expert's opinion. They must be expanded as desired, considering the problem's situation. The X_R change interval is calculated as in Equation 1.

$$X_R = (X_{mak}) - (X_{min}) \tag{1}$$

3. The shape of the membership functions is decided. When defining the membership functions, choosing the right triangle or trapezoidal for the first and last and choosing the trapezoidal or isosceles triangle for the membership functions in the middle will be more efficient for the model. Triangular fuzzy sets were decided to select since this method gives more positive results on triangular and trapezoidal membership functions.

The key values of each variable (*K1, K2, K3, … Kn*) and membership functions (*Ci*), unit width (*UW*), expanded unit widths (*EUW*) symmetrically extended for each membership function, and two neighboring membership function's overlapping value (O) is determined. Also, the number of right triangles (*nu*) in Fuzzy triangular sets must be known (Figure 1). For example, for a membership function with five Fuzzy subsets in Figure 1, *K1* and *K5* are the values at the centroid of the first and last right triangles, and the remaining middle key values (*K2-K4*) are the centroids of the triangles in between (*Ci - 1*, *Ci*, *Ci + 1*). These magnitudes of the dependent and independent variables for the Fuzzy SMRGT model are calculated with equations 1 - 9 using the formulas below.

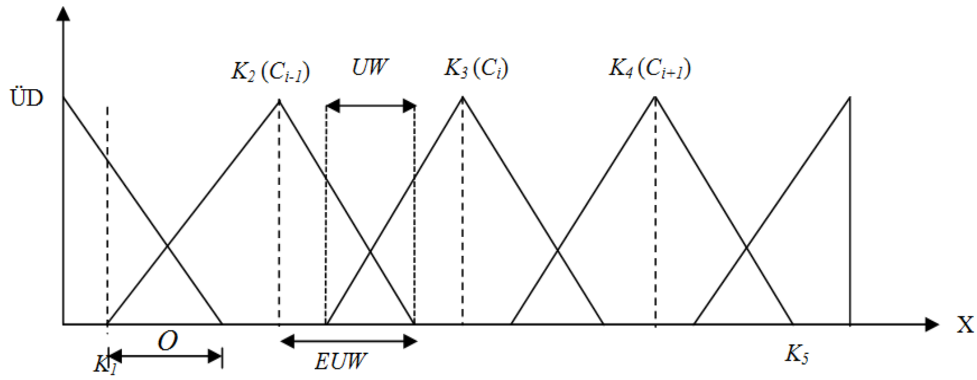

Figure 1. The notation of key value, core value, and unit width for the model.

$$C_{i-1} = K_i = \frac{C_i - X_{min}}{2} + X_{min} \quad (2)$$

$$C_i = \frac{X_R}{2} + X_{min} \quad (3)$$

$$C_{i+1} = X_{mak} - \left(\frac{X_{mak} - K_i}{2}\right) \quad (4)$$

$$UW = \frac{X_R}{n_u} \quad (5)$$

$$O = \frac{UW}{2} \quad (6)$$

$$EUW = \frac{X_R}{n_u} + O \quad (7)$$

$$K_1 = X_{min} + \frac{EUW}{3} \quad (8)$$

$$K_5 = X_{max} - \frac{EUW}{3} \quad (9)$$

4. According to SMRGT, membership functions of all independent variables must consist of at least three fuzzy sets. If more clusters are selected, it must be an odd number. The model error decreases, and the processing volume increases as the number of fuzzy sets in membership functions increases.

5. Overlapping the right triangle parts of fuzzy sets up to the centroid (1/3 and 2/3) in membership functions reduces the error.

6. The key values of the first and last fuzzy sets in the membership function of each independent variable determine the validity range of the fuzzy model. In other words, the model will be valid between the first and last key values of that variable(s). For this reason, it is always helpful to expand the limit ranges of the independent variables. In such a case, the error percentage will automatically decrease when the centroid method is used in the clarification process.

7. Key values such as K1, K2, and K3 are inputs of the fuzzy model.These parameters are determined by trial and error. Based on these parameters, a conclusion can be made in advance.

8. After these processes and work, the dependent variable, in other words, the values of the output, will be determined in response to these selected values of each variable. Output values against these calculated values of the inputs are obtained either experimentally or by an experienced expert. A safe formula in the literature can be used for this purpose. The values obtained in this way will be the key values of the fuzzy sets of the output. The membership function of the output is found in this way. The membership function of the

output will give the fuzzy rule base. Therefore, each key value of the output will yield a rule. Then, the number of fuzzy sets in the membership function of the output will be equal to the number of fuzzy rules, and no combination will be skipped.

9. In this way, after determining both membership functions and rules, the next step is the process. In this process, the fuzzy SMRGT model is optionally run in a package program. The most suitable package program for this job is MATLAB.

10. Input and output files prepared in this program are loaded into the program with a ".dat" extension. If necessary, 4 data files (input and output) can be prepared and loaded into the program for each test and calibration stage. The program is loaded into the program with a ".fis" extension. Then, a file with the ".m" extension is prepared to run the program. Model results are obtained by running this file with the ".m" extension.

11. Preparing the program with this method will save it from the trial and error process. The process volume will be low and short even if it does not. If the membership functions of the output are more intertwined than they usually are, two or more intertwined membership functions must be reduced to one (Toprak, 2009; Torak et al., 2017).

Study Area and the Data Used in the Study

The Kalecik basin, which is the study area, is located in the Upper Euphrates sub-basin of the Euphrates-Tigris Basin in the Eastern Anatolia Region covering Karlıova (Bingöl), Güroymak (Bitlis), and Muş cities and surroundings (Oğuz, 1993). The location of the basin is given in the Figure 2. ; The basin covers the center of Muş, Korkut (Muş), and Varto (Muş) counties, Güroymak (Bitlis) county, and almost half of Karlıova (Bingöl) county.

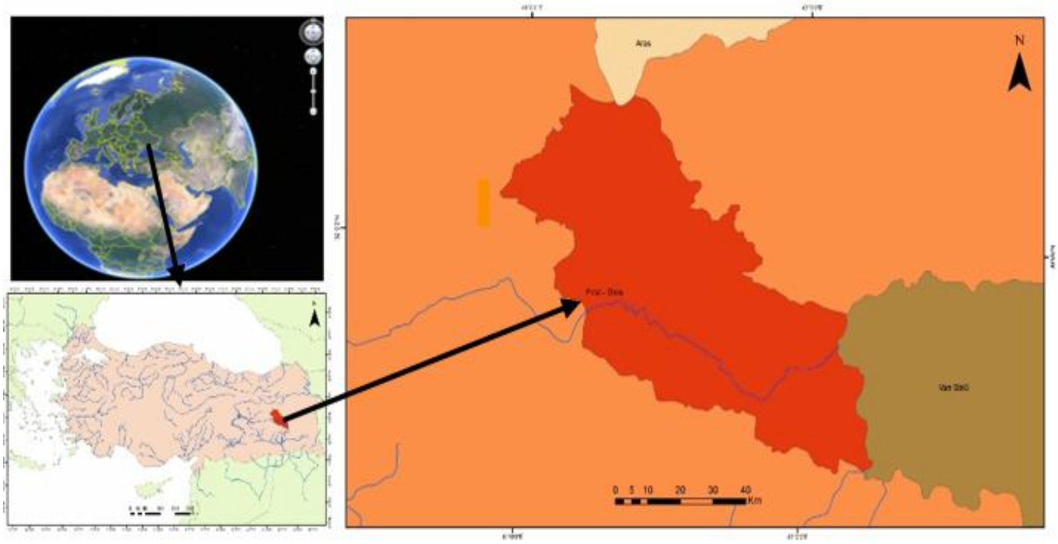

Figure 2. The location map of the Kalecik basin.

The variables affecting the runoff

The effect of the variables related to meteorological and terrain characteristics was reflected in the runoff in the present study.

Meteorological variables

Precipitation

Runoff is directly related to precipitation. Although the amount of precipitation increases in the basin, especially when Güroymak county is approached, it decreases as it approaches Varto and Karlıova counties. In the present study, precipitation data were obtained with the Kriging Method and are given in Figure 3. The range of values found was calculated as the lowest at 583 mm and the highest at 922 mm. However, a minimum 500 mm and a maximum 1200 mm interval were selected for the use and generalization of the model in different basins in the present study.

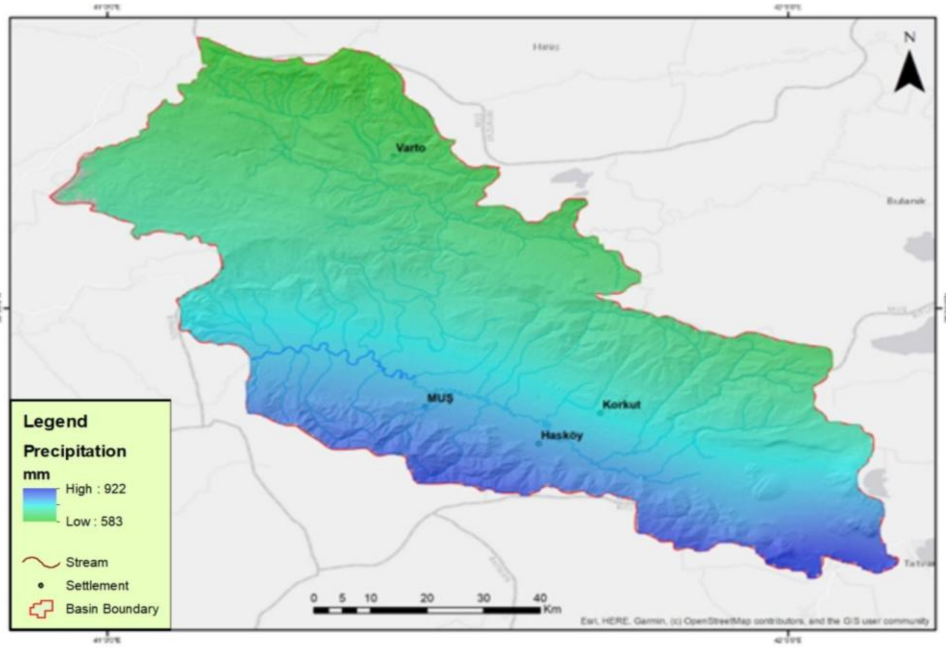

Figure 3. The precipitation map of the Kalecik basin.

Corrected

Evaporation

Evaporation drops to a minimum level in almost half of Karlıova county. The effect of this variable is especially included in the model because it is considered that the remaining amount will runoff after the leakage, retention, and evaporation losses occurring after precipitation are calculated. When the map of the basin was examined, it was seen that evaporation was highest, especially in close place to Güroymak county, and evaporation decreased as it approached Varto and Solhan. In the map obtained with the Kriging Method given in (Figure 4), the basin's lowest evaporation amount for six months was taken as 500 mm after the interpolation process, and the highest value was accepted as 1000 mm.

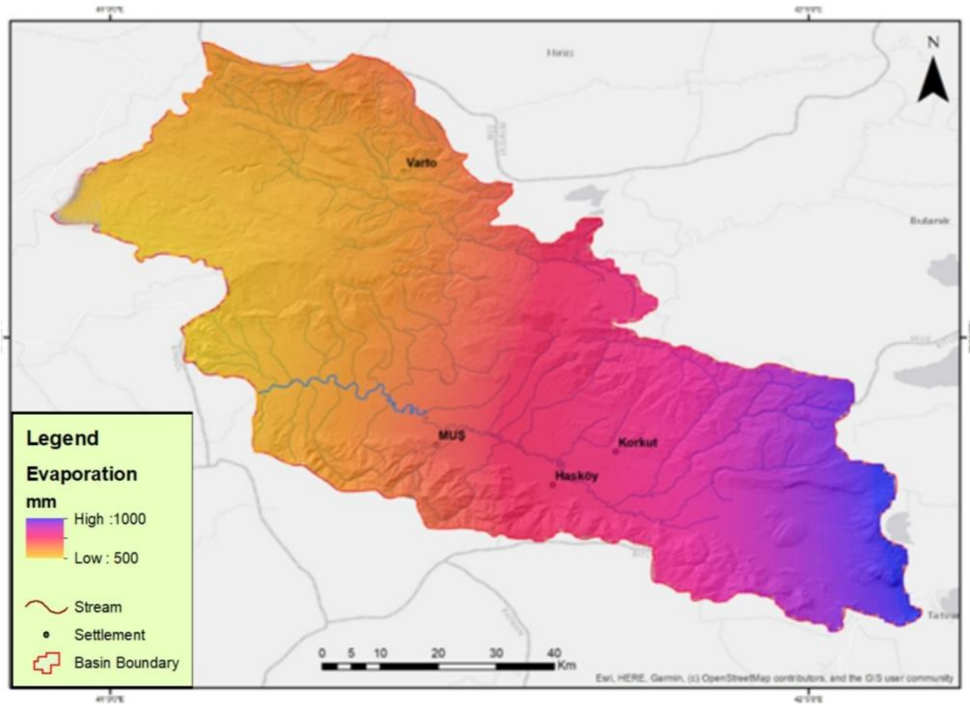

Figure 4. The evaporation map of the Kalecik basin.

The variables dependent on land characteristics

Slope

As a variable, the slope must be used in models and calculations because it significantly affects the runoff when calculating floods in basins. In the Kalecik basin's slope map, especially the areas within the Muş center have the lowest slope values. In this model, the least authority was given to the slope input. It was also noticed that the slope generally increased as the water approached the water separation lines of the basin. In the slope values produced by using DEM in the map in (Figure 5), the minimum slope of the basin was 0°, the average slope was 9.2°, and the maximum slope was 57.2°. The slope values were expanded and chosen as minimum 0° and maximum 90° to generalize the model and allow it to be used in most

basins in our country and the world.

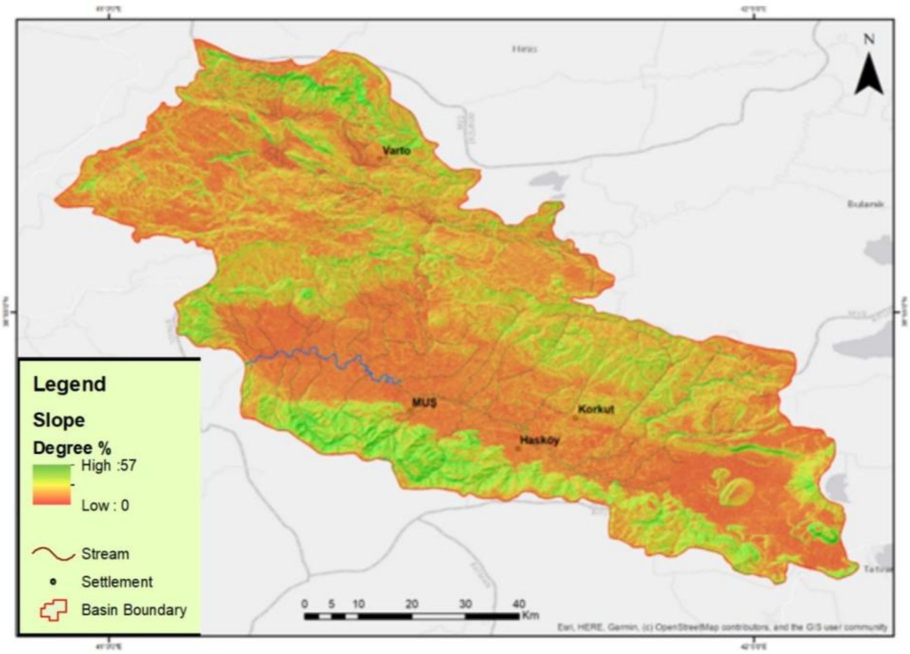

Figure 5. The slope map of the Kalecik Basin.

Land type and use

The residual precipitation after actual precipitation, evaporation and other losses progresses on the ground according to the land type and permeability. Here, land type and use (LTU) was divided into five classes regarding precipitation runoff. Starting from the least permeable, these classes were; "mountainous-rocky", "settlement areas", "sand alluvium," "agricultural and pasture areas," and "forest areas," respectively. To generalize the Fuzzy SMRGT Model developed within the present study's scope to be valid for all types of land use, LTU was taken between 0 and 100%, which showed the infiltration rate or runoff of the remaining precipitation after it changed from precipitation to evaporation. The LTU map produced by the Corin data of the basin is given in (Figure 6). According to this map, agricultural areas primarily covered the basin, followed by forestland, mountainous rocky, sand alluvial, and residential regions.

Results

The application of the fuzzy SMRGT model

The SMRGT Method was used in the present study to determine the fuzzy rule base and membership functions (Table 1). Karakaya et al., (2018) employed the SMRGT Method to determine the runoff coefficient as in the present study. Karakaya et al., (2018) Fuzzy SMRGT Model's was developed using a university's campus data. In this study, the runoff coefficient depended on the slope, land use data, land conditions, impermeability, and saturation degree data were determined using the meteorological runoff coefficient. The meteorological runoff coefficient is determined by temperature and wind data. Şırnak University campus was chosen as the study area. The arithmetic average of these coefficients was converted into a single runoff coefficient. It can be argued that obtaining one single coefficient would be more accurate than the three coefficients developed in Karakaya et al., (2018). However, it would be more realistic to take the weighted average of the three coefficients produced instead of the arithmetic average. Also, the study area remains very small compared to any river basin. The importance of the present study was that the Kalecik Basin is much larger than the Şırnak campus, representing an exemplary study among other basins. Another difference was that four independent variables representing three different basin characteristics were studied as the model's input, and one single coefficient was determined (Karakaya et al., 2018).

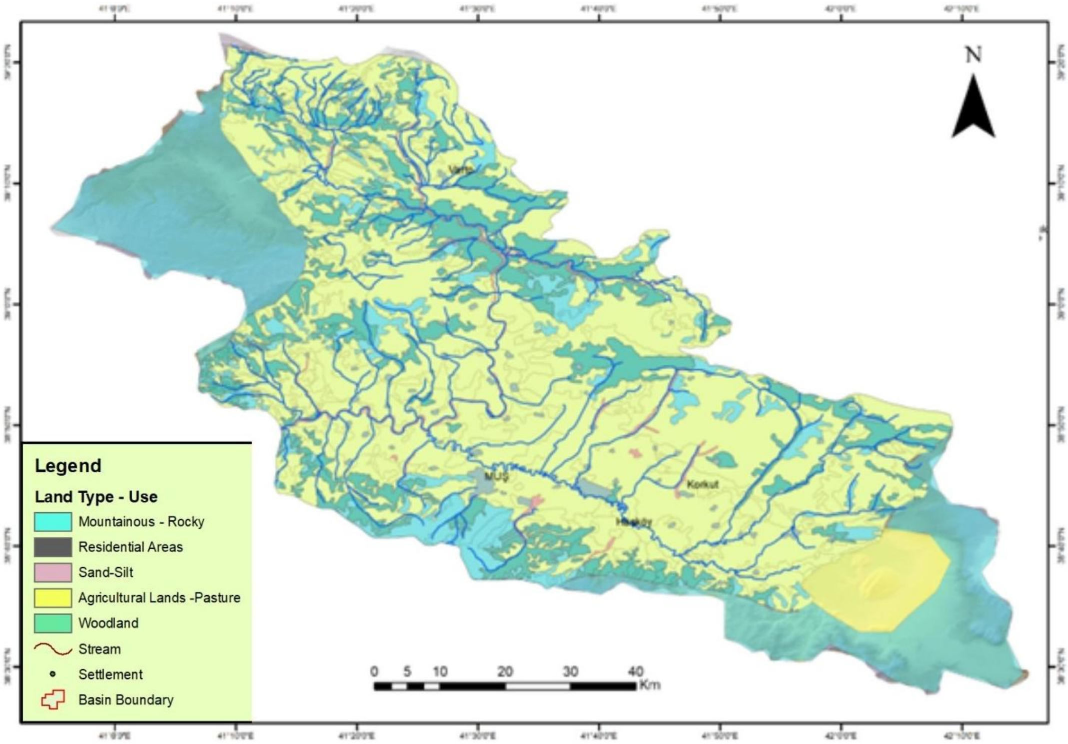

Figure 6. The land type and use map of the Kalecik basin.

Table 1. The key values of the model variables are determined by the SMRGT.

Inputs	Xmin Xmax	XR	UW	EUW	O	K1	K2 = Ci - 1	K3 = Ci	K4 = Ci + 1	K5
Y	500 1200	700.00	87.50	131.25	43.75	543.75	675.00	850.00	1025.00	1156.25
B	500 1000	500.00	62.50	93.75	31.25	531.25	625.00	750.00	875.00	968.75
LTU	0 100	100.00	12.50	18.75	6.25	6.25	25.00	50.00	75.00	93.75
E	0 90	90.00	11.25	16.875	5.625	5.625	22.50	45.00	67.50	84.375
a	0 1	1.00	0.0102	0.0229	0.0051	0.0051	0.0204	0.500	0.5255	0.99491
The relation employed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)

Model results and evaluation

First, the physical relationship between the system inputs and output, which consisted of the dependent and independent variables was determined. The fuzzy relationship was determined by blurring and fuzzy rule base, and the clarification process was determined by the centroid method. SMRGT was used in the fuzzification and determination of the fuzzy rule base. The fuzzy rule base was determined by considering appropriate physical conditions such as “IF”, “WHEN”, and “CONCLUSION”. A few rules about the study are given below as examples.

R1: IF (PRECIPITATION is VL) and (EVAPORATION is VL) and (LTU is VL) and (SLOPE is VL) then (RUNOFF is VL)

[1] The final key value is K_{50} for a (runoff coefficient) given in Table 1.

R2: IF (PRECIPITATION is L) and (EVAPORATION is VL) and (LTU is VL) and (SLOPE is VL) then (RUNOFF is VH)

R3: IF (PRECIPITATION is M) and (EVAPORATION is VL) and (LTU is VL) and (SLOPE is VL) then (RUNOFF is H)

R4: IF (PRECIPITATION is H) and (EVAPORATION is VL) and (LTU is VL) and (SLOPE is VL) then (RUNOFF is M)

R5: IF (PRECIPITATION is VH) and (EVAPORATION is VL) and (LTU is VL) and (SLOPE is VL) then (RUNOFF is L)

Since the model results in 625 rules (14 pages) in total, with all inputs and outputs, fuzzy rule base, and model error, only ten are given in (Table 2) as an example. In the established model, the effects of precipitation, evaporation, LTU, and slope on the runoff coefficient were taken differently with the following equation (Equation 10).

$$a = Y - B \times (1 - \frac{E}{100}) - (B \times \frac{ATK}{100}) \times (1 - \frac{E}{100}) \tag{10}$$

In Equation 10, a refers to the runoff coefficient, Y is the precipitation, B is the evaporation, LTU is the land type and use, and E is the slope.

Table 2. The Fuzzy Rule Base of the SMRGT Model.

Rule No	PRECIPITATION	EVAPORATION	LTU*	SLOPE	$C_{CALC.}$	C_{MODEL}	MARE
1	543.7500	531.2500	6.2500	5.6250	0.0097	0.0025	74.25
2	543.7500	531.2500	6.2500	22.5000	0.0995	0.1019	2.38
3	543.7500	531.2500	6.2500	45.0000	0.2193	0.2243	2.29
4	543.7500	531.2500	6.2500	67.5000	0.3390	0.3266	3.67
5	543.7500	531.2500	6.2500	84.3750	0.4289	0.4286	0.06
6	543.7500	531.2500	25.0000	5.6250	0.0000	0.0025	0.00
7	543.7500	531.2500	25.0000	22.5000	0.0251	0.0204	18.80
8	543.7500	531.2500	25.0000	45.0000	0.1665	0.1631	2.03
9	543.7500	531.2500	25.0000	67.5000	0.3078	0.3062	0.53
10	675.0000	531.2500	6.2500	5.6250	0.1260	0.1223	2.95

For instance, for the median values of each variable, in other words, the precipitation was 850 mm, the evaporation was 750 mm, the LTU was 50%, and the slope was 45°, the output of the model, in other words, the runoff coefficient, was obtained as 0.183.

Another example is given for high values. In this respect, although the precipitation was 1156.25 mm, evaporation was 531.25 mm, LTU was 6.25%, and the slope was 84.4°, the runoff coefficient took the maximum value as 0.996.

The basic logic in Equation 10 corrected is the continuity equation. In other words, if precipitation and slope are minimum and evaporation and LTU are maximum, the runoff coefficient will take the smallest value of 0.00248. If evaporation is minimum, but precipitation and slope are maximum, the runoff coefficient will take its maximum value of 0.996. In this respect, the runoff coefficient has a positive statistical relationship with precipitation and slope variables and a negative statistical relationship with evaporation and LTU variables. In other words, although the independent variable increases with the two variables affecting it, it decreases with the increase of the other two. These examples show that the model works not only mathematically but also physically. If the precipitation is high, the slope is high, the evaporation is low, and the seepage is low, the runoff will be maximum.

Also, statistical quantities were used to compare the model with the data. These statistical quantities were minimum (X_{min}), mean (X_m), maximum (X_{max}), standard deviation (S_x), coefficient of variation ($C_v x$), coefficient of skewness ($C_s x$), and correlation coefficient (R) and Mean Absolute Relative Error (MARE) was chosen as the error type. Statistical comparison results are given in (Table 3). The comparison is also given graphically in (Figure 7) and (Figure 8) with a scatter diagram and a series of graphics.

As seen in the scatter diagram in (Figure 7), the data and the model results are distributed very close to the linear regression line that makes an angle of 45° with the horizontal axis. Note that scatter diagram shows a nearly linear trend line. This trend indicates that the model's predictive power is very high. The trend line angle (regression line) with the horizontal is 45° indicating that the model behaves unbiasedly.

Table 3. The statistical values and errors of the model result.

	Statistical Values							Error
Calculation	Xmin	Xm	Xmax	Sx	CvX	CSx	R	MARE (%)
	0.0000	0.2819	10.000	0.2828	10.033	0.6503	0.992	22.799
Model	0.0018	0.2825	0.9965	0.2819	0.9878	0.6545		

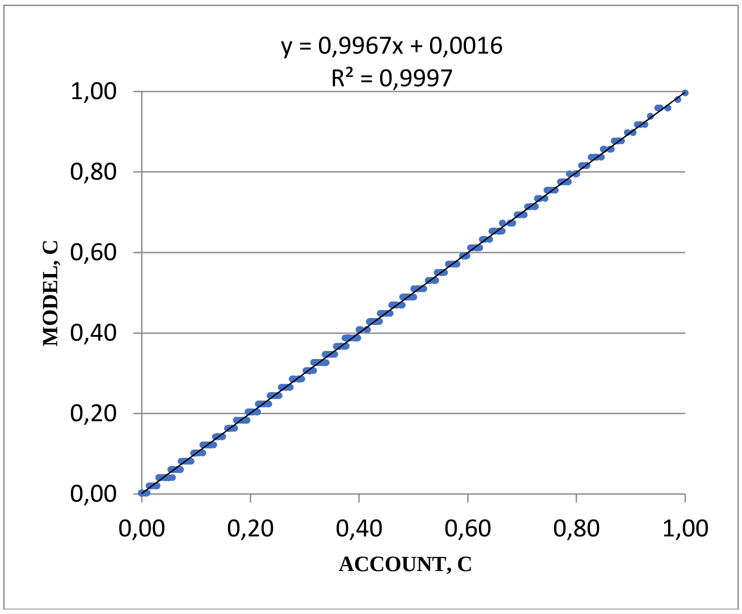

Figure 7. The data obtained as a result of the calculation and the results of the model scatter diagram.

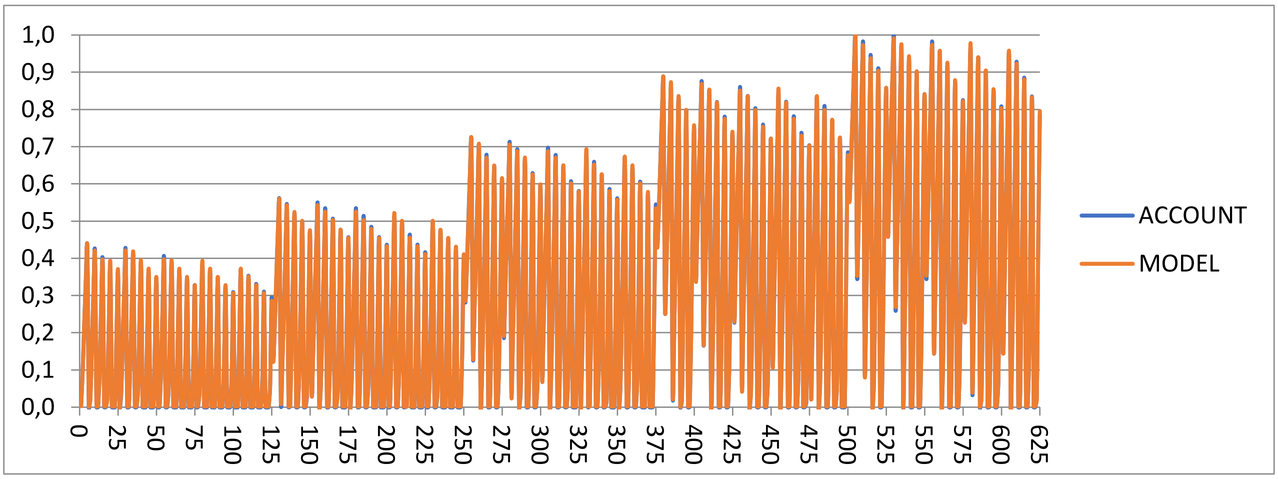

Figure 8. The serial graph of the model results with the data obtained as a result of the calculation.

It is seen in (Figure 8) that there is a perfect fit between the calculation and the model and the lines completely overlap in the series plot between the data and the results. This is considered important because it shows that the model predicts very well, just like the scatter diagram.

The calculated values of the quantities employed in the comparison for the model are given in (Table 3). The statistical relationship between them was measured with the Pearson Correlation Coefficient, calculated as 0.992. Such a high Pearson Correlation Coefficient value indicates a high statistical relationship between the available data and the model results.

Negative values appear during the calculation of the runoff coefficient with Equation 10 . These values are set to zero because negative runoff is not physically possible. When the mean absolute relative error is calculated, infinite values are obtained by dividing by zero. For this reason, negative runoff cases were not considered when calculating the mean absolute relative error. MARE was calculated as 2.2799% due to the calculation in the absence of negative values. (Table 3) shows the statistical sizes of the model results and data. It is seen in (Table 3) that the statistical sizes of the model results (maximum, minimum, average, standard deviation, variation, and skewness coefficients) and the statistical sizes of the data produced by Equation 10 are quite close to each other. The average absolute relative error is low, the statistical quantities are very close to each other, and the correlation coefficient is relatively high, which shows the model's success. In other words, statistical comparison supports visual comparisons positively. For this reason, the Fuzzy SMRGT model is quite successful. In other words, it gives realistic results.

Mapping of the model results

Parameters used in mapping

When the runoff coefficient map was prepared, each input's weight coefficient was calculated with the following equations.

$$b_1 = r_1 \times \frac{1}{\sum_{i=0}^{n}|r|} = 0.2672 \tag{11}$$

$$b_2 = r_2 \times \frac{1}{\sum_{i=0}^{n}|r|} = -0.0928 \tag{12}$$

$$b_3 = r_3 \times \frac{1}{\sum_{i=0}^{n}|r|} = -0.1673 \tag{13}$$

$$b_4 = r_4 \times \frac{1}{\sum_{i=0}^{n}|r|} = 0.4727 \tag{14}$$

Here;
$r_1 =$ The correlation between precipitation and runoff coefficient
$r_2 =$ The correlation between evaporation and runoff coefficient
$r_3 =$ The correlation between LTU and runoff coefficient
$r_4 =$ The correlation between slope and runoff coefficient
If b_1, b_2, b_3 and b_4, are normalized correlations (normalized r_1, r_2, r_3 and r_4)

$$c = 2 \times |b_2 + b_3| \tag{15}$$

$$c = 2 \times |-0.0928 - 0.1673| = 0.5202$$

$$d_1 = \frac{b_1}{b_1 + b_4} \tag{16}$$

$$d_1 = \frac{0.2672}{0.2672 + 0.4727} = 0.3612$$

$$d_4 = \frac{b_4}{b_1 + b_4} \tag{17}$$

$$d_4 = \frac{0.4727}{0.2672 + 0.4727} = 0.6388$$

$$e_1 = b_1 + c \times d_1 \tag{18}$$

$$e_1 = 0.2672 + 0.5202 \times 0.3612 = 0.4551$$

$$e_4 = b_4 + c \times d_4 \tag{19}$$

$$e_4 = 0.4727 + 0.5202 \times 0.6388 = 0.8050$$

Here;
$c =$ Twice the absolute value of the normalized negative correlations
$d_1 =$ The normalized state of positive correlations of b_1 among themselves
$d_4 =$ The positive correlations of b_4 normalized among themselves
$e_1 =$ The map weight coefficient of precipitation
$e_2 =$ The map weight coefficient of evaporation $= b_2$
$e_3 =$ LTU's map weight coefficient $= b_3$
$e_4 =$ The map weight coefficient of slope

Here, evaporation and LTU have a reducing effect because of negative values. In this way, when the average runoff coefficient obtained with the fuzzy SMRGT model is processed on the map, it takes 45.51% of its value from precipitation, 9.28% as an absolute value from evaporation, 16.73% as an absolute value from LTU, and 80.50% from the slope. When the adverse impact is considered, the total is 100%.

According to the runoff coefficient map given in (Figure 9), it is seen that the runoff is very high in the mountainous parts of Muş province, and the runoff increases at some places in Hasköy and Korkut counties. Also, the rise in elevation and slope within short distances in these areas where the mountains meet the plain has a significantly increasing effect on the runoff because Hasköy is located at the foothills of the southern mountains of Bitlis. Also, when the runoff coefficient map given in (Figure 9) is examined, these areas located in the south of the basin are where the precipitation value is higher than in the northern part of the basin, which causes the precipitation to runoff rapidly. It is also seen that the lowest runoff is in Varto, and although it is a high plain area, the decreased amount of precipitation towards the north of the basin ensures that the runoff is low. Between Karlıova and Solhan, there are severe decreases in the runoff. Kalecik basin is an intermountain basin of tectonic origin. Towards the east, the basin narrows in the north-south direction. The streams that originate from mountainous areas and the precipitation water can rapidly be transported to these areas because of the increase in slope and elevation. The groundwater is closer to the surface toward the southeast of the Kalecik basin. Moreover, the presence of iron reeds in this area indicates this case. The rise of the syncline, where a part of it is located in the basin, causes the groundwater to be close to the surface.

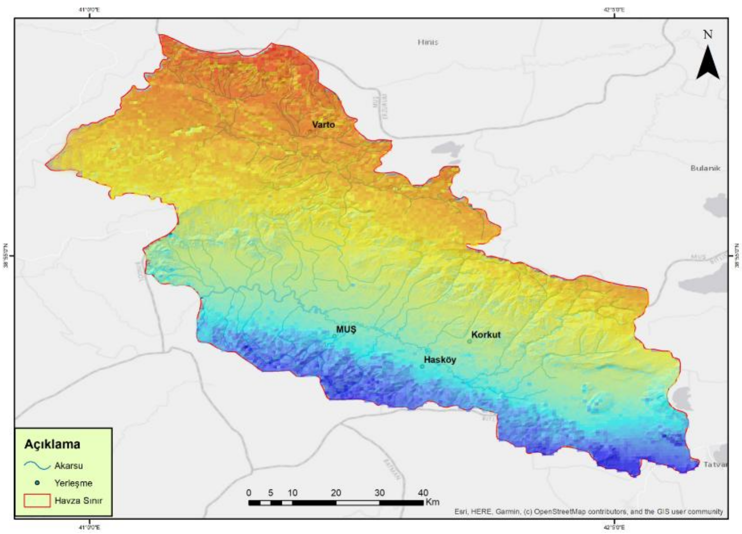

Figure 9. The map of the runoff coefficient.

Conclusion

The accurate calculation of the runoff coefficient, the most crucial variable for bankfull discharge, is essential. However, outdated runoff coefficients calculated with outdated classical methods and transferred to tables according to basin or regions are used instead of calculating the runoff coefficient again with new and more reliable methods specific to the basin. However, the basin's fixed (basin area, LTU) and dynamic (meteorological, hydrological) characteristics must be taken as the basis for calculating the runoff coefficient. Because these features change from basin to basin, the data representing features contain uncertainty. Using uncertain data, it is not realistic to determine the runoff coefficient with deterministic methods. Similarly, using methods that include uncertainty but work as a Black Box method to solve this ambiguous problem can be considered unrealistic. For this reason, it is the most accurate and realistic way to calculate or model the runoff coefficient with methods that contain uncertainty but also include physical cause-effect relationships. The Fuzzy SMRGT, which gives this opportunity, was used in the present study. The SMRGT was used to determine the membership functions of the input and output variables and the fuzzy rule base. The Kriging method was used for precipitation and evaporation maps of the basin, and the Digital Elevation Model was used for slope and LTU maps.

A fuzzy model with four inputs and one output was prepared to determine the runoff coefficient.

In the fuzzy model, the runoff coefficient is calculated by using the following variables. Meteorological precipitation and evaporation, land use and types depend on land characteristics and geomorphological slope variables. The weight coefficient of each model variable was calculated, and the runoff coefficient map was prepared. The data results were compared with the model results using six statistical quantities. These quantities are maximum, minimum, mean, standard deviation, coefficient of variation and skewness, Pearson Correlation Coefficient, and Mean Absolute Relative Error (MARE). Also, the comparison results were visualized with a scatter diagram and different graphics. All criteria based on comparison show that the model yields realistic results.

The following conclusions may be inferred from the test results obtained in this study. The models trained with pure datasets in the calculations of the runoff coefficient will only be valid for that basin and region. They will only partially reflect the reality of another basin and area. Therefore, they cannot be generalized. However, the fuzzy SMRGT Model developed explicitly for Kalecik Basin's model can be used with small interventions for other basins. The Fuzzy SMRGT Method is preferred because it allows for reflecting the expert opinion on the model in an accurate way. Finally, according to DSI data, the average runoff coefficient of the basins in Turkey was 0.37. The Kalecik Basin's runoff coefficient is 0.28. Therefore, considering Turkey's average, the water-holding capacity of the basin is relatively higher, and the probability of floods is low.

References

Altaş, E., Aydın, M. C., & Toprak, Z. F. (2018). Modeling water surface profile in open channel flows using Fuzzy SMRGT method. *Dicle University Journal of Engineering (DUJE), 9*(2), 975–981.

Cleveland, T. G., He, X., Asquith, W. H., & Fang, X. (2006). Instantaneous unit hydrograph evaluation for rainfall-runoff modeling of small watersheds in north and south central Texas. *Journal of Irrigation and Drainage Engineering, 132*(5), 479–485. https://doi.org/10.1061/(ASCE)0733-9437(2006)132:5(479)

Gunal, A. Y., & Mehdi, R. (2023). Forecasting the flow coefficient of the river basin using adaptive fuzzy inference system and fuzzy SMRGT method. *Journal of Ecological Engineering, 24*(7), 96–107. https://doi.org/10.12911/22998993/160331

Karakaya, D., Toprak, Z. F. (2018). Classification Water Losses in Water Distribution Networks Using ZFT Algorithm. *Su Kaynakları,* 3(2), 22-30.

Kumar, P., Lohani, A. K., & Nema, A. K. (2017). Rainfall-runoff modeling using MIKE 11 NAM model. *Current World Environment, 14*(1), 27–34. https://doi.org/10.12944/CWE.14.1.04

Merz, R., Blöschl, G., & Parajka, J. (2006). Spatio-temporal variability of event runoff coefficients. *Journal of Hydrology, 331*(3–4), 591–604. https://doi.org/10.1016/j.jhydrol.2006.06.017

Mimikou, M., & Rao, A. R. (1983). Regional monthly rainfall-runoff model. *Journal of Water Resources Planning and Management, 109*(1), 75–93. https://doi.org/10.1061/(ASCE)0733-9496(1983)109:1(75)

Nayak, T., & Jaiswal, R. (2003). Rainfall-runoff modelling using satellite data and GIS for Bebas River in Madhya Pradesh. *Journal of the Institution of Engineers, India. Civil Engineering Division, 84*(Mai), 47–50.

Oğuz, E. (1993). Natural regions and environs of Turkey. *Aegean Geographical Journal, 7*(1), 13–41.

Palta, Ş., Yurtseven, İ., & Aksay, H. (2019). Rainfall-runoff interactions of Göksu River Basin. *Journal of Bartin Faculty of Forestry, 21*(3), 860–872.

Parida, B. P., Moalafhi, D. B., & Kenabatho, P. K. (2006). Forecasting runoff coefficients using ANN for water resources management: The case of Notwane catchment in Eastern Botswana. *Physics and Chemistry of the Earth, Parts A/B/C, 31*(15–16), 928–934. https://doi.org/10.1016/j.pce.2006.10.004

Savenije, H. H. G. (1996). The runoff coefficient as the key to moisture recycling. *Journal of Hydrology, 176*(1–4), 219–225. https://doi.org/10.1016/0022-1694(95)02763-3

Sedki, A., Ouazar, D., & Mazoud, E. El. (2009). Evolving neural network using real coded genetic algorithm for daily rainfall-runoff forecasting. *Expert Systems with Applications, 36*(3), 4523–4527. https://doi.org/10.1016/j.eswa.2008.06.085

Toprak, Z. F. (2009). Flow discharge modeling in open canals using a new fuzzy modeling technique (SMRGT). *CLEAN–Soil, Air, Water, 37*(9), 742–752. https://doi.org/10.1002/clen.200900027

Toprak, Z. F. (2019). Bilimsel araştırmalarda yöntem seçimi. In *Proceedings of the 2nd International Congress on Engineering and Technology Management* (pp. 1–7). Mardin, Turkey.

Toprak, Z. F., Songur, M., & Hamidi, N. (2013). Determination of losses in water-networks using a new fuzzy technique (SMRGT). *Global Journal on Technology, 3*(2013), 833–840. https://doi.org/10.18844/gjt.v3i2013.1220

Toprak, Z. F., Toprak, A., & Aykaç, Z. (2017). Practical applications of fuzzy SMRGT method. *Dicle University Journal of Engineering (DUJE), 8*(1), 123–132.

Tsykin, E. (1985). Multiple nonlinear statistical models for runoff simulation and prediction. *Journal of Hydrology, 77*(1–4), 209–226. https://doi.org/10.1016/0022-1694(85)90212-5

Üneş, F., Demirci, M., Zelenakova, M., Çalışıcı, M., & Taşar, B. (2020). River flow estimation using artificial intelligence and fuzzy techniques. *Water, 12*(9), 2427. https://doi.org/10.3390/w12092427

Üstün, İ., Üneş, F., Mert, İ., & Karakuş, C. (2020). A comparative study of estimating solar radiation using machine learning approaches: DL, SMRGT, and ANFIS. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 44*(4), 10322–10345. https://doi.org/10.1080/15567036.2020.1825135

Yalaz, S., & Arife, A. (2016). Fuzzy linear regression for the time series data which is fuzzified with SMRGT method. *Süleyman Demirel University Journal of Natural and Applied Sciences, 20*(3), 405–413.