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The impact of land use and slope change in flow coefficient estimation

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Abstract

The prediction of floods, which are widely recognized as one of the most devastating hazards on our planet, poses significant challenges primarily stemming from the absence of a dependable forecasting model. Following seismic events, floods rank as the costliest natural calamity in Turkey. The mitigation of existing challenges can be significantly enhanced through the utilization of flow coefficient calculations, which serve as the foremost determinant of flood flow dynamics. The extant body of literature encompasses a diverse range of methodologies for modelling flow coefficients. However, the majority of these methods depend on black-box techniques that lack transferability. The selection of the fuzzy SMRGT Method for this investigation was based on its consideration of the underlying physics of the event, making it a novel approach. The land use and slope data of the Aksu river basin were utilized. The outcomes generated by the model were compared to the empirical data. The evaluation of the model's performance encompassed various metrics, such as root mean square error, mean absolute error, mean absolute relative error, and coefficient of determination. The findings indicated that the fuzzy inference system that was proposed exhibited a high level of predictive accuracy, as evidenced by an overall coefficient of determination (R^2) of 0.998.

1. Introduction

The flow coefficient is a metric that measures the amount of surface water flow in a particular region during a precipitation event. The parameter being discussed is highly important in hydrological modelling and plays a critical role in designing stormwater management systems and other water-related infrastructure. The estimation of the flow coefficient in river basins is of great importance in the field of water resource management. The process involves estimating the flow of water in a river or stream, which is a crucial factor in water resource planning, decision-making, flood control, water allocation, and environmental preservation. Various techniques are used to calculate the flow coefficient in a river basin. These techniques include empirical equations, hydrological modelling, and data-driven methodologies. The methodologies rely on different input variables, such as precipitation, temperature, land use, topography, and soil properties in the specified research area. There has been a growing trend towards the development of machine learning and artificial intelligence techniques to estimate flow coefficient in recent times. These methodologies have the ability to effectively manage large and complex datasets, resulting in more accurate estimations compared to traditional approaches.

Surface flow is a result that occurs when climate, topography, and land utilization interact within a hydrological basin. Climate change has the ability to change the way precipitation is distributed over space and time, which in turn affects the amount and distribution of flow. Changes in land use and slope can have an effect on flow processes, which in turn can impact the occurrence of surface flow. It is important to recognize the significant impact of human activities in addition to the alteration of climate patterns on the modification of runoff patterns [1]. The hydrological processes of river basins are significantly affected by the global implications of land cover and climate change [2,3]. The hydrological processes of basins are directly influenced by land-use changes, as these changes are closely tied to the characteristics of land cover [4-7]. Regions with high levels of precipitation but limited vegetation are known for their significant and rapid flow. Consequently, these areas are particularly susceptible to immediate consequences resulting from alterations in land use. Conversely, regions characterized by reduced precipitation and ample vegetation exhibit comparatively diminished and postponed consequences. The veracity of this information is corroborated by a scholarly investigation [8].

The flow coefficient is affected by various factors, including slope, land use, soil type, and vegetation cover. This response will focus on predicting the flow coefficient value based on slope and land use. The slope is an important factor that affects the flow coefficient. In general, the steeper the slope, the higher the flow coefficient, as water is able to run off more quickly on steep slopes. However, the relationship between slope and flow coefficient is not linear, and other factors such as soil type and vegetation cover can also affect the relationship. Land use is another important factor that affects the flow coefficient. Different land use types, such as urban areas, forests, and agricultural land, have different surface characteristics that affect how water flows over them. For example, urban areas typically have large impervious surfaces, such as pavement and buildings, which can increase the flow coefficient by preventing water from infiltrating the soil. On the other hand, forests and other natural areas typically have more vegetation cover, which can reduce the flow coefficient by increasing infiltration and reducing flow. By developing accurate predictive models, we can better understand how water flows through different types of landscapes and make more informed decisions about managing and protecting our water resources.

This study utilizes a unique methodology, first introduced by Toprak [9], to develop a model for the flow coefficient of the Aksu River basin. The SMRGT approach is a versatile methodology that takes into account the causal relationship between physical factors. This makes it applicable to a wide range of scenarios. The use of basic membership functions and the creation of fuzzy rules enables the incorporation of expert knowledge and domain-specific data. This makes this approach applicable to a wide variety of problem types. As a result, it was considered more favorable in this study.

2. Material and Method

2.1. Materials

The Aksu River Basin has been chosen as the focal area for this research, with geographical coordinates ranging from 36 to 38 degrees north latitude and 30 to 31 degrees east longitude. The Aksu River spans a distance of approximately 370 kilometres, while its mouth exhibits a width of 100 metres. The Aksu River Basin sub-basin, which is situated within the Antalya Basin, holds significant importance as a water resource in the region. It serves as a crucial supplier of irrigation water for agricultural activities and fulfils the drinking water requirements of the local populace. The organization is currently confronted with various challenges pertaining to the management of water resources, the promotion of environmental sustainability, and the facilitation of socio-economic development. Therefore, it offers a significant domain for scholarly investigation and examination of diverse subjects pertaining to sustainable development, water resource management, and environmental preservation.

2.2. Methods

2.2.1. Simple membership functions and fuzzy rules generation technique

The development of a fuzzy database model encompasses two crucial stages: the establishment of a membership function (MF) and the definition of fuzzy rules (FR). Numerous methodologies and algorithms have been suggested for the construction of membership functions (MFs) and fuzzy rules (FRs). The aforementioned techniques encompass genetic algorithms [10], artificial neural networks (ANNs) [11], Kalman filters [12], and probability measurements [13]. Nevertheless, there has been a lack of comprehensive attempts to optimize both MFs and FRs simultaneously. Several strategies have been suggested for estimating the dimensions and configuration of multifractals (MFs), as well as the quantity and structure of fractal regions (FRs). Nevertheless, the implementation of these strategies requires a significant amount of time and substantial computational resources. The process of ascertaining MFs (membership functions) and FRs (fuzzy rules) necessitates a greater investment of time and effort in comparison to alternative methodologies. Notwithstanding the utilization of these methodologies, it may still be imperative to employ a trial-and-error methodology.

The estimation of membership functions (MFs) and fuzzy rules (FRs) should ideally have high levels of accuracy, intuitiveness, and require minimal data processing. The objective of this study was to determine the flow coefficient of the Aksu River Basin using the Simple Membership functions and the fuzzy Rules Generation Technique (SMRGT). This methodology was introduced by [9]. This approach requires a small number of key values for the membership functions of both input and output variables. As a result, it is easier to use and more reliable compared to other methodologies. The SMRGT model offers users the flexibility to choose both the minimum and maximum values of the model. This feature enhances its suitability for a wide range of intended values. This methodology takes into account the cause-and-effect relationship between physical factors and their impacts, making it potentially applicable to different basins or regions. Accurately estimating the flow coefficient in rivers is crucial for efficiently managing water resources, designing water structures, and reducing the risks associated with flood disasters.

2.2.2. Model procedure

The following steps can be summarized as the procedure of the model used:

1- The independent variables (inputs) and dependent variables (outputs) were identified. The independent variables included the Aksu River basin's land use and slope information, while the dependent variable was the flow coefficient. The methodology used in this investigation did not require the data sets to be divided into a calibration and testing subset due to its nature.
2- For each variable, the maximum and minimum values were assigned. These intervals can remain as large as desired. For land use (LU) range was (0-100), and the slope (S) was (0 - 90°).
3- The Membership function for each independent variable was created using five fuzzy sets labelled as very low (VL), low (L), medium (M), high (H), and very high (VH) (Figure 1). According to [9], having a large number of membership functions can reduce the error of the model, but this can also increase the program load, which refers to the volume of processing. The shape of the membership functions (MFs) was determined to be triangular, as generally preferred in the literature.

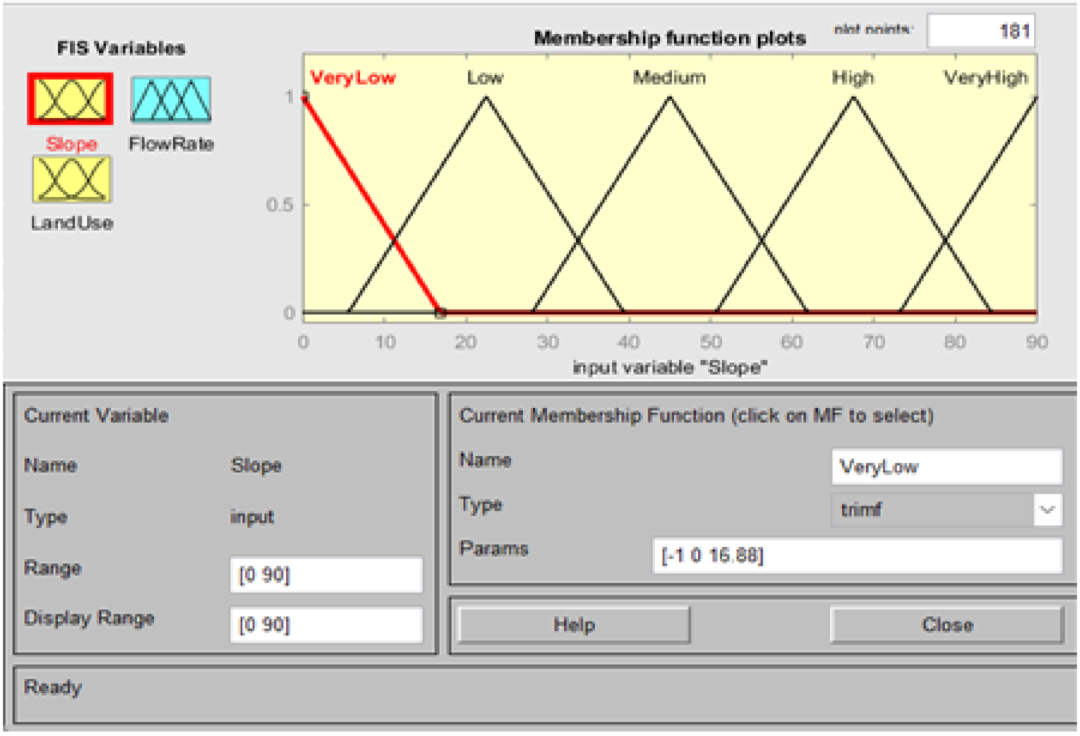

Figure 1. MFs of the inputs.

4- The Equation 1-9 were used to calculate the key values (K_1- K_5) and the core value (C_i) of the membership functions, the unit width (UW), the symmetrically extended unit width (EUW) for each membership function, the value (O) of the two intersecting neighbor membership, and the number of right-angled triangles (nu) in the fuzzy triangular set for each independent variable (Figure 2):

$$Vr = (LU, S)\max - (LU, S)min \tag{1}$$

$$Ci = K3 = \frac{Vr}{2} - (LU, S)min \tag{2}$$

$$UW = \frac{Vr}{nu} \tag{3}$$

$$O = \frac{UW}{2} \tag{4}$$

$$EUW = UW + O \tag{5}$$

$$K4 = Ki = Ci + 1 = \left(\frac{Ci - (LU,S)min}{2}\right) + (LU,S)min \quad (6)$$

$$K2 = Ci - 1 = (LU,S)max - \left((LU,S)max - \frac{Ki}{2}\right) \quad (7)$$

$$K1 = (LU,S)min + \left(\frac{EUW}{3}\right) \quad (8)$$

$$K5 = (LU,S)max - \frac{EUW}{3} \quad (9)$$

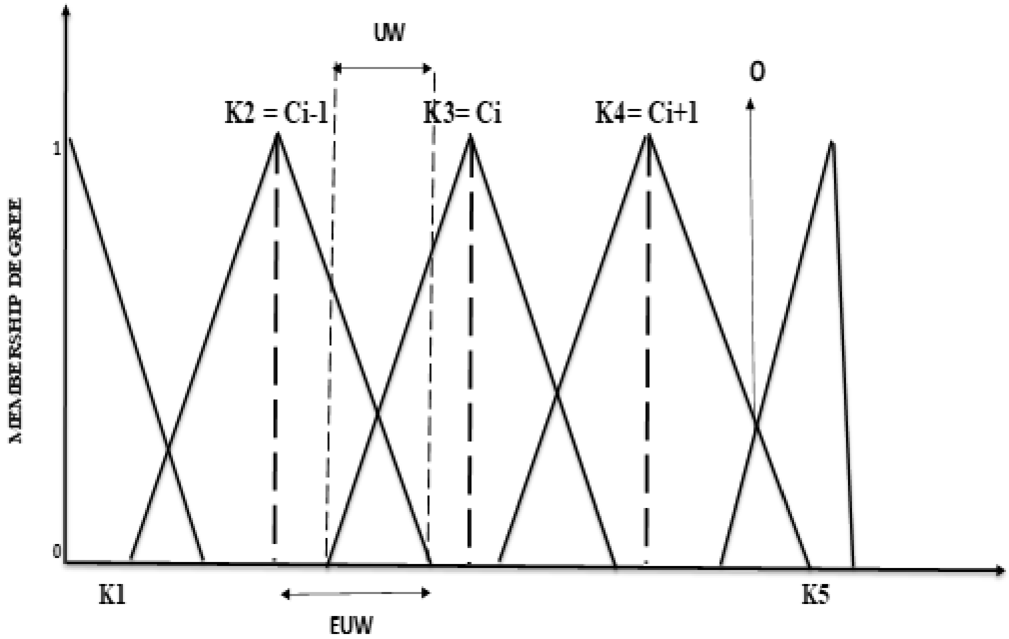

Figure 2. Construction of triangular MFs.

The calculated key values are the inputs of the model for each land use (LU), and slope (S) key values are shown in Figure 3 and Figure 4.

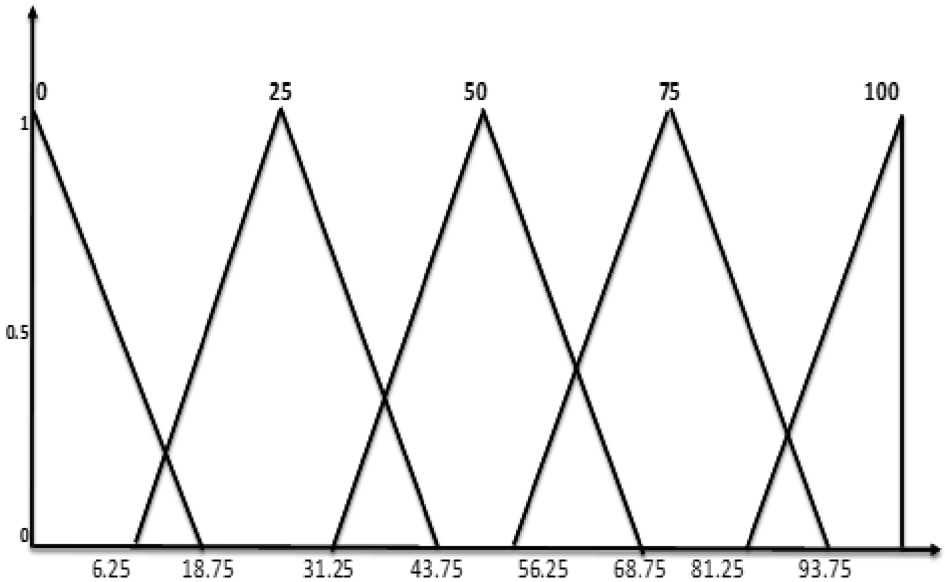

Figure 3. Key values of the land use (LU).

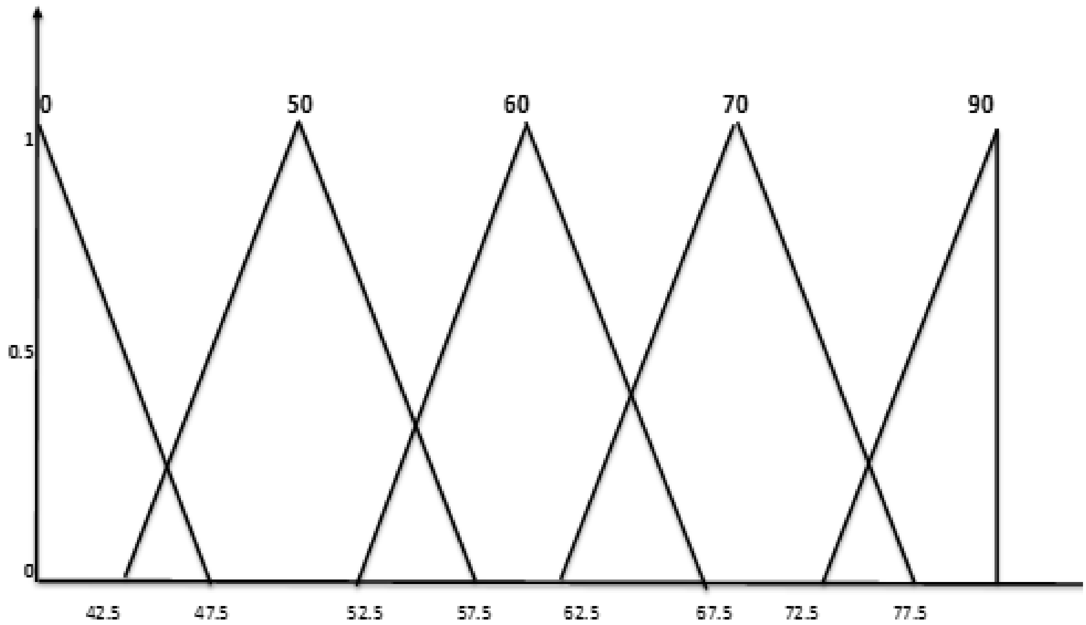

Figure 4. Key values of the slope (S).

5- Once the fuzzification process is complete, the fuzzy rules base is created. The fuzzy rules base is determined by taking into account relevant physical conditions such as "IF", "AND", and "THEN", as shown in Figure 5.

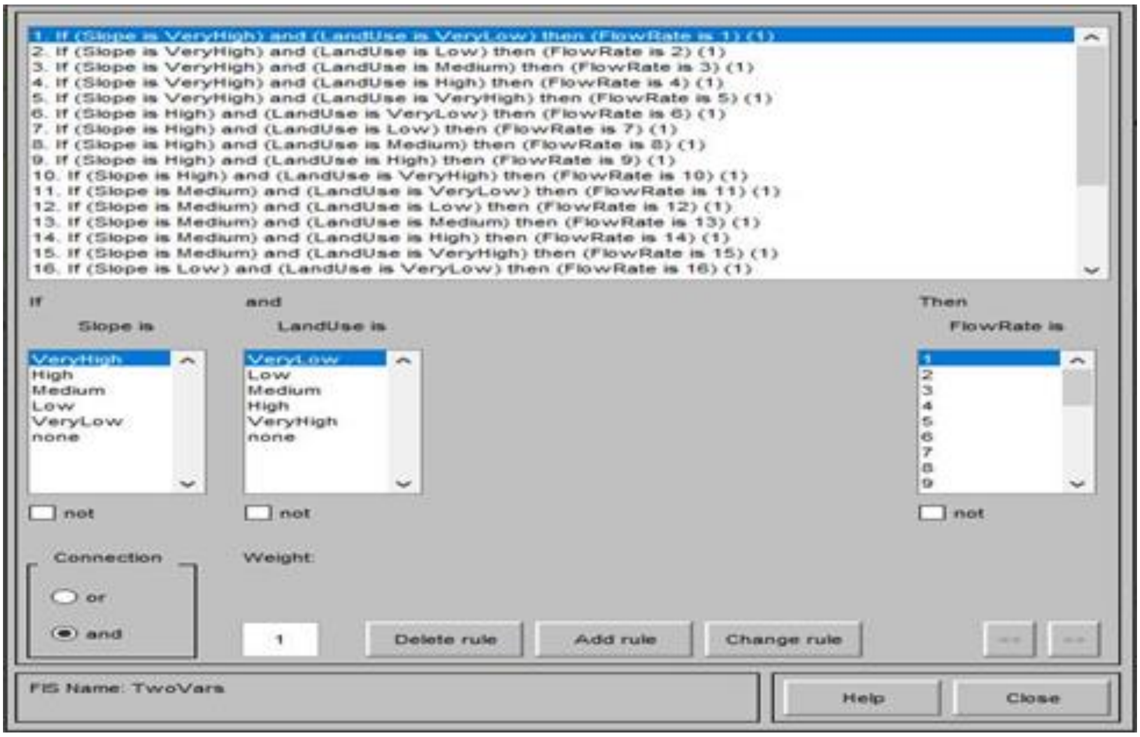

Figure 5. Fuzzy rules generation.

6- The model was implemented using MATLAB software, and the Mamdani algorithm was used as the operator. The centroid method was chosen for the defuzzification procedure. Input and output files were prepared with a .dat extension and added to the program. The program was then loaded with a .fis extension, and a .m extension file was created to run the program. This approach minimized the trial-and-error process. Finally, a table of the fuzzy set was generated to obtain the model results. Membership functions of the model output are shown in Figure 6.

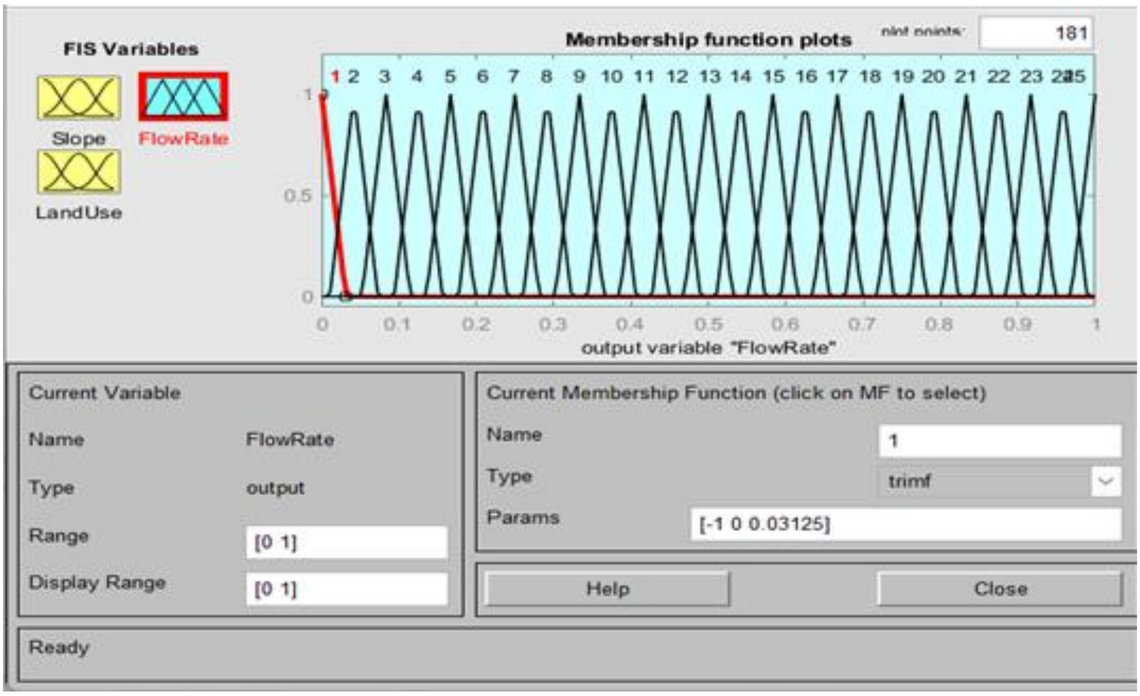

Figure 6. MFs of the model output.

2.2.3. Model performance evaluation

The evaluation of the model results was conducted in order to assess the accuracy and reliability of the SMRGT model. The performance evaluation metrics employed encompassed the mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and Nash-Sutcliffe efficiency (NSE). A NSE value of 1 signifies an ideal correspondence between the modelled and observed values, while a value of 0 indicates that the model predictions are as precise as the mean of the observed values. A negative value of the Nash-Sutcliffe Efficiency (NSE) implies that the model's predictive performance is inferior to that of the mean of the observed values. The parameters are formally defined in Equation 10-13.

$$MAE = \frac{1}{n}\sum_{1}^{n}|\mathrm{Ar} - \mathrm{Pr}| \tag{10}$$

$$MARE = \frac{1}{n}\sum_{1}^{n}\left|\frac{(\mathrm{Ar} - \mathrm{Pr})}{\mathrm{Ar}}\right| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(Ar - Pr)^2} \tag{12}$$

$$NSE = 1 - \frac{\sum_{1}^{n} Ar - Pr}{\sum_{1}^{n} Ar - \bar{A}} \tag{13}$$

Where Ar is the actual data, Pr is the predicted data, and A (bar) is the mean value of the actual data.

3. Results

The main aim of this study was to determine the flow coefficient value in the Aksu River Basin by employing a fuzzy logic model implemented via MATLAB software. The selection of the Mamdani method was made for the operating system, with the centroid method being employed for the process of defuzzification. The determination of input and output key values involved the utilization of precise mathematical formulas. Based on the SMRGT method, it is recommended that the number of rules be equivalent to the model output, specifically the flow coefficient, as determined to be 25 in the present study. Upon executing the model, the outcomes were acquired. Table 1 presents comprehensive information regarding the inputs and outputs of the model.

Table 1. Fuzzy sets.

Rule No	Slope		Land use		Flow Coefficient	Flow Coefficient	MARE
	Numerical	Verbal	Numerical	Verbal	(data)	(model)	
1	5.625	Very low	6.25	Very low	0.01	0.00869	0.000
2	5.625	Very low	25	Low	0.0345	0.044	0.138
3	5.625	Very low	50	Medium	0.08	0.0835	0.707
4	5.625	Very low	75	High	0.122	0.125	0.863
5	5.625	Very low	93.75	Very high	0.162	0.167	0.709
6	22.5	Low	6.25	Very low	0.2021	0.2	1.112
7	22.5	Low	25	Low	0.2412	0.25	1.000
8	22.5	Low	50	Medium	0.28	0.29	0.462
9	22.5	Low	75	High	0.325	0.33	0.179
10	22.5	Low	93.75	Very high	0.362	0.375	0.174
11	45	Medium	6.25	Very low	0.4026	0.417	0.570
12	45	Medium	25	Low	0.4487	0.46	0.404
13	45	Medium	50	Medium	0.489	0.5	0.283
14	45	Medium	75	High	0.525	0.542	0.130
15	45	Medium	93.75	Very high	0.568	0.58	0.085
16	67.5	High	6.25	Very low	0.613	0.625	0.355
17	67.5	High	25	Low	0.652	0.663	0.321
18	67.5	High	50	Medium	0.675	0.7	0.148
19	67.5	High	75	High	0.7133	0.75	0.091
20	67.5	High	93.75	Very high	0.75	0.79	0.068
21	84.375	Very high	6.25	Very low	0.8	0.83	0.545
22	84.375	Very high	25	Low	0.812	0.875	0.522
23	84.375	Very high	50	Medium	0.855	0.917	0.409
24	84.375	Very high	75	High	0.944	0.958	0.306
25	84.375	Very high	93.75	Very high	1	0.996	0.036

Based on the data presented in the table, it is evident that the flow coefficient value varied within the range of 0 to 1. The highest flow coefficient value recorded was 0.99, which was attained under conditions of extremely high land use (98%) and steep slope (87.7°) (Figure 7). Conversely, the lowest flow coefficient value observed was 0.00832, which occurred when land use was exceptionally low (4.47%) and slope was relatively gentle (4.27°) (Figure 8).

Figure 7. The maximum value of the output.

Figure 8. The minimum value of the output.

In order to assess the performance of the SMRGT model, various parameters including mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and Nash-Sutcliffe efficiency (NSE) were employed. The outcomes of the statistical comparisons are presented in Table 2, as depicted in Figure 9. Furthermore, the comparison was illustrated using a scatter diagram (Figure 10) and a variation plot (Figure 11).

Table 2. Statistical parameters for model testing.

Coefficient of Determination (R^2)	0.98
Nash-Sutcliffe efficiency (NSE)	0.993
Mean Absolute Error (MAE)	2%
Mean Absolute Relative Error (MARE)	10%
Root Mean Square Error (RMSE)	2.30%

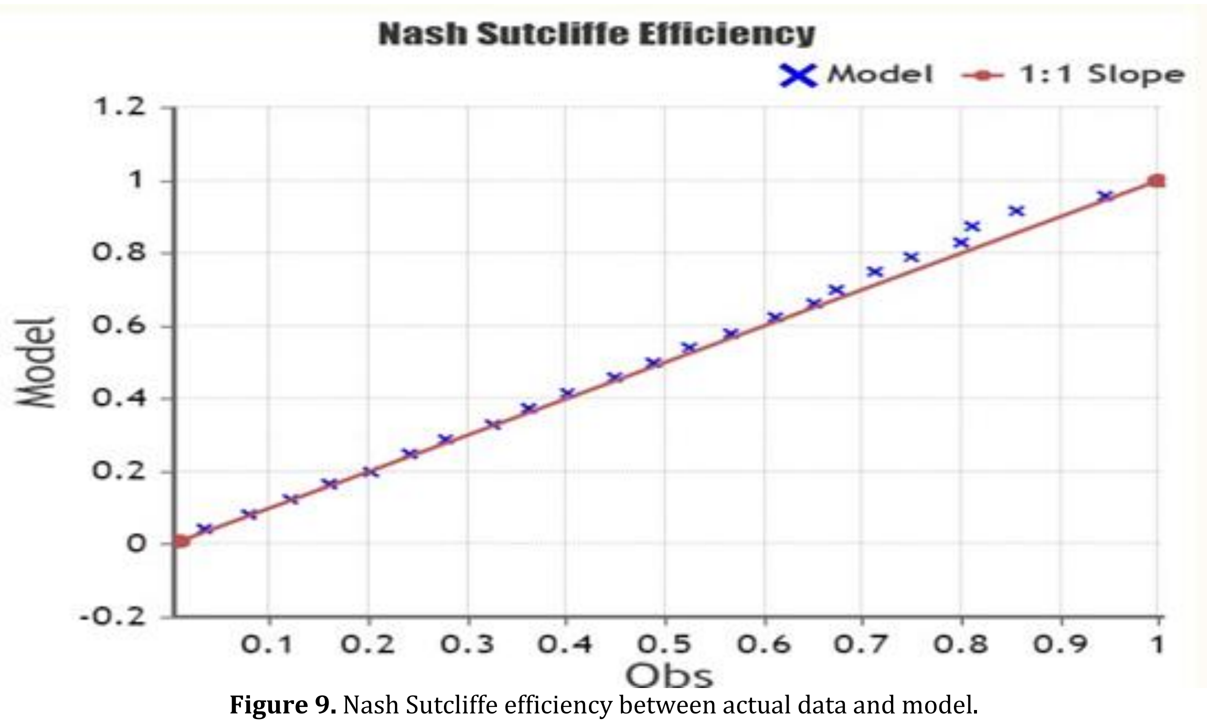

Figure 9. Nash Sutcliffe efficiency between actual data and model.

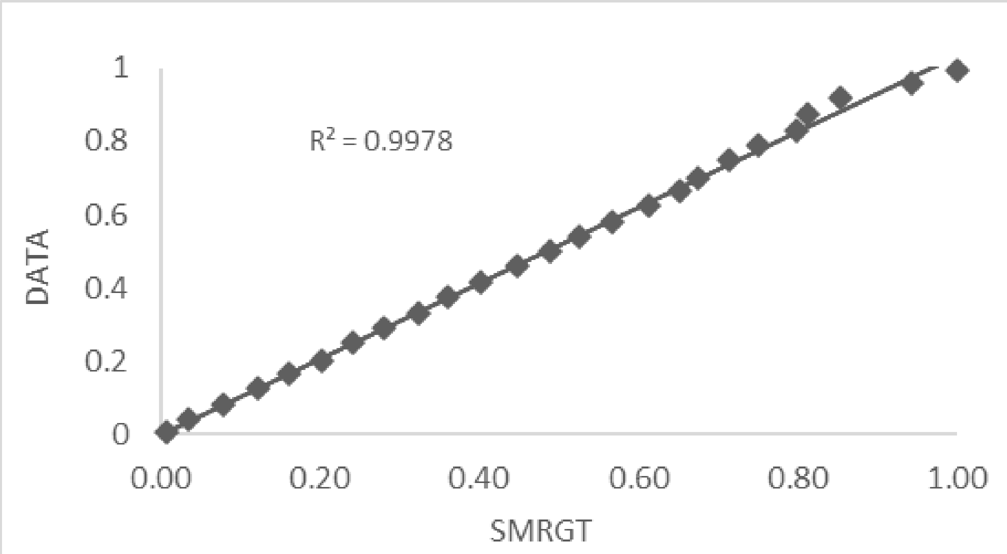

Figure 10. Scatter diagram of the data and model.

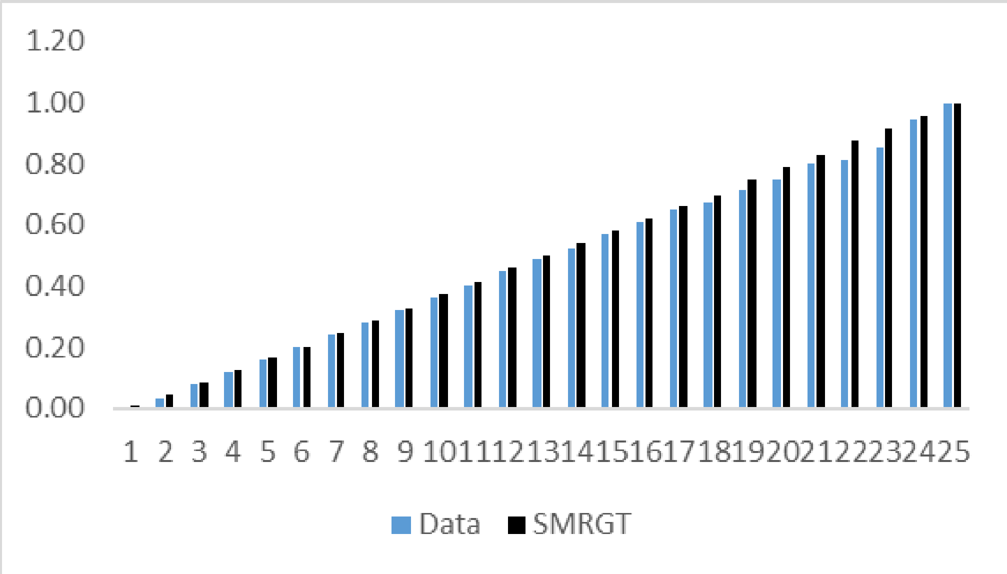

Figure 11. Variation plot of the data and model.

4. Discussion

Based on the empirical evidence, it can be observed that there is a negative correlation between the flow coefficient and both the slope and land use. Specifically, when both the slope and land use are low, the flow coefficient tends to be low as well. Conversely, when both the slope and land use are high, the flow coefficient tends to be high. This finding validates the prevailing knowledge that flow coefficients exhibit higher values in regions characterized by a greater proportion of impervious surfaces, such as urban areas, while displaying lower values in regions with a higher prevalence of vegetation, such as forests or grasslands. In a similar vein, it can be observed that regions characterized by gradual inclines exhibit greater flow coefficients in contrast to areas with steep inclines. This observation suggests that the model is capable of generating outcomes that closely resemble reality. The scatter plot demonstrates that the regression line intersects the horizontal axis at an approximate angle of 45 degrees. This suggests that the model is unbiased, meaning that it does not consistently overestimate or underestimate the predicted values in relation to the observed data. The substantial coefficient of determination (R^2 = 0.98) indicates that there exists a statistically significant relationship between the model and the data, which can be mathematically represented. Furthermore, the model successfully captures the underlying pattern observed in the data. The majority of the data points are situated in close proximity to the regression line, suggesting a strong numerical agreement between the model's outcomes and the observed data. Figure 12 depicts the spatial correlation between the dependent and independent variables in a three-dimensional manner.

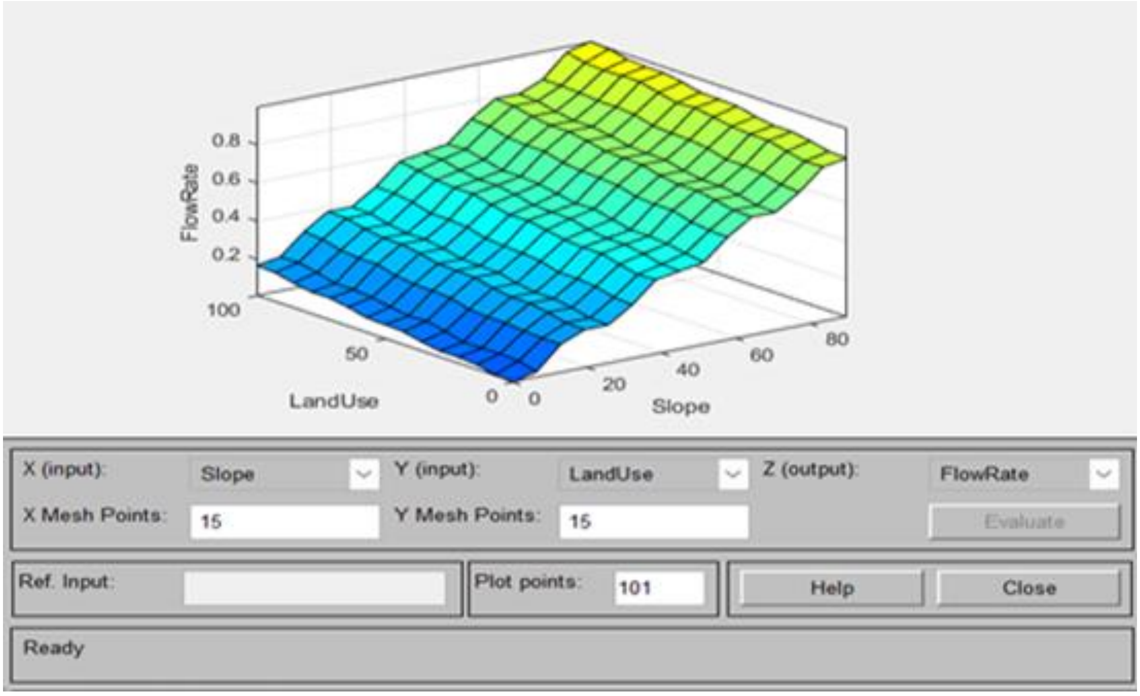

Figure 12. The 3D variation of the inputs as a function of the outputs.

5. Conclusion

The assessment of the model outcomes demonstrated that the SMRGT model, when utilized in conjunction with the Mamdani algorithm and the centroid defuzzification method, represents a proficient and pragmatic approach for estimating the flow coefficient of the Aksu River Basin. The model has the potential to be applied in various domains such as water resources management, water structure design, and flood disaster prevention within the region. This is due to its ability to generate dependable estimates of the flow coefficient by utilizing land use parameters. In the determination of flow coefficients, it is imperative to consider all pertinent factors related to the study area, encompassing meteorological attributes, land utilization, and soil properties, rather than solely relying on pre-established tabulated values. Determining the number of variables, fuzzy sets, and the shape of membership functions can be easily accomplished. On the other hand, the SMRGT method takes into account the physical cause-and-effect relationship, making it applicable to various basins or regions. In future research, the SMRGT model has the potential to incorporate various shapes, including trapezoidal, Gaussian, Sigmoid, and others.

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Author contributions

Ruya Mehdi: Data curation, Writing-Original draft preparation, Software, Validation. **Ayse Yeter Gunal:** Conceptualization, Methodology, Software, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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