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Prediction of Runoff Coefficient under Effect of Climate Change Using Adaptive Neuro Inference System

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Abstract

The complex characteristics of the rainfall- runoff mechanism, along with its non-linear attributes and inherent uncertainties, have prompted scholars to explore alternative approaches inspired by natural phenomena. In order to tackle these obstacles, artificial neural networks (ANN) and fuzzy systems (FL) have been utilised as feasible substitutes for conventional physical models. Furthermore, the procurement of comprehensive data is considered essential for precise analysis and modelling. This study's primary objective was to use pertinent climatic data such as; Precipitation (P), Temperature (T), Relative humidity (Rh), and Wind speed (Ws) to predict the runoff coefficient using the Adaptive Neuro-Fuzzy Inference System (ANFIS) model. Different ranges (60:40; 70:30; 80:20) were used for the training and testing phases. The model was employed to predict the runoff coefficient in the Aksu river basin in Antalya province in Turkey. The study conducted a comparative analysis of the results, taking into account various performance indicators of the model, such as mean absolute error (MAE), Nash-Sutcliffe efficiency coefficient (NSE), root mean square error (RMSE), and correlation coefficient (R^2). Based on the findings presented, the (60:40) range showed the best results as evidenced by its low RMSE and MAE values and its high R2 and NSE values (RMSE:0.056, MAE:1.92, NSE:0.868, R2 :0.996). It was concluded that the ANFIS model magnificently predicts runoff coefficients with an exceptional level of precision, also the study findings indicate that accurate runoff coefficient estimation can be achieved using meteorological data without incorporating more intricate and interrelated data.

Keywords: ANN; runoff coefficient; ANFIS; River Basin; Fuzzy logic.

1. Introduction

The evaluation of water accessibility is of considerable significance in the tactical development of water resource strategies. The comprehension of the hydrological characteristics of a watershed and the assessment of its runoff yield are essential prerequisites for the formulation of a watershed development plan. The primary step in assessing water availability entails computing the runoff resulting from precipitation within river basins.

The runoff coefficient refers to the proportion of the volume of water that runs off or is discharged during a specified time interval relative to the volume of precipitation during the same interval. The runoff coefficient is a metric that quantifies the ratio of precipitation that transforms into runoff while also taking into account the impact of geographical features within the watershed on the relationship between precipitation and runoff [1]. The variability of the runoff coefficient is a well-established phenomenon, with numerous factors exerting a non-linear influence on its magnitude. The relationship between multiple influencing factors and runoff coefficient is complex and multidimensional, rendering the construction of a prediction model through experimental physical mechanism description a challenging task. Certain international cities place significant emphasis on the precise computation of runoff coefficients in areas where rainfall is collected and have even undertaken the creation of tables for runoff coefficients [2-3]. The literature [4] presents mathematical models for rainfall intensity, duration, and runoff coefficient based on the mechanisms of production and confluence. The best-fit formulae for the Rainfall Amount - Runoff Coefficient relation (RA-RC relation formulae) were also established for various sub-surfaces based on hydrological data [4]. This paper introduces an Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS) model to more precisely depict the non-linear relationship between influencing factors and runoff coefficients and includes example measurements and comparative analysis.

The presence of multiple efficacious parameters in converting rainfall to runoff, coupled with intricate and non-linear interrelationships among these parameters, has posed a significant challenge in the precise estimation of the runoff volume resulting from precipitation. The inputs and outputs of watershed systems play a crucial role in the prediction of runoff quantities. Numerous endeavors have been undertaken to approximate the quantity of water runoff within a specific catchment area due to precipitation. Nonetheless, the outcomes were deemed unsatisfactory due to the aforementioned factors. Hence, scholars have ascertained that intelligent neural systems are valuable instruments and have resorted to nature-inspired techniques, including Artificial Neural Networks (ANN), ANFIS, and GA. Furthermore, the utilization of the aforementioned intelligent techniques has become imperative due to the benefits of time and cost savings, particularly in areas with limited or nonexistent hydrometric and meteorological stations. In recent decades, numerous researchers have utilized intelligent techniques to investigate the intricate process of rainfall-induced runoff production. The authors [5] employed ANFIS and GA methodologies to forecast and optimize the runoff quantity. The [6] study utilized the artificial neural network (ANN) approach to examine a six-year dataset of monthly precipitation in South Tangerang City. The utilization of a fuzzy inference system was implemented by [7] in the context of modeling the relationship between rainfall and runoff. The study conducted by [8] utilized an enhanced ANFIS methodology to compute runoff and contrasted the results with those derived from the Auto-Regressive Integrated Moving Average (ARIMA) technique. The ANFIS technique was utilized by the author [9] to construct a rainfall-runoff simulation model that relies on event occurrences. The study conducted by [10] showed an analysis of the effects of alterations in climatic factors on the flow of rivers and, as a result, on the production of hydroelectric power.

The utilization of the ANFIS model was implemented to assess the runoff coefficient within the Aksu River basin during the period spanning from 2005 to 2020. The inputs utilized in the analysis were precipitation, temperature, humidity, and wind speed, based on the available data. The primary objective of this investigation was to employ ANFIS for the purpose of modeling runoff coefficient, utilizing solely climatic data as input, and

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subsequently assessing the efficacy of the employed technique in terms of its predictive capabilities.

2. Materials and Methods

2.1 Research data and Study area

The geographical location of the Aksu River Basin falls within the coordinates of 36-38 degrees north latitude and 30-31 degrees east longitude (see Figure 1). The Mediterranean Region is delineated by the geographical limits that encircle the basin. The Aksu River spans roughly 370 kilometers and exhibits a collective width of 100 meters at its estuary [11]. As per the ArcGIS measurements, the basin displays a drainage area of roughly 7505 square kilometers. The Aksu River originates from the Taurus Mountains, a significant mountain range situated in the southern part of Turkey. The Aqueous Channel navigates through the Aksu Canyon and eventually flows into the Mediterranean Sea. The dataset was organized by employing the monthly averaged precipitation, average temperatures, humidity, and wind speed from 2005 to 2020. The data was acquired from the authorized meteorological agency of the Turkish government.

Figure1. Location of the study region.

2.2 Adaptive Neural Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a computational approach that combines the advantageous features of neural networks and fuzzy logic in machine learning. The ANFIS method was introduced by [12] to model complex systems by combining data-driven learning with expert human knowledge. The utilization of the ANFIS has been observed in various fields, such as control systems, pattern recognition, time-series forecasting, and optimization challenges, as noted by [13]. The ANFIS employs imprecise rules to articulate the correlation between the input and output of a specific system. For this

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study, the rules are shown in Figure 2. The representation of a set of IF/THEN rules for a first-order Sugeno system with four inputs and one output is standardized as outlined below:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$ (1)

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$ (2)

Rule 3: If x is A_3 and y is B_3, then $f_3 = p_3 x + q_3 y + r_3$ (3)

Rule 4: If x is A_4 and y is B_4, then $f_4 = p_4 x + q_4 y + r_4$ (4)

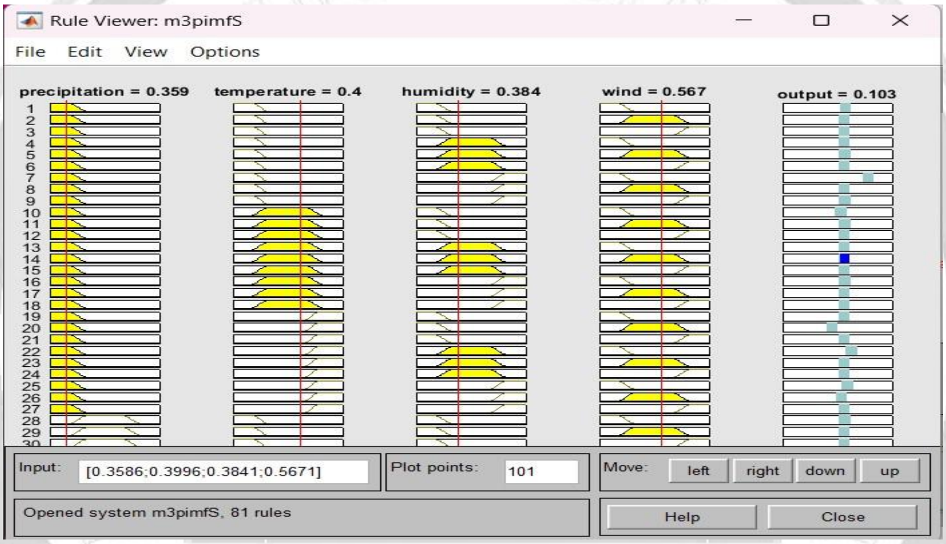

Figure 2. MATLAB view of the Fuzzy - Sugeno rules.

A machine learning algorithm is utilized to streamline the creation of regulations by incorporating input-output data alongside human expertise in the form of linguistic variables and fuzzy sets. The ANFIS utilizes the previously mentioned rules to produce results for novel input data. According to [12] postulation, the ANFIS structure comprises five distinct layers, namely the input layer, fuzzification layer, fuzzy rule layer, defuzzification layer, and output layer (see Figure 3).

Fuzzification layer

According to the first layer, the membership function can be any suitable parameterized membership function, such as B. Generalized bell-shaped function [14].

$$\mu A(x) = \frac{1}{1+\left|\frac{x-Ci}{ai}\right|^{2b}} \tag{5}$$

Where: $\{a_i, b_i, c_i\}$ is the parameter set, and $\mu A(x)$ is the membership function of the fuzzy set A.

Fuzzy Rule layer

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In this layer, every individual node is a stationary entity that generates an output equivalent to the summation of all incoming signals [14, 15]:

$$O2, i = wi = \mu Ai\ \mu Bi\ (y),\ i = 1, 2 \qquad (6)$$

Where: μAi and μBi are the degree of memberships of input terms A and B, respectively.

Normalization layer

This layer is characterized by the symbol N, denoting that all of its nodes are stationary. The i-th node specifies the proportion of its rule's trigger intensity in relation to the aggregate trigger intensities of all rules [14]:

$$O_{3,\,i} = \overline{W} = \frac{Wi}{W1+W2}\ ,\ i= 1, 2 \qquad (7)$$

Where W1 and W2 represent the firing strengths of the two rules, and Wi represents the firing strength of rule i.

Defuzzification layer

This layer's node denoted as "I" possesses an adaptive characteristic and is equipped with a function specific to nodes [16]:

$$O_{4,\,i} = \overline{w} f_i = \overline{wi}\ (\rho_i x + q_i y + r_i) \qquad (8)$$

Where $(\overline{wi})$ represents the normalized firing strength of rule i, ρi, qi, and ri are the consequent parameters associated with rule i, and x and y represent the input variables.

Output layer

The computation of the total output in this layer is performed by a solitary, stationary node, which is designated for this purpose. The node calculates the sum of all input signals:

$$O_{5,\,i} = f = \sum_{i=1}^{n} \overline{W}ifi \qquad (9)$$

Where $\overline{W}ifi$ represents the normalized firing strength, which is typically calculated by dividing the firing strength of rule i by the sum of the firing strengths of all rules.

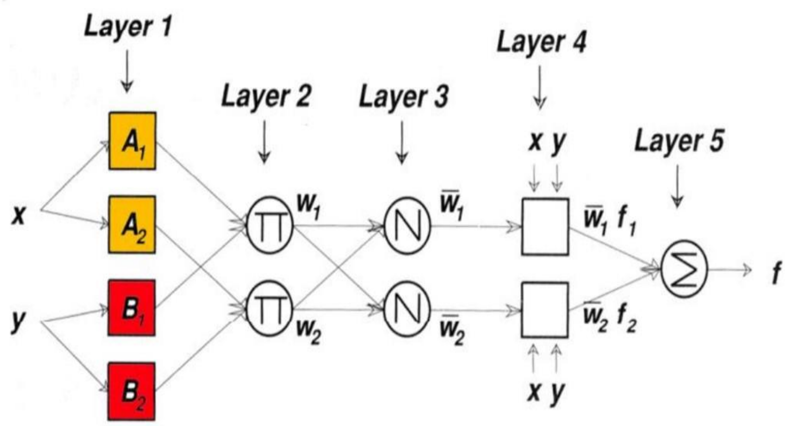

Figure 3. A basic structure of the ANFIS [17]

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The ANFIS model necessitates the tuning of significant parameters, including the membership function parameters for each input, the consequent parameters, and the number of rules. The training process consists of two essential stages, specifically Structure Learning and Network Configuration. The initial stage entails the identification of the most suitable network architecture, which encompasses the segmentation of the number of membership functions for every input and the determination of the number of rules. The following step entails parametric learning, whereby the recommended membership functions and corresponding parameters are determined. The hybrid learning algorithm is commonly employed as the primary mode of instruction. The algorithm consists of two discrete phases, specifically the forward propagation and the backward propagation. After initializing all relevant parameters, the functional signals are propagated forward to the fourth layer during the forward pass. The following parameters are identified by employing the method of least square errors. After the pertinent parameters have been identified, the functional signals persist in propagating until the error metric is computed. During the process of backpropagation, the error rates are retroactively propagated in a reverse direction, and the parameters of the premise are iteratively updated through the utilization of gradient descent.

To reduce excessive preprocessing computations, the data are normalized to the range (0-1) using the following equation:

$$Xnor. = \frac{X - Xmax}{Xmin - Xmax} \tag{10}$$

Where $X_{nor.}$ is the normalized data, x is the original data, X_{min}, and X_{max} are the minimum and maximum values of the original data, respectively?

2.3 Model Assessment Criteria

The model's performance was assessed using four distinct parameters, namely the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), the coefficient of determination (R^2), and Nash-Sutcliffe efficiency (NSE) for NSE, a value of 1 indicating a perfect match between the modeled and observed values, and a value of 0 indicating that the model predictions are as accurate as the mean of the observed values. A negative NSE value indicates that the mean of the observed values is a better predictor than the model. These parameters are defined in equations (11-13). Therefore, optimal models would exhibit Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values equivalent to zero. The coefficient of determination refers to the ratio of the variance accounted for by the regression line to the total variance observed in a linear regression model. The coefficient of determination (R^2) for a regression line that represents the average value of a dataset would be zero, whereas a perfect model would have an R^2 value of one [18,19].

$$MAE = \frac{1}{n} \sum_1^n |\mathrm{Ci} - \mathrm{Cp}| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (Ci - Cp)^\wedge 2} \tag{12}$$

$$NSE = 1 - \frac{\sum_1^n (Ci - Cp)2}{\sum_1^n (Ci - \bar{A})2} \tag{13}$$

Where: C_i is the actual data, C_p is the predicted data, and A (bar) is the mean value of the actual data.

3. Results and Discussion

In this study, the Adaptive Neural-Fuzzy Inference System (ANFIS) was used to predict the runoff coefficient of the Aksu River basin in the Mediterranean region – Turkey; 15 years of climatic data was utilized. The input variables were the Precipitation, Temperature, Wind speed, and Relative humidity data. The ANFIS analysis involved using Gaussian membership functions (gaussmf) (4 x 4 x 4 x 4) for the training phase, and π shaped membership function (pimf) for the testing phase (see Figure 4 and Figure 5), and Grid partition section with 50 iterations, assuming the output as linear. The dataset was divided into the training and testing phases, with different ranges (60% -40%; 70% -30%; 80% - 20%). After this step, a fuzzy inference system (FIS) is generated and evaluated, which can produce MAE and RMSE.

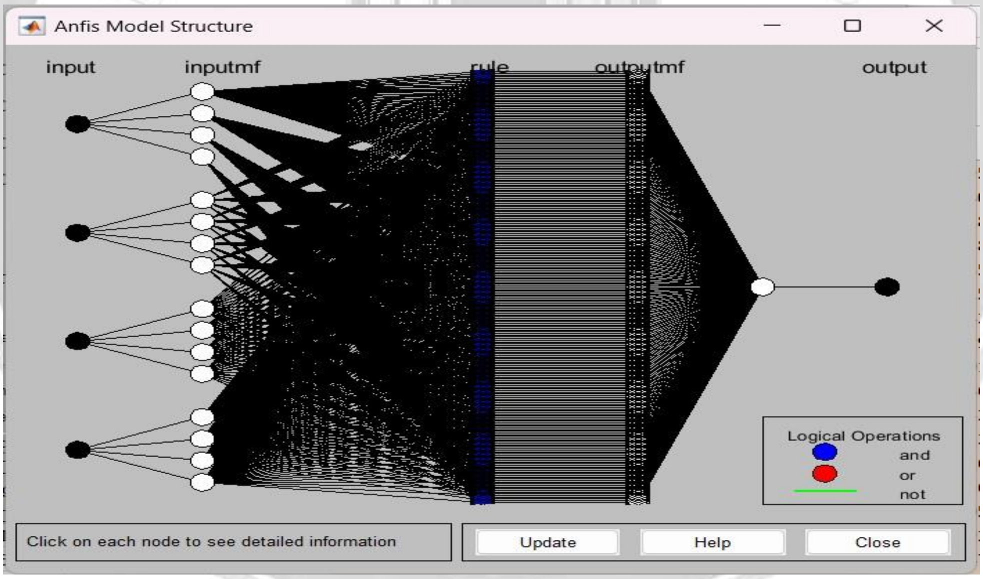

Figure 4. Structure of the ANFIS model.

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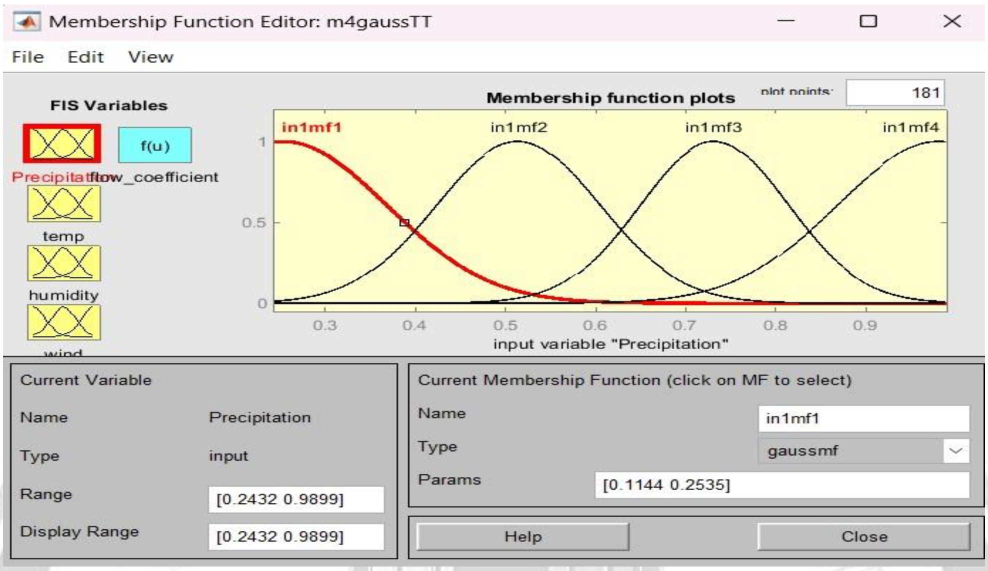

Figure 5. Gaussian membership function of the inputs.

The results of each interval are illustrated in Figures 6 – 8 and presented in Table 1. The implementation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) utilizing a training-testing phase of range (60%-40%) characterized by the lowest values of root mean square error (RMSE) at 0.75%, mean absolute error (MAE) at 2.25%, and highest value of Nash-Sutcliffe efficiency (NSE) at 0.868, and R^2 at 0.87, demonstrated effective performance in estimating the runoff coefficient.

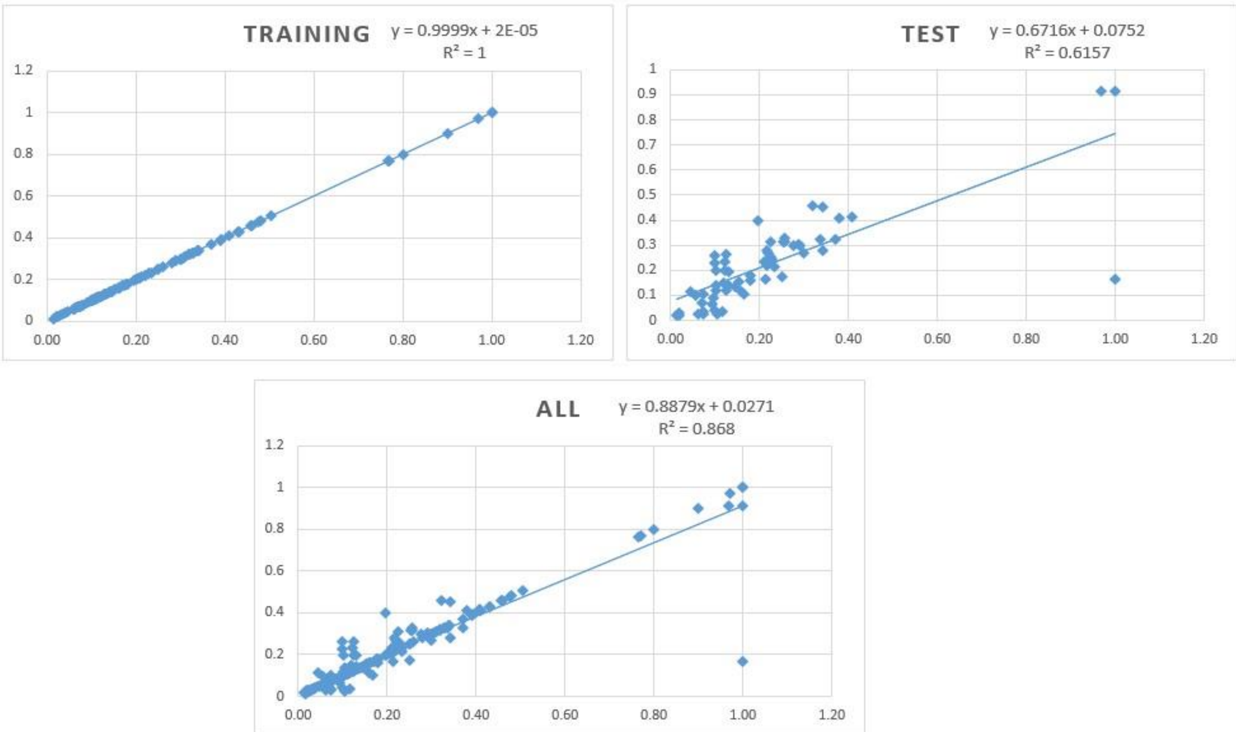

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Figure 6. (60-40)% range results.

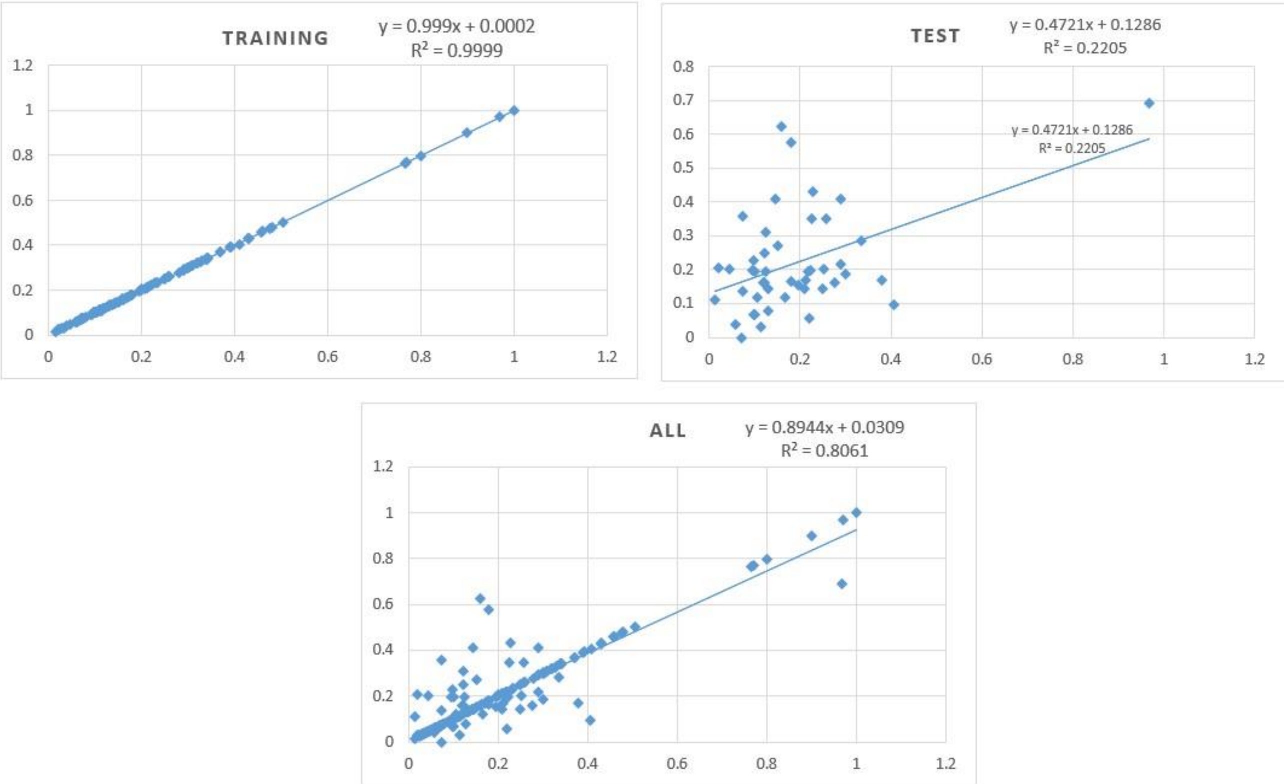

Figure 7. (70-30)% range results.

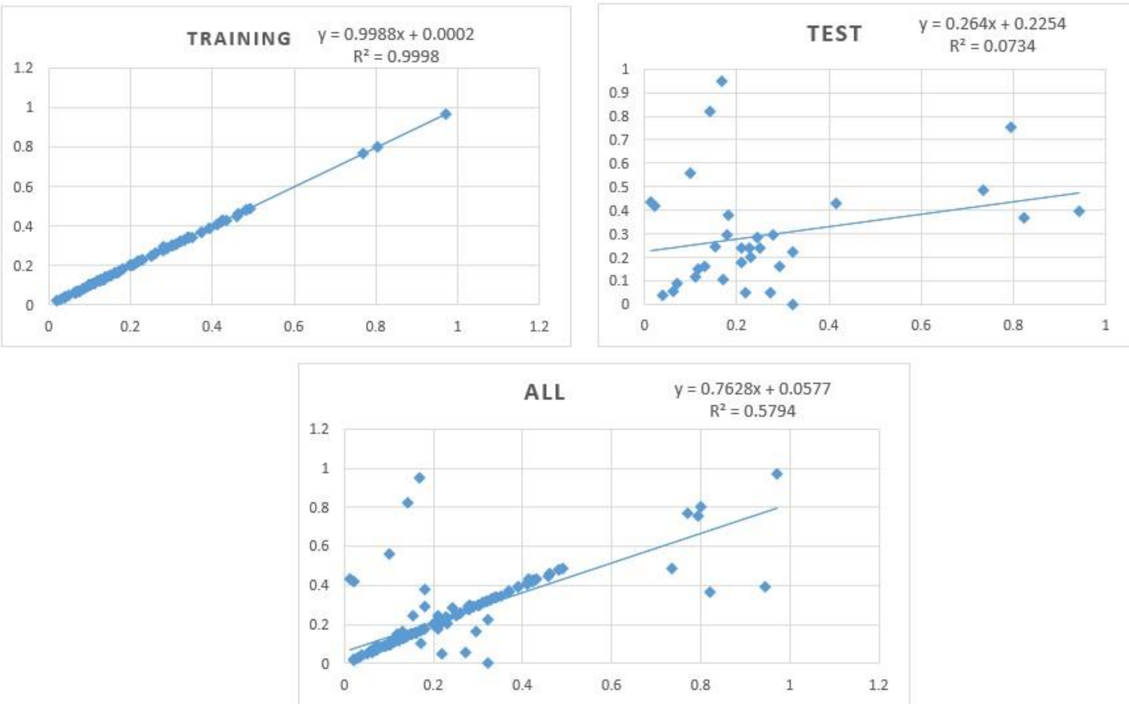

Figure 8. (80-20)% range results.

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Table 1. the results of the ANFIS model

Statistical parameters / Ranges	RMSE	NSE	MAE	R^2
60%-40%	0.75	0.868	2.26	0.87
70%-30%	0.82	0.796	3.30	0.8
80%-20%	1.20	0.52	3.30	0.58

The ANFIS results were graphically represented through scatter plots, as illustrated in Figure 9. A robust correlation was observed between the predicted and actual data. The ANFIS model was observed to exhibit a high degree of concordance with the actual values. The clustering of data points in close proximity to the 45° line is indicative of the ANFIS network's robustness, as observed in the analysis. As illustrated in Figure 10 and Figure 11 presented below, the average testing error for the training phase was 0.00025, and for testing was 5.08. The high coefficient of determination between the model and the data, and low values of MAE and RMSE all demonstrate that the ANFIS model is reliable, accurate, and can be used with confidence for runoff coefficient calculations which is an important parameter in hydrological modeling and water resources management.

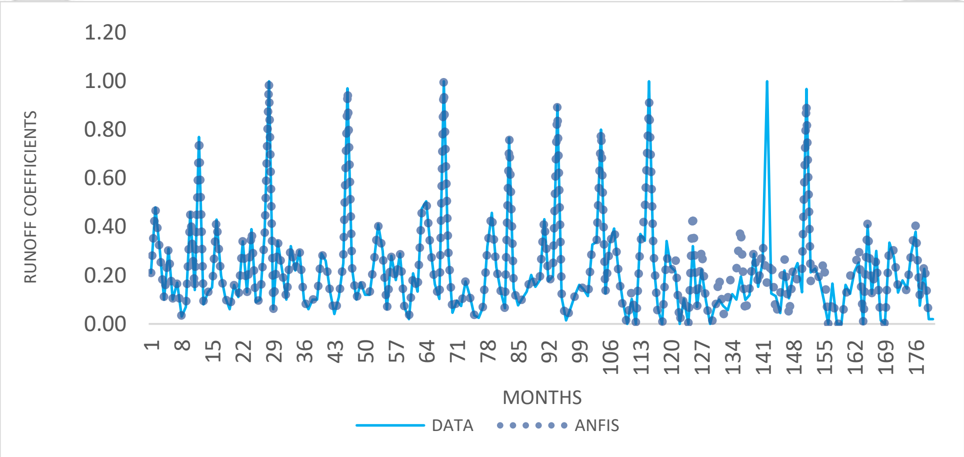

Figure 9. Observed and predicted runoff versus different months of the studied period.

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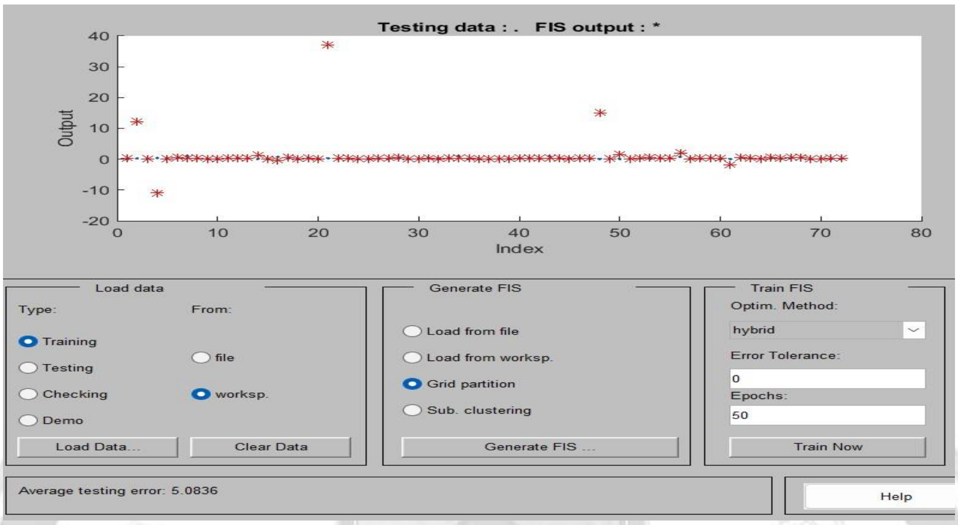

Figure 10. View of the testing phase.

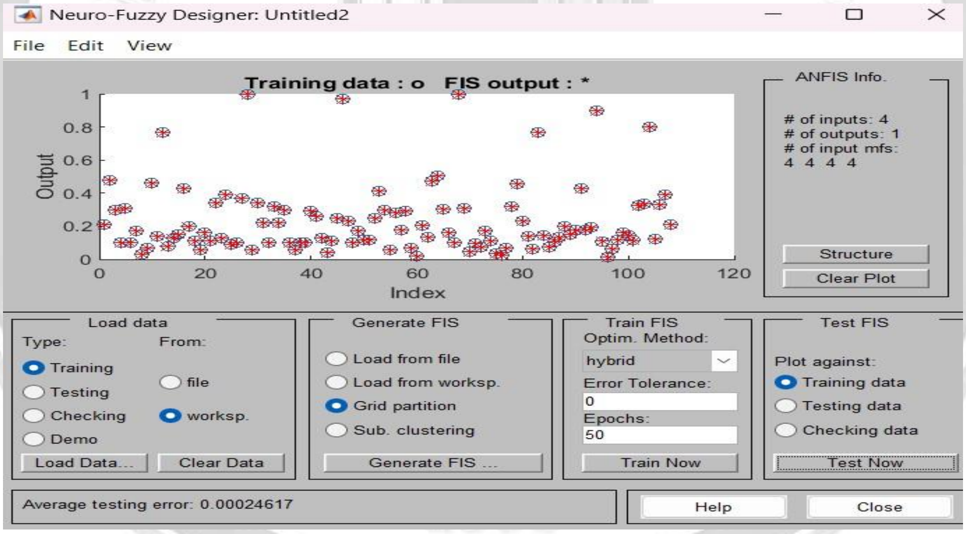

Figure 11. View of the training phase.

The diagrams presented in Figure 12 depict the variation of the runoff coefficient, a dependent variable, in three dimensions concerning the model's independent variables, namely the amount of precipitation mm, temperature °C, relative humidity %, and wind speed m/s. This variation is depicted in a three-dimensional spatial context.

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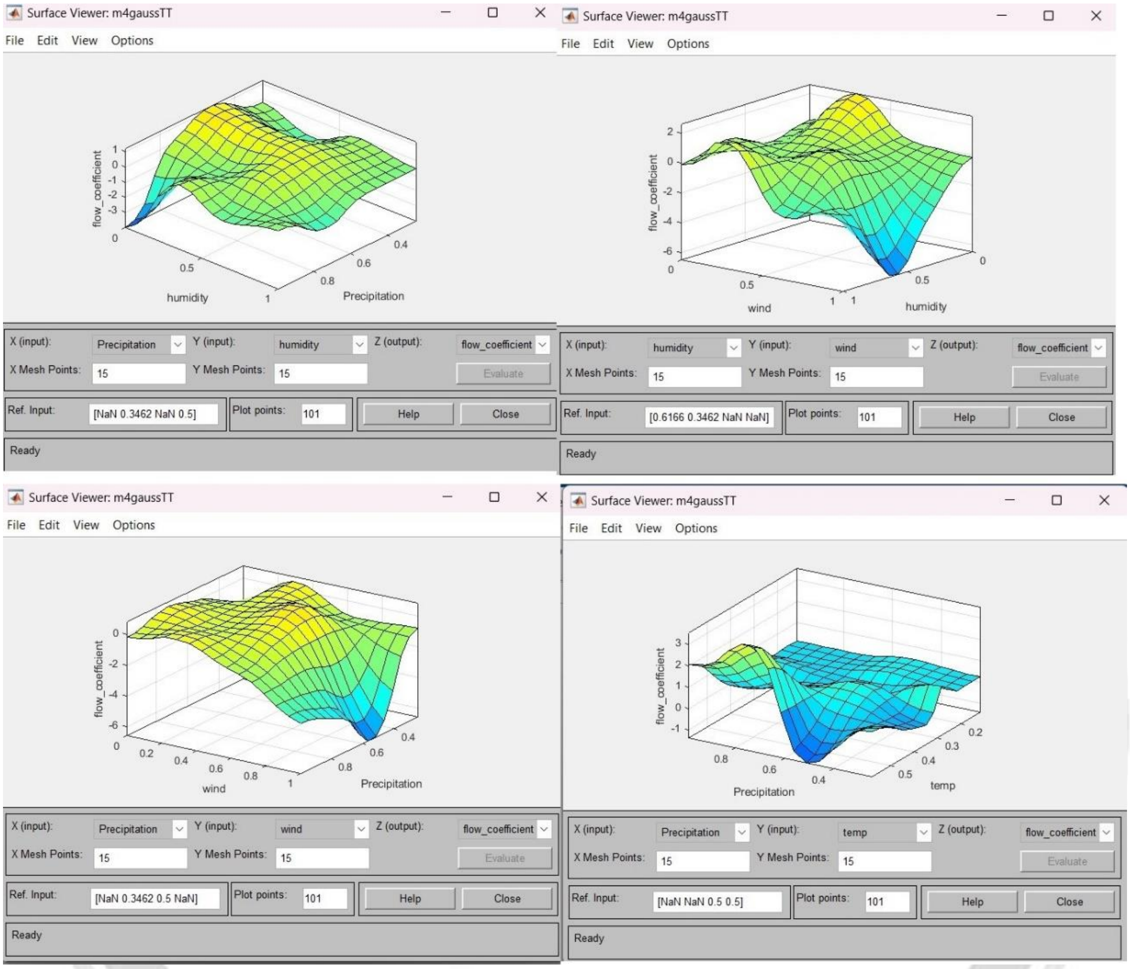

Figure 12. Results 3D surface.

The 3-dimensional surface is generated through the assessment of the membership functions of every input variable, followed by their amalgamation utilizing fuzzy inference rules to ascertain the extent of membership in the output fuzzy sets. The outcomes are frequently expressed in the form of a membership degree with fuzziness or a precise output value obtained through defuzzification. Every point located on the surface denotes a particular amalgamation of input variables and their corresponding output value, as determined by the fuzzy inference procedure. The topography of the three-dimensional surface can offer valuable insights into the correlation between the inputs and the output within the context of the fuzzy logic system. The manifestation of intricate patterns, non-linear associations, or ambiguous boundaries is contingent upon the selected membership functions and the fuzzy inference rules. The examination of the three-dimensional surface has the potential to facilitate comprehension of the impact of alterations in the input variables on the output, thereby assisting in the formulation of decisions or the development of control systems predicated on the fuzzy logic model.

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4. Conclusion

The utilization of fuzzy logic theory can provide benefits in the evaluation of conventional systems that exhibit lower levels of complexity and do not entail substantial uncertainties or challenges. The ANFIS technique has been extensively employed in diverse hydrological contexts. The ANFIS approach is founded on utilizing adaptive neural networks and fuzzy inference systems capable of managing intricate and non-linear associations within the data. Some academics argue in favor of incorporating a substantial number of independent physiographic and climatic variables. Issues of complexity and insufficient data often hinder the estimation of runoff coefficients in many basins. This study aims to offer an easy and feasible solution to this challenge. The fuzzy neural model proposed in this study is based on only four climatic parameters. Despite the model's simplicity, the outcomes demonstrate satisfactory precision. The enhancement of neuro-fuzzy systems' results exhibits a direct correlation with the augmentation of the number of membership functions.

Nevertheless, if the quantity of input membership functions is equivalent to or surpasses 4, the computational capacity escalates while the computational speed diminishes. Meanwhile, the utilization of ANFIS yielded outcomes indicating that the implementation of the linear output membership function was more precise in comparison to that of the constant output membership function. It can be inferred that the extent of the training and testing phases is a crucial factor in determining the accuracy of the results. Upon examination of the ANFIS results, it was observed that the input parameters provided sufficient accuracy in estimating the runoff coefficient within the basin under study. The reliable estimation of runoff coefficient with climatic data using ANFIS demonstrates its efficacy and applicability in similar projects. The utilization of easily accessible climatic data to calculate the runoff coefficient is suggested as a straightforward, practical, and sufficiently precise approach.

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تنبؤ معامل الجريان السطحي تحت تأثير تغير المناخ باستخدام نظام الاستدلال العصبي التكيفي

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جامعة غازي عنتاب/ قسم الهندسة المدنية

الخلاصة

دفعت الخصائص المعقدة لآلية جريان الأمطار ، جنبًا إلى جنب مع سماتها غير الخطية والشكوك المتأصلة ، العلماء إلى استكشاف مناهج بديلة مستوحاة من الظواهر الطبيعية. من أجل معالجة هذه العقبات ، تم استخدام الشبكات العصبية الاصطناعية (ANN) والأنظمة الضبابية (FL) كبدائل مجدية للنماذج الفيزيائية التقليدية. علاوة على ذلك ، يعتبر شراء البيانات الشاملة أمرًا ضروريًا للتحليل الدقيق والنمذجة. كان الهدف الأساسي لهذه الدراسة هو استخدام البيانات المناخية ذات الصلة مثل ؛ هطول الأمطار (P) ودرجة الحرارة (T) والرطوبة النسبية (Rh) وسرعة الرياح (Ws) للتنبؤ بمعامل الجريان السطحي باستخدام نموذج نظام الاستدلال العصبي الضبابي التكيفي (ANFIS). تم استخدام نطاقات مختلفة (60:40 ؛ 70:30 ؛ 80:20) لمرحلتي التدريب والاختبار. تم استخدام النموذج للتنبؤ بمعامل الجريان السطحي في حوض نهر أكسو في مقاطعة أنطاليا في تركيا. أجرت الدراسة تحليلاً مقارناً للنتائج ، مع مراعاة مؤشرات الأداء المختلفة للنموذج ، مثل متوسط الخطأ المطلق (MAE) ، ومعامل كفاءة ناش-ساتكليف (NSE) ، وجذر متوسط الخطأ التربيعي (RMSE) ، والارتباط. معامل (R2). بناءً على النتائج المقدمة ، أظهر النطاق (60:40) أفضل النتائج كما يتضح من قيم RMSE و MAE المنخفضة وقيم R2 و NSE العالية (RMSE: 0.056 ،MAE: 1.92 ،NSE: 0.868 ،R2 : 0.996). استنتج أن نموذج ANFIS يتنبأ بشكل رائع بمعاملات الجريان السطحي بمستوى استثنائي من الدقة ، كما تشير نتائج الدراسة إلى أنه يمكن تحقيق تقدير دقيق لمعامل الجريان السطحي باستخدام بيانات الأرصاد الجوية دون دمج بيانات أكثر تعقيدًا وترابطًا.

الكلمات الدالة: ANN؛ معامل الجريان السطحي ANFIS. حوض النهر ؛ منطق غامض.