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Application of a new fuzzy logic model known as "SMRGT" for estimating flow coefficient rate

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Abstract

Since we all have our own set of limitations when it comes to perceiving the world and reasoning profoundly, we are constantly met with uncertainty as a result of a lack of information (lexical impression, incompleteness), as well as specific measurement inaccuracies. It has been found that uncertainty, which shows up as ambiguity, is the root cause of complexity, which is everywhere in the real world. Most of the uncertainty in civil engineering systems comes from the fact that the constraints (parameters) are hard to understand and are described in a vague way. The ambiguity comes from a number of sources, including physical arbitrariness, statistical uncertainty due to using limited information to estimate these characteristics, and model uncertainty due to using overly simplified methods and idealized depictions of actual performances. Thus, it is better to combine fuzzy set theory and fuzzy logic. Fuzzy logic is well-suited to modelling the indeterminacy and ambiguity that results from multiple factors and a lack of data. In order to improve upon a previous predictive model, this paper uses a smart model built on a fuzzy logic system (FLS). Precipitation, temperature, humidity, slope, and land use data were all taken into account as input variables in the fuzzy model. Toprak's original explanation of the simple membership function and fuzzy rules generation technique (SMRGT) was based on the fuzzy-Mamdani methodology and used the flow coefficient as its output. The model's results were compared to available data. The following factors were considered in the comparison: 1) The maximum, minimum, mean, standard deviation, skewness, variation, and correlation coefficients are the seven statistical parameters. 2) Four types of error criteria: Mean Absolute Relative Error (MARE), Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). 3) Scatter diagram.

1. Introduction

"As a system learns, our ability to make accurate and consistent statements about its behaviour diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost reciprocally inimitable features," writes Zadeh [1]. It is now evident that a plausible mathematical structure of any physical reality is often impossible to describe and generate. Fuzzy logic is the technological revolution in computer logic. It aids computers and logical applications similarly to how it aids human behaviour. In 1965, Lutfu Askerzade published the first information regarding fuzzy principles [1]. According to Zadeh, the majority of human thought is hazy and uncertain. In 1965, Zadeh initiated a new review of systems containing uncertainty. Limiting the properties of assets and objects to two values (0; 1), according to Zadeh, is insufficient, as the real world consists of thousands of similarities, ranges, and opposites between 0 and 1. However, these ideas were criticized by the western world. This philosophy brought a simple and contemporary solution to difficult and complex problems in a vast array of applications and fields such as science, maths, and engineering [2,3]. For the frequency fuzzy logic theory, Freksa stated that the facts are fuzzy, but their rules cannot be disregarded [4]. In 1975, Mamdani and Assilian implemented the concept of fuzzy logic for the first time in the control system of a steam engine [5].

Events in the natural world that change and evolve together affect one another. Therefore, the number of factors that can affect an event, as well as the strength and scope of those factors' effects, can shift over time and space. It is also challenging to replicate observations made in nature under identical laboratory conditions or to recreate conditions similar to those used in the original experiments. Factoring in measurement and observation errors increases the magnitude of the uncertainties. It can be challenging to incorporate the concepts and interpretations of the observed natural phenomenon into the model, even when these are complete. If that's the case, then people will always face a degree of uncertainty whenever natural disasters occur. It is exceedingly challenging to make accurate predictions or models of natural events because of these uncertainties. Given these data, it's reasonable to conclude that error exists in the supposedly error-free models' development. For the prediction of natural events, the exact reason is not known. These errors generally depend on the assumptions and omissions, in short idealizations, errors in the measurements and recordings, differences in the experimental or observational conditions, the quality and quantity of the parameters considered, and so on. The ambiguity remains, and computers are unable to resolve or interpret it. However, they do make it easier to process data that has been entered numerically quickly. Humans, in contrast to computers, are able, depending on their cognitive abilities, to perform operations and define concepts with limited, incomplete, and uncertain data and information. Human thought, description, and representation typically involve some degree of doubt (approximation). That is to say, fuzzy thinking is common, and similarly imprecise definitions are often used to describe how people think. What this means is that people are typically verbal rather than numerical thinkers and communicators. Due to idealizations, measurement and observation errors, and a lack of complete and accurate data about natural phenomena, scientific uncertainty has persisted. According to Sen [6], "fuzzy sources" are any information that is both complete and imprecise, such as complexity and uncertainty, and Zadeh [7] said that the more closely a real-world problem is examined, the less clear the solution becomes. Therefore, complexity and uncertainty are inherent to the field of science.

The primary purpose of this investigation is to provide evidence that the proposed fuzzy model has the ability to make accurate predictions regarding the flow coefficient. A complete comprehension of river flow is necessary for the effective management of water resources, the planning and construction of water infrastructure, and the mitigation of the effects of natural disasters. There are two scenarios in which the use of fuzzy logic systems can prove to be extremely beneficial: the first is when the performance of extremely complex systems is not completely understood, and the second is when an efficient and approximative solution is acceptable. The differences between a classical system and a fuzzy system are illustrated in Figure 1 and Figure 2, respectively. The optimal construction of membership functions (MFs) and fuzzy rules (FRs) is the primary concern in any fuzzy system. The question at hand is how to achieve maximum efficiency.

This paper proposes a straightforward technique to assist those who are uncertain about the number, shape, and logic of the MFs and FRs in any fuzzy system. For open canal flow modelling, Toprak [8] introduced Simple Membership functions and the fuzzy Rules Generation Technique, which uses only a few key numbers to calculate all MFs of input and output variables. The MF shape (triangular, trapezoidal, etc.) and the defuzzification method determined the key numbers (centroid, maximum membership degree, etc.). This study favors the centre of gravity (centroid method) because it is more compatible with the fuzzy SMRGT method. The SMRGT model does not require any particular conditions. The user can specify the minimum and maximum values for the model. This is also the range of values for which the model is valid and easy for the user to determine. As a result, the Fuzzy SMRGT method is easier to implement and more reliable than other methods described in the literature. The new procedure employs the physical cause-and-effect relationship. As a result, it can be generalized and applied to any basin or region.

The following is the organization of the manuscript: The second section of this report provides an overview of the area under investigation and discusses the datasets that were provided by the General Directorate of State Hydraulic Works and the Turkish State Meteorological Service (TSMS). In Section 3, the author demonstrates the extensive scope of the necessary process and analyses that can be carried out utilizing Simple Membership Functions and the Fuzzy Rules Generation Technique. These are two of the tools that are discussed (SMRGT). The most important findings from our research are summarized in the fourth section, along with a discussion of the results of the processing and hydrological analysis performed on the study area. In Section 5, we present some generalizations and interpretations regarding the findings as a whole.

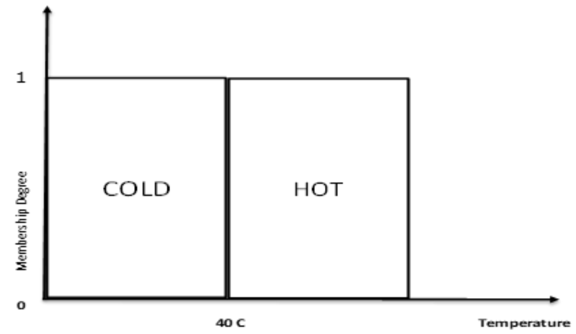

Figure 1. Classical set.

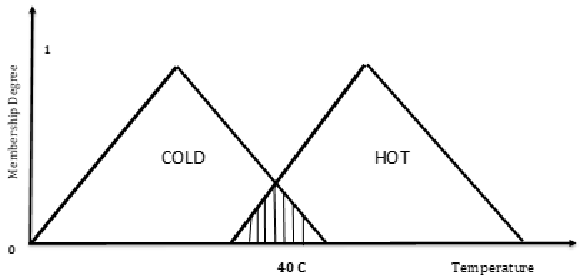

Figure 2. Fuzzy set.

2. Method

The first step in all hydrological studies is to collect the necessary data, such as Current measurements, evaporation, precipitation, temperature, etc. The hydrological processes must be as natural as possible. Therefore, it is necessary to provide sufficient tools and measurements. Latitudes 36–38 degrees north and longitudes 30–31 degrees east define the boundaries of the study area. It is one of the ten sub-basins that make up the Antalya Basin. According to observations of the river's flow made over a prolonged period, the Aksu has an annual average flow of 94.98 hm^3. The Mediterranean Sea forms the southern boundary of the basin, while the sub-basins Korkuteli and Duden Stream make up the western boundary. The closed Konya Basin can be seen from the northeast, the Buyuk Menderes Basin and the Akarcayi Basin can be seen from the north, and the Koprucayi Sub-basin can be seen from the east. A Mediterranean climate and a continental climate coexist in the Aksu stream basin. Both of these climates are distinct from one another. The northern portion of the basin is characterized by the continental climate of Central Anatolia, which is characterized by hot, dry summers and cold, snowy winters. In contrast, the southern portion of the basin is characterized by a Mediterranean climate. The dataset containing information on precipitation, temperature, humidity, land use, and slope in the Aksu River Basin over a long period (1990-2020) was used in this study.

In hydrological design, watershed management, and other types of research, it is helpful to make accurate predictions of the flow coefficient rate. The development of more accurate models has widely used various methods; however, improving the accuracy of predictions is still a pressing issue for decision-makers in a wide range of fields. In virtually every fuzzy system, the primary concern is determining how to construct the membership functions (MFs) and fuzzy rules (FRs) so that the system generates the most accurate results possible. The creation of membership functions (MFs) and fuzzy rules (FRs) are the two aspects of a data-based fuzzy model that are considered to be of the utmost significance. After the MF types have been chosen, the problem then becomes one of optimizing the number of MFs and FRs as well as their logic and the shape they take. The construction of MFs and the simple generation of FRs has recently seen the development of a large number of methods and algorithms, including genetic algorithms (GA) [9–16], the combined use of GAs and artificial neural networks (ANNs) [17, 18], ANNs [19–23], Kalman filters [24], probability measurement [25–31], and a great number of others. Many academics have proposed methods for modifying or optimizing only the number of MFs [9 -10,19,20,24-33], while others present methods for identifying only the FRs [21-23]. In addition, there were very few works that attempted to optimize both the MFs and the FRs at the same time [11–18]. The studies that were discussed earlier, with a few notable exceptions, do not contribute to the joint determination of FRs and MFs. In addition, many researchers are hesitant to use these methods because of how difficult it is to put them into practice. As a direct result of this, the methods of trial and error continue to be favored. Thus, the purpose of this study is to provide assistance to individuals who have difficulty determining the number, shape, and logic of the MFs and FRs in any fuzzy system by presenting a new fuzzy method. The new fuzzy technique that has been presented in this study is solely based on a select few primary numbers and that applies to all MFs of both the input and output variables. The key numbers were selected in accordance with the MF shape (triangular, trapezoidal, etc.) and the defuzzification technique (centroid, maximum membership degree, etc.). The SMRGT method was first introduced by [8], the Mamdani fuzzy system was selected as an operator, and has been utilized successfully in numerous types of research, including those conducted by [34-40]. As a result, they concluded that this new method for determining membership functions (MFs) and fuzzy rules (FRs) is reliable. For effective results with the new method presented in this study, the following steps can be summarized:

i. The independent and dependent variables that affect the current event have been selected. The independent variables serve as inputs to the fuzzy system, while the dependent variables serve as outputs. This study was designed with five inputs (precipitation, temperature, humidity, slope, and land use) and one output see Figure 3. These variables should be bounded by a certain range. Thus, the maximum and minimum values must be determined. These ranges can be as broad as desired based on the current event. Equation 1 can be used to calculate the X_R value.

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

i. There must be at least three temporary membership functions defined for each independent variable. A large number of membership functions decreases the error of the model [41] but increases the program load (processing volume). This study employed five MFs labelled as Very low, Low, Medium, High, and Very high.

ii. The membership functions (MFs) were designed to be triangular. The initial and final membership functions should be right-angled triangles, while the middle membership functions should be isosceles triangles [8]. A fuzzy system is valid for data distributed between the key values of the first and last MFs for each independent variable.

iii. For each variable, the key values (K1, K2... KN) and core value (Ci) of the membership functions, the unit width (UW), the symmetrically extended unit width (EUW), and the value (O) of the two intersecting neighbour membership functions are determined. Furthermore, the number of right-angled triangles (nu) in the triangular fuzzy set was determined.

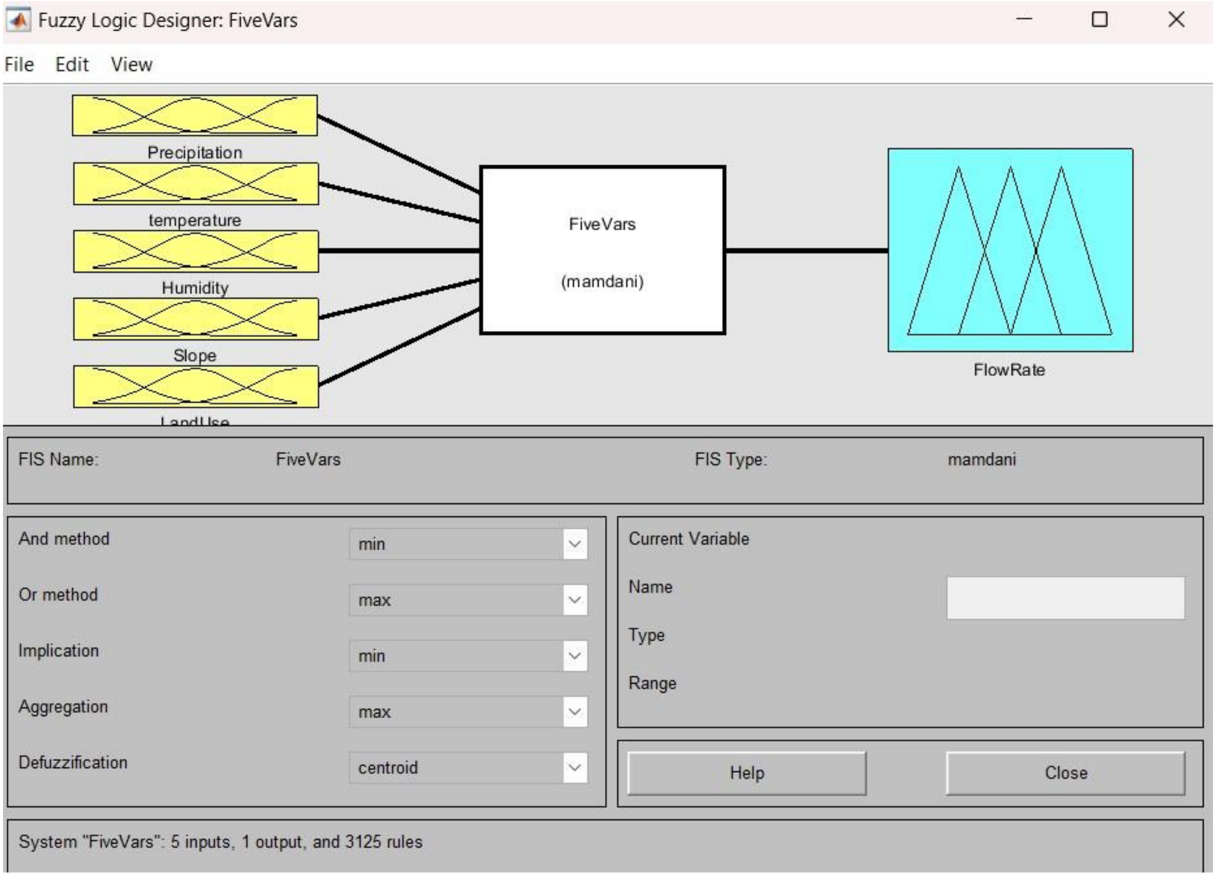

Figure 3. View of the inputs and output.

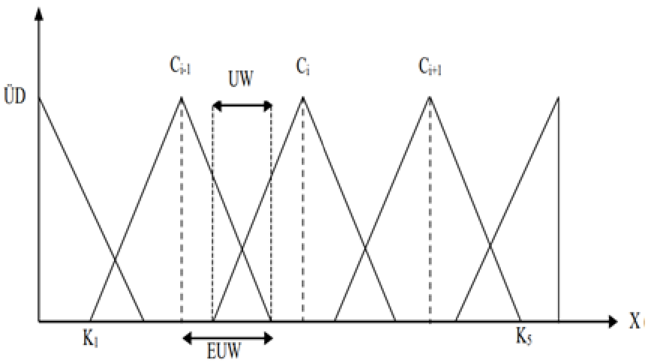

Figure 4. Core values, key values, and unit width for the model.

$$UW = \frac{XR}{nu} \tag{2}$$

$$O = \frac{UW}{2} \tag{3}$$

$$EUW = \left(\frac{XR}{nu}\right) + O \tag{4}$$

$$Ci = K3 = \left(\frac{XR}{2}\right) + Xmin \tag{5}$$

$$K4 = Ci + 1 = \left(\frac{(Ci - Xmin)}{2}\right) + Xmin \tag{6}$$

$$K2 = Ci - 1 = Xmax - \left(Xmax - \frac{Ki}{2}\right) \tag{7}$$

$$K1 = Xmin + \left(\frac{EUW}{3}\right) \tag{8}$$

$$K5 = Xmax - \frac{EUW}{3} \tag{9}$$

ii. It was decided that the number of key values for each independent variable should equal the number of MFs. These are the inputs to the fuzzy model. It is advantageous to select the same number of membership functions (MFs) as fuzzy rules for the outputs (FRs).

iii. The fuzzy rules base is determined by considering re levant physical conditions such as "IF," "AND," and " THEN." (see Figure 5) Package program (MATLAB) was set to include the fuzzy set. In total, 3125 rules were set for this study.

iv. Using calibration data, the input and output data files for the relevant package program were prepared. Using the test data, identical and instantaneous input and output files are generated. Consequently, two data files were generated for each calibration and test phase: one for input and one for output. Using the corresponding package program, the fuzzy system was then developed. A simple subprogram was utilized to execute and evaluate the program. If the output membership functions are excessively intertwined, they must be reduced by combining two or more functions into one [8], and [42].

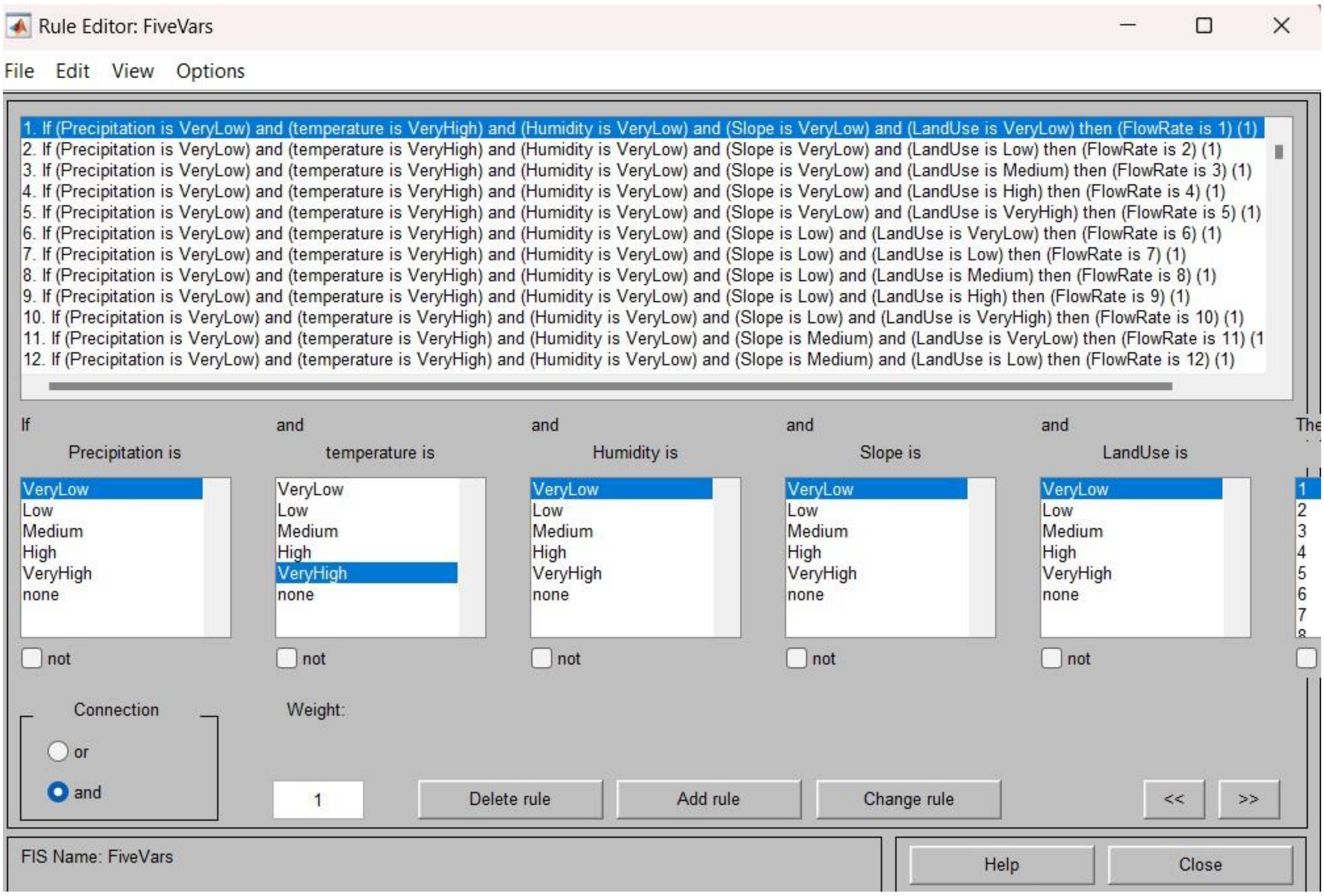

Figure 5. Fuzzy rules set for the model.

3. Results

The flow coefficient value of the study area was attempted to be determined. Both the MATLAB computer program and the fuzzy logic module were utilized to accomplish this. The SMRGT method was used to make the decisions regarding the input and output variables in order to achieve the most accurate result possible. The centroid method was chosen to serve as the defuzzification system, and specific formulas were utilized in order to ascertain both the input and the output key values. Table 1 provides a listing of the most significant values for each variable. To resolve the unique equation that, based on basin characteristics, calculates the flow coefficient, a specialist is sought out for assistance. The extent to which the available independent variables had an impact on the results of the model was determined in a manner that was specific to each variable. The SMRGT method dictates that the model output (flow coefficient) for this investigation should be equal to the number of rules, which in this case is 3125. When there is no precipitation, the minimum and maximum value ranges for the flow coefficient are changed to 0 and 1, respectively. These values are used to calculate the flow coefficient. The impact of precipitation, temperature, humidity, slope and land use on the flow coefficient was evaluated differently.

Where P is the precipitation (mm), T is the temperature (°C), H is humidity (%), S is the slope, LU is land use, and a is the flow coefficient. The flow coefficient reached its maximum value of (1) when the precipitation was 2000 mm (very high), the temperature was 0° C (very low), the humidity was 100% (very high), the slope was 90° (very high), and the land use was 100% (Very high) see Figure 6. When the precipitation was 200 millimetres, which is a very low value, the temperature was 50 degrees Celsius, which is a very high value, the humidity was 0%, which is a very low value, the slope was 0 degrees, which is a very low value, and the land use was 0% (Very low).

Table 1. Key values of each variable.

	X_R	K_2	K_3	K_4	K_1	K_5
P	1800	650	1100	1550	312.5	1887.5
T	50	12.5	25	37.5	3.125	46.88
H%	100	25	50	75	6.25	93.75
S	90	22.5	45	67.4	5.625	84.375
LU	100	25	50	75	6.25	93.75
a	1	0.125	0.5	0.25	0	1*

*(The last key value of the output is K_{3125})

Statistical parameters such as minimum (Xmin), mean (Xm), maximum (Xmax), standard deviation (σ), coefficient of variation (Cvx), coefficient of skewness (Csx), and correlation coefficient (r) were used to compare the model's output with the data in order to test the model's ability to accurately predict the outcomes of future events. Many types of errors include Mean Absolute Relative Error (also abbreviated as MARE), Mean Square Error (also abbreviated as MSE), Mean Absolute Error (also abbreviated as MAE), and Root

Mean Square Error (RMSE). The results of the statistical comparison are shown in Table 2. In addition, graphical representations of the comparison were created using a scatter diagram and a series graph (see Figure 7, and Figure 8).

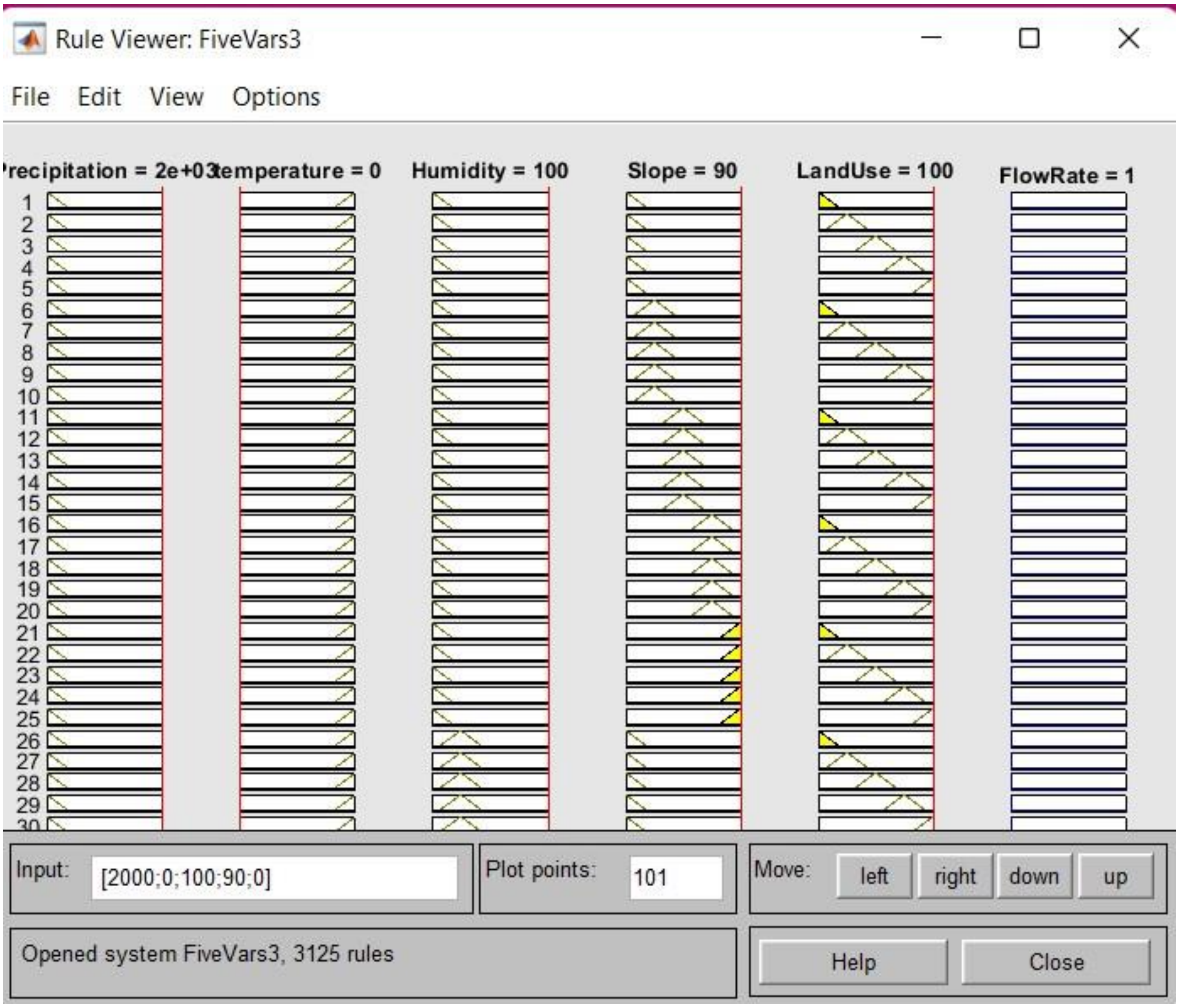

Figure 6. MATLAB view of the fuzzy rules.

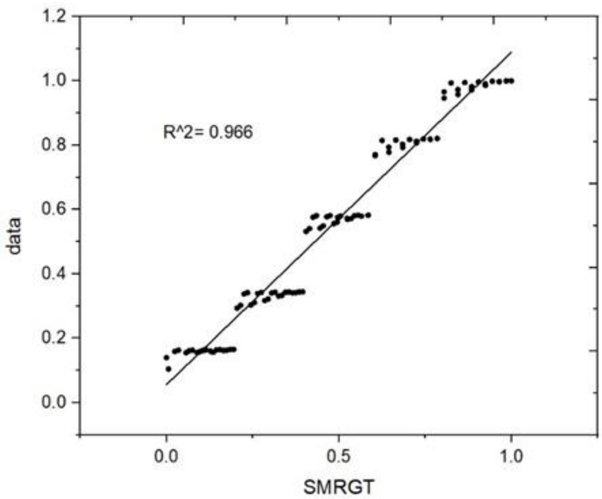

Figure 7. The scatter diagram of data and SMRGT.

Figure 8. Series graph of the data and SMRGT.

Table 2. Comparison between data and model.

Statistical Parameters & Errors	Data	Model
Max.	1.00	1.00
Min.	0.10	0.00
Mean	0.57	0.50
Standard Deviation	0.304	0.288
Skewness	-0.008514	-0.00291
Coefficient of Variance	0.532	0.577
Correlation Coefficient	0.966	
Mean Square Error	0.91 %	
Mean Absolute Error	11 %	
Mean Absolute Relative Error	18.3 %	
Root Mean Square Error	9.3 %	

4. Discussion

In this paper, a fuzzy logic approach was used to model the flow coefficient. In addition, a straightforward membership function and a fuzzy rule generation technique known as SMRGT were incorporated into the fuzzy modelling process. The fact that the flow coefficient value is dependent on the input data demonstrates that the model is not only mathematically accurate but also physically accurate. This is supported in the literature by [35,37,39,40], among other references. The relationship that exists between the output variable and the variables that were used to create it, is statistically significant in both directions. There is a positive correlation between flow coefficient and precipitation, humidity, slope, and land use; however, there is an inverse correlation between flow coefficient and temperature. It can be seen from the scatter plot that the regression line crosses the horizontal axis at an angle that is approximately 45 degrees. To put it another way, the model does not generate predictions that routinely deviate from the data that has been collected. The fact that the coefficient of determination is so high (R^2 = 0.966) suggests that the statistical relationship that exists between the model and the data can be expressed in a mathematical manner. Figure (9-11) illustrate how the model result—a dependent variable called the flow coefficient—varies in three dimensions as a function of the model's independent variables (Amount of rainfall, temperature, and humidity, as well as slope and land use). This variation is shown in three-dimensional space.

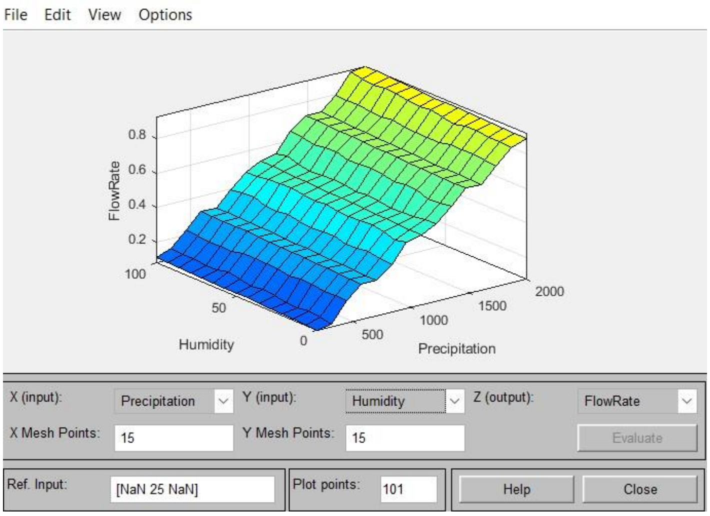

Figure 9. Variation of output as a function of inputs (P&H).

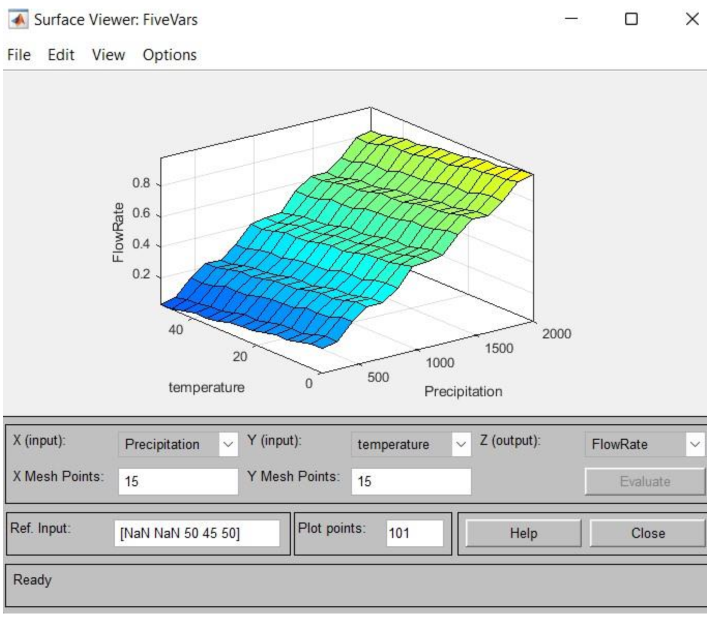

Figure 10. Variation of output as a function of inputs (P&T).

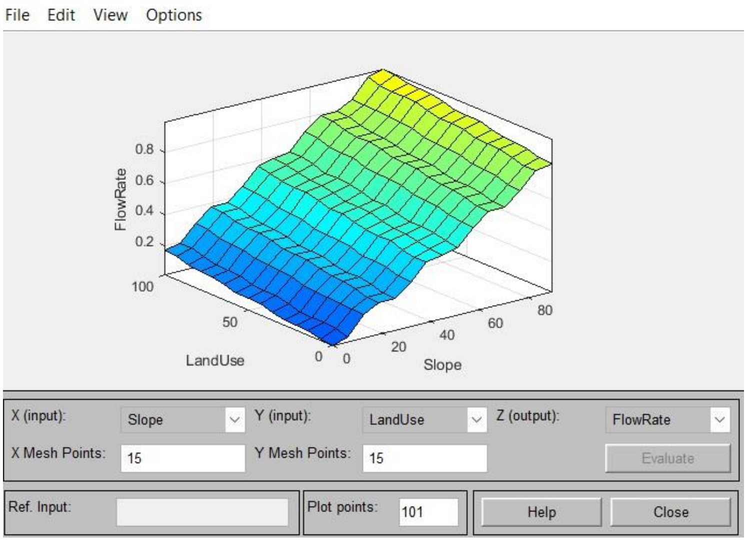

Figure 11. Variation of output as a function of inputs (S&LU).

5. Conclusion

The concept of fuzzy logic has the potential to be practical when applied to the analysis of conventional, less complicated systems. For certain kinds of issues, for instance, giving very specific responses is not always necessary. A solution that is approximative but quick can be particularly useful in generating initial design decisions, as an initial assessment in a more precise numerical process to reduce computational costs, or in the many instances where the inputs to the problem are unclear, ambiguous, or not understood at all. This is especially true in situations where the inputs to a problem are unclear, ambiguous, or not understood at all. It has been determined that when calculating flow coefficients, it is necessary to take into account all aspects of the study area. These must include the weather conditions, the land use, and the properties of the soil instead of relying on the information that can be found in prefabricated tables. The use of fuzzy logic in the study of hydrological phenomena, such as precipitation and flow, is essential because these phenomena are inherently fraught with uncertainty. The fuzzy SMRGT method makes it possible to calculate the flow coefficient in a precise and straightforward manner. The model was successful in determining the flow coefficient rate as evidenced by its impartiality and linearity in scatter diagrams, high determination and correlation coefficients between the data and the model's estimation, lowness in the mean absolute relative error of the models, and similarity between statistical characteristics of the data and the model's estimations. Calculating membership functions, their shapes, and the number of variables that are involved can all be done with a reasonable amount of ease. The SMRGT technique, on the other hand, applies to any basin or region because it takes into account the physical cause-and-effect relationship. The role of the trial-and-error method is reduced significantly as a result of the new method. SMRGT is not only quick and simple to use, but it also produces more reliable results. When it comes to modelling the flow coefficient, many people believe that the fuzzy SMRGT method and other similar physics-based modelling techniques ought to be used more frequently because it gives the opportunity to reflect an expert's opinion on the model in comparison to other methods that have been described in the literature. In addition, it has been determined that a relatively limited number of studies have been carried out in order to get an accurate reading of the flow coefficient.

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Author contributions

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

Conflicts of interest

The authors declare no conflicts of interest.

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