OKU Fen Bilimleri Enstitüsü Dergisi
9(4): 2290-2300, 2026

OKU Journal of The Institute of Science and Technology, 9(4): 2290-2300, 2026

Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi

Osmaniye Korkut Ata University Journal of The Institute of Science and Technology

Malatya İli için Bulanık Mantık Modeli Kullanılarak Kayısı Verimlilik Artışı Modellemesi

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Araştırma Makalesi

Makale Tarihçesi:
Geliş tarihi: 27.10.2025
Kabul tarihi: 02.03.2026
Online Yayınlanma:09.09.2026

Anahtar Kelimeler:
Kayısı verimliliği
Matematiksel modelleme
Bulanık mantık

ÖZ

Bu çalışmada, sıcaklık ve yağışın kayısı verimliliği üzerindeki etkisi bulanık mantık modeli kullanılarak incelenmiştir. Malatya hava koşullarının kayısı verimliliğindeki artışın modellenmesindeki etkisini göstermek için bir bulanık mantık modeli geliştirilmiştir. Malatya ili için 1970-2023 yıllarına ait sıcaklık ve yağış verileri girdi, verimlilik ise çıktı olarak Matlab programındaki Bulanık Mantık Araç Kutusu kullanılarak modellenmiştir. İki girdi ve bir çıktıdan oluşan bir model elde edilmiştir. Kurulan model tarafından bulunan değerler gerçek değerler ile karşılaştırılmıştır.

Apricot Productivity Increase Modeling for Malatya Province Using Fuzzy Logic Model

Research Article

Article History:
Received: 27.10.2025
Accepted: 02.03.2026
Published online: 09.09.2026

Keywords:
Apricot productivity
Mathematical modeling
Fuzzy logic

ABSTRACT

In this study, the effect of temperature and precipitation on apricot productivity is investigated using a fuzzy logic model. A fuzzy logic model is developed to show the effect of Malatya weather conditions in modeling the increase in apricot productivity. Temperature and precipitation data for the years 1970–2023, for Malatya province, are modeled as inputs and productivity as outputs using the Fuzzy Logic Toolbox in the Matlab program. A model with two inputs and one output is obtained. The values found by the established model are compared with the real values.

To Cite: Şahiner A., Değirmenci P., Yılmaz N. Apricot Productivity Increase Modeling for Malatya Province Using Fuzzy Logic Model. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2026; 9(4): 2290-2300.

1. Introduction

In climate conditions, land agreements allow many plants and fruits to be grown efficiently. Apricot fruits, which cover a wide area from its homeland Turkestan to Western China, are one of them (Asma, 2000). Although apricot production is mostly concentrated along the Mediterranean coast in the world, large amounts are also made in Asia and Europe. With an annual fresh apricot production capacity of 500-850 thousand tons, it ranks first in the world and meets %23 of the total production as fresh and %63 as dried apricots (Akın and Aygül, 2022). Turkey is the first in the world in fresh apricot production.

In Turkey, where approximately %10-15 of the world's fresh apricot production is made, apricots are produced as fresh and dried. %80 of the apricots in Turkey are produced in Malatya. The majority of the apricots in Malatya are dried and the Malatya region meets approximately %85-90 of the world's dried apricot production. The low annual rainfall and high summer temperatures cause severe drought. The scarcity of spring water in the basin and the inefficient use of existing water have caused irrigation problems in agriculture. The inadequacy of rainfall and irrigation has forced the people living in the basin to turn to fruit growing. This necessity has placed Malatya province and its surroundings in the first place in the world in apricot production (Sunkar and Hatun, 2010). For this reason, Malatya is the country where the highest apricot production is carried out in Turkey and the world, and it is also noteworthy that it is used in products such as fruit leather and jam. This situation provides income from agricultural production in Malatya (Ministry of Agriculture and Forest, 2026). However, harvest time losses also occur in apricots from time to time due to frost, temperature and rainfall. The coefficient of variation for apricot yield was found to be %43.72 in the period 1991-2007. This shows that the yield risk is high in the relevant period. The "Apricot Research Report" was prepared by the Fırat Development Agency in 2010. This report states that apricot trees were damaged due to severe winter or spring frosts in 1936, 1941, 1944 and 1951, when extreme climate conditions were experienced, and that Malatya apricot production was negatively affected. It states that farmers who were damaged by frost in the early 1960s uprooted their apricot trees and planted apple saplings instead or returned to vegetable farming; and that as a result of the increase in dried apricot exports and economic importance from the 1970's onwards, a tendency towards apricot production began again. While the report touches upon many problems related to apricot production, the impact of climate change on apricot production and the economy is not mentioned (Ünal, 2010). When the effects of temperature and precipitation values on apricot yield were examined, it was observed that precipitation during the flowering period had a positive effect on apricot yield, while humidity and minimum temperatures had a negative effect. It was determined that high temperatures at the planting time for apricot trees also had a negative effect on yield (Güleryüz and Bolat, 1992; Çukur and Saner, 2008; Gündüz, 2015; Balcıoğlu et al., 2022).

This study, which was conducted to increase apricot productivity, was inspired by some studies using fuzzy logic and modern techniques (Sahiner et al., 2014; Sahiner et al., 2015; Şahiner et al., 2016; Sahiner, 2018). In this article, fuzzy logic modeling was used to estimate apricot productivity. Using fuzzy logic modeling, it was tried to estimate which temperature and rainfall range would give the best apricot yield.

2. Material and Methods

Fuzzy Logic Toolbox is based on fuzzy sets and subsets. According to classical set theory, there are only two options for any object: either it is inside the set or it is completely outside it. Mathematically, this is expressed as "1" (element) or "0" (not an element) in terms of the object's relationship to the set (Zadeh, 1965). Fuzzy logic generalizes classical set theory by eliminating this strict distinction.

Definition 1: If X is a collection of objects denoted by x, then a fuzzy set A in X is a set of ordered pairs

$$A = \{(x, \mu_A(x)) : x \in X\}.$$

where $\mu_A(x)$ is a membership function and it takes values between 0 and 1.

Definition 2: Let A be a subset of X. The support of A is denoted by $supp(A)$ and is a strict subset consisting of all elements with positive $\mu_A(x)$ for all $x \in X$ with degree of membership greater than zero in A:

$$supp(A) = \{x \in X : \mu_A(x) > 0\}.$$

Definition 3: Let A and B are fuzzy subsets of a classical set. We say that A is a subset of B if $A(t) \leq B(t)$ for all $t \in X$.

Definition 4: Fuzzy sets that contain at least one element with a membership degree of 1 are defined as normal fuzzy sets.

When a fuzzy set does not contain any element with a membership degree equal to 1, it is considered non-normal. To normalize such a set:

$$\frac{\mu_A(x)}{max\, \mu_A(x)}$$

is used to.

Definition 5: (Savas, 2004) A fuzzy set is called a fuzzy number if the following properties hold:

- The fuzzy set A is normal.
- The fuzzy set A is convex, i.e.

  $$\mu_A(\lambda x_1 + (1-\lambda)x_2) \geq \mu_A(x_1) \wedge \mu_A(x_2) \qquad \forall x_1, x_2 \in \mathbb{R}, \quad \lambda \in [0,1],$$

- μ_A isuppersemi-continuous,
  - $supp(A)$ is limited, where $supp(A) = cl(\{x \in X : \mu_A(x) > 0\})$ and cl indicates the closure operator

Definition 6: The core of a fuzzy number A is the set of all points that surely belong to A , i.e

$$core(A) = \{x \in R : \mu_A(x) = 1\}$$

We will now define various operations on fuzzy sets:

Definition 7: The membership function of the intersection of two fuzzy sets and is defined as:

$$\mu_{A \cap B}(x) = min(\mu_A(x), \mu_B(x)), \quad \forall\, x \in X$$

Definition 8: For the union, the membership function is defined as:

$$\mu_{A \cup B}\,(x) = max(\,\mu_A(x), \mu_B(x))\ , \forall\, x \in\ X$$

Definition 9: For the complement, the membership function is defined as:

$$\mu_A(x) = 1 - \mu_A(x), \quad \forall x \in X$$

The Mamdani and Takagi-Sugeno models are the two most famous ways to use fuzzy inference. Both of these Fuzzy Inference Systems have been proposed at various times, but there is no conclusive evidence to prove that one is superior to the other. The Takagi-Sugeno model is fast and works well

with linear control methods because its outputs are functional, but it doesn't always have the intuitive interpretability that is needed for making complicated decisions. On the other hand, the Mamdani approach uses linguistic fuzzy sets for both the "if" and "then" parts of the rules. This feature makes it more like how people think and keeps the system's semantic meaning (Mamdani, 1974; Mamdani and Assilian, 1975; Sugeno and Takagi, 1983; Takagi and Sugeno, 1985). In this study, the Mamdani type fuzzy inference system is used to ensure that the model is easy to understand and effectively incorporates expert knowledge in its structure. Mamdani systems consist of 3 parts. These parts are:

1. **Fuzzification:** It is the conversion of clear data into fuzzy data or Membership Functions
2. **Fuzzy Inference:** Derives the fuzzy output by combining membership functions with control rules.
3. **Defuzzification:** It is a method of converting fuzzy numbers into crisp numbers.

In fuzzy logic, the net values of input and output variables are first converted into fuzzy values. This process is done using membership functions. We employ triangular and trapezoidal membership functions whose graphs are defined as follows between different recording boundaries, such as triangular, trapezoidal, Z-shaped, Gaussian, sigmoidal, and S-shaped. The triangular membership function is defined by

$$\mu(x;a,b,m)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{m-a}, & a<x\le m\\ \dfrac{b-x}{b-m}, & m<x\le b\\ 0, & x>b\end{cases}$$

where a is the lower bound, b is the upper bound and $a<m<b$ and trapezoidal membership function is defined by

$$\mu(x;a,b,c,d)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{b-a}, & a\le x\le b\\ 1, & m\le x\le c\\ \dfrac{d-x}{d-c}, & c\le x\le d\\ 0, & x>d\end{cases}$$

where $a<b<c<d$ where is the lower limit, d is the upper limit and b and c are the values in between. Within the fuzzy logic framework, the language rules that control the behavior of the system are formulated. These rules specify the relationships between inputs and outputs. Subsequently, the value obtained by aggregating the fuzzy output set is determined. In the final stage of fuzzy logic, fuzzy values are defuzzified into crisp values.

In the present model, the boundaries of the membership functions are determined based on the statistical distribution of the historical data covering the years 1970-2023. The range of values for temperature and precipitation is segmented to ensure that the data density is represented effectively across the linguistic variables. Furthermore, for the defuzzification process the Centroid Method is utilized due to its widespread acceptance and ability to provide smooth control surfaces.

3. Result and Discussion

In the fuzzy logic model, linguistic rules that govern the system's behavior are defined. These rules establish the relationships between inputs and outputs. Subsequently, the value obtained by aggregating the fuzzy output set is calculated. In the final stage of fuzzy logic, fuzzy values are defuzzified into crisp values.

Annual temperature values are measured for Malatya province and the effects of annual precipitation values on apricot change parameters. These data are presented in Table.1 together with apricot differences.

Table 1. Annual data for Temperature, Precipation and Apricot Procutivity.

YEAR	Annual Temperature Values (C)	Annual Precipitation Values (mm)	Apricot Productivity (kg/tree)
1970	14.2	24.4	25
1971	13.2	36.3	27
1972	12.2	31.6	31
1973	12.8	31.6	36
1974	12.8	28.6	35
1975	13.1	24.7	33
1976	12.1	46.5	26
1977	13.4	27	28
1978	13.8	29.2	27
1979	14.4	47.6	30
1980	13.3	35.5	35
1981	14.1	35.4	34
1982	13.2	25.8	56
1983	13	42	62
1984	13.8	32.4	57
1985	13.9	21	61
1986	14.3	35.7	58
1987	13.4	35	49
1988	12.9	49.8	86
1989	14.7	23.1	83
1990	13.9	23.2	34
1991	13.3	28.7	51
1992	11.4	34.8	52
1993	12.4	34.8	28
1994	14.3	28	75
1995	13.8	31.6	35
1996	13.9	36.5	21
1997	12.9	31.7	36
1998	14.5	33.9	73
1999	14.5	21	38
2000	13.5	27.6	72
2001	14.9	26.3	56
2002	13.9	29.2	26
2003	13.9	32.8	46
2004	14.1	30.8	14
2005	14	26.7	78
2006	14.9	29.4	37
2007	14.5	25.6	40
2008	14.5	22.8	53
2009	14.3	29.9	49

2010	16.3	23.9	32
2011	13.9	30.1	59
2012	14.5	33.7	72
2013	14.6	27.4	58
2014	15.7	36.4	5
2015	15.1	30.1	45
2016	15.1	24.6	50
2017	15.1	22.1	88
2018	16.1	39.2	53
2019	15.2	31.8	50
2020	15.7	31.9	45
2021	15.7	11.9	23
2022	15.2	19.6	42
2023	15.1	41.9	41

We create a fuzzy logic model by calling the input variables temperature (s) and precipitation (y) and the output variable efficiency (v). The general structure of the model is shown in Figure 1.

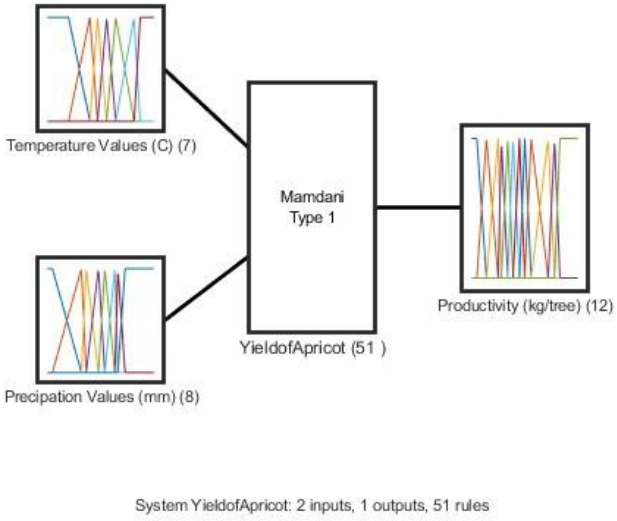


Figure 1. The general structure of the model.

In Fuzzy Logic Toolbox, the scores that can be obtained from the membership functions temperature are divided categorized into seven distinct groups. Scores within the range of 10 to 12.8 are categorized as s1, scores within the range of 11 and 13.3 as s2, scores within the range of 12.8 and 13.9 as s3, scores between 13.3 and 14.5 as s4, scores between 13.9 and 15.7 as s5, scores between 14.5 and 16.1 as s6, and scores between 15.7 and 17 as s7. The results are shown in Figure 2.

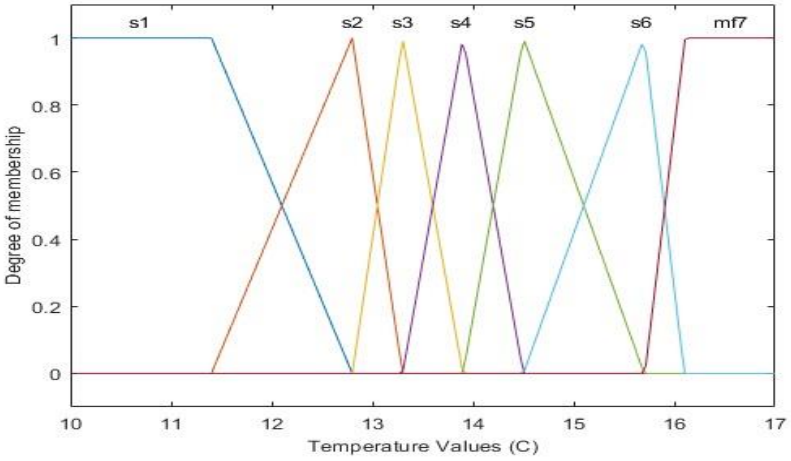


Figure 2. Membership functions of Temperature values.

Membership functions in the Fuzzy Logic Toolbox are classified into eight categories using precipitation data. Scores in the range of 10 to 22.8 are categorized as y1, and scores in the range of 11.8 to 24 are categorized as y2, scores between 22.8 and 29.5 as y3, scores between 24.5 and 31.6 as y4, scores between 29.5 and 35.4 as y5, scores between 31.6 and 36.5 as y6, scores between 35.4 and 39.2 as y7, and scores between 36.5 and 50 as y8. The results are shown in Figure 3

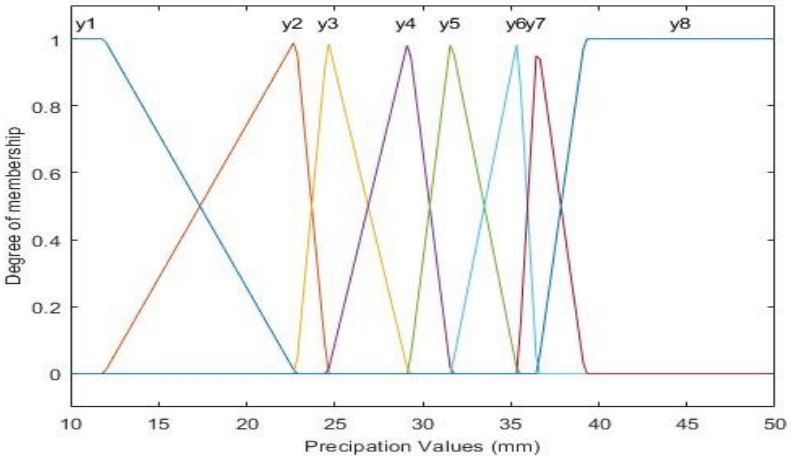


Figure 3. Membership functions of Precipitation values.

In Fuzzy Logic, the scores obtained from the recording capacity are divided into two categories. Scores within the range of 0 to 14 are categorized as v1, scores between 5 and 25 as v2, and scores from 14 to 28 as v3, scores between 25 and 34 as v4, scores between 28 and 39 as v5, scores between 34 and 45 as v6, scores between 38 and 50 as v7, scores between 45 and 56 as v8, scores between 50 and 72 as v9, scores between 56 and 78 as v10, scores between 72 and 80 as v11, and scores between 78 and 100 as v12. The results are presented in Figure 4.

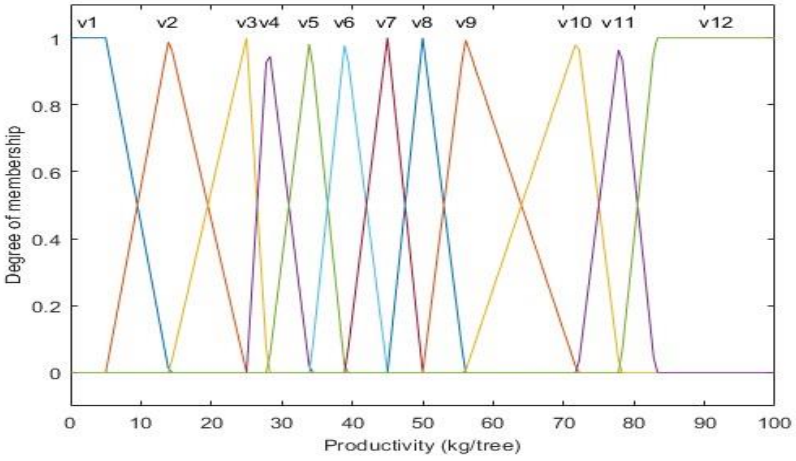


Figure 4. Membership functions of Productivity.

The fuzzy rule base is constructed using a data-driven approach derived directly from the historical observation data provided in Table 1. Each year's record constitutes a potential rule. For example, considering the data for a specific year where the temperature is high and precipitation is moderate, the corresponding realized productivity level determines the consequent part of the IF-THEN rule. This ensures that the expert system reflects the actual climatic impacts observed in Malatya over the last 53 years. Therefore, some of the rules used in the fuzzy logic model are:

1. If (Temperature Values is s4) and (Precipitation Values is y3) then (Apricot Productivity is v3)
2. If (Temperature Values is s2) and (Precipitation Values is y7) then (Apricot Productivity is v4)
3. If (Temperature Values is s1) and (Precipitation Values is y5) then (Apricot Productivity is v4)
4. If (Temperature Values is s3) and (Precipitation Values is y5) then (Apricot Productivity is v6)
5. If (Temperature Values is s3) and (Precipitation Values is y4) then (Apricot Productivity is v6)
6. If (Temperature Values is s2) and (Precipitation Values is y3) then (Apricot Productivity is v5)
7. If (Temperature Values is s1) and (Precipitation Values is y8) then (Apricot Productivity is v3)
8. If (Temperature Values is s3) and (Precipitation Values is y4) then (Apricot Productivity is v4)

According to the created model, apricot productivity surfaces are shown in Figure 5 by simulating the Mamdani method.

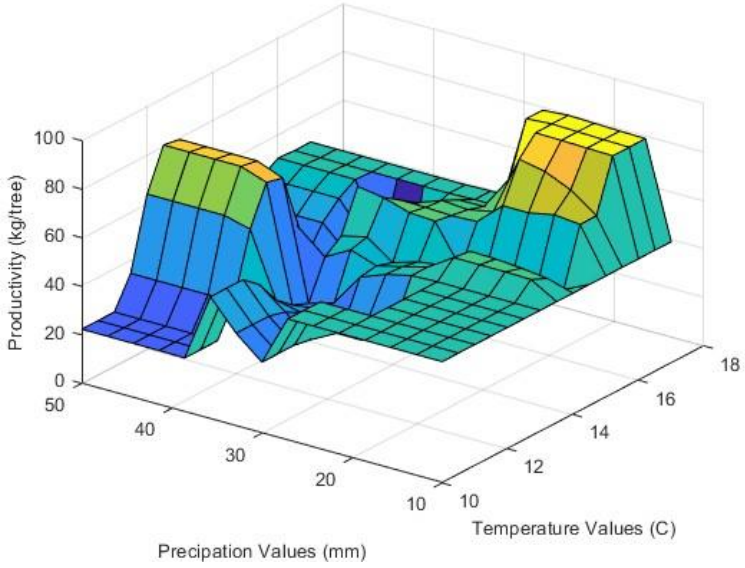


Figure 5. Fuzzy surface of the model.

The correlation coefficient derived from regression analysis indicates an 82% similarity between apricot yield and the fuzzy logic results, as illustrated in Figure 6.

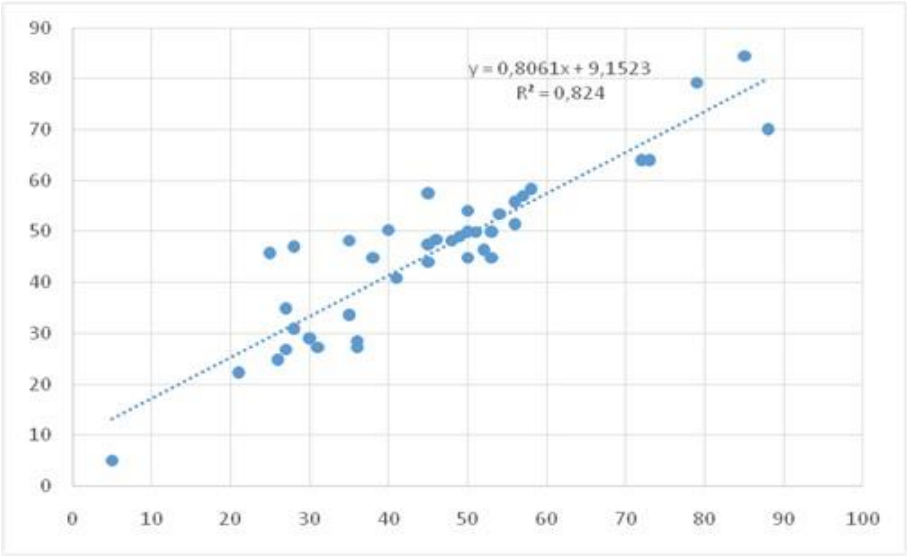


Figure 6. Correlation coefficient between measured and estimated values .

To quantitatively evaluate the performance of the proposed Fuzzy Logic model, statistical error metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2) were calculated. The formulas for these metrics are given as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - yp_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - yp_i|$$

where y_i are measured values and yp_i are estimatited values for $i = 1,2,\ldots,n$. The performance results are summarized in Table 2.

Table 2. The performance results.

Performance Metrics	Values
RMSE	7.2529
MAE	4.7495
R^2	0.824

As seen in Table 2, the high R^2 value and low error rates indicate that the model successfully predicts apricot productivity based on climatic inputs.

4. Conclusion

In this study, apricot yield was analyzed using a fuzzy logic model based on temperature and rainfall rates. The data were obtained by measuring the levels of temperature and rainfall rates and evaluating the apricot yield at the end of the harvest period. Temperature and rainfall rates were defined as input values, while apricot yield was defined as the output value. A system was developed using a fuzzy logic model to model the relationship between the input and output values. The purpose of this model is to explain the relationship between membership functions and to make predictions regarding productivity in apricot production.

As a result of the analyses, it was observed that neither an optimal temperature nor an optimal rainfall rate alone ensures high productivity. It was determined that both temperature and rainfall rates must be at appropriate levels to increase apricot yield. In cases where either temperature or rainfall is unfavorable, a decline in productivity was observed. It was concluded that these two factors must be in harmony for successful apricot production.

As a result of the comparison between real data and model predictions, a correlation coefficient of % 82 was obtained. Consequently, it was concluded that a high level of apricot yield can be achieved when both temperature and rainfall rates are at appropriate levels.

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